A Comprehensive Assessment of Vehicle-to-Grid Systems and Their Impact to the Sustainability of Current Energy and Water Nexus

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A COMPREHENSIVE ASSESSMENT OF VEHICLE-TO-GRID SYSTEMS AND THEIR IMPACT TO THE SUSTAINABILITY OF CURRENT ENERGY AND WATER NEXUS

by

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ABSTRACT

This dissertation aims to explore the feasibility of incorporating electric vehicles into the electric power grid and develop a comprehensive assessment framework to predict and evaluate the life cycle environmental, economic and social impact of the integration of Vehicle-to-Grid systems and the transportation-water-energy nexus. Based on the fact that electric vehicles of different classes have been widely adopted by both fleet operators and individual car owners, the following questions are investigated: 1. Will the life cycle environmental impacts due to vehicle operation be reduced? 2. Will the implementation of Vehicle-to-Grid systems bring environmental and economic benefits? 3. Will there be any form of air emission impact if large amounts of electric vehicles are adopted in a short time? 4. What is the role of the Vehicle-to-Grid system in the transportation-water-energy nexus? To answer these questions: First, the life cycle environmental impacts of medium-duty trucks in commercial delivery fleets are analyzed. Second, the operation mechanism of Vehicle-to-Grid technologies in association with charging and discharging of electric vehicles is researched. Third, the feasible Vehicle-to-Grid system is further studied taking into consideration the spatial and temporal variance as well as other uncertainties within the system. Then, a comparison of greenhouse gas emission mitigation of the Vehicle-to-Grid system and the additional emissions caused by electric vehicle charging through marginal electricity is analyzed. Finally, the impact of the Vehicle-to-Grid system in the transportation-water-energy nexus, and the underlying environmental, economic and social relationships are simulated through system dynamic modeling. The results provide holistic evaluations and spatial and temporal projections of electric vehicles, Vehicle-to-Grid systems, wind power integrations, and the transportation-water-energy nexus.

Dedicated to my family and friends

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1 INTRODUCTION

1.1 The Electrification of the Transportation Sector

The U.S. electricity and transportation sectors are, respectively, the largest and second largest contributors to greenhouse gas (GHG) emissions in the U.S.; altogether accounting for almost 60% of the total U.S. GHG emissions (U.S. EPA, 2015). As industrial and residential energy/fuel needs continue to grow over time, the resulting increase in the consumption of petroleum fuels have led to growing climate change and energy dependency concerns. As a result, although fossil fuels are still the dominant energy source today; clean energy and green transportation have received a great deal of attention in research and industry.

Within the transportations sector, currently there are more than 260 million registered vehicles in the United States; the majority of which are passenger cars and light duty trucks (U.S. Bureau of Transportation Statistics, 2015). Most of the light duty vehicles are powered by gasoline and approximately 23 million are alternative-fuel vehicles (U.S. Energy Information Adiministration, 2017). Hybrid electric vehicles and battery electric vehicles consist of about half of the alternative-fuel vehicle stock. These electric cars or trucks either recapture braking energy or obtain electric power directly from the grid as power source; such technology can increase fuel efficiency reducing the overall fuel consumption.

The largest sources of transportation-related GHG emissions are passenger cars and light-duty trucks. These sources account for over half of the emissions from the transportation sector (U.S. EPA, 2015). Therefore, the electrification of vehicles has been a widely accepted and effective green transportation practice (Hu et al., 2015a; Hu et al., 2013). Electric vehicles (EVs)-including Hybrid Electric Vehicles (HEVs), Battery Electric Vehicles (BEVs) and recently introduced Electric Range Extended Vehicles (EREVs)-have thus been strongly promoted by federal and state governments. The environmental advantage of light-duty EVs is that the electric drive system is especially suitable for driving in congested traffic. From a life cycle perspective, EVs have proven to have significant environmental impact mitigation potential if the local electricity sources are renewable (Onat et al., 2015b).

1.2 Overview of Alternative Vehicles and Infrastructures

Widely adopted alternative-fuel vehicles include natural gas vehicles, hybrid vehicles and battery electric vehicles; due to the difference of the powertrain, these vehicles have different configurations, price, fuel consumptions and impact on the environment. The alternative-fuel vehicle types analyzed in this study are categorized as follows:

Compressed Natural Gas (CNG) Vehicle: usually modified from a conventional gasoline or diesel vehicle. A CNG vehicle is typically not as expensive as other alternative-fuel vehicles and generates less tailpipe emissions. However, the natural gas storage tank are usually very large and may reduce the loading capacity of the vehicle. In addition, in order to maintain a CNG vehicle fleet, the fleet owner might have to construct a natural gas fueling station, which requires a significant amount of initial investment. Liquefied natural gas (LNG) can also be used as fuel and the storage tank is smaller, but the number of LNG fueling stations is even scarcer.

Hybrid Electric Vehicle (HEV): currently the most-adopted hybrid vehicle (i.e. Toyota Prius). HEVs are independent from the grid; the onboard battery allows recapturing of braking power and reuse of stored energy when the vehicle is stopped reducing the demand on the output of the gasoline engine. The conventional gasoline engine reengages when the vehicle needs to reach a higher speed; hence HEVs are well suited for driving in congested urban areas.

Electric Range Extended Vehicle (EREVs): hybrid electric vehicle are equipped with a larger battery that can be charged from the grid therefore permitting the vehicle to be powered by electricity for longer ranges. EREV can also recapture braking energy or use an internal combustion engine (ICE) after the electric range limit has been reached. It uses a 2-Liter engine (which is much smaller than the displacement size of a normal 6 cylinder light truck) to drive the induction motor and provides additional driving power. This "battery-and-generator" combination makes EREVs more effective than ICE trucks in terms of fuel consumption.

Battery Electric Vehicle (BEV): entirely powered by electric, and have the largest battery pack among all electric vehicles. These are also known as All Electric Vehicle (AEV). There is no tailpipe emission during the operation of the vehicle; however, the life cycle air emission depends entirely on the upstream phase. The manufacturing of the battery is also environmentally-intensive.

1.3 Electricity Markets and Vehicle-to-Grid Systems

Electricity is a unique commodity because it can easily go to waste if not stored in the event of a fluctuation between power supply and power demand. Although electricity demand can be predicted on a seasonal or monthly basis, it is virtually impossible in practice to precisely estimate the exact electricity demand of a load zone at a certain time, as electrical loads at businesses and homes are constantly being turned on and off. Therefore, when electricity demand is less than the current electricity generation level, the generated electricity in excess of the energy demand will ultimately be wasted. Electricity technically can be stored during times when energy production from power plants (especially from renewable electricity sources such as wind power, solar power, etc.) exceeds energy consumption, but the current electric power grid has negligible storage capacity (U.S. Energy Information Adiministration, 2000). If the electricity demand surges at a certain time of the day, the extra power required must be generated by turning on or ramping up gas turbine generators (Kempton and Tomić, 2005a). Baseload coal or nuclear power plants are not suitable for such a sudden adjustment requirement, and the frequent turning on and turning off of gas turbine generators leads to a relatively low fuel efficiency.

From the grid operators' perspective, the current electricity market provides four different types of electricity services:

- Baseload power, a.k.a. "bulk" power, is generated most commonly by large coal or nuclear power plants on a round-the-clock basis. It has the lowest electricity unit cost, but the generators commonly take days to start up or shut down, making it practically impossible for them to respond to rapid system fluctuations.
- Peak load power is typically generated by natural gas turbines when high electricity usage is predicted, such as during summer afternoons. Peak power has higher prices in the electricity market and, due to the peak power market's relatively predictable demand pattern, generators can be adjusted in advance to accommodate the additional demands.

In addition to generating baseload and peak power, the grid also needs ancillary services to maintain grid reliability and stability. Two types of ancillary services are spinning reserves and regulation services.

- Spinning reserves mainly provide backup capacity to the grid and stabilize system frequencies in the event of a generator failure or other such emergency.
- Regulation services, namely Automatic Generation Control (AGC) services, serve as grid stabilizers, maintaining system voltages and grid frequencies as needed, which is currently accomplished by ramping up/down the output of the generator in question, in accordance with an ISO's regulation up/down signals.

Regulation services are mainly controlled by Independent System Operators (ISOs) and/or Regional Transmission Organizations (RTOs). These entities are responsible for nondiscriminatory access to electricity transmission within a region, monitoring transmission, and maintaining reliability of the grid. Although they do not own transmission, they help coordinate transmission as well as plan for future transmission needs. They accomplish these objectives through the use of energy, capacity and ancillary services markets. Due to rapid but short demand periods and high electricity unit prices, the ancillary services market requires flexible power supply methods and sources. studies have shown that electricity storage methods such as batteries not only have extremely fast response times, but may also be two to three times as effective as gas turbine generators for grid balancing purposes (Lin, 2011; Makarov et al., 2012).

Currently in the U.S. there are several stationary battery facilities that provide grid stabilizing services, with capacities ranging from 1 MW to 20 MW (Lin, 2011). These high-capacity battery packs usually require an enormous capital investment and are thus far used only for energy storage. However, if the existing U.S. light vehicle fleet were electrified, the resultant total power capacity would be about 24 times more than that of the entire electricity generation system (Kempton and Tomić, 2005b).

Vehicle-to-Grid technology utilizes the existing battery capacity of idle EVs as a means to store electricity and then respond to grid operator request signals on a minute-by-minute basis, making it a great ancillary service option. EV battery capacity is already routinely plugged into the grid for charging, and has significant potential to serve as grid storage and capacity to be used for grid stabilization services. Furthermore, with the introduction of government incentives and reductions in manufacturing costs due to large-scale battery production, EVs are expected to have greater market penetration levels over the next 15 years (Noori and Tatari, 2016). In fact, every major car manufacturer today has already manufactured one or more electric vehicle models with significantly higher fuel economy levels than Internal

Combustion Engine Vehicles (ICEVs). Passenger cars are parked for most of the time in any given day, and even during rush hours in California, only 10% of vehicles are on the road, while the remaining 90% of vehicles are potentially available to the grid (Kempton et al., 2001). For Plug-in Electric Vehicles (PHEVs) and Battery Electric Vehicles (BEVs), given certain upgrades, existing systems are technologically capable of supporting the grid. Therefore, with limited onboard meter and home wiring upgrades, EVs can be used as an ideal grid electricity storage solution.

And from the service carriers' perspective, alternative vehicle technologies, such as BEVs, have the potential to minimize the negative environmental impacts of the transportation sector, but there are several barriers to their widespread adoption, such as high initial cost; lack of a public charging infrastructure network; apprehension about the limited range of EVs; and the long charging times of EVs (Jones and Zoppo, 2014). One potential benefit that could drive adoption in spite of these challenges, is the potential for an electrified vehicle fleet to generate new revenue streams for the businesses and individuals who own alternative fuel vehicles (Onat et al., 2014b). Modeling customer behavior is an important step towards identifying the barriers to widespread adoption of BEVs and developing strategies to harness this technology efficiently. BEVs can serve as a storage system for the electric power grid, termed V2G system, and may create monetary saving opportunities, help widespread adoption of BEVs, and minimize negative environmental impacts of both the energy and transportation sector. In this study, the regional life cycle emissions savings and net revenue of V2G ancillary service (regulation) are explored from a customer perspective.

The power provided by a single vehicle is little more than a noise to the grid (Guille and Gross, 2009), but the combined power of 100 EVs with average power outputs of 15 kW each amounts to approximately 1MW of grid support, which is a typical ancillary service minimum contract amount (Kempton and Tomić, 2005b). The contract for such a V2G ancillary service could be between vehicle drivers and utility companies and/or grid operators, and while V2G services are being provided, each individual driver could preset the upper limit of the electricity that he/she is willing to provide via the service, with the driver receiving compensation and/or rewards for providing both the additional power capacity or capability and the actual energy output.

1.4 Vehicle-to-Grid Systems and the Water-Energy Nexus

Electric power and transportation systems are the most important networks that connect all the functional units in a city. A well-designed transportation system helps people whom are the essential elements of the society to reach their destination or the necessities of life. However, renewable energy sources such as wind or solar are intermittent. Hence a high level of wind or solar power penetration requires a significant amount of ancillary services to stabilize grid fluctuations. On the other hand, massive adoption of electric vehicles may also cause marginal generation which mainly relies on non-renewable energy sources if the charging behavior of electric vehicles are not regulated.

A system which further combines the electric power system and the public or private transportation systems through vehicle-to-grid (V2G), vehicle-to-home (V2H), vehicle-to-building (V2B) and vehicle-to-infrastructure (V2X) system helps integrate all the elements in the gird. These elements include large-scale renewable energy, community-level renewable energy, roof top solar panels, homes, commercial buildings and grid operators, and electric vehicles. Electric vehicles will serve as mobile storage with great flexibility after a certain BEV or HEV market penetration is reached.

Meanwhile, the supply of water and the generation of electric power are heavily interconnected. To achieve an overall improvement in water preservation, GHG emission mitigation and energy consumption reduction, the water-energy nexus must be addressed as a whole. The current U.S. energy generation system relies mostly on coal or natural gas; yet both the extraction of gas process and the operation of thermoelectric plants are water-intensive. The majority of renewable energy sources consisting of biomass relies heavily on water due to crop irrigation. On the other hand, the treatment and the transportation of water consumes a significant amount of water. Furthermore, the structural stability of the water-energy nexus will be challenged because of water demand increases due to residential and agricultural expansion as well as energy consumption and GHG emission caused by transportation.

There are three methods to improve the reliability of the nexus but there is no ultimate solution without any tradeoff:

- Improving the cooling system of thermoelectric power plants (Sovacool and Sovacool, 2009). Advanced power plants with closed-loop may reduce the water withdrawals but may also increase water consumption. And the speed of efficiency improvement could not catch up the growth of electricity demand.
- Reducing peak demand in industrial and residential sector (Sovacool and Sovacool, 2009). By doing so, the inefficient operation of combustion turbines could be mitigated. However, such method requires cooperation from the industry and a well-established smart grid system.
- Deploying renewable energy. Florida has good solar and offshore wind power potential, and these power sources have limited or zero carbon and water footprint. However, wind and solar are intermittent, so to balance the fluctuations of different time intervals ancillary services which rely on low-efficiency combustion turbine have to be purchased.

V2G technologies provide solutions to two of the aforementioned tradeoffs. It utilize the battery capacity as grid storage methods which have been proven to be two to three times more efficient than combustion turbines (Lin, 2011). With the help of bidirectional chargers, the owner of the EV could plug their vehicle into the grid and provide power capacity services to the grid operators in exchange for financial benefits. And with the extra storage capacity online, significantly more wind and solar energy can be balanced and stored, making renewable energy more cost-effective. Hence the entire electricity mix could be "cleaner" in terms of energy and water consumption. Furthermore, as the smart grid being implemented, residential or commercial electricity users can choose to avoid the electricity usage peak or even supply a certain amount of energy back to the grid through their EVs or battery units so that the peak of the grid could be "shaved".

1.5 Problem Statement and Research Objectives

To fully understand the feasibility and potential outcomes of integrating EVs into the water-energy nexus, the following questions should be investigated:

1. Although hybrid or battery electric vehicles can effectively reduce tailpipe emissions, will the life cycle environmental impact be reduced given various electric power source percentage? And what's the impact comparison between EVs and other alternative technologies?

2. With the consideration of energy loss and battery pack replacement, will the implementation of V2G systems mitigate the overall GHG emissions and create revenue for EV owners?

3. Will there be any form of air emission impact if large amount of electric vehicles being adopted in a short amount of time? Will the unregulated charging of EVs generate significant amount of emissions?

4. Taking the spatial electricity market variance and future clean energy integration plan into

account, will V2G systems provide sufficient storage capacity to the grid and facilitate the integration of more clean energy?

5. What is the role of future V2G systems in the water-energy nexus, what are the interactions between V2G systems and other social and economic aspects, and will it facilitate the optimization of the current energy structure with the consideration of its economic and social impacts?

6. What are the other underlying relationships that may affect the transportation-energy-water network? Taking the uncertainties into consideration, will the V2G system as a connection between the transportation and energy systems have positive influences?

To answer these questions, a series of studies from an individual vehicle level to a water-energy system level are conducted in this dissertation. In Chapter 2, the alternative fuel options of medium-duty trucks in commercial delivery fleets, which are most likely the first carriers of V2G technologies, are analyzed; and their life cycle environmental impacts are evaluated in different regions of the U.S. In Chapter 3, the operation mechanism of V2G technologies in association with the charging and discharging of electric vehicles are researched; and the life cycle greenhouse gas emissions of this system are calculated based on various grid fluctuation and vehicle battery degradation scenarios to assess the feasibility of the V2G system. In Chapter 4, the spatial and temporal variance and system uncertainties of the feasible Vehicle-to-Grid system is further studied; the projection of the future emission mitigation is also included in this phase. In Chapter 5, based on the assumption that V2G systems are utilized to provide ancillary service for newly integrated wind power, the comparison of greenhouse gas emission mitigation of the V2G systems and the additional emissions caused by electric vehicle marginal charging is studied. In Chapter 6, the research scope is further expanded to explore the impact of V2G systems in the water-energy nexus, and the environmental, economic and social networks are simulated through system dynamic modeling. As a further development of Chapter 5, the system dynamics model is consolidated, and incorporated with an uncertainty analysis to predict the impacts of the V2G system to the future transportation-energy-water network.

The six research objectives from Chapter 2 to Chapter 7 expands from one vehicle to a multi-system nexus with the consideration of social, environmental and economic factors. Figure 1 depicts the flow of study and methodologies of each research phase.

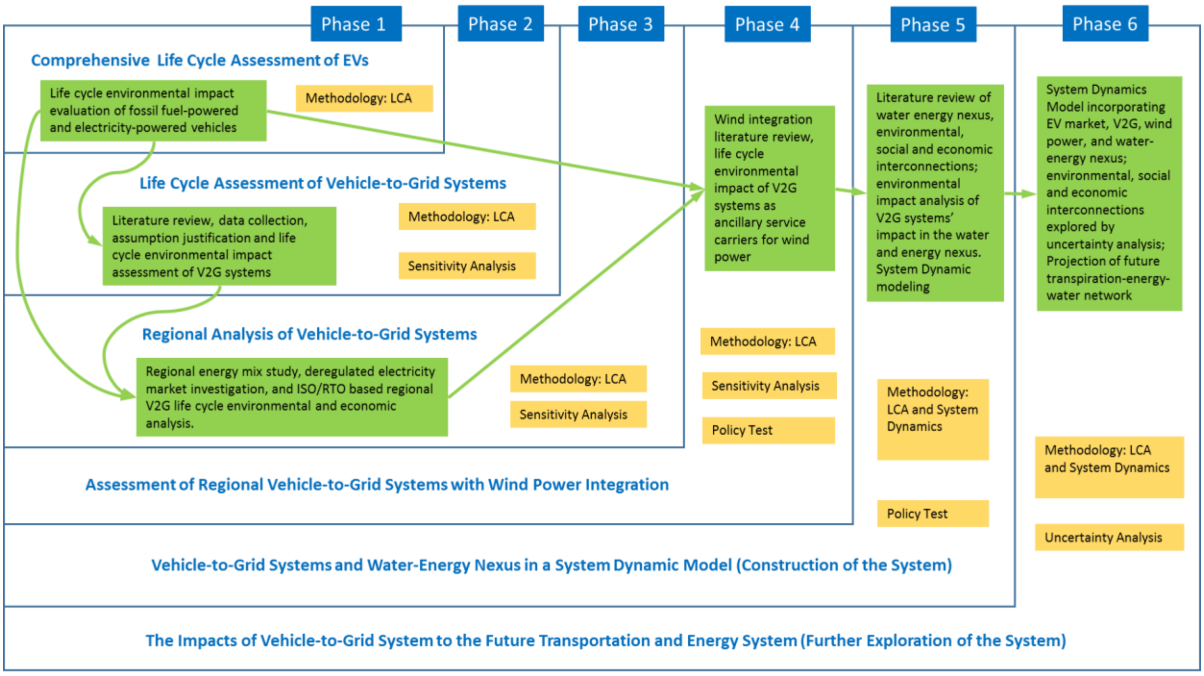


Figure 1 Hierarchical relationships and methodologies of the research objectives

The schedule of study including the tasks in each phase are shown in Table 1.

Table 1 Research schedule

Phases	Research Objectives	Spring 2015	Summer 2015	Fall 2015	Spring 2016	Summer 2016	Fall 2016	Spring 2017	Summer 2017	Fall 2017
Phase 1	LCA of medium duty delivery trucks									
	Optimization of delivery truck fleet									
	LCA of heavy duty refuse collection truck									
Phase 2	Literature review and preliminary study of V2G systems									
Phase 3	Regional study of V2G-Cars									
	Regional study of V2G-Delivery Trucks									
Phase 4	Literature review and preliminary LCA study of V2G-Wind power integrations									
	Policy analysis of V2G-Wind power integrations through ABM									
Phase 5	Literature review and preliminary study of the role of V2G systems in a Water-Energy nexus **(Candidacy Exam in April)**									
	Expanding the V2G-Water-Energy nexus to a comprehensive policy testing tool									
	Dissertation Format Review **(By the end of Sep)**									
	Dissertation Defense **(By the end of Oct)**									
	Dissertation Final Submission **(By the beginning of Nov)**									

2 *HYBRID MULTI-REGIONAL INPUT-OUTPUT LIFE CYCLE ASSESSMENT OF ELECTRIC DELIVERY TRUCKS*

A partial work of this chapter has been published in the Journal of Transportation Research Part D: Transport and Environment with the title of *"Carbon and energy footprints of electric delivery trucks: A hybrid multi-regional input-output life cycle assessment"* (Zhao et al., 2016b)

Due to frequent stop-and-go operation and long idling periods when driving in congested urban areas, the electrification of commercial delivery trucks has become an interesting topic nationwide. In this study, environmental impacts of various alternative delivery trucks including battery electric, diesel, diesel-electric hybrid, and compressed natural gas trucks are analyzed. A novel life cycle assessment method, an environmentally-extended multi-region input-output analysis, is utilized to calculate energy and carbon footprints throughout the supply chain of alternative delivery trucks. The uncertainties due to fuel consumption or other key parameter variations in real life, data ranges are taken into consideration using a Monte Carlo simulation. Furthermore, variations in regional electricity mix greenhouse gas emission are also considered to present a region-specific assessment for each vehicle type. According to the analysis results, although the battery electric delivery trucks have zero tailpipe emission, electric trucks are not expected to have lower environmental impacts compared to other alternatives. On average, the electric trucks have slightly more greenhouse emissions and energy consumption than those of other trucks. The regional analysis also indicates that the percentage of cleaner power sources in the electricity mix plays an important role in the life cycle greenhouse gas emission impacts of electric trucks.

2.1 Electric Delivery Truck Introduction and Literature Review

By the year 2015, there were 260 million registered vehicles in the US, more than 20% of which are pickup trucks or step vans (Hedges & Company, 2015), and the average fuel economy of these trucks is 10 mile per gallon (MPG). The low fuel economy is because these Class 3 to Class 6 trucks operate on lower speed urban roads in stop-and-go traffic and have significantly longer idling times than trucks of other sizes. Consequently, 21.1%-34.1% of the total fuel consumption was used during non-productive moments because of the relatively long idling time (Gaines et al., 2006). A study from the National Academy of Sciences showed that the Fuel Consumption Reduction Potential of a “class 6 box truck” is 47% (National Research Council, 2010). And with the great potential of fuel saving, the National Highway Traffic Safety Administration (NHTSA) set a standard for diverse truck fleets to reduce fuel consumption and GHG emissions from delivery trucks by 10% by model year 2018 (The White House, 2014). Therefore, due to their operation feature and environmental impact reduction potential, medium duty urban commercial (parcel) delivery trucks are considered as suitable applications for alternative fuel types.

In addition to conventional diesel delivery trucks, trucks using alternative fuels can also be utilized to reduce environmental impacts; given the long idling time and frequent stop-and-go driving patterns, a diesel electric hybrid vehicle might be a good solution because of its braking regeneration feature. The National Renewable Energy Laboratory (NREL) has conducted a 36-month evaluation of United Parcel Service (UPS) Diesel hybrid-electric delivery vans (Lammert and Walkowicz, 2012). Compressed natural gas (CNG) vehicles also have their own advantages, such as limited cost of conversion from existing diesel-powered trucks and low CNG fuel prices The CNG delivery trucks have been tested in the NREL truck evaluation project (Chandler et al., 2002). Finally, the most widely discussed and tested vehicle type is the plug-in all-electric vehicle. Companies like FedEx, Staples, and Frito Lay all have cooperated with NREL and evaluated pure electric vehicles like Navistar (National Renewable Energy Laboratory, 2014a) and Smith Newton since 2009 (National Renewable Energy Laboratory, 2014b). The electrification of delivery trucks has unique advantages, first, that truck drivers do not have “range anxiety” as personal electric car drivers because of the fixed driving routine, and second, that a large fleet size of electric vehicles makes centralized charging stations available, reducing overall charging cost through charging schedule optimization or vehicle-to-grid (V2G) services.

Regarding commercial delivery trucks, research has been conducted focusing on comprehensive analyses of life cycle ownership cost minimization, electric vehicle range, fleet size, and energy consumption (Davis and Figliozzi, 2013). There is also a study available about fleet replacement strategies based on the purchase prices and maintenance costs of Lithium battery trucks and conventional trucks (Feng and Figliozzi, 2013). A Life Cycle Assessment (LCA) of batteries and diesel trucks has also been studied with respect to energy, GHG emissions, and cost effectiveness (Lee et al., 2013a). However, there is no study available in current literature that involves a comparative input-output LCA among diesel, hybrid, CNG, and battery electric delivery trucks. Furthermore, previous studies are conducted mainly based on a 2002 EIO-LCA model, which may not be able to reflect the environmental impacts of current industrial sectors. In this regard, This study is conducted based on an environmentally-extended multi-region hybrid LCA, and the life-cycle (both upstream/indirect and downstream/direct) environmental impacts of conventional diesel trucks, diesel-electric hybrid trucks, CNG trucks, and two types of plug in electric trucks are evaluated to provide answers and insights to the following questions:

- Considering all life cycle phases and the entire supply chain, which has a better environmental performance: a conventional truck, or an alternative-fuel truck?

- Considering how the electricity generation mix makes a significant difference with respect to GHG emissions from region to region, which regions are more suitable for replacing conventional trucks with electric trucks?

- Which alternative-fuel truck has a higher GHG emission reduction and energy saving potential?

2.2 Method

2.2.1 Life cycle assessment

Life Cycle Assessment (LCA) is an established but still evolving technique designed to assess environmental impacts and resource consumption associated with all stages of a product's life cycle from raw material extraction to end-of-life disposal or recycling (Finnveden et al., 2009; Onat et al., 2014a, b). By compiling an inventory of relevant material/energy inputs and environmental releases, LCA can help us to assess a product's life cycle environmental impact by evaluating the potential impact associated with the identified input and output. There are three main LCA methods: Process-based LCA, Input-Output LCA, and Hybrid LCA. Process-based LCA was initially created to capture the life cycle impact of a product from "cradle to grave", but its "holistic" nature is both process based LCA's strength and limitation (Guinée, 2001). Some part of the system has to be cut off or neglected because even the simplest product is produced by an extremely complicated upstream system (Mattila et al., 2010). Input-Output LCA, on the other hand, was used to analyze impacts by categorizing products or services with respect to local industry sectors. Input-Output LCA is able to reflect emissions from the entire supply chain, avoid truncation error, and provide a holistic analysis (Kucukvar et al., 2014a; Kucukvar and Tatari, 2013). However, because of the aggregation of the Input-Output LCA approach, some products or processes with diversity have to be allocated to the same sector. Also, the Input-Output approach can provide information for only typical processes that are well represented by Input-Output categorizes, while all other processes can be modeled via the process-based method (Suh et al., 2004). For example, in this study, the processes of burning fuel are not incorporated in the Input-Output method, and so we need to hybridize the model by including process-based LCA (P-LCA). The Input-Output based LCA models provide a top-down analysis using sectorial monetary transaction matrixes considering complex interactions between the sectors of a single country. Although single-region Input-Output models have been widely used in previous LCA studies for electric vehicles (Onat et al., 2015a; Onat et al., 2015b; Onat et al., 2016b; Onat et al., 2015c), Multi Region Input-Output (MRIO) models represent the state-of-the-art in the estimation of environmental footprint of production at global scale (Feng et al., 2011; Kucukvar et al., 2016; Kucukvar and Samadi, 2015). In a MRIO framework, these flows present the value of imports and exports per country and economic sector. All imports and exports are then merged into one consistent financial accounting framework. This combined inter-industry transaction matrix is linked to primary inputs between economic sectors and final demand categories including household consumption, private fixed investments, and government purchases and investments (Wiedmann, 2009; Wiedmann et al., 2011). Among the MRIO initiatives, the Externality Data and Input-Output Tools for Policy Analysis (EXIOPOL) is one of the most developed MRIO initiatives distinguishing 163 industry sectors and products, and supported by the European Commission under the 6th framework programme for research. This project aims to advance global symmetric MRIO tables for 43 countries including 27 EU member states and 16 other major countries (95% of world economy). The EXIOPOL database includes several environmental and socioeconomic indicators such as global warming potential, total material requirement, land use, water use, employment, external costs, etc. In this paper, a standard MRIO analysis that is extended with greenhouse gas emissions and energy use data is developed. Using the EXIOPOL database, the environmentally-extended multi-region hybrid LCA (EE-MR-HLCA) model that integrate the advantages of both Process-based LCA and EE-MR-HLCA approaches is developed, and these different types of hybrid LCA approaches are well illustrated in literature (Bilec et al., 2006). The hybrid LCA used in this study follows these procedures: First the scope of the life cycle phase of each type of vehicle is defined, and then the cost of each phase is identified and calculated. Life cycle cost data is then used as input data and plugged into an EE-MR-HLCA model (Exiobase 2, 2015). The output was derived in terms of environmental indicators.

2.2.2 Scope of analysis

Figure 2 depicts the flow chart of different life cycle phases utilized for the LCA study, as well as the system scope, which includes the vehicle and battery manufacturing phases, the maintenance/repair phase, the fuel and infrastructure production phases, and the vehicle operation phase. There is no available data for the delivery truck recycling percentage as well as a unified technology of recycling/reusing the vehicle body components or the battery, hence, the end-of-life (EOL) phases of the vehicle and battery are not included in this study. The GHG emissions and energy consumption of vehicle manufacturing, fuel (including diesel, CNG and electricity) production phase, vehicle maintenance phase and charging/refueling infrastructure are evaluated by a 2007 regional EE-MR-HLCA model (Exiobase 2, 2015). However, the manufacturing of high capacity lithium ion battery is environmental intense and cannot be represented by the "primary battery manufacturing" sector in the EE-MR-HLCA model. And as mentioned in Section 2.1, the tailpipe environmental impact is not included by the EE-MR-HLCA model. Therefore, the GHG emission and energy consumption of the vehicle battery manufacturing phase and tailpipe phase are analyzed by process-based LCA, these two phases are further discussed in Section 2.4.1 and Section 2.4.2. The direct and indirect impacts of these phases are evaluated based on 150,000 (15,000 per year) Vehicle Miles of Travel (VMT) for each type of vehicle, the functional unit being the lifetime VMT of the truck.

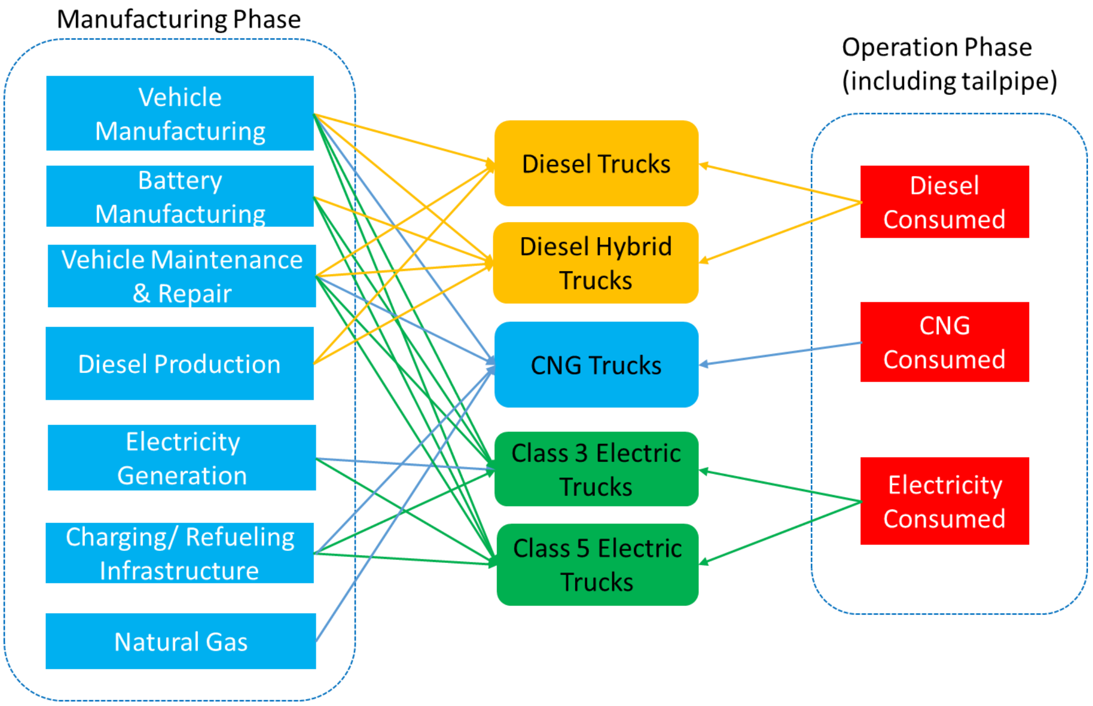


Figure 2 System boundaries

2.2.3 Vehicle characteristics

Table 1 shows the basic features and characteristics of the researched vehicles. The UPS 2006 P70D diesel step van with a freightliner chassis is used as a reference object. It is a class 4 delivery truck with a curb weight of 9,450 lb., a payload of 7,250 lb., and an average diesel fuel efficiency of approximately 10 miles per gallon (Lammert and Walkowicz, 2012). These specific types of diesel truck, as well as other trucks with similar chassis, body and payload design, have been widely used by shipment and logistics departments and companies like UPS and FedEx. Other vehicles of different fuel types were incorporated in the assessment for comparison to conventional diesel delivery trucks. The diesel-electric hybrid truck Freightliner P70D, which has braking regeneration function but a slightly lower Gross Vehicle Weight (GVW), had been tested by the National Renewable Energy Laboratory (NREL) as an alternative-fuel truck option (Lammert and Walkowicz, 2012). It should be noted that this hybrid truck is powered by diesel and has no grid accessibility; hence its battery capacity is fairly small. Since CNG trucks are commonly modified from diesel trucks, they are assumed to have the similar feature as diesel trucks except for the additional natural gas storage tank weight, therefore, the truck curb weight increases to 10,710 lb. and the payload of the truck reduces to approximately 6,000 lb. (Argonne National Laboratory, 2016). The average fuel efficiency of CNG trucks is shown as diesel equivalent in Table 1. For battery electric trucks which are powered purely by the electricity stored in the battery, the class 3 Navistar E-star (E-3) and class 5 Smith Newton (E-5) battery electric delivery trucks are evaluated in this study. The curb weight, payload and fuel efficiency of the two types of electric trucks are concluded from multiple testing results including the evaluations from NREL (Chambers, 2010; National Renewable Energy Laboratory, 2014a, b; Vlack, 2013). These two battery electric trucks are powered by high-capacity lithium ion battery packs which produce significant environmental impacts during manufacturing, the battery-related impacts are further discussed in the following section.

Table 2 Basic vehicle characteristics

Fuel Type	Diesel	Diesel Electric Hybrid	CNG	Class 3 Battery Electric	Class 5 Battery Electric
Weight Class	4 or 5	3 or 4	4	3	5
Curb Weight (lb.)	9,450	9,450	10,710	7,700	9,700
Payload (lb.)	7,250	7,000	5,990	4,000	12,324
Average Fuel Economy	10.73 MPG	13.01 MPG	8.62 (MPG Equivalent)	0.91 (KWh/mile)	1.93 (KWh/mile)
Battery Capacity (KWh)	-	1.80	-	80	100
Battery Weight (lb.)	-	-	-	1,357	1,696

* Truck Make, Model and Year: Diesel (Freightliner P700 UPS Delivery Truck, year 2006), hybrid (Freightliner P70H UPS Low Emission Hybrid Delivery Truck, year 2007), CNG (Grumman Olson UPS CNG Truck, year 1997), E-3 (Navistar E-Star FedEx Class 3 Step Van, year 2010), E-5 (Smith Newton Class 5 Truck, year 2006)

2.3 Life cycle inventory, parameters and assumptions

For all of the trucks researched, each truck's components and life cycle phases are divided into the manufacturing phases, the operation phase, and the charging infrastructure phase as categorized by the sectors of Environmentally Extended Supply and Use/Input Output Database (Exiobase 2, 2015), which are summarized in Table 3. Due to the model year variation of the researched trucks, some of the data is from different years, so the year 2007 was set as the base year and all life cycle monetary value are converted to 2007 US dollars, using the Producer Price Index (PPI) for comparability.

As shown by Table 3, the GHG emissions and energy consumptions of electricity generation, transmission and distribution vary based on the electricity power source. In 2015, 33% of the U.S. electricity generation comes from coal, 33% from natural gas, 20% from nuclear, 6% from hydropower, 1% from petroleum and 7% from renewable energy which consists 1.6% biomass, 0.4% geothermal, 0.6% solar and 4.7% wind power (U.S. Environmental Protection

Agency, 2015c). And the reginal electricity mix varies significantly, some areas rely heavily on coal as energy source (such as Midwestern regions) while some areas have adopted large amount of clean energy (California or northeastern regions). Therefore, two analyses are conducted in this research, the first national analysis is performed based on national electricity mix, and the second analysis is a regional environmental impact comparison that reflects how the electricity mix affects the environmental performance of different types of delivery trucks. As noted before, electric truck battery manufacturing and vehicle tailpipe emissions/energy consumption are not included in the EE-MR-HLCA inventory; they are calculated separately through process-based LCA.

Table 3 Exiobase EE-MR-HLCA multipliers

Life Cycle Phases	Exiobase Sector	CO_2 (metric ton/ per million $)	CH_4 (metric ton/ per million $)	CH_4-CO_2 Equivalent (metric ton/ per million $)	N_2O (metric ton/ per million $)	N_2O CO_2 Equivalent (metric ton/ per million $)	Energy (TJ/per million $)
Electricity Generation, Transmission and Distribution	Production of electricity by coal	24,476.12	0.26	6.56	0.39	117.25	290.82
	Production of electricity by gas	12,014.79	0.22	5.57	0.04	12.11	216.71
	Production of electricity by nuclear	60.71	0.00	0.09	0.00	1.31	320.55
	Production of electricity by hydro	74.79	0.00	0.10	0.01	1.55	9.70
	Production of electricity by wind	76.91	0.00	0.11	0.01	1.60	6.75
	Production of electricity by petroleum	20,266.89	0.75	18.75	0.99	293.67	289.52
	Production of electricity by biomass and waste	7,721.27	9.15	228.67	1.23	365.07	351.65
	Production of electricity by solar photovoltaic	87.87	0.00	0.12	0.01	1.78	6.88
	Production of electricity by Geothermal	82.82	0.00	0.11	0.01	1.70	6.63
	Transmission of electricity	125.96	0.01	0.20	0.01	2.83	5.00
	Distribution and trade of electricity	110.16	0.01	0.18	0.01	2.68	3.33
Vehicle Manufacturing	Manufacturing of motor vehicles, trailers and semi-trailers	488.01	0.02	0.48	0.02	6.93	11.98
CNG Production	Extraction of natural gas and services related to natural gas extraction, excluding surveying	1,044.53	0.03	0.73	0.03	8.04	21.05
Vehicle Maintenance and Repair	Maintenance, repair of motor vehicles, motor vehicles parts	187.86	0.01	0.21	0.01	3.81	5.19
Diesel Production	Extraction of crude petroleum and services related to crude oil extraction, excluding surveying	312.41	0.01	0.34	0.02	5.30	8.27
Charging Infrastructure	Manufacture of electric machinery and apparatus	336.71	0.97	24.20	0.01	3.69	5.76
Refueling Infrastructure	Manufacture of machinery	509.26	1.42	35.41	0.02	5.16	8.43

Table 4 includes the data sources and the assumptions regarding the parameters. The vehicle retail prices are obtained from multiple sources. The price of each vehicle type varies within a certain range, so the retail price is assumed to follow a uniform distribution. The corresponding minimum and maximum value are listed in Table 4. There is no available price data for the CNG truck, however, CNG trucks are often modified from regular trucks and the modification cost is approximately $20,000 for a medium duty delivery truck (Argonne National Laboratory, 2016). Also, because of the CNG truck tested in the literature is a fairly earlier model, it may not reflect the fuel economy of current CNG trucks, to tackle this issue, in addition to the fuel economy data set obtained from the 2002 CNG truck testing report (Chandler et al., 2002), an additional group of data concluded by multiplying the diesel truck fuel economy by 0.9 has also been added to the CNG truck fuel economy distribution calculation. The reason is that the fuel economy (diesel equivalent) of a medium duty CNG truck is approximately 90% of the fuel economy of a regular diesel truck (Argonne National Laboratory, 2015) due to the weight of the additional compressed natural gas tank. It should be noted here that the high capacity battery pack accounts for a fairly large portion of the vehicle price; hence the battery price is excluded from the battery electric vehicle retail price. The environmental impact of battery manufacturing is evaluated by process-based LCA. The maintenance costs are concluded from the tests conducted by NREL in different years, so they are converted to 2007 price through PPI. Based on the testing results, it is assumed that the fuel economy of the trucks follows a normal distribution. The mean and standard deviation are shown in Table 4 as well. With the data provided in Table 4, the purchasing cost, life cycle maintenance cost, battery cost and fuel cost of the researched trucks are prepared for the EE-MR-HLCA calculation

Table 4 Vehicle data source

	Parameters	Unit	Data	Data Source
Diesel Truck	Vehicle retail price	$	Min: 42,864 Max: 65,000	(Argonne National Laboratory, 2016; Lammert and Walkowicz, 2012)
	Maintenance cost	$/mile	0.13	(Lammert and Walkowicz, 2012)
	Fuel economy	mile/gallon	Mean: 10.73 StD: 1.067	(Lammert and Walkowicz, 2012)
Hybrid Truck	Vehicle retail price	$	Min: 60,000 Max: 105,000	(Argonne National Laboratory, 2016; Lammert and Walkowicz, 2012)
	Maintenance cost	$/mile	0.141	(Lammert and Walkowicz, 2012)
	Fuel economy	mile/gallon	Mean: 13.01 StD: 0.577	(Lammert and Walkowicz, 2012)
CNG Truck	Vehicle retail price	$	Min: 62,864 Max: 105,000	(Argonne National Laboratory, 2016)
	Maintenance cost	$/mile	0.0684	(Chandler et al., 2002)
	Fuel economy	mile/gallon (diesel equivalent)	Mean: 8.62 StD: 0.974	(Chandler et al., 2002; Lammert and Walkowicz, 2012)
Class 3 Battery Electric Truck	Vehicle retail price	$	Min: 87,000 Max: 117,000	(Argonne National Laboratory, 2016; Gallo and Tomic, 2013)
	Battery capacity	KWh	80	(National Renewable Energy Laboratory, 2014a)
	Maintenance cost	$/mile	0.072	(Gallo and Tomic, 2013)
	Fuel economy	KWh/mile	Mean: 0.91 StD: 0.09	(National Renewable Energy Laboratory, 2014a)
Class 5 Battery Electric Truck	Vehicle retail price	$	Min: 30,000 Max: 65,000	(Kurczewski, 2011)
	Battery capacity	KWh	100	(National Renewable Energy Laboratory, 2014b)
	Maintenance cost	$/mile	0.0975	(Gallo and Tomic, 2013)
	Fuel economy	KWh/mile	Mean: 1.93 StD: 0.259	(National Renewable Energy Laboratory, 2014b)
Other Parameters	Producer Price Index (PPI)	-	PPI Index from 2001 to 2014	(U.S. Bureau of Labor Statistics, 2001, 2007, 2009, 2013, 2014)
	Specific energy	KWh/kg	0.13	(Argonne National Laboratory, 2016)
	Diesel price	$/gallon	2.40 (federal and state tax excluded)	(U.S. Energy Information Adiministration, 2016b)
	Electricity price	cent/KWh	9.65	(U.S. Energy Information Adiministration, 2014)
	CNG price	$/thousand cf	8.5	(U.S. Energy Information Adiministration, 2012)
	CNG-diesel conversion	cf/gallon diesel	134.65	Converted by heat content
	Battery price	$/KWh	600	(Gallo and Tomic, 2013)

2.3.1 Manufacturing phase

The retail price of each vehicle is converted to the producer price by a retail-manufacturing rate. For diesel, hybrid and CNG trucks, this rate is assumed to be 0.8 (Samaras and Meisterling, 2008). Nevertheless, the retail-manufacturing rate of electric vehicles are assumed to be 0.7 (Rogozhin et al., 2009) because of the higher profit potential. Also, as mentioned before, the main difference between electric vehicles evaluation and non-electric vehicles evaluation is the battery manufacturing phase of the former, so the manufacturing phase consists of both non-battery automobile manufacturing and high-capacity battery making, the latter of which is evaluated by process-based LCA. The process-based LCA data is obtained from the GREET (Argonne National Laboratory, 2015) model, where GHG emissions and energy consumption is assumed to be proportional to the battery capacity/weight. And according to this model, the battery specific energy is assumed to follow a uniform distribution of which the minimum value is 0.106 KWh/kg and the maximum value is 0.133 KWh/kg. The literature indicates that ideally, the battery of an electric truck is supposed to be replaced every 150,000 mile (Electrification Coalition, 2010), however, due to the intensity of the operation, fast charging might be required and hence the battery life is shortened. Therefore, it is assumed that two batteries are needed during the 150,000-mile vehicle life time.

2.3.2 Operation Phase

The operation phase can be divided into two main sectors: the automobile maintenance and repair sector, and the fuel sector. The latter, more specifically, includes diesel production, electric power generation, transmission, and distribution, and natural gas distribution. Furthermore, the fuel sector includes direct and indirect impacts. The indirect impact, also known as the "upstream impact" or "supply chain impact" of the three fuel types, is calculated through a similar method. First the monetary value, or the "Total Fuel cost", was calculated by multiplying the 2007 fuel price (Table 4) by the vehicle's lifetime fuel consumption. After obtaining the monetary values for all fuel types, each value is entered into the Exiobase EE-MR-HLCA model separately. On the other hand, the direct impact consists of tailpipe GHG emissions and energy loss due to the combustion of diesel, natural gas or the consumption of electricity. The direct impacts calculation methods are illustrated in the equations below. Aside from the fuel sector, the lifetime automobile repairing and maintenance cost is derived by multiplying the average life cycle repairing and maintenance cost per mile from NREL evaluation reports by a lifetime VMT of 150,000 miles.

The following equations depict the calculation of overall environmental impacts. First the energy consumption and GHG emissions of the diesel and diesel-electric hybrid vehicle can be calculated by the following equations in the form of "Indirect + direct" (Hendrickson et al., 2006), noting that the hybrid truck studied in this paper is not a plug-in hybrid and therefore does not derive electricity from the grid:

$$GHG\ emission = GHG\ multiplier \times \frac{VMT}{FE} + \frac{VMT \times C_{content}}{FE} \times \frac{44}{12} \quad (1)$$

$$Energy\ Consumption = Energy\ multiplier \times \frac{VMT}{FE} + \frac{VMT \times E_{comb}}{FE} \quad (2)$$

Since there are no tailpipe emissions for battery electric vehicles, the GHG emissions and energy consumption of the two electric vehicles can be obtained from the equations below:

$$GHG\ emission = GHG\ multiplier \times FE' \times VM \quad (3)$$

$$Energy\ consumption = Energy\ multiplier \times FE' \times VMT + FE' \times VMT \times \frac{3.6 \times 10^6}{10^{12}} \quad (4)$$

Where FE is the fuel economy of the diesel, hybrid and CNG truck in MPG, FE' is the fuel economy of the electric truck in KWh/mile, $C_{content}$ is the grams of carbon per gallon of diesel, and E_{cmb} is the energy content of diesel fuel (Hendrickson et al., 2006). One gallon diesel contains 128,700 btu energy and 1 btu equals to 1,055J. EE-MR-HLCA multipliers are derived from the Exiobase model, VMT is assumed to be 150,000 miles, and the parameters of the vehicles are as shown in Table 3 and 4. For the CNG truck, the GHG emission and energy consumption calculation follows Equation (1) and (2) but the $C_{content}$ and E_{cmb} are replaced by the carbon and energy content of natural gas.

2.3.3 Charging and refueling infrastructure

The charging equipment (level 2) cost of battery electric vehicles is assumed to be $7,500 (Gallo and Tomic, 2013), and is categorized as "Miscellaneous electrical equipment manufacturing". And it is assumed that each electric truck requires one charging device.

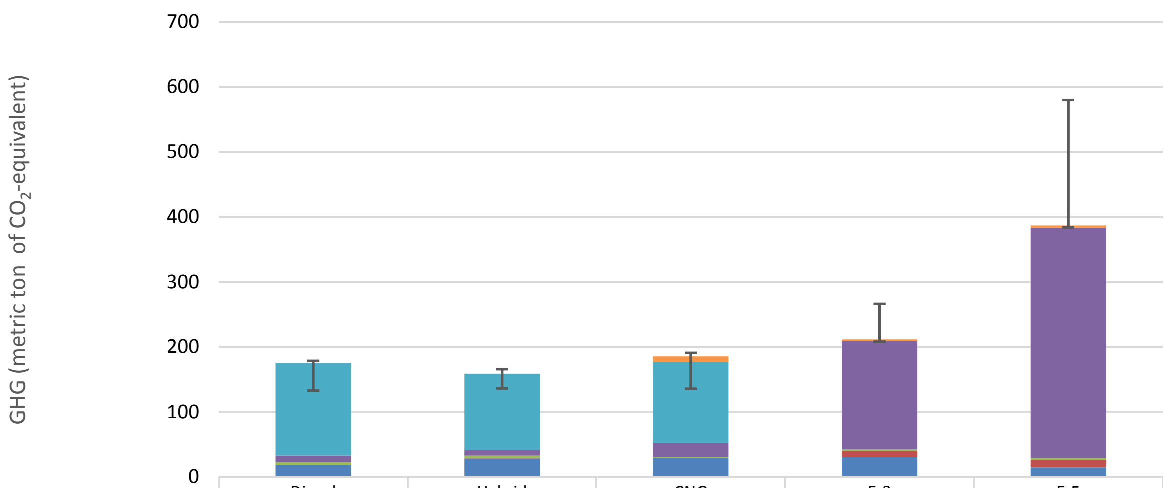
It is assumed that the diesel and hybrid trucks are refueled by existing gas stations, but the operation of a CNG commercial delivery truck fleet requires a new CNG refueling station, which mainly consists of a gas compressor and electronic devices. A typical parcel delivery truck fleet has 20 to 30 trucks, and the CNG refueling station for a truck fleet of such size costs approximately $20,000 ($13,000 for the compressor and $7,000 for the electronic devices) (Gonzales, 2014). And the total cost of the refueling station is distributed to the 30 CNG trucks in the fleet.

2.4 Results

Analysis results are presented in the following subsections based on the environmental impacts of alternative commercial trucks and the comparison of regional GHG emission from each of these trucks. In order to simulate a practical situation and to take uncertainties into consideration, a Monte Carlo Simulation (MCS) method is used in the calculation.

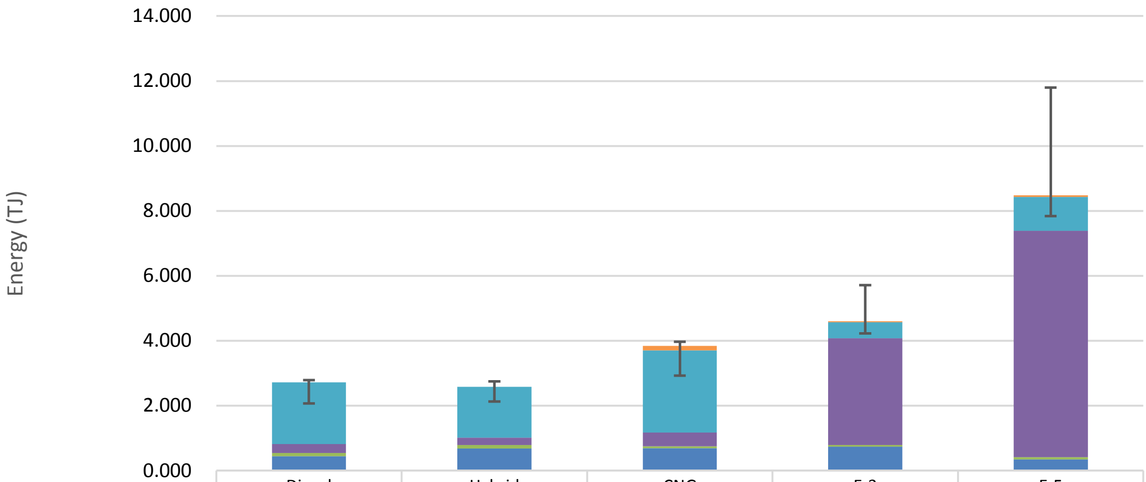
2.4.1 Environmental impacts of commercial electric trucks

This research was first conducted by plugging in mean values for each vehicle's life cycle fuel/electricity consumption, and as shown by Figure 2 and Figure 3, the direct and indirect GHG emissions and energy consumption of the fuel combustion account for the largest portion out of all of the life cycle phases considered. However, due to the significance and large variability of the operation phase, a single-value fuel economy is obviously not sufficient to represent the vehicles' behavior (McCleese and LaPuma, 2002), because in real life, even for vehicles of the same model and year, the diesel or CNG consumption of internal combustion engine vehicles and the electricity usage of electric vehicles varies significantly due to factors such as maintenance, road conditions, and local traffic. Therefore, in this case, a Monte Carlo Simulation is used as a probabilistic method to simulate the vehicles' real world environmental impacts during all the life cycle phases.



	Diesel	Hybrid	CNG	E-3	E-5
Infrastructure	0.00	0.00	8.90	2.21	3.31
Tailpipe	142.40	117.44	124.47	0.00	0.00
Fuel Consumption	10.70	8.82	20.98	167.17	354.55
Maintenace and Repair	3.66	3.96	2.05	1.96	2.65
Battery Manufacturing	0.00	0.21	0.00	9.36	11.71
Vehicle Manufacturing	18.53	28.35	28.84	30.67	14.28

Figure 3 Life cycle GHG emissions of the researched truck types



	Diesel	Hybrid	CNG	E-3	E-5
Infrastructure	0.000	0.000	0.138	0.035	0.052
Tailpipe	1.898	1.565	2.534	0.491	1.042
Fuel Consumption	0.278	0.229	0.419	3.285	6.968
Maintenace and Repair	0.099	0.107	0.056	0.053	0.072
Battery Manufacturing	0.000	0.000	0.000	0.000	0.000
Vehicle Manufacturing	0.448	0.685	0.697	0.742	0.345

Vehicle Manufacturing   Battery Manufacturing   Maintenace and Repair   Fuel Consumption   Tailpipe   Infrastructure

Figure 4 Life cycle energy consumption of the researched truck types

NREL's testing reports included fuel economy data for 11 diesel and hybrid delivery trucks (Lammert and Walkowicz, 2012) and for 12 CNG delivery trucks (Chandler et al., 2002), as well as seven quarters' research for Navistar E-star from July 2012 to June 2014 (National Renewable Energy Laboratory, 2014a) and 11 quarters' research for Smith Newton from November 2011 to June 2014 (National Renewable Energy Laboratory, 2014b). Based on the observation of these data sets, they are assumed to follow a normal distribution, so the mean values and standard deviations are calculated, and used as variables in the Monte Carlo Simulation.

