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Environmental Assessment of Plug-In Hybrid Electric Vehicles in Michigan:
Greenhouse Gas Emissions, Criteria Air Pollutants, and Petroleum Displacement

Gregory Keoleian, Jarod Kelly, Jason MacDonald, Aaron Camere, Caroline de Monasterio, Allison Schafer

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Abstract

The environmental and electric utility system impacts from plug-in hybrid electric vehicle (PHEV) infiltration in Michigan were examined from years 2010 to 2030 as part of the Michigan Public Service Commission's (MPSC) PHEV pilot project. Total fuel cycle energy consumption, greenhouse gas and criteria air pollutant emissions for Michigan's light duty vehicle fleet were analyzed, as well as gasoline displacement due to the shift to electrified travel.

PHEVs consume both liquid fuel and grid electricity for propulsion. While this fueling strategy can significantly reduce gasoline consumption and related emissions, it is important to understand the impacts that these PHEVs have on the electrical system and its associated emissions. A MATLAB® model was developed to quantify the regional emissions and energy use of this interaction for Michigan.

Each year the model examined vehicle charging behavior, PHEV sales infiltration, changes to the electric grid, and electricity dispatch. Individual PHEV energy consumption was determined from a database of actual vehicle trips, and scaled to the number of on-road PHEVs. The electricity to charge PHEVs was added to Michigan's baseline hourly electrical demand and new generating capacity was added to the grid to meet renewable portfolio standards and capacity reserve mandates. Lastly, generating assets were dispatched to serve the load, and total fuel cycle (TFC) emissions were calculated. Several scenarios were developed to capture the range of possible outcomes examining PHEV infiltration, charging behaviors, and future grid mixes.

In all scenarios, an increased number of PHEVs led to decreased statewide GHG emissions, ranging from a 0.4% to 10.9% reduction in 2030, and displaced from 0.6 to 9 billion gallons of gasoline from 2010-2030. Under the high PHEV infiltration and using capacity factor dispatch, the emissions intensity of PHEV travel in 2030 for the scenarios examined ranged from 215 to 296 gCO_2e per mile (using average allocation). Substituting nuclear generators for some of Michigan's predominately coal baseload power plants had a large effect on reducing emissions, a 46% reduction in annual electricity sector GHG emissions between 2010 and 2030, and reduced PHEV emissions intensity up to 25% in 2030. Criteria air pollutant emissions were reduced in most scenarios. However, SO_X emissions could increase with the addition of PHEVs.

Acknowledgements

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List of Acronyms and Key Terms

AEO	Annual Energy Outlook
CH_4	Methane
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CV	Conventional Vehicle
eGRID	Emissions & Generation Resource Integrated Database
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EPRI	Electric Power Research Institute
eSOC	Energy State of Charge
GHG	Greenhouse Gas
GREET	Greenhouse gases, Regulated Emissions and Energy use in Transportation
HEV	Hybrid Electric Vehicle
MDEQ	Michigan Department of Environmental Quality
MEFEM	Michigan Electricity, Fleet and Emissions Model
MPSC	Michigan Public Service Commission
MWh	Megawatt Hours
N_2O	Nitrous Oxide
NGCC	Natural Gas Combined Cycle
NO_X	Nitrogen Oxide
NREL	National Renewable Energy Laboratory
OEM	Original Equipment Manufacturer
Pb	Lead
PECM	PHEV Energy Consumption Model
PHEV	Plug-in Hybrid Electric Vehicle
$PM_{2.5}$	Particulate matter of less than 2.5 micrometer diameter
PM_{10}	Particulate matter of less than 10 micrometer diameter
RPS	Renewable Portfolio Standard
SO_X	Sulfur Oxide
VOC	Volatile organic compound

Nomenclature

PHEV Energy Consumption (Section 3.1)

C_n	Usable Energy state of charge of vehicle n (percentage)
D_{trip}	Distance of a trip (miles)
e_n	Average rate of electricity consumption of vehicle n (kWh/mile)
E_{batt}	Size of usable battery (kWh)
t_{start}	Start time of a trip (hr,min)
t_{end}	End time of a trip (hr,min)
$\frac{dC_n}{dt}+$	Rate of charging, (kW)
I_c	Charging current (amps)
V_c	Charging voltage (volts)
η_c	Charging efficiency
ΔG_n	Consumption of gasoline of vehicle n during a trip (gallons)
F_n	Fuel consumption rate of vehicle n (miles per gallon)
D_{elec}	Distance of a trip driven electrically (miles)
$\mathcal{P}_{day}$	Aggregated and normalized charging load profile for a single week day, at wall outlet (kW, at each hour)
N_{NHTS}	Number of vehicles in an NHTS sample
w_n	Vehicle weight factor for vehicle n
$\mathcal{P}_n$	Charging load profile for vehicle n, at wall outlet (kW, at each hour)
t	Time of day (hours)

Fleet Modeling (Section 3.2)

y	Simulation time (years)
G_{CV}	Gas consumption for on-road conventional vehicles (gallons)
G_{BAU}	Gasoline consumption from an entirely conventional vehicle fleet (gallons)
ΔG	Gasoline avoided by electrically driven miles for PHEVs (gallons)
N_{all}	Total number of vehicles in the vehicle fleet
F_{stock}	Average fuel consumption rate for the conventional vehicle fleet (miles per gallon)
M	Annual VMT for a vehicle in PECM (miles per year)
I	Annual technology improvement factor for conventional vehicles
N_{PHEV}	Number of PHEVs sold each year by size class
F_{new}	Fuel consumption rate for new vehicles by size class (miles per gallon)

Electricity Generation Capacity (Section 3.3)

E_{need}	Deficit in renewable energy generation to meet RPS goals (MWh)

R_{goal}	Annual RPS goal for percent of generation that is from renewable sources (percentage)
E_{demand}	Annual total system energy demand (MWh)
E_{RnwGen}	Renewable generation of the assets currently in the system (MWh)
P_{need}	Power needed to meet the reserve margin capacity limit (MW)
m	Capacity reserve margin
P_{peak}	Peak power of the current year (MW)
P_{cap}	Total available capacity of all assets currently in the system (MW)

Electricity Dispatch Modeling (Section 3.4)

D_H	System electricity demand after wind and hydro have been dispatched, at generation source (MW, at each hour)
$L_{N,min}$	Minimum level of system load defining dispatchable power plant N's power band (MW)
$L_{N,max}$	Minimum level of system load defining dispatchable power plant N's power band (MW)
P_N	Electrical power output of power plant N (MW)
D	Total system electricity demand (MW, at each hour 't')
D_W	System electricity demand after wind generators are dispatched (MW, at each hour)
P_{wnd}	Normalized wind power curve (MW, at each hour)
f_{wnd}	Average capacity factor of wind generators
t_y	Length of time in a simulation year (hour)
$\tilde{D}_W$	Monthly load duration curve for use in hydro dispatch (MW, at each hour)
$\tilde{D}_N$	Electric demand (in load duration form) that hydroelectric plant N will dispatch to. (MW, at each hour)
$\tilde{P}_N$	Sorted (according to load duration curve) hydroelectric plant output for plant N (MW, at each hour, sorted)
$P_{N,NPC}$	Plant N's nameplate capacity(MW)
t_s	Split duration point (hour)
E_N	Total monthly energy generated by plant N (MWh)
t_m	Total time in a month (hour)
D_H	Electricity demand after last hydroelectric plant has been dispatched (MW, at each hour)
f_N	Historical capacity factor for generating asset N
a_N	Availability factor of generating asset N
HR	Heat rate of a power plant, in fuel energy consumed per unit electricity generated (Btu/kWh)
C_{fuel}	Total cost of fuel ($/mmBtu)
E_{gen}	Electricity generated (MWh)
E_{fuel}	Fuel energy consumed (Btu)
$\bar{C}$	Total cost of generation ($/MWh)
$\frac{C_{GHG}}{m_{GHG}}$	Cost of GHG emissions ($/metric ton of CO_2e)

C_{GHG}	Total cost of GHG emissions ($)
m_{CO2}	Total CO_2 emissions (kg)
m_{CH4}	Total CH_4 emissions (kg)
m_{N2O}	Total N_2O emissions (kg)

Emissions Calculation (Section 3.5)

$\frac{m}{E}$	Power plant emission factor (kg pollutant/kWh generated)
$\dot{m}$	Total electricity emission rate (kg pollutant/hour, at each hour)
E_{PHEV}	Total hourly PHEV electrical load (MW, at each hour)
$\dot{m}_{PHEV}$	PHEV electricity emission rate (kg pollutant/hour, at each hour)
m_{PHEV}	Total annual electricity emissions allocated to PHEVs (kg pollutant)
m_1	Total electric system emissions calculated in a scenario *with* PHEVs (kg pollutant)
m_2	Total electric emissions calculated in a scenario *without* PHEVs (kg pollutant)

Infiltration Scenarios (Section 4.1)

N_{PHEV}	The number of PHEVs in each size class that are sold each year
S_{2009}	Number of new vehicles sold in 2009 for each size class
G	New Vehicle sales growth, by size class, for each year
I	PHEV sales infiltration (percent of new sales that are PHEVs) each year

1. Executive Summary

Plug-in hybrid electric vehicles (PHEVs) have been recognized for their potential to reduce transportation related petroleum consumption, on-road greenhouse gas and criteria air pollutant emissions by supplementing their drive cycle with electric energy. Since PHEVs consume both gasoline and electricity, evaluation of these vehicles necessitated modeling the transportation sector and the electric sector collectively. Plug-in hybrids created new demands on the electricity supply system that depended on the charging behavior (i.e., time of charge), the infiltration rate (i.e., how many PHEVs were on the road), the available charging infrastructure (i.e., locations where charging was available), and how the PHEVs are designed (i.e., battery size). These additional power demands affected dispatch of power generating as well as increased the need for additional generating capacity. In order to analyze the environmental impacts of plug-in hybrids it was necessary to understand the dynamic interactions between the transportation and electric sector and the overall effect on energy use and related emission levels. This executive summary defines the objectives of this study, discusses modeling methodology, states major assumptions and scenario parameters, addresses emission allocations issues and highlights the main findings and conclusions of the report.

In 2008, the Michigan Public Service Commission (MPSC) initiated a pilot program to investigate the capability of PHEVs within Michigan. As a subtask of this program, this report investigated the environmental and electric utility system impacts of PHEVs in Michigan. Specifically, the purpose of this study was to evaluate total fuel cycle energy, greenhouse gas, and criteria air pollutant impacts from widespread plug-in hybrid deployment in Michigan over a time period of 2010 to 2030. Two MATLAB ® based models were developed for this purpose, the *PHEV Energy Consumption Model* (PECM) and the *Michigan Electricity and Fleet Emissions Model* (MEFEM). PECM was created to develop individual PHEV consumption patterns using aggregated National Household Travel Survey (NHTS) data. Using the output of PECM, MEFEM characterized the electricity grid and simulated the dispatch operation of generation assets on an hourly basis. The impact on hourly electricity demand and system emissions from the additional PHEV demand was evaluated from the outputs of MEFEM.

Simulations were conducted under a variety of scenario combinations in order to evaluate the potential effect of varying certain parameters and different possible futures. Eight charging scenarios were developed for PECM which varied recharge timing, charging infrastructure, and battery size. MEFEM simulated four PHEV fleet infiltration scenarios and four electric grid mix scenarios. Combinations of these scenarios then yield the necessary outputs. The outputs quantify greenhouse gases, criteria air pollutants, total fuel cycle energy and gasoline displacement associated with each scenario. A highly simplified system diagram showing the interaction between the models is shown in Figure 1.

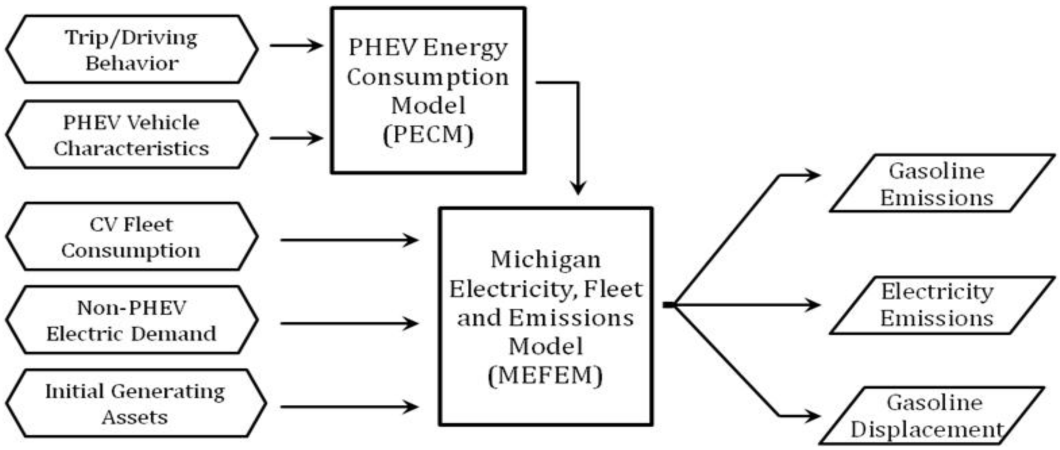

Figure 1. High level system diagram

Comparison of total fuel cycle energy and emissions from plug-in vehicles to those associated with conventional gasoline vehicles required analysis on a well-to-wheels basis. These well-to-wheel emissions included those at the tailpipe, those associated with electricity generation, and emissions upstream of both electricity generation and vehicle combustion. Emissions and energy use associated with conventional vehicles as well as hybrids occur mainly during vehicle operation. In a plug-in vehicle, the well-to-tank emissions associated with generating electricity comprise an important component of total fuel cycle emissions. The mix of electricity generation technologies can have a significant impact on emissions associated with PHEV battery charging.

Modeling and accounting for the emissions associated with the additional demand from PHEVs is currently open for debate within the academic community. In this study, two methods were used for attributing emissions from electricity generation to PHEVs: average and marginal allocation. The mix of power plants that provided for the additional PHEV demand is referred to as the marginal generation mix, and the emissions associated with this additional mix are assigned to PHEVs. Average emissions were calculated from the instantaneous generation-weighted emissions average for all electricity generated in the specified time, and then assigned to the PHEV demand. In addition to the emissions associated with electricity generation, emission changes were also estimated from gasoline displacement. The issue of allocating emissions and which method should be the standard practice is still undecided. Therefore, the results for both methods are presented equally in this report.

1.1 Modeling Methodology and Scenarios

The models developed simulated the evolution of the transportation and electric sectors over the 2010 to 2030 study timeframe. A series of scenarios were developed to assess the impact of PHEVs over a range of different possible development pathways for these sectors. This section provides a description of the MEFEM and PECM models. The desired outputs of the combined model were energy consumption and greenhouse gas and criteria pollutant emissions from vehicle use and electricity generation.

1.1.1 PHEV Energy Consumption

The PHEV Energy Consumption Model (PECM) was used to determine fleet average electricity and gasoline use. These values were normalized to a single vehicle. PECM used trip data from the 2009 National Household Travel Survey (NHTS) to generate the daily profiles for vehicle charging and total gasoline usage. Results were generated for seven vehicle size classes under specified charging constraints and scaled by the number of PHEVs in each class in the Michigan light duty vehicle fleet to obtain aggregate fleet consumption.

Several electric demand profiles from battery charging were simulated. PECM contains a number of parameters that were manipulated to affect the time of charging and therefore the number of electrically driven miles that a fleet average PHEV underwent. PHEV charging parameters included charging locations, minimum dwell time, charge onset delay, charging blackout periods, last minute charging, charging rates and battery size. Other vehicle trip behaviors, such as trip start and end times and locations were established by evaluating daily vehicle trips and vehicle miles traveled from the aggregated national NHTS data. The charging behavior of PHEV owners determined the PHEV electric demand profile, which in turns determined the impact of PHEVs on the electric grid. PHEVs represented a significant potential shift in the use of electricity and the operation of the electric power system, especially if vehicles were charged during times of peak or elevated demand.