Figure 2 depicts the GHG emission impacts throughout the life cycle phases of all the truck types. Based on the national average electricity mix, although there is no tailpipe emission during the operation phase, battery electric trucks generate more GHG emissions than other trucks from a life cycle perspective. For the electric delivery trucks, the majority of emissions come from the electricity generation phase, in another word, the GHG emissions are moved from tailpipe phase to the power generation phase. By comparing the GHG emission result of diesel, hybrid, CNG and class-3 electric vehicle, it can be concluded that hybrid trucks produce the least GHG emissions. The reason is that the overall fuel economy of the hybrid truck is improved by the braking power regenerating system, but this system does not require a high capacity battery, and no electricity is drawn from the grid, moreover, the manufacturing cost of hybrid trucks is less than that of battery electric trucks. Although the retail price of battery electric trucks is much higher than the price of other types of trucks, the vehicle manufacturing phase has limited impacts comparing to the fuel consumption or tailpipe emission phase. Although the overall fuel cost of CNG trucks are generally considered cheaper than that of diesel fuel, the GHG emission impact at CNG production phase is higher than the emission impact of the diesel production. The CNG refueling infrastructure accounts for a relatively small portion among all the other life cycle phases, but it should be noted here that the impacts are distributed to 30 trucks, so this portion will vary significantly if the fleet size changes. In the meantime, the charging infrastructure impacts of electric trucks are almost negligible. And as shown by the last column of Figure 2, the life cycle emissions of class 5 electric trucks is almost twice as much as the impact of other truck types, the main reason is that the payload of class 5 electric truck has a much larger payload, which leads to more electricity consumption during the operation. The error bars in the figures indicate the uncertainties caused by the manufacturing price difference, fuel economy variations and the uncertainties during battery manufacturing (the uncertainties are shown in Table 4). Based on the Monte Carlo Simulation results, emission impact uncertainties of diesel, CNG and class 3 electric truck are similar, but there is a larger chance for class 3 electric truck to generate more emissions than other types of trucks, it is due to the electricity generation phase has the largest emission impact in the entire life cycle and the electricity generation is environmental-intensive. And also, the class 5 electric truck has the largest uncertainties because of the significant larger electricity consumption.

Figure 3 shows the lifetime energy consumption results for the five types of delivery trucks. The energy consumption performance of all the trucks is similar to the GHG performance with slight differences. The tailpipe phase of diesel, hybrid and CNG trucks and the electricity generation phase of electric trucks are still the dominant phase respectively. However, the influence of vehicle manufacturing phase has increased in terms of energy consumption. The combustion of fossil fuels undoubtedly consumes more energy than the consumption of electricity, but again, the main energy consumption phase for battery electric trucks is the electricity generation phase where the coal or natural gas are consumed to generate electricity. Although there is fairly large amount of GHG emissions produced during battery manufacturing phase, the energy consumption during battery making is negligible.

2.4.2 Regional comparisons of alternative commercial trucks

The GHG emission and energy consumption evaluation are performed based on national average electricity source mix. The environmental performance of battery electric vehicles relies on the source of the electricity (Weber et al., 2010), clean energy such as wind or solar power has very limited life cycle impacts comparing to coal or gas power. Although in most regions the power generation relies heavily on fossil fuel, the GHG emissions of different source varies significantly, i.e. the emission factor of coal is twice as much as that of natural gas (Table 3). On the other hand, although the process of generating electric power from renewable energy (which accounts for a small portion in most regions) consumes very few energy, the energy consumption for other power source are identical, therefore, the energy consumption is not included in the regional analysis. To evaluate the life cycle GHG emissions of battery electric trucks in different regions, the North American Electric Reliability

Corporation (NERC) regional electricity source mix are integrated with the Exiobase EE-MR-HLCA multipliers (Table 5)(U.S. Environmental Protection Agency, 2015a).

Table 5 NERC region electricity source mix and GHG emission multiplier

Electricity source (%)	FRCC	MRO	NPCC	RFC	SERC	SPP	TRE	WECC	EE-MR-HLCA multiplier (metric ton/ per million $)
Coal	19.42	61.26	3.11	48.72	41.11	55.37	30.51	26.19	24,599.9278
Gas	68.06	5.35	48.55	18.02	28.26	30.15	49.05	30.26	12,032.4688
Nuclear	8.46	11.44	29.52	28.77	25.50	3.73	10.67	8.12	62.1023
Hydro	0.07	5.87	11.98	0.70	2.27	1.41	0.11	25.79	76.4366
Wind	0.00	13.84	1.64	1.66	0.24	7.52	8.29	5.20	78.6170
Petroleum	2.13	0.62	1.54	1.19	0.77	0.72	1.15	0.61	20,579.3012
Biomass	1.76	1.60	3.63	0.90	1.84	1.06	0.20	1.32	8,315.0142
Solar	0.09	0.00	0.03	0.04	0.01	0.05	0.03	0.43	89.7780
Geo-thermal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.08	84.6381

* Abbreviations: FRCC (Florida Reliability Coordinating Council), MRO (Midwest Reliability Organization), NPCC (Northeast Power Coordinating Council), RFC (Reliability First Corporation), SERC (SERC Reliability Corporation), SPP (Southwest Power Pool), TRE (Texas Regional Entity), WECC (Western Electricity Coordinating Council)

In addition, the payload of the truck, which is the key determinant of the operation phase emissions, varies for different types of trucks. In order to eliminate the payload difference and to compare the emission when transporting the same amount of cargo, the payload factor is also included. And as noted before, the most commonly used diesel parcel delivery truck which has a 7,250 lb. designed payload is selected as the reference truck for payload adjustment, the payload factors are calculate through dividing the payload of other types of truck by the payload of the diesel truck (Table 6).

Table 6 Payload adjustment

Truck Type	Payload (lb.)	Payload factor
Diesel	7,250	1.00
Hybrid	7,000	1.03
CNG	5,990	1.21
E-3	4,000	1.81
E-5	12,323	0.58

Figures 5 shows the GHG emissions comparison the diesel, hybrid, CNG, and class 3 electric trucks, the latter results shown for each of the eight NERC regions based on electricity generation companies, and all the emission data are adjusted based on payload factors, in another word, the comparison is made based on the assumption that the trucks are at the same payload level. As shown in Figure 5, the electric truck GHG emissions in all the regions exceed the GHG emissions of diesel, hybrid and CNG trucks. This means that, it is possible for the class 3 electric trucks to generate less GHG emissions than diesel or CNG trucks (Figure 2) if the payload factor is not taken into consideration, however, when operating with the same amount of payload, class 3 electric produce more emissions in any region. Also, in regions like SPP (Southwest Power Pool) and MRO (Midwest Reliability Organization) where over half of the electric power generated from burning coal, the operation of electric trucks lead to the most severe GHG emission impact. The NPCC region (Northeast Power Coordinating Council), in which the electric truck had the best performance out of all eight regions, uses a variety of cleaner power sources, such as hydraulic power, nuclear power, and natural gas. This also indicates that the electricity generation phase is the most influential part for electric trucks among all the other life cycle phases, and hence a clean electricity mix is crucial to GHG emission mitigation. Figure 6 represents the class 5 electric truck's regional performance compared to that of other truck types. After the payload factor adjustment, the class 5 electric truck has overall better performance than the class 3 truck, because the size and payload of the class 5 electric truck are both higher than that of the class 3 electric truck, thereby the electricity consumption of transporting per unit weight of cargo is lower. However, fossil fuel trucks still outperform electric trucks in most regions, and similar to the result of class 3 electric truck regional comparison, the GHG emission mitigation can only be achieved in regions where clean or low emission energy is in dominant position.

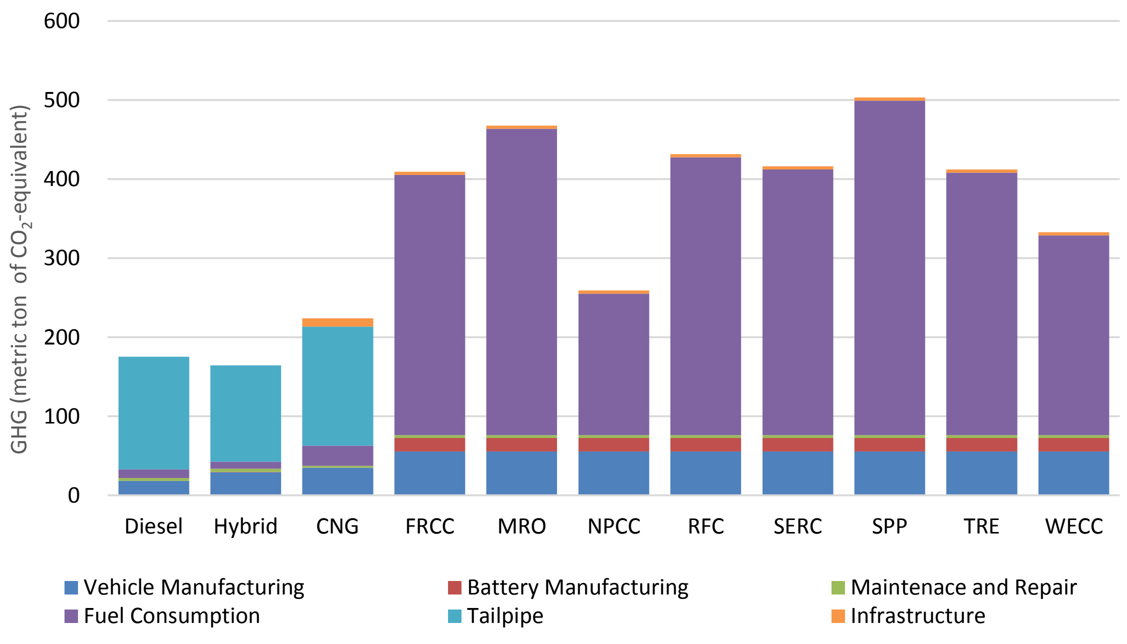


Figure 5 Class 3 electric truck regional performance comparison

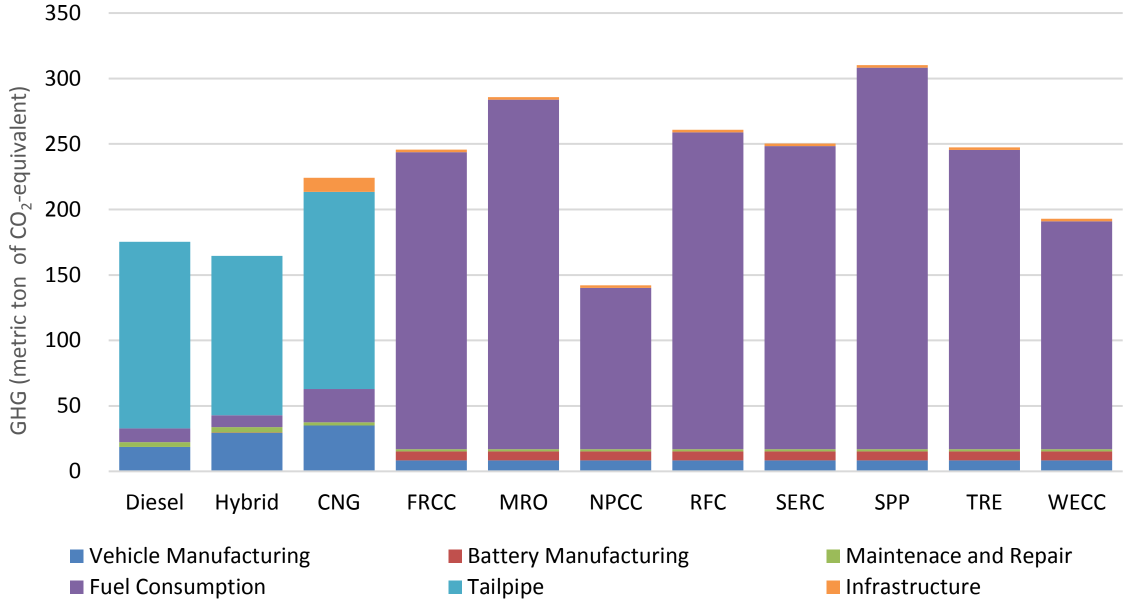


Figure 6 Class 5 electric truck regional performance comparison

3 *HYBRID LIFE CYCLE ASSESSMENT OF THE VEHICLE-TO-GRID APPLICATION IN LIGHT DUTY COMMERICAL FLEET*

A partial work of this chapter has been published in the journal of Energy with the title of *“A hybrid life cycle assessment of the vehicle-to-grid application in light duty commercial fleet”* (Zhao and Tatari, 2015)

The Vehicle-to-Grid system is an approach utilizing the idle battery capacity of electric vehicles while they are parked to provide supplementary energy to the power grid. As electrification continues in light duty vehicle fleets, the application of Vehicle-to-Grid systems for commercial delivery truck fleets can provide extra revenue for fleet owners, and also has significant potential for reducing Greenhouse Gas emissions from the electricity generation sector. In this study, an economic input-output based hybrid life cycle assessment is conducted to analyze the potential Greenhouse Gas emissions emission savings from the use of the Vehicle-to-Grid system, as well as the possible emission impacts caused by battery degradation. A Monte Carlo simulation is performed to address the uncertainties that lie in the electricity exchange amount of the Vehicle-to-Grid service as well as the battery life of the electric vehicles. The results of this study show that extended range electric vehicles and battery electric vehicles are both viable regulation service providers for saving Greenhouse Gas emissions from electricity generation if the battery wear-out from regulation services is assumed to be minimal, but the Vehicle-to-Grid system becomes less attractive at higher battery degradation levels.

3.1 Introduction and Literature Review

Electricity has a unique nature in that its generation and consumption must take place simultaneously for it to be truly efficient; otherwise, if the demand for electricity is less than its generation level, the abundant electric power generated is ultimately wasted because, aside from the limited power storage of hydroelectric pumps, the current power grid has very little storage capacity (U.S. Energy Information Adiministration, 2000). On the other hand, extra electricity must be generated on short notice if the peak hour demand exceeds scheduled generation; this is now mainly accomplished by turning large generators on and off to meet the fluctuating end user load (Kempton and Tomić, 2005a). Nevertheless, studies have revealed that electricity storage methods are not only helpful for smoothing out grid fluctuations in a much shorter response time, but may also be two to three times as effective as a conventional gas turbine for grid supporting purposes (Makarov et al., 2012)

Although electric passenger cars have undoubtedly the largest capacity potential available, the willingness of users to provide Vehicle-to-Grid (V2G) services remains unclear, whereas a small amount of vehicle connection would only add noise to the power grid (Guille and Gross, 2009). Therefore, this study will use commercial delivery fleet vehicles as its research objective, as the operation and/or parking times of such fleet vehicles tend to be more predictable (Tomić and Kempton, 2007). Also, electric truck batteries usually have large capacities, as 18 light trucks with average outputs of 60 kW are able to provide a maximum of 1 MW in electricity support (Hill et al., 2012), which is a typical ancillary service contract's minimum quantity (Kempton and Tomić, 2005b). Based on this data, a fleet of 20 to 30 electric vehicles would have the potential to be an ancillary electricity provider.

Electricity provided by vehicles has been proven to be far less competitive in the base-load market than conventional large-scale power plants, which tend to have lower generation costs (Kempton and Kubo, 2000). Likewise, peak power generation, due to its relatively predictable pattern, can still be achieved by adjusting generator output. Ancillary services, on the other hand, accounted for 5% to 10% of electricity costs (a $12 billion market value), and 80% of this payment is made for spinning reserves and/or regulation services (Letendre and Kempton, 2001). The high electricity unit price and the short but rapid power demand requirements of these ancillary services make V2G a perfect option. However, since spinning reserve services would require the vehicle(s) in question to be plugged in all the time (Hill et al., 2012), which may jeopardize the fleet's normal business operation, this study will only consider the use of the V2G system for regulation services.

Zhang and his colleagues presented the GHG emission impact and charging cost of electric vehicles in different operating conditions, and the "smart grid charging" (providing V2G service) scenario has been proved to be more economically appealing (Zhang et al., 2013). Kempton et al. (2001) conducted a study comparing the availability and capacity of battery electric vehicles (BEVs), hybrid electric vehicles (HEVs) and fuel cell vehicles, as well as the relevant costs of V2G application and the value of the V2G system from the perspectives of utility companies and customers. The fundamental elements of the V2G system have also been researched in two different studies in terms of both market availability (Kempton and Tomić, 2005b) and vehicle owner's revenue (Kempton and Tomić, 2005a), the former of which revealed that V2G technologies are highly suitable for electricity ancillary services (more specifically, regulation services) and also designed and analyzed real life V2G operation strategies and business models. The latter study offered a quantitative understanding of the revenues of various types of vehicles as well as how electric vehicles can be incorporated as part of the grid. Theoretically, BEVs, HEVs and fuel cell vehicles can all be connected to the grid and provide electric power, but only HEVs and BEVs were considered in this study because there is no currently available fuel cell vehicle that has power grid accessibility. Sioshansi and Denholm (2010) simulated the V2G system's ancillary services through a unit commitment model and thereby proved its positive effects to the grid and to vehicle fleet owners, demonstrating that HEVs providing grid supporting services take less time than other vehicle types to repay the initial capital investments.

In addition, an experiment has been performed using a real life HEV for frequency regulation service (Kempton et al., 2008), during which the regulation signal/value and the battery state of charge (SOC) during connection were recorded and analyzed. Guille and Gross (2009) analyzed the features of the V2G system's components and proposed a possible framework based on their analysis, as well as possible V2G implementation procedures. The operational cost as well as benefits of electric vehicles providing V2G services in a smart grid have been analyzed (Kiviluoma and Meibom, 2011). More specifically, an upcoming EREV has been studied in terms of commercial truck fleet owners' economic risks and benefits (Hill et al., 2012), and scenarios are assumed based on the uncertainty of battery regulation cycle lifetimes and the unpredictability of regulation signals. Similarly, the integration of electric commercial fleets to the grid has been proven to be reasonable and profitable (Tomić and Kempton, 2007). The long-term impact to global energy system and electricity market brought by V2G application has been explored and discussed (Turton and Moura, 2008).

In addition to the economic aspects covered previously, the GHG reduction potential of vehicle-to-home (passenger car V2G system) was also studied from a life cycle perspective (Kudoh et al., 2013), while another study calculated GHG emission impacts in the U.S. based on various HEV market penetrations with V2G services (Sioshansi and Denholm, 2009). Battery degradation, as the most important trade off consideration in V2G application, has also been evaluated in multiple studies: Cicconi and his colleagues summarized the lifetime of typical vehicle batteries and presented that second-life batteries can be reused in V2G systems (Cicconi et al., 2012). And the battery degradation caused by V2G service has also been proved to be minimal (Peterson et al., 2010). The aforementioned literature summarized the feasibility of the V2G system and the roles and functions of HEVs or BEVs within the system, as well as the positive economic and environmental effects of fleet-level electricity storage. However, few studies are currently available that have analyzed the GHG emission impacts caused by integrating V2G technology into a commercial delivery truck fleet. To this end, this study will conduct an Input-Output based hybrid life cycle assessment with respect to both EREVs and BEVs, first under a "business as usual" scenario (i.e. without the V2G system included), and a "V2G regulation service" scenario to simulate the impacts of the V2G system.

3.2 Method

3.2.1 Scope of the Analysis

The objectives in this session more specifically pertain to HEVs and BEVs. However, the mass-produced conventional hybrid vehicles have considerably less electric drive power than mechanical power, and have low capacity batteries (1 to 2 kWh) and no connections to the grid, making them far less viable than other electric vehicle types as V2G units in the fleet (Kempton and Tomić, 2005a). On the other hand, EREVs, which have been called the next generation of hybrid vehicles, have much larger battery capacity (40 kWh) and are advertised as having a 100-MPG fuel economy (Razer Technologies, 2009). Hence, EREVs and BEVs have been chosen as the primary research vehicles for this study. According to the scope of the study defined for this study (Figure 7), the life cycle of the electric truck has been divided into two phases:

- The manufacturing phase, which includes vehicle, battery and charging equipment manufacturing, fuel/electricity supply production, and vehicle maintenance, and
- The operation phase, which represents the fuel consumed by the vehicle's onboard

generator and by the ancillary gas turbine generator.

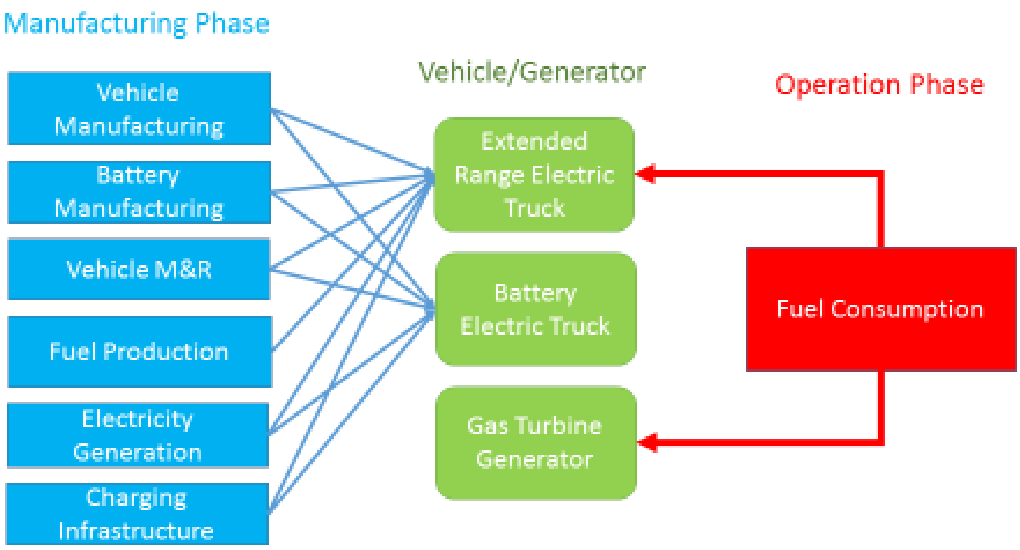


Figure 7 Scope of the analysis

3.2.2 Vehicle characteristics

Class 3 light duty trucks are normally used for commercial delivery duties; operating in heavily congested areas during peak traffic hours, these delivery trucks frequently accelerate and decelerate during operation, and therefore tent to have relatively low fuel economy levels at about 10 MPG on average, making the electrification of light truck fleets an inevitable trend in the automotive industry. Multiple public and/or private electric truck fleets have already been tested, and have proven thus far to have higher fuel economy levels than diesel truck fleets.

Razer Technologies has developed an advanced plug-in drive system that can be applied to a light-duty truck platform (Razer Technologies, 2009); the prototype truck can be powered entirely by its battery for the first 40 miles of travel, which is slightly higher than the typical daily mileage of a delivery truck. Unlike conventional HEVs, which capture braking energy or use an internal combustion engine (ICE) after the electric range limit has been reached, this

EREV uses a 2-Liter engine (which is much smaller than the displacement size of a normal 6 cylinder light truck) to drive the induction motor, and provide additional driving power. This "battery-and-generator" combination makes EREVs much more effective than ICE trucks in terms of fuel consumption. However, the advertised 100-MPG fuel economy of these EREVs is achieved when the vehicle is unloaded (Kilcarr, 2009); the real life fuel economy will be discussed further in Section 3.4.1.

For comparison, the Navistar E-star has been selected as the representative BEV for this study. This all-electric delivery van was first introduced into fleet operations in practice in 2010, and is also advertised to have a diesel-equivalent fuel economy of 100 MPG. The data used in this study for the BEV was obtained from the two-year Navistar E-star performance evaluation conducted by the National Renewable Energy Laboratory (National Renewable Energy Laboratory, 2014a). The general characteristics of these two types of light trucks are summarized in Table 7.

Table 7 EREV and BEV vehicle characteristics

	Extended Range Electric Vehicle	Battery Electric Vehicle
Vehicle Make & Model	RASER PHEV Drive System	Navistar E-star
Curb Weight (lbs.)	5,720.00	7,022.00
Payloads (lbs.)	2,000.00	5,100.00
Battery Capacity (kWh)	40.00	80.00
Fuel Economy (Wh/mile)	843.20	843.20
Vehicle Retail Price (2014$)	70,000.00	150,000.00
Maintenance Cost(2014$)	0.10	0.07
Pure Electric Range(mile)	20.00	40.00
Infrastructure(2014$)	7,500.00	5,000.00

3.2.3 Scenarios and Initial Assumptions

First, the life cycle assessment of both trucks is conducted under the business-as-usual (BAU) scenario, meaning that the vehicle in the fleet operates during the day and connects to the grid solely for charging purposes at night. The results of this assessment will then be used as the reference point for the second assessment, this time with respect to the V2G case, in which the vehicle operates normally during the day, but is charged to a bidirectional charger at night, during which time it may provide electricity regulation service to local utility companies.

For the BAU case, the truck is assumed to operate in a fleet of 20 to 30 commercial delivery trucks, each with an annual mileage of 15,000 miles and a 10 year lifespan before end-of-life salvaging (Lee et al., 2013b). The 36-month UPS delivery van evaluation (Lammert and Walkowicz, 2012) indicates that the daily VMT of a parcel delivery truck is about 40 to 50 miles, or 1,400 to 1,700 miles per month; considering the annual mileage assumption discussed previously, this would assume that each electric truck travels 40 miles per day. A real life V2G test (Kempton et al., 2008) indicated that a vehicle with identical battery capacity consumes 36% of its total power storage, while Navistar has a corresponding consumption rate of about 20% (National Renewable Energy Laboratory, 2014a) because it has twice as much battery capacity. It is therefore assumed that 40% of the battery storage is consumed after the truck's daytime operation, and based on the EREV's total capacity and power efficiency (Table 2), the EREV is assumed to have an all-electric range (AER) of 20 miles. This means that, despite the advertised 40-mile AER of the EREV, only half of the daily range can be powered solely by the battery in reality, while the remaining 20 miles must be powered by fuel combustion. Likewise, the claimed EREV fuel economy of 100 MPG was, as stated before, determined from an "unloaded" test; a real life test shows that the fuel economy of the EREV after the electric range drops to about 50 MPG (Hill et al., 2012), and another unloaded test of a similar EREV suggests that the minimum fuel economy of the EREV can be as low as 30 MPG. Hence, considering the real-life payload and the actually smaller battery capacity, the fuel economy of the EREV after the electric range will be assumed to be 30 MPG.

For the V2G regulation service case, this study will assume that the fleet owner is already running a business with an electric fleet, and has signed a contract with a local utility company to provide frequency and/or voltage regulation service. It is considered that these regulation services will not affect normal delivery operations because of fleet dispatch flexibility, meaning that the relevant parameters of the daytime operation phase are mostly the same as in the reference (BAU) case. The available literature shows that delivery fleets usually operate from 8 a.m. to 8 p.m., so the regulation service period is assumed to be from 8 p.m. on a given night to 8 a.m. the next day. Furthermore, based on available literature (Turton and Moura, 2008), it is assumed that the onboard fuel is not to be used for regulation service. Likewise, Kempton and Tomić (2005a) calculated the V2G cost based on the assumption that fuel and vehicle wear-out only apply to the vehicle operation phase, so it is assumed that the electric power exchange during regulation service will depend only on the remaining power in the battery. Furthermore, with respect to the V2G case, two parameters (battery degradation and regulation up/down signal value) remain unclear in the literature. Since battery degradation is a deterministic factor of the worth of V2G technology for this application, three scenarios representing different battery cycle lifetimes are assumed based on current literature, and a Monte Carlo Simulation will be used to address uncertainties related to regulation signal values. Both of these uncertainties will be discussed further in Section 3.4.4. All of these assumptions and general parameters are summarized in Table 8, along with their input data sources as applicable.

Table 8 Assumptions and input data sources

	Parameters	Unit	Value	Data Source
EREV	Electricity Efficiency	Wh/Mile	843.20	Assumed to be the same with BEV's
	Fuel Economy	MPG	30	See the explanation above
	Maintenance Cost	$/Mile	0.10	(Gallo and Tomic, 2013)
	Vehicle Retail Price (Battery cost excluded)	$	50,000	(Hill et al., 2012)
	Infrastructure Cost	$	7,500	(U.S. Department of Transportation, 2012)
BEV	Electricity Efficiency	Wh/Mile	843.20	(National Renewable Energy Laboratory, 2014a)
	Maintenance Cost	$/Mile	0.07	(Gallo and Tomic, 2013)
	Vehicle Retail Price (Battery cost excluded)	$	110,000	(Feng and Figliozzi, 2013)
	Infrastructure Cost	$	5,000	(Gallo and Tomic, 2013)
Others	Producer Price Index	-	-	(US Bureau of Labor Statistics, 2002); (U.S. Bureau of Labor Statistics, 2014)
	Diesel Price*	$/Gallon	0.78	(Duffy, 2006)
	Electricity Price	Cent/kWh	7.89	(U.S. Energy Information Administration, 2013)
	Current Battery Price	$/kWh	600	(Gallo and Tomic, 2013)
	Future Battery Price	$/kWh	450	(Gallo and Tomic, 2013)

3.2.4 Manufacturing phase

The environmental impacts of vehicle manufacturing are derived from the EIO-LCA model, and the 2002 producer prices (excluding battery price) of the two researched truck types are calculated as input data. Nevertheless, the available price data consists mostly of vehicle retail prices, so a producer-retail ratio of 0.8 is assumed for purposes of this study (Samaras and Meisterling, 2008). Due to their environmentally intensive nature and high manufacturing cost, the impacts and costs of the large capacity battery packs are calculated separately. For the BAU case, the vehicle battery is assumed to be changed every 150,000 miles (Electrification Coalition, 2010). Because the inevitably fast charging activity may accelerate battery degradation, it is assumed that two batteries will be needed during the vehicle's entire lifespan. Furthermore, battery price declines due to future large-scale production levels have also been taken into consideration.

3.2.5 Operation phase and tailpipe impacts

The operation-phase GHG emissions generated by fuel and/or electricity production and by vehicle maintenance are evaluated as stated before. The maintenance and repair costs for electric vehicles are considerably lower than those of ICE vehicles because batteries and motors require little regular maintenance and have fewer fluids (oil, power-steering fluid, etc.) that need to be changed and/or replaced. Nevertheless, electricity generation is still considered to be a major pollutant, as power plants are the largest GHG emission sources in the United States. In order to obtain the lifetime vehicle operation "upstream" impacts, the fuel and/or electricity consumption and the maintenance cost over each vehicle's ten-year lifespan are calculated accordingly. Remember that, as noted in Section 3.4.1, half of the EREV's total VMT is powered by electricity, while the other half is powered by onboard fuel consumption.

The tailpipe (i.e. "direct" or "downstream") emissions are those emissions generated by the combustion of fossil fuels. These emissions cannot be calculated by the EIO-LCA model, so a processes-based LCA method is used to account for these impacts instead. The following equation is used in this study to obtain the tailpipe emissions of the EREV (Hendrickson et al., 2010):

$$\text{GHG emission of EREV} = \frac{VMT}{MHFE} \times C_{content-diesel} \times \frac{44}{12} \quad (5)$$

Where MHFE is the Metro-Highway Fuel Efficiency, $C_{content\text{-}diesel}$ is the carbon content of the diesel in grams per gallon, and as explained before, the VMT used in this equation is half of the EREV's lifetime mileage. On the other hand, the BEV has no tailpipe emissions because it is powered only by stored electricity, and there is no equation for the oil-powered gas turbine generator's direct emissions. The latter of these emissions are therefore calculated as the product of the amount of electricity generated by gas turbine generators and the generator emission multiplier (U.S. Energy Information Adiministration, 2015b).

3.2.6 Infrastructure

Although the application of a V2G system to passenger cars may involve additional costs for home wiring upgrades, such as wiring capacity upgrades and on-board device and bidirectional interfaces (Kempton and Tomić, 2005b), only limited modifications are needed to upgrade an existing plug-in electric vehicle system, and centralized charging stations for commercial fleets may further reduce infrastructure costs (Kempton and Tomić, 2005b). Based on the summary of multiple studies found in the literature as well as future component replacement considerations, bidirectional charger costs are assumed to be $7,500 for EREVs and $5,000 for BEVs. Charging equipment falls under the "Miscellaneous electrical equipment manufacturing" sector in the EIO-LCA model.

3.2.7 Electricity saving of regulation service and battery degradation

The power grid requires rapid response rates and short duration adjustments as needed to fine-tune the system voltage and grid frequency while also balancing power generation and usage. These ancillary services are currently provided via gas turbine generators with typical response times of 10 to 15 minutes, but with low fuel efficiency and a high GHG emission factor.

The electric vehicles connected to the grid serve as extra energy storage systems, storing power whenever grid power generation exceeds customer usage (regulation down) and giving power back to the grid when an additional power boost is needed (regulation up). Nevertheless, one of the shortcomings of the V2G system is that the rapid electric power exchange may accelerate the battery degradation. A V2G system test (Kempton et al., 2008) demonstrated that, during the time that the vehicle is plugged into the grid (8 p.m. to 8 a.m.), about 20 to 30 regulation up/down signals have been received, but the amounts of electricity exchanged and the corresponding battery degradation levels are still unclear. The assumptions and methods used in this research to address these two uncertainties are discussed in further detail below.

Firstly, the aforementioned V2G test (Kempton et al., 2008) was conducted for a passenger car with a battery capacity of 40 kWh, which is the same as the battery capacity assumed for the EREV in this study, and approximately 30 regulation up/down cycles can be observed from the data record for this study. Although the electricity demand of a region can be predicted based on hourly or seasonal historical patterns, the regulation signal characteristics (positive or negative) and regulation request values have been described in the literature as "unpredictable" (Kempton and Tomić, 2005b), and the real-life V2G system test also shows a random request record (Kempton et al., 2008), because the grid frequency and voltage are affected by the turning on and turning off of millions of the appliances. The PJM regional electricity demand pattern (PJM Interconnection LLC, 2015) and single-user level regulation signal are shown in Figure 8.

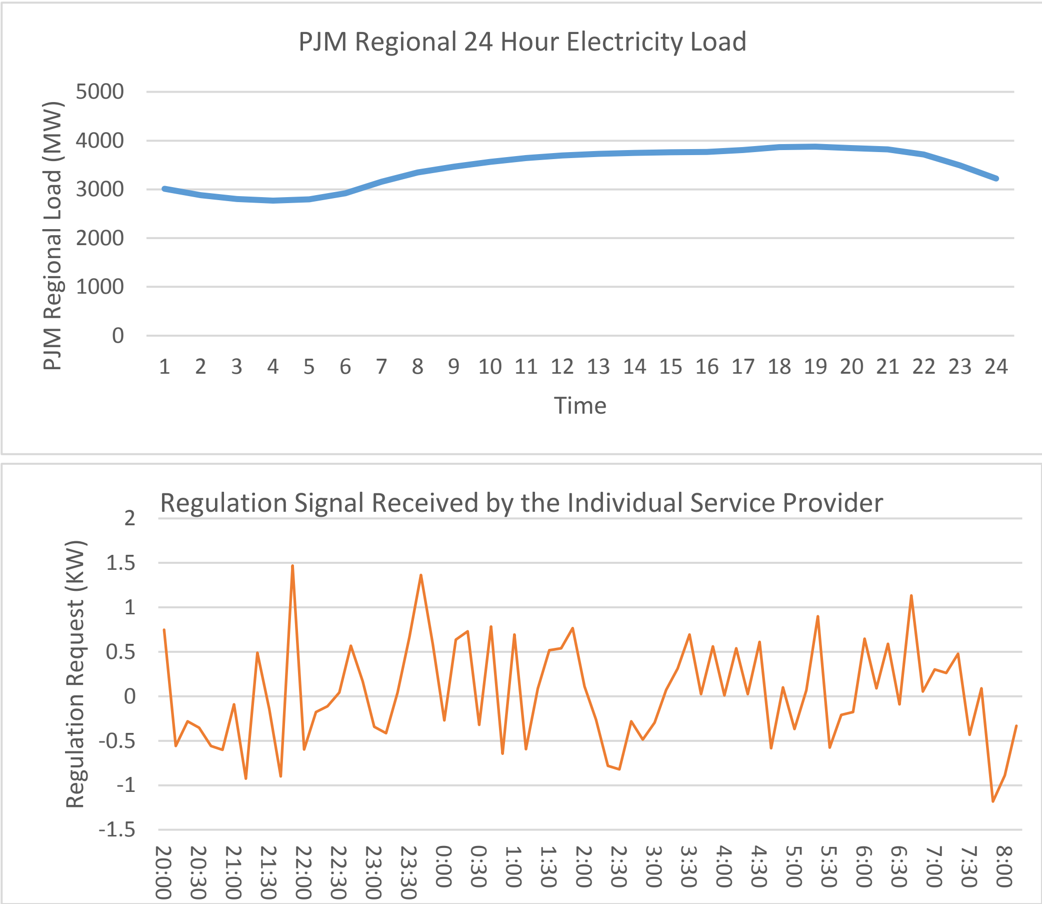


Figure 8 PJM average 24-hour electricity demand (a) PJM regulation signal (b)

Although regional regulation market data is available (PJM Interconnection LLC, 2014), there is few regulation signal data available at an individual regulation service provider level. However, it is clear that regulation requirements are due to seasonal and daily grid load patterns (Kirby, 2005), meaning that a regulation up signal will be triggered if there is a sudden increase in electricity usage, while a sudden decrease in power consumption will result in a regulation down signal. Therefore, during a 12-hour connection period, the following regulation signal patterns will be assumed:

- *High-Demand Periods*: 20 regulation up and 10 regulation down signals;
- *Moderate-Demand Periods:* 15 regulation up and 15 regulation down signals; and

- *Low-Demand Periods:* 10 regulation up and 20 regulation down signals.

The demand level, on the other hand, can be determined from the 10-month U.S. electricity demand data provided by the U.S. Energy Information Administration (U.S. Energy Information Administration, 2011). To match the time period of this study, the hourly-based U.S. electricity demand data are extracted for the time period from 8 p.m. to 8 a.m. It can be observed that almost all of the 3,648 electricity demand data points within this period tend to range from 10,000 MW to 15,000 MW. After sorting these data points, it was found that 1,577 points fall below the average electricity demand (12,500 MW), 1,149 points lie between 12,500 MW to 15,000 MW, and only 922 points are larger than 15,000 MW demand level. It is therefore concluded that 43% of the total nighttime in a single year consists of low power demand levels, while the corresponding percentages are 32% for moderate demand and 25% for high demand. To validate this conclusion, The PJM (RTO of 13 states and District of Columbia) detailed historical regulation signal data has been randomly sampled and calculated as appropriate; the results indicate a distribution of 50% regulation down (negative) signal levels, 35% moderate regulation up (positive) signal levels, and 15% high regulation up signal levels, meaning that the demand levels previously assumed are adequate.

Another uncertainty factor that affects the total electricity exchange during regulation services is the requested amounts of power demand (positive or negative) in each regulation cycle. The literature thus far has used an average regulation demand of 1.30 kWh per regulation up cycle and 0.88 kWh per regulation down cycle (Hill et al., 2012). However, to improve calculation accuracy, the regulation up and regulation down values (measured in kW) are extracted along with their corresponding regulation periods (measured in hours) as variables with uncertainties from the test conducted by Kempton et al. (2008). To adequately reflect the uncertainties connected to the regulation signals, a Monte Carlo Simulation is applied separately with respect to the extracted regulation up and down data sets. Therefore, instead of presenting the ultimate GHG emission savings as a fixed value, these savings will be represented by probability intervals.

Per the assumptions discussed previously, 40% of the stored electricity is consumed during daytime delivery operations. Kempton and Tomić (2005a) used similar assumptions in their study (i.e. 50% of the battery is depleted before V2G connection), so this study will assume that the battery's State of Charge (SOC) is 60% when the battery is plugged in for regulation service., Table 9 summarizes the battery SOCs under different power demand situations and the electricity amounts provided by the vehicle, based on the average (most likely) results from the aforementioned Monte Carlo Simulation. The lifetime electricity savings (and, in turn, the GHG emission impact savings) can then be calculated by combining the demand level possibilities mentioned above, with an additional 10% charging energy loss and a 7% discharging energy loss included in these calculations as well (Sioshansi and Denholm, 2010). As shown in Table 9, there is a possibility that the vehicle can actually gain electricity during regulation provision time, meaning that less electricity is needed to recharge the battery to its full capacity.

Table 9 Regulation service data

Demand Level	Regulation Up Cycles	Regulation Down Cycles	EREV Energy Storage before Service (kWh)	EREV Energy Storage after Service (kWh)	EREV SOC after Regulation Service	Electricity Provided by EREV (kWh)
High-demand	20	10	24	18.1	45.25%	11.0
Moderate-demand	15	15	24	23.4	58.50%	8.3
Low-demand	10	20	24	28.7	71.75%	5.5
High-demand	20	10	48	42.1	52.63%	11.0
Moderate-demand	15	15	48	47.4	59.25%	8.3
Low-demand	10	20	48	52.7	65.88%	5.5

Secondly, it must be noted that the currently available literature has not yet reached any definitive agreement regarding batteries: the most cost-intensive and environmentally intensive consumables in a V2G system. The study performed by Guille and Gross (2009) suggested that the battery life is a function of the Depth of Discharge (DOD), as have many other V2G studies. On the other hand, other researchers argue that, for V2G purposes, the DOD is not a deterministic factor for battery life (Peterson et al., 2010). Another V2G feasibility demonstration project conducted by Brooks (2002) even cited a battery capacity increase of 10% after a V2G test.

To address the uncertainties related to battery wear-out, two questions have to be answered first: (1) how many battery cycles will take place while regulation services are being provided? And (2) how will regulation services affect the battery life? Regarding the first question, the battery SOC figure provided by Kempton, Udo (Kempton et al., 2008) indicates that, during the selected time period (8 p.m. to 8 a.m.) during which regulation services are provided, the battery experiences SOC variations of approximately 150%, or roughly 0.75 of a full battery cycle, while Hill et al. (2012) argue that each V2G connection period takes up about 0.25 of a full cycle. As for the second question, a typical lithium-ion battery has a battery life of 500 to 3000 cycles (Cicconi et al., 2012); given the relatively short lifespan (less than 15 years) and 40% daily driving depletion as previously noted, a battery life of 2000 battery cycles is an adequate assumption for driving purposes. Another study by Peterson et al. (2010) shows that V2G services are half effective in degrading battery life, Kempton and Tomic (Kempton and Tomić, 2005a) argue that the battery has 3 times as many regulation cycles as it has pure driving cycles, and a fleet V2G system study also shows that the battery regulation cycles is two times higher than normal battery lifetime cycles (Hill et al., 2012).

Given all of the uncertainties with respect to battery charging/discharging cycles per night and battery regulation cycles, this study assumes three different battery wear-out scenarios for both vehicle types, as summarized in Table 10. The first scenario represents the least battery wear-out, with one regulation cycle equal to 1/4 driving cycle while the battery also has the longest regulation life. The second scenario represents a mid-level wear-out effectiveness and an average battery regulation life. Lastly, the third scenario represents the maximum possible battery wear-out due to regulation service. The last column of Table 10 indicates the number of additional batteries needed under each scenario to compensate for providing regulation services.

Table 10 Battery regulation life cycle scenarios and battery numbers

Battery Scenarios		Cycles per Night	Battery Regulation Life	Number of Extra Battery
EREV Battery Scenarios	Minimum Battery Wear Out	0.25	6000	0
	Medium Battery Wear Out	0.75	4000	1
	Maximum Battery Wear Out	1	2000	2
BEV Battery Scenarios	Minimum Battery Wear Out	0.125	6000	0
	Medium Battery Wear Out	0.375	4000	0
	Maximum Battery Wear Out	0.5	2000	1

* The BEV uses only half as many cycles as the EREV, because the BEV's battery capacity is twice as much as that of the EREV

3.3 Results

The assessment results are shown in Figure 9. Figure 9a compares the life cycle GHG emissions of the EREV and the BEV under BAU conditions, with regulation services not included. This figure indicates that, in a business-as-usual case, the GHG emission impacts of the BEV are almost twice as much as those of the EREV in terms of vehicle/battery manufacturing and electricity supply. This is because BEV manufacturing requires large amounts of light-weighted materials and large-capacity battery packs, so the overall manufacturing cost is higher than those of EREVs or conventional fossil-fuel powered vehicles, although the larger battery capacity of the BEV affords it a higher payload and longer

AER than the EREV. The lifetime maintenance and infrastructure impacts for both truck types are relatively lower than those of other life cycle phases, and are identical for both trucks, except that the BEV has no fossil-fuel related emissions thanks to its all-electric power system. It should also be noted that, unlike traditional hybrid trucks with powertrain still mostly reliant on fuel combustion, the EREV's main power source is electricity, making the EREV's tailpipe emissions considerably lower than those of diesel powered trucks.

Figures 9b through 9d illustrate the life cycle GHG emissions of the two truck types when V2G regulation services are provided, with each figure represents the vehicles' environmental performances with low, average, and high levels of battery wear-out, respectively. The negative electricity saving values in each of these figures indicate a net savings in GHG emissions from providing regulation services. Taking the most likely Medium Battery Wear-Out scenario (Figure 9c) as an example, the vehicle receives electricity during charging and, through the use of V2G regulation services, may then give electrical power back to the grid for voltage stabilizing as necessary, reducing the amount of electricity that would otherwise need to be generated by gas turbines and thereby "saving" approximately 40 tons of GHG emissions from regulation services. Moreover, the emission savings results in Figures 9b through 9d are shown after multiplying the initial result by two because, as noted before, electricity storage methods are twice as effective as electricity generation in terms of ancillary service (Lin, 2011). In short, for every 1 MW of electricity provided by V2G services, a gas turbine regulation service would need to consume enough fuel to provide 2 MW of electricity.

A parallel comparison among Figures 9b through 9d shows that the emission impacts of battery manufacturing increase significantly as the degree of battery wear-out aggravates. The error bars on the "electricity savings" and "electricity supply" columns in each figure represent the results of the Monte Carlo Simulation as previously discussed, with the two extreme values on each error bar indicating the possible maximum and minimum impact values, while the column value indicates the average (i.e. most likely) impact value. In Figure 9b (low battery wear-out), the battery degradation impacts of both electric vehicles are less than their respective emission savings, indicating a net savings in GHG emissions. The results based on medium battery wear out (Figure 9c) show that, although the EREV's battery manufacturing emissions are still less than the environmental benefits of regulation services, the corresponding benefits for the BEV are almost offset by the BEV's battery wear out. Finally, in Figure 9d (high battery wear-out), the EREV can still serve as a V2G regulation service provider, but the large amount of GHG emissions from battery manufacturing exceeds the EREV's electricity emission savings. Furthermore, given the uncertainties with respect to regulation services, the BEV as a V2G provider is still hardly an eligible option if the maximum level of battery wear-out is assumed, as the BEV's average electricity supply emissions are roughly equivalent to its electricity emission savings. Furthermore, the error bars in Figure 9 all have wide ranges, which also suggests that the electricity exchange amounts of each regulation cycle and regulation request frequencies will also have a significant effect on the total electricity emission savings

However, when comparing Figure 9a to either Figure 9b, 9c, or 9d, it becomes clear that the inclusion of the V2G system significantly reduced the electricity supply emissions for both vehicle types. This is because, due to the inherently unpredictable regulation signals, the vehicle battery can be either depleted to a certain SOC or fully charged by the end of the night, so there is a possibility that the total electricity inflow is larger than the total outflow, in which case the net electricity gain can be considered as "free energy". Furthermore, the relatively small error bars on the electricity supply columns of Figures 9a through 3d show that electricity supply emissions tend to be stable with or without the V2G system.

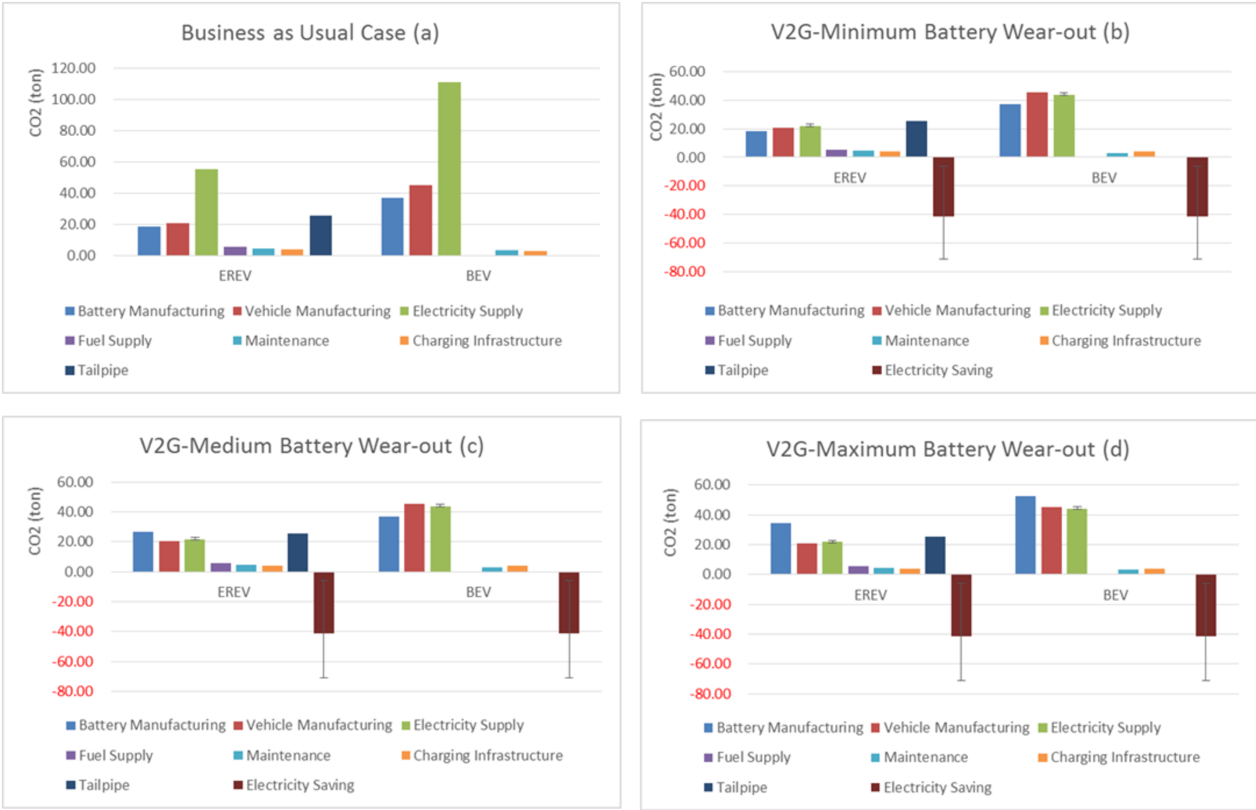


Figure 9 Life-cycle GHG emissions (a) BAU (b) V2G with low battery wear-out (c) V2G with mid-level battery wear-out (d) V2G with high battery wear-out

4 ECONOMIC AND ENVIRONMENTAL BENEFIT ANAYSIS OF VEHICLE-TO-GRID SERVICES PROVIDED BY ELECTRIC DELIVERY TRUCKS

A partial work of this chapter has been published in the journal of Applied Energy with the title of *“Vehicle to Grid regulation services of electric delivery trucks: Economic and environmental benefit analysis”* (Zhao et al., 2016a)

Concerns regarding the fuel costs and climate change effects associated with petroleum combustion are among the main driving factors for the adoption of electric vehicles. Future commercial delivery truck fleets may include BEVs and EREVs; in addition to savings on fuel and maintenance costs, the introduction of these grid accessible electric vehicles will also provide fleet owners with possible V2G opportunities. This section investigates the potential net present revenues and GHG emission mitigation of V2G regulation services provided by electric trucks in a typical fleet. The total cost of ownership and the life-cycle GHG emissions of electric trucks are also analyzed and compared to those of traditional diesel trucks. To account for uncertainties, possible ranges for key parameters are considered instead of only considering fixed single data values for each parameter.

4.1 Introduction and Literature Review

EVs have proven to have significant environmental impact mitigation potential if the local electricity sources are renewable (esp. hydropower or wind power). More importantly, Vehicle to Grid (V2G) systems, a further integration of electric power grids and EVs, utilize the battery capacity of idled EVs as grid storage, allowing them to improve the reliability of the power grid, reduce GHG emission impacts as opposed to the low-efficiency operation of traditional power plants, provide additional revenue for vehicle/fleet owners, and help to promote the implementation of clean energy and to further increase the market penetration of EVs. However, despite the benefits that V2G technologies provide, the implementation of this relatively new concept may face economic or sociological problems (Sovacool and Hirsh, 2009). To explore the feasibility of the application of V2G systems, this article will evaluate the GHG emission savings and potential revenues for fleet operators using EREVs or BEVs as V2G regulation service providers. The system boundary will follow the most cited studies (Kempton and Tomić, 2005a, b; Kempton et al., 2001; Tomić and Kempton, 2007), including fuel/electricity production phase, battery manufacturing phase and V2G-related vehicle operation phase, which is the main focus of this study. Vehicle manufacturing and end-of-life disposal will not be involved considering that these two phases have no effect on V2G-related analysis. On the other hand, V2G regulation services may accelerate the degradation of batteries and battery manufacturing and disposal are emission intensive, hence, battery degradation scenarios will also be analyzed in detail. To address the spatial differences and uncertainties of the parameters, the research will be conducted in five Independent System Operator (ISO) and Regional Transmission Organization (RTO) regions, and the resulting revenues and life cycle emission savings will be projected for 15 years (2016-2030). The methods as well as calculations used in this study are shown in Figure 10.

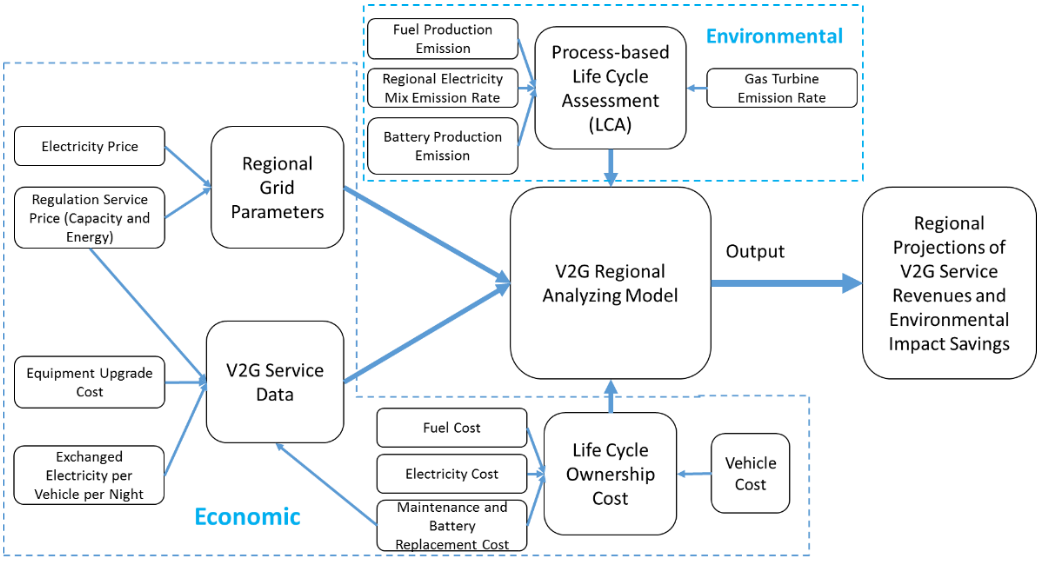


Figure 10 Framework of the model

The feasibility and benefits of electric drive vehicles providing ancillary services have been studied by Kempton et al. (Kempton et al., 2001). Their study answered the fundamental question as to the best practical application of V2G systems; instead of generating electricity as a power source, the value of the V2G system is that, as a storage media, it allows the grid operator to control the precise timing of the valuable electricity flows into or out of the grid. Therefore, as a grid stabilizer, the V2G system's main economic drive is the high value of the electricity that it processes. As we all know, renewable energy sources (wind, solar, etc.) are subject to a great deal of fluctuation as the availability of these sources cannot be predicted accurately for any given time period, and one promising application of the V2G system is to more closely integrate with renewable energy sources (Lund and Kempton, 2008). Kempton and Tomic conducted a separate study further exploring the actual available power of the vehicle, as well as V2G regulation service revenue and the effects of battery degradation (Kempton and Tomić, 2005a), and in another study, they also evaluated real-life implementation strategies for V2G technologies, possible business models, and the most valuable application of V2G systems, i.e. incorporating them with clean but highly fluctuating renewable energy sources (Kempton and Tomić, 2005b). Zhong et al. proposed a coordinated control strategy for AGC that involves large-scale electric vehicle charging/ discharging (Zhong et al., 2014). Similarly, an optimal charging scheduling model has been developed by Jian et al. (Jian et al., 2015). As the EV market penetration increase in the future, the impact of connecting these EVs into the grid has been studied by Foley et al. (Foley et al., 2013). Noel and McCormack studied the potential savings in ownership costs via V2G services, which are the main drive for fleet operators to adopt EVs and the V2G system (Noel and McCormack, 2014). PHEVs, BEVs, and fuel cell vehicles have been researched in all of the aforementioned studies, but not all of these vehicle types are practical or available for light duty trucks; for instance, fuel cell vehicles as V2G service providers may face challenges such as grid accessibility, hydrogen storage and conversion losses (Hu et al., 2015b). On the other hand, an advanced plug-in hybrid vehicle, the EREV, has been introduced and studied at a delivery fleet level (Hill et al., 2012). Within this study, light duty truck fleets serve as functional units providing regulation services, and the fleet as a whole proved to be more feasible than private cars as V2G providers. Kempton et al. have also performed a real-life experiment testing the behavior of EV batteries in response to PJM regulation requests, recording the random signal patterns of the regulation requests as well as the shallow charge/discharge patterns of the battery.

In addition to the economic aspects of V2G systems, the environmental benefits of such systems have also been studied in the literature. An energy-system model was used to project the long term transformation of both energy and transportation systems from the use of a V2G system, as well as the resulting GHG emission savings (Turton and Moura, 2008). The Life Cycle Assessment (LCA) method has been widely used as a tool to analyze the environmental impact of a product or process over its lifetime (Ercan et al., 2015). Kudoh et al. studied one V2G application, the Vehicle-to-Home system, from a LCA perspective, and the result showed significant emission savings (Kudoh et al., 2013).

Battery degradation is the most potentially troublesome downside of V2G services, and as such it has been discussed in multiple studies. Cicconi et al. summarized the life cycles of typical vehicle batteries and argued that second-life batteries are actually good options for V2G services (Cicconi et al., 2012), and in fact Peterson et al. proved that the battery wear-out due to regulation services is minimal (Peterson et al., 2010). Although regulation up (power request from the grid) and regulation down (storage of excess power) signals are rapid and repeated, the Battery State of Charge (SOC) variation in each regulation cycle is fairly small. Therefore, most studies in current literature agree that the degradation effects of V2G services on EV batteries is minimal (Bishop et al., 2013). Nevertheless, in addition to battery degradation-related cost issues, V2G contract issue may reduce customers' willingness to adopt V2G technologies (Hidrue and Parsons, 2015), there are many other sociological, economic or behavioral problems that may prevent the implementation of V2G systems (Sovacool and Hirsh, 2009). The effects of these problems will be further discussed in later sections. The aforementioned literature summarizes the framework of the V2G system, the roles of EVs in this framework, and the potential economic and environmental benefits of this system. However, light duty delivery truck fleets, as a promising first-step V2G service provider, have not been studied from a life cycle perspective, and few studies are currently available that have projected the future economic and environmental effects brought by light duty trucks as V2G service providers in different regions. To this end, this study will analyze the life cycle revenue/cost of V2G regulation services provided by BEVs and EREVs in five ISO/RTO regions, and as the key parameters such as fuel and electricity price changes in the future, these spatial results will be projected for the next 15 years. In addition, life cycle environmental impact saving and economic benefits will be compared among BEVs, EREVs and ICVs, and with the consideration such as federal and state incentives and potential carbon tax scenarios, decision makers in various ISO/RTO regions will be provided a holistic evaluation of V2G regulation services carried out by light duty electric trucks. Furthermore, in addition to the lack of forecast and spatial research, single data points are usually used as key parameters in the aforementioned studies, yet in real lives, these key parameters may vary within certain ranges. So the most important feature of this study is that instead of using fixed values, applicable ranges are applied to all key parameters to account for uncertainties.

4.2 Delivery Truck Fleets as Grid Storage Providers

Although the use of passenger cars as a whole has undoubtedly the largest capacity potential, the relatively smaller battery capacities of passenger cars limits their feasibility as V2G service providers, as such a small amount of connection is merely a "noise" to the grid (Guille and Gross, 2009). Hence, aggregators are needed to coordinate large amounts of EVs in a particular area, meanwhile the willingness of EV owners to provide V2G services still remains unclear. Commercial delivery truck fleets may therefore be a better preliminary application of V2G technologies, for a variety of reasons:

Capacity: The batteries of electric trucks have higher capacities and higher energy outputs than electric passenger cars. Typical electric truck battery capacities range from 80 kWh to 120 kWh per truck, and a delivery fleet of 18 trucks with average outputs of 60 kW each are able to provide a maximum capacity support of 1 MW (Hill et al., 2012), which is the minimum required capacity of a typical ancillary service contract (Kempton and Tomić, 2005b). For this reason, a fleet of 20 to 30 PHEVs or BEVs would be feasible as an individual ancillary service provider.

Centralized Coordination: Delivery trucks commonly operate from 8 a.m. to 8 p.m., and these relatively predictable fleet operation schedules as opposed to those of passenger cars make delivery trucks a better option in terms of system reliability. Moreover, the centralized charging stations at the depot where the trucks are parked when not in use would require lower infrastructure/upgrade costs overall (Kempton and Tomić, 2005b).

Rational Decision Making: Individual passenger car buyers often choose traditional vehicles over EVs based on considerations regarding the shape, color, and/or interior comfort of a passenger vehicle, whereas fuel economy and environmental impacts are seldom given any significant priority when purchasing a passenger vehicle (Sovacool and Hirsh, 2009). Fleet operators, on the other hand, have to more seriously consider fuel consumption rates and GHG emission levels as priorities for socio-economic and environmental reasons. Taking the frequent stop-and-go operational nature of electric delivery trucks into consideration, although electric trucks require high initial cost, the environmental impact during the operation phase is much less than that of traditional diesel trucks, and providing V2G services may give fleet owners an additional source of revenue that can offset operation costs.

No Range Anxiety: When calculating power availability for V2G provision, the buffering range has to be taken into consideration for car owners due to their relatively unpredictable operation patterns. On the other hand, delivery trucks normally operate on fixed routes. Hence, this range anxiety does not exist for delivery trucks, and so the buffering range need not be as large for delivery trucks as for passenger cars.

Electricity provided through the combustion of the vehicle on-board fuel has proven to be far less competitive than base-load electricity, which is generated by large-scale power plants and tend to have lower generation costs and emission rates (Kempton and Kubo, 2000). Likewise, peak power, due to its relatively predictable demand patterns, can still be generated by ramping up power plants. However, ancillary services account for 5% to 10% of the total electricity market value (about $12 billion) (Letendre and Kempton, 2001), have the highest electricity unit price, and require repeated rapid short-duration responses. The low capital costs of a given V2G system (compared to power plants) make V2G systems perfect for providing ancillary services. That said, since spinning reserves would require the vehicles to be plugged in at all times (Hill et al., 2012), which may not be realistically feasible given the normal delivery operations of any given fleet, this research will only focus on electric trucks providing V2G regulation services and the economic and environmental impacts due to this service.

4.3 Methods

4.3.1 Vehicle characteristics and assumptions

Vehicle characteristics are summarized in Table 11. To take uncertainty into consideration, key factors such as Vehicle Miles Traveled (VMT) and fuel efficiency are represented and calculated as ranges. Daily VMT, for example, is considered as a range between 35 and 55 miles (Lammert and Walkowicz, 2012), and since major delivery companies typically operate six days per week, the annual mileage therefore ranges from 10,920 to 17,160 miles. The real-life V2G test indicates that a vehicle with a 40 kWh battery capacity consumes 36% of its total energy storage for daily driving operations (Kempton et al., 2008), while a corresponding test for the Navistar E-star shows that its energy storage consumption is 20%. However, the test range for the Navistar E-star test was 20 miles, which is half of a typical delivery truck's average daily VMT. It is therefore adequate to assume that, instead of depleting the battery, delivery operation for a BEV truck consumes 40% of its total capacity, and that the trucks are able to provide V2G regulation services immediately after their daily operation period has concluded. Due to a lack of available data, the electric-range power efficiency of an EREV is assumed to be the same as that of a BEV; based on the battery capacity and assumed 40% energy consumption, this means that the EREV is able to travel 20 miles on stored electrical power alone. After the all-electric range has been used up, the advertised diesel fuel efficiency of 100 MPG was, as stated before, determined from an unloaded test; a corresponding real-life test shows that the fuel efficiency drop to 50 MPG (Hill et al., 2012) when the truck was loaded, and another discussion of a similar EREV indicates that this fuel efficiency can drop to as low as 30 MPG (Kilcarr, 2009). Therefore, the fuel efficiency of the EREV's all-electric range is assumed to range from 30 to 50 MPG. Since all delivery trucks operate on relatively fixed routes, it is assumed that no buffering range is needed for either of these trucks.

The variable $P_{vehicle}$ is an important factor measuring the power output level of a vehicle. Based on Kempton and Tomic's study (Kempton and Tomić, 2005a), $P_{vehicle}$ is calculated using Equation 6:

$$P_{vehicle} = \frac{(B_{cap} - \frac{D_d - D_{buffer}}{F_e})\, C_e}{T_{disp}} \tag{6}$$

Where B_{cap} is the capacity of the vehicle battery, D_d is the average Daily VMT (45 miles), D_{buffer} is the minimum backup range required for each EV, F_e is the fuel efficiency of each EV in miles/kWh, C_e is the electricity conversion efficiency (90% for grid-to-battery power and 93% for battery-to-grid power) (Sioshansi and Denholm, 2010), and T_{disp} is the effective regulation provision time (usually assumed to be 20 minutes) (Kempton and Tomić, 2005a).

Table 11 Diesel, EREV and BEV vehicle characteristics

	Internal Combustion Vehicle (Diesel)	**Extended Range Electric Vehicle (EREV)**	**Battery Electric Vehicle (BEV)**
Vehicle Make/Model	Freightliner P70D(Lammert and Walkowicz, 2012)	RASER PHEV Drive System(Razer Technologies, 2009)	Navistar E-star(National Renewable Energy Laboratory, 2014a)
Curb Weight (lbs.)	8,200	5,720	7,022
Payloads (lbs.)	6,160	2,000	5,100
Battery Capacity (kWh)	0	40	80
Energy Available after Operation	0	24	48
Fuel Economy (Electricity-Wh/mile)	---	---	843.2(National Renewable Energy Laboratory, 2014a)
Fuel Economy (Diesel-MPG)	8.8-11.7	30-50	---
Daily VMT (mile)	35-55(Walkowicz et al., 2014)	35-55(Walkowicz et al., 2014)	35-55(Walkowicz et al., 2014)
Buffering Range (mile)	0	0	0
DC to AC Conversion Efficiency(Kempton and Tomić, 2005a)	0	0.93	0.93
Dispatch Time (hr.)(Kempton and Tomić, 2005a)	0	0.3	0.3
P-vehicle (kW)	0	15.29	30.58
Retail Price ($)	50,000(Feng and Figliozzi, 2013)	80,000(Hill et al., 2012)	150,000(Feng and Figliozzi, 2013)

4.3.2 Vehicle characteristics and assumptions

The prices of regulation services, managed by local ISOs and/or RTOs, vary across the country from region to region, as do the prices of base-load electricity and diesel fuel. Due to a lack of available data, this study focuses on the California ISO (CAISO), PJM Interconnection (PJM), New York ISO (NYISO), Electric Reliability Council of Texas

(ERCOT), and ISO New England (ISONE) regions, all of which are illustrated in Figure 11.

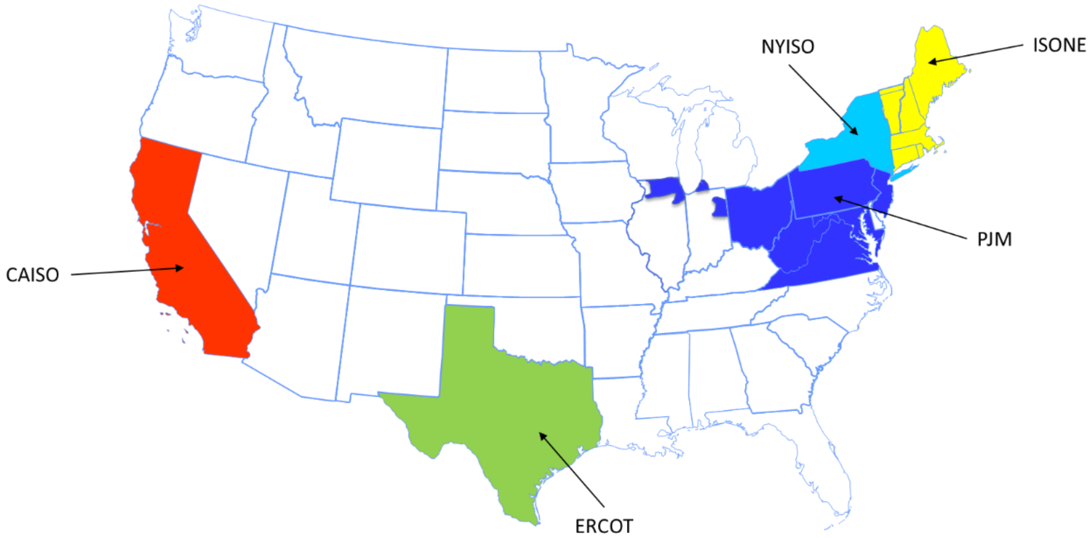


Figure 11 ISO/RTO regions

The data assumptions and uncertainty ranges of the V2G system are summarized in Table 12.

Table 12 Preliminary assumptions and data sources

Parameter	Source	Range, Distribution, or Data Source
Analysis Period	(Noori et al., 2015)	2016-2030
Discount Rate	(Bankrate, 2014)	0.65%-1.15%
Inflation Rate	(CBO, 2014)	-10%, +10% of CBO's projections
Electricity Price	(U.S. Energy Information Administration, 2014)	EIA & proposed method in (Noori et al., 2015)
Diesel Price	(U.S. Energy Information Adiministration, 2015a)	EIA diesel price projections from 2016 to 2030 in the five researched regions
Battery Lifetime, Production & Recycling Emissions	(Amarakoon et al., 2013)	Battery lifetime presented in Section 4.3.3 Battery related emissions, Presented in Section 4.3.8
Average Vehicle Lifetime	(Barnitt et al., 2010)	15 years
Vehicle Purchase Price	-	Presented in Table 4.
$Price_{cap}$	(Tomić and Kempton, 2007), (Kempton et al., 2008)	Presented in Section 4.3.4
$Price_{ele}$	(Noori et al., 2015)	Presented in Section 4.3.4
T_{plug}	(Hill et al., 2012)	8 to 12 hours per day
T_{cyc}	(Kempton et al., 2008)	Uniform (3.6, 9) minutes
P_{line}	(Kempton and Tomić, 2005a)	19.2 kW to 25 kW, Presented in Section 4.3.5
N_{disp}	(Kempton et al., 2008)	Uniform (30, 40) times
Battery Lifetime Cycles for Regulation Services	(Kempton and Tomić, 2005a), (Peterson et al., 2010), (Hill et al., 2012)	Uniform (2,000 to 6,000) cycles, Presented in Section 4.3.3
Depth of Discharge	(Kempton and Tomić, 2005b)	Uniform (3, 10)
Battery Price	(Gallo and Tomic, 2013)	(600 - year x 30) x battery capacity, Presented in Section 4.3.3
Battery Capacity	(Razer Technologies, 2009), (National Renewable Energy Laboratory, 2014a)	EREV 40 kWh BEV 80 kWh
Battery to Grid Efficiency	(Sioshansi and Denholm, 2010)	0.93 x 0.9
V2G charger cost and upgrade cost	(Kempton and Tomić, 2005a), (Gallo and Tomic, 2013)	Charger: $5000 Equipment Upgrade: Uniform ($1,900 to $2100)
Battery Lifetime	(Electrification Coalition, 2010), (Cicconi et al., 2012)	5 to 10 years, Presented in Section 4.3.3
Grid Electricity Emission	(Argonne National Laboratory, 2013), (U.S. Environmental Protection Agency, 2014b), (U.S. Energy Information Adiministration, 2015d)	-10%, 10% of the projected values Presented in Section 4.3.8
Traditional Regulation Service Emission	(Lin, 2011), (Makarov et al., 2012)	2-3 times of gas turbine power plant emissions Presented in Section 4.3.8

4.3.3 Battery degradation costs due to driving and V2G service provision

Based on the literature (Electrification Coalition, 2010), the battery of an electric truck is supposed to be replaced after every 150,000 miles of travel; based on the daily VMT range assumed for this study, this means that the battery must be changed approximately every 10 years. Another study argues that some vehicle batteries are able to last 15 years, but the actual battery capacity is often lower than the officially stated capacity, and other external factors such as fast charging or low-temperature environments may further reduce the lifetime of a vehicle battery. From a life cycle perspective, a typical lithium-ion battery has a total battery life of 500 to 3000 cycles (Cicconi et al., 2012). Given the conservative lifespan assumption of less than 15 years and the 40% daily energy consumption as previously noted, a battery life of 2,000 cycles (driving only) is an adequate assumption. Therefore the life span can be approximately computed as 2,000 / (52 x 6) = 6.4 years. Hence, the battery lifespan of the truck is assumed to range from 5 to 10 years. In addition to the battery degradation caused by normal operation, V2G regulation services will also accelerate battery wear-out, but as previously noted, the battery degradation incurred from V2G services is less than that caused by daily driving. In short, after summarizing the literature (Hill et al., 2012; Kempton and Tomić, 2005a; Peterson et al., 2010), the total battery life cycle for V2G regulation services alone is assumed to be 2,000 to 6,000 cycles.

When calculating the total cost of ownership, battery replacement costs must be considered when each battery reaches its life span. The unit price of the battery is predicted to decrease in the future, from $600/kWh in 2015 to $450/kWh 2020 and then to $300/kWh in 2025 (Gallo and Tomic, 2013). This trend indicates a linear decrease in battery unit prices, with prices starting at $600/kWh in the year 2015 and then decreasing by $30/kWh per year. Labor cost uncertainties have also been included in these calculations, with unit prices ranging from

$30/hour to $40/hour while work hours range from 7 to 13 hours per day.

The aforementioned battery replacement cost is caused by the normal operation of delivery trucks, but V2G services will also incur battery wear-out and thereby increase the total cost. Kempton and Tomic's method for calculating V2G-related battery degradation costs (Kempton and Tomić, 2005a), as summarized in Equations 15 through 17, will be applied in this study.

4.3.4 Electricity price

The Electric Vehicle Regional Optimizer (EVRO) model previously developed by the authors to calculate the electricity cost (Noori et al., 2015), $Price_{ele}$, is used in this study as well. EVRO is an optimization model that uses several previously established methodologies in Life Cycle Assessment of energy systems, Multi Criteria Decision Making (Nam, 2014; Noori et al., 2013), Decision Making Under Uncertainty (Noori, 2013), Intelligence Transpiration Systems (Al-Deek et al., 2014), Stochastic Optimization (Kucukvar et al., 2014b; Noori et al., 2014), and builds on the Argonne National Lab's Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) model (AFLEET, 2013) to estimate several specifications related to EVs in a regional basis. Figure 12 shows the estimated prediction of the levelized cost of electricity for each of the considered U.S. electric regions. These estimates are used to calculate the cost of electricity in each ISO/RTO region. The capacity price, $Price_{cap}$, is estimated using an extensive literature review and data configuration of reported clearing capacity prices for each studied ISO/RTO region. Efforts have been made to fit a distribution function on the reported prices (CAISO, 2015; ERCOT, 2015; ISO-NE, 2015 ; NYISO, 2015; PJM, 2015), but too many complications resulted while testing the estimated distribution function to obtain a random capacity price. Therefore, it is assumed that the capacity price in the studied region ranges randomly between the following limits, based on a uniform distribution function:

Table 13 Capacity price ranges for the ISO/RTO regions

Region	Minimum ($/MWh)	Maximum ($/MWh)
PJM	16.43	49.73
ISO-NE	9.3	30.22
NYISO	11.8	59.5
ERCOT	11.04	38.07
CAISO	10.6	41.06

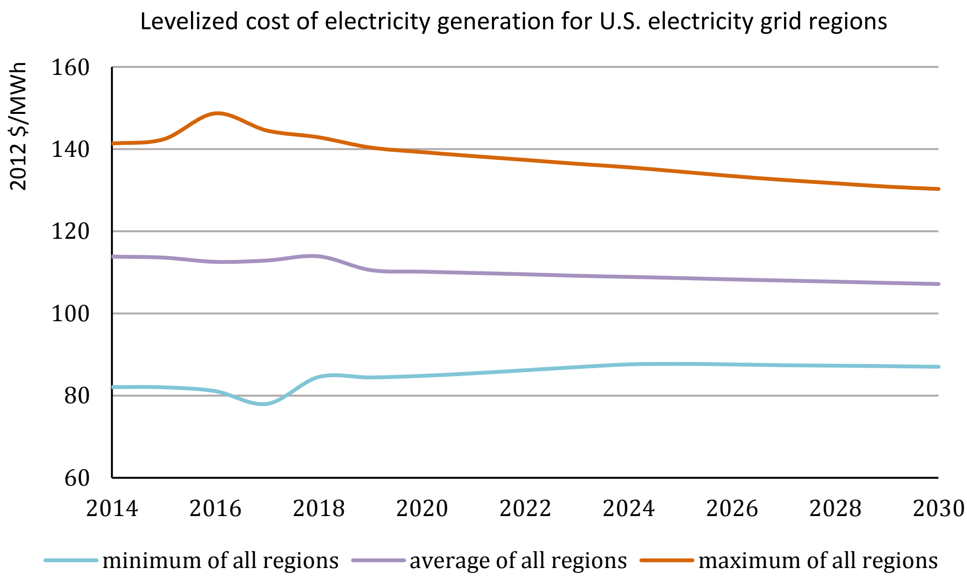


Figure 12 Electricity cost ranges for different U.S. electric grid regions ($/MWh)

4.3.5 V2G system power capacity

The power capacity of the V2G system is determined by the lower value between P_{line} and $P_{vehicle}$ (Kempton and Tomić, 2005a), where $P_{vehicle}$ is calculated using Equation 1 and P_{line} is determined depending on the charging equipment used. Electric commercial delivery trucks are charged with level 2 chargers, which have a power capacity of 19.2 kW each (Gallo and Tomic, 2013). In addition, upgrades may be applied to the equipment or to the wiring for higher V2G capacity, with the capacity of such modified chargers potentially reaching as high as 25 kW (Kempton and Tomić, 2005a). Thus, P_{line} is assumed to range from 19.2 to 25 kW.

In conclusion, the EREV power capacity is limited by the vehicle, whereas the corresponding BEV power capacity is limited by the charger, as the power capacity of the BEV exceeds the maximum power capacity of its charging equipment.

4.3.6 Maintenance cost

Low maintenance costs are a major advantage of electric drive vehicles over traditional vehicles, since the battery, motor and associated electronics all require little to no regular maintenance. There are fewer fluids to change, brake wear is significantly reduced due to regenerative braking features, and there are far fewer moving parts comparing to traditional vehicles. For this study, the maintenance cost of diesel trucks is derived from a real-life test (Lammert and Walkowicz, 2012), and is thusly assumed to have a triangular distribution ranging from $0.11/mile to $0.16/mile. BEV maintenance costs are usually $0.06 cheaper per mile than diesel maintenance costs (Gallo and Tomic, 2013), and EREV maintenance costs are assumed to be $0.03 cheaper per mile than diesel maintenance costs. The maintenance cost of the charging stations is assumed to be 10% of the initial equipment cost (Chang et al., 2012).

4.3.7 Diesel price

Diesel fuel price projections in the five researched regions (U.S. Energy Information Adiministration, 2015a) are used in this study to predict the fuel costs of diesel vehicles and of EREVs. In addition, to cover all relevant uncertainties in these diesel price projections, different case scenarios for high, low, and medium-level crude oil prices are considered. Figure 4 shows the medium-oil-price diesel price projections as an example. It should be noted that the price of diesel is measured in 2013 money, and is then converted to 2015 money to ensure data consistency.

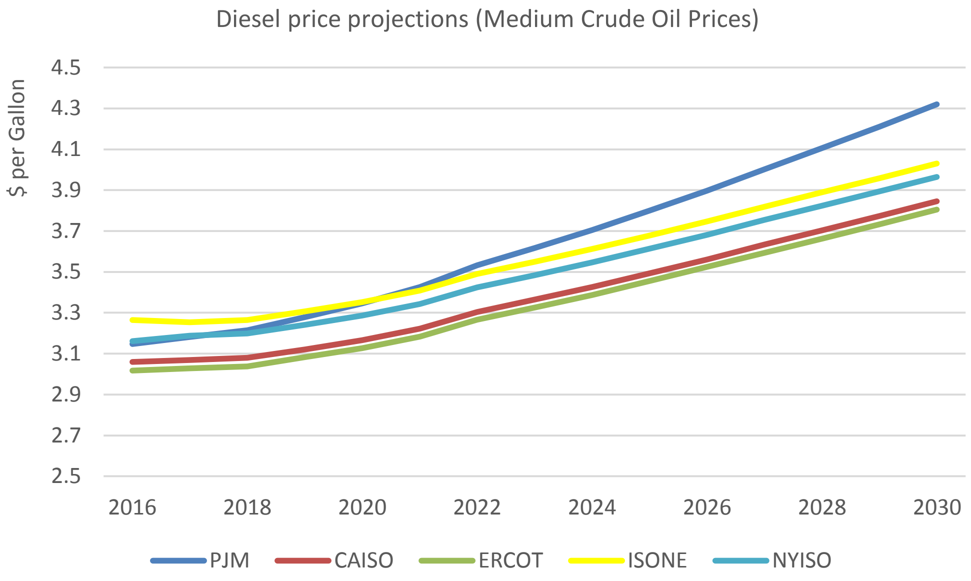


Figure 13 Diesel price projections in the researched ISO/RTO regions

4.3.8 Emission savings

Life Cycle Assessment is a well-established but still evolving method used to assess the potential environmental impacts and/or resource consumption levels of a product or a process throughout its entire life cycle, which is typically broken down into different phases as needed. In this study, the GHG impacts of the following life-cycle phases will be emphatically discussed to estimate the overall GHG emission savings of the V2G system: Gas turbine based electricity generation and distribution (direct and indirect emissions), diesel upstream production, downstream tailpipe emissions, and lithium-ion battery manufacturing.

The direct emissions of electricity are estimated using the reported emissions of power plants in the GREET model (Argonne National Laboratory, 2013). These emissions are then multiplied by the EIA's electricity mix projections in the studied regions (U.S. Energy Information Adiministration, 2015d) to estimate the regional direct emissions of electricity generation. The indirect emissions of electricity, i.e. those associated with the transmission and distribution of electricity, are estimated using the eGRID gross grid loss factors (U.S.

Environmental Protection Agency, 2014b). Therefore, the indirect emissions and the transmission losses from the purchase of electricity can be estimated using Equation 7 (Diem and Quiroz, 2012). The eGRID database is used to compute the well-to-pump emission rates of power plants, as shown in Equation 8. The GREET model (Argonne National Laboratory, 2013) and Hendrickson's diesel tailpipe impact equation (Hendrickson et al., 2010) are used to calculate the upstream and downstream GHG emissions, respectively, due to the production and combustion of diesel fuel.

$$Upstream_{kj} = \frac{(eGrid)_{kj}}{(1-GGL_j)} \tag{7}$$

Parameters:

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

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

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

k: $air\ pollutant\ index\ for\ GHG$

j: $region\ index$

$$Upstream_{kjy} = \sum_p (WTP)_{kp} \times (EnergyMix)_{pjy} \tag{8}$$

Parameters:

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

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

$EnergyMix_{pjy}$: $power\ source\ p, in\ region\ j, for\ year\ y$

Indexes:

k: $air\ pollutant\ index\ for\ GHG$

j: $region\ index$

y: $year\ index$

p: $power\ plant\ index$

Therefore the emissions savings of V2G for the regulation service can be estimated using the following formula:

$$Emi_{saving} = E_{disp} \times Emi_{traditional} - \left(E_{disp} \times Emi_{grid} + Emi_{battery\ wear\ out}\right) \tag{9}$$

Where E_{disp} is the dispatched electricity in kWh, , Emi_{grid} is the emissions rate of the electricity generated by the grid mix in the studied region, and $Emi_{battery\ wear\ out}$ is the emissions due to the battery wear-out from providing V2G services. It should be noted that the gas turbine generator as a regulation service method has relatively low efficiency due to the randomly ramp up/down of the power, and in fact it has been argued in the literature that the efficiency of energy storage is two to three times as much as that of gas turbine generators (Makarov et al., 2012). Therefore, in order to calculate the emission savings, $Emi_{traditional}$ is assumed here to be two to three times that of the stated gas turbine generator emission rate. The GREET, EPA and EIA regional electricity generating emission rates are also used to calculate emission savings. Moreover, in order to account for an additional level of uncertainty in these values, it has been assumed that they each range within $\pm 10\%$ of their respective projected values. The battery life cycle emissions were estimated using the EPA's report on EV lithium-ion batteries (Amarakoon et al., 2013), and the battery-related emissions for the material extraction, manufacturing, use, and end-of-life phase are all considered.

4.3.9 Net revenue

The net revenue of V2G regulation services is calculated by subtracting the total cost from the total revenue. Regulation service revenue depends on the market of the electricity that is sold to. The previously developed methodology by Kempton and Tomic (Kempton and Tomić, 2005a) is mostly used to estimate the net revenue of V2G regulation services. However, in order to account for uncertainty, different contributions are added to the existing methodology. Thus, the total revenue to a regulation service provider consists of two separate revenue types: capacity payments and energy payments.

Capacity payments are given for the availability of the power plugged in, and are measured based on the contracted power capacity and the time the EV is plugged. Capacity payments are calculated using Equation 5 below:

$$R_1 = Price_{cap} P_{disp} T_{plug} \tag{10}$$

Where R_1 is the total capacity payment revenue, $Price_{cap}$ is the regulation capacity price in \$/kWh, P_{disp} the contracted available power in kW, and T_{plug} is the total vehicle plug-in time in hours. The $Price_{cap}$ is estimated based on the historical data of each ISO/RTO region individually, and the regulation up and regulation down prices are assumed to be the same. P_{disp} is the smaller value between the power output of the vehicle and the maximum power capacity of the charging infrastructure.

Energy payments, on the other hand, are given for the actual exchanged electricity via regulation signal responses. Energy payment calculations are summarized in Equations 6 and 7:

$$R_2 = Price_{ele} E_{disp} \tag{11}$$

$$E_{disp} = \sum_{i=1}^{N_{disp}} P_{disp} \times T_{cyc} \tag{12}$$

Where R_2 is the total energy payment revenue, $Price_{ele}$ is the retail electricity price in $/kWh as derived from the authors' previous study (Noori et al., 2015), E_{disp} is the total dispatched electricity in kWh, N_{disp} the number of dispatches (regulation cycles), P_{disp} is the requested dispatched power in each regulation cycle in kW, and T_{cyc} is the actual time of one regulation cycle in hours. The number of accepted regulation requests (N_{disp}) is assumed to be uniformly distributed from 30 to 40. Due to the random nature of regulation requests, the value of T_{cyc} is randomly selected between 3.6 minutes and 9 minutes (Kempton et al., 2008). The annual exchanged electricity is taken by summing all the random daily exchanged electricity during 365 days of the year. This process is performed for 1000 replications for each year, meaning the analysis covers 1000 * 365 days combinations.

In summary, the total V2G regulation service net revenue is the sum of R_1 (capacity payments), R_2 (energy payments) and deducted by C (the battery degradation) as calculated in Equation 8.

$$R = R_1 + R_2 - C \tag{13}$$

Regulation service costs (excluding operation or maintenance costs due to regular vehicle usage) consist mainly of costs related to battery wear-out. The general formula for cost is expressed as follows:

$$C = \frac{C_{bat}}{L_{et}} E_{disp} + C_{ac} \tag{14}$$

Where C is the total regulation service cost, C_{bat} is the capital cost of the battery in $, L_{et} is the lifetime throughput energy in kWh, E_{disp} is the total dispatched electricity in kWh, and C_{ac} is the annualized capital cost in $. C_{bat} and L_{et} are calculated as shown in Equations 10 through 12 below.

$$C_{bat} = B_{cap} P_{bat} \tag{15}$$

$$L_{et} = L_c B_{cap} DoD \tag{16}$$

$$C_{ac} = \frac{C_{bat}}{L_{et}} E_{disp} \times \frac{d}{1-(1+d)^{-n}} \tag{17}$$

Where B_{cap} is the battery capacity, P_{bat} is the battery unit price in $/kWh (Gallo and Tomic, 2013), L_c is the battery lifetime, DoD is the depth of discharge (which affects the overall battery life), d is the discount rate, and n is the number of the year the battery will be used.

The aforementioned costs and revenues pertain solely to regulation services. The overall cash flow, the capital costs of the vehicle and of the charging facility (excluding taxes and licensing fees), and the operational costs (e.g. maintenance costs and fuel costs) in each year are also included, as shown in Equations 13 and 14 below.

$$ACF_{vjy} = Pur_v + Equip_y + Ch_y + Ele_{jy} - R_{vjy} + VM_{vy} + ChM_{\ y} + BRepl_{vy} - Sal_v \tag{18}$$

$$Net\ Present\ ACF_{vjy} = \frac{ACF_{vjy}}{(1+i)^y} \tag{19}$$

Indexes:

v: $vehicle\ type\ index$

j: $region\ index$

y: $year\ index$

Where ACF is the annual cash flow, Pur is the vehicle purchasing cost, Equip is the equipment upgrade cost, Ch is the charging station cost, Ele is the electricity cost, R is the total V2G regulation service revenue, VM is the vehicle maintenance cost, ChM is the charging station maintenance cost, BRepl is the battery replacement cost, Sal is the vehicle salvage value, and i is the discount rate. Among the relevant cost categories, purchasing costs for vehicles and for charging equipment purchasing are all added to the first year only, while vehicle salvage revenue applies are added only to the end of the life cycle. All other cost categories will be calculated and added to the total cost for each year.

The cost of a battery electric truck is three times as much as that of a diesel truck, and the capital cost is often a significant hurdle for potential EV owners. To promote the adoption of hybrid vehicles, plug-in electric vehicles, and related charging infrastructure, the federal government and about 40 state governments currently provide a variety of incentives, including income tax exemption, free parking, free registration, and free high-occupancy vehicle (HOV) lane access (National Cpnference of state Legislatures, 2015). In most states, the rebate or tax exemption for hybrid or electric cars can vary from $1,000 to $4,000. However, for electric delivery trucks, which have very expensive initial costs, the State of New York and the State of California currently provide a "first come first serve" fund to compensate battery electric truck owners for as much as $60,000 per vehicle and $50,000 per vehicle, respectively. Since not every state provides incentives for electric trucks or even for electric cars, the applicable federal and state-level electric truck incentives have also been taken into consideration for the studied regions. Table 14 shows the amount of incentives for hybrid and battery electric trucks in the representative states of each ISO/RTO region.

Table 14 Federal and state electric truck incentives in the researched regions

	Representative States	**PHEV (EREV)**	**BEV**
Federal Level	-	$4,000 (Jin et al., 2014)	$7,500 (Jin et al., 2014)
PJM	PA, WA, VA, DC, NJ	$2,000 (Jin et al., 2014)	$2,000 (Jin et al., 2014)
CAISO	CA	$1,500 (Wood, 2015)	$50,000 (California HVIP, 2015)
ERCOT	TX	$2,500 (National Cpnference of state Legislatures, 2015)	$2,500 (National Cpnference of state Legislatures, 2015)
ISONE	ME, NH	$0 (Jin et al., 2014)	$0 (Jin et al., 2014)
NYISO	NY	$0 (U.S. Department of Energy, 2015)	$60,000 (Truck Voucher Incentive Program, 2015)

4.4 Results

4.4.1 Cumulative costs of ownership and V2G regulation service net revenues of the BEV and the EREV

Although the first cost of an electric drive vehicle normally serves as an economic disincentive (which is even more significant for electric trucks), it is crucial to consider the total ownership cost of a vehicle throughout its entire lifetime instead of only considering the initial cost. Figures 14a through 14e depict the yearly cumulative ownership cost of the BEV in the five researched ISO/RTO regions. As noted in the previous sections, in order to account for uncertainty, ranges of key parameters are inputted to the developed model consisted by equations in the method section. The model is then run for 1,000 replications, during each run, random values within the preset ranges are selected for calculation. The ownership cost results are then presented based on scenarios for the lowest, highest, and average values. Moreover, the V2G implementation scenario (V2G) and the business-as-usual scenario without V2G services (No-V2G BAU) are compared in each figure to indicate the potential benefits of V2G services in each region. Overall, the cumulative cash flow in all five regions are incremental. The lines indicating average cash flow grow steadily and slowly, while the corresponding upper-range lines show two sharp increasing trends in the year 2021 and in the year 2026; both of these years correspond with time points at which batteries were replaced, and thus a relatively larger expenditure is added accordingly. On the other hand, the lower-range lines indicate that battery degradation, daily usage, maintenance costs, and other cost-related factors are minimal, and thus only one extra battery is needed throughout the vehicle’s lifetime. At the end of the research period, the slight decline of the total cost is due to a one-time inflow of revenue from the salvage of the vehicle. In the PJM, ISO-NE, and ERCOT regions, the average net present values of the total ownership cost are approximately $320,000. However, the NYISO and CAISO regions have significantly lower total ownership costs at $240,000 and $280,000, respectively, these lower ownership costs being due largely to the greater amount of state incentives in these regions.

When comparing the V2G and No-V2G BAU scenarios, the total ownership cost reduction is only significant for the maximum ownership cost scenarios in the PJM, NYISO, and CAISO regions (Figures 14a, 14c, and 14e, respectively). The ownership cost savings from providing V2G services are not significant for any region under the average-cost and minimum-cost scenarios, and in some cases are even negligible. Once the battery electric truck is purchased and the equipment is upgraded, more revenue would be gained as more electricity is processed through the system. Furthermore, in spite of the additional battery degradation caused by V2G regulation services, the battery wear-out cost is much less than the profit created, with only two extra batteries needed in the worst-case scenarios for all five regions. However, in the ISO-NE and ERCOT region (Figures 14b and 14d), the total ownership cost are not significant even if one assumes the maximum possible amount of exchanged electricity, owing to the relatively low regulation service capacity payment prospects in these two regions.

The net present value of the BEV's total ownership cost of ownership are summarized and compared for each region in Figure 15. Here, the NYISO region has the lowest total cost among all five regions, while the cost of implementing the V2G system is highest in the ISO-NE region. However, the aforementioned "insignificant" benefits of V2G regulation services in some regions or under some scenarios are compared based on a level lifetime ownership cost of $100,000. To this end, Figure 16 shows the total lifetime revenue (based on a 15-year lifetime) from V2G regulation services in the five ISO/RTO regions. As shown in the figure, the NYISO and PJM regions have the greatest and second greatest maximum potential revenues (approximately $58,000 and $50,000, respectively), while the ISO-NE region has the smallest maximum revenue. In addition, from the large whisker ranges in Figure 16, it can be concluded that the V2G net revenue not only varies among the regions, but also changes within each individual region depending on the amount of electricity exchanged through the system.

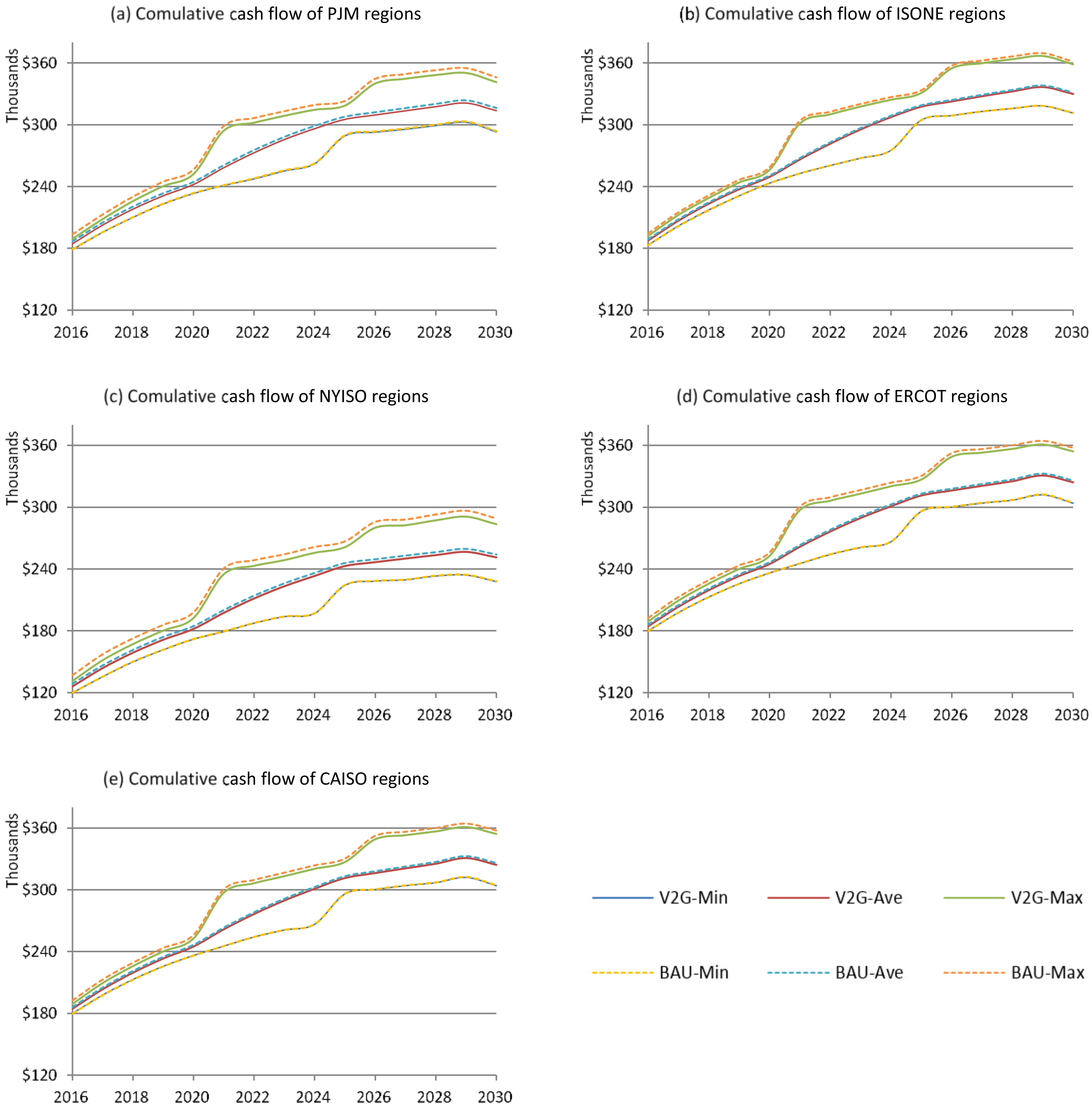


Figure 14 Cumulative cash flow due to V2G regulation services of BEVs in researched regions

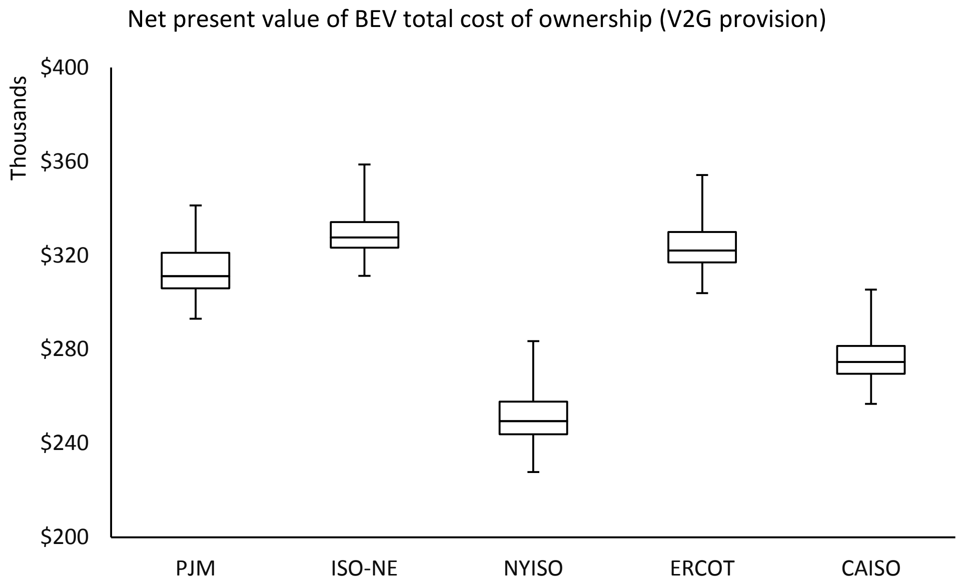


Figure 15 Net present value of BEV cost of ownership in researched regions

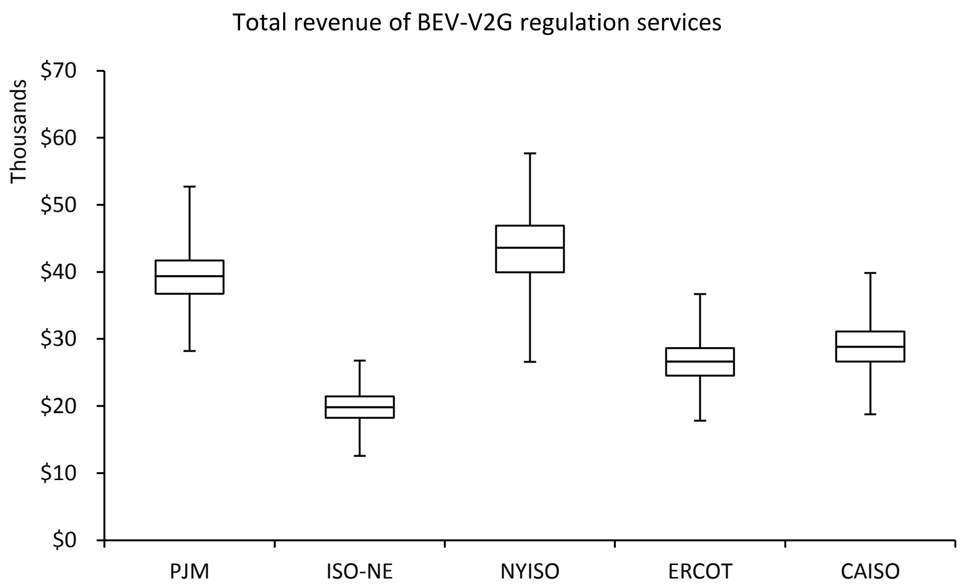


Figure 16 Total revenue of BEV-V2G services in researched regions

Figures 17a through 17e depict the yearly cumulative total ownership cost of the EREV, which has similar upper-level, lower-level, and average cash flow trend as the BEV, but since the initial cost of an EREV is typically lower than that of a BEV, the net present value of the lifetime ownership cost is also lower, now ranging between $210,000 and $230,000 for all five ISO/RTO regions; this is also shown in Figure 18. According to the results, the total ownership cost savings from providing V2G regulation services are only significant in the NYISO and PJM regions (Figures 17a and 17c). Moreover, the battery replacement costs are still differentiated from the normal ownership cost increasing trend, but the resulting costs are still lower for EREV batteries than for BEV batteries because the battery capacity of the EREV is only 50% as much as that of the BEV. Meanwhile, there is no large fund for hybrid trucks among state governments, so the spatial ownership cost variations for the EREV are not as significant as those for the BEV.

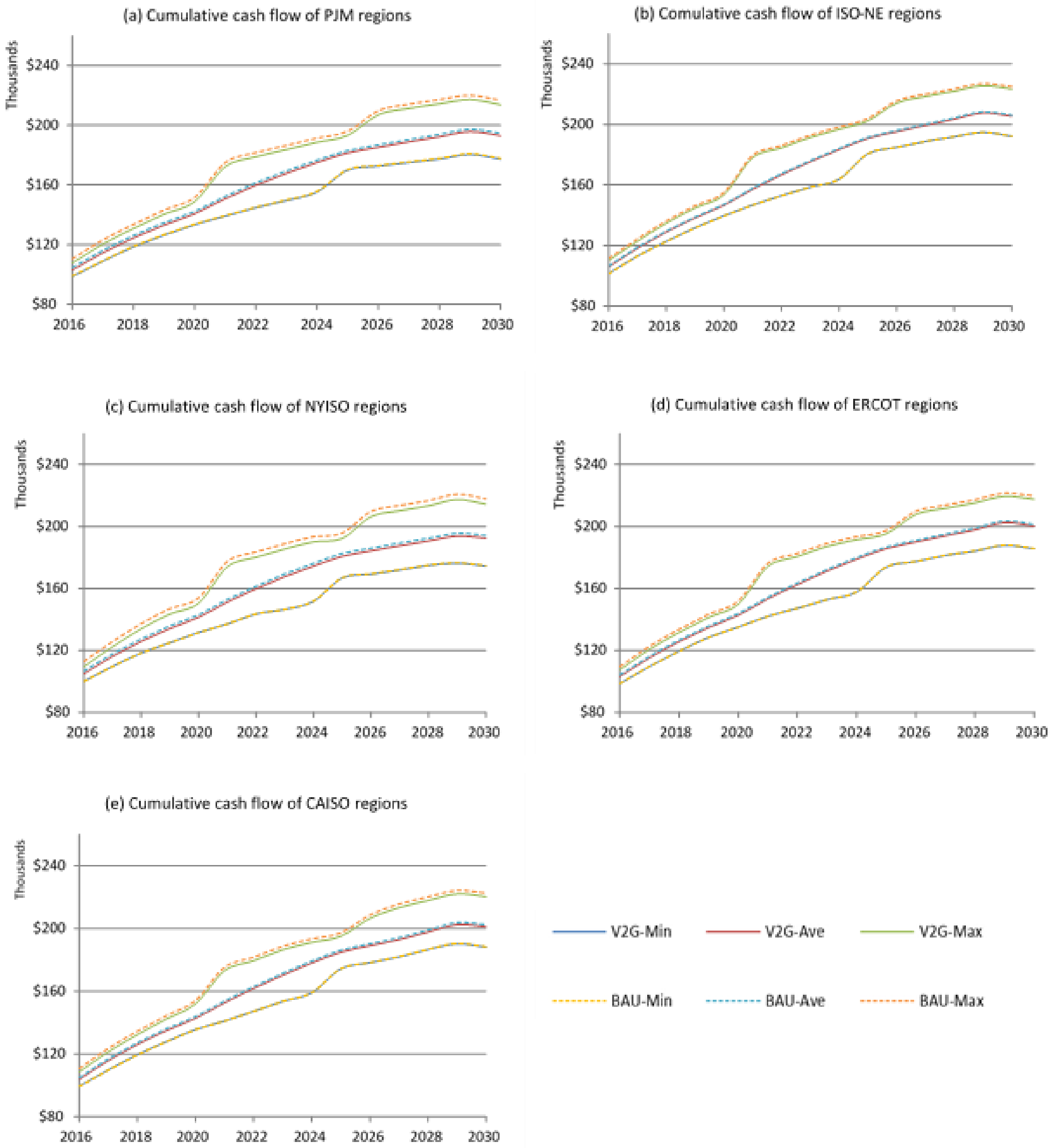


Figure 17 Cumulative cash flow due to V2G regulation services of EREVs in researched regions

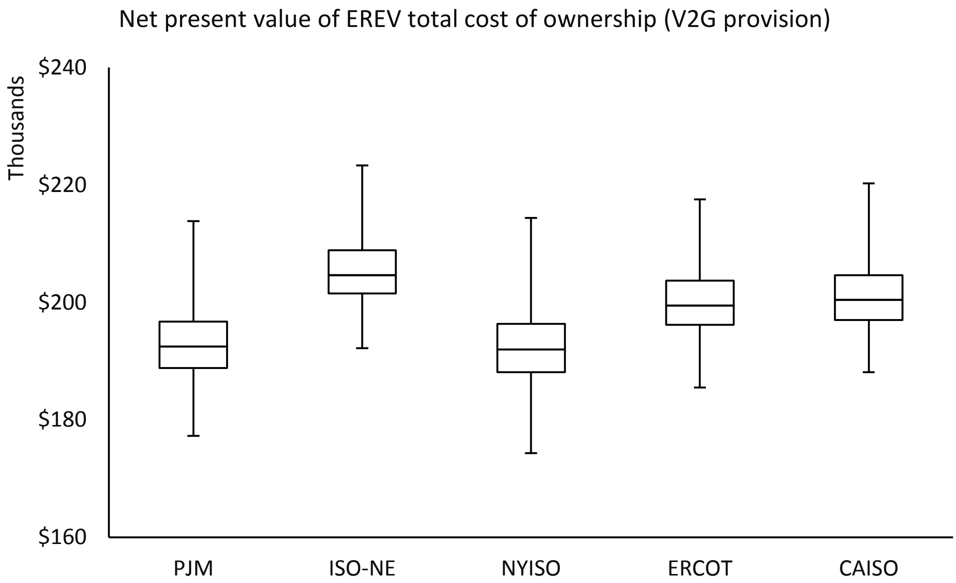


Figure 18 Net present value of EREV cost of ownership in researched regions

The net present value of the lifetime EREV V2G regulation service revenue is presented in Figure 10. These total revenues for each region are less than their corresponding values for the BEV because of the lower $P_{vehicle}$ results, which in turn are due to the EREV having a lower battery capacity than the BEV. However, based on the revenue results, EREVs can still be an affordable and viable option as V2G service providers.

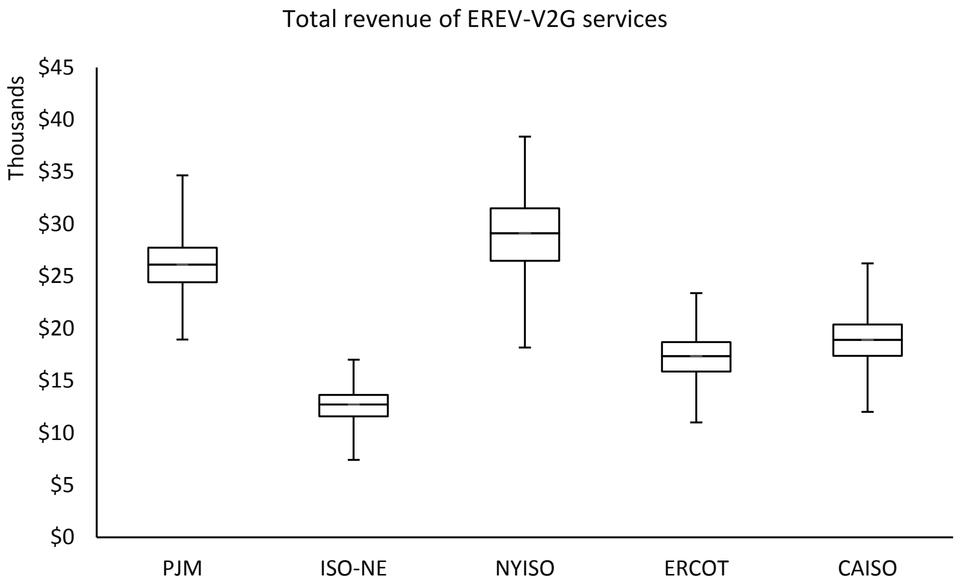


Figure 19 Total revenue of EREV-V2G services in researched regions

The diesel truck, as a reference case, has no accessibility to the grid and operates as a normal commercial delivery truck. As shown in Figure 11, although diesel fuel prices have been projected to vary in different regions, the total ownership costs of diesel trucks are identical from region to region, with only a slightly higher level of uncertainty evident for the NYISO region. That said, in spite of the much lower purchasing price of diesel trucks compared to EREVs, the net present values of diesel truck total ownership costs are almost the same (or higher in the PJM and NYISO regions) as those of the EREV (Figure 8f). This is because, although traditional diesel trucks have lower initial costs, their long-term maintenance and fuel costs can still add up to a relatively large sum of money.

As previously noted, a delivery truck fleet of 20 to 30 electric trucks is technically feasible for bidding an ancillary service contract, and recently, the minimum capacity requirement for ancillary service contracts have been lowered from 1MW to 100kW (Morash, 2013), meaning that delivery truck fleets consist of electric trucks are now more applicable to provide ancillary services. According to Figure 16 and 19, the equipment upgrade cost for V2G services (approximately $2,000) is considerably lower comparing to the overall V2G service revenues, and the initial upgrading cost can be easily returned within a few years. In addition, due to the excellent predictability of parcel delivery operations, idled electric trucks can be plugged to the grid through the coordination of a dispatching center and serve as reliable ancillary service providers.

4.4.2 GHG emission savings from providing V2G regulation services

Since the regulation service signals are random, there is no clear pattern of how much electricity is exchanged through the V2G system, the calculation of electricity exchanging follows a published work (Noori et al., 2016); as previously noted, a normal distribution function has been applied to simulate regulation service request. A possible example of yearly and 15-year cumulative GHG emission savings from providing V2G services is shown in Figures 20 and 21. It should be noted that the V2G GHG emission savings presented here do not include the life cycle emissions from regular vehicle operation.

Figure 20, as an example scenario of possible cumulative GHG emission savings, represents the emissions saved from using BEVs as V2G regulation providers in the PJM region. The emission savings in other regions have similar patterns, and therefore need not be explained in any further detail.