Eight vehicle-charging scenarios were designed and are summarized in Table 1 below. The scenarios chosen are not necessarily the most likely, but instead represent a broad spectrum of those factors which have the most potential to affect the shape of the load curve. The baseline charging scenario (CH1) represents home charging of a battery pack using 10.4 kWh (65% discharge of a 16kWh battery), at a charging level of 120V, 12 amp with no time-of-day charging constraints. Other charging scenarios, CH2-CH8, are described by the parameter departure from the baseline charging scenario.

Table 1. Charging scenario description

Acronym	Full Name	Departure from Baseline (CH1) conditions
CH1	Baseline	-
CH2	Last Minute	Delay charging until the 'last-minute'
CH3	Home and Work	Charging location includes work in addition to home
CH4	No-Charge Window	1 pm to 7 pm 'blackout' or no-charge window
CH5	Slow Charging	Charge at 8A, 120V
CH6	Fast Charging	Charge at 16A, 240V
CH7	Home and Work, Fast	Charge at 16A, 240V, charging both at home and work
CH8	Smaller Battery	5.2 kWh usable battery

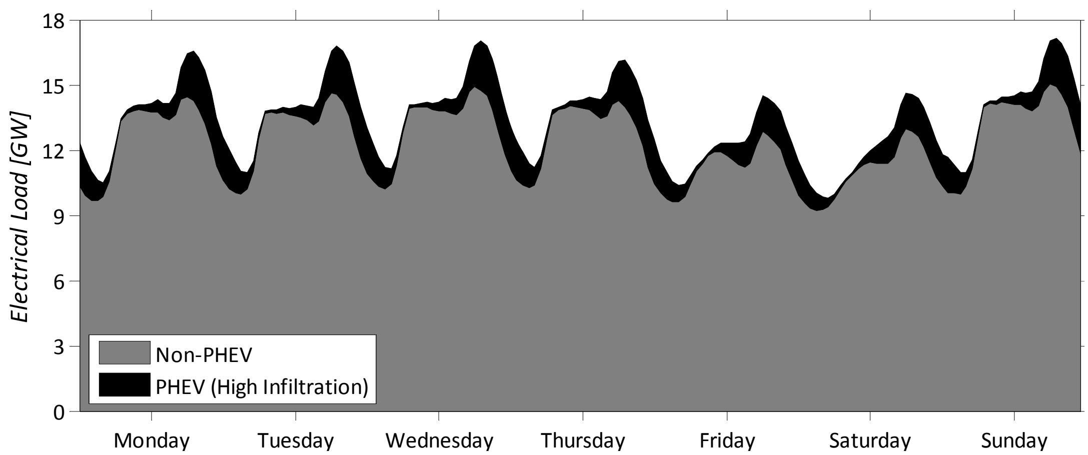

Figure 2. Electric system demand in Michigan, one week in January, 2030.

The Michigan electric system load profile for a week in January for the year 2030 is shown in Figure 2. This graph displays the additional demand from PHEV battery charging and how the shape of this demand overlays the baseline electricity demand. This demand represents three million PHEVs on road. The PHEV load profile shown in the figure is that of the high PHEV infiltration case under baseline charging conditions (CH1). Under these conditions, PHEVs cause a fairly substantial increase in system peak over that of the already existing baseline demand peak. This would indicate that, in order to meet the 15% reserve margin, additional generating capacity would need to be brought online. Also, it indicates that the plants serving the demand would be 'peaking' plants, or plants that would be more expensive to run than 'baseload' plants. The type of generation used has implications for emissions.

1.1.2 Fleet Infiltration

In addition to charging behavior, the effect of PHEVs on the grid will depend on fleet infiltration rates and the total number of PHEVs on the road. In this study, five fleet scenarios were examined: a zero infiltration rate (FI1), a low infiltration rate (FI2), a medium infiltration rate (FI3), a high infiltration rate (FI4) and a maximum infiltration rate (FI5). These infiltration curves over the 2010 to 2030 time frame are displayed in Figure 3 below. The Obama administration has set a goal of 1 million PHEVs on the road by 2015[1]. As Michigan represents approximately 1/30 of the national population, proportionally the state would support 33,000 PHEVs to achieve this goal. Within the inset graph of Figure 3 the dashed marker signifies this 33,000 vehicle target. As shown, the model in this study realizes at least this many PHEVs in the medium, high, and maximum infiltration scenarios. PHEVs have an assumed life of 10 years, and each PHEV is assumed to displace a CV in the same size class.

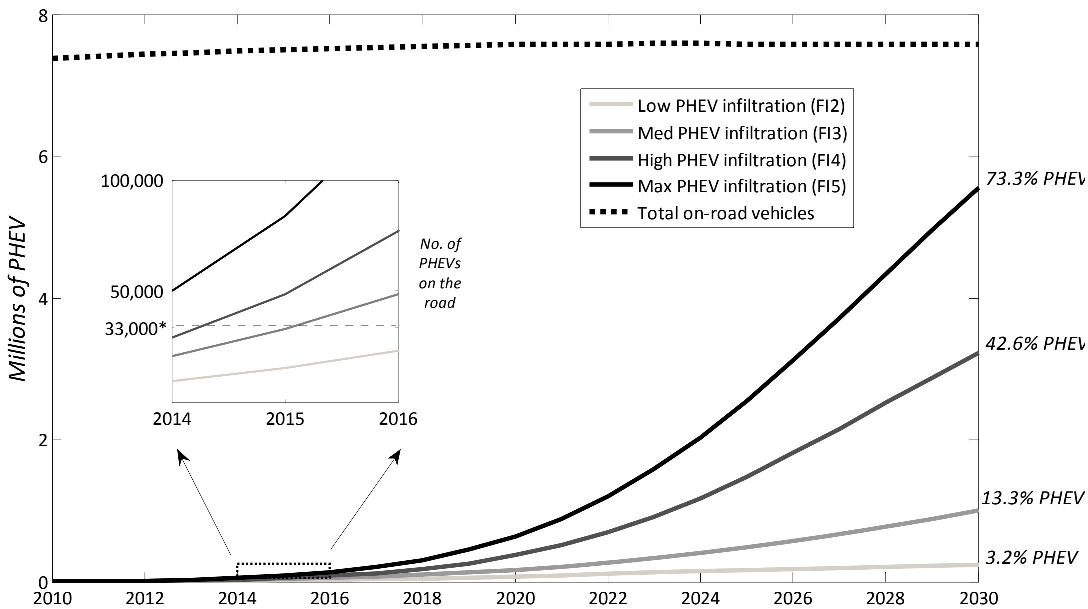

Figure 3. PHEV infiltration rates, 2010 - 2030

Electricity usage rates and fuel economies for PHEVs and conventional vehicles (CVs) were collected from OEM pre-production publications, academic research and Environmental Protection Agency (EPA) ratings. No technological improvements were assumed for the analysis of PHEVs, so emissions reduction from gasoline displacement may be conservative. Fuel economy improvement factors for CVs were taken from the 2009 Energy Information Agency (EIA) Annual Energy Outlook.

1.1.3 Electric Grid

Modeling the electricity sector is complicated due to its bid-based and nodally priced real time operation. Specific economic data, like marginal generation costs on individual generation assets in the Michigan electric grid, was proprietary information and therefore not available. The power dispatch methods in this study did not attempt to simulate a true economic dispatch, but rather approximated electricity dispatch. The electricity generation capacity model simulated decisions to add new generation to the grid or to retire existing capacity. The new generation capacity that is added determined the yearly grid fuel mix, assuring that renewable portfolio standard (RPS) and marginal spinning reserve requirements were met. Once decisions to retire existing or add new generation capacity were made, MEFEM dispatched generation assets to meet this electricity demand.

The electric power capacity factor dispatch model utilized four future grid scenarios that specified the fuel types of capacity additions made in the model over the 20 year time frame. These electric grid scenarios, EG1 through EG4, vary in the amount of renewable generation added, the amount of nuclear capacity added and the number of retirements to existing generation assets. A simplified economic dispatch algorithm was also explored in this study. In this economic dispatch model, additional scenarios were which that include variations in GHG costs. The capacity factor dispatch model uses historical power plant performance data from EPA's Emissions & Generation Resource Integrated Database (eGRID) to simulate future power plant operation. The economic dispatch model, dispatches generating assets based on fuel cost predictions and plant heat rates.

Figure 4 below shows the steps for electricity dispatch by using a load duration curve. The curve marked #1 is the total system electric demand (PHEV and non-PHEV load). In both dispatch methods, wind power is first applied to the total system demand as a negative load. This step is illustrated by the curve marked #2 in Figure 4 below. Simulated wind farm power outputs for multiple sites in Michigan were used (NREL wind integration database) to compile an 'average' wind load for Michigan. Next, hydro electric generation is applied to the system load in a 'peak-shaving' operation shown as curve #3 in Figure 4. The increase in the lower demand levels from curve #2 to curve #3 represent the Ludington pumped hydro storage plant. All other generating assets are then dispatched to meet the remaining demand via the Capacity Factor Dispatch or Economic Dispatch method.

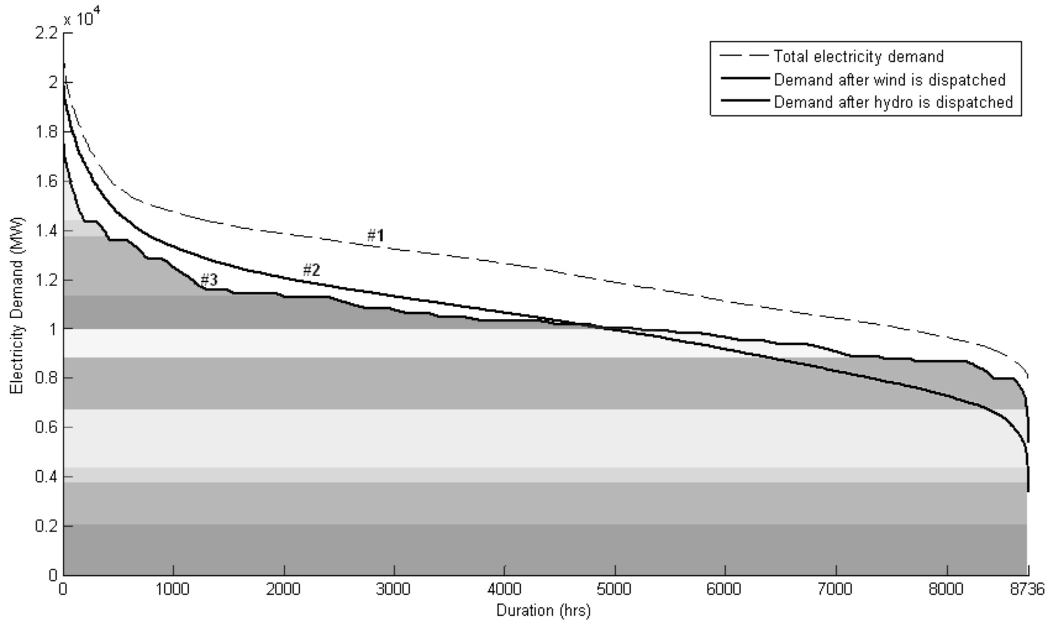

Figure 4. Load duration curve showing hydro and wind dispatch.

The evolution of Michigan's electricity supply system will be shaped by many factors including environmental regulations, generation technologies, regional demand, and economic conditions. Four scenarios were developed to simulate future pathways of the Michigan grid. In addition to the base case generation scenario options include high renewable, high nuclear, and a combination of both.

1.2 Key Findings & Conclusions

This study found that any level of PHEV infiltration will decrease greenhouse gas (GHG) emission in all the simulations analyzed. This reduction in total statewide system greenhouse gases from electricity and transportation, under the baseline charging and electricity grid mix, ranged from 0.4 to 11.0 billion kgCO_2e (GHGs) in 2030, a 0.4% to 10.9% reduction, depending on the infiltration level, as seen in Figure 5.

Over the course of the 20 year timeframe, infiltration of PHEVs reduces total GHG emissions by 0.7 to 20 billion kgCO2e. GHG emissions of a PHEV, per mile driven, range from 262 to 252 gCO2e per mile in 2030 depending upon the allocation method using baseline grids and charging methods. Gasoline consumption is reduced, as is expected from PHEVs.

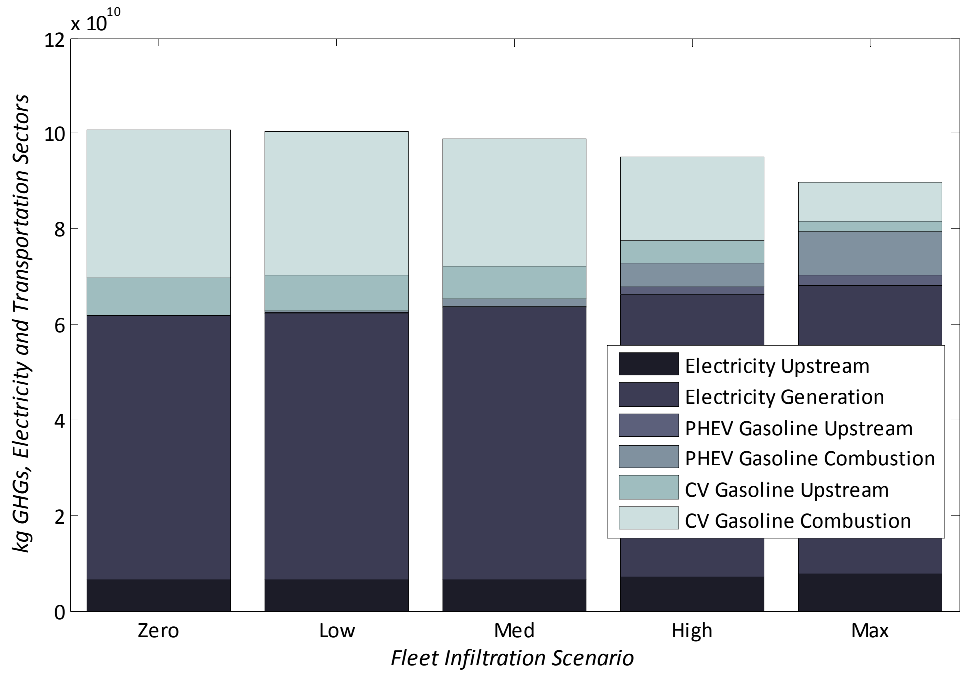

Figure 5. Total GHG emissions (transportation and electricity) for the year 2030 for all infiltration scenarios (EG1, CH1)

Decreased gasoline consumption of PHEVs reduced total system criteria pollutant emissions of CO, NO_X and VOC. Gasoline did not have associated lead emissions, so increased electricity generation always resulted in an increase of lead. This is a limitation of the dataset used for gasoline emissions, as it does not include values for lead emissions. While this is omission is reasonable for the combustion of gasoline, the upstream processes for gasoline should include electricity and thus some lead emissions. Conversely, the emissions data used for electricity generation did not differentiate between particulate matters, PM_{10} and $PM_{2.5}$. For electricity generation, it was assumed that all particulate matter was tracked as PM_{10}. Although lead emissions are reported one should remember that data is missing for the transportation sector. In each infiltration scenario, total system emissions of SO_X increased because of the additional electricity demands from PHEV battery recharging. The especially high SO_X is largely due to the fuels consumed for electricity generation versus gasoline, but the results may be inflated because the dispatch model used in this study did not take sulfur caps into account. Figure 53 displays these changes in total system criteria air pollutants for the baseline charging and grid scenarios. While some pollutant emissions did increase, these are local emissions at a limited number of power plants. Removing older plants and increasing new generation with high renewable decreases all criteria air pollutants compared to a baseline grid scenario, but SO_X emissions still increase with PHEV infiltration.