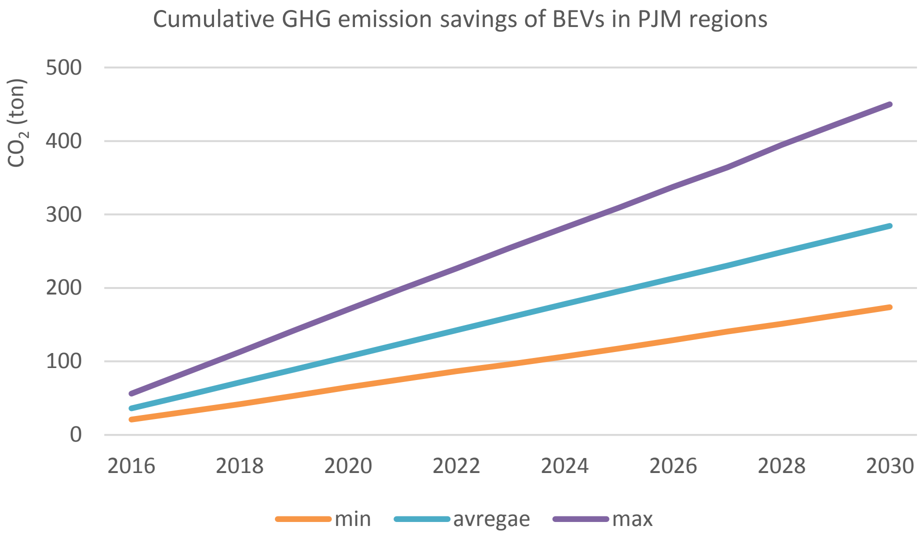


Figure 20 Life-time GHG emission saving of BEVs in PJM regions

Figure 21 shows the cumulative GHG savings of V2G regulation services in the five researched regions. From this figure, by plugging an idled BEV or EREV into the grid for V2G regulation services, a single vehicle is able to save as many as 200 to 500 tons of CO_2 over the entire 15-year lifetime of the fleet. In light of variations in the grid mixes (electricity source distributions) of each region, the ISO-NE region yields the most emission savings among all five regions, while NYISO region has the lowest emission savings. It can also be concluded from the figure that, in spite of the higher battery capacity and output power of a BEV as opposed to an EREV, BEVs do not necessarily yield more GHG emission savings than EREVs, as the total exchanged electricity amount is limited based on the amount of power requested by the grid operator rather than the power output of the vehicle; in other words, despite the relatively lower battery capacity (40kWh) of EREVs, the EREV's capacity is still sufficient to meet the relevant V2G regulation service requirements.

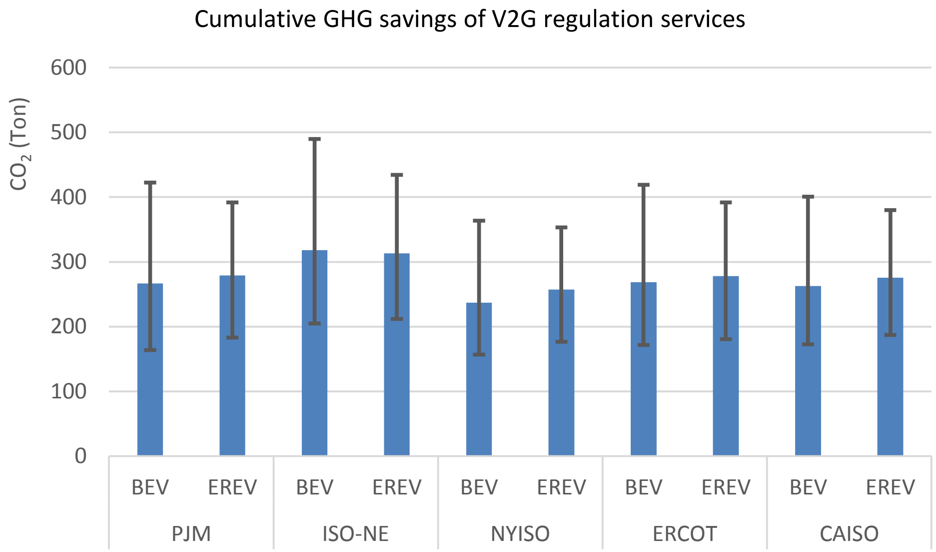


Figure 21 Cumulative GHG emission savings in the researched regions

4.4.3 Comparison of life cycle GHG emissions

In order to comprehensively evaluate the environmental benefits of electric trucks as electricity regulation service providers, a more thorough life cycle assessment including upstream and downstream/tailpipe emission of electricity and diesel is conducted for this study. Figure 22 compares the life cycle GHG emission impacts of BEVs, EREVs (after payload adjustment), and diesel trucks for each of the five researched ISO/RTO regions. In this figure, the negative values represent the business-as-usual life cycle GHG emissions of the three vehicle types, without the use of the V2G system. BEVs have no tailpipe emissions, and therefore have lower total emissions even when upstream and downstream electricity generation and transmission impacts are taken into consideration, and so BEVs have the lowest BAU GHG impacts in all regions. In addition, based on the GHG impact results alone, the NYISO and CAISO are the two most environmentally suitable regions for electric truck implementation because of the low GHG emission factors of their respective grid mixes. EREVs technically have lower GHG emission impacts than BEVs because, instead of driving with the engine directly as conventional hybrid vehicles do, EREVs are equipped with much a smaller engine that powers an electric motor in order to generate its electricity; however, while the researched diesel truck and battery electric truck have identical payloads, the payload of the EREV in this study is approximate 50% as much as that of the other two truck types, and so the EREV emissions shown in Figure 22 have been adjusted by a payload factor to ensure that all results are for the same overall payload. After adjusting for payload, the emission results of EREVs indicate no obvious advantages over diesel trucks, but the environmental advantages of EREVs become more apparent when V2G emission savings are taken into consideration. Over the 15-year research period, the emission savings of BEVs and EREVs exceed their respective life cycle emission impacts due to electricity consumption. Hence, although a considerably larger investment is needed to incorporate BEVs and EREVs into the current truck fleets, the long-term environmental benefits of integrating EVs with the grid are significant in most regions. In fact, with the potential introduction of carbon taxes, these emission savings have potential to yield their own economic benefits as well.

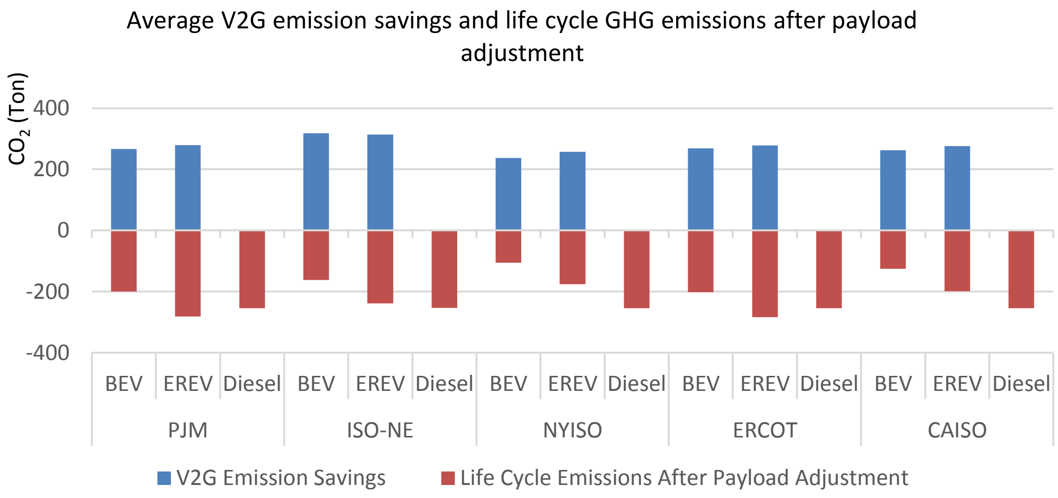


Figure 22 Average V2G emission savings and life cycle GHG emissions of vehicles in the researched regions

In order to demonstrate the potential economic value of GHG savings, a carbon tax projection is used to simulate the total tax savings of replacing current diesel trucks with battery electric trucks in the PJM region (Figure 23). These tax savings are computed by multiplying a proposed yearly federal carbon tax rate (2016-2030 projection) (Center for Climate and Energy Solutions, 2013) with the overall life cycle GHG emission savings, more specifically comparing a battery electric truck that provides V2G regulation services to a regular diesel truck. Since EVs providing V2G services are actually mitigating GHG from the environment instead of emitting to the environment, and carbon taxes are projected to increase in the future, the tax savings due to GHG emission reductions could add up to as much as approximately $18,000 by the year 2030.

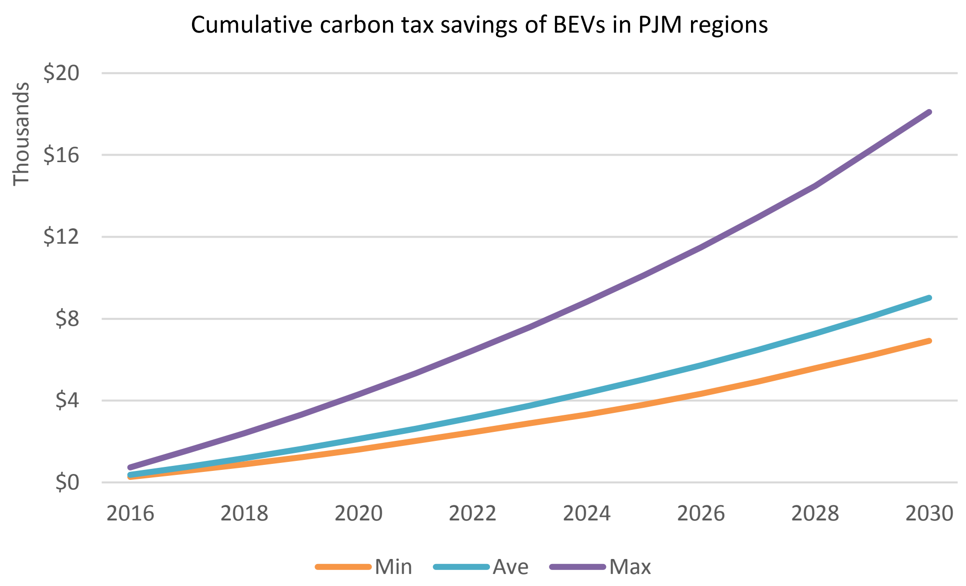


Figure 23 Cumulative carbon tax savings of battery electric trucks compared to diesel trucks in PJM regions

5 THE ROLE OF VEHICLE-TO-GRID SYSTEMS IN WIND POWER INTEGRATION

A partial work of this chapter has been submitted to the Journal of Energy Policy

The large-scale integration of wind power must be supported by regulation services, which are normally provided using combustion turbines. These regulation services can also be provided using vehicle-to-grid systems, which utilize idle electric vehicle batteries to store /re-supply energy from/to the grid. As discussed in Section 2 through Section 4, government or commercial fleets are able to unify enough power capacity from their electric vehicles for the regulation service provision in the initial phase of vehicle-to-grid system. However, a large number of electric vehicles is needed for a large-scale vehicle-to-grid network to be functional; and the potential to trigger marginal electricity generation by introducing numerous electric vehicles must also be taken into account. Therefore, an agent-based model is developed to simulate the integration of wind power into the power grid, as well as the regulation services provided by a vehicle-to-grid system, and then compare the resulting greenhouse gas emission savings from supporting the increased integration of wind power to the additional greenhouse gas emissions from the large-scale charging of electric vehicles. The results indicate that, by supporting the newly integrated wind power through a vehicle-to-grid system, greenhouse gas emissions can be effectively mitigated in most of the researched regions if electric vehicles are sufficiently available to meet the regulation requirements from vehicle-to-grid systems.

5.1 Background Information and Literature Review

5.1.1 ISOs/RTOs and wind power projections

The geological boundary of this study is based on seven ISO/RTO regions (Federal Energy

Regulatory Commission, 2016), specifically the CAISO, ERCOT, SPP, MISO, NYISO, PJM and ISONE regions. This is in part because the electric power exchange between the ISO and RTO regions is negligible, with only a 1% net exchange in 2010 (U.S. EPA, 2011); in fact, the inter-regional electricity exchange could potentially be beneficial, but is currently constrained by the limitations of current high-capacity transmission infrastructure (Flynn, 2008). Furthermore, the majority of the regional wind power transmission in the U.S. (about 80% (Gonzales et al., 2008)) is controlled by these same ISOs/RTOs, and the wind power capacity corresponding regulation requirements are separately managed by each grid operator. Lastly, current onshore wind projects are typically located in regions of high wind quality, particularly coastal and central areas (Flynn, 2008), which mostly overlap with the scope of the aforementioned ISO/RTO regions.

Some of the researched regions represent single states (the CAISO, ERCOT, and NYISO regions), while others cover several states (the SPP, MISO, PJM, and ISONE regions). Therefore, the wind power capacity at the ISO/RTO level is calculated as the sum of the capacities of all of the major states within each independent grid operator region, as summarized in Table 15. According to the U.S. Department of Energy's wind power report (Wiser et al., 2015), 7.7 GW of wind power will be integrated to the entire grid each year from 2015 to 2020, and 12.1 GW of wind power will be added to the grid each year from 2021 to 2030. Since these incremental introductions of wind power to the power grid will be integrated nationwide, the wind power projection of each ISO/RTO region must be weighted based on its current wind power capacity, and the installed wind power capacities and wind power projections in each region are summarized in Table 15. In particular, the wind power projections (last two columns from the left in Table 15) will serve as the key parameters in the wind projection simulation of the ABM model.

Table 15 Current wind power installation and wind power projection in ISO/RTO regions

ISO/RTO	Model Code	States	2015 Installed Wind Power (MW)	Capacity Ranking	Wind Project No.	Projects Under Construction	Weight	2016-2020 Yearly Projection (MW)	2021-2030 Yearly Projection (MW)
CAISO	Region 0	California	6,022	2	123	86	0.11	847	1,332
ERCOT	Region 1	Texas	16,406	1	112	6,343	0.30	2,309	3,628
SPP	Region 2	Nebraska	810	20	16	116	0.15	1,169	1,837
		Kansas	3,167	6	26	871			
		Oklahoma	4,330	4	29	1,199			
MISO	Region 3	North Dakota	1,886	11	22	736	0.34	2,653	4,170
		Minnesota	3,035	9	94	551			
		Wisconsin	648	22	18	0			
		Iowa	5,710	3	99	679			
		Illinois	3,842	5	46	250			
		Indiana	1,745	13	14	150			
		Michigan	1,531	14	23	30			
		Missouri	459	25	6	0			
NYISO	Region 4	New York	1,749	12	25	0	0.03	246	387
PJM	Region 5	Ohio	435	26	30	259	0.05	354	557
		West Virginia	583	23	5	0			
		Pennsylvania	1,340	16	24	0			
		Maryland	160	31	4	31			
ISONE	Region 6	Maine	465	24	12	423	0.02	121	191
		Massachusetts	107	34	44	8			
		New Hampshire	171	30	5	14			
		Vermont	119	33	8	0			

5.1.2 Wind integration and its impacts

In general, power grids are designed to accommodate a certain level of fluctuation. Nevertheless, the intermittency of wind power would be amplified significantly as substantial amounts of wind power are being integrated into the current power system, especially if such integration takes place in a relatively short time interval as previously explained. As a result, the minute-to-minute fluctuations in the power grid will increase significantly, and additional grid ancillary services will ultimately be required to balance the resulting increase in power supply fluctuations (Parsons et al., 2006). For simplification purposes, this paper will focus only on the impact of wind integration on regulation service demand.

Albadi and El-Saadany (2010) previously studied the relationship between wind power adoption and the corresponding ancillary service demand, and two important conclusions were drawn based on their research. Firstly, the cost of ancillary services increases significantly as wind power penetration grows, meaning that the increased integration of wind power could become economically inefficient once the grid allocation of wind power exceeds a certain limit. Secondly, the adoption of fast-responding generation/storage systems will be crucial to reducing the overall cost of wind power. A study conducted by Korchinski (2013) likewise confirms that large amounts of backup capacity must be online to ensure a stable power output from wind projects, and that in the event of low power demand compared to the wind power output at the time, the wind energy that might otherwise be wasted ("wind dumping") could instead be stored for later use as needed.

5.1.3 Electric vehicle market penetration projection

Based on the ABM simulation results with respect to wind power integration, the corresponding regulation requirements, and the degree of EV market penetration needed to meet these requirements are all calculated in this study using the methodology discussed in Section 5.1.3, and the required number of EVs is then compared to current EV projections; the smaller of these two values is then taken as the number of available EVs that will actually provide regulation services. The methodology for calculating EV market penetration is obtained from previous studies by the authors of this paper, and is also briefly introduced in this section.

The vehicle price, maintenance cost, refueling cost, environmental impacts, government subsidies, and other attributes related to EVs and/or traditional vehicles are all factors that can affect a potential buyer's choice regarding vehicle type, and these factors can also change on a temporal and spatial basis (e.g. variations in fuel prices, electricity prices, or federal/state rebates for EVs). Hence, a previously developed agent-based model (Noori and Tatari, 2016) is used to simulate the market penetration of EVs (including battery electric vehicles (BEVs).

To project the regional market penetration of EVs, firstly, vehicle attributes are first derived from a previously developed Electric Vehicle Regional Optimizer (EVRO) (Noori et al., 2015) with uncertainties taken into account as appropriate. Next, an agent-based model (including customers, vehicles, and regions as agents) is developed to simulate EV market penetration in the next 15 years. Finally, the Exploratory Modeling and Analysis (EMA) method is used to evaluate the results of the agent-based model. Since BEVs and EREVs both have grid accessibility and large-capacity batteries, the combined number of these plug-in EVs is used as the number of potentially available EVs in this study, and the resulting market penetration data is shown in Figure 24 below

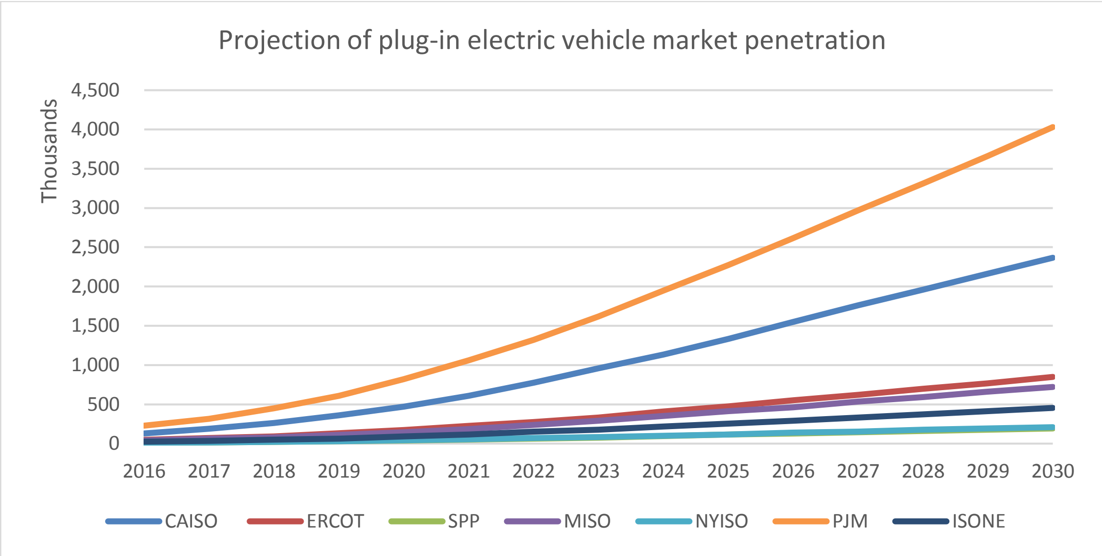


Figure 24 Regional EV market penetration projections

5.1.4 <u>Electric vehicle charging and marginal electricity</u>

Based on the conclusions of the authors' previous study (Section 5.2.4), with government incentives playing a critical role, the market penetration of plug-in EVs may increase to as much as 26% by the year 2030 (Noori and Tatari, 2016). Also, a large EV fleet will undoubtedly be a crucial connection between the transportation and electricity sectors and a vital part of a smart city system, but studies have also shown that the charging behaviors of EV owners may trigger marginal electricity generation (Ma et al., 2012) and thereby offset the GHG emission mitigation benefits of V2G systems (Siler-Evans et al., 2012). In one such study, McCarthy and Yang (2010) argue that a large-scale EV fleet may require extra electricity from low-efficient combustion turbines. A study conducted by Green et al. (2011) has likewise confirmed that the massive adoption of EVs may impact the electric network, and possible charging scenarios with respect to plug-in EVs and their subsequent load impacts have also been analyzed in the available literature (Hadley, 2006). In order to provide V2G services, EVs are usually connected to the grid at night, but as the number of EVs plugged into the grid increases significantly, a greater amount of marginal electricity demand is created as a result (Hittinger and Azevedo, 2015), whereas coal plants are commonly used as a primary marginal electricity generation source in some areas. Zivin et al. (2014) argue that the emissions due to EV charging may vary spatially because of the regional differences in average and marginal energy mixes, and have compared the marginal electricity emission rates of each ISO/RTO region. Similarly, Kintner-Meyer et al. (2007) analyzed the impacts of EV charging on the power grid in 12 ISO/RTO sub-regions.

5.1.5 System boundary

There are extensive studies in the available literature that analyze the impacts of wind integration, the possible contribution of a V2G system on a renewable power network, or the environmental impact of a large-scale EV fleet, and the potential of wind power and EVs to mitigate environmental emissions has also been studied extensively. However, the incremental or marginal effects of adding large amounts of wind power and EVs to the power grid have not yet been researched on a holistic basis. To this end, the innovation and also the first step of this study is to estimate the additional regulation requirement from the rapid growth of wind power capacity, and to calculate the EV fleet scale needed to meet this regulation requirement using V2G regulation services. Secondly, although some ISO/RTO regions have considerably high wind integration projections, and therefore higher demand for V2G services and/or EVs, the corresponding EV projections in each region may not be high enough to meet the demand. Hence, to compare the supply/demand relationship with respect to EVs in a future V2G-renewable power system, the EV projections from the authors' previous study are used here to represent the overall EV population, and this study will also compare the additional emissions from the marginal charging of this EV population to the GHG emission savings from the use of the available EVs to provide V2G regulation services. The third innovation of this study is its consideration of regional variations; all of the key factors in this study (wind power projections, EV projections, marginal emission rates, etc.) may vary from region to region, and the V2G-wind power system must therefore be analyzed separately for each of the seven considered regions. Another important novelty of this study is the policy analyses to be conducted. For instance, the wind project aggregation level and the actual V2G signal strength are both deterministic factors that can affect the regulation requirement level; the willingness of EV owners to provide V2G services and the charging behaviors of said EV owners could lead to different performance levels for a particular V2G-wind power system in any given scenario. Because these factors may be subject to change in reality, this study will use the agent-based model developed in this study to analyze different scenarios representing various combinations of key factors. The system boundary and the key elements of this model are all shown in Figure 25.

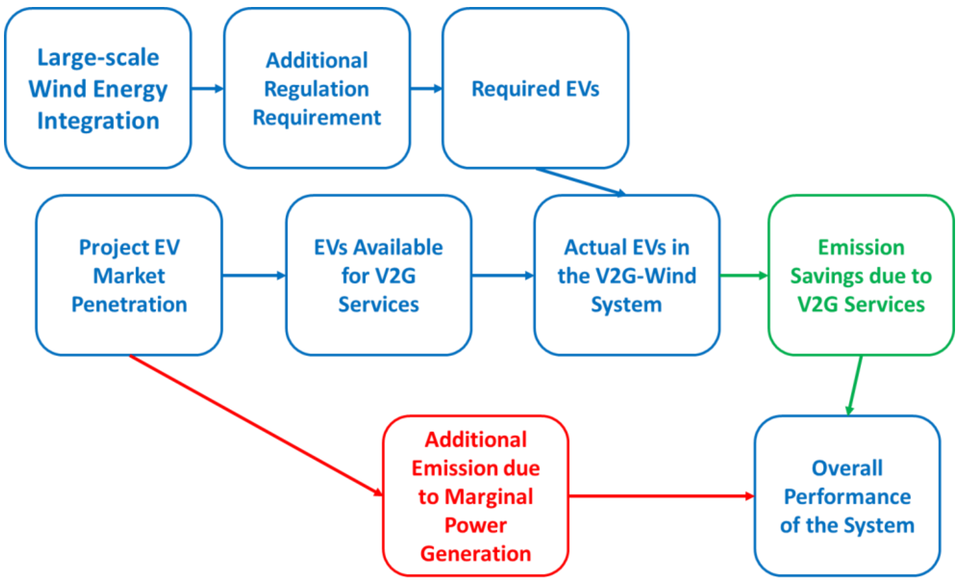


Figure 25 System boundary

5.2 Method

5.2.1 <u>Agent-based modeling</u>

Using AnyLogic software (Anylogic, 2015), an agent-based model is developed to evaluate and analyze the mechanisms of the V2G-wind power system to be considered in this study. The main agent in this model, which also functions as the basic modeling environment, is defined as one of the researched ISO/RTO regions. Within this main agent, regional wind power agents are introduced to represent the growth of wind power in the researched region (Table 15). Each wind power agent represents 1 MW of increased wind power capacity. The wind power is assumed to be zero at the start of the simulation (the beginning of 2016), since this study will focus on the incremental increase of wind power capacity and its subsequent impacts, and the wind power capacity will reach the projected amount (Table 15) by the end of the simulation. The wind power agent also reflects the aggregation of wind projects, which may increase grid stability and reduce regulation requirements. Based on estimated assumptions regarding the regulation requirement rate, the regulation services required each year are evaluated based on the population number of the wind power agent, thereby obtaining the required number of EVs to meet the demand. The number of required EVs in each year is then compared to the available number of EVs, which is simulated using a lookup function of the EV market penetration projections as previously discussed. The model is designed to select the smaller number of EV between these two values in each year, which is used to represent the total available number of EVs for providing regulation services. Finally, the model will calculate the overall emission savings in each year based on the model's key parameters (V2G signal data, combustion turbine emission rate, marginal electricity emission rate, etc.). The aforementioned processes are then repeated six more times with different data sets to cover the 15-year projections for each region. Each individual process in this methodology is explained in further detail in the following sections, and the outline of this methodology is also summarized visually in Figure 25.

5.2.2 Modeling of wind integration and aggregation

The regulation requirement of wind integration is ultimately due to the lag between the rapid growth of wind capacity in the power grid and the completion of an inter-regional cooperating/supporting system. The voltage or frequency of a local grid is inherently unstable because of the random turning on/off of millions of appliances at any given time, as well as the potential for the sudden failure of generators. The newly added wind capacity, due to its inherently intermittent nature, inevitably increases the level of uncertainty or variability in its host area.

Nevertheless, the corresponding regulation requirement may not always be linearly correlated to the incremental wind capacity, because wind projects have been found to benefit significantly from the aggregation of wind power (Kirby, 2005). One study (Kirby and Hirst, 2000) suggests that, when a large wind project has a capacity scale as large as its host area, and the overall incremental increase in wind capacity is 41% instead of doubling the total regulation requirement. Due to the complexity of such systems, there is currently no unified standard or regulation available as a reference to quantify the benefits of wind aggregation, but a study conducted by Kirby et al. (2012) has indicated that the optimized regulation requirement could range from approximately 30% to 50% of the total "stand-alone" regulation requirement of the wind projects in question, depending on the level of aggregation being considered.

The detailed simulation of the development of a well-coordinated national wind aggregation system is beyond the scope of this study. Instead, to represent this wind aggregation process as simply as possible without compromising the accuracy of the model, the increasing process of individual agents (each representing 1 MW of newly installed wind capacity) is divided into three phases as shown by the state chart in Figure 3: low aggregation, medium aggregation, and high aggregation. In other words, the increasing pattern and growth rate of wind power agents follows the projections previously cited in Table 15 (last two columns from the left). After the construction of the model, and at the beginning of the simulation, the wind power agents enter the low-aggregation state first. The arrows on the left-hand side of Figure 3 with a clock represent a "time out" function in Anylogic, meaning that the agents stay in this state for a certain period of time and then enter the next state. The rates of the two time out functions "AggregationPhase1" and "AggregationPhase2" are both assumed to be five years, meaning that the newly added wind capacity is at a low aggregation state, or stand-alone state, from 2015 to 2020, due to insufficient transmission infrastructure for higher aggregation levels. Hirst and Hild (2004) found that the regulation requirement rate for wind projects is 0.5%, while Hudson et al. (2001) argue that this rate could be as high as 6%; since both rates have been confirmed in a separate study (Kempton and Tomić (2005b), the low aggregation regulation requirement rate is assumed to be 6% on average, ranging from 2% to 9%. Similarly, the wind power agents shifting from a low aggregation state to a medium aggregation state stay in the medium aggregation state for another five years, and then change to high aggregation state through the time out function "AggregationPhase2"; the regulation requirement rate in this state is assumed to range from 1% to 5%, with a default value of 3%. It should be noted here the regulation requirement is reflected in the main agent and subsequently used as one of the key parameters in later calculations. The arrows on the right side of the state chart are used to simulate the wind aggregation process. The arrow within the second state, "AggregationPotential1", is a rate function (its rate being equal to the first-order delay in stock and flow diagrams (Osgood, 2011)) that sends a message ("Aggregation") to a random agent in the last state ("LowAggregation"); whichever agent in the low aggregation state receives this message has a certain probability to change to the medium aggregation state. For purposes of this model, the rates "AggregationPotential1" and "AggregationWillingness" are both assumed to be 0.5. The messaging and shifting process in this model simulates the aggregation process: by the time agents accumulate in the medium aggregation state, based on the infrastructure projections previously discussed, a preliminary network will have been formed to some extent, and the current wind capacity and/or new wind projects will therefore have a chance to reach out and connect to the capacity of currently "stand-alone" and/or low-aggregation project, the probability of which is simulated in the rate "AggregationPotential1". When this chance emerges, it then becomes possible that the projects involved could successfully integrate with each other and thus share the reduced regulation burden equally; this probability is represented using "AggregationWillingness", which is initially assumed to have a value of 0.5. The values of these two rates are empirical, and may therefore change accordingly during the policy tests to be conducted in this study. The aggregation process is likewise repeated for agents shifting from medium aggregation to high aggregation, at which point the agents will stay in a high-aggregation state for five years until 2030. During this period, the highly aggregated wind power network could be supported with a relatively lower regulation rate, which is thus assumed to range from 0.5% to 3%. The movement of the wind power agent is shown in Figure 26.

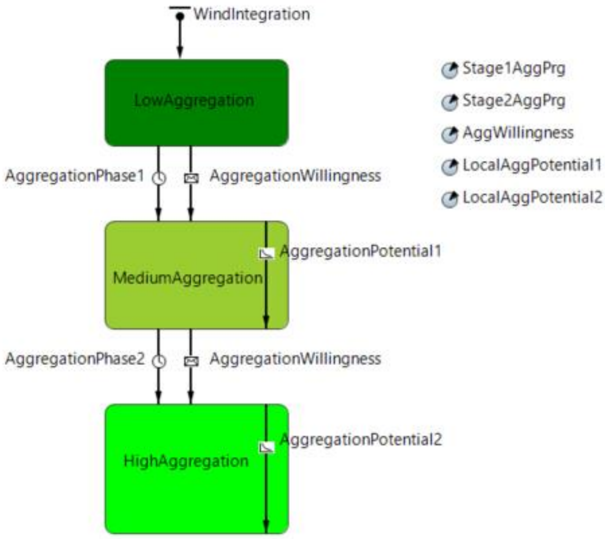


Figure 26 State chart of wind aggregation in a typical wind power agent

5.2.3 Required number of EVs and projected EV market penetration levels

The total regulation requirement throughout the research period is obtained by multiplying the total added wind capacity at each stage by the corresponding regulation requirement rate, after which the calculated regulation requirement value is used as an input to calculate the total number of required EVs.

The required number of EVs for a V2G regulation service contract can be calculated by dividing the total regulation requirement by the average power output of an individual vehicle providing V2G services (Hill et al., 2012). The power output, or available power, of each EV is calculated using Equation 1, which has been developed in a previous study (Kempton and Tomić (2005a). In addition, a battery agent is included in the model to reflect any potential variations in the power output.

$$P_{vehicle} = \frac{\left(B_{cap} - \frac{D_{vmt} - D_{buffer}}{F_e}\right) C_e}{T_{dispatch}} \qquad (20)$$

Where $P_{vehicle}$ is the total available power capacity in kW, and B_{cap} is the battery capacity of the vehicle in kWh. The battery capacity of common EREVs, such as the Nissan Leaf S, currently range from 20 kWh to 24 kWh (Nissan, 2015; Plugincars, 2015; Volkswagen, 2016). However, accounting for the average battery capacity of the entire EV fleet, it is conservatively assumed that the average EV battery capacity is initially 20 kWh in the year 2016 and then increases linearly to 26 kWh by the year 2030. D_{vmt} is the average daily vehicle mileage travelled by personal cars, which is assumed to be 30 miles based on the available literature (Statistic Brain Research Insititute, 2015; U.S. DOT, 2009), and D_{buffer} is the range that an EV driver would like to conserve as backup and/or to avoid range anxiety; this value is usually 20 miles on average (Kurani et al., 1994), but since EREVs have gas as a backup power source, and with the growing development of charging infrastructure, the buffering range is assumed to drop from 20 miles to 16 miles over the 15-year simulation period, meaning that the available power from the vehicle increases slightly over time. F_e is the fuel efficiency of an EV in miles/kWh, which is assumed in this model to have an average value of 3.5 based on available manufacturer data (Nissan, 2015; Plugincars, 2015). C_e is the transmission efficiency of the transfer of electricity from the EV batteries to the power grid, which is assumed to have a value of 0.93 (Sioshansi and Denholm, 2010). And finally, $T_{dispatch}$ is the accumulative regulation signal answering time (not the plug-in time) in hours, the value of which is conservatively assumed to be 0.3 hours (18 minutes) (Kempton and Tomić, 2005a). Accounting for all of the relevant assumptions and parameters as the model runs, the growth pattern of EV output power over the course of the simulation period is presented in Figure 27, where the y-axis of the graph is the power capacity in kW.

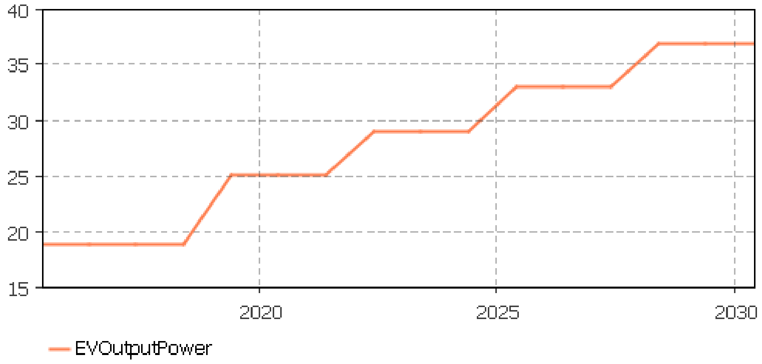


Figure 27 EV output power

The number of required EVs in each year is then calculated and compared to the number of available EVs, the latter of which is calculated as shown in Equation 21 below:

$$Number\ of\ Available\ EVs = EVMP_{ij} \times Wr \times Ar \tag{21}$$

Where $EVMP_{ij}$ is the EV market penetration during year i in region j, Wr is the percentage of EV owners who are willing to provide V2G services (assumed to be 0.05 on average, with a range from 0.01 to 0.1), and Ar is the rate of availability with respect to V2G service providers (assumed to be 0.3 on average, with a range from 0.1 to 0.5). The values and ranges of both the willingness rate and the availability rate are derived from relevant studies in the available literature (Kempton and Tomić, 2005b; Parsons et al., 2014), and these changeable ranges will be necessary for testing different scenarios and/or policies as explained in more detail in this study.

A separate algorithm is designed within the main agent to select the smaller value between the number of required EVs and the number of available EVs, and the result of this algorithm is taken as the actual number of EVs that will provide V2G services for the wind projects in the model.

5.2.4 V2G emission savings and additional emissions from marginal generation

Most of the total grid ancillary service requirement is currently provided by flexible yet low-efficiency combustion turbines, such as gas turbines or combined-cycle generators, and the repeated ramping up/down of these generators may cause significantly more GHG emission impacts compared to energy storage methods, so the GHG emission impacts of fossil fuel combustion can be mitigated by replacing traditional combustion turbines with EV batteries through the use of a V2G system. However, there is no data in the available literature regarding regulation signals from wind intermittency, so the relevant parameters with respect to V2G regulation signals are instead obtained from the available literature where available, and are assigned ranges in this manner in order to explore the potential variations from the implementation of different policy scenarios; a similar method has also been used in the previous sections. V2G emission savings are calculated using Equation 3 below:

$$ES = EV_{ij} \times P_{cycle} \times N_{dispatch} \times T_{cycle} \times Emission_{ct} \times ER \times EL \times 365 \qquad (22)$$

Where ES is the emission savings from the use of V2G regulation services, EV_{ij} is the actual amount of EVs that can provide V2G services as previously calculated in Section 5.3.3, P_{cycle} is the signal strength of each regulation request in MW (with an assumed default value of 0.0075 and an overall possible range from 0.001 to 0.01), $N_{dispatch}$ is the number of regulation cycles per night (which ranges from 30 to 40 with a median value of 35), and T_{cycle} is the time interval of each regulation up/down request (which ranges from 0.06 to 0.15 hours, or 3.6 to 9 minutes). P_{cycle}, $N_{dispatch}$, and T_{cycle} are the key parameters that determine the amount of exchanged electricity per vehicle per night, the values and ranges of which have all been already well explained in previous sections; furthermore, these parameters' values are changed as appropriate for different scenarios. $Emission_{ct}$ is assumed to be equal to 0.567 tons/MWh, which is the GHG emission rate of gas turbines as previously published by the

Environmental Protection Agency (EPA). The parameter “ER” represents the higher efficiency rate of energy storage means over traditional combustion turbines, the value of which ER is assumed to be 2.5 based on previous studies from the available literature (Lin, 2011; Makarov et al., 2012). Finally, EL is the energy loss factor for battery charging/discharging, the value of which is assumed to be 0.837 (Kempton et al., 2001).

On the other hand, the charging of a newly introduced large-scale EV fleet may add a considerable burden to the grid; for example, in the worst-case scenario, if one million EVs were charged at the same time, there would be a 6 GW surge on the grid (Zivin et al., 2014). Equation 4 below uses the relevant parameters to calculate the additional emissions from marginal electricity generation.

$$\mathrm{AE} = EVMP_{ij} \times NCR \times \frac{SOC_{var}}{1000} \times B_{cap} \times \frac{MEmission_j - AEmission_j}{2000} \times 365 \quad (23)$$

Where AE is the additional GHG emissions in lb/MWh, NCR is the fraction of EVs that are charged at night with marginal electricity (which ranges from 0.7 to 0.8 (Hittinger and Azevedo, 2015)), SOC_{var} is the percentage variation of the battery’s state of charge (SOC), and $MEmission_j$ - $AEmission_j$ represents the difference between the marginal emission rate and the average grid mix emission rate in region j (Rothschild and Diem; U.S. Environmental Protection Agency, 2015b). The detailed data resulting from these calculations is summarized in Table 16

Table 16 Marginal and average emission rate of the researched regions

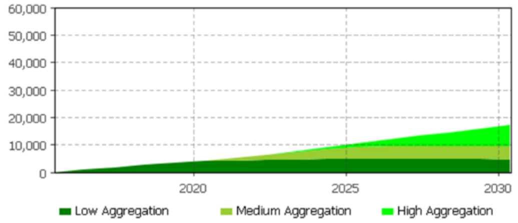
ISO/RTO	Model Code	eGRID Sub-region	Electricity Mix Average Emission Rate (lb./MWh)	Non-baseload Combustion Plants Emission Rate (lb./MWh)	Average Mix and Non-baseload Difference (lb./MWh)	Annual Generation (MWh)	Weight	Weighted Emission Rate (lb./MWh)
CAISO	Region 0	WECC California	652.72	956.36	303.64	206,633.04	1.00	303.64
ERCOT	Region 1	ERCOT All	1,147.21	1,412.91	265.70	360,221.52	1.00	265.70
SPP	Region 2	SPP North	1,730.49	2,133.66	403.17	69,447.96	0.31	235.20
		SPP South	1,545.32	1,704.14	158.82	152,734.00	0.69	
MISO	Region 3	MRO East	1,531.00	1,971.54	440.53	28,629.06	0.05	599.17
		MRO West	1,433.25	2,106.28	673.03	203,915.89	0.37	
		SERC Midwest	1,719.68	2,067.19	347.51	132,935.70	0.24	
		SERC Mississippi Valley	1,056.65	1,410.46	353.81	182,134.13	0.33	
NYISO	Region 4	NPCC Long Island	1,205.90	1,206.44	0.55	12,121.64	0.09	521.04
		NPCC NYC/Westchester	698.08	1,109.82	411.74	45,503.84	0.32	
		NPCC Upstate NY	410.31	1,068.02	657.71	82,550.86	0.59	
PJM	Region 5	RFC East	862.68	1,504.24	641.56	262,972.20	0.29	543.69
		RFC Michigan	1,577.34	1,811.01	233.66	86,819.39	0.09	
		RFC West	1,386.55	1,932.32	545.77	567,064.67	0.62	
ISONE	Region 6	NPCC New England	642.75	1,012.24	369.49	120,324.52	1.00	369.49

5.3 Results

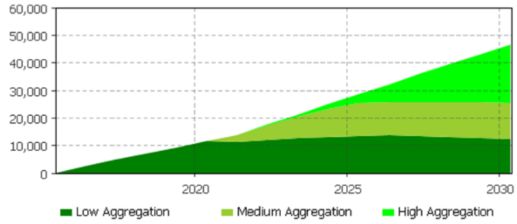
The developed model is run to analyze the performance of the V2G-wind power system, and the results are shown and explained in this section, including the projections and aggregations of newly installed wind capacity, the regulation requirements in each of the ISO/RTO regions due to increased wind power integration, comparisons of the number of EVs required to meet the regulation requirement and the actual available number of EVs, and most importantly, the overall emission savings performance of the modeled system under various realistic scenarios.

Figures 28a through Figure 28g depict the increasing market penetration and aggregation levels of wind power in all seven ISO/RTO regions. The three layers of the overall wind power capacity in one region represent the wind power projects that are stand-alone projects (low aggregation), partially aggregated (medium aggregation) and fully aggregated (high aggregation) with respect to their nearby wind power supply area (or host area), and the increase in aggregation starts in the year 2020 and progress every five years afterward. As shown in the figures, the MISO and ERCOT regions have the largest wind power projections, the SPP and CAISO regions have relatively mid-level projections, and the projections in the NYISO, PJM and ISONE regions are fairly small. The degree of wind power integration in each region follows an identical pattern over time, but as the predicted 765 kV transmission network is built within a 15-year interval, the later-incorporated and highly aggregated wind power projects will require less regulation support and thereby decrease the overall regulation requirement at the end of the simulation period. Also as shown in the figures, the medium-aggregation and high-aggregation phases start in 2020 and in 2025 respectively, thus validating the coding of the wind power agent.

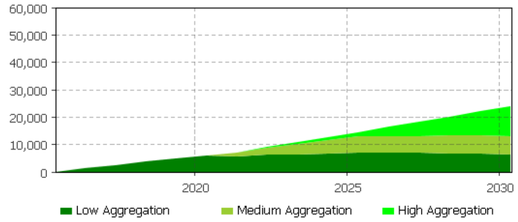
In addition, as stated before, this study analyzes the performance of the V2G-wind power system under different policies or scenarios, and five scenarios are tested within the model for this purpose. The first scenario is the “average-case” scenario, or the most-likely scenario, in which all of the parameters are set to their average (i.e. most likely) values as observed from the relevant literature. The second scenario examines the system performance when the desired level wind aggregation hasn’t been achieved as planned, resulting in the regulation rate being higher than expected. For comparison purposes, the third scenario simulates what would happen if the wind aggregation exceeds expectations and thus further reduces the overall regulation requirement. Next, the fourth scenario represents a situation in which the EV owners are well incorporated into a smart grid network, and are thus more willing to provide V2G services and to charge their EVs in accordance with an optimized charging schedule. Finally, the fifth scenario explores the impact of having fewer V2G participants than necessary for the V2G system to operate effectively, resulting in unregulated charging behaviors.



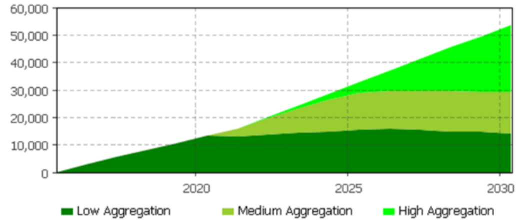
a. CAISO



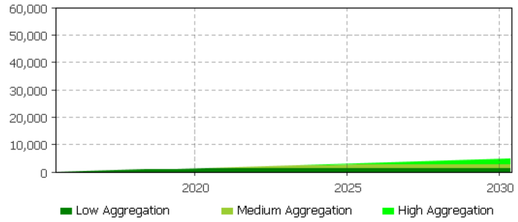
b. ERCOT



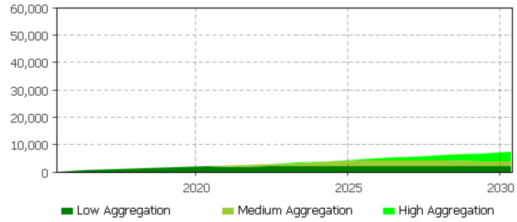
c. SPP



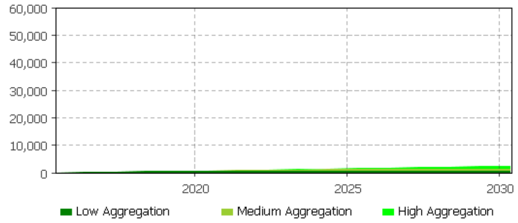
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 28 Regional wind integration and aggregation (MW)

5.3.1 Average-case scenario

Under this scenario, the values of all of the key parameters within the model (regulation rate, V2G signal strength, participation willingness, night charging ratio, etc.) are all set to their most likely values as observed from the literature, meaning that the results of this scenario reflect the most likely impacts of using V2G systems to support the increased adoption of wind power in the power grid. Figure 6 indicates the regulation requirement projections in each of the seven regions. As shown in this figure, the regulation requirement is positively correlated with the wind power projection; for instance, the MISO and ERCOT regions have the highest wind power projections and each require approximately 1,200 MW and 1,000 MW in regulation services, respectively. Conversely, the regulation requirements in the SPP and CAISO regions increase more gradually, and due to their lower wind integration projections, the PJM, NYISO and ISONE regions all tend to have minimal regulation requirement levels. Furthermore, the results shown in Figure 29 also validate the model. First, the growth rate of the total regulation requirement is linear in the first five years due to the low aggregation levels of wind projects at the time. Then, from 2020 to 2025, the growth rate of the overall regulation requirement begins to take on a smoother pattern, and after 2025, the total regulation requirement starts to decrease in most regions because the high level of aggregation of wind power at that point ultimately reduces the variability of its output and thus reduces the need for regulation services.

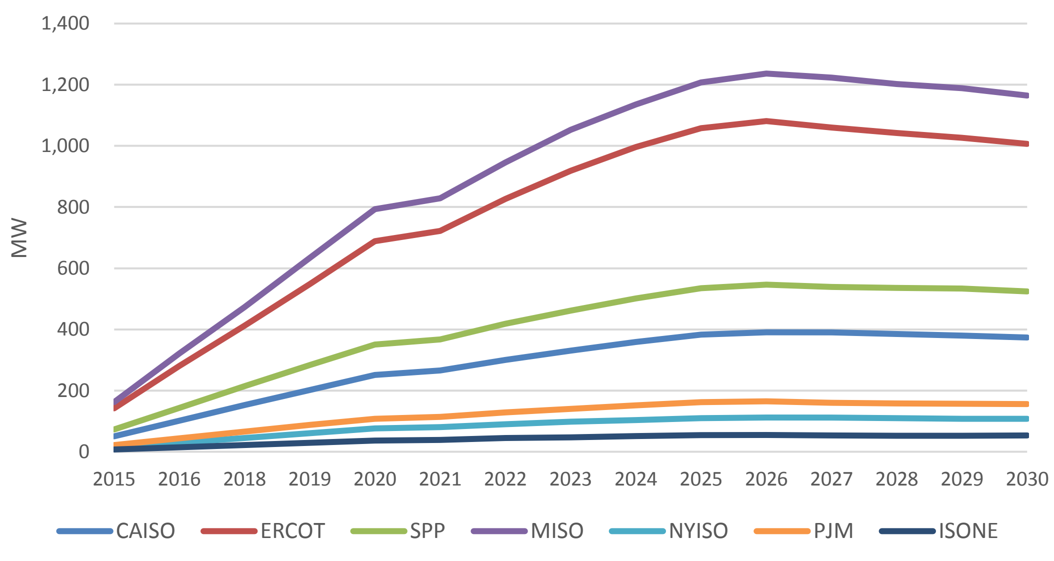
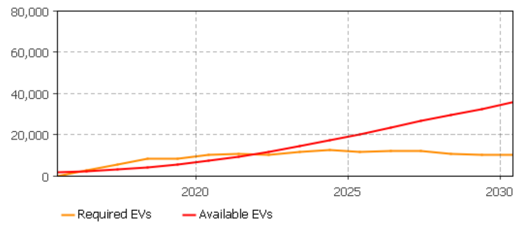
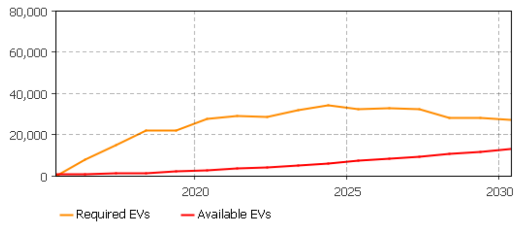


Figure 29 Regional projection of regulation requirement (Scenario 1)

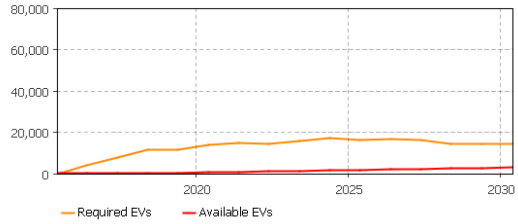
The number of EVs needed to provide these regulation services is compared to the total available number of EVs in each region, as shown in Figure 30a through Figure 30g. The CAISO region has a relatively large EV market penetration projection, and although the total EV population cannot provide the total required number of EVs in the first seven years of the simulation period, the availability of V2G providers increases significantly after 2022. Conversely, the lower EV projections in regions such as the ERCOT, SPP, MISO and NYISO regions lack the potential to support a V2G system even though most of these regions have considerably large wind power market penetration levels (thus requiring more EVs). On the other hand, the in PJM region has the highest EV projection, but its need for V2G services is relatively low. The ISONE region has the lowest available EV and required EV projections, suggesting that the power and transportation structure in the ISONE region may remain unchanged for the next 15 years.



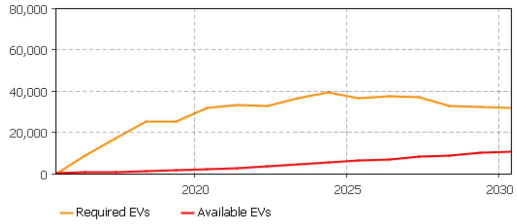
a. CAISO



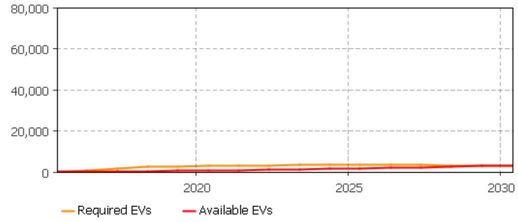
b. ERCOT



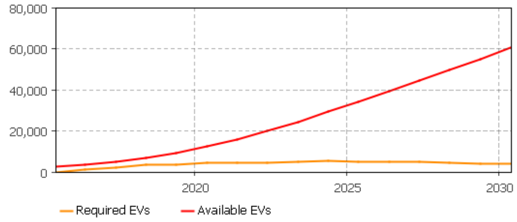
c. SPP



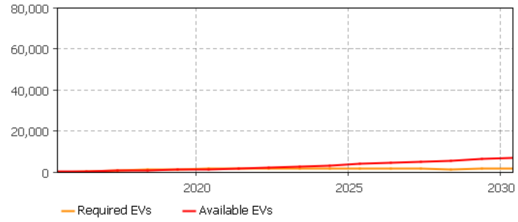
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 30 Comparison of the required EV and the available EV in researched regions (Scenario 1)

The final and most important results (net overall GHG emission savings) are calculated by subtracting the emission savings of the V2G system from the additional emissions due to the consumption of marginal electricity, and the results are shown in Figure 31. Although the CAISO region has a relatively mid-level wind power projection, it also yielded the most net overall emission savings, mainly because the EV projection in the CAISO region is enough to fully support the V2G-wind power system. Moreover, in spite of their higher wind integration projections and emission saving potentials, the smaller EV populations in the MISO and ERCOT regions ultimately limit their net GHG emission mitigation benefits. Similarly, the emission savings goals of the V2G system in the PJM region are ultimately achieved because of the PJM region's future EV market penetration rates.

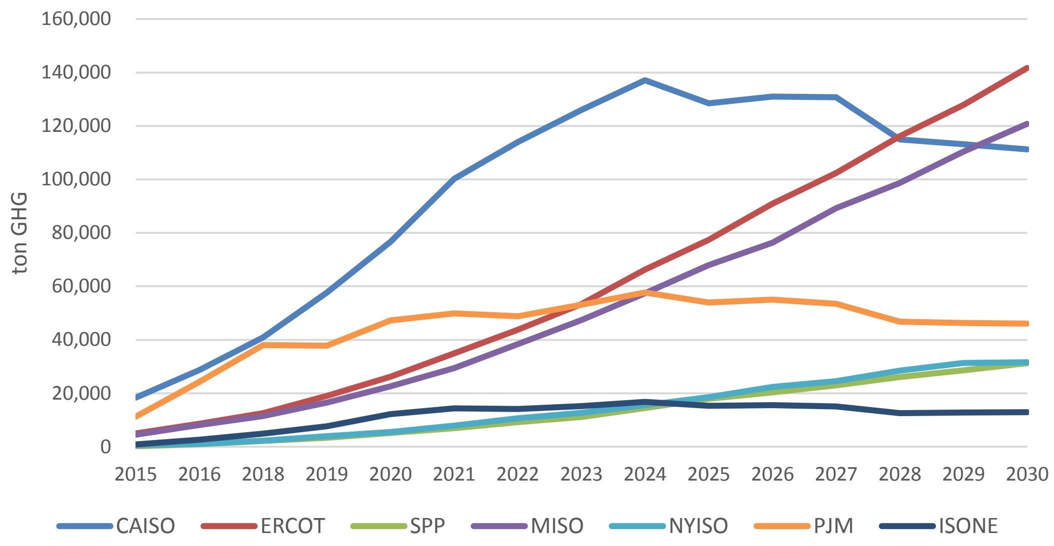


Figure 31 Overall GHG emission savings in researched regions (Scenario 1)

5.3.2 Low wind aggregation scenario and high wind aggregation scenario

In order to simulate a scenario in which the overall wind power aggregation level is less than expected, the regulation requirement rates at each regulation level are set at their maximum values prior to running the simulation and the three parameters related to V2G signal strength related (P_{cycle}, $N_{dispatch}$ and T_{cycle}) are also set at their maximum values. Figure 32 shows the regulation requirement projections for each region in this scenario. The pattern and sequence of the regulation requirements in the researched regions are identical to those of the average-case scenario (Figure 29), the main difference being that the MISO, ERCOT, SPP and CAISO regions each require about 200 MW of additional regulation capacity due to their low aggregation levels. Additionally, as shown in Figure 33a through Figure 33g, the patterns of the required number of EVs and the available EV populations are also identical to those of the average-case results in all regions, except for a slightly larger number of required EVs since more V2G service capacity is needed due to the lack of aggregation, and it also takes ten years for the CAISO region to meet (and later exceed) its EV requirements. It can likewise be concluded from Figure 34 that, although the potential of V2G systems to save on GHG emissions is limited in most regions due to the low availability of EVs, the overall GHG emission savings are still two to three times as much as those of the average-case scenario, primarily due to the V2G regulation signal strength. Since the aggregation level of the new wind capacity is low, the use of independently operated wind projects introduces more variability (and thus instability) to the power grid, meaning that more electricity is exchanged during V2G operation, and the overall GHG emission savings are increased as a result.

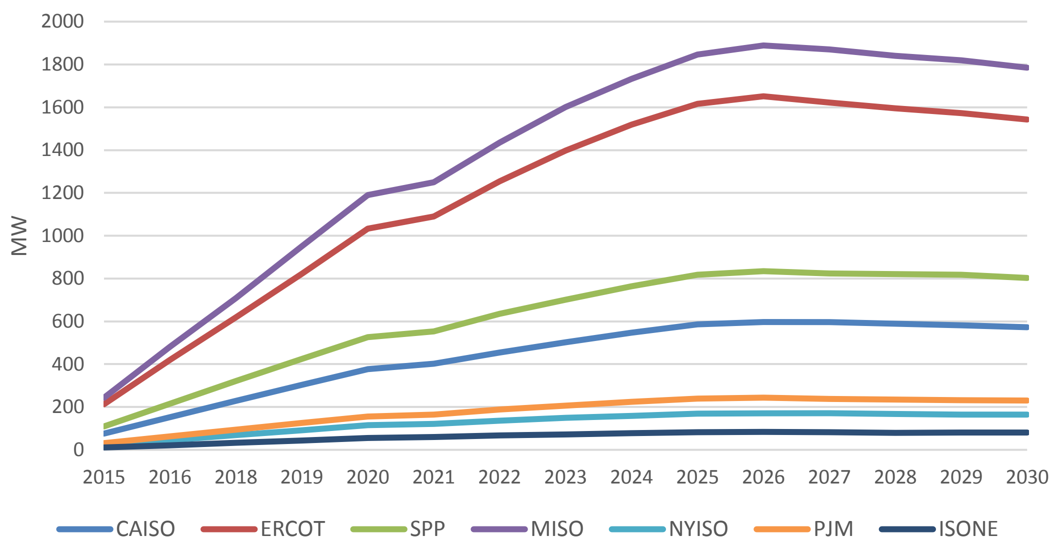
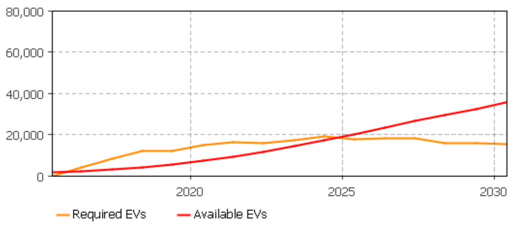
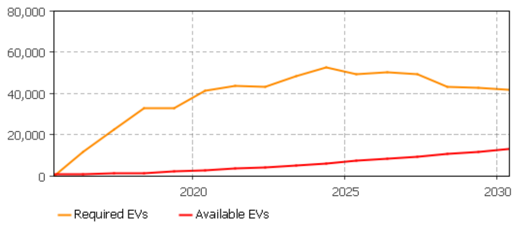


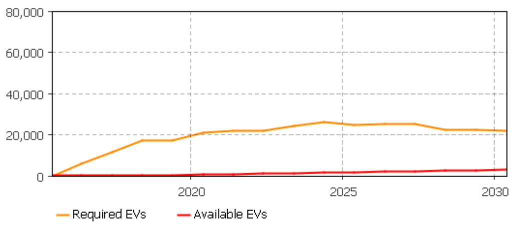
Figure 32 Regional projection of regulation requirement (Scenario 2)



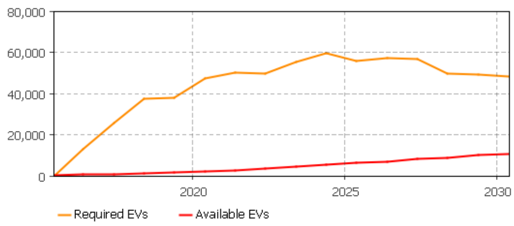
a. CAISO



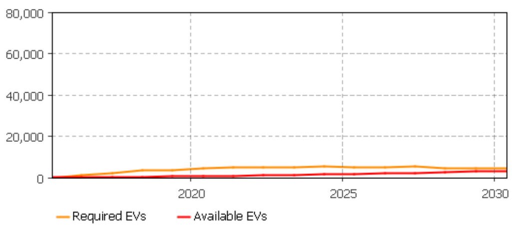
b. ERCOT



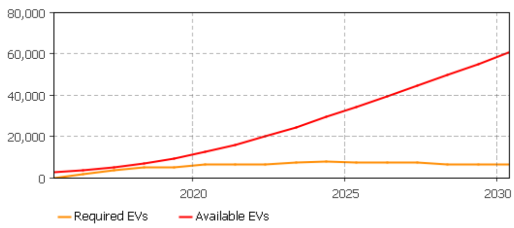
c. SPP



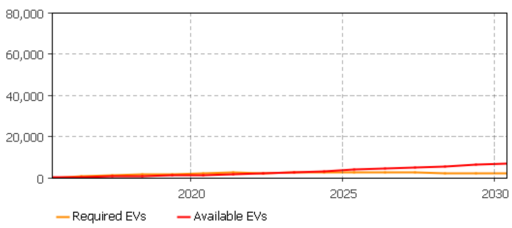
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 33 Comparison of the required EV and the available EV in researched regions (Scenario 2)

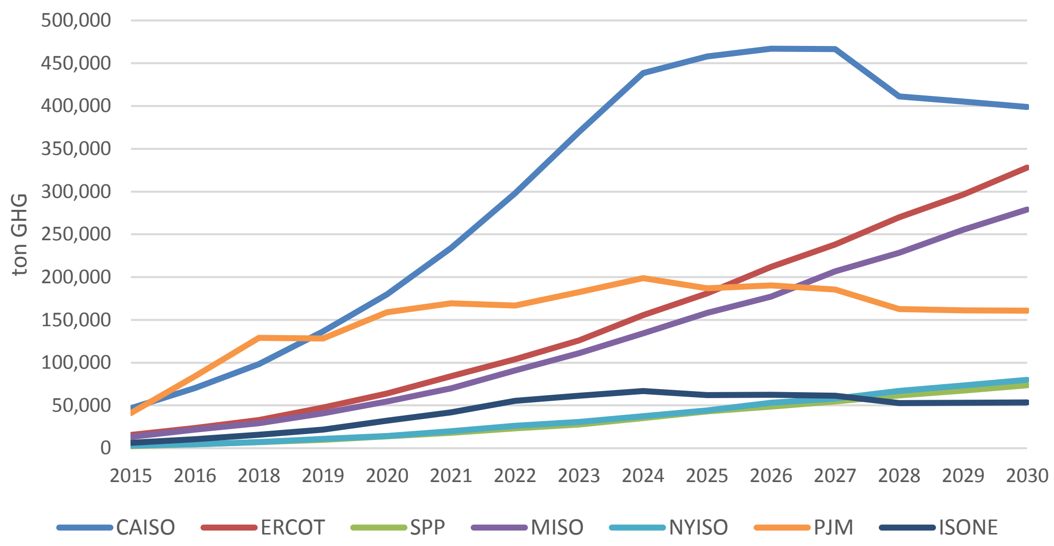


Figure 34 Overall GHG emission savings in researched regions (Scenario 2)

Unlike the low wind aggregation scenario, an optimal scenario assuming the achievement of a higher level of wind aggregation than expected due to the completion of regional transmission networks and the cooperation of local grid operators. To simulate this scenario, the regulation rates of each aggregation level are set at their minimum values. A highly aggregated wind power network is also introduced into the model to mitigate the fluctuations associated with wind intermittency, and the V2G signal strength is therefore set at its minimum value as well. The resulting regulation requirement projections are presented in Figure 35. Once again, the pattern and sequence are similar to the results of the formal two scenarios, except that now the required regulation service capacities are much lower than those of the average-case scenario. However, due to the significantly reduced regulation requirements, fewer EVs are required, and the required number of EVs in each region is less than the corresponding number of available EVs in most of the studied regions (Figure 36a through Figure 36g), except in the ERCOT, SPP and MISO regions, where the wind power projections are still much higher than in the average-case scenario. Figure 37 depicts the overall GHG emission savings based on these assumptions, and as shown in this figure, the resulting emission savings are shown to be much lower than those of the average-case scenario. The ERCOT and MISO regions have the largest amount of emission savings, because although the required number of EVs in each of these two regions is still larger than the number of available EVs, the difference between the two is considerably small (Figure 36b and Figure 36d), meaning that the V2G emission savings potential is still well utilized because the available EV population is still relatively sufficient comparing to the required number of EVs. Furthermore, the wind power projections in these two regions are higher, and more emissions can therefore be saved through the use of a V2G system. Lastly, the availability of EVs in the CAISO region is still better than those of other regions, but in this scenario, the reduced wind power projections is a major limitation in terms of GHG emission mitigation. It should be noted in this regard that the emission savings in the ISONE region is shown to have a negative value, because the V2G regulation requirement is fairly low and thus only a very small amount of GHG emissions can be saved through the use of a V2G system in this region, while the newly adopted EVs consume a significant amount of marginal electricity and results in a net increase in GHG emissions, hence the negative result.

By comparing Figures 33 and 36 to Figure 30, it can be concluded that, as the regulation requirement rate increases, the required number of EVs for regulation services in all regions also increases, and vice versa. Moreover, the amount of required EVs is positively correlated with the scale of incremental wind power installation in each region. Altogether, these relationships validate the mathematical structure of the model developed for this study.

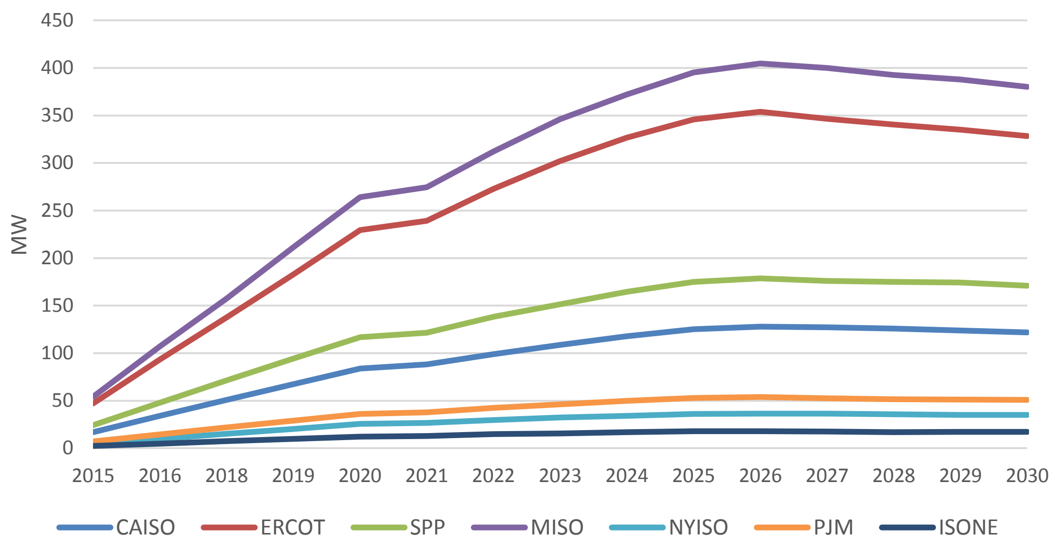
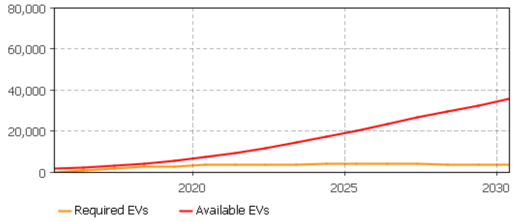
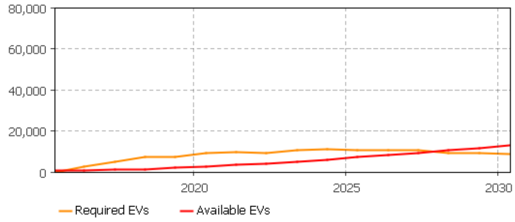


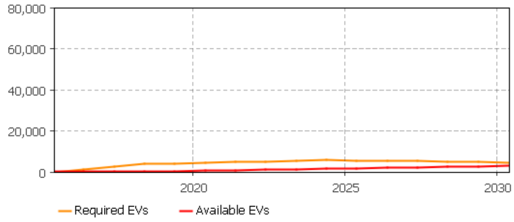
Figure 35 Regional projection of regulation requirement (Scenario 3)



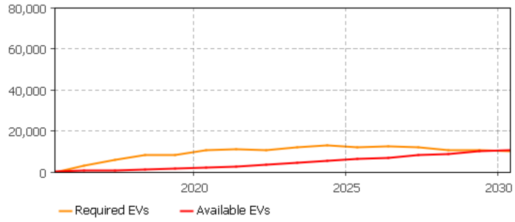
a. CAISO



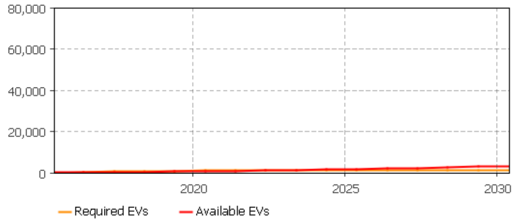
b. ERCOT



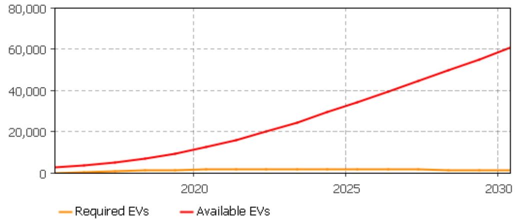
c. SPP



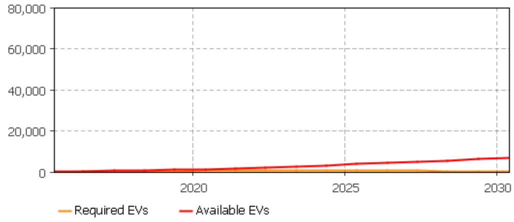
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 36 Comparison of the required EV and the available EV in researched regions (Scenario 3)

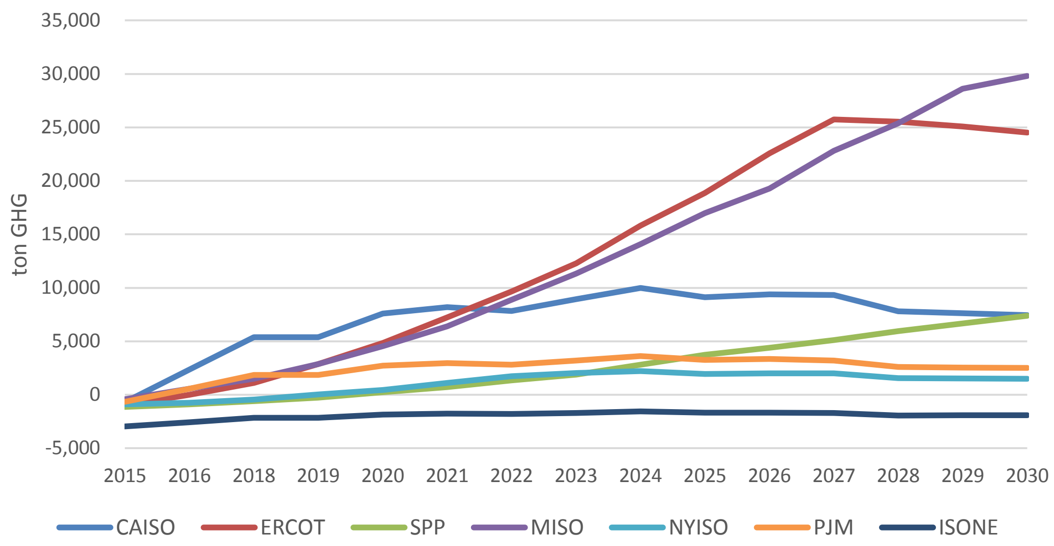
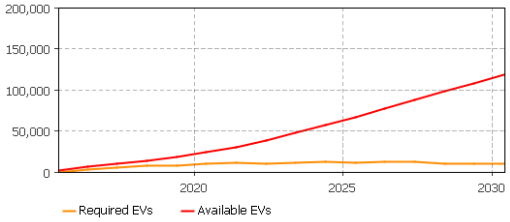


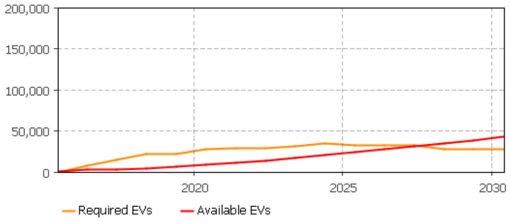
Figure 37 Overall GHG emission savings in researched regions (Scenario 3)

5.3.3 High participation/regulated charging scenario & low participation/unregulated charging scenario

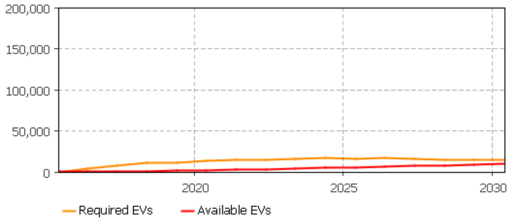
From a V2G service provider's perspective, the willingness of EV owners to provide regulation services is a deterministic factor that directly affects the availability of EVs for the V2G-wind power system, and EVs, as a basic and crucial element in a smart grid and/or smart city system, can not only function as stabilizers, but can also operate on an optimized schedule. Therefore, in a sophisticated EV network, the V2G service participation ratio is high, and more EVs are charged at ideal times to maximize environmental and economic benefits. To simulate this scenario, the willingness and availability of EV owners to provide V2G services are each set at their maximum values, while the night charging ratio and SOC variations are each set at their minimum values. The regulation requirement projections in this scenario are the same as those of the average-case scenario because both scenarios reflect the uncertainties from the V2G service supplier's perspective. Figure 38a through Figure 38g illustrate the comparison between the number of available EVs and the number of required EVs in each region. The overall number of available EVs increases significantly in this scenario, especially in the PJM region with up to 200,000 available EVs, and EV availability likewise does not limit the demand for V2G services. However, some regions, such as the SPP or MISO regions, still do not have enough EVs to meet this demand, mainly because the initial number of EVs in each of these regions is small. The total emission savings in this scenario are approximately two times as much as those in the average-case scenario (Figure 39). In the first five years, the CAISO region is initially still dominant in terms of GHG savings due to its larger initial EV projections, while the ERCOT and MISO regions have the greatest overall emission savings because they have more EVs to facilitate the use of the V2G system in the long run. Overall, however, the emission savings in each region depends more on its wind power market penetration.



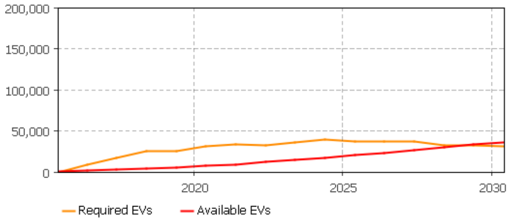
a. CAISO



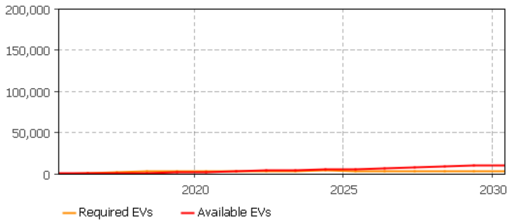
b. ERCOT



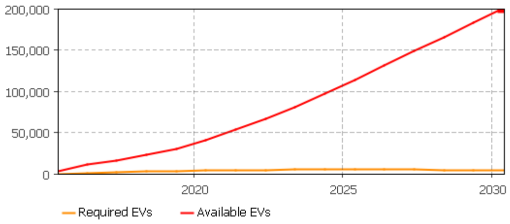
c. SPP



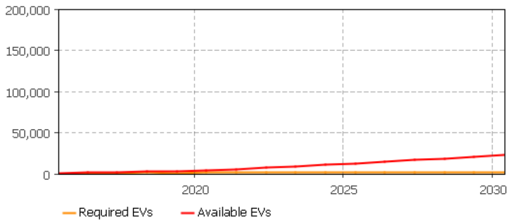
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 38 Comparison of the required EV and the available EV in researched regions (Scenario 4)

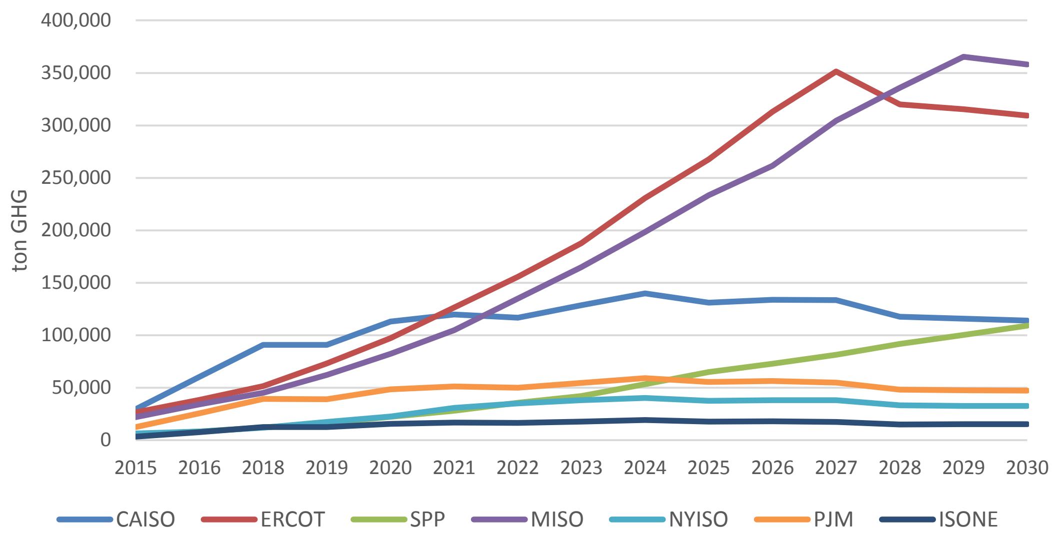
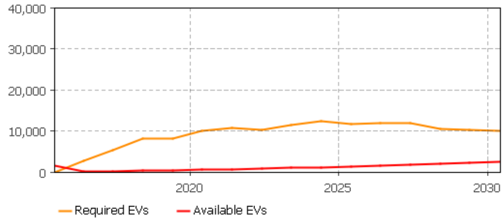
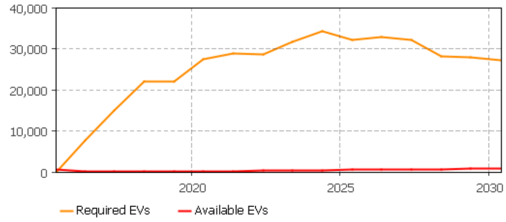


Figure 39 Overall GHG emission savings in researched regions (Scenario 4)

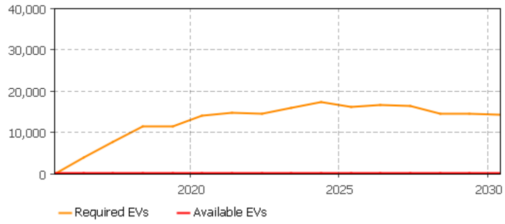
Another scenario with low EV participation and unregulated charging is also tested in this study, and unlike the last scenario, the parameters corresponding to the willingness of EV owners to provide V2G regulation services are set at their minimum values, while parameters corresponding to marginal charging are set at their maximum values. As shown in Figure 40a through Figure 40g, the available number of EVs is less than the number of required EVs in all seven regions, the differences being especially large in the ERCOT, SPP and MISO regions due to their lower availability settings. Furthermore, the overall emission savings results vary significantly compared to those of the previous four scenarios. From 2015 to 2025, the emission savings in most regions are negative, meaning that the GHG emission burden from the marginal electricity consumption of the entire EV fleet outweighs the potential emission savings through the use of a V2G-wind power system. Only in the PJM and CAISO regions, where available EV projections are much higher than those in other regions, can a certain amount of emission savings be achieved. Also, by comparing Figure 41 with Figure 24, it can be concluded that the number of available EVs becomes the dominant factor in the model if the V2G regulation service participation ratio is minimal.



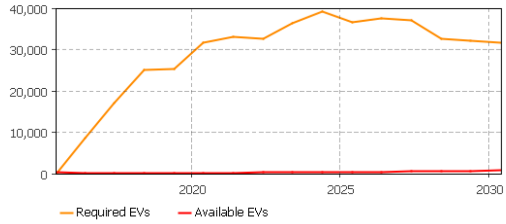
a. CAISO



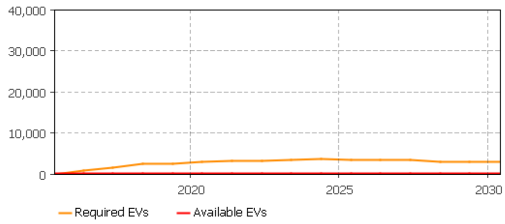
b. ERCOT



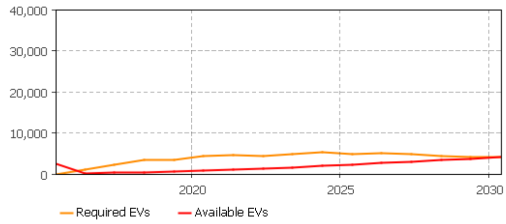
c. SPP



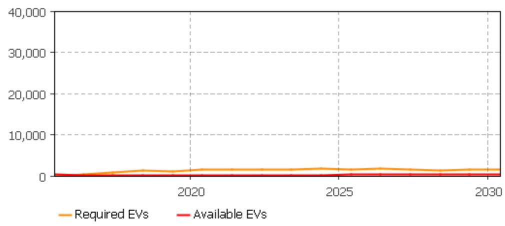
d. MISO



e. NYISO



f. PJM



g. ISONE

Figure 40 Comparison of the required EV and the available EV in researched regions (Scenario 5)

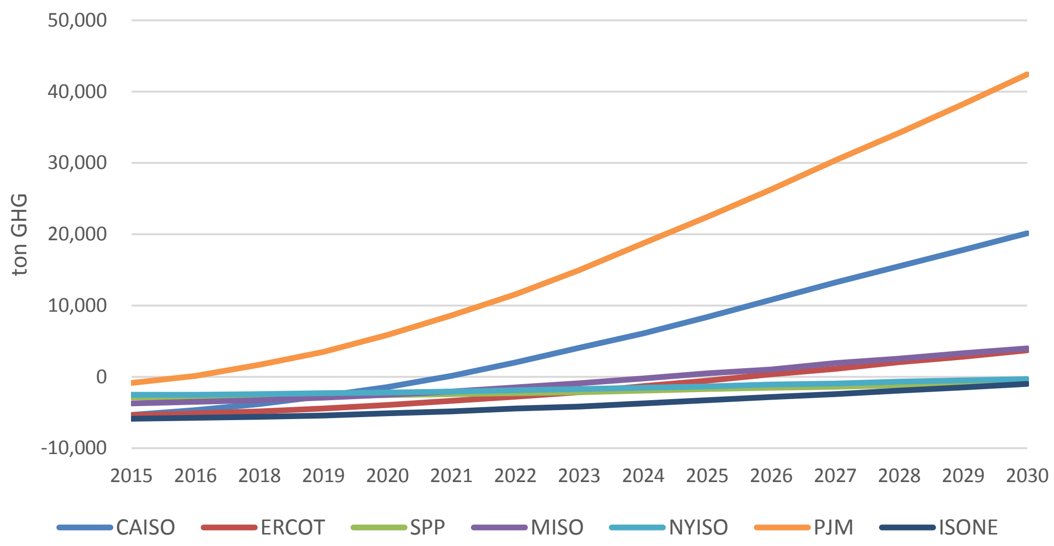


Figure 41 Overall GHG emission savings in researched regions (Scenario 5)

A comparison of Figures 38 and 40 with Figure 30 once again confirms the validity of the developed model: as the willingness of EV owners to contribute to a V2G system increases/decreases, the number of the available EV increases/decreases accordingly. Moreover, the overall GHG emission savings decrease significantly as the number of available EVs decreases.

6 VEHICLE-TO-GRID SYSTEMS IN THE WATER AND ENERGY NEXUS – A SYSTEM DYNAMICS MODELLING APPROACH

A partial work of this Chapter has been submitted to the Journal of Energy

V2G is a further integration of the energy and the transportation system, utilize the battery capacity of idled electric vehicles as grid storage, allowing them to improve the reliability of the power grid and to accommodate larger partition of intermittent renewable power. The research in section 4 has shown that with appropriate incentives, both commercial/government fleets and private car owners (Noori et al., 2016) could be V2G ancillary service carriers and gain certain amount of financial benefits. And because of the higher efficiency of battery storage which can absorb excess energy as well as the absence of the combustion of fossil fuel, V2G systems could significantly reduce carbon emissions during ancillary service provision. As more and more electric vehicle options being released to the market and charging devices being encouraged to be installed, 700 GW of wind capacity could be integrated to the system if approximately 3% of the U.S. fleet was V2G available (Kempton and Tomić, 2005b). And an energy system with higher renewable power penetration will provide cleaner power source for the transportation sector and further facilitate the shift of the electrification of the transportation system.

6.1 Introduction

Water and electricity are interconnected; the generation of electricity requires water for cooling, and the treatment and delivery of freshwater also consumes electricity. Due to the combustion of fossil fuels (coal, natural gas, petroleum, etc.), the electricity generation sector is the largest single contributor to greenhouse gas (GHG) emissions in the U.S. (U.S. Environmental Protection Agency, 2016), the second largest GHG emission contributor being the transportation sector. There are currently 260 million registered vehicles in the U.S., approximately 11% of which are powered by alternative fuels, and the projected growth rate of hybrid electric vehicles (HEVs) and plug-in electric vehicles (PEVs) in the U.S. are the highest out of all other vehicle types (U.S. Energy Information Adiministration, 2017). The electrification of transportation brings vehicles and the power grid together in a single system and thereby reduces fossil fuel usage at the end-user phase of a vehicle, while HEVs or PEVs can increase fuel efficiency and partially or entirely eliminate tailpipe emissions. However, whether or not carbon emissions and/or water consumption can really be mitigated depends on the percentage of renewable energy in the system.

The two largest renewable energy sources (wind power and solar photovoltaic (PV) power) are both intermittent, so, more ancillary service capacity must be online to accommodate renewable energy output and to facilitate the stability of the power grid. Vehicle-to-Grid (V2G) systems, which serve as a further integration of the electric power and transportation sectors, use the battery capacity of idle electric vehicles as grid storage, allowing them to improve the reliability of the power grid and to accommodate larger partitions of intermittent renewable power output. In addition, due to the higher efficiency of battery storage that can absorb excess energy as well as the absence of the combustion of fossil fuels, V2G systems can significantly reduce carbon emissions while providing ancillary services. The water consumption rate of thermoelectric power generation varies from 100 to 700 gallon per MWh depending on the type of cooling used (Macknick et al., 2011), and the life-cycle energy intensity in cities is 3.3 to 3.6 MWh for every 1 million gallons of water consumed (Copeland, 2014). Since more than 80% of electricity in the U.S. is generated from coal, natural gas, and/or nuclear power (U.S. Environmental Protection Agency, 2014a), all of which withdraw and consume significant amounts of water for cooling purposes, V2G technology can further reduce water withdrawal and water consumption rates from electricity generation. In short, with sufficient market penetration for HEVs and PEVs, a well-developed power grid network, and sophisticated V2G scheduling, the water-energy structure will be optimized, and overall GHG emissions will be more effectively mitigated. V2G systems will therefore inevitably affect and be affected by other social, economic, and environmental factors, and the various interactions between all of these factors will change dynamically. Therefore, in this paper, a system dynamic modelling approach is combined with a life cycle assessment (LCA) method to study how the use of V2G systems and/or a smart grid would affect the interactions between the passenger car transportation industry and the water-energy nexus. The system is evaluated from the associated social, economic, and environmental perspectives, after which projections are estimated (based on the mathematical relationships within the model), and different policies are tested to evaluate the overall impacts and benefits of the studied V2G system. The state of Florida has been selected as the studied region for purposes of this study, and the simulation time of the model will run from 2000 to 2030.

6.2 Literature Review

Electricity is a unique commodity in that it has to be generated and consumed at the same time; otherwise, any excessive electricity generation is ultimately wasted since the current power grid lacks any means of energy storage (U.S. Energy Information Adiministration, 2000) while, if the electricity demand surges beyond the available energy generation at a certain time point, gas combustion turbines must then be turned on or ramped up to compensate for the added fluctuation in energy demand (Kempton and Tomić, 2005b). Studies have shown that battery storage methods have lower response times (usually within a matter seconds) than combustion turbine generators (Kempton and Tomić, 2005b), and the efficiencies of such storage methods are typically one to two times higher than those of traditional turbines (Lin, 2011; Makarov et al., 2012).

Renewable energy sources (wind, solar, etc.) typically emit less GHG emissions and consume less water, but the output of renewable power in most cases is subject to significant fluctuation. Parsons et al. (2006) studied the cost of integrating wind energy in different Independent System Operator (ISO) and Regional Transmission Organization (RTO) regions, and concluded that additional regulation capacity will be required as the percentage of wind energy increases. Since the current energy system cannot sustain unlimited wind energy generation, Bird and Lew (2012) have suggested that a wind energy penetration of approximately 20% to 35% will be feasible given the limitations of the current power grid. A wind intermittency study conducted by Albadi and El-Saadany (2010) reached two separate conclusions with respect to wind energy; first, as the wind penetration grows, the cost of ancillary service will increase significantly, and hence the economic considerations might be a main obstacle which prevents the adoption of wind energy; and second, fast-responding ancillary service generators can reduce the overall operational cost of wind energy generation. Studies have been conducted to explore the feasibility of supporting wind energy integration through V2G technology (Kempton and Tomić, 2005a, b), and another study has also confirmed that a smart energy network with the inclusion of PEVs could help to facilitate wind energy integration (Short and Denholm, 2006).

From the water-energy nexus's perspective, Cooper and Sehlke (2012) have pointed out that reducing or maintaining GHG emissions within a reasonable level will require changes in various environmental, economic, and societal aspects, and that effective methods to reduce water consumption include the integration of wind energy and/or solar power into the power grid, the introduction of high-efficiency baseload coal power plants, and the development of more efficient vehicles. In addition, a review paper (Nair et al., 2014) has reported the importance of identifying the underlying complex relations between water consumption and energy generation. A separate study carried out by Sovacool and Sovacool (2009) confirmed the need to introduce more renewable energy into the power grid to improve the overall efficiency of the water-energy nexus.

There is currently no available literature that either investigates or projects the environmental, social, and economic interactions of a V2G system integrated with the future water-energy nexus from a life cycle perspective; to address this research gap, a system dynamics model is built in this study to simulate such a system and its relevant interactions with other environmental, social, and economic factors, including the integration of renewable energy technologies, as well as GHG emissions, population, health factors, and the Gross Domestic Product (GDP). Moreover, this study will test four possible scenarios with different assumptions representing different levels of EV adoption, V2G service participation, and wind energy integration.

6.3 Methods

System dynamics is an approach used in today's research to investigate complex system problems, especially those that involve large networks with complicated dependency relationships, feedback mechanisms, and multidimensional causal relationships. The available literature indicates that, in order to comprehensively study a complex system such as the U.S. transportation system or the power grid, the underlying environmental, social, and economic consequences of any given scenario must all be taken into consideration (Lee et al., 2012). The network of the proposed model of this study is constructed at three different scales:

- First, at an individual vehicle level, the available ancillary power output and the amount of exchanged energy both depend on the service provision time, the battery State of Charge (SOC), and other relevant variables;

- Second, at the electricity grid level, a V2G system not only replaces traditional gas turbines as ancillary service providers and thereby reduces GHG emissions, but also increases the overall ancillary service capacity within the hosting area, allowing more intermittent wind power to be brought online;
- Third, at the electricity grid and water-energy nexus level, the overall grid mix, the average GHG emission rate, and the average water consumption rate are all interconnected with the GDP, human health factors, and EV market penetration levels.

The outline of the overall system is shown in Figure 42 below.

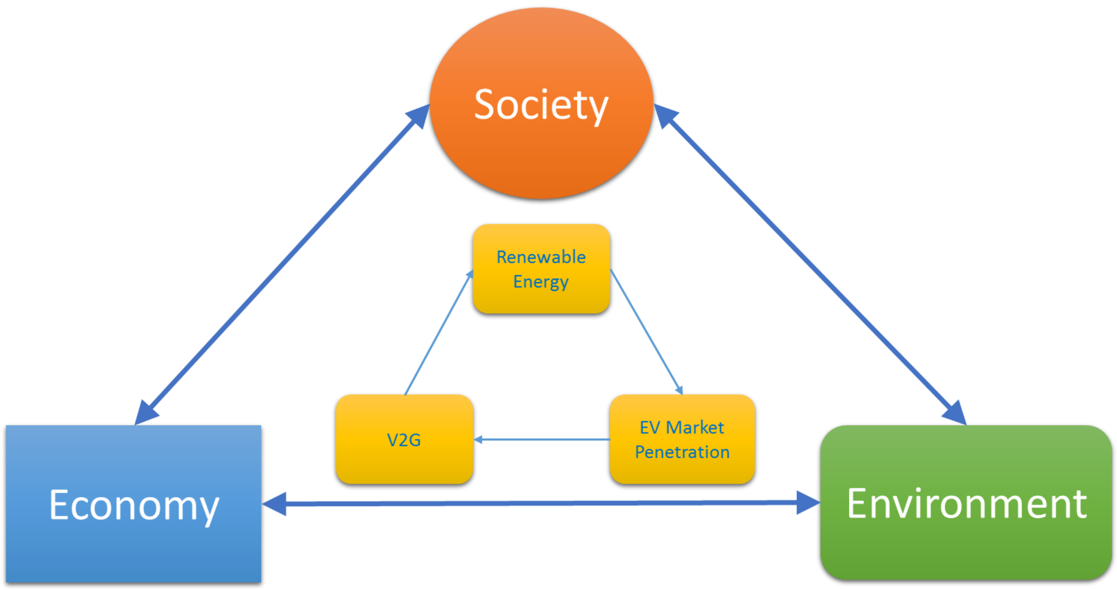


Figure 42 Overall system outline

6.3.1 Scope of study, variables, and initial assumptions

The state of Florida has been selected as the researched region for purposes of this paper, as it has the fourth largest economy in the nation with approximately 5% of the total GDP of the U.S. (U.S. Department of Commerce, 2017b); the population of Florida is about 20 million, making Florida the fourth most populated state in the U.S., and the majority of the electricity in Florida is produced from natural gas. Although Florida is not one of the deregulated markets where electricity transmission and generation are divided among different parties, the state has made a significant effort to promote transportation electrification; for instance, hybrid and electric vehicles are both exempted from high occupancy lane rules (Florida DMV, 2015), and rebates and other such incentives are also available for purchasing EVs and/or EV charging equipment (National Conference of state Legislatures, 2015). Also, the Florida roadway design criteria will soon include specific standards to accommodate large-scale EV adoption rates. In addition to the aforementioned HEVs and PEVs, internal combustion engine vehicles (ICEVs) are still going to be the main vehicle type on the market, so ICEVs are also included in this study.

To study and reveal the underlying causal relationships of the proposed model, a causal loop diagram is first created to illustrate the conceptual structure and qualitative relationships within the model. As shown in Figure 43, the GDP, population, and GHG and other air pollutant emissions all represent the macro-level economic, societal, and environmental aspects of the system, respectively, and the water-energy nexus as it relates to the V2G system is incorporated within this macro-level structure as well. The green loops in Figure 43 represent the major reinforcing loops, or the potentially positive effects caused by the adoption of V2G systems; as demonstrated in these loops, the application of the V2G system allows for the greater installation of ancillary service providers, which would therefore accommodate more wind power; this wind power generation not only emits much less GHG/air pollutant emissions but also requires less water for cooling purposes, and therefore less energy is needed to deliver or to treat this reduced quantity of water; the overall reduced GHG/air pollutant emissions then encourages policy makers to promote EV sales more effectively, resulting in more EVs being made available for V2G services.

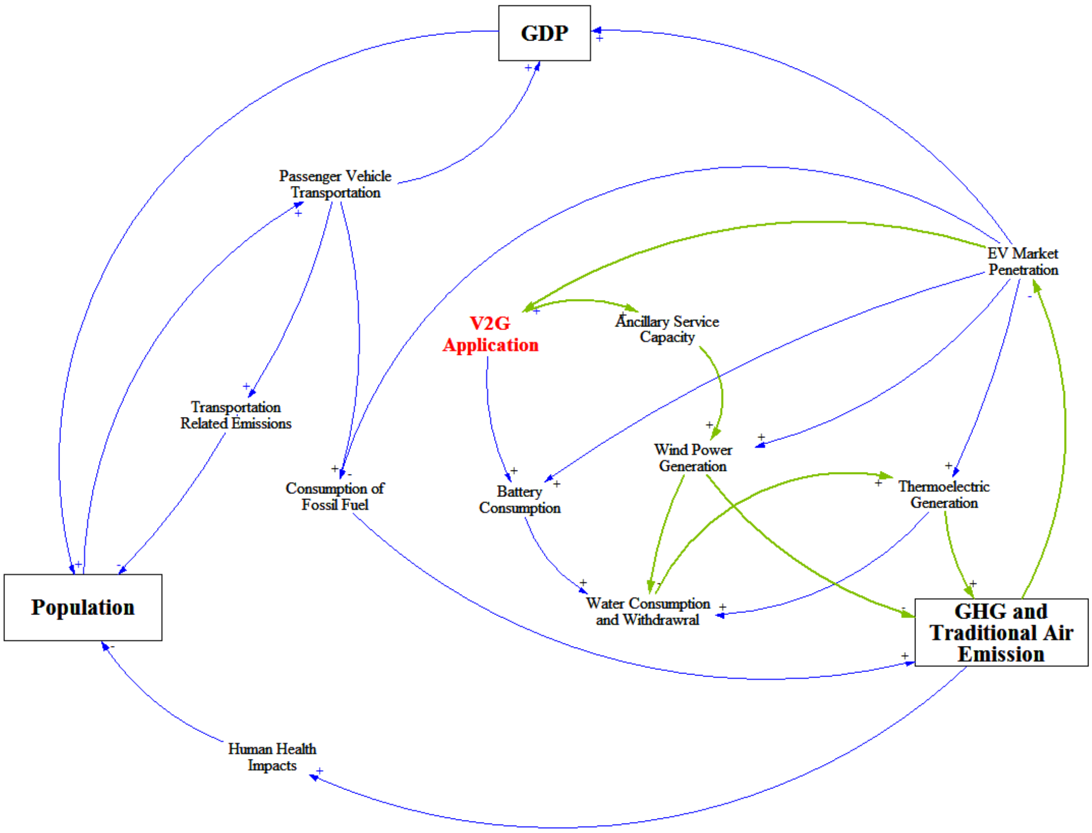


Figure 43 Causal loop diagram

Based on the developed causal loop diagram (Figure 43), the quantitative relationship among the variables within all the loops are further divided into three sub-models:

1. The GDP, population, and passenger vehicle transportation sub-model,
2. The passenger transportation emission and V2G system sub-model, and
3. The water-energy nexus model.

Next, stock and flow diagrams are developed for each sub-model, each containing all of the associated the variables and their mathematical relationships (Section 5.3.2 to Section 5.3.4). Some of these variables ("exogenous variables") are used to reference historical and/or projected data sets that are out of the scope of this study, while the values and/or outputs of other variables ("endogenous variables") may change depending on logical and/or mathematical relationships with other variables. The exogenous and endogenous variables within this model are all summarized in Table 17.

This study focuses on the water consumption needed for electricity generation and on the energy consumption required for treating and/or recovering the amount of the water lost for cooling purposes in power plants; residential and irrigation-related water consumption are not included because the influence of the V2G system on these activities is negligible. The authors' previous studies have shown that V2G regulation services are economically appealing to EV owners (Noori et al., 2016; Zhao et al., 2016a), so it is also assumed that sophisticated infrastructure and networks will be available to aggregate all of the individual EV owners into separate clusters with stable capacities and output rates for ancillary services provision (Kempton and Tomić, 2005b).

Table 17 Endogenous variables and exogenous variables

	Endogenous variables	**Exogenous variables**
GDP, population, and passenger vehicle transportation sub-model	GDP from the passenger car transportation sector	GDP from the rest of the sectors
	total GDP	GDP increasing rate
	GDP per capita	reproductive lifetime
	fertility rate	life expectancy
	maturation rates	market share of passenger vehicles
	death rates	Percentage of HEVs, PEVs, and ICEVs
	adjusted life expectancy	manufacturing cost data of HEVs, PEVs, and ICEVs
	population	maintenance and fuel cost data of HEVs, PEVs, and ICEVs
	number of potential drivers	vehicle configuration data of HEVs, PEVs, and ICEVs
	marginal human health impact from emissions	annual VMT
	new passenger vehicle sales	
	number of HEVs, PEVs, and ICEVs	
	V2G promotion effect percentage	
Passenger transportation emission and V2G system sub-model	annual PEV GHG emissions	average GHG emission rate before 2015
	annual HEV GHG emissions	average traditional air emission rate before 2015
	annual ICEV GHG emissions	
	annual PEV traditional air emissions	battery manufacturing GHG emission rate
	annual HEV traditional air emissions	battery manufacturing traditional air emission rate
	annual ICEV traditional air emissions	gasoline upstream and tailpipe GHG emission rate
	electricity mix GHG emissions	gasoline upstream and tailpipe traditional air emission rate
	electricity mix traditional air emissions	V2G ancillary service related data
	V2G emission savings	
Water-energy nexus sub-model	HEV and PEV ancillary service capacity	HEV and PEV available power
	renewable power capacity growth	ancillary service requirement ratio
	capacity of different power sources	emission rate of different electricity sources
	annual generation of different power sources	water withdrawal rate of electricity sources
	future electricity GHG emission rate	water evaporation rate
	future electricity traditional air emission rate	energy intensity ratio of water treatment
	saline water withdrawal	
	fresh water withdrawal	
	fresh water evaporation	
	electricity consumption for water treatment	

6.3.2 GDP, population, and passenger vehicle transportation sub-model

Each of the individual sub-models are depicted separately; grey variables indicate variables that are also connected to one or more other variables within the model, and red, green, and light blue variables indicate the main inflows or outflows to other sub-models, as discussed in further detail with respect to each of the relevant figures. In this section, the GDP is separated into the contribution of the passenger car transportation industry to the GDP and the combined contribution of all other economic sectors to the GDP. As shown in Figure 44, the "total GDP" variable receives inputs from both the "GDP of passenger car transportation" variable and the "GDP from the rest of the sectors" variable. Data for the overall GDP of the state of Florida is available from the literature (Federal Reserve Bank of St. Louis, 2016). The GDP data of other sectors prior to 2015 is likewise obtained from the Bureau of Economic and Business Reserve (2015), and used in the model as a lookup function since this portion of the GDP is beyond the scope of this study. GDP growth is represented in terms of annual GDP growth as a stock that increases relative to a certain rate each year. It is assumed that there will be a 2.9% GDP increasing rate after 2015 (U.S. Department of Commerce, 2017a). The annual GDP of the passenger car transportation sector consists of the manufacturing cost of all of the cars that are sold in a given year and their associated yearly operation costs; the relevant variables are shown as grey variables in Figure 44 and are illustrated in further detail in Figure 46, while the relevant detailed data and data sources are listed in Table 2.

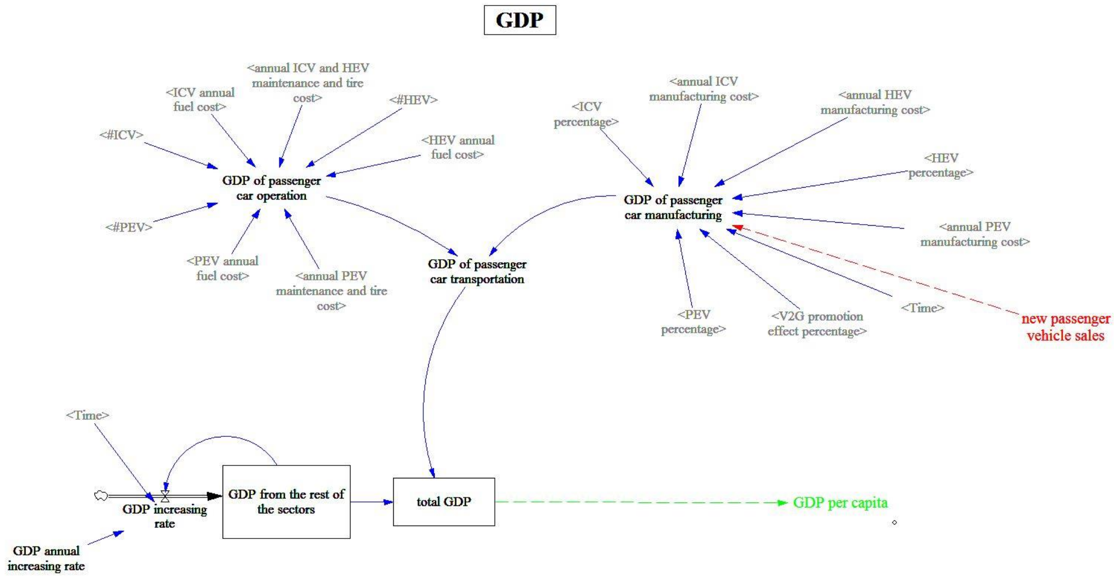


Figure 44 GDP stock-flow diagram

In Figure 44, the red variable indicates that the GDP of passenger car manufacturing is calculated based on the new car sales in each year. On the other hand, the outgoing "GDP per capita" variable (the green variable in Figure 44) is calculated by dividing the total GDP by the overall population, which is shown in Figure 45. The "GDP per capita" variable affects two critical variables (the fertility rate and new passenger vehicle sales), which are both illustrated further in Figure 45. The fertility rate is a deterministic factor for the population section of the model, and its mathematical formula is as shown in Equation 24 below.

$$fertility\ rate = (GDP\ per\ capita \times 9.57) - (0.233 \times adjusted\ life\ expectancy) + 19.97 \quad (24)$$

The adjusted life expectancy is a function of the projected life expectancy (State of Florida Department of Health, 2012), which is in turn affected by the marginal human health impact associated with the passenger car transportation sector, the variable for which is shown in light blue in Figure 45. The verification of Equation 24 is discussed in detail in Section 6.4. The population section is a multi-stage stock and flow diagram that simulates individuals being born and progressing through each life stage. The births of the population is a function of "population 15 to 44", the fertility rate, and the reproductive lifetime (which is assumed to be 30). The two important outputs of the population section is the overall population, which is connected to the "GDP per capita" variable as part of a feedback loop, and the number of potential drivers, which is assumed to be equal to the total portion of the population that is older than the age of 15. Based on historical data for passenger vehicle market shares (Bureau of Transportation Statistics, 2015b) and the output from the "GDP per capita" and the "number of potential drivers", the "new passenger vehicle sales" variable is calculated as shown in Equation 25 below:

$$new\ passenger\ vehicle\ sales = \left(market\ share\ of\ passenger\ vehicle\ (Time) \times \frac{(GDP\ per\ capita \times 7.3284 \times 10^{7}) - (1.2596 \times number\ of\ potential\ drivers) + (3.3242 \times 10^{7})}{5}\right) - 3 \times 10^{5} \qquad (25)$$

Like with Equation 24, the verification of Equation 25 is also explained in more detail in Section 6.4. The overall numbers of HEVs, PEVs, and ICEVs are each based on the percentages of the overall sales rate pertaining to each vehicle type, which are adjusted as necessary in different scenarios as discussed further in Section 6.3.5. In addition, a sophisticated EV infrastructure with economic benefits and emission mitigations from V2G services may further increase the market share of EVs, so the market shares of HEVs and PEVs are both also marginally affected by the variable "V2G promotion effect percentage".

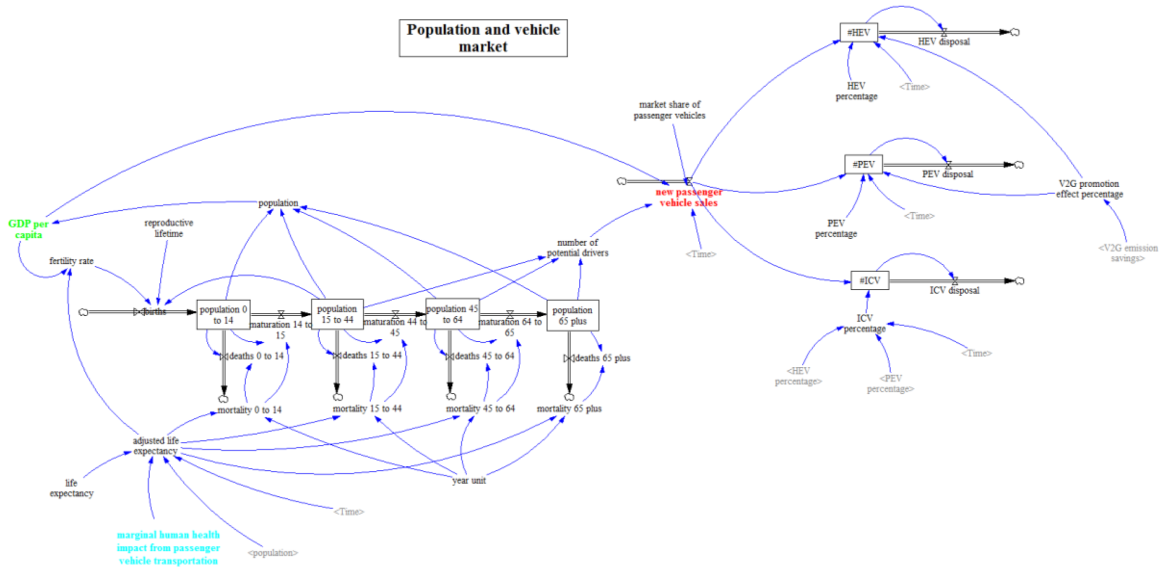


Figure 45 Population and vehicle market stock-flow diagram

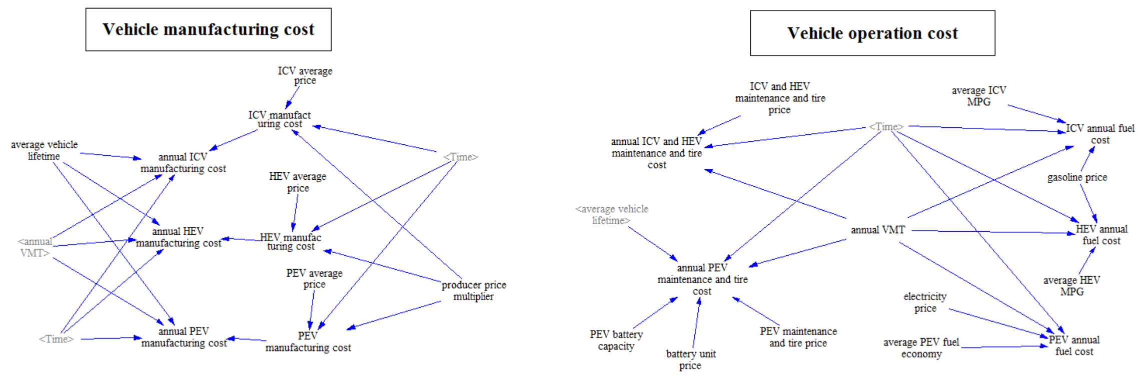


Figure 46 Passenger car related cost stock-flow diagram

6.3.3 Passenger transportation emission and V2G system sub-model

The life cycle GHG emissions and traditional air pollutant emissions of the passenger car transportation sector and of the V2G system are analyzed and modeled in this section. To simplify the necessary calculations, GHG and air pollutant emissions are each measured in terms of CO_2 and Particular Matter (PM) emissions, respectively. The vehicle configuration and all parameters related to emissions and costs are all summarized in Table 18.

Table 18 Data sources for critical parameters

Parameter	Value and unit	Data source
ICEV price	\$28,465 to \$21484 (2000 to 2030)	(U.S. Department of Energy, 2013a)
HEV price	\$35,581 to \$26,855 (2000 to 2030)	(Papaioannou, 2015)
PEV price	\$50,000 to \$35,000 (2000 to 2030)	(UCLA Luskin Center, 2012)
manufacturing cost/retail price ratio	0.8	(Samaras and Meisterling, 2008)
annual VMT	9,516 to 12,866 miles (2000 to 2030)	(Florida Department of Transportation, 2015)
average lifetime mileage	200,000 miles	(Florida Department of Transportation, 2015)
ICEV and HEV maintenance and tire cost	0.053 to 0.0703 \$/mile (2000 to 2030)	(Bureau of Transportation Statistics, 2015c)
PEV maintenance and tire cost	70% of ICV and HEV maintenance cost	(Gallo and Tomic, 2013)
average ICEV MPG	28.5 to 39.6 mile per gallon (2000 to 2030)	(Bureau of Transportation Statistics, 2015a)
average HEV MPG	40 to 70 mile per gallon (2000 to 2030)	(U.S. Energy Information Adiministration, 2015f)
average PEV fuel efficiency	0.35 kWh/mile	(U.S. Department of Energy, 2013b)
PEV battery capacity	30 kWh	(Nissan, 2015)
battery unit price	600 to 300 \$/kWh	(Gallo and Tomic, 2013)
gasoline price (historical and projected)	1.513 to 2.92 \$/gallon	(U.S. Energy Information Adiministration, 2016a)
electricity price (historical and projected)	0.0757 to 0.1153 \$/kWh	(U.S. Energy Information Adiministration, 2015c)
battery manufacturing GHG emission rate	0.14 ton CO_2/kWh	(Kim et al., 2016)
battery manufacturing PM emission rate	0.01 ton PM/kWh	(Carnegie Mellon University Green Design Initiative, 2003)
PEV buffering range	30 miles	(Kurani et al., 1994)
V2G dispatch time	0.3 hours	(Kempton and Tomić, 2005a; Zhao et al., 2016a, 2017)
DC to AC conversion efficiency	0.93	(Kempton and Tomić, 2005a)
Dispatch time	0.3	(Kempton and Tomić, 2005a)

Figure 47 illustrates the calculations required for life cycle GHG emissions and traditional air pollutant (i.e. PM) emissions. The concept of the LCA is to consider all relevant upstream and downstream environmental impacts. For HEVs and ICEVs, the overall emissions consist of those due to gasoline production and tailpipe emissions, and for PEVs, the overall emissions include those associated with electricity generation and battery manufacturing. For example, Equations 26 and 27 are used to calculate the annual PEV GHG emissions and the annual ICEV GHG emissions, respectively:

$$annual\ PEV\ GHG\ emissions = (annual\ VMT(Time) \times average\ PEV\ fuel\ economy \times electricity\ mix\ GHG\ emission\ rate) + (battery\ manufacturing\ GHG\ emission\ rate \times PEV\ battery\ capacity) \quad (26)$$

$$annual\ ICV\ GHG\ emission = annual\ VMT(Time) \times average\ ICV\ MPG(Time) \times (gasoline\ supply\ GHG\ emission\ rate + gasoline\ tailpipe\ GHG\ emission\ rate) \quad (27)$$

It should be noted that the GHG emission rate of the electricity mix as described in Equation 26 is a dynamic function related to the market shares of each energy source available to the power grid and their corresponding emission rates. This overall emission rate for the Florida power grid is knows from 2000 to 2016, and starting from 2017, the evaluated emission rate fully reflects the impacts of the rest of the model on the overall power grid emission rate.