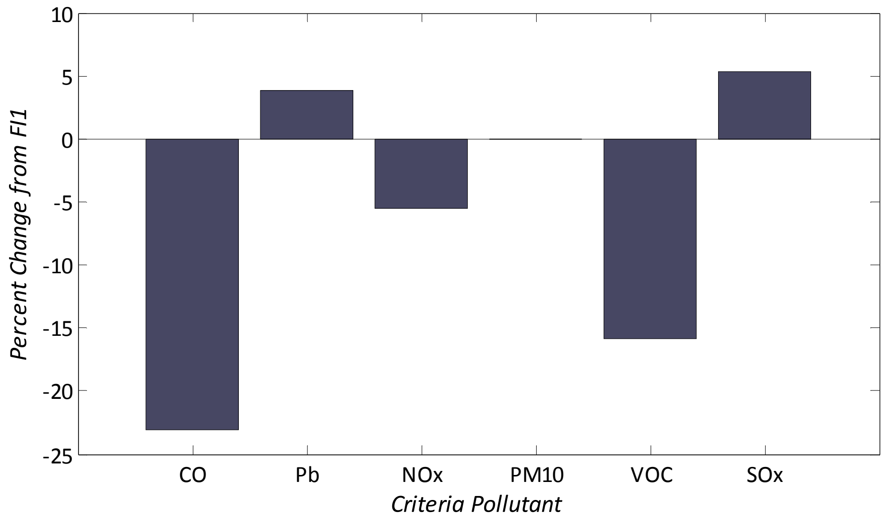

Figure 6. Change in total system emissions between FI1 and FI4 (EG1, CH1, 2030)

Total fuel cycle energy, or well-to-wheels energy use for PHEVs, under the baseline charging and electric grid mix scenarios was lower than that of the average per mile rate of the CV fleet. By consuming gasoline, a vehicle with a fuel economy of 30 miles per gallon, the average for the 2030 CV fleet, 5.2 MJ are consumed per mile accounting for upstream and combustion energy consumption for gasoline. Depending on the allocation method, for the CH1 scenario on road PHEVs consumption ranged from 3.7 to 4.3 MJ per mile in the base grid scenario. Since the per mile total fuel cycle consumption is lower for PHEVs, increasing the number of PHEVs in the fleet reduces the total transportation sector energy use.

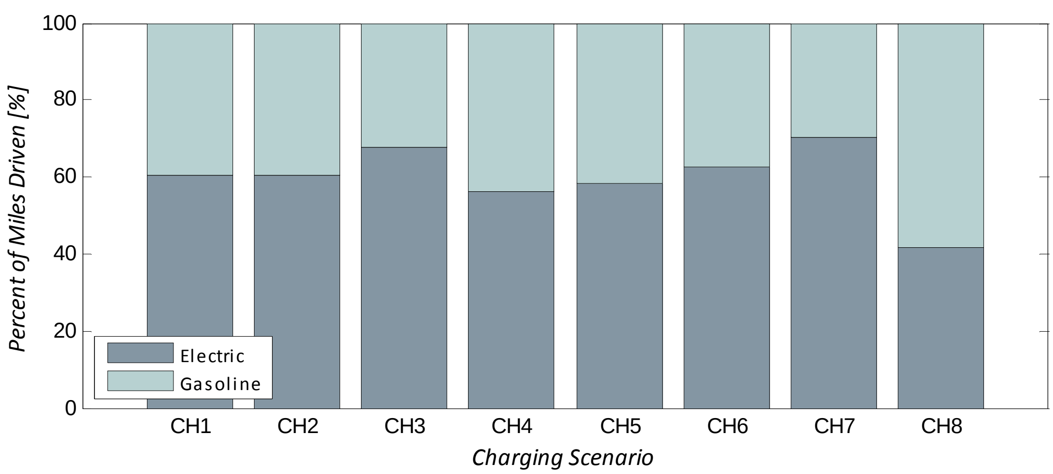

Figure 7. Percentage of travel driven electrically by charging scenario

Within the different charging scenarios, the greatest decreases in greenhouse gas emissions and total fuel cycle energy were observed with increasing the fraction of miles driven electrically, shown in Figure 7. Charging constraints and smaller battery sizes decreased the fraction of miles driven electrically, and thus increased greenhouse gas emissions, while fast charging, and scenarios where charging was allowed at both home and work locations increased the percent of electrically driven miles. Per mile emissions for PHEVs under the different charging scenarios are shown in Figure 51. For comparison, an average conventional vehicle in 2010 emitted 0.530 $kgCO_2e$ per mile, while in 2030 a conventional vehicle was expected to emit 0.375 $kgCO_2e$ per mile. PHEVs in 2010 emitted 0.265 kg/mile.

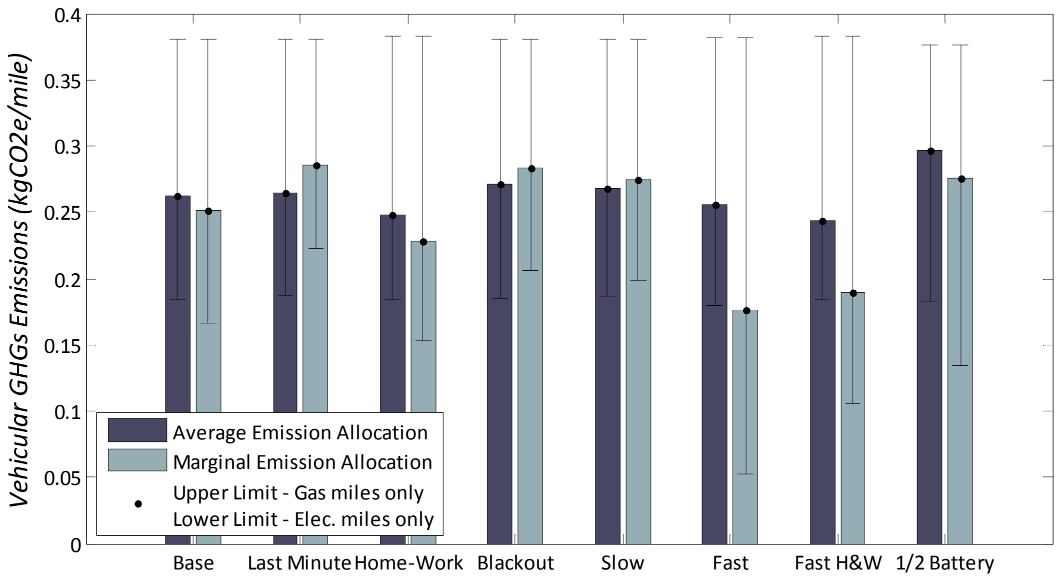

Figure 8. Transportation greenhouse gas emissions per mile traveled for each charging scenario

The future fuel mix for electricity generation greatly affected emissions. Retiring old coal-fired generators and increasing the amount of renewable energy sources reduced greenhouse gas emissions in the electricity sector and decreased the impact of PHEV charging. In the base grid scenario, PHEVs increased greenhouse gas emissions related to electricity by 5.4%. The high RPS scenario decreased this to 4.8%, but the high nuclear simulation, which accelerates the retirement of coal-fired baseload and builds more nuclear generation to supply baseload power, reduced the marginal increase in GHG emissions of the PHEV load to a 2.0% increase, while reducing the overall grid GHG emissions to 54% of the original 2009 grid. In this high nuclear scenario in 2030, coal generation drops substantially from the baseline grid mix scenario, going from 38% of total generation to 17%, and nuclear generation increases from 26% to 39% of total generation.

Since manufacturing of power plants is outside the life cycle scope of the project, renewable generation has no associated total fuel cycle energy. Increasing the amount of renewable generation in the system has a significant impact on the total fuel cycle energy. By retiring coal plants and increasing nuclear and natural gas generation, the high nuclear scenario had a greater effect on emissions than the high RPS scenario. However, PHEVs within the high RPS scenario had the lowest per mile energy consumption, at 3.4 MJ/mile using a marginal allocation method, while the high nuclear scenario increased PHEV per mile energy use to above the base scenario rates. For all the grid scenarios, per mile PHEV energy use was still lower than CV energy use.

1.3 Recommendations and Future Work

The results of this study imply that PHEV adoption should be encouraged within the state because in every scenario extrapolating a future Michigan grid, increasing the infiltration of PHEVs decreased greenhouse gases, transportation energy, and most criteria pollutants. Increasing PHEVs also reduced the state's petroleum use.

The examination of the charging scenarios indicate that in order to avoid creating new peaks in electricity demand, more charging locations and last minute charging are the best strategies. Fast charging would force new, cleaner generation into the grid; however, this would come about by creating new peaks in the system electrical demand that, in this model, creates the need for new cleaner generating capacity. Home and work charging provides a similar electric-to-gasoline miles ratio as fast charging, and home and work charging produces similar reductions in GHG emissions to fast charging without creating such large peaks in demand using the average allocation method. If the goal is to avoid creating large peaks while still increasing total electric miles driven, then investments in work charge infrastructure will work better than investments in fast charge infrastructure.

Within the model new generating assets are assumed to be state of the art, and much of Michigan's power is supplied by an aging coal fleet. To bring about the greatest environmental improvements, older coal-fired power plants should be retired and replaced with cleaner generating sources. When the grid was improved, the additional emissions attributed to PHEVs were also reduced.

One of the greatest difficulties encountered in developing the methodology for the report was assigning emissions from electricity to the PHEVs. While not a policy recommendation, a standardized methodology for assigning electricity generation emissions due to PHEV charging is needed to definitively quantify the environmental effects of PHEVs. Standard allocation methodology between surveys would facilitate comparison among research studies.

2. Introduction

In 2008, the Michigan Public Service Commission (MPSC) awarded a grant to research the proposed Plug-in Hybrid Electric Vehicle (PHEV) Pilot Project. This research is a collaborative effort between the University of Michigan, Detroit Edison Energy and General Motors. The goals of the project are to investigate the capability of PHEVs within Michigan as an economic development catalyst, determine the vehicle-electric utility interface in the near, mid- and long-term, and understand the regional environmental and electric utility system impacts of PHEVs in Michigan. This report outlines the methodology, findings and recommendations of the research addressing Subtask 4.1 of the project proposal, an analysis of environmental impacts of PHEVs in Michigan.

While this report is focused on effects within Michigan, several related studies have been conducted to examine the environmental consequences of PHEV adoption, and a brief overview of these studies is provided.

Two MATLAB® based models were created to analyze the environmental impacts associated with PHEV adoption in Michigan. The structure and application of this model is detailed in this document. Simulation results employing a variety of scenario combinations are presented. Finally, the implications of those results are discussed, and recommendations are offered toward both future research goals as well as policy initiatives to reduce the environmental impacts of light duty vehicles in Michigan.

2.1 Previous Research and Context

Interest in alternatively fueled vehicles such as hybrids, plug-in electric vehicles, and fuel cell vehicles has been spurred in recent years by high gasoline prices and renewed concerned for national energy independence and the environmental impacts of the transportation sector. Several earlier studies were examined to aid the development of the methodology utilized for the evaluation of environmental impacts of PHEVs. An abbreviated review of current literature is presented to orient the reader on the current state of research into PHEV environmental evaluation and to show the need for this project's in-depth charging, infiltration, and electricity dispatch models.

In 2008, a group at MIT[2] conducted a broad investigation into alternatively fueled vehicle trends through the year 2035. While the group dismissed many new technologies as too expensive, especially when compared to established gasoline vehicle lines, concluding that investment in fuel efficiency of conventional vehicles would reduce greenhouse gas emissions at a lower retail consumer price, plug-in electric vehicles were selected as the alternative fuel vehicle of choice for the near term. PHEVs were selected as the best option because they have the same range as current vehicles and provide reductions in emissions without the need for extensive infrastructure overhauls as would be the case to support a large fleet of hydrogen fuel cell or pure battery electric vehicles. Kromer and Heywood, two researchers within the MIT group put together another assessment of advanced powertrains including battery electric vehicles, hybrid electric vehicles, and plug-in hybrid electric vehicles[3]. They found that electrified vehicles offer an improvement to the environment over the long term, generating less lifecycle greenhouse gases than conventional gasoline vehicles despite higher material production costs. However, this study promoted HEVs over PHEVs, citing that the added financial expense of PHEVs was not justified since PHEVs did not result in a direct reduction of emissions due to the uncertainty of grid emissions. Their study utilized three different 'grid mixes' to apply a factor to PHEV electricity consumption. This uncertainty in emissions allocation was also supported by Stephan and Sullivan in their 2008 report[4]. They found that when a PHEV was charged using electricity generated solely by fuel oil or inefficient coal plants, greenhouse gas emissions could be as high as 440 gCO_2e/mile. However, they also noted that a PHEV driving short trips and charged using clean, renewable sources had an effective emissions rate of 0 gCO_2e/mile, not accounting for upstream renewable production emissions.

There have been many studies dedicated to evaluating the greenhouse gas emissions of plug-in electric vehicles. In Section 5.6, a comparison is made between the Michigan simulation results and other published per mile emissions, showing average emissions rates ranging from 145 gCO_2e/mile to 385 gCO_2e/mile (For reference, Grimes-Casey, et al. place total fuel cycle emissions for conventional vehicles at roughly 585 gCO_2e/mile)[5]. This large range in per mile emissions stems from the methodology employed in quantifying and attributing electricity generation emissions to the transportation sector as well as the types of electricity generating assets, used to meet vehicle electricity demand . The Electric Power Research Institute (EPRI) Environmental Assessments of Plug-In Hybrid Electric Vehicles[6] alone reports a range of about 150-325 gCO_2e/mile, depending solely on the carbon intensity of the grid scenario they used. Uncertainty in resulting criteria air pollutants emissions is similarly associated with the fuels used to produce electricity.

Three methodologies for determining electricity emissions have emerged in the literature. The simplest solution is to assume that all PHEV charging energy is sourced from one fuel type. Kromer and

Heywood as well as Stephen and Sullivan used this method in their analyses. They assumed the grid was fueled from a single generation technology type and examined the variation in emissions from a single PHEV, applying this resulting range of emissions to future PHEVs anywhere within the country. This can be a good way to develop regional emissions rates if, within a specific region, the specific power plant fuel type that will be used to charge PHEV is known. In 'Environmental Benefits of Plug-in Hybrid Electric Vehicles: the Case of Alberta,' University of Calgary researchers looked at using PHEV charging loads to absorb nightly wind generation, resulting in a zero emissions rate[7].

A slightly more in depth solution to emissions allocations would be applying an average grid emissions factor to the energy consumed by PHEV. Samaras' lifecycle analysis for PHEVs applies a national grid average to PHEV energy consumption. Again, this can be regionalized if the target grid is known. In 2007, a Minnesota task force[8] concluded that a PHEV fleet would increase emissions compared to an HEV fleet due to the high proportion of coal generation in the state. The report used an average emissions factor that was based on an 80% coal, 20% wind grid to estimate the actual emissions in the fleet. Note that, as mentioned in Samaras' lifecycle study[9], this method considers PHEV charging part of the total load rather than a marginal load to be met by additional generation. This distinction is explained in greater detail in Subsection 3.5.3. A report by the University of California, Davis' Institute of Transportation Studies[10] explored the interaction of PHEVs with the California grid, finding that the additional load from off-peak PHEVs would be met by relatively inefficient natural gas generators, and compiled both marginal and average emissions rates at hourly intervals. Assigning these additional emissions to PHEV yields a reduction over conventional vehicles about (200 gCO_2e/mile), but if the charging is conducted as load leveling (restricted to certain hours of the night) rather than simply off-peak (but still allowed to charge throughout the day, away from peak times), the result is slightly lower due to the difference in fuel mix expected to serve that additional load. However, in either charging scenario, the result is a higher electricity emissions rate than the roughly 80% (NGCC)/20% (renewable generation) mix used to develop California's Low Carbon Fuel Standard.

Some reports attempt to model the grid to investigate the effect of PHEV infiltration on power plant dispatch and new capacity additions. While the EPRI report examined PHEV infiltration at the national level, it utilized the Energy Information Agency's National Electricity Modeling System (NEMS) to calculate electricity supply, demand, and prices nationwide and the National Electric System Simulation Integrated Evaluator to simulate the addition of new electricity generating capacity and the retirement of older assets. Other studies have modeled regional grids by assuming some fuel types will be utilized to meet demand first, such as renewable and nuclear sources, while typically more expensive fuel sources would only be utilized when demand is high. Kinter-Meyer, Schneider, and Pratt at the Pacific National Lab[11] looked at PHEVs on a regional level, ‘stacking’ generating assets by fuel type, and estimating the number of PHEVs that could be charged using the region’s available capacity. While the study found that greenhouse gases in each region dropped, PHEVs could lead to either an increase or decrease in criteria pollutants depending on the mix and extent of use of generating assets in each region. Using a similar methodology within the PJM ISO, which includes Pennsylvania, New Jersey, Delaware, and Maryland, a study by Thompson, Webber, and Allen[12] analyzed a baseload mix of coal and nuclear generation similar to Michigan’s grid. The historical plant output levels were ‘stacked’, and any remaining capacity left undispatched (the ‘valley’ in the load) was allocated to PHEV load. The amount of charging within this valley determined the number of miles that PHEVs could theoretically travel in the PJM, which allowed determination of displaced gasoline. Greenhouse gas emissions were reduced, but ozone and SO_X emissions increased in some localities due to the restricted ‘valley-filling’ charging times, which caused the use of more coal generated electricity. Sivaraman[13] used a similar stacking method, but plant stacking was done by according to capacity factor rather than fuel type. Capacity factor is a historical indicator of how often a plant is used. Plant capacity factor often correlates to plant fuel type but treats plants separately. This report uses a dispatch method similar to Sivaraman plant stacking, outlined in subsection 3.4.

When using an average or single source emissions factor, only the amount of charging is necessary to calculate the resultant emissions. However, for more detailed studies modeling the grid response to demand, the emissions due to PHEV charging depends not only on the amount of power being pulled from the grid, but also the timing. Mentioned briefly, Kinter-Meyer, Schneider, and Pratt[11] and Thompson, Webber, and Allen[12] both assumed charging fell into a ‘valley-filling’ pattern, or that PHEV owners charged during periods of low system demand, and subsequently drove enough that the charging filled the low system ‘valley’ periods to capacity. In the EPRI report PHEV charging was more driver-focused, employing a symmetric PHEV load pattern for an aggregate fleet that places about 75% of charging during off-peak, night hours, between 10pm and 6am. However, the study notes that this is just one possible scenario developed by heuristic driver assumptions such as primary home charging and incentivized off-peak charging. None of the models described utilized actual driver behavior to describe the time of charging, which may have a significant impact on the generating assets dispatched to meet PHEV electrical demand, and thus affect the emissions outcomes of the vehicles. The

PECM model was designed to determine time of charging from actual driver behavior (Subsection 3.1).

Many studies report that the adoption of PHEVs would increase or decrease air emissions but this seems to vary considerably by methodologies for emissions allocation, the treatment of electricity generation assets, the region being examined and the assumptions placed on the temporal location and magnitude of the electric load due to electric vehicle charging. An in-depth analysis examining PHEV infiltration level, with a more sophisticated PHEV charging model and a specific electricity generation mix tailored for Michigan has yet to be completed and can provide a more complete understanding of impacts to the region and how similar methodologies might be applied to other regions to inform policy development.

2.2 Research Objectives

This study analyzes the potential impact that PHEVs will have on the environment and includes the following two main objectives:

1. Understand the impact of widespread PHEV adoption on full fuel-cycle greenhouse gas (GHG) emissions from a Michigan light-duty vehicle fleet perspective.
2. Model the impact of a high level of PHEV adoption on air pollutant emissions in Michigan.

Overall emissions, both greenhouse gases and criteria air pollutants, will depend on the level of PHEV infiltration within the fleet, time of charging, and changes to the electricity generation mix over time. The model, to be discussed in later sections, also examines changes in non-renewable and renewable energy resource utilization as a consequence of PHEV adoption, tracking petroleum displacement, total fossil fuel cycle energy consumption, and renewable energy use from wind, water, biomass, and other sources.

The results of the study are intended to inform the MPSC about the potential environmental benefits and consequences of PHEVs and the impacts of bringing on new electricity generation assets and regulating dispatch decisions to meet increased electricity demand from PHEV charging.

Figure 9 describes the organization of the PHEV Pilot Project and highlights the relative position of this study within the overarching pilot structure.

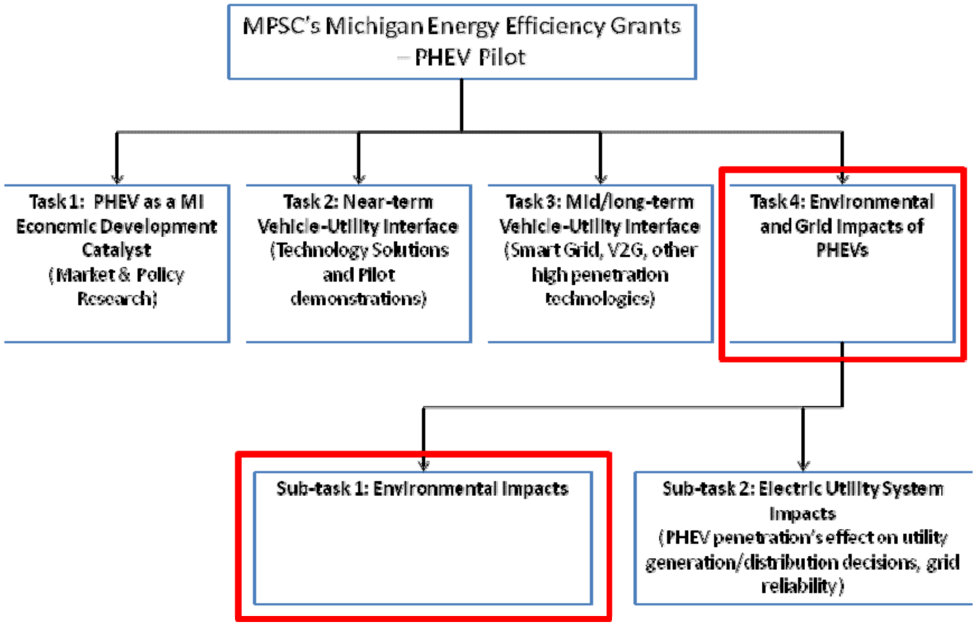

Figure 9. Project organization diagram of MPSC PHEV pilot project

2.3 Scope and System Definition

The geographic boundary of this study is the state of Michigan, and the vehicle fleet and power generation initial conditions for the model are based on Michigan-specific data. Predictions, such as population changes or vehicle fleet growth, are also based on Michigan-specific data. Emissions from imported power sources and upstream processes, which occur out of state, but can be attributed to Michigan consumption, are also tracked. The timeframe for the analysis spans 20 years, from 2010 to 2030, with the first year, 2009, developed based on current data without PHEVs or new power plants. A longer timeframe was not investigated to reduce greater uncertainties in projections and results. Each year is simulated with 364 days in order to have a year length of exactly 52 weeks, which simplifies analysis.

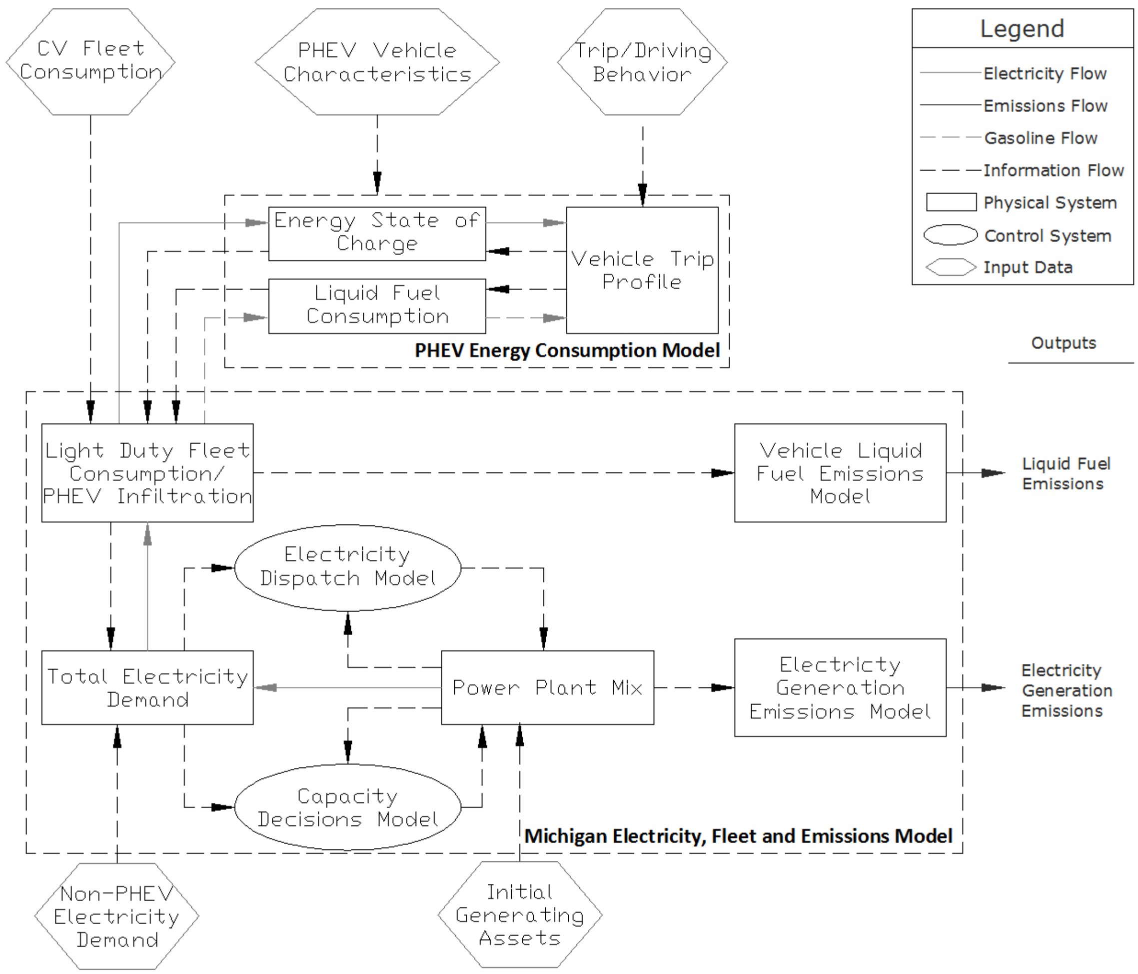

Figure 10. High level schematic of overall system structure

Figure 10 shows the system model as an overview of the information and energy flows within the system. The *PHEV Energy Consumption Model* (PECM) was built to simulate the energy consumption of a single PHEV. The output of PECM is used by the *Michigan Electricity, Fleet and Emissions Model* (MEFEM) to simulate the electric demand of a large group of PHEVs in hourly resolution. MEFEM was designed to simulate the potential interactions and effects that an increasing number of on-road PHEVs would have on overall vehicle fleet emissions, including the interaction of additional electricity demand with the electricity dispatch system and generating assets in the state of Michigan. Scenarios that varied the infiltration levels of PHEVs, the types of new generating assets, the method of electricity dispatch, and the charging behaviors of drivers were simulated, the results presented and the implications discussed within this report.

2.4 Report Organization

This report is organized as follows: Section 2 described the related literature and context for the present research and defined the objectives, purpose and system structure of the study. Section 3 discusses the modeling method in detail. Section 4 defines and documents the scenarios examined to provide context for the results. Section 5 contains the results of the simulations and discusses their implications. Section 6 concludes the main body of the report with a discussion of key findings and policy implications and suggestions for further research in the discipline.

3. Methodology

This section provides a description of the MEFEM and PECM models developed for this analysis. The desired outputs of the combined model are energy use and greenhouse gas and criteria pollutant emissions from vehicle use and electricity generation. Figure 10, on page 19, is a schematic of data and information flow within the model. The model is based on many publically available datasets, represented as hexagonal inputs on the diagram, which feed into their designated simulation modules and are either fed back as additional inputs to complementary systems or serve as components in the output emission calculations. The roles and details of the major system modules are discussed in the subsections below. Within the methodology section, subsection 3.1 focuses on PECM, while subsections 3.2 through 3.4 are devoted to MEFEM. Subsection 3.5 discusses the assumptions for emissions and energy metrics and how these are allocated to PHEVs.

3.1 PHEV Energy Consumption Model

The PHEV Energy Consumption Model (PECM) is used to determine fleet average electricity and gasoline use normalized to a single vehicle. This model uses trip data from the 2009 National Household Travel Survey (NHTS)[14] to generate the daily profiles for vehicle charging and total gasoline use. Results are generated for seven vehicle size classes under specified charging constraints. These results can then be scaled by the number of PHEVs in each class in the Michigan light duty vehicle fleet to obtain aggregate PHEV fleet consumption.

3.1.1 PHEV Characterization

In PECM, PHEVs are assumed to be in one of four operation states at all times: Parked and not charging, parked and charging, driving in charge depletion mode, and driving in charge sustaining mode. To describe a PHEV's operation in each of these states, they are characterized by their battery size, the average rate that they consume electricity on the road, and their average liquid fuel economy. Battery size is measured in kWh and has a default value of 10.4 kWh of usable energy for all vehicle types. 10.4 kWh represents a 16 kWh battery being utilized for 65% of its SOC range, which would approximate a 40 mile range in a midsize vehicle. Consumption characteristics are assigned based on average values for vehicle size classes and are given in Table 2. PECM examines PHEVs in seven size classes, corresponding to the EPA's light duty vehicle classifications. These include subcompact, compact, midsize car, large car, van, SUV, and pickup. Each class has associated average electricity and fuel consumption values taken from academic, OEM publications, and EPA fuel economy statistics[15]. Please see Appendix F for a comprehensive discussion on defining the vehicle characteristics.

Table 2. PHEV consumption parameters

Size Class	Electricity Consumption (kWh/mi)	Fuel Economy (mpg)
Subcompact	0.240	50
Compact	0.246	43.5
Midsize Car	0.274	32.8
Large Car	0.3	26
Van	0.346	26.14
SUV	0.330	26.14
Pickup	0.372	21

3.1.2 The National Household Travel Survey

The 2009 National Household Travel Survey[14] is the primary source of information used to determine driving behavior for PHEV users in PECM. Survey participants were asked to keep a log of information about their daily trips during one day. The survey has over one million entries that include trips by walking, biking, public transit, light duty vehicles, and larger vehicles. It contains a variety of information including household demographics, when the data was collected, and information describing each trip. The specific data that the model uses from the NHTS is the day of the week, the vehicle class, an identifier for the vehicle driven, the start and end times of each trip, the trip distance, the trip destination, and a weighting factor for the vehicle. The NHTS data required processing before being entered into PECM. It was sorted such that all trips that did not pertain to light duty vehicles and those that were missing important information or were duplicates of other vehicle trips were removed. A household weight factor from the NHTS vehicle file was added to the NHTS trip data so that each vehicle's trip day was weighted by that vehicle's use pattern. The data was then partitioned into subgroups by vehicle class and day of the week.