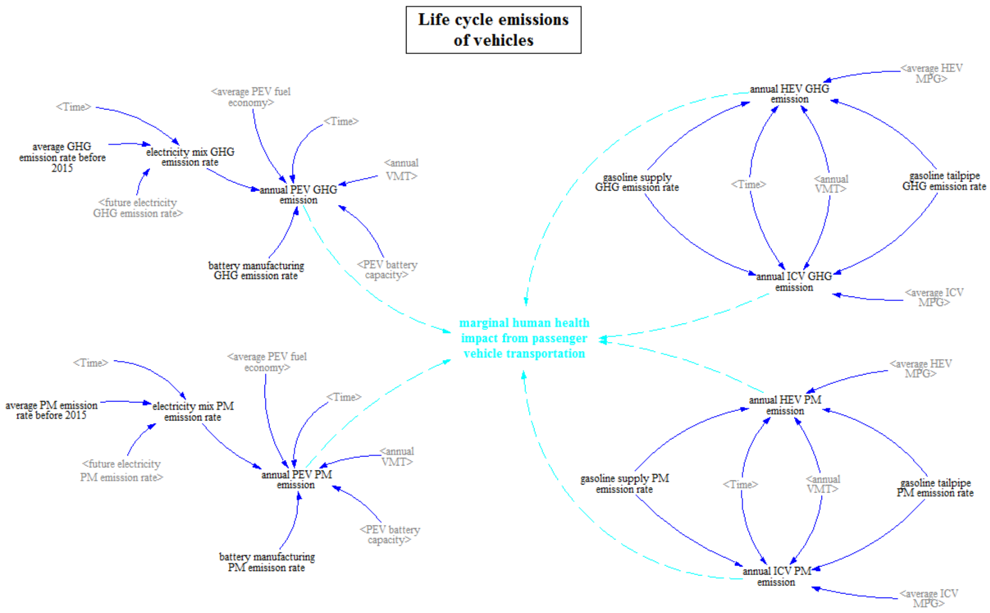


Figure 47 Stock-flow diagram for the life cycle GHG emissions and traditional air emissions of HEVs, PEVs, and ICEVs

Figure 48 simulates the emission savings of the V2G system with respect to the power grid, as well as the potential availability of ancillary service capacity from PEVs and HEVs. Based on the literature (Kempton and Tomić, 2005a, b) and the authors' previous studies (Zhao et al., 2016a, 2017; Zhao and Tatari, 2015), individual EVs are aggregated in V2G systems and serve as additional storage capacity, so when the grid operator needs a certain amount of energy to balance off a sudden and unpredicted demand peak, the electricity previously stored in the EVs' batteries is extracted and supplied back to the power grid; likewise, whenever the energy demand is lower than the standard energy supply rate, the extra electricity can be stored in the vehicles' batteries for the next cycle or until it is needed again. This process is also called regulation services, and providing such regulation services using a V2G system can effectively reduce the need to use traditional combustion turbines (gas or oil powered), which have fast responding times but generate two to three times as much GHG emissions. The electricity exchanged through a vehicle's battery for V2G regulation services is determined by its available power and the V2G provision time, as shown in Equation 28:

$$PEV_{ap} = \frac{(B_{capacity} - \frac{Daily_{vmt} - Range_{buffer}}{F_e})\, C_e}{T_{dispatch}} \tag{28}$$

Where PEV_{ap} is the "PEV available power" variable, $B_{capacity}$ is the PEV battery capacity, $Daily_{vmt}$ is the annual VMT divided by 365, $Range_{buffer}$ is the buffering range, F_e is the average fuel efficiency of PEVs, C_e is the conversion efficiency (which is used to represent the energy loss during the process), and $T_{dispatch}$ is the average time interval of each regulation cycle. The values and data sources of these parameters have all already been listed in Table 18. Based on the internal calculations for this section of the model and the authors' previous study (Zhao et al., 2017), the available power of PEVs for regulation services is approximately 30 kW. On the other hand, the available power of HEVs is difficult to simulate because, during daily driving routines, HEV engines can consume the onboard gasoline to recharge the battery once the electric range is reached, so it is assumed that the HEVs in this model have a fixed available power of 15 kWh.

The V2G emission savings from each participating HEV or PEV per night is calculated by multiplying the available power in each vehicle by the V2G service provision time. Existing data indicates that an EV providing regulation services may receive and respond to 30 to 40 regulation requests (including regulation up and regulation down requests), and each cycle lasts approximately 3.6 to 9 minutes (Kempton et al., 2008), meaning that the overall service provision time is assumed to be 3.675 hours per night. The overall emission savings can be calculated by multiplying the emission savings per vehicle by the number of EVs and by the participation ratio of these EVs. The owner participation ratio is discussed in further detail with respect to the scenarios discussed in Section 6.3.5.

In addition, the "marginal human health impact from passenger vehicle transportation" variable (the light blue variable in both Figure 47 and Figure 48) indicates that the life cycle emissions of all of the considered research cars and the V2G emission savings will both contribute to the overall emission rates of the entire modeled system. The outgoing variable "renewable capacity growth" (shown in purple in Figure 48 and Figure 49) indicates that the overall available ancillary service capacity/power can be used to encourage renewable power integration, and this relationship is further discussed in the water-energy nexus sub-model (Section 6.3.4). Moreover, a restriction variable ("max wind power capacity") is included to ensure that the wind power capacity does not exceed a certain ratio; this ratio is regulated based the scenarios discussed in Section 6.3.5.

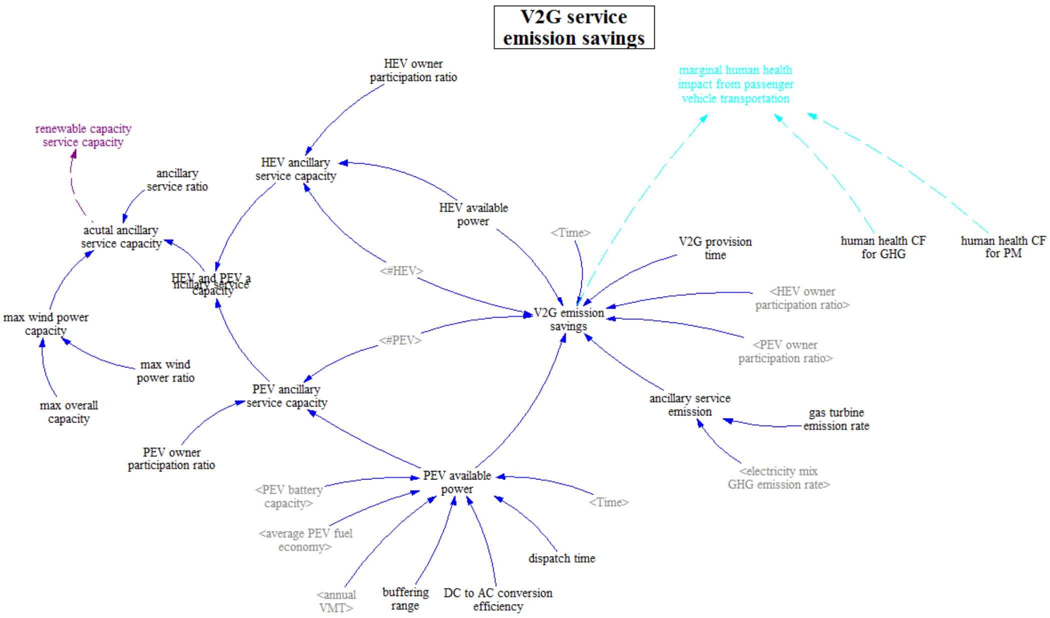


Figure 48 Stock-flow diagram for GHG emission savings and traditional air emission savings from the use of V2G regulation services

6.3.4 <u>Water-energy nexus</u>

The structure of the water-energy nexus with ancillary service support from V2G regulation service is illustrated in Figure 49 and Figure 50. Although there is very little wind power currently online, this model explores the system's reaction to the introduction of V2G systems as V2G regulation service carriers, which will each allow the current grid to accommodate more wind power without significantly increasing the cost of energy generation.

To accommodate a large amount of wind power, the required ancillary service capacity will be approximately 6% of the newly integrated power capacity (Hudson et al., 2001; Kempton and Tomić, 2005b). One of the main assumptions of this study is that, instead of deploying combustion gas turbines, the required ancillary services are all provided using all of the participated HEVs and PEVs, and with respect to the "renewable capacity growth" variable (shown in purple in Figure 49), an "if then else" function is used in this variable to simulate the wind power that can be supported by V2G regulation service from 2000 to 2030:

$$Renewable\ capacity\ growth = IF\ THEN\ ELSE$$

$$(Time < 2016\,, 0,\ \frac{HEV\ ancillary\ service\ capacity + PEV\ ancillary\ service\ capacity}{ancillary\ service\ requirement\ ratio}) \qquad (29)$$

Where the value of the "ancillary service requirement ratio" variable is 6%. Since the market penetration of EVs with grid accessibility increased significantly approximately between the year 2015 and the year 2016 (Alternative Fuel Data Center, 2015), it is assumed that the use of V2G services is available after 2015 and that, with the additional ancillary service capacity, the associated increase in wind power market penetration is evenly distributed over the following 15 years (from 2016 to 2030). In addition, this gradual increase in wind power effectively replaces the original thermoelectric power capacity, and it is assumed that this replacement ratio is based on the original ratio of each electric power source. The five stock and flow components in this section each indicate, with respect to each energy source, the causal flow from the rate of increase in power capacity to the total power capacity in kW before finally leading to the total energy generation in kWh. However, the future relationship between the capacity and generation of each power source remains unknown, so the corresponding mathematical relationships are derived from regression analyses with respect to historical power capacity and generation data (U.S. Energy Information Adiministration, 2015e), and the relevant data and equations are illustrated in Figure 51 for each energy source. The x-axis represents the power capacity of a power source from 2000 to 2014, and the y-axis represents the corresponding power generation in each year. The overall GHG emission rate and the overall traditional air pollution rate are both calculated based on the corresponding weights from each energy source; these two emission rates are represented in Figure 49 as the "future electricity GHG emission rate" and "future electricity PM emission rate" variables, respectively. In addition, the overall grid emission rates will in turn affect the life cycle emissions of the EVs as part of the associated feedback loops.

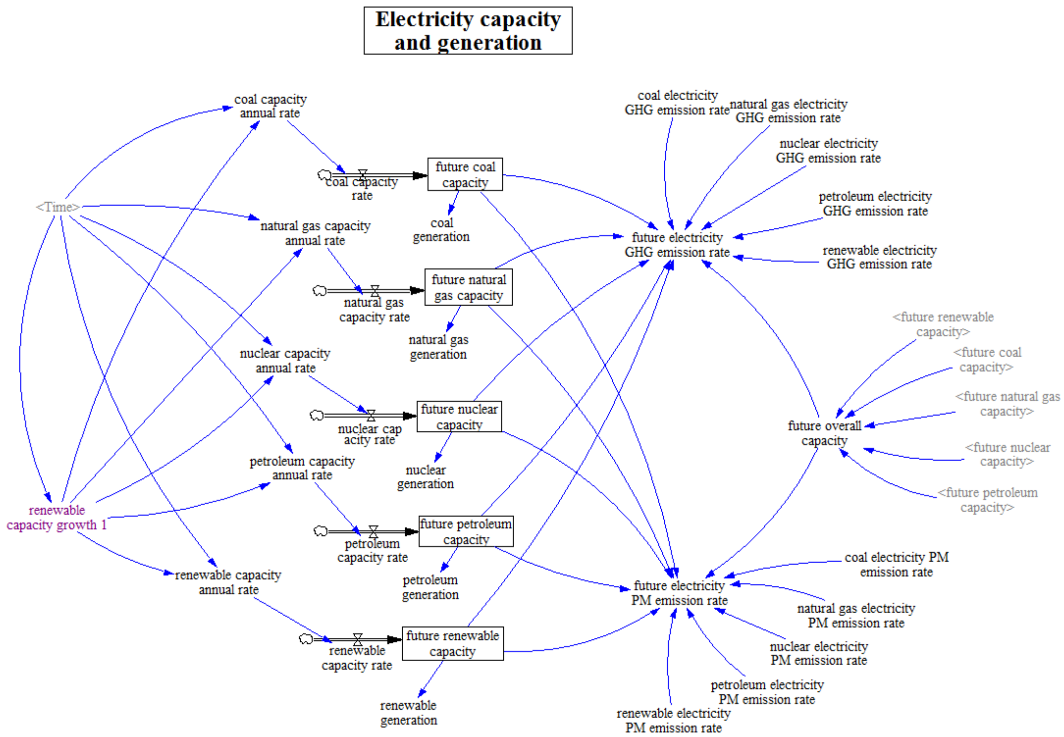


Figure 49 Stock-flow diagram for the electricity grid with renewable power integration

The water consumption rates for power plant cooling are modeled in Figure 50. In Florida, surface water is the primary source of the water used for electricity generation (Borisova and Rogers, 2014), and 7% of all water consumed for cooling purposes is fresh water while 93% is saline water (Scroggs, 2014). Therefore, the water consumption rates of each energy source are derived from the literature (Macknick et al., 2011; Torcellini et al., 2003), multiplied by the total generation from each corresponding energy source, and distributed among the two stock and flow sections in Figure 50 to reflect the respective consumption rates for saline water and for freshwater. The freshwater is lost through evaporation, and the amount of energy required for the treatment of the consumed fresh water is obtained using the evaporation rate and the energy intensity ratio (Copeland, 2014).

The energy consumption and air emission rates due to water consumption and treatment are calculated in this section, along with the emissions from the passenger car sector due to the combustion of gasoline (Figure 47), the emission savings from providing V2G services using PEVs (Figure 48), and the emissions from the power grid and from the charging of the newly adopted PEVs (Figure 47 and Figure 49, respectively), after which all of the calculated emission rates and emission savings are connected back to the variable “marginal human health impact from passenger vehicle transportation”. Lastly, based on the estimated human health impact factors of GHG emissions and traditional air emissions (Onat et al., 2016a), all of the aforementioned emissions are translated into human health impacts simulated as reductions in life expectancy (Figure 52).

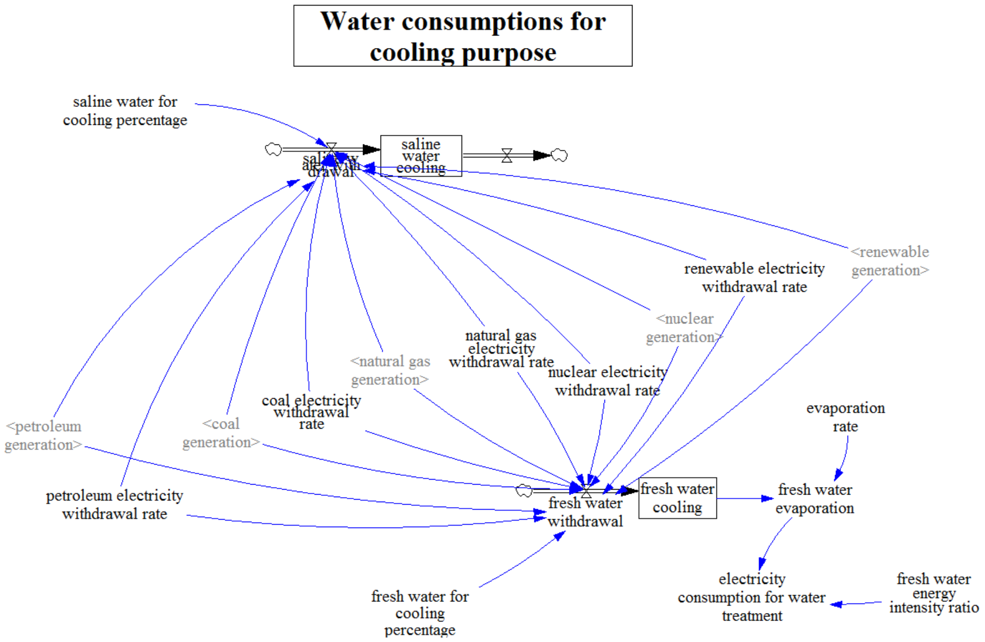
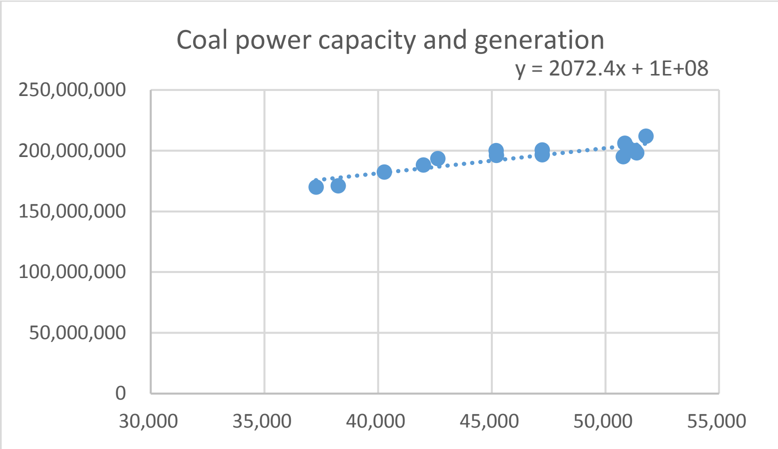
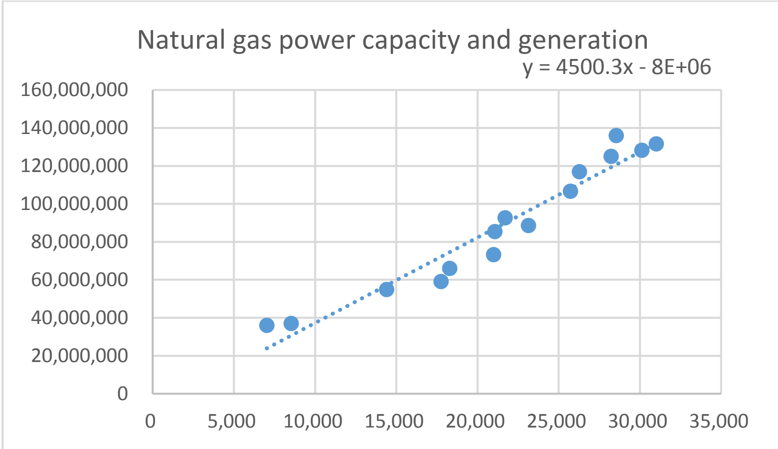
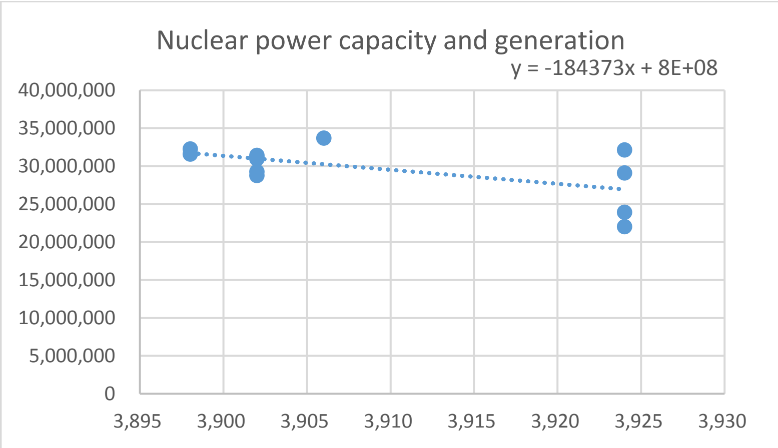


Figure 50 Stock-flow diagram for water consumption for thermoelectric generation







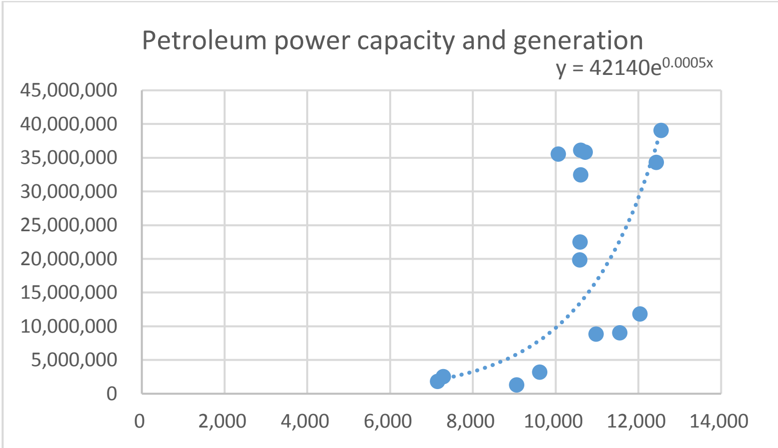


Figure 51 Electricity capacity and generation regression graphs (x-axis = capacity in MW; y-axis = generation in MWh)

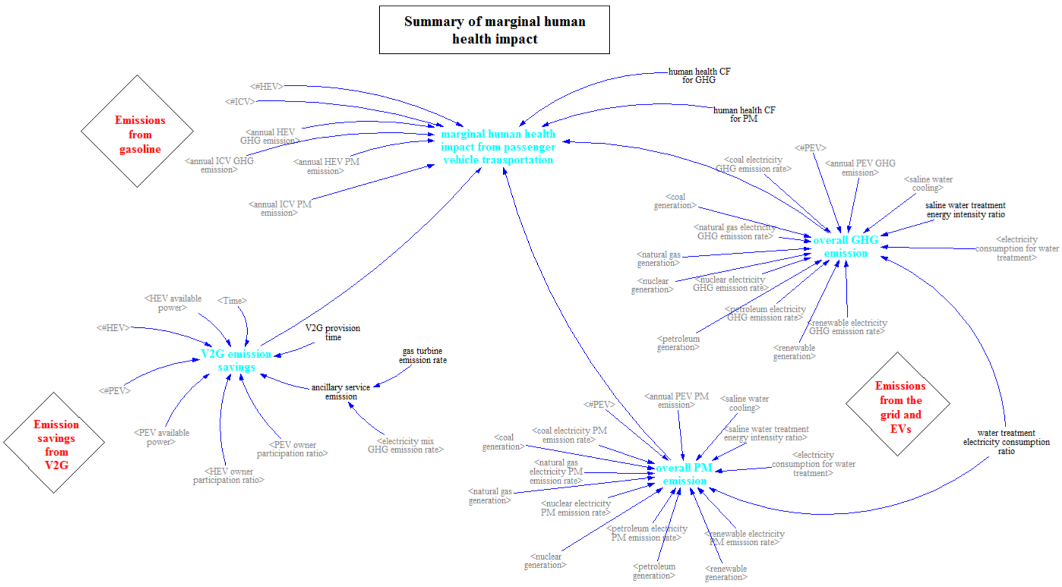


Figure 52 Summary of all the variables with emission impacts

6.3.5 <u>Scenarios</u>

In this model, the future market penetration rates of HEVs and PEVs, the V2G regulation service participation ratio, and the maximum wind power percentage are all included as exogenous variables and these variables are critical indicators of the overall sustainability level of the transportation-water-energy nexus. As indicated by the feedback loops in this model, these indicators are all positively related; for instance, a larger EV user base would provide more potential customers and/or market scale for the use of V2G technology; with the increased adoption of V2G regulation services, the storage capacity and response times of the power grid would both be improved; furthermore, with more clean energy (e.g. wind energy) being integrated into the power grid, the overall air pollutant emission rate of electricity generation can be reduced, further reducing the life cycle emissions of EVs. Hence, the following assumptions are made in order to test the reaction of the model to different realistic scenarios and/or policies:

First, based on historical data with respect to HEV and PEV sales (Block et al., 2015), the baseline HEV and PEV percentages are assumed to have an increasing trend in future years, as illustrated in Figure 53.

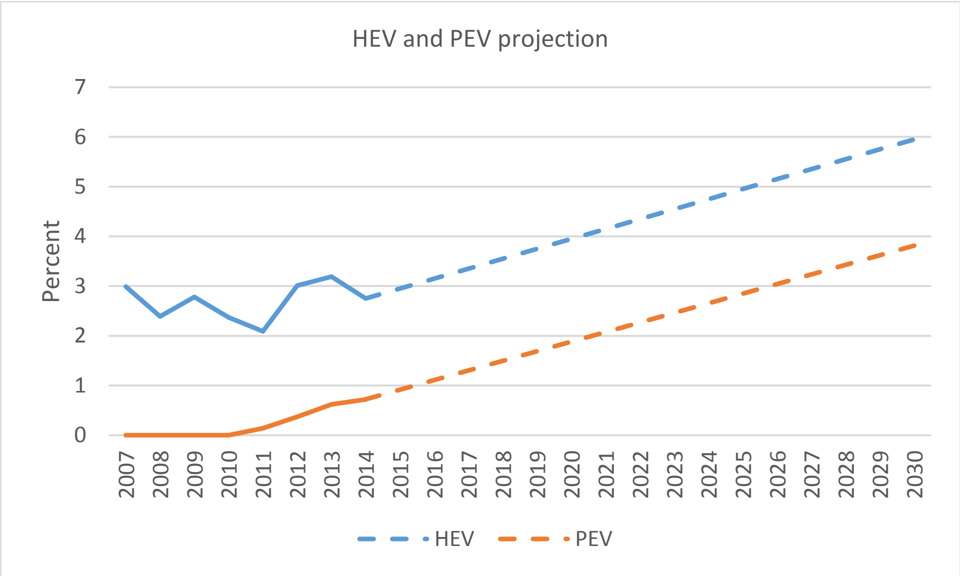


Figure 53 Historical and projected HEV and PEV market penetration rates

The solid line in Figure 53 indicates the historical data, while the dashed line indicates the projected future trend. The assumed increasing rate in the baseline scenario (i.e. the most likely scenario) is 0.2% for HEV and 0.19% for PEV, based on their respective average increasing rates from 2010 to 2014. In addition, three more increasing rates are tested to reflect three other possible scenarios, one scenario being more conservative than the baseline scenario while the other two scenarios assume higher market penetration rates for both EV types; the projected increasing rates for both EV types are set at 0.1% for the more conservative scenario and at 0.3% and 0.4% for the two more optimistic scenarios.

The willingness ratio for V2G regulation service participation has been discussed in the literature, but can vary significantly. Hidrue and Parsons (2015) have argued that 17.8% of EV owners would be willing to participate, although this number can also be as high as 52.8 % (Parsons et al., 2014), while a more conservative participation ratio of 3% to 4% has been used in a previous study (Zhao et al., 2017). In this study, the baseline EV owner participation ratio is conservatively assumed to be 1%; this value is set as 0.5% for the low-projection scenario and at 2% and 4% for the two more optimistic scenarios.

The National Renewable Energy Laboratory predicts a market share of 20% for wind energy by 2030 (Lindenberg et al., 2008), so based on this projection, the maximum wind energy market penetration levels will be set to 15% for the low-projection scenario, 20% for the baseline scenario, and 25% and 30% for the two high-projection scenarios.

The selected parameters for each of the four scenarios are summarized in Table 19 for three separate. It should be noted that the values specified in Table 19 apply to both HEVs and PEVs.

Table 19 Assumptions of the scenarios

	HEV and PEV increasing rate	**HEV and PEV V2G participation ratio**	**Maximum wind ratio**
conservative scenario	0.1	0.005	0.15
baseline scenario	**0.19 for HEVs 0.20 for PEVs**	**0.01**	**0.20**
high projection scenario	0.3	0.02	0.30
maximum projection scenario	0.4	0.04	0.40

6.4 Model validation and verification

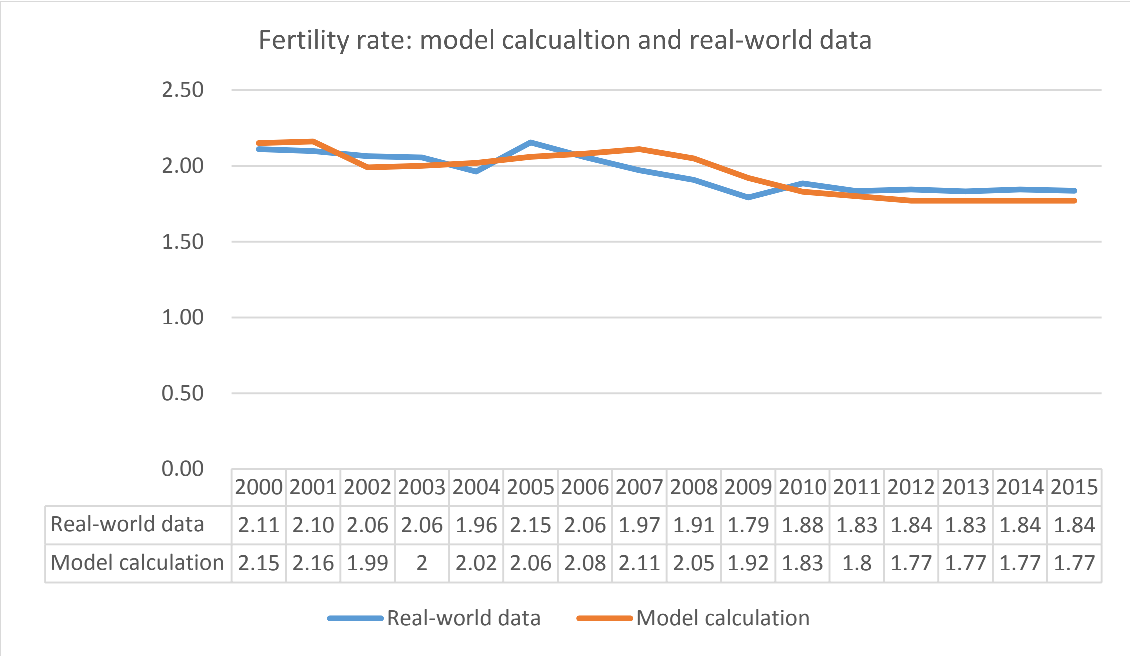
The model is verified and validated from three different angles:

- First, the critical inter-section equations that deliver the environmental and/or economic impacts to variables such as population in the social section of the model are verified by plugging in real-world data.
- Second, the outputs (i.e. calculation results) of the applicable variables are compared with real world historical data and/or projections.
- Third, since the V2G system (which mainly impacts renewable energy capacity) has

not yet been adopted in the real world, the ranges of environmentally oriented results of the model are compared with the corresponding real world projections.

The first two angles are discussed in this section, and the range check for the third angle is discussed in more detail in the “Results and discussion” section (Section 6.5).

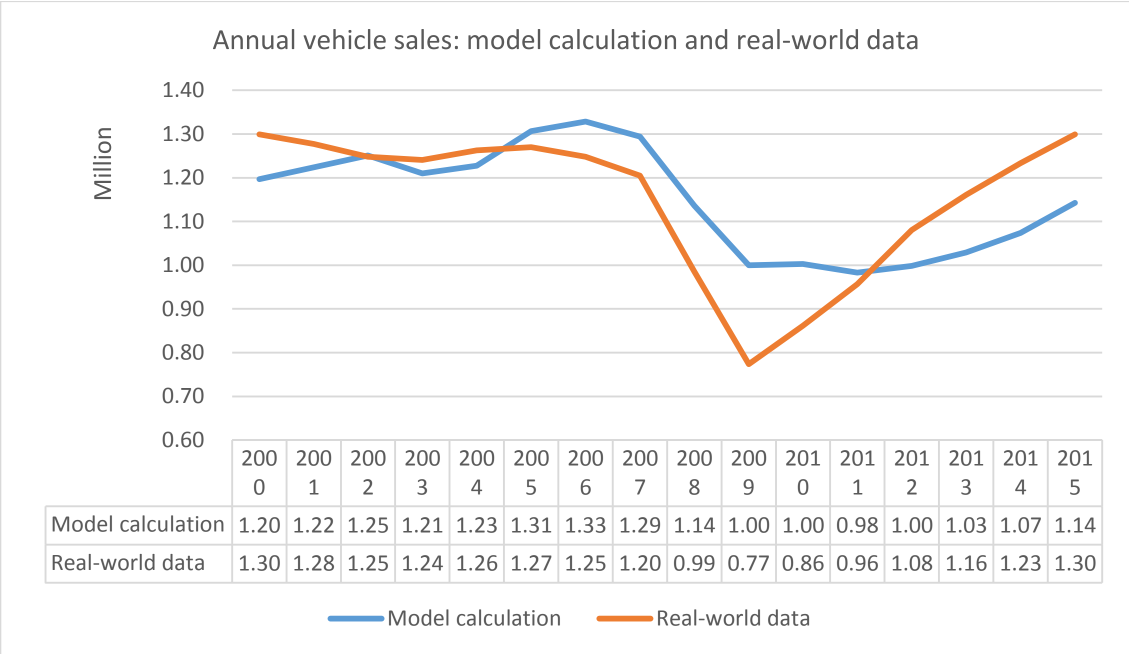
In the GDP, population, and vehicle market section of the model (Figures 44 and 45), Equation 24 links the GDP-related variables to the population section through the relationship between the GDP per capita and the fertility rate of the population. Likewise, Equation 25 links both the GDP section and the population section, and also determines the amount of passenger vehicle sales (which is a critical element of the model), so to verify the model, Equations 24 and 25 are first tested by applying both equations with existing data from 2000 to 2015. The historical GDP data for Florida is obtained from the Federal Reserve Bank of St. Louis (2016), while the historical population data is obtained from the World Population Review (2015), the life expectancy data is provided by the (Florida Department of Health, 2015), and the real-world fertility rate data for the state of Florida is also likewise derived from the literature (National Center for Health Statistics, 2017). The existing data sets for GDP per capita and for life expectancy are both plugged into Equation 24 and are then compared with the real-world fertility data through a regression analysis. The results of this analysis indicate that the results of the above-cited calculations are coherent with respect to the corresponding real-world data (R^2 = 0.67). This comparison is also shown visually in Figure 54.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Real-world data	2.11	2.10	2.06	2.06	1.96	2.15	2.06	1.97	1.91	1.79	1.88	1.83	1.84	1.83	1.84	1.84
Model calculation	2.15	2.16	1.99	2	2.02	2.06	2.08	2.11	2.05	1.92	1.83	1.8	1.77	1.77	1.77	1.77

Figure 54 Fertility rate comparison between real-world data and model calculations

Likewise, for Equation 25, the number of potential drivers (Florida population aged 16 or older), GDP per capita, and overall population data are all derived from the literature as previously cited, and are then applied to Equation 25 and then compared to the actual annual vehicle sales from 2000 to 2015 (Federal Reserve Bank of St. Louis, 2017). This comparison (regression result R^2=0.52) is shown visually in Figure 55.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Model calculation	1.20	1.22	1.25	1.21	1.23	1.31	1.33	1.29	1.14	1.00	1.00	0.98	1.00	1.03	1.07	1.14
Real-world data	1.30	1.28	1.25	1.24	1.26	1.27	1.25	1.20	0.99	0.77	0.86	0.96	1.08	1.16	1.23	1.30

Figure 55 Annual vehicle sales comparison between real-world data and model calculations

In addition to the verification of the two critical equations, ANOVA tests are applied to the model outputs and actual historical/projected data for GDP and population.

The total GDP as simulated in this model consists of the GDP contribution from the passenger car sector and the overall GDP contribution from all other economic sectors, so in order to verify the structure and the mathematical relationships among these variables, the historical GDP of Florida (Federal Reserve Bank of St. Louis, 2016) and the projected GDP growth rate (U.S. Department of Commerce, 2017a) are both analyzed along with the GDP output (in millions of dollars) from the model. The ANOVA test results are summarized in Table 20, and the results in this table show that the F value is much less than the F critical value, meaning that there is no significant statistical difference between the real-world data and the model output.

Table 20 ANOVA test of GDP data sets

Groups	Count	Sum	Average	Variance		
Real-world GDP	31	27998326	903171.7979	60758568314		
Baseline output GDP	31	28808405	929303.3871	66405803858		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	10584329256	1	10584329256	0.166466898	0.684723	4.001191
Within Groups	3.81493E+12	60	63582186086			
Total	3.82552E+12	61				

The population is modeled through a series of stocks and flows (Figure 45), so to verify this section, the historical and projected populations of the State of Florida (World Population Review, 2015) are compared with the corresponding output from the variable "population" in the model. The results of the ANOVA test for this comparison are shown in Table 21; this table shows that the F value for this comparison is significantly less than the critical F value, indicating that there is no significant statistical difference between the model output for the population and the actual Florida population data.

Table 21 ANOVA test of population data sets

Groups	Count	Sum	Average	Variance
Real-world population	31	638898995	20609644.99	9.28314E+12
Baseline output population	31	659131300	21262300	5.14038E+12

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	6.60236E+12	1	6.60236E+12	0.915498604	0.342499	4.001191
Within Groups	4.32706E+14	60	7.21176E+12			
Total	4.39308E+14	61				

6.5 Results and discussion

First, the model results for the GDP, population, and overall GHG emissions are shown in Figure 56, Figure 57 and Figure 58, respectively; these variables serve as the primary indicators of the economic, social, and environmental aspects of the modeled system. It can be concluded from Figure 56 that, in the baseline (most likely) scenario, the overall GDP of Florida increases from \$500 billion to \$1,400 billion, but it is also evident that the overall GDP is not affected significantly by increasing/decreasing either the EV market penetration or the V2G participation ratio. The columns on the right side represent the changes in the overall GDP in each of the other three scenarios. The conservative assumptions lead to a slight decrease in GDP; meanwhile, in more optimistic scenarios with respect to EV market penetration, the V2G participation ratio, and the maximum wind energy market share, the overall GDP grows accordingly. However, at a trillion-level scale, variations at a hundred-million-level scale are barely visible on the charts. Also, as previously noted, the GDP as simulated in this model is divided into that of the passenger car sector and that of all other sectors combined, the latter of which is simulated as an exogenous lookup function and therefore does not change under any scenario assumptions, so the variations in GDP indicated in Figure 56 are due entirely to the increased market penetration levels of HEVs and PEVs, although the market shares of HEVs and PEVs are both still under 10% (Figure 44 and Figure 45), so it can be concluded that, although EVs are considered to have lower maintenance cost, a relatively small percentage of EV still results in a positive impact on the economy.

Figure 57 shows model results with respect to the population. In the baseline scenario, from 2000 to 2030, the population of Florida gradually increases from 17.3 million to 24.8 million. As with the GDP results (Figure 56), the impacts from the GDP and the overall emission rates are almost negligible, with a reduction of approximately 100 relative to a 20-million level base population). By studying the connections and mathematical relationships between the applicable variables, two reasons can be found for this result:

- First, as a deterministic factor for population, the fertility rate is calculated based on the variables "GDP per capita" and "adjusted life expectancy", but since the GDP is only slightly affected by other variables, the model output for GDP per capita (Figure 58) is not affected by changing any scenario assumptions.
- Second, the variable "marginal human health impact from passenger vehicle transportation" (first introduced in Figure 45) does reflect changes at a certain scale (Figure 58) and is a dimensionless factor in the model, but when connected to the "adjusted life expectancy" variable, the value of the variable is divided by the total population, meaning that very little of this change translates as a change in the adjusted life expectancy.

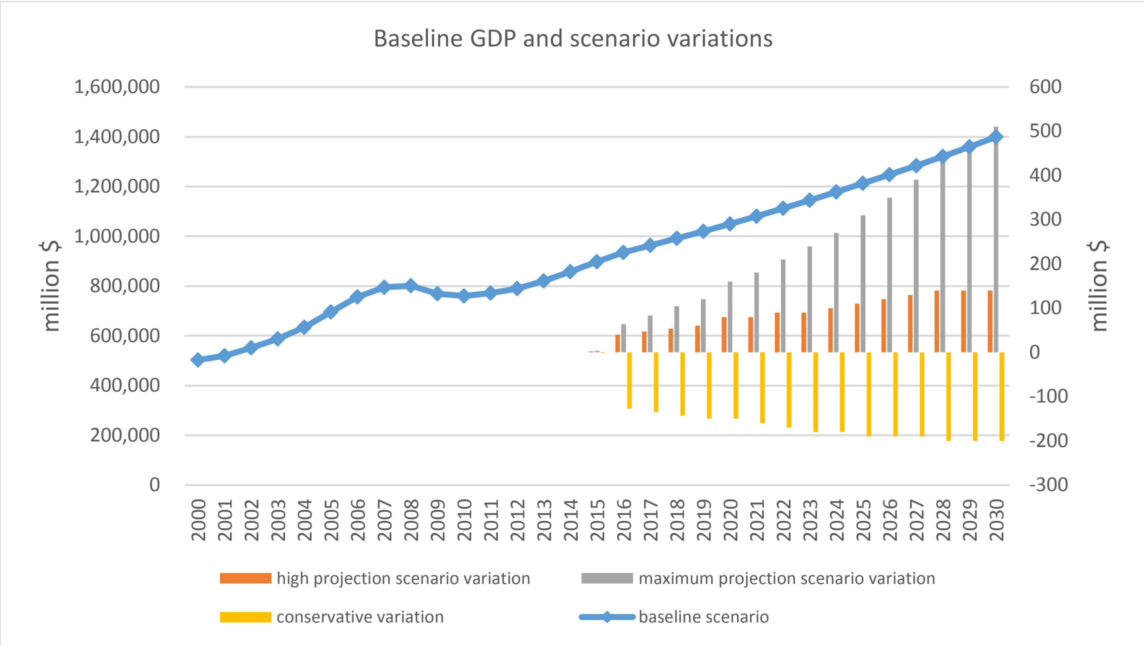


Figure 56 GDP results of four scenarios

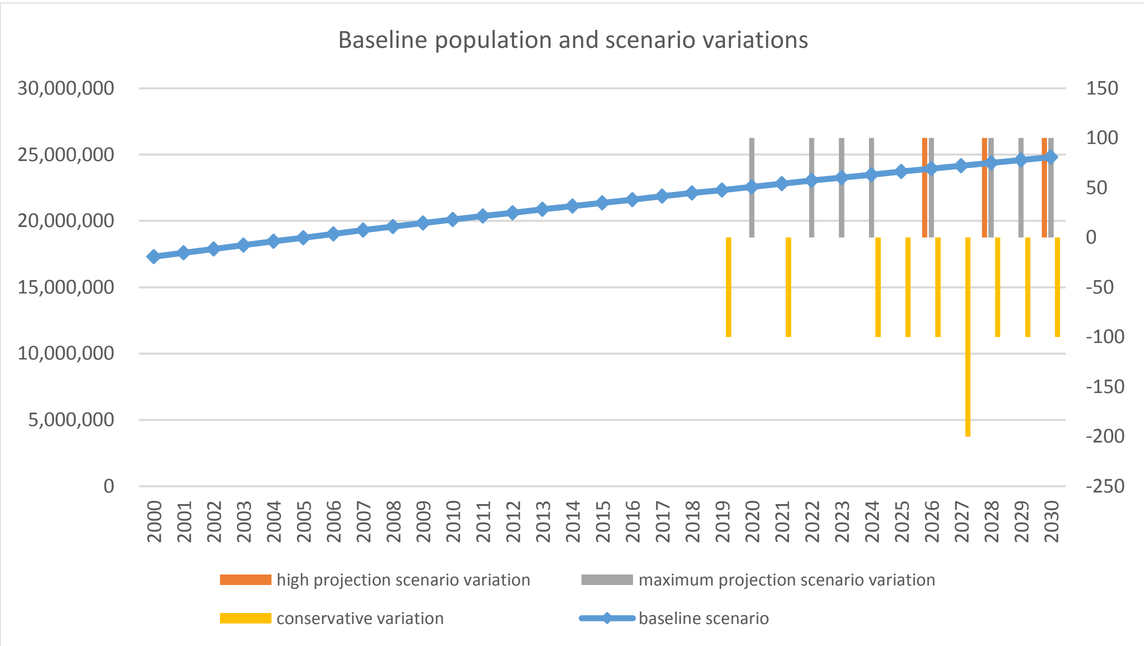


Figure 57 Population results of four scenarios

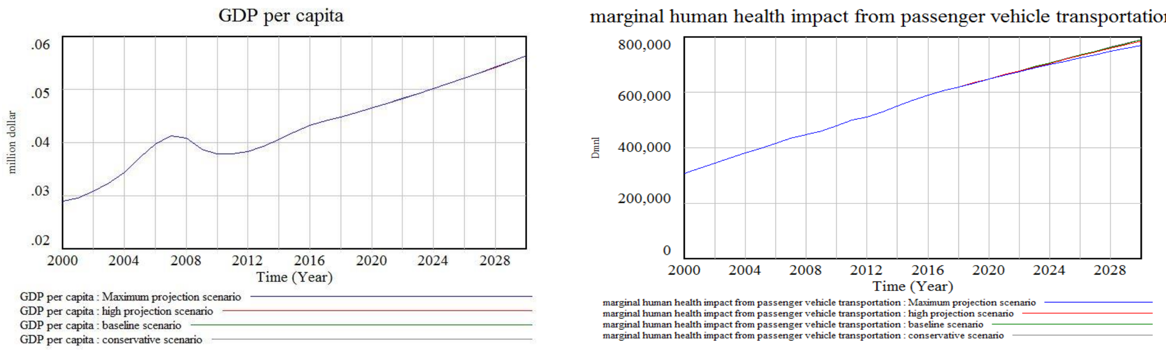


Figure 58 Results for GDP per capita and the marginal human impact factor

Unlike the results for the GDP and for the population, the overall GHG emission rate from the entire passenger car section and from water-energy nexus is sensitive to the different scenario assumptions previously discussed. The overall GHG emission rate is modeled as the total sum of the life-cycle GHG emissions of all vehicles (including HEVs, PEVs, and ICEVs), the GHG emissions due to electricity generation, and the GHG emissions resulting from the necessary energy consumption for water treatment. As shown in Figure 59, with the adoption of V2G systems in 2015, the increasing trend in overall GHG emissions is visibly slowed down. According to the result prior to 2015, which were calculated using historical data, the overall GHG emission rate from both passenger transportation and electricity generation increased from 202 million tons to 254 million tons, and there is a high possibility that this number will continue to increase without further policy intervention, as there has currently been no significant change in energy infrastructure and no significant market shares of clean power sources for the passenger transportation sector have yet been introduced. Based on conservative market estimates (conservative scenario in Table 19), the 0.1% HEV and PEV increasing trend leads to 2030 market penetration levels of 4.3% for HEVs and 2.3% for PEVs. If 0.5% of these EV owners are willing to participate in V2G regulation services, the overall GHG emissions can be stabilized at a level of 260 million tons without requiring a significant increase; it must also be noted that this scenario is most likely to be achieved in the future if large-scale off-shore wind power capacity achieves a market share of up to 15% of the overall power grid capacity.

The results of the conservative and baseline scenarios are identical, but in scenarios with more optimistic projections for EV and wind power market penetration, GHG emissions after the year 2023 decrease to less than the current GHG emission rate of 260 million tons. In the maximum EV adoption/wind power integration scenario, where the final (2030) market penetration levels are at their highest estimated values, the corresponding 2030 market shares are 9.15% for HEVs, 7.12% for PEVs, and 40% for wind power capacity, while the V2G participation ratio is estimated at 4%; under these conditions, approximately 10 million tons of GHG emissions can be saved.

In addition, it is noted that the total GHG emission rate of the entire transportation sector (not just the passenger car sector) and the electricity generation sector is about 268 million ton in 2007 (Florida Department of Environmental Protection, 2010), confirming that the results of the model fall within a reasonable range.

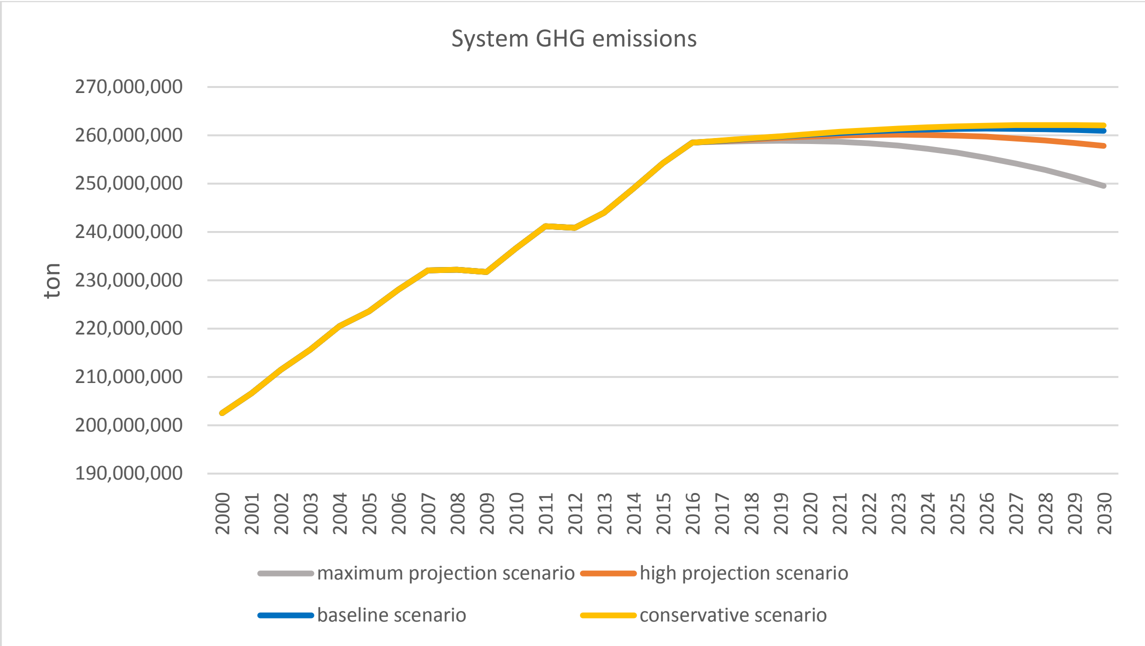


Figure 59 Overall GHG emission results of four scenarios

Significant amount of GHG emissions can be mitigated in the maximum projection scenario because of the reinforcing loop activated through the use a V2G system. In this feedback loop, the growing EV market penetration provides more ancillary service capacity and helps to encourage the integartion of wind power, while the higher market share of clean energy in the power grid decreases the overall emissions due to EV usage and cooling water requirements, and these reduced emissions further encourage the adoption of EVs in future years. Figure 60 illustrates the changes invehicle market penetration under each of the four studied scenarios. In the baseline scenario, the increase in HEV market penetration starts at around 2001 and gradually reached to 0.64 million by 2030; in the maximum projection scenario, the number of HEVs reaches one million by 2030. PEVs are introduced into the market after 2012; the overall number grows to 320,000 in the baseline scenario, and under the maximum feasible projections (when the increasing trend in PEV market shares) is set to 4% per year), the final 2030 market share of PEVs reaches up to 689,000. ICEVs are still the domniant vehicle type, and from 2006 to 2017, the overall number of ICEVs has remained more or less consistent at around 17 million. However, with the introduction of EVs, the number of ICEVs was reduced to approxiamtely 16 million. The annual GHG emissions of ICEVs and PEVs in the baseline scenario is also shown in Figure 60; these results also indicate that, by replacing one ICEV with one PEV each year, approxiamtely 0.5 tons GHG emission can saved per year.

Additionally, a study performed by Block et al. (2015) estimates that the number of PEVs in Florida can reach to 288,000 by the year 2024, and this number is close to the corresponding number of PEVs under the high projection scenario. This also confirms that the scenario assumptions made for the vehicle market penetration section of the model are adequate.

Figure 60 Market penetration results for HEVs, PEVs, and ICEVs

The baseline scenario in Figure 61 indicates that about 55,000 tons of GHG emissions were mitigated in 2016 through the use of PEVs and HEVs to provide V2G regulation services, and this number increases to almost 200,000 tons of GHG emission savings by 2030. The output of the conservative scenario shows a more gradual trend, due to less EV market penetration as well as a smaller participation ratio. On the other hand, if the future EV adoption rate can reach the maximum projected value and the market can implement a more sophisticated business mode, a more widely available aggregator, and well-built infrastructure, the resulting emission savings can be as high as 1.6 million tons.

In addition to mitigating emissions by providing cleaner regulation services, the fundamental goal of shifting the energy structure away from thermoelectric energy in favor of renewable energy sources can also be achieved by V2G technology. It can be concluded from the results in Figure 62 that, by introducing more wind power with the support of the studied V2G system, the overall emission rate from the power grid can potentially be reduced from 0.68 ton/MWh to less than 0.55 ton/MWh. This is an important finding with respect to the adoption of V2G technology because this reduced grid emission rate not only affects the emission rates from electricity generation alone but also reduces the overall GHG emission rate from the passenger car sector.

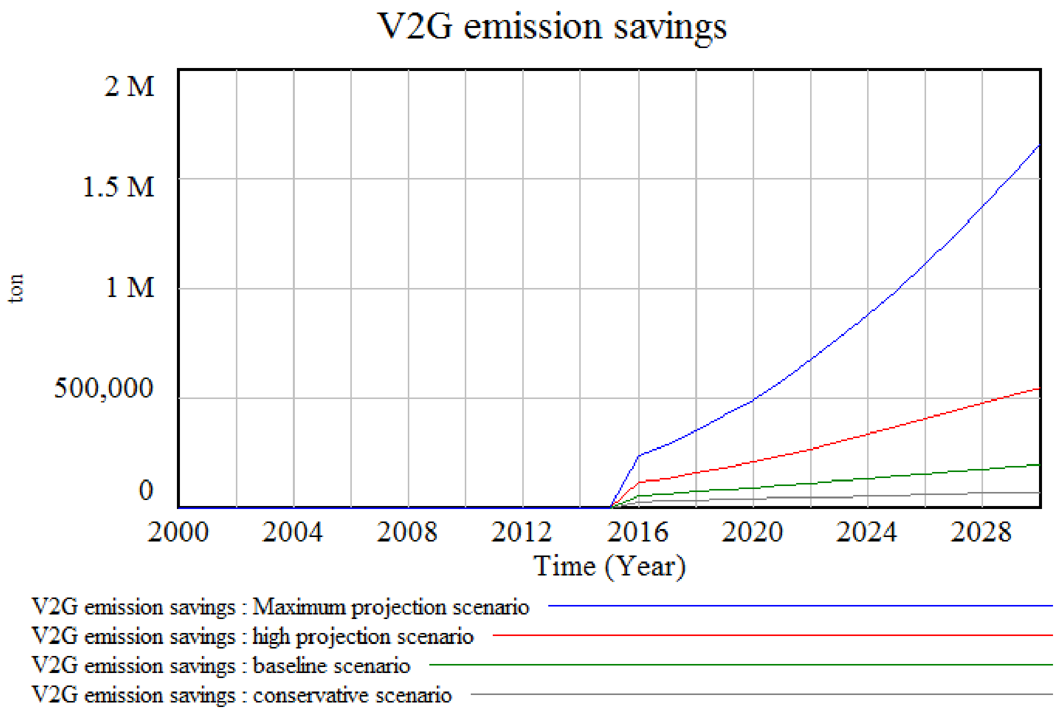


Figure 61 V2G emission savings

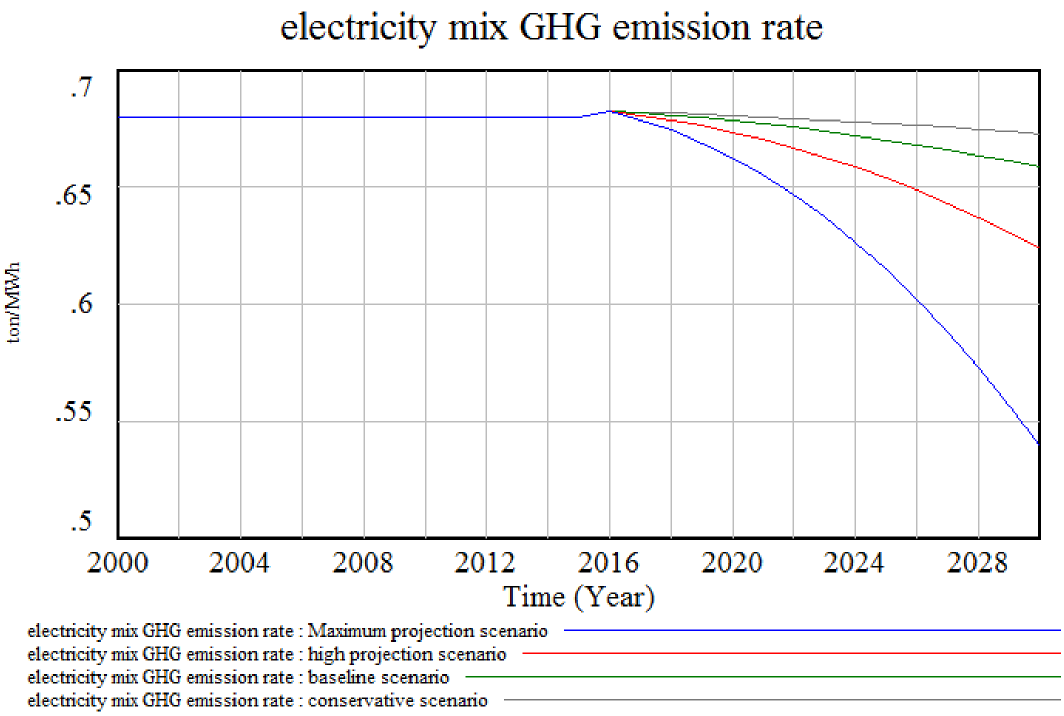


Figure 62 GHG emission rate of the power grid

6.6 Conclusion

This study evaluated the interactions between a hypothetical V2G system and the water-energy nexus via a combination of the system dynamics modeling approach and the life cycle assessment method. The underlying complex relationships among the applicable social, economic, and environmental variables were investigated, and the future development of the system was predicted accordingly. Four scenarios representing different possible futures for EV and V2G adoption levels were likewise tested. Some of the important findings from this study are listed below:

1. V2G technology could be an ideal solution for problems related to the optimization of the water-energy nexus and for the decarbonization of current electricity grid, as V2G systems are essentially an aggregation of several idle EV batteries, each of which can achieve a bidirectional energy transmission with limited modifications and/or investments from vehicle owners; the additional capacity provided by these batteries can increase the efficiency of the power grid and accommodate cleaner renewable power sources despite the inherent intermittency of their power outputs.
2. In addition to lower fuel and maintenance costs, the potential revenue of providing V2G regulation service may also be appealing to car buyers, making V2G systems a potentially critical element of a reinforcing feedback loop to facilitate the formation of a more sustainable system overall, including a larger EV fleet with higher energy efficiencies and lower tailpipe emissions. Based on the V2G services that can be provided by this fleet, the efficiency of the grid can also be increased, and more wind power can therefore be integrated. Subsequently, the newly adopted large-scale wind capacity not only decreases the emissions of electricity generation and further reduces the life-cycle emissions of EVs but also consumes less water; the latter in particular leads to less overall energy consumption within the system.
3. Sophisticated business modes and a good scheduling and controlling mechanism will

both be required from system operators, and more importantly, a certain amount of willing participants among the EV customer base will be essential to ensure an adequate V2G system. The results under a more conservative scenario indicated that a minimum EV market share of approximately 10%, combined with an availability/participation ratio for regulation services of at least 0.5%, would provide sufficient support for large-scale wind power integration.