The NHTS only has four classes that correspond to the seven EPA size classes identified for use in the simulation: car, van, SUV, and pickup truck. The NHTS car vehicle class is used as the basis for the trip behavior for the EPA classes sub-compact, compact, midsize car, and large car in PECM. Appendix E relates size classes in the NHTS with their EPA counterpart. More than 700,000 vehicle trips are input to PECM from the NHTS via 28 matrices, one for each day (7) and class (4) combination.

3.1.3 Vehicle Trip-days

To determine how a PHEV would be driven and charged, the model groups the trip data by vehicle. Figure 11 shows visual depictions of a grouping of twenty nine trips by the five vehicles that took them. The trip information in the NHTS indicates when the vehicle was on the road, how far it went, and where it parked. Since each participant was only surveyed for one day, the assumption is made that the vehicle's final location at the end of the day is also the vehicle's starting location at the beginning of the day. Information on vehicle location and how long the vehicle will rest informs the model on whether or not the vehicle would be charging at a particular point in time. The model takes a single day's travel for each vehicle and tracks the vehicle's on road energy consumption and battery charging.

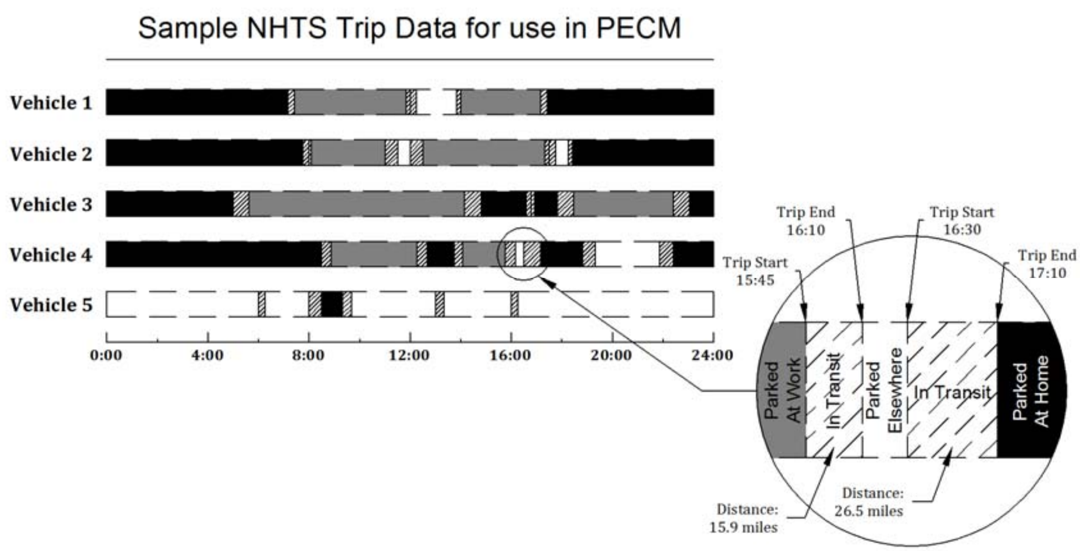

Figure 11. Vehicle trip-day depictions of NHTS data

3.1.4 Modeling PHEV Energy Consumption

To determine the average energy consumption of a PHEV in a particular size class, the model tracks the energy state of charge (eSOC) for each vehicle trip-day in the NHTS for that class and day of the week. It then aggregates all of the gasoline usage and electric power consumed for charging on a minute resolution. These values are normalized by the weighted number of vehicles used in the aggregation. This is performed for each day of the week, and then a weekly profile is created for that size class. The weekly profile is repeated 52 times to get a single PHEV electricity and gasoline consumption profile for an entire year. The model outputs unique vehicle charging profiles and annual gasoline consumptions for each of the seven size classes.

Tracking eSOC for each vehicle in the NHTS allows approximation of the timing and energy consumption for a vehicle undergoing the specific use pattern described by an NHTS trip-day. Vehicles are assumed to begin the day at 100% useable energy state of charge. When a trip is begun, electricity is consumed at the rate specified by the vehicle size class characteristics and by the trip's average speed. The eSOC is calculated at the end of the trip and recorded. Equation 1 describes the slope of the vehicle n's consumption of electricity while on a trip. $C_n(t)$ is the energy state of charge of vehicle n, D_{trip} is the distance of the trip, e_n is the average rate of electricity consumption of vehicle n, E_{batt} is the size of the usable battery, and t_{start} and t_{end} are the start and end times of the trip, respectively.

$$\frac{dC_n}{dt}_- = (-1) \cdot \frac{D_{trip}}{t_{end} - t_{start}} \cdot \frac{e_n}{E_{batt}}$$

Equation 1

If the vehicle finishes the trip at a location where it is allowed to charge and it is not restricted by any of the other charging constraints imposed by the model, it begins to charge at a rate specified at the start of the model run. It will charge until the next trip in the trip-day or until the vehicle's battery is at 100% usable state of charge. The rate of charging, $\frac{dC_n}{dt}_+$, is described in Equation 2. I_c is the current that vehicles charge at, V_c is the charge voltage, η_{ch} is charging efficiency, and $\mathcal{P}_n(t)$ can be thought of as the charging load of vehicle n on the grid at time t.

$$\frac{dC_n}{dt}_+ = I_{ch} \cdot V_{ch} \cdot \eta_{ch} = \mathcal{P}_n(t) \cdot \eta_{ch}$$

Equation 2

Figure 12 shows the SOC profile for the trip-day for sample vehicle 1 shown in Figure 11. In the eSOC plot, the vehicle takes four trips and charges at 12A, 120V when it arrives at home at the end of the day. Charging efficiency in PECM is set to 88%[11, 16]. This profile was developed using the same set of charging constraints as the baseline charging scenario as outlined in Section 4.

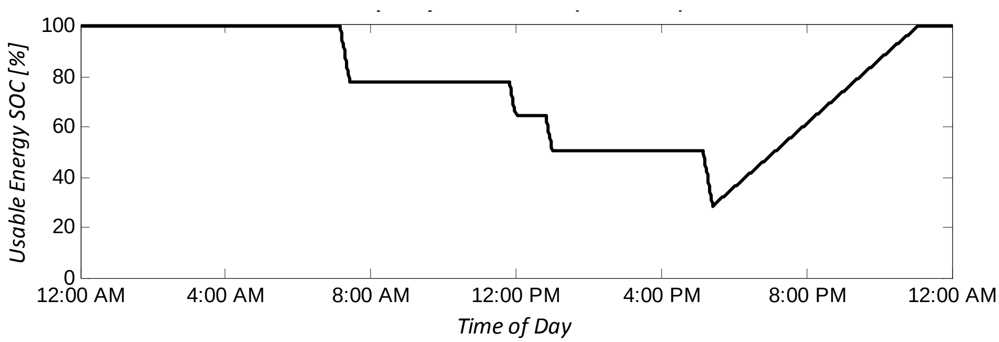

Figure 12. Energy SOC plot for sample vehicle trip-day 1

It is important to note that the fuel a vehicle consumes on the road, battery electricity or gasoline, is determined by the vehicle's mode of operation: charge depleting or charge sustaining. In charge depleting mode, the vehicle consumes solely battery electricity for propulsion. This is the default mode. Once the usable battery electricity is depleted (eSOC drops to 0% of its usable range), the vehicle switches to the charge sustaining mode. In this mode it operates very similarly to a standard hybrid vehicle, consuming only gasoline. The consumption of gasoline, ΔG_n, during charge sustaining mode is governed by Equation 3, below, where F_n is the fuel economy of vehicle n, D_{trip} is the distance of the trip, D_{elec} is the distance of that trip that was driven on electricity before the eSOC went to zero.

$$\Delta G_n = \frac{(D_{trip} - D_{elec})}{F_n} \qquad \text{Equation 3}$$

Figure 13 shows the eSOC plot for trip pattern of sample vehicle 3 from Figure 11. It indicates when the vehicle is operating in different modes. The PECM model assumes that all vehicles can drive in either of the two consumption modes for any drive cycle, and ignores a blended operation or speed limitations that may exist in some PHEVs.

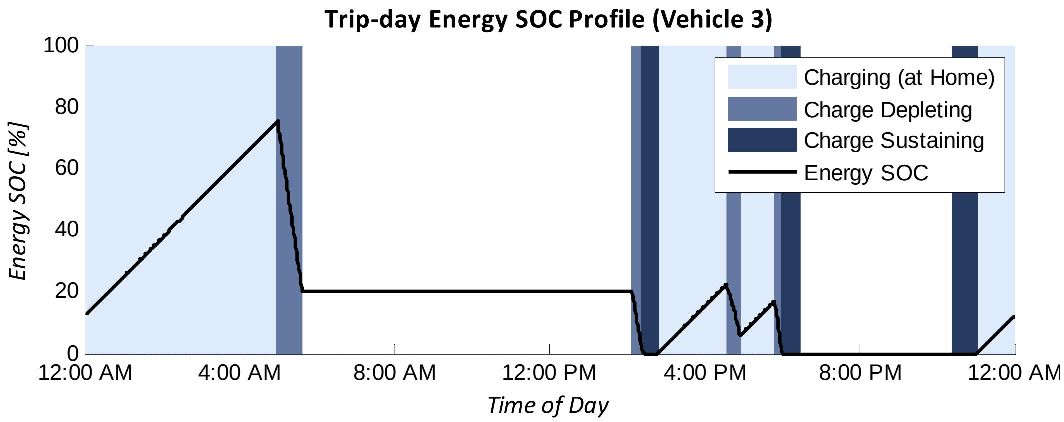

Figure 13. Energy SOC plot showing operational mode

In Figure 13, the vehicle does not start the day with 100% usable state of charge. This is due to an iterative procedure that ensures that the energy consumed by a vehicle on the road is reflected in the amount of gasoline consumed and electricity consumed to charge the battery. When a vehicle finishes a trip-day with an eSOC that is less than what it began the day with, the trip-day is repeated but the starting eSOC is assumed to be what the last iteration found as its final eSOC. If the vehicle was charging at the end of the last iteration, it will start the next one charging as well.

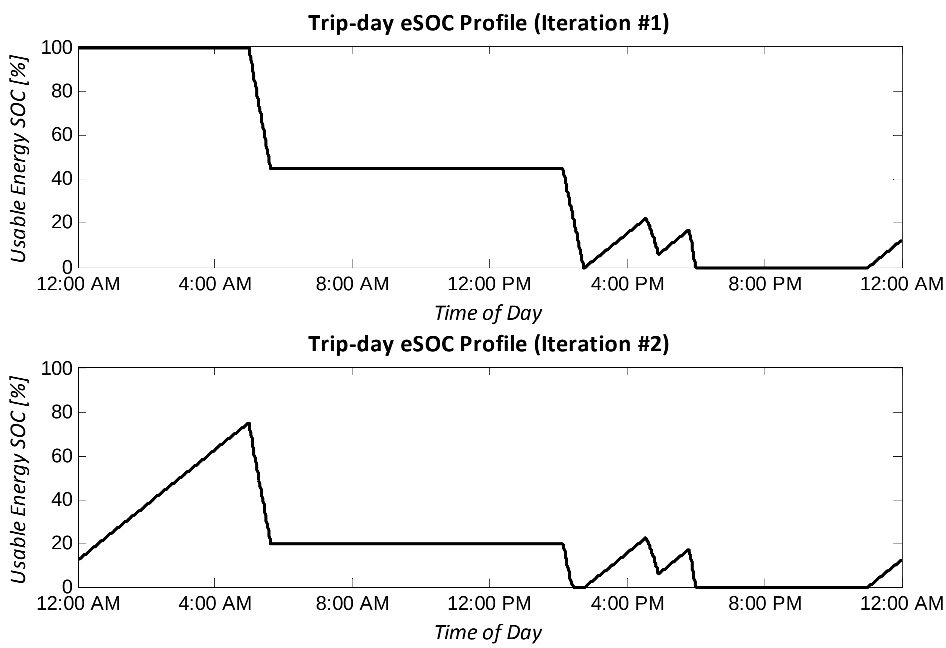

Figure 14. Iterative trip-day eSOC profile for Sample Vehicle 3

Figure 14 shows the iterative procedure for Vehicle 3's trip-day. The model required two iterations to account for all energy consumed by the vehicle on the road. In the first iteration, more of the second trip is in charge depleting mode. The iterations also show that the vehicle did not have enough time to completely charge overnight at the prescribed charge rate, this is not necessarily true of all iterated trip-days as many will be able to reach 100% eSOC overnight.

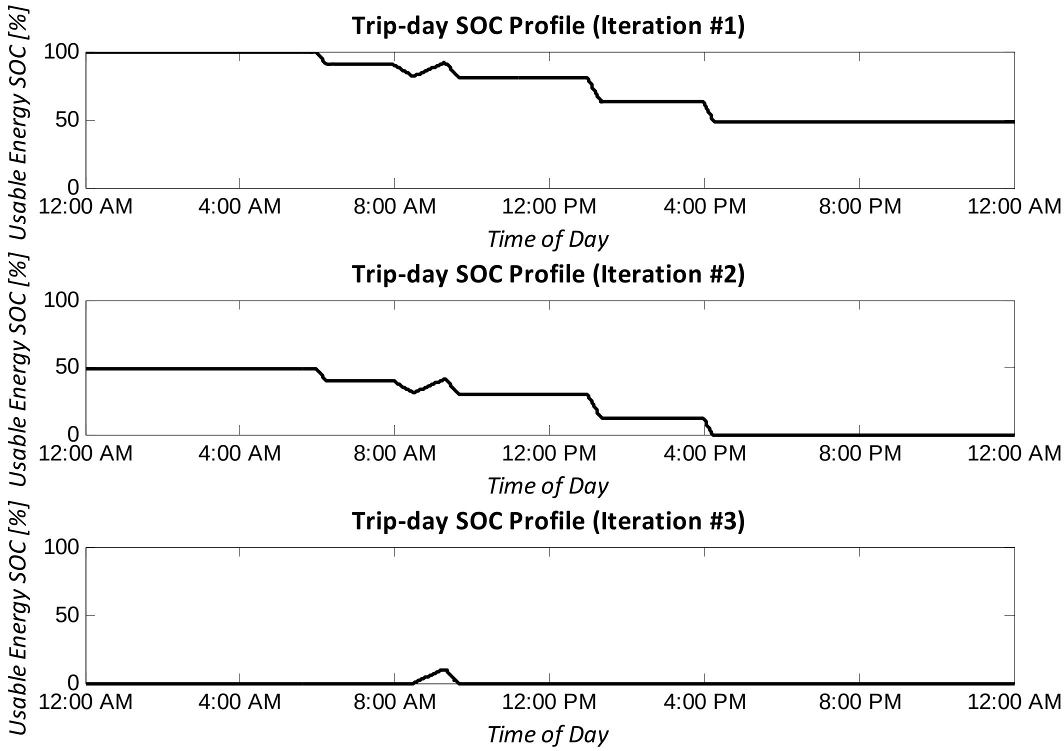

Figure 15. Iterative trip-day eSOC plot for sample vehicle 5

Some trip-days require more than a single iteration, as seen in Figure 15. Figure 15 shows the iterated eSOC profile for Sample Vehicle 5, which travels mostly on gasoline because it is not in a charging location for most of the day.

3.1.5 Charging Parameters and Constraints

PECM contains a number of parameters that can be manipulated to affect the time of charging and therefore the number of electrically driven miles that a fleet average PHEV undergoes. These charging parameters include vehicle characteristics, the rate of charging, and charging constraints. Charging constraints, which could be driven by utility price incentives, policy or technology limitations, include charging locations, minimum dwell time, charge onset delay, charging blackout periods, and last minute charging.

Charging rate - The power level at which a vehicle charges can dramatically affect the duration and the amount of battery charging. Charging rate is defined in terms of both the voltage and current of the charge. Voltage in the model can either be 120V or 240V, representing the two most common residential electrical circuits permissible in the United States. The 120V circuits are limited to 12A, which is a common wall outlet rating in the US, and the 240V circuits tend to be limited by the vehicle software themselves[17]. The project examines three potential charging rates: 12A at 120V, 8A at 120V, and 16A at 240V. These are based on published possible charge rates by OEMs[17].

Charging Location – This parameter defines where the vehicle is allowed to charge based on NHTS vehicle location data. The default charging location is only at home. Home and work charging is also examined.

Minimum Dwell time - The model can also mandate a minimum dwell time in which a vehicle must be at the charging location in order to begin charging. This represents the likelihood that a PHEV owner will choose not to plug in their vehicle if they do not intend to stay long at their location[18]. Preliminary PECM results showed that a minimum dwell time did little to affect charging outcomes, and minimum dwell time is not examined in depth in the study.

Charge Onset Delay - A delay on the start of charging can be enforced in the model. This exists to represent a period of time in which the vehicle may need to cool down before it is available to take a charge[4, 6].

Charging Blackout Period - The model can enforce time restrictions on vehicle charging. This is meant to represent a limitation on charging placed on customers by utilities, or a customer's wish to charge off-peak to reduce the cost of electricity. The user identifies a window of time, at an hourly resolution, in which a PHEV owner cannot charge their vehicle.

Last Minute Charging - The model can also choose to charge PHEVs at the last possible moment such that the vehicle still receives a full charge before it leaves for a trip. This has been suggested as the most effective way to prevent battery degradation in some lithium ion chemistries [19]and also has the added benefit, from an electric utility's point of view, of pushing much of vehicle charging to off-peak times. This implies that the vehicle owner has the ability to schedule the time of the vehicle's next trip, and that vehicle software waits to charge until the 'last minute' while still guaranteeing full charge at the start of the trip. If there is not enough time between trips to charge the battery fully, it charges for the entire duration the vehicle is parked at a charging location.

3.1.6 Aggregation and Normalization

After PECM completes a vehicle trip-day, it adds the weighted vehicle's charging profile and gasoline consumption to the running aggregate. Once the program has simulated all the vehicle trip-days for a specific day and class, it normalizes them by the weighted number of vehicles that the sample represents. Equation 4 describes this aggregation and normalization of the charging profile (a similar process is done for gasoline consumption), where $\mathcal{P}_{day}(t)$ is the aggregated and normalized hourly charging pattern for PHEVs, N_{NHTS} is the number of vehicles in the sample, $\mathcal{P}_n(t)$ is the charging pattern of vehicle n, and w_n is its weight factor.

$$\mathcal{P}_{day}(t) = \frac{\sum_{n=1}^{N_{NHTS}}[\mathcal{P}_n(t) \cdot w_n]}{\sum_{n=1}^{N_{NHTS}}(w_n)} \qquad \text{Equation 4}$$

Figure 16 shows the charging for each trip-day, for each sample vehicle. Each vehicle's charging is assumed to be on at full power instantly, which explains the binary behavior of charging with time in the figure. Figure 17 shows those sample trips weighted, aggregated, and normalized. Certain vehicles have more influence on the charging pattern than others due to their weight factor. By comparing Figure 16 and Figure 17 it can be seen that sample vehicle 4 has the most dominant charging pattern, implying it has the largest weight factor.

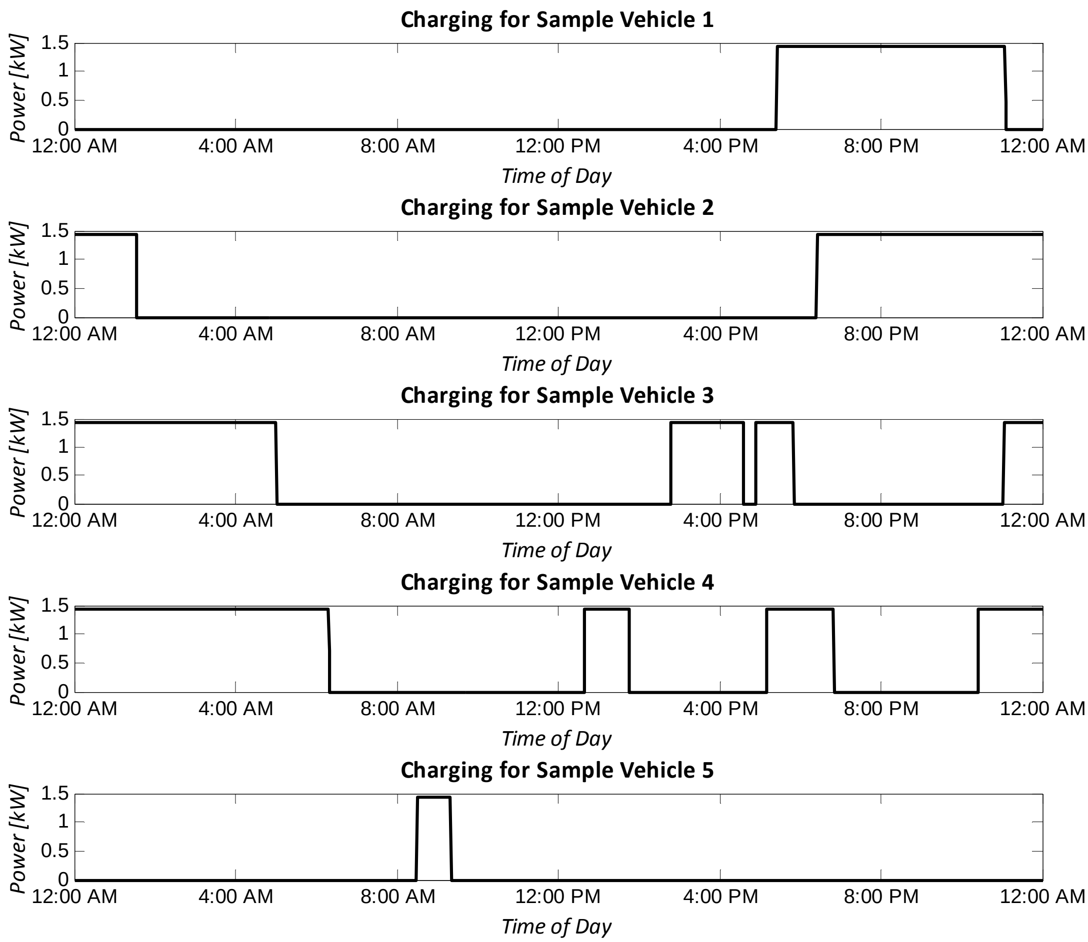

Figure 16. Charging for profile for each of the sample vehicle trip-days

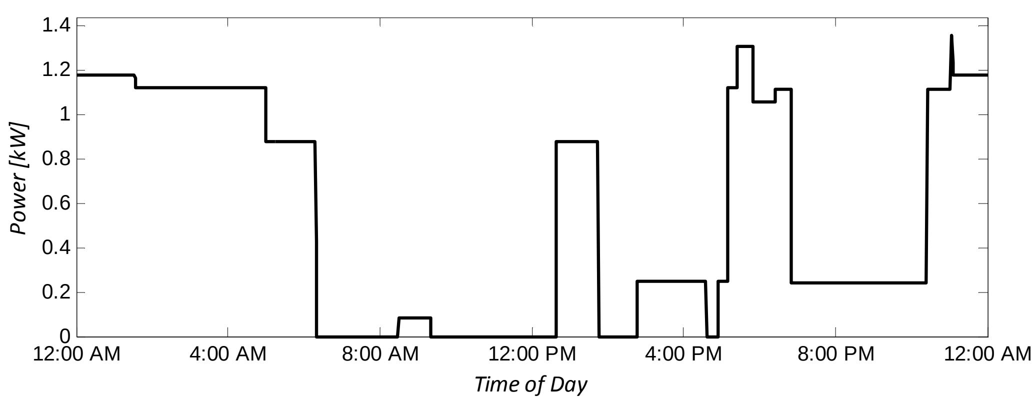

Figure 17. Weighted, aggregated, and normalized charging profile for sample vehicle trip-days

Figure 18 is an example of a weighted, aggregated and normalized charging pattern for a Tuesday that uses the entire set of car trips from the NHTS for that day. When the sample size gets large, the aggregate smoothes out and displays a discernable pattern for vehicle charging.

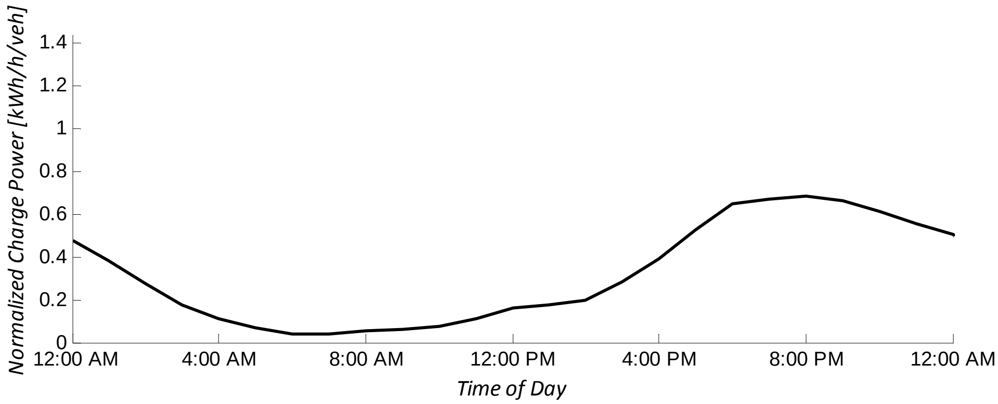

Figure 18. Normalized aggregate charging profile for a complete NHTS sample

This process of aggregation is repeated for each day of the week. The daily profiles are then combined to create a vehicle class' charge profile for an entire week. The model assumes that there is no seasonal changes in driving patterns and thus replicates these weekly charging profiles over the course of a year. The charging profiles generated by PECM do not reflect the actual charging pattern of a single vehicle. However, they approximate the aggregate charging behavior of a light duty vehicle fleet when multiplied by the number of vehicles in each class.

Source List

Vehicle Travel Behavior	NHTS[14]
PHEV Consumption Characteristics	Appendix F
Charging Efficiency	Academic Publications [11, 16]

3.2 Michigan Light Duty Vehicle Fleet Modeling

After the electric and gasoline consumption parameters for individual PHEVs have been determined these are then scaled to the greater fleet. Vehicles are tracked by size class, with different initial vehicle sales, sales rates, infiltrations, consumption parameters, and new vehicle conventional fuel consumptions for subcompact, compact, midsize, and large passenger car sizes, and van, SUV, and pickup sizes. A diagram of the vehicle class mapping method can be found in Appendix E.

3.2.1 Distribution of vehicles

In this study, plug-in vehicle infiltration is modeled as a function of sales. This approach differs from previous studies, which simply estimate PHEV counts as a percent of on-road vehicles. New vehicle sales for the year 2009 were determined by comparing the number of new-model-year vehicle registrations in Michigan between May 2008 and May 2009. For the years following 2009, vehicle sales were extrapolated using regional sales data from the 2009 Annual Energy Outlook (AEO)[20]. Each year, a portion of these sales are designated as PHEVs according to the selected infiltration scenario. Detailed information regarding infiltration scenarios is provided in Section 4.2.

Each year the number of total vehicles, both conventional and plug-in, is determined by two values: population and vehicles per 1000 people. These figures, taken from the Michigan Census[21] and Michigan motor vehicle registrations [22], are specified in Equation 5 with the symbol 'Nall'. The assumption is made that the number of conventional vehicles is the number of total vehicles less the number of PHEVs (N_{PHEV}) in that year. The conventional vehicle fleet includes conventional hybrids.

3.2.2 Conventional Vehicle Consumption

The 'business as usual' total gasoline usage by internal combustion vehicles was determined through application of a 'stock miles per gallon,' (F_{stock}). This represents the average fuel consumption parameter for all on-road conventional vehicles. For the year 2009, this number is determined by examining total gasoline consumption in Michigan, a value which was extrapolated from gasoline tax receipts and vehicle miles traveled from traffic volume trends. Both datasets are part of the Federal Highway Statistics series[23]. For years beyond 2009, an improvement factor is applied, which mimics the removal of older, less efficient vehicles and the introduction of newer, more fuel efficient vehicles (including conventional hybrids). This yearly improvement factor (I) is based on the improvement of the 'stock mpg' as reported in the AEO[20], but with an initial fuel economy that better reflects the Michigan population. Miles driven per vehicle in the simulation is a result of PECM, abbreviated as (M).

Since PHEV purchases replace new conventional vehicle purchases, the amount of avoided gasoline cannot be determined from this stock mpg, as the new vehicles are more efficient than the average fleet. Therefore, the amount of gasoline that would have been consumed in a year, at year 'y' called 'avoided gasoline' or ΔG, is determined by multiplying the number of PHEVs by the projected new vehicle fuel consumption from the AEO[20] for each size class (F_{new}). Note that PHEVs are assumed to retire after 10 years in the vehicle fleet; therefore the total avoided gasoline is for all the PHEV sold in the current year as well as the previous ten years. The number of PHEVs sold as well as the new vehicle fuel economies are individually calculated for each size class.

Gas consumption for on-road conventional vehicles (G_{CV}) for a year, 'y', is determined by subtracting the avoided gasoline (ΔG) from the total gasoline consumption (G_{BAU}) as shown in the following equation:

$$G_{CV}(y) = G_{BAU}(y) - \Delta G(y)$$

$$G_{BAU}(y) = \frac{N_{all}(y)M}{F_{stock}I(y)}$$

$$\Delta G(y) = \sum_{k=y-10}^{y} \frac{N_{PHEV}(k)M}{F_{new}(k)}$$

Equation 5

3.2.3 Plug-in Vehicle Consumption

PECM outputs the annual gasoline consumption and a normalized charging demand curve for each vehicle size class. Both of these parameters are then scaled by the number of PHEVs in each size class. The net PHEV electric demand is then increased by 1.09 for transmission and distribution losses [24] and then added to the base electric demand. Consumption information has been used in a PHEV versus CV analysis, found in Appendix L.

Source List

Initial vehicle sales	MI motor vehicle registrations [22]
New Vehicle sales rates	AEO 2009 [20]
Yearly Population	MI Census [21]
Vehicles per 1000 people	MI motor vehicle registrations [22] , MI Census [21]
Initial total gasoline consumption	Federal Highway Statistics [23]
Initial total vehicle miles traveled	Federal Highway Statistics [23]
Stock improvement	AEO 2009 [20]
New Vehicle fuel consumptions	AEO 2009 [20]

3.3 Electricity Generation Capacity Changes

Electricity generation capacity changes refer to the power plant retirements or the addition of new plants to the MI electricity grid. In MEFEM, the initial list of generating assets, based on those reported in the eGRID 2005 database[25], can be seen in Appendix A and changes to this generating capacity occur at the start of each simulation year. Retirements occur first, followed by additions to meet Renewable Portfolio Standards (RPS) and lastly, additional capacity to meet the reserve margin requirement imposed on utilities by the Midwest Independent Service Operator (MISO) is added.