4. The results of the simulations in this study indicated that the electrification of the passenger vehicle fleet will increase the GDP of the passenger car sector, but when combined with GDP from other sectors, the EV market has a fairly small impact on the population. Hence, the most effective connection between the environmental and economic sections of the overall system will be the incentives provided to encourage the adoption of EVs; in real life, this would most likely be in the form of economic incentives, such as lower prices for EVs.

5. With all of the relevant life cycle factors taken into consideration, the overall mitigation potential for GHG emissions was still found to be positively correlated with the number of EVs and the participation ratios with respect to V2G regulation services. The result of all four scenarios indicated a certain level of GHG emission mitigation, and among all of the assumptions made for these four scenarios, increasing wind power capacity was found to be the most effective way of reducing these emissions from the system as a whole.

Even though a wide variety of social, economic, and environmental variables have been investigated and simulated in this study, vehicle configurations and the behavior of the owner within each vehicle type were still considered within a relatively generic context. To build a more detailed model that can reflect a person’s decision and the subsequent impacts on the system, a future study incorporating an agent-based modeling (ABM) approach into the established framework can be performed and thereby analyze the modeled system from a more realistic perspective.

7 THE IMPACT OF VEHICLE-TO-GRID SYSTEM TO THE FUTURE TRANSPORTATION AND ENERGY SYSTEM – A SYSTEM DYNAMICS MODELLING APPROACH WITH UNCERTAINTY ANALYSIS

The introduction of clean energy source such as wind or solar power can effectively reduce the fuel consumption, air emissions and water consumption of the energy system. However, large-scale clean energy integration requires ancillary services or energy storage capacity to eliminate the intermittent power output. In this paper electric vehicles are assumed to be the ancillary service carriers for wind power through Vehicle-to-Grid systems. The connections and dynamics among electric vehicle adoption, wind power integration, water-energy nexus of power generation, effects of air emissions to human health, and the economic impacts of Vehicle-to-Grid technology to vehicle owners are simulated through a system dynamics model. In addition to the system dynamics model developed from last Section, an uncertainty analysis is incorporated in this section to address the uncertainties of the studied variables and the unknown business model or operation details.

7.1 Introduction

Electricity generation and transportation generate the largest and second largest share of greenhouse gas (GHG) emissions in the U.S. (U.S. Environmental Protection Agency, 2016). Both sectors rely heavily on fossil fuels, currently more than 80% of U.S. electricity is generated from fossil fuel or nuclear power, and approximately 90% of the 260 million registered vehicles are powered by gasoline or diesel. As the economy and population grow, the increasing commuting needs and poor traffic conditions would further worsen the air pollution situation, and cause cardiovascular and respiratory issues to urban residents. Other than air emissions, thermoelectric power plants which generate electric power from petroleum combustion or nuclear reaction consume significant amount of water for cooling purpose.

To increase fuel efficiency, vehicles partially or fully powered by electricity have been introduced to the market. Hybrid electric vehicles (HEV) capture braking energy and power utilize it for a certain speed range; some plug-in hybrid electric vehicle (PHEV) models have larger battery packs and can obtain electric power directly from the grid; the newer plug-in electric vehicles (PHEV) operate entirely on electric powertrain and are fully independent from fossil fuel. However, for vehicles using electricity as power source, whether or not air emissions can really be reduced depends on the percentage of the “clean” power sources in the energy structure. Electricity is a unique commodity in that it must be generated and consumed at the same time. So, the electricity market can be generally divided into energy-related market and power-related market. Electricity in energy-related market is generated by coal or nuclear power plants at a stable rate. On the other hand, power-related market is consisted by ancillary services such as regulation service or spinning reserve, and these services balance the demand and supply and ensure the reliability of the grid. Wind or photovoltaic power are clean yet intermittent power sources, so comparing with traditional power generation, wind power plants require more ancillary services to maintain a stable output.

Vehicle-to-Grid (V2G) system further integrates electricity generation and transportation sectors by allowing electric vehicles (EV) supplying electricity back to the grid as ancillary capacity providers. By plugging EVs into the grid, local aggregators can coordinate and allocate the backup power capacity (in kW or MW) to compensate the fluctuated power output from wind farms. So, traditional combustion turbines as ancillary service carriers, can be replaced by the aggregated battery capacity of EVs. Studies have shown that, with a sophisticated network, commercial fleets (Hill et al., 2012; Zhao et al., 2016a) and private EV owners (Noori et al., 2016) can gain economic benefits from providing V2G regulation services. More importantly, the large-scale renewable energy supported by contracted EVs can reduce the emission rate of the entire energy system and further mitigate the carbon footprint of the transportation sector. In addition, with a higher renewable energy ratio, water withdrawal and consumption of the energy sector can be mitigated.

As V2G technology connects the electricity generation and transportation sectors, a network consists of social, environmental, and economic aspects is formed. In this network, elements from individual scale including vehicle price, operation and maintenance cost, V2G service revenue, and consumer's choice, to high-level systems such as GDP, population, GHG emissions from transportation sector, water consumption from energy structure, and the integration of wind as energy source interconnect with each other and affect the dynamics of the network. Therefore in this paper, the transportation-V2G-energy network is simulated by a system dynamics model; social, environmental, and economic aspects of the model is represented by GDP/population, GHG/particular matter (PM), and vehicle life cycle cost respectively. Reinforcing and balancing loops of the systems are identified, and quantitative relations of all the variables in the model are computed and validated based on historical data. The uncertainty of critical variables are studied by a sensitivity analysis. The state of Florida is the study region and the modelling time is from 2000 to 2030. The rest of the study is categorized in following sessions:

- A literate review is conducted in Section 7.2
- The main method, the sub-models, and the model verification and validation is explained in Section 7.3
- The results are illustrated and discussed in Section 7.4
- The conclusion and findings are summarized in Section 7.5

7.2 Literature review

The bulk of the electricity is from the baseload energy market, the baseload electricity is typically generated from coal or nuclear plants at fairly low cost, however, this type of generation lacks the ability to alter its output in a short period of time. The other type of electricity on the energy market is peak power, which typically generated from gas turbine. Peak power is purchased to cope a seasonal demand peaking. Other than the bulk energy generation, ancillary regulation service, also known as automatic generation control (AGC) on the power market is also required to ensure the balance on the grid. In deregulated power markets, regulation services are commonly provided by independent system operators (ISO) and regional transmission organizations (RTO). EVs aggregated via V2G system are promising regulation service providers because of the great potential capacity the future EV fleet has and the high-efficiency nature of storing and supplying electricity through batteries (Kempton and Tomić, 2005a). The main advantage of V2G system as regulation service carrier over traditional gas turbine system to avoid constantly altering the power output of the gas turbine and mitigate GHG emissions (Lin, 2011). In addition, V2G system is virtually already exist since the power system is bi-directional, and the implementation of such system presents great economic value (Kempton et al., 2001). Studies also have shown both commercial fleets and private EVs can achieve GHG emission reduction and economic benefits (Noori et al., 2016; Zhao et al., 2016a). The emission source of EVs are mainly in the electricity generation phase, therefore life cycle assessment (LCA) method combined with uncertainty analysis has been adopted in V2G studies (Noori et al., 2016; Zhao et al., 2016a).

A study has revealed that significant more backup capacity will be required to accommodate large-scale wind power output (Korchinski, 2013), yet current energy structure lacks both storage and transmission ability (Flynn, 2008). In regarding of the integration of V2G and large-scale wind power, Albadi and El-Saadany (2010) have reached two conclusion, the cost of traditional ancillary services may increase significantly, and fast-responding means such as energy storage might reduce the operational cost. A study has also be done to consolidate the quantitative relationships of EVs in a wind power and V2G system (Kempton and Tomić, 2005b). A study conducted by Ekman (2011) also confirmed the feasibility of utilizing V2G system to provide ancillary regulation service for wind farms. Zhao et al. (2017) analyzed the environmental impacts of supporting new wind power through V2G systems in various ISO/RTO regions.

As an important indicator of the scale of the future V2G system, the market penetration of EVs has been studied. Agent based modelling approaches have been used to simulate individual potential consumers' choices (Eppstein et al., 2011) or the interactions between a group of consumer (Noori and Tatari, 2016). EVs typically have a higher initial cost than that of internal combustion vehicles (ICV), however, the fuel cost of EVs is lower, and the battery price is decreasing as technology advances. In addition, federal and most state governments provide cash incentives or tax credit to EV buyers, which may encourage more potential buyers to choose EV. A study performed by Jenn et al. (2013) have indicated that, statistically, gasoline price and government incentives have significant impact to buyers' choice. Another study confirmed the significance of gasoline price but argues the incentives' impacts are not as high (Diamond, 2009). Based on a survey of consumers' choices, the study conducted by Curtin et al. (2009) have summarized that environmental and non-economic factors have higher influences over economic factors. Other studies have reached conclusions that charging infrastructure (Sierzchula et al., 2014), financial, and battery-related factors (Krupa et al., 2014) play important roles in buyers' decision making.

The water-energy nexus within the electricity generation sector has been studied by (Cooper and Sehlke, 2012), and their finding is that the mitigation of GHG emission at a system level also requires changes from economic and social aspects, and the most efficient approaches include incorporating more clean energy and developing vehicles with higher fuel efficiency. A review study has pointed out that it is critical to identify the underlying improvements in the water usage of energy generation (Nair et al., 2014). A water-energy nexus research (cite a literature review) has pointed out that there are great potentials in reducing energy consumption from water treatment, and the optimization of energy structure is critical to decrease the consumption of water.

The EV market penetration, social, economic and environmental impacts of renewable energy integration via a V2G network, and the water-energy nexus within the energy system have not been studied as a whole, and current literature lacks the uncertainty analysis of the future energy-transportation system. To this end, a system dynamics model is built to reflect the quantitative relationships among the single vehicle level variables with system level social, economic and environmental variables. The goal of this study is to explore the underlying interconnections and reinforcing and balancing loops of the EV-V2G-wind power network; and based on the validated model, uncertainties are given to critical parameters (such as incentive or V2G regulation service price) and the overall future system behavior is explored and predicted.

7.3 Methods

Exploratory Modeling and Analysis (EMA) is a research approach that uses scenario-based model to analyze complex and uncertain problems (Kwakkel and Pruyt, 2013). As a future oriented technology, the specific operation details and business models remain unknown. To study the system integrated with GDP, population, and air emissions from energy and transportation sectors, the EMA method is used to construct a system dynamic model and to answer the following questions:

- Will there be sufficient amount of EVs to support large-scale wind power integration?

- What are the factors that may influence the market penetration of EVs, and will EV become a favorable option in the future?
- Will the economic benefit of V2G system prompt the adoption of EVs?
- What would be the GHG and PM emissions of the transportation and energy sector?
- What are the impacts of the EV-V2G-wind power network to GDP and population?
- Will the V2G system provide the foundations to optimize energy structure?
- Will there be positive impacts to the water-energy nexus?
- Which variables will have higher influence to the network?

7.3.1 Scope of study, model structure and initial assumptions

The state of Florida is selected as the research region. Florida has the fourth largest economy in the U.S. with approximately 5% of the overall GDP (U.S. Department of Commerce, 2017a); Florida also has the fourth largest population in the nation, and about 20 million registered vehicle on the road. As of 2014, natural gas has become the majority of the electricity sources. Although Florida is currently not one of the deregulated markets where transmission and generation of electricity are operated by different entities, there's no physical obstacle preventing EV owners' from providing V2G regulation services. The state promotes EV adoption by exempting high occupancy lane rules for EVs (Florida DMV, 2015) and provide incentives for purchasing vehicle charging equipment(National Conference of state Legislatures, 2015). As the electrification of transportation taking place, the infrastructure in Florida has started to incorporating more features for large-scale electric or autonomous vehicles in the future (Florida Department of Transportation, 2016).

The system dynamics model in this study is built and utilized in the following steps:

Firstly, the basic logic of the model is preliminary identified based on existing literature. By identifying a series of reinforcing or balancing effects among the variables, a causal loop diagram is concluded to reflect the conceptual interconnections of the variables (Figure 63). The links with plus signs indicate that the variables are positively correlated, and the links with subtraction signs represent a negative correlation.

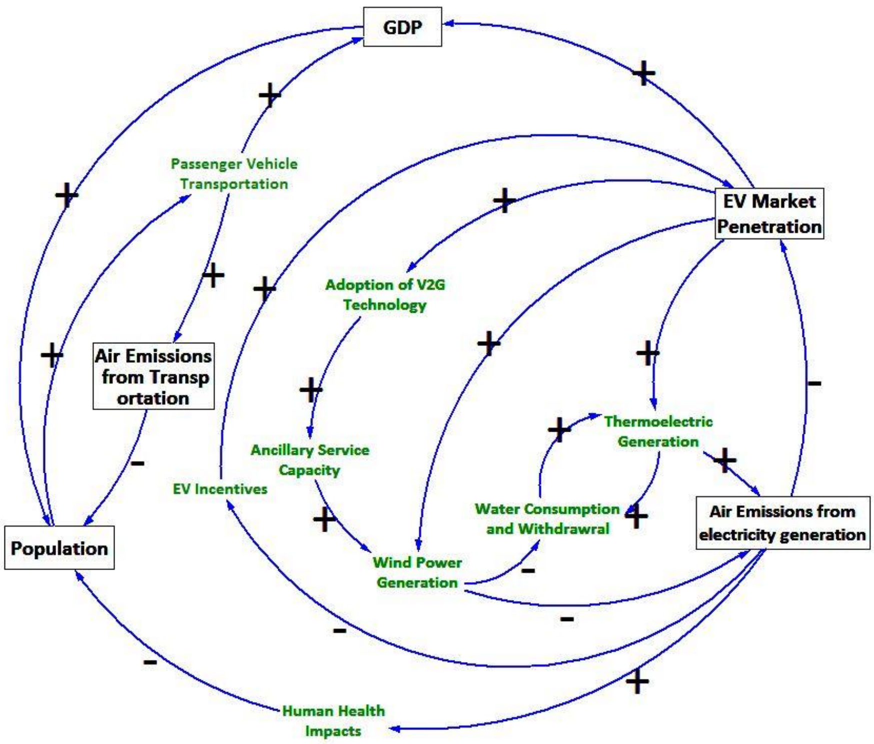


Figure 63 Causal loop diagram

Secondly, exogenous variables and endogenous variables are identified. Exogenous variables are the variables that can only be affected by factors outside of the model. Some of the exogenous variables are macro level indictors such as GDP or population with historical record, which, can also be used to verify the model. Endogenous variables are affected by one or multiple variables through equations or logical algorithms. The variables in the model are categorized in Table 22. It should be noted that, critical or unknown variables are given various distributions to reflect the uncertainty in the result.

Thirdly, based on the causal loop diagram, a stock-and-flow diagram is developed to reflect the mathematical functions among the variables. The functions are direct calculations between variables within one sector, i.e. vehicle fuel economy and vehicle annual fuel consumption; some functions that link different sectors are calculated based on regression of historical data and then validated, i.e. the economy of vehicle transportation and overall GDP; and there are also other functions that links micro and macro level variables, i.e. the function that calculate the potential ancillary service capacity based on individual EV available power output.

Lastly, the model is ran from the year of 2000 to 2030, the results of the first 15 years are used for model verification and validation, and the possible outcomes of different scenarios are projected from 2015 to 2030.

Table 22 Endogenous and Exogenous variables

	Endogenous variables	Exogenous variables
Sub-model 1: Vehicle life cycle cost and V2G service income	annual manufacturing cost of Vehicles	manufacturing cost data of Vehicles
	annual maintenance and fuel cost of Vehicles	maintenance and fuel cost data of Vehicles
	PEV battery degradation multiplier	vehicle configuration data of Vehicles
	gasoline price increment	annual VMT
	PEV and HEV available power	PEV battery cost
	PEV and HEV energy provision/night	battery price multiplier
	PEV and HEV V2G provision income	gasoline and electricity price
	PEV and HEV capacity income	fuel economy of Vehicles
		V2G capacity price
		EV plug-in time
Sub-model 2: GDP, population, and vehicle market penetration	GDP from passenger car transportation	GDP from the rest of the sectors
	total GDP	GDP increasing rate
	GDP per capita	reproductive lifetime
	fertility, maturation and death rate	life expectancy
	adjusted life expectancy	market share of passenger vehicles
	population	baseline percentage of Vehicles
	number of potential drivers	
	marginal human health impact from emissions	
	new passenger vehicle sales	
	number of HEV, PEV and ICV	
	V2G promotion effect percentage	
	mortality rates at various life stage	
	PEV and HEV incentives	
Sub-model 3: Air emissions and emission saving	annual GHG emission of Vehicles	average air emission rate before 2015
	annual PM emission of Vehicles	battery manufacturing air emission rate
	electricity mix GHG and PM emission	gasoline life cycle GHG emission rate
	V2G air emission savings	gasoline life cycle PM emission rate
	future electricity air emission rate	gas turbine GHG and PM emission rate
	overall air emission from electricity consumption	V2G request signal strength
		cycle number
Sub-model 4: Water-energy nexus	HEV and PEV ancillary service capacity	HEV and PEV available power factors
	renewable power capacity growth	ancillary service requirement ratio
	capacity of power sources	emission rates of different electricity sources
	annual generation of power sources	water withdrawal rates of electricity sources
	saline water withdrawal	water evaporation rate
	fresh water withdrawal	energy intensity ratio of water treatment
	fresh water evaporation	renewable generation multiplier
	electricity saving of water treatment	evaporation rate
		fresh water energy intensity ratio

The EVs in this study is assumed to be generic, so instead of attribute probability to indicators, the influence of various factors are interpreted as equations to increase or decrease the percentage of newly purchased PEVs or HEVs. Since V2G regulation service does not require deep charging or discharging, both PEVs and HEVs are assumed to be able to connect to the grid. As the literature shows that V2G ancillary service can be economically appealing to drivers, it is also assumed that there is a sophisticated service system with aggregators (i.e. utility companies or vehicle dealers) to gather the power capacity from individual vehicles. Currently there is limited renewable power capacity in the power system of Florida, the model is built on the assumption that the newly integrated wind power is supported by the ancillary service capacity of EVs via V2G system. In the water-energy nexus sub-model, only the water withdrawal and consumption within the energy generation sector is considered; residential and irrigation water usage is not included.

Based on the baseline assumptions, the model is divided into several sub-models and explained through Section 7.3.2 to 7.3.5. The connections of the sub-models are shown in Figure 64

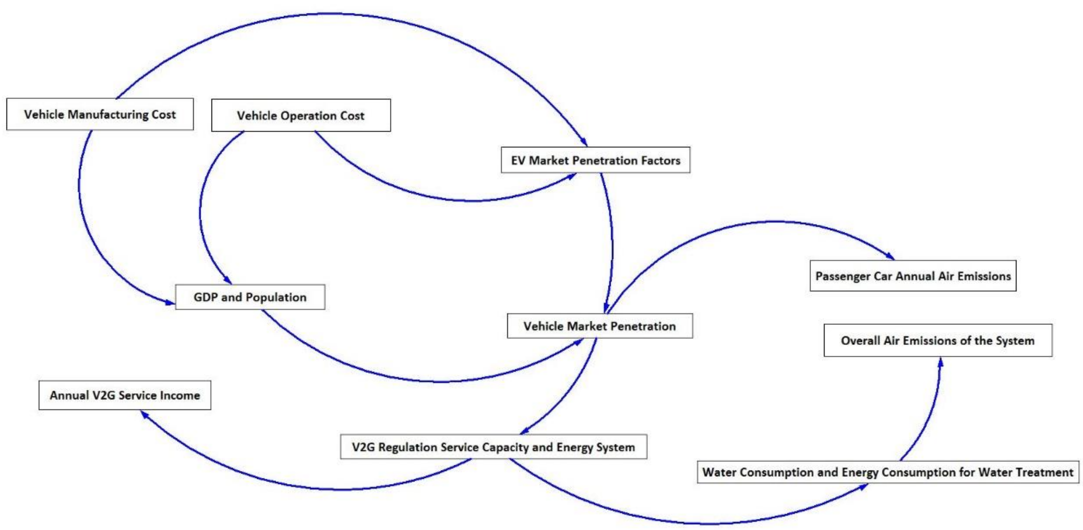


Figure 64 Sub-models of the system

7.3.2 Vehicle life cycle cost and V2G service income

The vehicle life cycle cost of the researched three vehicle types consists vehicle manufacturing cost and vehicle operation and maintenance cost. As the base line vehicle type which is independent from the energy and V2G system, the historical and projected ICV average cost is defined by a look up function; the price of HEV is assumed to be the ICV price plus the additional cost of the hybrid system (German, 2015); the cost of PEV battery is the major part of the overall vehicle cost, hence the price of PEV is calculated by the basic vehicle price plus the cost of the battery pack, and the battery price is assumed to be decreasing (Table 23).

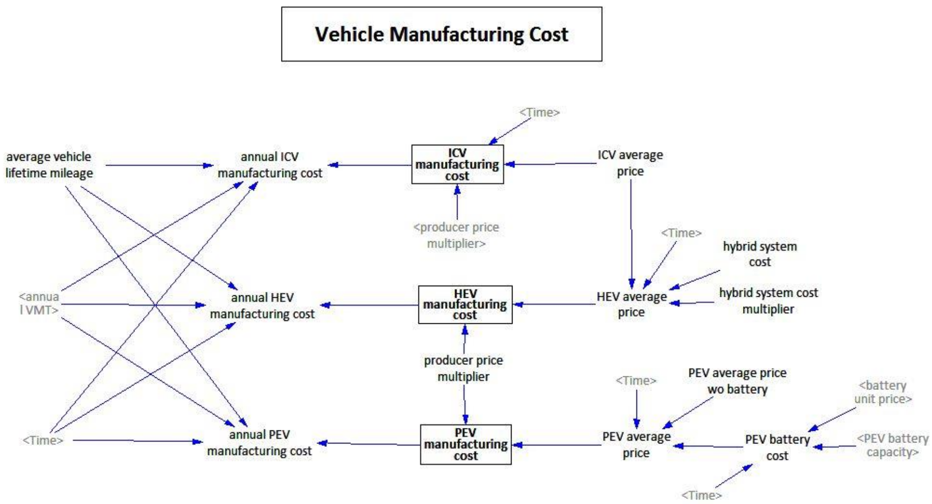


Figure 65 Vehicle purchasing price and manufacturing cost

Figure 65 shows the variables included in vehicle manufacturing cost calculation. The variable “<Time>” is an index variable mainly used in the equations to reflect the value of a certain variable at the current model time when the model is running. The other variables in grey color are shadow variables that introduce value or logic from other parts of the model; and shadow variables also reflect the causal relationships among the sub-models.

The manufacturing cost of the vehicles are calculated in association with the producer price multiplier, which is assumed to be 0.8 (Samaras and Meisterling, 2008). Then, as the contribution to the GDP of transportation sector, the annual vehicle manufacturing cost is computed using Equation 30:

$$Annual\ vehicle\ manufacturing\ cost_j = \frac{Vehicle\ manufacturing\ cost_j \times Annual\ VMT_i}{average\ vehicle\ lifetime\ mileage} \quad (30)$$

$Indexes$:

i: $time\ index\ (2000\ to\ 2030)$

j: $vehicle\ type\ index$

The vehicle maintenance and fuel cost, including battery pack replacement cost for PEV, is calculated based on the annual vehicle mileage travelled (VMT) (Figure 66). The maintenance and tire cost per mile for HEV and ICV are assumed to be the same since HEVs also have onboard combustion engines; the unit maintenance cost for PEVs is typically 70% of that of ICVs considering PEVs have less complex transmission systems (Gallo and Tomic, 2013). The gasoline and electricity prices are historical and projected data concluded from the literature. The fuel efficiency of ICV and HEV are also dynamic, increasing gradually as technology advances in fuel saving. Although the maintenance and fuel cost of PEV might be lower, the battery replacement of PEV can be a major cost for PEV owners, and V2G regulation service provision may further accelerate battery degradation. The nature of V2G regulation service is to respond to the rapid and short-period regulation up (supplying energy to the grid) and regulation down (storing excessive energy from the grid), and these signals will only cause shallow charging and discharging of the battery, hence most studies have concluded that the battery degradation effect of V2G service is minimal (Bishop et al., 2013; Peterson et al., 2010). In the model, the battery degradation is positively correlated to the cycle numbers of regulation service a PEV performs per night, and through the "PEV battery degradation multiplier", the life time battery replacement is controlled to 1 to 1.5 depending on the service load. In addition, the battery unit price is assumed to be decreasing, and to integrate the uncertainty analysis, the variable "battery price multiplier" is used to simulate the level of battery price decrement. The variables with uncertainties are shown in green color and further discussed in Section 7.3.7.

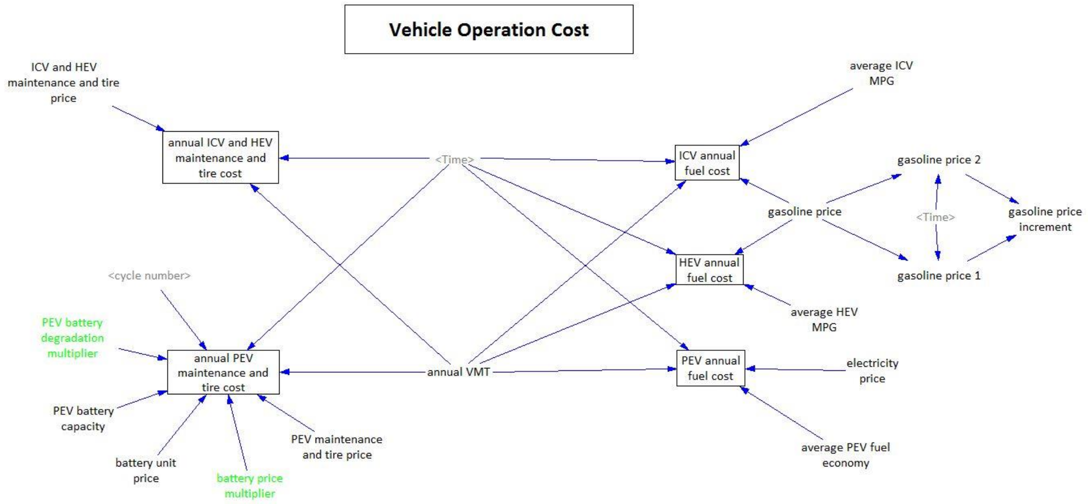


Figure 66 Vehicle maintenance and fuel cost

The vehicle lifetime cost-related data sources are summarized in Table 23. In addition, the yearly gasoline price increment is also computed here and linked to the vehicle market penetration sub-model as a factor that affects HEV and PEV adoption rate.

Table 23 Vehicle life cycle cost data

Parameter	Value and unit	Data sources
ICEV price	\$28,465 to \$21,484 (2000 to 2030)	(U.S. Department of Energy, 2013a)
HEV price	\$35,581 to \$26,855 (2000 to 2030)	(Papaioannou, 2015)
PEV price	\$50,000 to \$35,000 (2000 to 2030)	(UCLA Luskin Center, 2012)
manufacturing cost/retail price ratio	0.8	(Samaras and Meisterling, 2008)
annual VMT	9,516 to 12,866 miles (2000 to 2030)	(Florida Department of Transportation, 2015)
average lifetime mileage	200,000 miles	(Florida Department of Transportation, 2015)
ICEV and HEV maintenance and tire cost	0.053 to 0.0703 \$/mile (2000 to 2030)	(Bureau of Transportation Statistics, 2015c)
PEV maintenance and tire cost	70% of ICV and HEV maintenance cost	(Gallo and Tomic, 2013)
average ICEV MPG	28.5 to 39.6 mile per gallon (2000 to 2030)	(Bureau of Transportation Statistics, 2015a)
average HEV MPG	40 to 70 mile per gallon (2000 to 2030)	(U.S. Energy Information Adiministration, 2015f)
average PEV fuel efficiency	0.35 kWh/mile	(U.S. Department of Energy, 2013b)
PEV battery capacity	30 kWh	(Nissan, 2015)
battery unit price	600 to 300 \$/kWh (2000 to 2030)	(Gallo and Tomic, 2013)
gasoline price (historical and projected)	1.513 to 2.92 \$/gallon	(U.S. Energy Information Adiministration, 2016a)
electricity price (historical and projected)	0.0757 to 0.1153 \$/kWh	(U.S. Energy Information Adiministration, 2015c)

The V2G service revenue is consisted by capacity income and energy income (Kempton and Tomić, 2005a). The capacity payment is made by the grid operator to ancillary service providers for connecting their vehicles to the grid for a certain amount of time. The energy payment is made to the service provider for the actual exchanged amount of electricity, and the price is assume to be the same as regular electricity price.

The power capacity an EV can provide after the day time driving is the available power that can be used for V2G service, based on the literature (Kempton and Tomić, 2005a), the vehicle available power of PEV can be calculated by the following equation:

$$Available\ power = \frac{battery\ capacity - (\frac{annual\ VMT_i}{365} + buffering\ range_i \times fuel\ economy \times conversion\ efficiency)}{max\ dispatch\ time\ each\ cycle} \quad (3\ 1)$$

Where the buffering range is set as 30 miles on average (Kurani et al., 1994) and decreasing after 2015 as the availability of charging infrastructure increases in the system, and conversion efficiency is 0.93 (Kempton and Tomić, 2005a). The maximum dispatch time each cycle is assumed to be 0.3 hour in the literature (Kempton and Tomić, 2005a), and in this model, it is conservatively set to 0.5 hour for longer dispatching cycles. HEVs, on the other hand, typically have lower battery capacity yet still consume onboard gas for driving purpose, hence the available power for HEV is assumed to be 12 kW.

Once vehicle available power is defined, the V2G capacity income can be calculated by multiplying the available power, EV plug in time, and V2G capacity price (Figure 67). The plug in time is assume to be 10 hours, and this value is expanded to a range in the uncertainty analysis. The capacity price can be concluded from wholesale regulation market price (Shinzaki et al., 2015), so based on previously summarized capacity price in other ISO/RTO regions (Zhao et al., 2016a), the price is assumed to be \$0.03/kWh.

The actual duration of regulation service is obtained by multiplying cycle number and duration of each cycle. The duration of each cycle is assumed to be 6 minutes (Kempton et al., 2008). Then, the vehicle energy exchange in kWh is calculated by multiplying vehicle available power, V2G provision time per night, and the V2G request signal strength, which is a multiplier for uncertainty analysis. It should be noted here, vehicle plug in time does not equal to V2G provision time; the former is the time that the vehicle takes to respond to V2G regulation signal (typically 3.6 to 9 mins each cycle), while the latter is the contracted duration that the owner connected the vehicle for (usually one night, 8 to 12 hours).

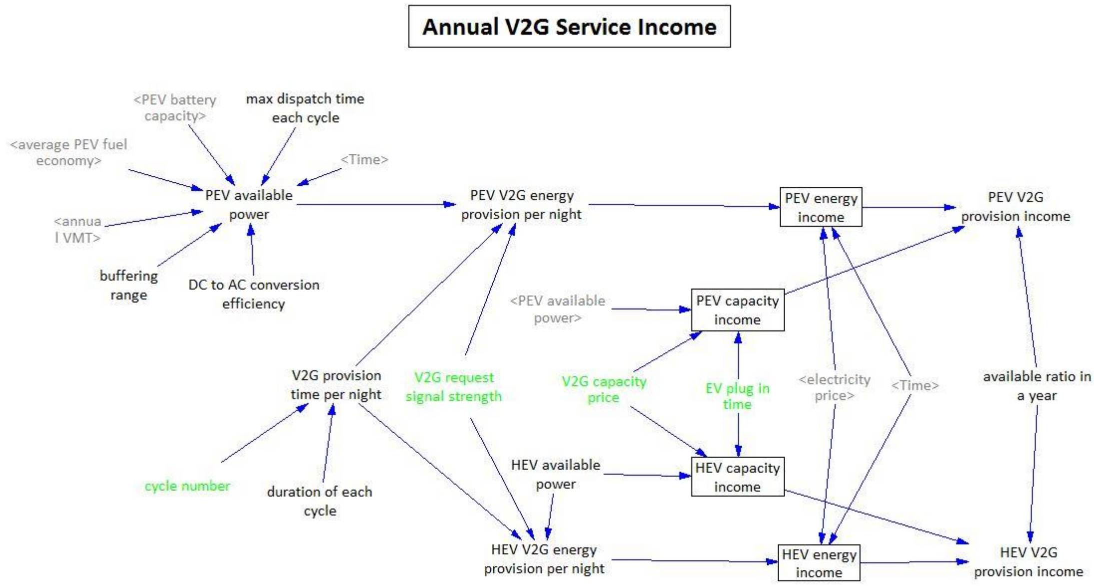


Figure 67 Annual V2G service revenue

7.3.3 GDP, population, and vehicle market penetration

The micro level vehicle driving and V2G service providing activities are simulated in Section 7.3.2, and in this section, the scope of the system is expanded to macro level through the population amount and percentages of each type of vehicle on the market.

As shown by the stock and flow diagram in Figure 68, the variable “total GDP” is the sum of “GDP of passenger car transportation” and “GDP from the rest of the sectors”. GDP from the passenger car transportation summarizes the life cycle cost of each vehicle type and multiplies with the amount of the vehicle respectively; the GDP from all the other economic sectors prior to 2015 is reflected by a look-up function of the historical data (Bureau of Economic and Business Reserve, 2015), and after 2015, the “GDP annual increasing rate” variable is set to 2.9% based on the GDP growth rate prediction (U.S. Department of Commerce, 2017a). The per capita GDP is computed by dividing the total GDP by population. The fertility rate is a deterministic variable for the population model, and the calculation is shown is Equation 32:

$$fertility\ rate = (GDP\ per\ capita \times 9.57) - (0.233 \times adjusted\ life\ expectancy) + 19.97 \qquad (32)$$

The adjusted life expectancy is a function that reflects the impact of marginal human health impact of air emissions to the projected life expectancy (State of Florida Department of Health, 2012). The air emission here includes GHG and PM emissions generated by both transportation and energy sectors. The verification of this equation is shown in Section 7.3.6. The adjusted life expectancy also affects the mortality rate of each life stage.

The population mode is a multi-stage stock and flow diagram simulates individuals from being born and progress through life stages. The births of the population is a function of fertility rate, population 15 to 44, and reproductive lifetime (assumed to be 30). There are two important outcomes of the population model, the first is the "population" variable which influences the "GDP per capita" variable; and the other is the population from 15 to 65 which consist the potential driver variable.

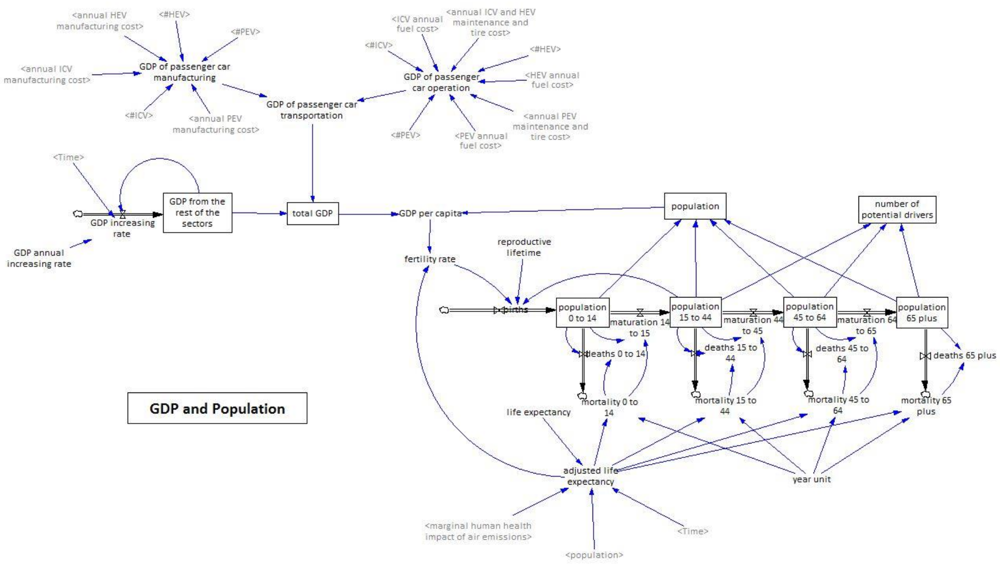


Figure 68 GDP and population

As shown by Figure 69, the new passenger vehicle sales is concluded from the regression of the historical data of "number of potential drivers", "GDP per capita", and "market share of passenger cars", the equation is shown below:

$$new\ passenger\ vehicle\ sales = market\ share\ of\ passenger\ vehicle_{\ i} \times \frac{(GDP\ per\ capita \times 7.3284 \times 10^7) - (1.2596 \times number\ of\ potential\ drivers) + (3.3242 \times 10^7)}{5} \quad (33)$$

In addition to the potential driver and per capita GDP variables which are derived from the population and GDP models, the variable "market share of passenger cars" is a look up function that represents the ratio of passenger cars comparing with all the registered vehicles, and it is also a look up function varies as model time progresses (Bureau of Transportation Statistics, 2015b).

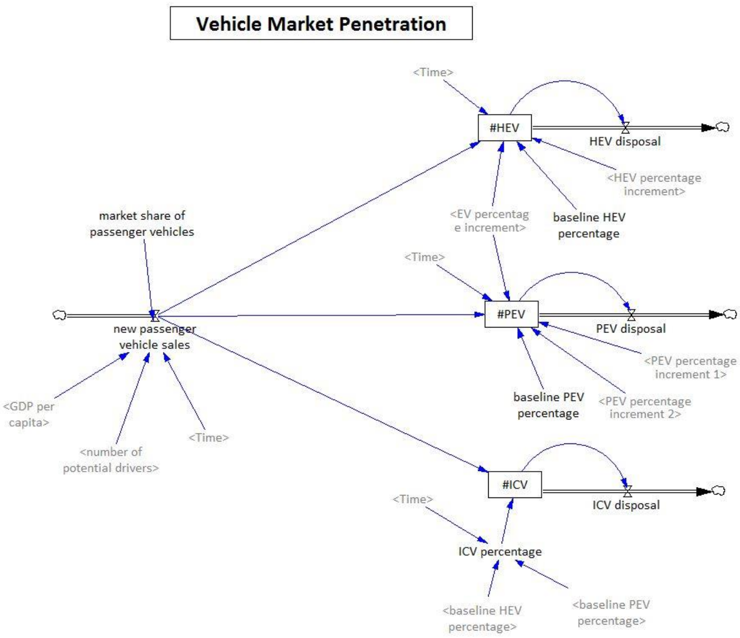


Figure 69 Market penetration of HEV, PEV, and ICV

The market penetration of each type of vehicle is calculated as percentages of the overall new passenger vehicle sales. The percentage of HEV and PEV on the market is affected by several factors: first, the baseline increasing rate (Block et al., 2015), which is a conservative rate that reflects the growth of HEV and PEV numbers without the impact of V2G system;

second, gasoline price, which is a major factor that affects drivers choice of whether to purchase an EV or not (Sierzchula et al., 2014), and the correlation is assumed that every 1% gasoline price increment leads to 1% increase of EV market penetration (Jenn et al., 2013); third, government incentives (cash or tax credit) also plays important role in the promotion of EV adoption. Currently there's no cash incentives in Florida, yet the exemption of HOV rule, free registration and other discounts can also be considered as promotions. It is assumed that that will be 4.6% adoption increment per $1,000 incentive (Jenn et al., 2013), and the uncertainty is also controlled by the "incentive multiplier" variable; fourth, the decreasing price of EVs can also increase the adoption rate, and based on the literature, per dollar drop of the price difference between PEV and ICV leads to a 0.5% PEV market penetration increment (Curtin et al., 2009), and this rate is assumed to be 1% for HEV, identically, the impact of the maintenance cost is also included, but it may decrease the adoption rate of PEV since the cost of battery replacement is also included in the maintenance cost. The variables and their relations are shown in Figure 70.

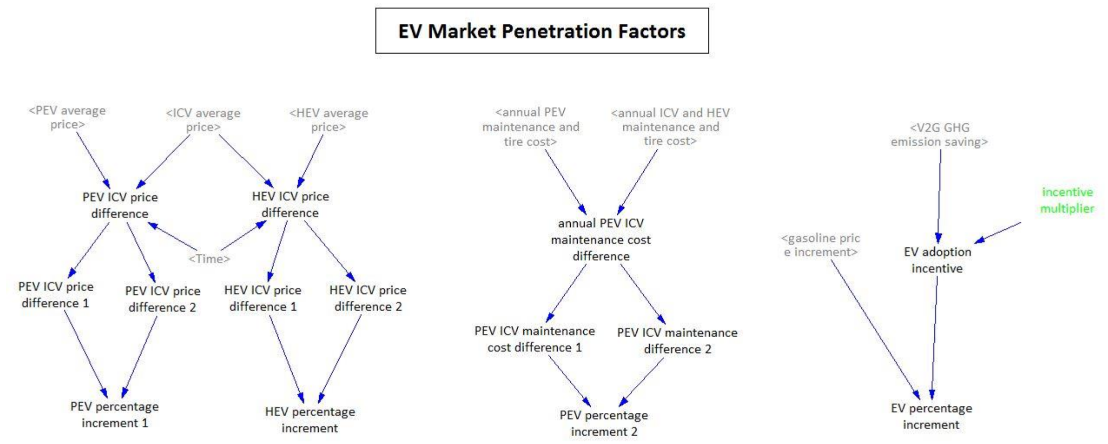


Figure 70 HEV and PEV market penetration factors

7.3.4 Air emissions and V2G emission saving of the system

The air emission and V2G emission saving sub-model includes the annual GHG and PM emissions generated by passenger cars and electric power generation, and the air emission saving of the V2G system.

Figure 71 indicates the annual GHG and PM emissions of each type of vehicle. For PEV, the emissions are mainly generated at the power generation phase. So, in the model, the historical average grid emission rates are used prior to 2015, and after 2015, the emission rate is dynamic and correlated to the percentages of each energy source. As an energy intensive process, the emissions generated by battery manufacturing is also included. To simplify the calculation, all GHG emissions are converted to CO_2, and all traditional air emissions are converted to PM_{10}.

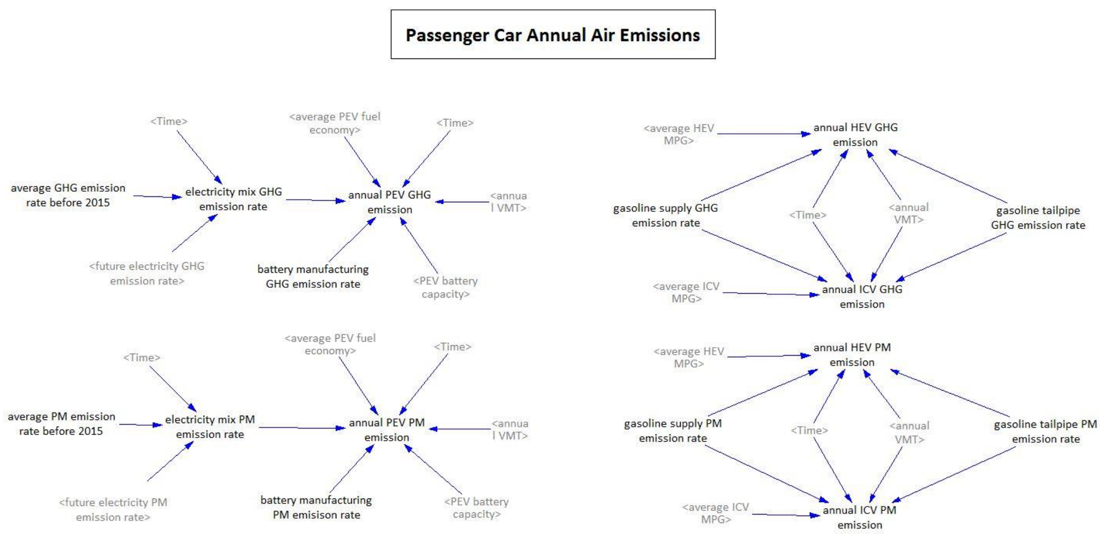


Figure 71 GHG and PM emissions of HEV, PEV, and ICV

As illustrated by Figure 72, the annual air emissions due to fossil fuel combustion in transportation sector is summarized by multiplying the GHG or PM emissions of HEVs and ICVs with the market penetration of the vehicle respectively.

V2G emission savings represents the emissions that are reduced by utilizing the battery of the EVs to respond the regulation service signals instead of consistently adjusting gas turbines to compensate the fluctuations on the grid. The calculation of V2G GHG emission saving is shown by Equation 34:

$$GHG\ emission\ saving = IF\ THEN\ ELSE(Time \leq 2015, 0, \frac{(\#HEV \times HEV\ V2G\ energy\ provision\ per\ night + \#PEV \times PEV\ V2G\ energy\ provision\ per\ night) \times EV\ owner\ willingness\ to\ participate}{1000} \times ancillary\ service\ GHG\ emission\ rate \times 365) \quad (34)$$

The "If then else" logic ensures the V2G emission saving is zero prior to model time 2015. After 2015, the low-efficiency energy mitigation is the summation of all the exchanged energy of HEVs and PEVs during the V2G regulation service provision period. The denominator 1,000 is to convert the unit from kWh to MWh for calculation at the electric grid level. The ancillary service GHG emission rate is computed by deducting the electricity mix GHG emission rate by the traditional ancillary service turbine emission rate since the electricity stored in the vehicle batteries is charged from the grid, and the emission rate of gas turbines providing ancillary service is typically 2.5 times than that of regular gas turbines (Lin, 2011). The calculation of V2G PM emission saving follows the same calculation method with PM emission rate.

Other than the electricity consumed by the newly added EVs, the electricity generation sector in this sub-model also includes electricity consumptions out of the transportation sector and the electricity saving due to the integration of wind power. The latter two parts are linked to the water-energy sub-model. Finally, with all the air emissions summed up, the marginal human health impact is calculated by multiplying the annual air emissions with GHG and PM related human health impact factor (Onat et al., 2016a).

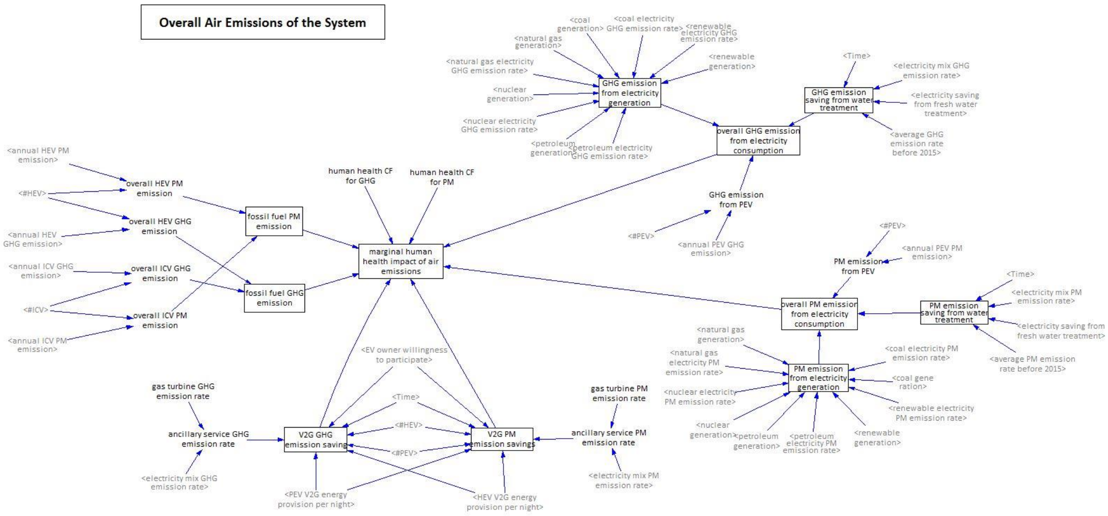


Figure 72 Overall GHG and PM emissions of the System

7.3.5 Water-energy nexus

The electric power system as well as the water-energy nexus are shown by Figure 73 and Figure 74. Currently the electricity mix of Florida consists 18% coal, 60% natural gas, 13% petroleum, 6% nuclear energy, and 3% other sources including renewable energy. The energy system sub-model predicts the average air emission rate of the electricity mix based on the assumption that the high-efficiency V2G services provided by EVs is sufficient to support a certain level of new wind power capacity; and as the renewable power capacity increases, thermoelectric generation can be replaced. A higher ratio of renewable capacity not only mitigates the overall air emissions of power generation, but also reduces water usage for cooling purposes, hence less energy will be consumed for water treatment.

First the ancillary service capacity of HEV and PEV is derived, the calculation for HEV is shown as an example by Equation 35:

$$HEV\ ancillary\ service\ capacity = \frac{\#HEV \times HEV\ available\ power \times EV\ owner\ willingness\ to\ participate \times EV\ owner\ availability}{1000} \quad (35)$$

The number of EV and the available power of HEV are variables in the vehicle market penetration sub-model and V2G income sub-model (Section 7.3.2 and Section 7.3.3). The willingness of EV owners participating V2G service is unknown at current stage, so, uncertainty analysis is also conducted to this variable, and based on the literature, the baseline value is set as 4% (Parsons et al., 2014). The EV owners' availability is assumed to be 50% (Kempton and Tomić, 2005a), meaning half of the participants are available at all time.

In Figure 73, the "ancillary service requirement ratio" (in green color) represents the ratio of the ancillary service comparing to the new wind capacity. Based on the host area or the scale of the wind power installation, this ratio may vary from 0.5% to 6% (Kempton and Tomić, 2005b), so, uncertainty analysis is also performed here. With the regulation service capacity of the passenger car fleet, the annually new wind power capacity that can be supported by V2G system is derived.

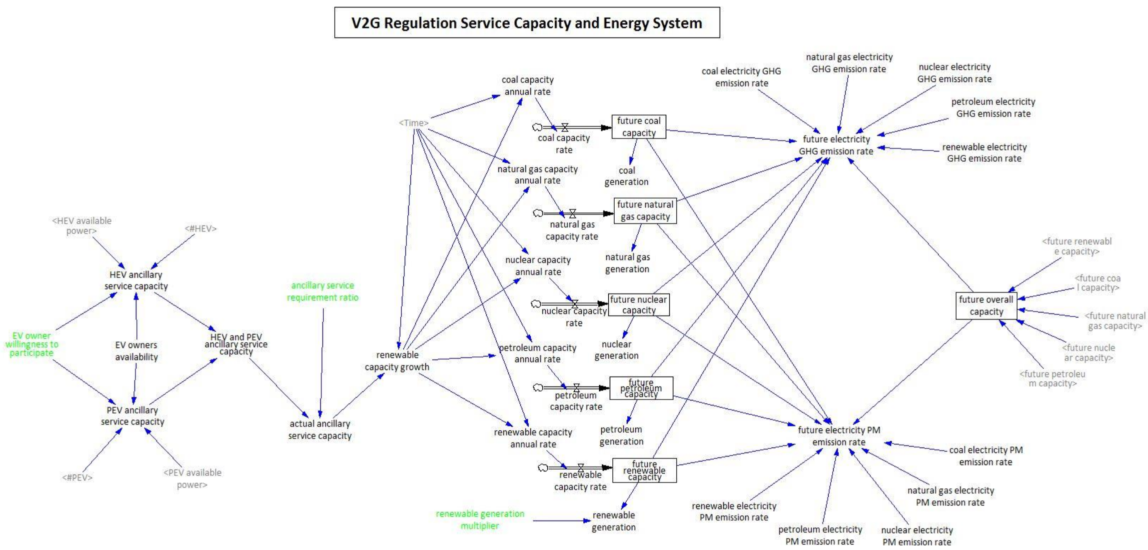


Figure 73 V2G ancillary service capacity and the energy structure

As the EV market penetration varies, the wind power capacity also changes. As is shown by the links between the variable "renewable capacity growth" with all the other power sources, it is assumed that the newly integrated renewable power gradually replaces thermoelectric power sources, and the amount of the capacity of each source being reduced is proportional to its current percentage in the grid. Based on the historical increasing or decreasing trends, the annual operation hours of each power source is projected and multiplied with its capacity to obtain the energy generation in MWh. The energy generation of the new wind installation is unknown, hence a range of 4,000 to 6,000 hours per year is used for uncertainty analysis.

The outcome of the energy system sub-model is the simulation of both historical and future capacity and generation of each power source, and combining with the GHG and PM emission rates, the overall electricity mix emission rates are derived and linked to the V2G emission saving sub-model.

By replacing thermoelectric power sources, wind power generation consumes virtually no water for cooling. In Florida, surface water are mostly used for electricity generation, and the majority (93%) of the water consumed is saline water (Scroggs, 2014). Therefore, in the water-energy sub-model, the replaced thermoelectric power generation is derived from the energy system sub-model and multiplied with water withdrawal rate of each source to obtain the amount of water withdrawal mitigated by wind power generation. Depending on the power source and plant type (once-through or closed loop), the water withdrawal rates vary within certain ranges, hence uncertainties are also included to these rates, the data are concluded from the literature (Macknick et al., 2011; Yang and Yamazaki, 2013). The sources of the water withdrawal is mainly sea water, which leaves 7% of the cooling achieved by utilizing fresh ground water. Through the variable “evaporation rate” and “fresh water intensity ratio”, the final outcome of the water-energy nexus sub-model is the mitigated energy consumption that would otherwise be utilized for water treatment purpose, and the “electricity saving from fresh water treatment” variable reaches back to the V2G emission saving sub-model.