Before delving into the details of Electricity Generation Capacity Changes and Electricity Dispatch, three important parameters that affect a power plant's behavior must be defined and discussed: Nameplate Capacity, Capacity Factor and Availability Factor. A power plant's size is generally defined as the plant's Nameplate Capacity, referred to in equations as $P_{N,NPC}$, which is the maximum instantaneous power output of the *n*th power plant. Theoretically, if a power plant runs at its maximum throughout an entire year, it should provide a total electricity generation E_{max} of

$$E_{max} = P_{N,NPC} \cdot t_y$$

Where t_y is the length of year in hours. A power plant running at maximum for an entire year is unlikely due to maintenance requirements and varying load levels, but E_{max} does provide an upper limit to the amount of electricity a plant can generate. Capacity Factor is the fraction of the theoretical maximum electricity generated that was actually produced in a year, referred to in equations as f_N

$$f_N = \frac{E_{actual}}{E_{max}}$$ **Equation 6**

This is a value that varies significantly between plants, and is due to the real world economics of power plant dispatch. In a given year, older plants that are less efficient to run will tend to have lower capacity factors than new power plants. Plants that run on relatively expensive fuels such as natural gas will have lower capacity factors. Plants whose power output levels are difficult to change, such as nuclear plants and coal, will likely be used to meet baseload and thus have very high capacity factors. The eGRID capacity factors are used as an input to MEFEM.

Finally, Availability Factor is the fraction of the year that the plant is operational. This is referred to in equations as a_N. Availability factor can be thought of as a practical limit to capacity factor that ignores economics. Even if a plant would be economically inclined to run at E_{max}, scheduled and unscheduled maintenance would still require the plant to shut down at times. The only exceptions are plants with uncontrollable outputs, such as wind, because their power output cannot be relied upon due to the varying nature of the wind, and as a result the availability of wind power is low. Availability factor is treated as a constant throughout all power plants of the same fuel type.

3.3.1 Generating Asset Retirements

In MEFEM, a retirement refers to the scheduled partial or complete decommissioning of a particular generating asset. The retirements are defined based on the age of each asset, as outlined in the Capacity Need Forum's (CNF) 21st century report [26]. The CNF makes the assumption that generating assets will be retired at 70 years of age. In some electricity generating capacity scenarios (discussed in subsection 4.2), MEFEM employs a more aggressive retirement schedule for coal-fired generating assets. In this accelerated retirement schedule, the baseline schedule from the CNF is supplemented by a list of retirements that occur at age 60 in addition to the retirements that already occur at 70 years. A list of the retirements for both the baseline and accelerated decommissions are found in Appendix B.

3.3.2 Generating Asset Additions to Meet Renewable Portfolio Standards

New plants are brought online for one of two purposes: to meet Renewable Portfolio Standard (RPS) requirements or to maintain a 15% reserve capacity margin. An RPS requires that a percentage of total annual electricity must be generated from renewable resources. MEFEM identifies four resources that are considered renewable and satisfy RPS generation requirements: biomass-fired, hydroelectric, wind and landfill gas. While this is not a comprehensive list, other renewable resources, such as solar and geothermal, are not as viable in Michigan, and thus are not explicitly included in the model. MEFEM employs one of two RPS conditions: either based on an extended MI RPS or on California's RPS. The extended MI RPS begins by following the specifications of the 2008 Michigan Clean, Renewable and Efficient Energy Act (PA 295) Part 2, Subpart A[27], which specifies renewable goals for years 2012 – 2015. It then is extended by linearly interpolating to 20% in 2025, which represents a target proposed by Governor Granholm[28].

In order to calculate the deficit in renewable energy generation for a particular year, existing renewable energy, in MWh, is calculated as the product of the existing renewable generating assets' name plate capacities, their capacity factors and the hours in a year. For any given year, the deficit in renewable energy generation to meet the RPS requirements, E_{need}, is calculated from the equation:

$$E_{need}(y) = R_{goal}(y)E_{demand}(y) - E_{Rgen}(y)$$ **Equation 7**

Where $E_{Rgen}(y)$ is the annual amount of renewable energy generation using current assets, $E_{demand}(y)$ is the amount of total energy demand for the current year, and $R_{goal}(y)$ is the fraction of net generated electricity to be met by renewable sources. New renewable capacity is built if E_{need} is greater than zero.

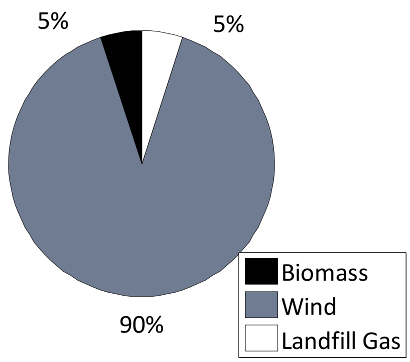

Figure 19. RPS fuel mix for capacity additions.

The type and size of renewable plants built are based on generation percentages derived from renewable energy plan averages published by DTE Energy and Consumers Energy[29-30]. The nameplate capacity of each renewable plant built is based on predetermined capacity factors for new assets. The capacity factor for new wind plants is derived from NREL's Wind Research Assessment[31] while those for the other options come from EPRI's 2007 Technology Assessment Guide Reference Data [32].

3.3.3 Generating Asset Additions for Reserve Margin

Once MEFEM has completed any required additions to meet the year's RPS, it begins the calculation of additional generating capacity to satisfy the reserve margin requirement. Unlike RPS, which is based on energy requirements, the reserve margin is a power based metric. The reserve margin is the difference between available generating capacity to meet peak demand, in kW, and the maximum hourly demand. Reserve margins are an important component of capacity planning because they ensure adequacy and reliability of the electricity supply. The 15% used in this model is the planning reserve margin dictated by MISO[33]. In the model, a generating asset's available capacity to meet peak demand is equivalent to the product of its nameplate capacity and the fuel-type specific availability factor. This factor was taken from industry average data from the North American Electricity Reliability Corporation's (NERC) Generating Availability Data System[34]. Each simulation year, the amount of capacity expansion necessary, P_{need}, to meet marginal reserve requirements is calculated from the equation:

$$P_{need} = (1 + m)P_{peak} - P_{cap}$$ **Equation 8**

In Equation 8, P_{cap} is the sum of the available capacity to meet peak demand of all generating assets. Available capacity is defined as the nameplate capacity of an asset multiplied by the plant's availability factor. The other variables, P_{peak} and m, are the maximum hourly electricity demand for the given year and the reserve margin requirement (equal to 0.15)[35], respectively.

New capacity to satisfy margin is added according to a percentage mix which varies depending on the year and the selected 'grid mix' scenario, discussed in subsection 4.3. This percentage mix combined with the availability factors assigned to each fuel type is then used to determine the reserve margin power and hence nameplate capacity to be built for each additional generating unit. This altered generating capacity mix can now be dispatched to meet demand for the current year.

3.4 Electricity Dispatch Modeling

Once the total electric demand is quantified and all the power plants are defined, the plants must be dispatched in order to serve this hourly load. In practice, this is a very complicated undertaking based on physical and economic constraints. As precise economic data is proprietary information, the dispatch in this model does not attempt to simulate a true dispatch system, but seeks to approximate electricity dispatch in two separate ways. One method, the *Capacity Factor Dispatch* model, uses historical power plant performance to forecast how power plants will be used in the future. Another method, the *Economic Dispatch* model, uses cost predictions to determine which power plants will be used first. Both of these methods have their advantages and disadvantages and both will be examined to determine the sensitivity of PHEV electricity emissions to dispatch method.

In the model, the electric demand is managed as a point source independent of geographical location or transmission constraints. While this lack of spatial information may introduce error into the simulation results, the addition of new generating assets to the system makes it to difficult to accurately model at this level of complexity.

Wind and hydroelectric plants are dispatched before all other generating assets. Their dispatch is effectively modeled as changes to the total electricity demand. Wind assets are treated as a must-run and are implemented as negative demand in the model. Hydroelectric generating assets are only operated at times of peak load and are thus dispatched as peak shavers after wind generation has been dispatched. Pumped hydroelectric plants also increase demand in the hours of minimum demand to account for pumping load.

After wind and hydroelectric load modifications, all remaining power plants are dispatched based on a stacked power system. The remaining plants are ordered, or 'stacked', by either their capacity factor or the cost of generation depending on the type of dispatch algorithm employed. Each of these assets are then assigned a range of system electrical load, termed here as a power band, which represents the required minimum levels of hourly system load under which a given plant will be dispatched to generate electricity.

A power plant's power band is defined with two values, $L_{N,min}$ and $L_{N,max}$, where *N* indicates the location of the current power plant in the dispatch order. Let $D_H(t)$ be the system electric demand after wind and hydro, and let $P_N(t)$ be the output of the *Nth* power plant at any time *t*. $P_N(t)$ will be:

$$P_N(t) = \begin{cases} 0 & if\ D_H(t) < L_{N,min} \\ D_H(t) - L_{N,min} & if\ L_{N,min} < D_H(t) < L_{N,max} \\ L_{N,max} - L_{N,min} & if\ D_H(t) > L_{N,max} \end{cases} \qquad \text{Equation 9}$$

Since there are no geographical and transmission constraints, this stacked power system effectively keeps only one power plant running at partial output, with all other power plants either on or off completely. "On" in this case refers to the power plant outputting $L_{N,max} - L_{N,min}$, which is less than the plant's nameplate capacity. It is possible that the highest power level that the generating assets can provide (the maximum value of $L_{N,max}$) is actually below the highest level of electric demand. If this is the case, the deficit is assumed to be met from outside the state as imported electricity. This can be thought of as an additional power plant with its own emission factors. This system of electric dispatch assumes that all power plants can come online instantaneously, are capable of following load perfectly, can shut down instantaneously, and do not have any minimum output levels.

A convenient way to represent the electric demand and the effect of Equation 9 is by using a load duration curve. In it, the electric demand profile $D_E(t)$ is sorted in descending order, from highest to lowest power demand. This will be differentiated in equations by using $\ddot{D}_E(t)$. In this representation of electrical demand, chronological time has been replaced by the duration of time at which the system is greater than the corresponding load value. The area under the curve, representing the net electrical demand at the generating sites, is still the same. This area can be divided up into horizontal stacks which graphically represent the power bands, thus the name “stacking” dispatch. Figure 11 shows a sample load duration curve with three power plants for illustration purposes.

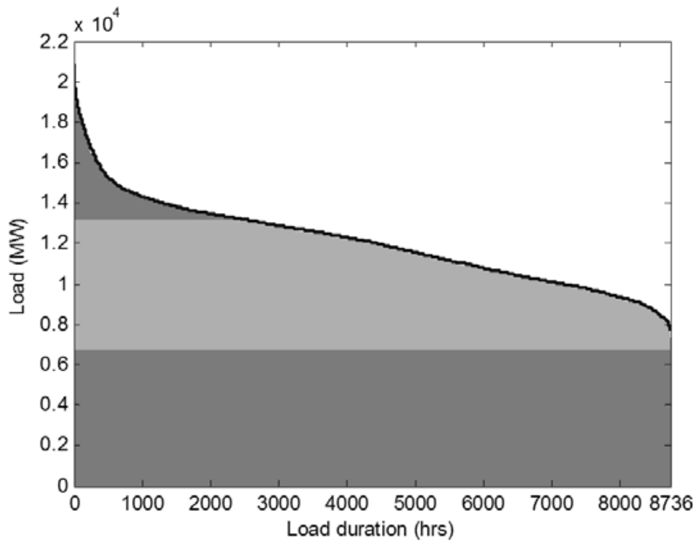

Figure 20. Load duration curve example with 3 plants

Under this method, the dispatch model can determine the power output of every power plant for every hour in each simulated year, which will be used to determine total electrical system emissions rate. The Capacity Factor Dispatch and Economic Dispatch models calculate the power bands differently. Capacity Factor Dispatch requires historical capacity factors for the initial year to determine what power bands would be needed for that year. It then scales the power bands for the changing load and asset mix for all future years. The power plant electricity generation of the base year will be exactly equal to its historical amount. The downside of Capacity Factor Dispatch is that by extrapolating a single year's dispatch behavior it assumes that all of the market and fuel supply conditions inherent in historical data are constant for the next 20 years, which is unlikely. The economic dispatch model sorts power plants by cost of generation and dispatches them to their available capacity. While being an inaccurate predictor of base year capacity factors, Economic Dispatch is capable of responding to changes in fuel prices and additional emissions taxation.

The entire electricity dispatch follows these steps, illustrated in Figure 21. Let $D(t)$ be the total electric system demand for a year.

1. Dispatch wind assets. $D(t)$ reduces to $D_W(t)$.
2. Dispatch hydroelectric assets and pumped hydroelectric storage assets. $D_W(t)$ changes to $D_H(t)$.
3. Determine the power bands for all remaining power plants using either Capacity Factor Dispatch or Economic Dispatch algorithm.
4. Dispatch all remaining power plants for an entire simulation year using Equation 9 and $D_H(t)$.

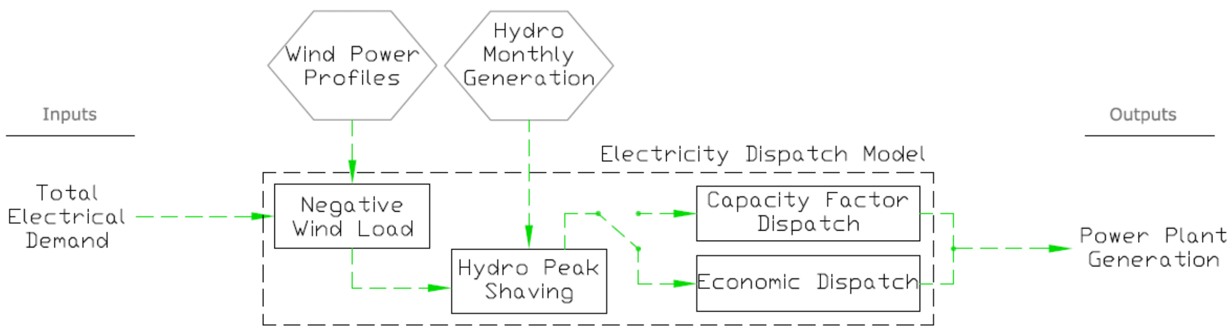

Figure 21. System diagram for electricity dispatch

3.4.1 Wind Assets

Wind assets are the first generating units dispatched, and are treated as a negative load on the system. The remaining system load is calculated as follows:

$$D_W(t) = D(t) - p_{wnd}(t)\left[\sum_{Wind} P_{KNPC}\right] \qquad \text{Equation 10}$$

Where $D(t)$ is the total electricity demand (baseload plus additional PHEV demand plus line losses), $p_{wnd}(t)$ is the normalized wind power curve and $D_W(t)$ is the remaining demand or system load that serves as an input to the hydroelectric dispatch model. The normalized wind power curve is analogous to capacity factor, but calculated hourly. The sum of the nameplate capacity of all the wind assets multiplied by this curve yields the hourly power output of all the wind assets in Michigan. Wind's yearly capacity factor, f_{wnd}, is calculated by integrating the normalized wind power curve and dividing by the simulation year length, t_y, as in Equation 11.

$$f_{wnd} = \frac{1}{t_y}\int_0^{t_y} p_{wnd}(t)\,dt$$

Equation 11

This is necessary for the capacity decisions model to correctly determine the amount of renewable energy output, and allows it to build the correct amount of wind when needed. Only one normalized wind output curve is to be used, meaning that all wind assets will have the same capacity factor for every simulation year. Although this could mean that current existing wind farms will perform better than expected, the only existing wind farm in Michigan as of 2005 is relatively small and thus is not a significant source of error. The normalized wind output curve comes from the NREL Wind Integration Datasets [31]. These were developed as part of a larger study to evaluate the impacts of large wind infiltration. This data was based on high-resolution simulations of the historical climate performed by a mesoscale numerical weather prediction. In Michigan, thirteen wind farms of varying nameplate capacity were simulated in 10-minute intervals throughout 2004-2006 (Figure 22).