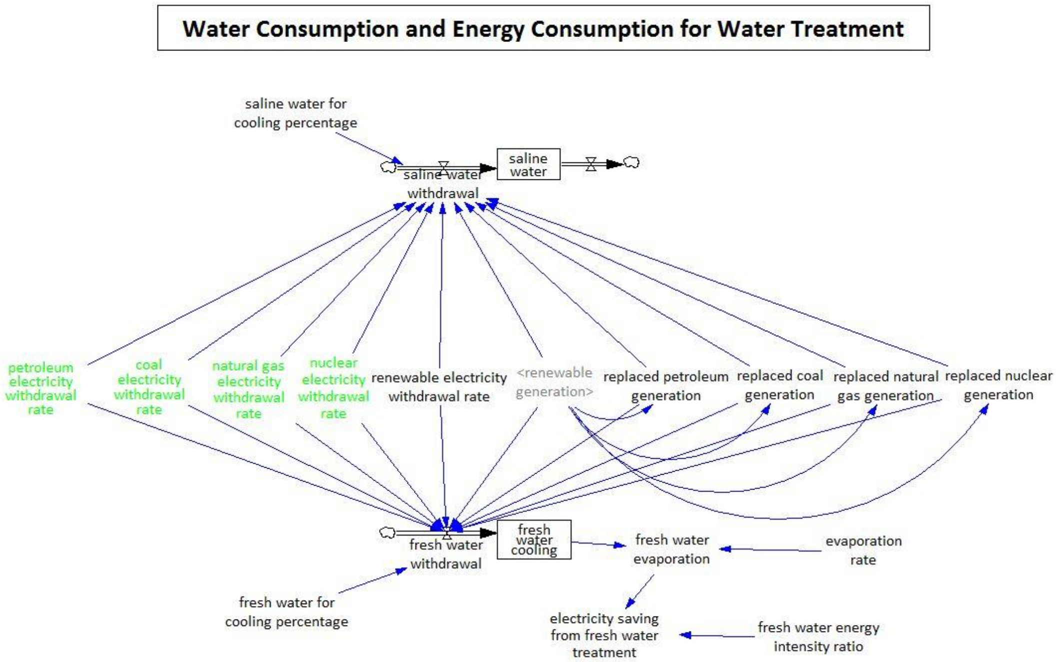


Figure 74 Water-energy Nexus and energy saving

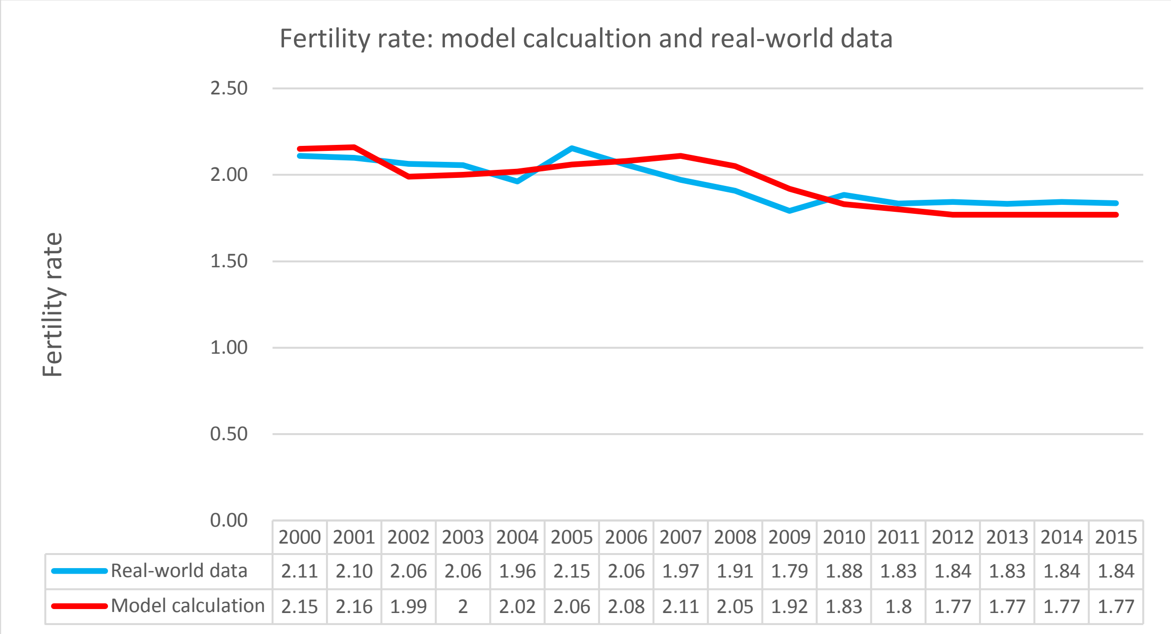
7.3.6 Model validation and verification

Prior to uncertainty analysis, the model is ran with “baseline” or average value given to uncertainty-related variables, and the model is verified and validated from the following three angles:

- First, the inter-sector equations that derived from regression analysis and include social or economic influences are verified by plugging in real word data
- Second, the output of critical indicators are validated by comparing the model result prior to 2015 with real-world data
- Third, the model is also validated by observing whether the correlation of the variables comply with initial assumptions

In the GDP and population sub-model, fertility rate is determined by GDP per capita and adjusted life expectancy; and the parameters of Equation 32 is obtained through a regression which analyzed the relationship among GDP, life expectancy and fertility rate (with R^2=0.67).

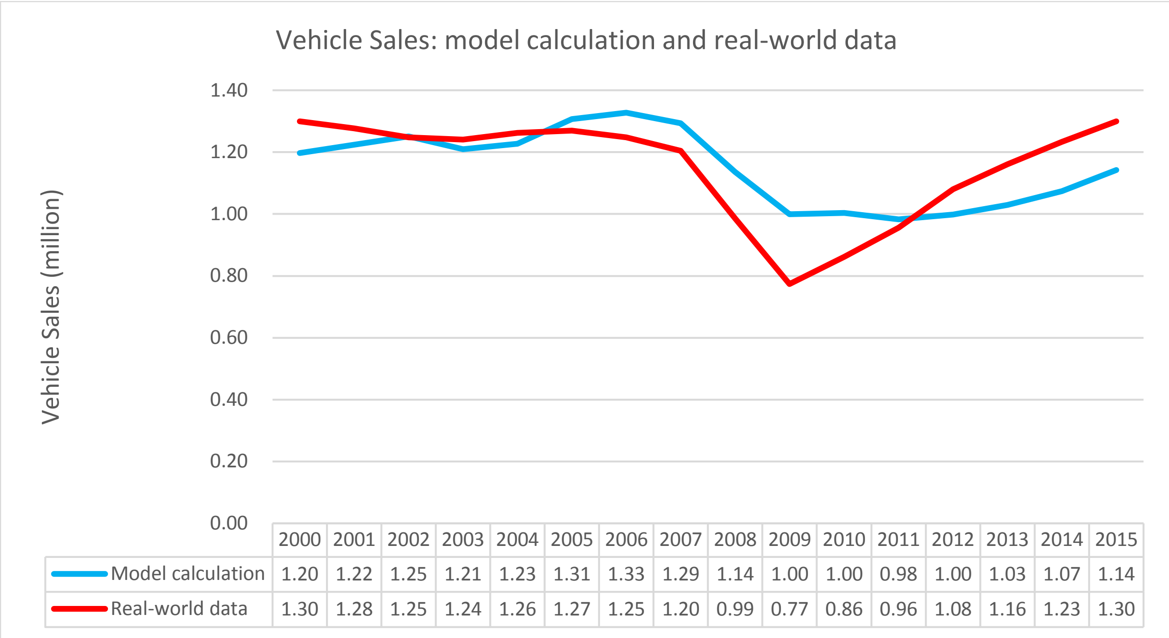
To verify this equation, the historical GDP data of Florida (Federal Reserve Bank of St. Louis, 2016), the population record (World Population Review, 2015), life expectancy data (Florida Department of Health, 2015), and the historical fertility data (National Center for Health Statistics, 2017) are derived from the literature. By plugging in the first three data sets, the output of Equation 32 is extracted and compared to the real-world fertility data, the comparison is shown in Figure 75. The ANOVA test indicates there is no significant differences between the two groups of data.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Real-world data	2.11	2.10	2.06	2.06	1.96	2.15	2.06	1.97	1.91	1.79	1.88	1.83	1.84	1.83	1.84	1.84
Model calculation	2.15	2.16	1.99	2	2.02	2.06	2.08	2.11	2.05	1.92	1.83	1.8	1.77	1.77	1.77	1.77

Figure 75 Fertility equation validation

Similarly, Equation 33 is also derived through a linear regression with the amount of potential drivers and GDP per capita as independent variables (R^2=0.52). The calculation result is then compared to real-world data of Florida vehicle sales, the result is shown in Figure 76. The ANOVA test indicates there is no significant differences between the two datasets.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Model calculation	1.20	1.22	1.25	1.21	1.23	1.31	1.33	1.29	1.14	1.00	1.00	0.98	1.00	1.03	1.07	1.14
Real-world data	1.30	1.28	1.25	1.24	1.26	1.27	1.25	1.20	0.99	0.77	0.86	0.96	1.08	1.16	1.23	1.30

Figure 76 Vehicle sales equation validation

In addition to the validation of the equations used for fertility and vehicle sale calculation. The model output of two macro level indicators: Population and GDP are verified by comparing to real-world historical data and projections.

Figure 77 shows the extracted population data with baseline assumption and the real-world population projection (World Population Review, 2015). The result of the ANOVA test is shown in Table 24, and the F value in of the test is smaller than the F critical value, which suggests that there is no significant difference between the model output and the real-world data. It indicates that the population model is relatively accurate.

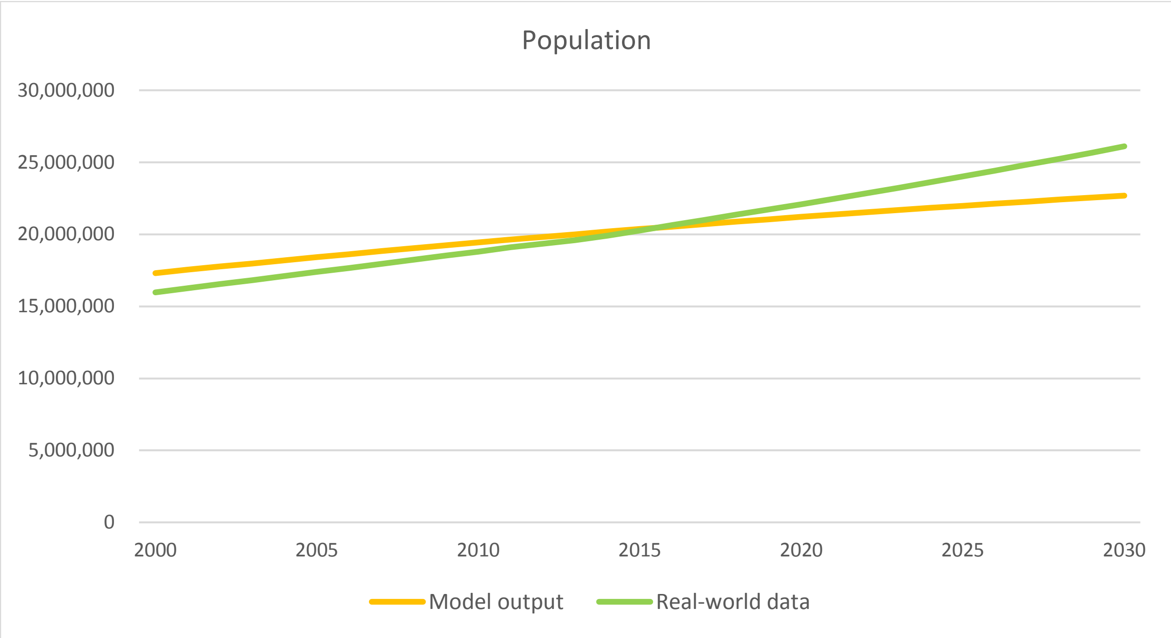


Figure 77 Population-model output and real-world data

Table 24 ANOVA test of population

Groups	Count	Sum	Average	Variance		
Model	31	627340000	20236774.19	2.64961E+12		
Real-world	31	638898994.7	20609644.99	9.28314E+12		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	2.15501E+12	1	2.15501E+12	0.361191813	0.550109	4.001191
Within Groups	3.57982E+14	60	5.96637E+12			
Total	3.60138E+14	61				

Figure 78 shows the GDP model output and the real-world Florida GDP (Federal Reserve Bank of St. Louis, 2016; U.S. Department of Commerce, 2017a). The ANOVA test results are summarized in Table 25, and the smaller F value comparing to F critical value also suggests that there is no significant differences between the model output and the real-word data. This indicates that the assumptions of separating passenger vehicle purchasing and operation cost from the economic sectors and the calculation of vehicles' life cycle cost is accurate.

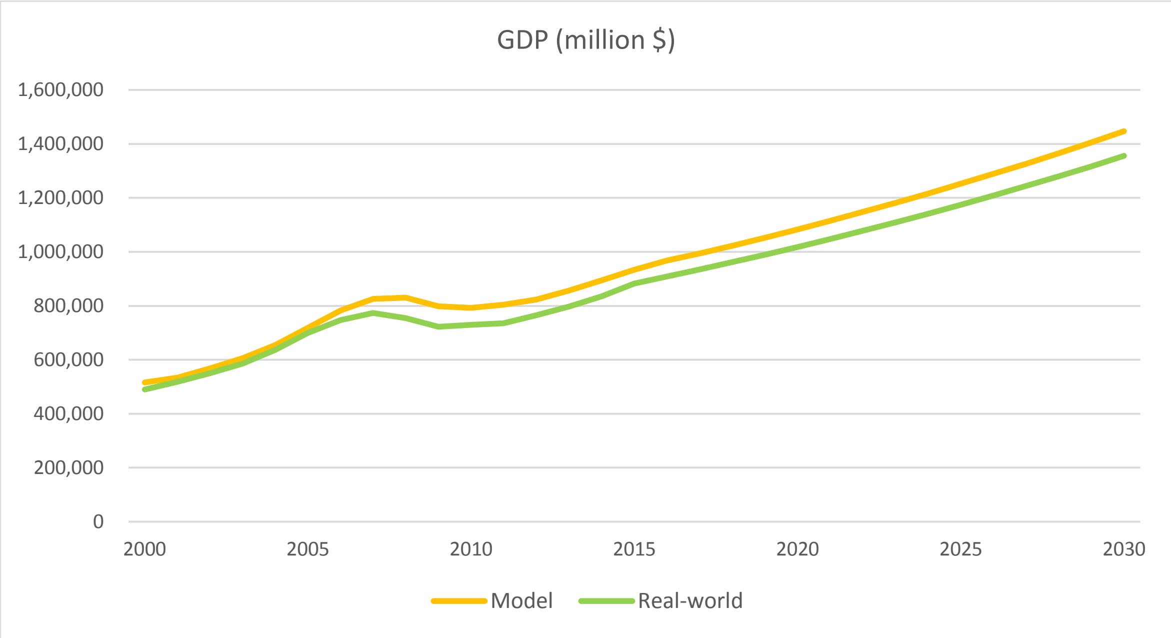


Figure 78 GDP-model output and real-world data

Table 25 ANOVA test of population

Groups	Count	Sum	Average	Variance		
Model	31	29809650	961601.6129	70647743209		
Real-world	31	27998326	903171.7979	60758568314		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	52917670793	1	52917670793	0.805405314	0.373069	4.001191
Within Groups	3.94219E+12	60	65703155761			
Total	3.99511E+12	61				

7.4 Results and discussions

The model is first constructed based on variables with average or "most likely" value yet certain single-value variables may not be able to cover all the possibilities of the system. To perform a holistic prediction of the future social, economic, and environmental impacts of the V2G system, various uncertainties are summarized from the literature and incorporated to the model through variables with unknown factors. Other than the computation of a baseline scenario, a Monte Carlo Simulation is performed at the same time. 10,000 iterations are conducted based on the distributions, therefore, the economic effects of unknown business models and environmental impact predictions of the V2G-water-energy nexus can be reflected by the results. Table 26 lists the uncertainty types and ranges of these variables.

Table 26 Variable uncertainties and data ranges

Variables with uncertainties	Distribution type	Data ranges		
PEV battery degradation multiplier	triangular	35	38	40
battery price multiplier	uniform	0.70	1.00	
V2G capacity price	triangular	0.02	0.03	0.04
EV plug-in time	uniform	8.00	12.00	
incentive multiplier	uniform	0.80	1.20	
V2G request signal strength	triangular	0.50	1.00	1.50
cycle number	uniform	30.00	40.00	
EV owner willingness to participate	triangular	0.01	0.03	0.05
ancillary service requirement ratio	triangular	0.04	0.06	1.00
coal electricity withdrawal rate	triangular	27,046	36,350	50,000
natural gas electricity withdrawal rate	triangular	10,000	14,000	20,000
nuclear electricity withdrawal rate	triangular	25,000	44,350	60,000
petroleum electricity withdrawal rate	triangular	10,000	35,000	60,000
renewable generation multipliers	uniform	1.00	1.50	

As the results of the Monte Carlo Simulation, the spectrum in the result figures represent the confidence level of the variable output. The baseline scenario result are generated from the value of the average or “most-likely” constants in the model, and is shown by the blue color line in the figures. The outer bounds of 100% uncertainty show the maximum and minimum output of the variables.

7.4.1 GDP, vehicle, and population results

The GDP results are shown in Figure 79. According to the plot, the overall GDP of Florida increases gradually from 2010 to 2030 after a slight drop in 2008, and reaches to approximately 1,400 billion dollars. However, the narrow width of the uncertainty band indicates that the assigned uncertainty distributions do not impact the overall GDP significantly. The reason is that the overall GDP is consisted by the GDP of passenger car transportation sector and the combination of all the other economic sectors. Even though HEV, PEV, and ICV have different life cycle costs, the economic impacts are not significant to the GDP of the state at a trillion-level scale. The GDP of passenger car transportation is shown in Figure 80. The range of the results increases to about 50 billion at the end of the model time, and the fundamental reason is the EV market penetration variation.

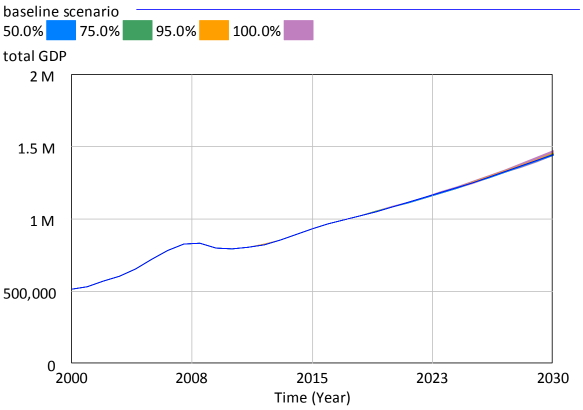


Figure 79a Total GDP result (million $)

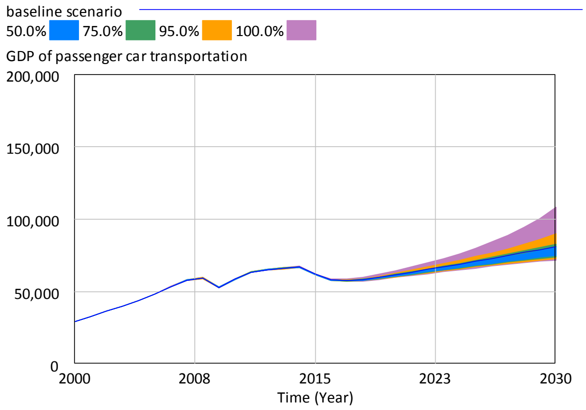


Figure 79b GDP of passenger car sector (million $)

Figure 79 GDP results

The accumulated amount of HEVs, PEVs, AND ICVs are reported in Figure 80. It can be observed that ICVs are still the dominant vehicle type on the market, and since both the GDP per capita variable and passenger car percentage variable in Equation 33 have incremental trend, the number of ICVs on the road gradually increases to 21 million and remains stable. Since the percentage of ICV is not affected by any incentives for EVs (Figure 69), the uncertainty of the accumulated amount of ICV is limited. In the meantime, the baseline results of HEVs and PEVs indicate that the average number of HEV and PEV reach to 3.48 million and 3 million respectively in 2030; and the maximum projection can be as high as 8 million for both vehicle types. In addition, there is a small-scale drop off for both EV type. It is caused by the assumption that gasoline price has high-influence over the potential buyers' choice (Diamond, 2009), and the gasoline market price experienced a major drop down in 2015, and the functions that convert economic factors to vehicle market penetration is given one year delay (instead of immediately react to gasoline price or government incentives). Therefore, in the model time 2016, the low gasoline price has a negative impact to the increment of EV numbers. As a main factor influencing EV market penetration, Figure 80d depicts the combined incentive impacts of both gasoline price and government incentives (variables shown in Figure 70), and the percentage value becomes negative during 2015 to 2017. As critical components of the vehicle life cycle cost and dependent variables for vehicle market penetration, the vehicle maintenance and fuel cost comparison are reported in Figure 81. The annual vehicle maintenance cost of EVs and ICV are shown in Figure 81a. Typically the maintenance cost of EVs is 70% of average ICV maintenance cost, yet the result indicates that the annual maintenance cost of PEVs can be approximately $1,400. It is because of the assumption that the V2G regulation service may cause one or more than one extra battery replacement, which, may cost as much as $18,000 at the beginning of the model time. The battery unit price decreases from $600 to $300, hence the overall maintenance cost of PEV continues to drop after 2015. The battery replacement assumption is a conservative consideration; because of the much lower life cycle fuel cost (Figure 81b), the market penetration of EV may increase significantly if one battery is assumed to be sufficient during the vehicle life cycle. In fact, multiple studies have concluded that V2G regulation services won't cause significant battery degradation (Bishop et al., 2013; Peterson et al., 2010). As the technology of vehicle battery advances and the utilization of second-life battery, it is possible that the market penetration of EVs reach a higher level. Other than the battery replacement assumption, other assumptions such the government incentives or gasoline price stimulations are incorporated in the model to reflect the reaction of the market to economic factors, but the parameters are set at conservative levels based on the literature.

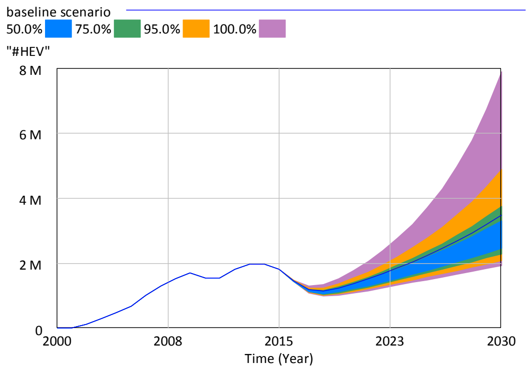


Figure 80a Number of HEV

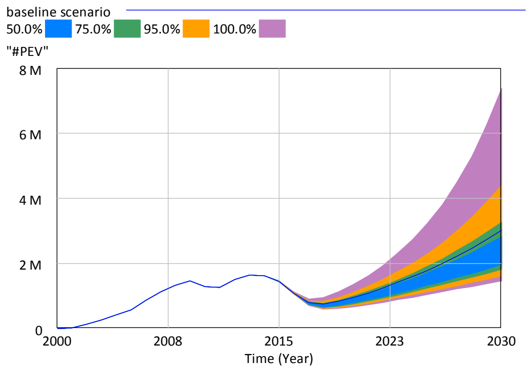


Figure 80b Number of PEV

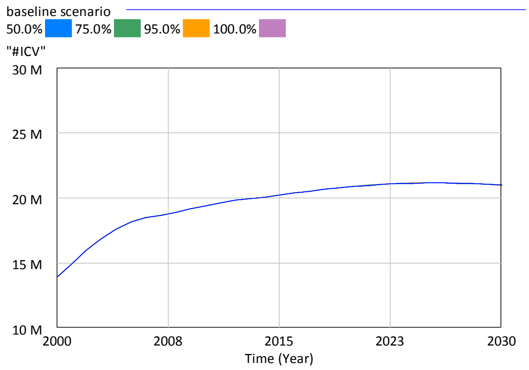


Figure 80c Number of ICV

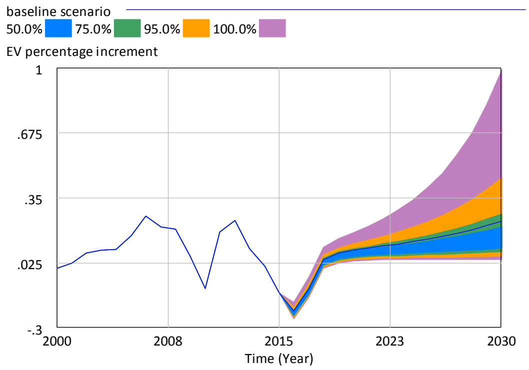


Figure 80d EV incentive impacts

Figure 80 Accumulated vehicle numbers and EV incentive impacts

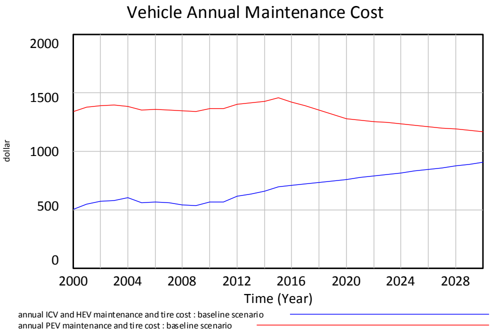


Figure 81a Maintenance cost comparison

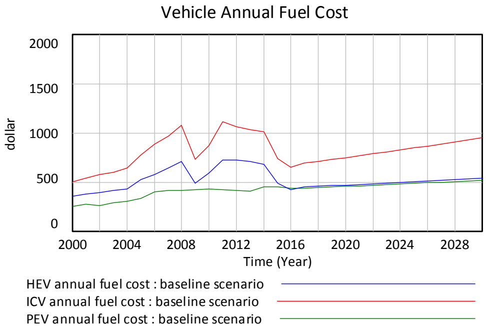


Figure 81b Fuel cost comparison

Figure 81 Vehicle operation cost comparison

The other sub-model affected by the economic sector is the population. The overall population is determined by a multi-stage stock and flow diagram; and with the input of GDP per capita variable from the economic sub-model and marginal human impact variable from the environmental sub-model, the population is projected and shown in Figure 82a. Figure 82b shows the marginal human health impact caused by GHG and conventional air emissions, the result is dimensionless and reflects the strength of the influence. It can be concluded that the number of population increased from 17.3 million to 22.7 million gradually even the marginal health impact varies significantly after 2015. The reason is that the marginal health impact influences the population sub-model via the variable "adjusted life expectancy" (Figure 68), where the numeric value shown in Figure 82b is divided by the total number of population.

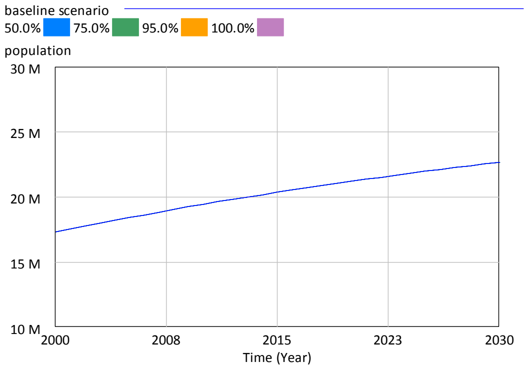


Figure 82a Population

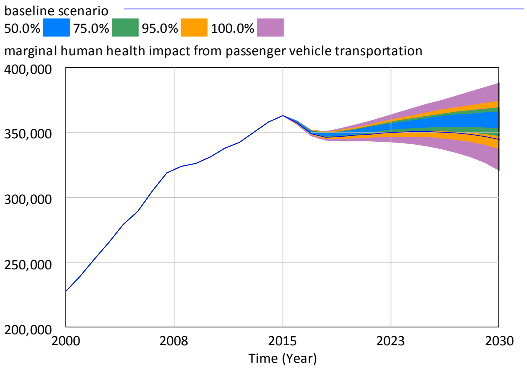


Figure 82b Marginal health impact

Figure 82 Population and health impact results

7.4.2 <u>GHG emission and V2G system results</u>

The overall GHG emission result of the studied system is reported in Figure 83. As previously illustrated in Figure 72, the overall emission is consisted by the emission from both passenger car transportation sector and electricity generation sector; and on the other hand, the operation of V2G system, the overall reduced electricity mix emission rate, and the decreased water consumption are all factors that contribute to the emission mitigation. As shown by the figure, the overall GHG emission of the system increases from 142 million ton in 2000 to 224 million ton in 2015; with the increased adoption of EVs and implementation of V2G system and wind power generation, the increasing trend of the GHG emission is changed to decreasing. The baseline scenario indicates that the overall GHG emission can be reduced to 206 million ton in 2030. In the meantime, the uncertainty spectrum shows that the maximum emission scenario leads to a rather flat increasing trend at 220 million ton level, while the minimum emission scenario results in a more drastically decrement to around 175 million ton emission at the end of the model time.

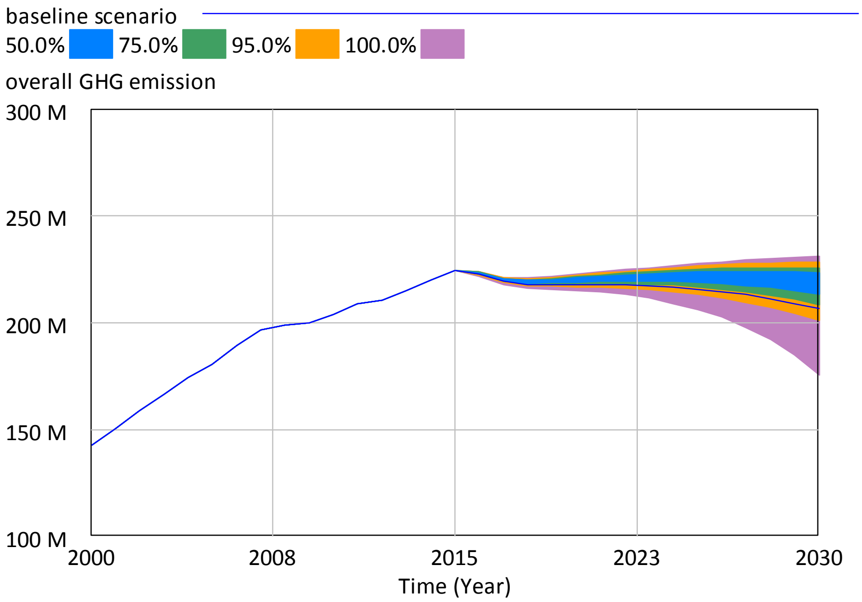


Figure 83 Overall emission (ton)

The average annual GHG emissions of HEV, PEV, and ICV are compared in Figure 84. Based on the output of the variables, PEV generates the most GHG emissions among all vehicle types (approximately 6.5 ton per year), and HEV has the lowest annual GHG emission (approximately 2.4 ton per year). The magnitude as well as the increasing/decreasing trend of the emission results can be explained by comparing the input variables and assumptions: First, the GHG emission calculation (Figure 71) includes both upstream (supply) emissions and downstream (tailpipe) emissions. For vehicles consuming gasoline, both fuel production phase and tailpipe phase contribute to the overall emission value. For PEV, there is no tailpipe emission yet the generation of electricity is based on an energy system relies heavily on thermoelectric power sources (more than 90%). Moreover, the manufacturing of large capacity battery pack is also environmental-intensive. However, the annual emission of PEV starts to decrease after 2016, which complies with the percentage change of each power source. Second, the emission ICV remains stable, because both the fuel economy and annual VMT assumptions for ICV have limited fluctuation (data sources in Table 23). Third, HEV shows the best emission performance due to the assumption that the future HEV may have a fuel efficiency of 70 MPG yet no need to replace large capacity battery pack.

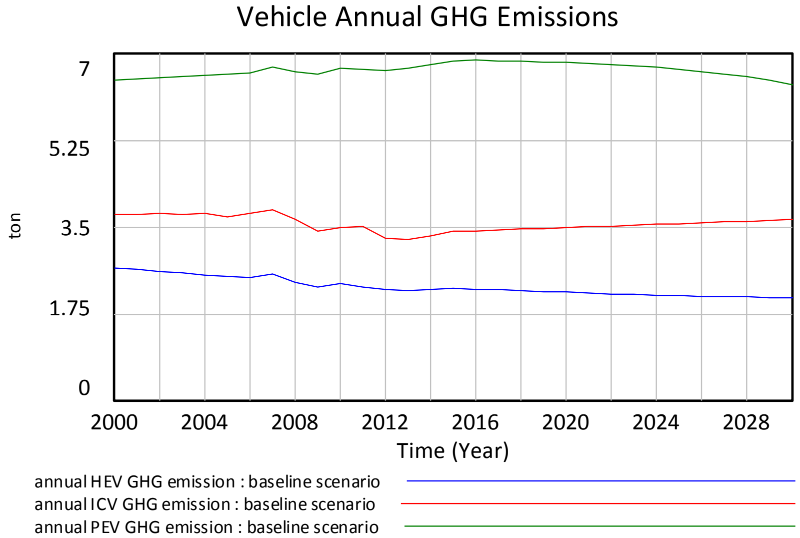


Figure 84 Vehicle GHG emission comparison

The GHG emissions of the entire passenger car sector, GHG emissions of the electricity generation sector, emission savings from V2G service, and emission savings from reduced water consumption are summarized in Figure 85. The GHG emissions from the passenger car sector keeps increasing after 2015 (Figure 85a). Although part of the passenger car fleets is replaced by HEVs the baseline value indicates the emission reaches to about 83 million ton in 2030; the reason is the continuous growing overall vehicle number and the increasing annual VMT. The upstream phase GHG emission of PEVs is allocated to the overall emission from electricity generation sector (Figure 85b); due to the increasing ratio of wind power integration, the overall emission from the generation of electricity actually decreases even part of the energy consumption of the transportation need is shifted to the electricity sector. This also means that although the life cycle GHG emission of PEVs is higher than that of HEVs and ICVs, the overall GHG emission in the system can still be mitigated as long as the electricity mix contains certain percentage of renewable power. Comparing to the overall

GHG emissions in the system which is around 200 million ton per year, the emission savings achieved through V2G system can be as high as 20 million ton per year (Figure 85c), mainly by replacing the low efficiency ancillary gas turbines; and the slightly drop around 2016 is also due to the changes of EV market penetration. Finally, since wind power generation requires virtually no water for cooling purpose, the replaced thermoelectric power generation also leads to less water withdrawal and therefore less water evaporation and consumption; also, as energy is required to purify such amount of water which could be used for other purposes, the amount of the energy saved from water treatment is reflected in Figure 85d. More than 50,000 ton GHG emission can be mitigated in the year of 2030.

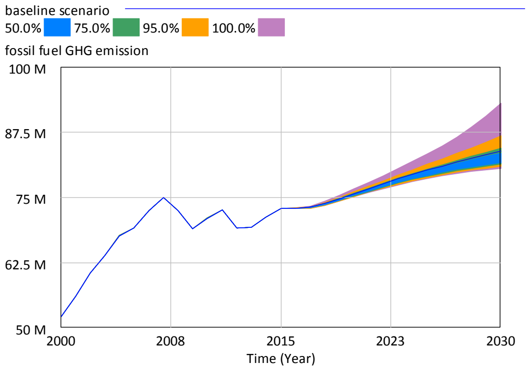


Figure 85a Overall emission from HEV and ICV

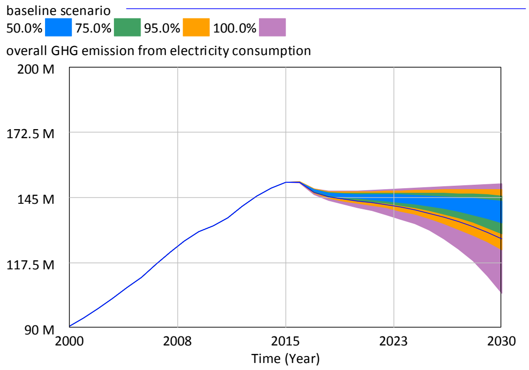


Figure 85b Overall emission from electricity generation

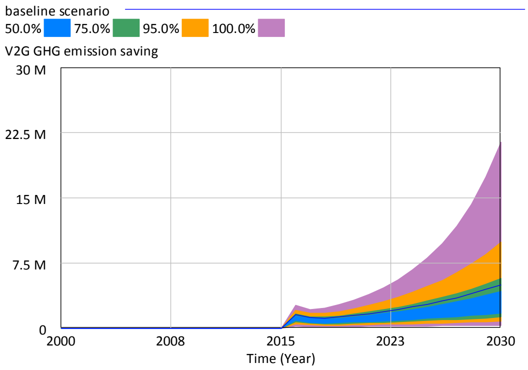


Figure 85c V2G emission saving

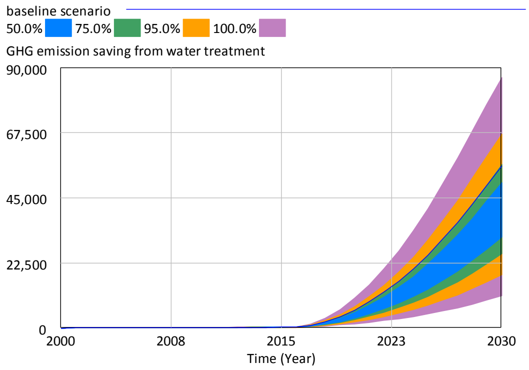


Figure 85d emission saving from water-energy nexus

Figure 85 GHG emissions and emission savings of transportation and electricity generation sector (ton)

One of the critical question regarding the implementation of V2G system is whether the EV number is sufficient to provide a sufficient ancillary service potential. The method of calculating the available power of a single vehicle for V2G regulation service is discussed in Section 7.3.2 and Figure 67. The results of the total available power of the passenger car fleet as well as the potential revenue for EV owner through V2G regulation service is provided in Figure 86. As shown by Figure 86a, the total regulation service capacity fluctuated slightly after 2015 and gradually increases to about 2,000 MW, and the maximum scenario might even reach 9,000 MW; and since the ancillary service-power capacity ratio of wind power is typically 6%, meaning that more than 30,000 MW wind power can potentially be integrated to the grid in 2030. The output of the V2G income variable is also closely related to the available power of an individual EV. The revenue output of PEV is shown in Figure 86b. It can be concluded that the revenue of providing V2G service after 2015 is mora than $3,000 per year; and based on Equation 31, this revenue rate is sensitive to the capacity of the battery, the EV owners' buffering range decision, EV plug-in duration, and, mostly importantly, the regulation up/down signal strength. So, from the perspective of the entire transportation-energy system: a more sophisticated charging infrastructure system will lead to less range anxiety and more power reservation for V2G service; the more the energy system relies on V2G system, the stronger the regulation request signals, and hence more revenue for participants; the large-scale participants will stimulate the EV production, thus lower vehicle or battery price and more EV buyers; at last, a robust EV market will be able to support more renewable energy and reduce the environmental impact of driving an EV.

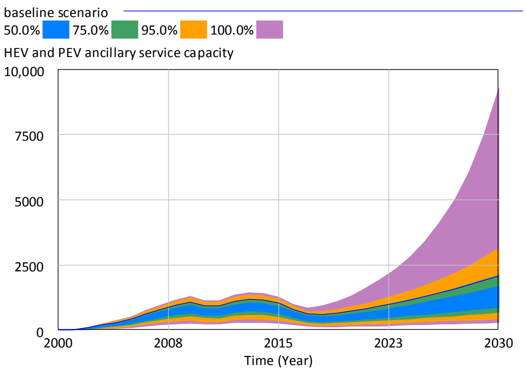


Figure 86a Total ancillary service capacity (MW)

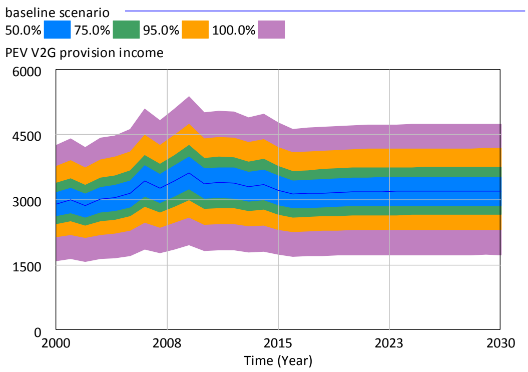


Figure 86b Potential revenue ($)

Figure 86 Total ancillary service capacity and potential revenue

The energy system outputs are reported in Figure 87. Due to the integration of new wind power supported by the V2G system, the average electricity mix emission rate declines from 0.8 to 0.5 ton/MWh (Figure 87a), and the uncertainty analysis shows this rate can be as low as 0.2 ton/MWh. Also, the generation projection is assumed based on historical running time of each type of power facility, the projected generation rates are provided in Figure 87b; and at the end of the model time, about 83 million MWh electricity can be generated through wind farms, which, will significantly optimize the structure of the V2G-water-energy system.

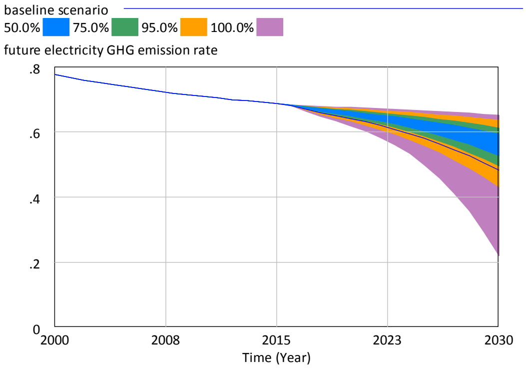


Figure 87a Electricity mix emission rate (ton/MWh)

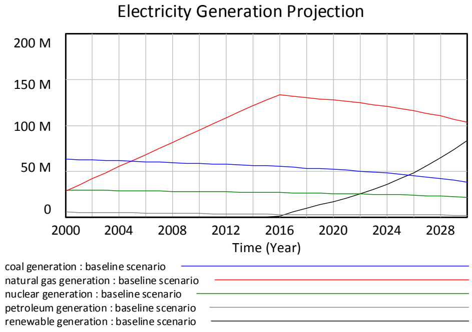


Figure 87b Electricity source generation comparison (MWh)

Figure 87 Electricity mix results

7.5 *Conclusions*

This study evaluated the environmental, economic and social interactions within a future transportation and power generation network connected by V2G system. A system dynamic modelling approach is used to identify and reflect underlying relationships and causal loops among critical variables such as population, GDP, vehicle market penetration, GHG emission, water consumption, wind power, and the V2G system. The model is simulated for 30 years, the results of the first 15 years is validated with historical data while the output of the last 15 years is explored as a projection for the future system. Due to the unknown operation pattern of the future V2G system, an uncertainty analysis is incorporated to the model, and the results are shown with various confidence level to indicate the quantitative result and test the feasibility of each link of the system.

By constructing the system dynamics model and interpreting the simulation results, the questions raised at the beginning of the study are answered:

Electric vehicles including PEVs and HEVs can be a feasible energy storage solution for increasing the ancillary service capacity of the energy system. The result indicates approximately 20% EV ratio can support 30% of the electricity system to be wind power. However, the electrification of the passenger car fleet cannot impact the GDP and population sector significantly.

V2G system can reduce the overall emission of the transportation-energy network by replacing low-efficiency gas turbines, supporting newly integrated wind power, and reducing the water consumption within the energy system. Based on relatively conservative assumptions, the total emission savings can be as high as 10 million ton per year; and the higher ratio of wind power in the electricity grid is the fundamental change of the network.

Government incentives and lower battery unit price are the two most influential factors that affect the adoption of EVs; the annual income from V2G regulation service can be appealing to potential vehicle buyers. Hence a sophisticated EV infrastructure with V2G service aggregators, the reduction of the battery unit price and environmental footprint will facilitate the implementation of the V2G system.

All the aforementioned results combined together is the most important finding of this study, a system with reinforcing loops that have positive impacts to environment, economy and society. The increasing EV adoption rate and the progressing roadway or parking infrastructure provides an opportunity to implement V2G system; with a much higher ancillary capacity, the grid is able to integrate more clean energy source; the optimized electricity mix reduces the life cycle environmental footprint of an EV, and the economic benefits of V2G service provision also further facilitates the electrification of the transportation system; finally, the EV or new travelling mode, either autonomous vehicle or vehicle share, provide a robust foundation for the further decarbonization, and ultimately, a fully developed smart transportation and energy sector.

8 CONCLUSIONS

Based on the analysis in Chapter 2, it can be concluded that due to the special driving patterns and the heavy populated operation areas of parcel delivery trucks, the frequent acceleration and deceleration as well as long idling times lead to considerably lower fuel efficiency. Problems related to these driving patterns might be solved by the adoption of battery electric trucks, which have higher fuel efficiency during low speed driving, and also, the simpler motor and transmission system makes vehicle maintenance easier and cheaper. With all these advantages, electric delivery trucks are becoming a very competitive alternative for fleet owners. However, despite the complete absence of tailpipe emissions, the environmental impacts generated during other life cycle phases of an electric truck might suggest the opposite. To tackle this issue, the life cycle GHG emission and energy consumption of diesel, hybrid, CNG and two types of battery electric trucks have been evaluated by an economic input-output based hybrid life cycle assessment. And instead of using single value, the uncertainties of key parameters such as the vehicle manufacturing cost, fuel economy and high capacity battery manufacturing impacts have been integrated through a Monte Carlo Simulation. In addition, a regional GHG emission analysis has also been performed based on the adjusted payload factors.

Despite the zero tailpipe emission of electric delivery trucks as opposed to delivery trucks of other fuel type, electric trucks do not show lower environmental impacts as expected. The national evaluation indicates that the class 3 electric truck has similar and even slightly larger life cycle GHG emissions and energy consumption comparing to the diesel, hybrid or CNG truck. The life cycle CO2-equivalent GHG emission of the aforementioned four types of vehicle vary approximately from 160 ton to 200 ton, the class 5 electric truck, due to its higher payload, has higher emission rate, which is about 400 ton. The overall energy consumption of the diesel and the hybrid truck are less than 2.5 TJ, while that of the CNG and the class 3 electric truck is around 4 TJ. It can also be concluded from the result that the majority of environmental impacts of electric trucks are generated at the electricity generation phase, meaning that the impacts are moved from downstream to upstream. Therefore, the adoption of electric truck will not be able to mitigate GHG emission level until more high-emission-rate power sources are replaced by cleaner power sources.

The regional analysis in Chapter 2 shows that, in regions where electricity generation depends heavily on coal burning, electric trucks have significantly more GHG emissions than those of diesel or CNG powered trucks. And the electric vehicle GHG emission saving potential can only be shown in regions that have large share of cleaner energy as their main electricity sources. Therefore, it can be concluded that there is a strong relation between the local electricity generation source and the applicable degree of electric trucks in commercial delivery truck fleets. Since the year 2000, however, the use of coal as the largest electricity source in the US has been decreasing continuously, while the use of natural gas and other sources like wind and solar has been increasing. Therefore, with continuing changes in electric grid structure and lower manufacturing and retailing prices of electric vehicles due to future technological improvement, electric trucks may have greater applicability in the future.

This study in Chapter 3 quantitatively compares the GHG emissions of EREVs and BEVs from a life cycle perspective with and without the use of V2G regulation services, with three battery wear-out scenarios assumed, analyzed and interpreted to account for uncertainties related to various degrees of battery wear-out. To address the uncertainties pertaining to regulation response times, a Monte Carlo Simulation is integrated along with an analysis of relevant historical data. The results shows that EREVs and BEVs are both viable regulation service providers for saving GHG emissions from electricity generation if the battery wear-out from regulation services is assumed to be minimal, but the V2G system becomes less attractive at higher battery degradation levels.

Based on the uncertainty analysis conducted in Chapter 3, it is also observed that the electricity emission savings with the V2G system are sensitive to regulation signal frequency and strength, and the total regulation values while providing V2G regulation services are likewise positively correlated with the emission savings. However, it must also be noted that, once V2G system is implemented, more electric power exchanges will take place, and more electricity generation emissions will be avoided as a result. In conclusion, based on the overall battery degradation levels, ancillary service profits, environmental merits, and future battery price considerations, regulation/ancillary services are a promising future application for V2G technology.

However, the widespread implementation of EV and V2G system may face obstacles from different angles. Firstly, the initial cost of EVs are significantly higher than traditional vehicles (i.e. the price of the researched BEV is $150,000, which is two times higher than a diesel truck). Secondly, the lack of EV charging infrastructure may cause the “range anxiety” and prevent potential customers from purchasing EVs. Thirdly, a sociological research revealed that drivers seldom consider fuel cost as an important household expenditure and alternative fuel vehicles ae often related to “low quality” or “cheap” and resisted by customers (Turton and Moura, 2008). Furthermore, the aggressive driving behavior; rural and urban community conflicts due to moving environmental impact from the city to suburban traditional/renewable power facilities and impediments from petroleum companies can all obstruct the integration of the EV and electricity system (Sovacool and Hirsh, 2009). Electric delivery trucks, on the other hand, are immune to some of the aforementioned problems. For instance: In order to promote clean delivery trucks, state of New York (New York State Department of Transportation et al., 2015) and State of California (California Environmental Protection Agency, 2015) initiated “first come-first served” electric truck incentive programs, which provide $50,000 and $60,000 incentives respectively as well as tax exemptions for EV fleet owners. Delivery trucks operate on a fixed routine and therefore the driver has no range anxiety. And from the perspective of a fleet operator, when purchasing a new vehicle, the fuel economy and the GHG emission will be first priorities instead of the shape, color and interior comfortability of the truck. Moreover, the acceleration or top speed can also be regulated by the fleet operator to optimize the efficiency of the electric truck. In conclusion, in spite of the obstacles, commercial delivery fleets can be the first step of a mature V2G system.

The conclusions of the V2G systems, V2G-wind power, and V2G with the transportation-water-energy network (Chapter 4 to Chapter 7) are summarized below:

- While electric passenger car owners as V2G service providers require aggregators to operate and coordinate due to the low battery capacity and scattered locations of passenger vehicles, electric delivery truck fleets have inherent advantages as the preliminary application of V2G technologies, particularly since a fleet with 30 trucks or above is able to sign contracts with electric grid operators, a delivery truck typically parks 10 to 12 hours a day, and the centralized coordination and fixed routes of standard truck operation can help to ensure the contractual capacity of the fleet.
- For BEVs in the PJM, NYISO, and CAISO regions, a significant total ownership cost reduction can be achieved by providing V2G regulation services. In areas where regulation service prices are high, such as the NYISO region, the lifetime V2G regulation service revenue could even reach as much as $60,000, which leads to a considerably large amount of profit compared to the initial cost of the EVs.
- The total ownership costs of BEVs are significantly lower in the NYISO and CAISO regions, because the state governments in these two regions are currently promoting the adoption of electric trucks with a large amount of incentives. However, these funds are not unlimited and are provided on a first-come-first-serve basis, so as the electrification

of truck fleets in these two areas continues, the availability of incentives and the total ownership costs of electric trucks will inevitably be altered in the future.

- For EREVs, the total ownership cost reductions due to regulation services are only significant in the PJM and NYISO regions, where the revenues are approximately \$20,000 to \$30,000 more than the total life cycle ownership cost. However, this is still profitable given the relatively lower purchasing price of EREVs as opposed to BEVs.
- Based on the calculated revenues of each type of vehicle in each region, apart from the power output availability of the vehicle, the capacity payment revenues of electricity regulation services will play a crucial role in the net revenue of V2G services, and EVs in high regulation-capacity-price regions (such as the PJM or NYISO regions) will tend to have higher V2G service revenues.
- Compared to the average net revenue from V2G regulation services, the initial equipment grid-accessibility upgrade cost (excluding the cost of the EVs themselves) are relatively small and can typically be repaid in full within the first year.
- V2G regulation services are more profitable in regions where the grid is highly fluctuated. The more electricity processed by the V2G system, the more GHG emissions are reduced, as the emissions from less efficient gas turbine generators will be mitigated while V2G service providers receive more revenue.
- Even though EREVs have lower battery capacities than BEVs and therefore cannot provide as much to the grid, EREVs are still able to meet regulation service demand levels. However, the larger battery capacity of BEVs means that fewer BEVs are needed to meet the same regulation contract requirement, leading to a more flexible operation schedule for a BEV fleet than for an EREV fleet.

- In addition to economic benefits for fleet operators, the use of the V2G system with delivery truck fleets is proven to have significant GHG emission mitigation effects. On average a BEV or EREV in each researched region could save approximately 300 tons of GHG emissions. The GHG emissions of BEVs are mainly generated at electricity generation and transmission phases, but the life cycle GHG emission savings from providing V2G services could offset all of the electricity-related or petroleum-related emissions, as shown in Figure 37. In other words, by integrating EVs into the grid, "zero" or even "negative" net GHG emissions could be achieved. Furthermore, more savings will be available for fleet owners once carbon taxes are introduced.
- Although BEVs have proven to be more profitable in terms of V2G service revenue, BEVs did not achieve any significantly greater emission savings than EREVs when V2G regulation services were considered (Figure 36). This is because, despite the higher power availability of BEVs, this power availability could not be fully utilized based on the grid fluctuation balancing demand researched in this study, while the batteries of BEVs are twice as large as that of EREVs, meaning that each battery replacement for BEVs would result in a larger GHG impact.
- Whether or not the emission savings potential of the V2G-wind power system can be fully achieved depends heavily on the availability of EVs as V2G regulation providers. For instance, in the MISO and ERCOT regions, where wind power projections are considerably higher, the overall emission savings are lower because of the limited EV population relative to the required number of EVs to meet the regulation demand.
- The marginal emissions due to unregulated charging could not outweigh the emission savings of V2G services in most cases. For example, in the average-case scenario, the projection wind power integration in the CAISO region is only one-third of the

corresponding projection in the MISO region, but the CAISO region still yields a much larger overall amount of emission savings comparing to the MISO region due to the larger amount of EVs available in the CAISO region to meet the V2G regulation demand from increased wind power integration.

- The marginal emissions may still offset the environmental benefits of the V2G system when EVs are adopted on a sufficiently massive scale in a particular region with unregulated charging schedules, and/or when the region's regulation requirements are limited. Hence, the balance between EV projections and wind power projections in any given region is crucial, especially in regions where a significant degree of wind power integration is expected, in which case the adoption of EVs and V2G systems should be promoted to reduce the overall carbon emissions from both sectors.
- Once a V2G-wind power system has been properly established in a particular region, more electricity is exchanged through the system as the regulation requirement signals become stronger, allowing more additional energy to be saved or given back to the grid.
- The results of Chapter 5 indicates that wind power aggregation could effectively mitigate the variability of the system as a whole and thus reduce the ancillary service burdens among individual participants, making this aggregation a promising solution for regions where the projected ancillary service requirements for wind power integration are high while EV market penetration is low.
- V2G technology could be an ideal solution for problems related to the optimization of the water-energy nexus and for the decarbonization of current electricity grid, as V2G systems are essentially an aggregation of several idle EV batteries, each of which can achieve a bidirectional energy transmission with limited modifications and/or investments from vehicle owners; the additional capacity provided by these batteries can

increase the efficiency of the power grid and accommodate cleaner renewable power sources despite the inherent intermittency of their power outputs.

- In addition to lower fuel and maintenance costs, the potential revenue of providing V2G regulation service may also be appealing to car buyers, making V2G systems a potentially critical element of a reinforcing feedback loop to facilitate the formation of a more sustainable system overall, including a larger EV fleet with higher energy efficiencies and lower tailpipe emissions. Based on the V2G services that can be provided by this fleet, the efficiency of the grid can also be increased, and more wind power can therefore be integrated. Subsequently, the newly adopted large-scale wind capacity not only decreases the emissions of electricity generation and further reduces the life-cycle emissions of EVs but also consumes less water; the latter in particular leads to less overall energy consumption within the system.
- Sophisticated business modes and a good scheduling and controlling mechanism will both be required from system operators, and more importantly, a certain amount of willing participants among the EV customer base will be essential to ensure an adequate V2G system. The results under a more conservative scenario indicated that a minimum EV market share of approximately 10%, combined with an availability/participation ratio for regulation services of at least 0.5%, would provide sufficient support for large-scale wind power integration.
- The results of the simulations in this study indicated that the electrification of the passenger vehicle fleet will increase the GDP of the passenger car sector, but when combined with GDP from other sectors, the EV market has a fairly small impact on the population. Hence, the most effective connection between the environmental and economic sections of the overall system will be the incentives provided to encourage the

adoption of EVs; in real life, this would most likely be in the form of economic incentives, such as lower prices for EVs.

- With all of the relevant life cycle factors taken into consideration, the overall mitigation potential for GHG emissions was still found to be positively correlated with the number of EVs and the participation ratios with respect to V2G regulation services. The result of all four scenarios indicated a certain level of GHG emission mitigation, and among all of the assumptions made for these four scenarios, increasing wind power capacity was found to be the most effective way of reducing these emissions from the system as a whole.
- The result in Chapter 7 indicates approximately 20% EV ratio can support 30% of the electricity system to be wind power. However, the electrification of the passenger car fleet cannot impact the GDP and population sector significantly.
- V2G system can reduce the overall emission of the transportation-energy network by replacing low-efficiency gas turbines, supporting newly integrated wind power, and reducing the water consumption within the energy system. Based on relatively conservative assumptions, the total emission savings can be as high as 10 million ton per year; and the higher ratio of wind power in the electricity grid is the fundamental change of the network.
- Government incentives and lower battery unit price are the two most influential factors that affect the adoption of EVs; the annual income from V2G regulation service can be appealing to potential vehicle buyers. Hence a sophisticated EV infrastructure with V2G service aggregators, the reduction of the battery unit price and environmental footprint will facilitate the implementation of the V2G system

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