In order to develop the normalized wind power curve, nameplate capacities of the sited wind farms were used to normalize each power output entry. Then, all three years for all thirteen sites were reduced to hourly resolution, and all 39 data sets (thirteen sites multiplied by three years) were then averaged to end with a single vector of 8736 values. This is $p_{wnd}(t)$ from the equations above. Since each simulation year is only 364 days, the last two days in the 2004 data and the last day in 2005 and 2006 data will be ignored.

Figure 22. The 13 Michigan sites simulated by the NREL wind integration dataset

The resulting normalized wind output curve has a yearly capacity factor of 29.8%. Figure 23 displays two weeks of this curve; one in January and one in June. In general, winter months have higher outputs than summer months.

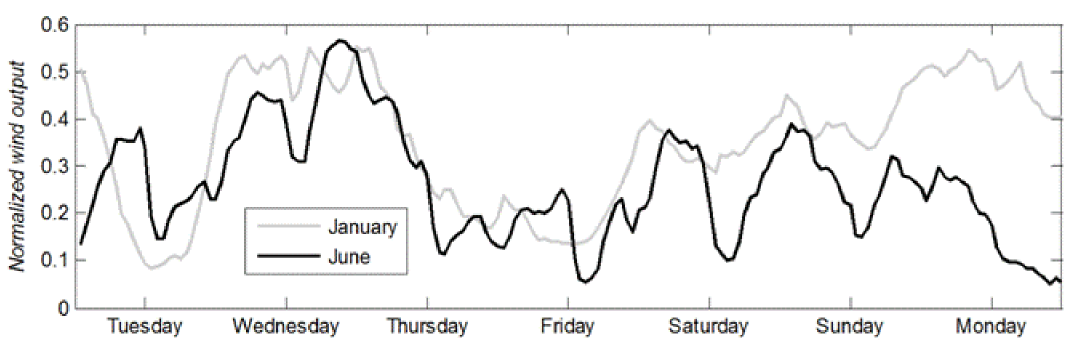

Figure 23. Sample of normalized wind power generation curve (week in Jan. and June)

The integration of wind into system dispatch effectively decreases the power demand curve. However, the variability of wind plant power output increases variability in the electric load. Figure 24 shows the effect of wind dispatch on the system electric load for four days.

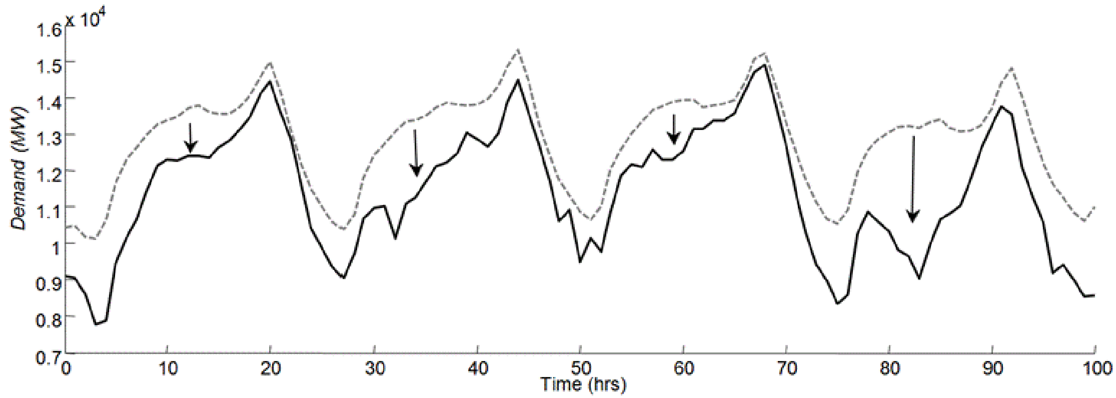

Figure 24. Wind dispatch's effect on system demand

3.4.2 Hydroelectric Assets

Like wind, water assets, such as run of river turbines and pumped storage dams are dispatched prior to the economic or capacity factor stacking dispatch. It is assumed that hydroelectric plants would be dispatched at times of greatest load, and are deployed to 'shave' the peak load. The amount of peak shaving that occurs is based on historical monthly generation values from 2005[36], thus assuming that the energy generated in 2005 is indicative of the energy that would be produced in subsequent years. No water assets are retired in the simulation, and no new water assets are brought online.

After the wind output is treated as negative load, the remaining load is split into monthly load curves, and the hydro assets are deployed separately each month. Within a month, the hours are sorted from time of highest to lowest demand to create a monthly load duration curve, $\ddot{D}_W(t)$. Since each hydroelectric plant is treated separately, a subscript $\ddot{D}_N(t)$ is defined to represent the electric demand that the Nth hydroelectric plant will dispatch to. $\ddot{D}_1(t)$ would then be equal to $\ddot{D}_W(t)$.

The peak shaving algorithm dispatches the hydroelectric plants in two ways. First, the plant dispatches at nameplate capacity until it reaches a duration level t_S, named the *split duration*. Then, the dispatch levels drop to zero following the shape of the demand duration curve. These two portions of dispatch will be named the *Nameplate Dispatch* and the *Decreasing Dispatch*, respectively. Let $\ddot{P}_N(t)$ be the sorted hydroelectric plant output for the Nth hydroelectric power plant:

$$\hat{P}_N(t) = \begin{cases} P_{N,NPC} & if\ t < t_S \\ \hat{D}_N(t) - [\hat{D}_N(t_S) - P_{N,NPC}] & if\ t \geq t_S \end{cases}$$ **Equation 12**

where $P_{N,NPC}$ is the plant's nameplate capacity, and $\hat{D}_N(t_S)$ is the demand at the split duration point (a constant value). Figure 25 shows an example of the electric dispatch for an exceptionally large hydroelectric plant using Equation 12, with the split duration occurring at about hour 75.

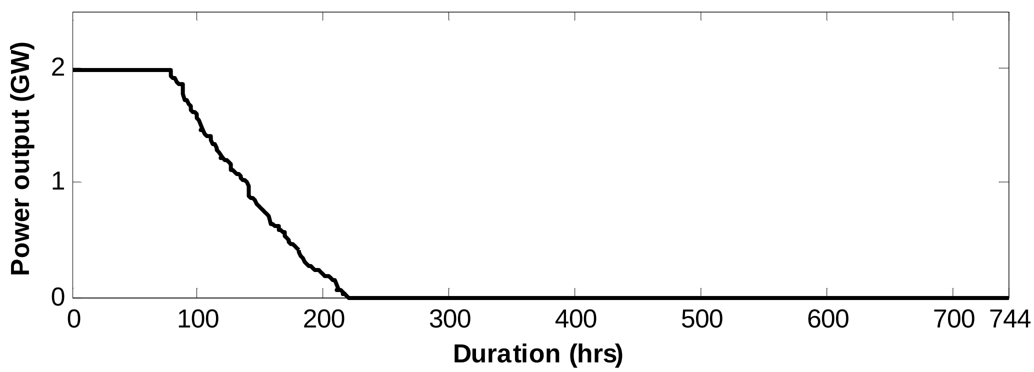

Figure 25. Example of the sorted dispatch shown for a very large hydroelectric plant.

From EIA form 906[36], the energy provided by each plant, E_N, for each month is known. The objective of the peak shaving dispatch model is to find the split duration point such that the energy output of the plant matches E_N:

$$E_N = \int_0^{t_m} \hat{P}_N(t)dt$$ **Equation 13**

t_m represents the number of hours in a month. The algorithm finds tS by starting with a tS value of one hour, and then increases tS by one hour until Equation 13 is met. Each hydroelectric asset is dispatched in this same manner, effectively reducing the demand as described in Equation 14:

$$\hat{D}_{N+1}(t) = \hat{D}_N(t) - \hat{P}_N(t)$$ **Equation 14**

The dispatch algorithm then moves onto the next hydro plant. Figure 26 demonstrates the effect that the example plant has on the sorted electric demand. The nameplate dispatch portion follows the electric demand curve perfectly: at each point, the electric demand is lowered by $P_{N,NPC}$. At the split duration point, the electric demand curve now flattens out at P_{min}: the electric demand curve at the split duration point minus the plant's nameplate capacity. The sum of the nameplate dispatch and decreasing dispatch areas will equal E_N. It is possible that the algorithm cycles through all possible split duration points and E_N is not met. The plant will run at nameplate capacity throughout the entire month, and the excess energy that was recorded will not be used in the model. This amounts to approximately a 6% error in hydroelectric energy output between historical generation as reported by the EIA in 2005 and the output of MEFEM.

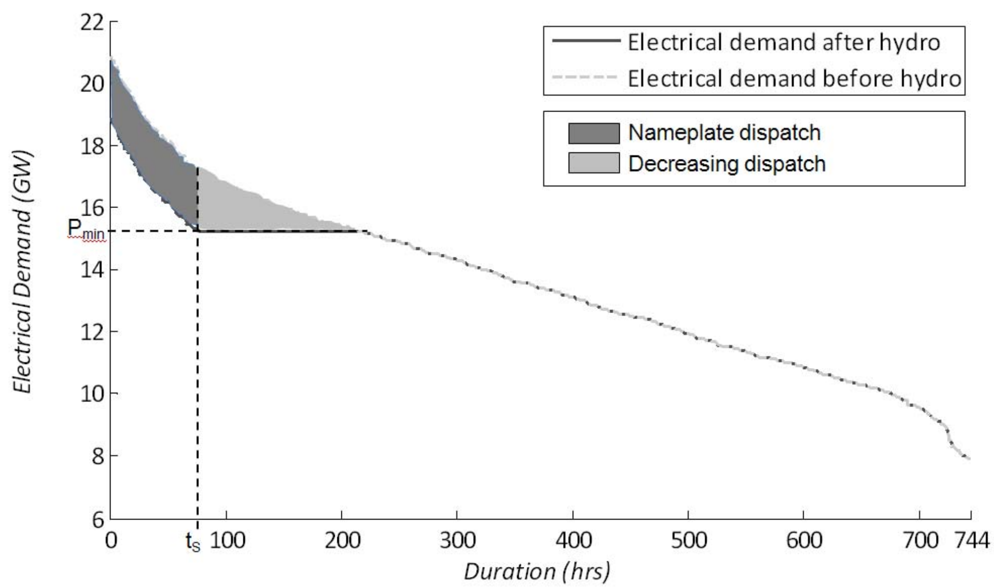

Figure 26. Effect of applying the sorted dispatch from Figure 25 to a July load.

This process is repeated for all hydroelectric plants. Then, after the last hydroelectric plant has been dispatched, $D_H(t)$ can be calculated via:

$$D_H(t) = D_{Max(N)}(t) - P_{Max(N)}(t) \qquad \textbf{Equation 15}$$

The load is rearranged into a chronological time arrangement, and this load is input to the stacking dispatch function (either Capacity Factor Dispatch or Economic Dispatch) for dispatch of the remaining generating assets. Figure 27 shows the initial sorted demand for July as the topmost sloping line, the dispatched run of river plants as the cascading lines below the initial demand, and finally the dispatched Ludington Pumped storage plant.

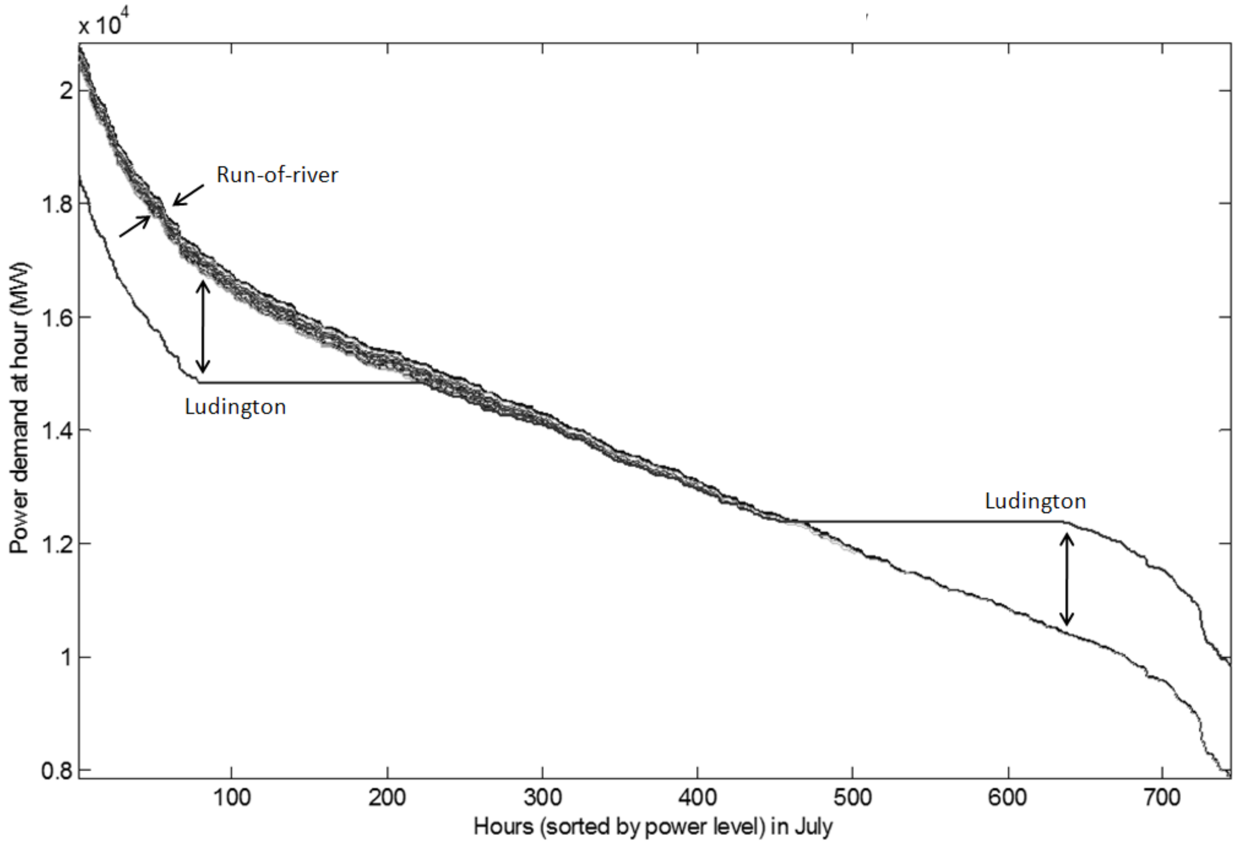

Figure 27. Sorted demand curve and hydro asset deployment

A key feature of the Michigan generation mix is the Ludington pumped storage plant, represented by the anomalous load duration curve in Figure 27. This plant, unlike the other run of river hydro assets, is an extremely large reservoir that empties out into Lake Michigan and pumps back up during cheaper generation times, assumed here as the times of lowest demand in the model. For all hours that power was delivered, the generator places additional demand in the 'off hours' according to the energy consumed for pumping[36], starting from the time of lowest demand. Figure 28 shows the new hourly load curve in bold, which has been 'flattened' after the hydroelectric dispatch. For the dispatch algorithm, Ludington is treated separately, and follows the same area fit algorithm but starting at the highest duration point and adding load instead of removing it.

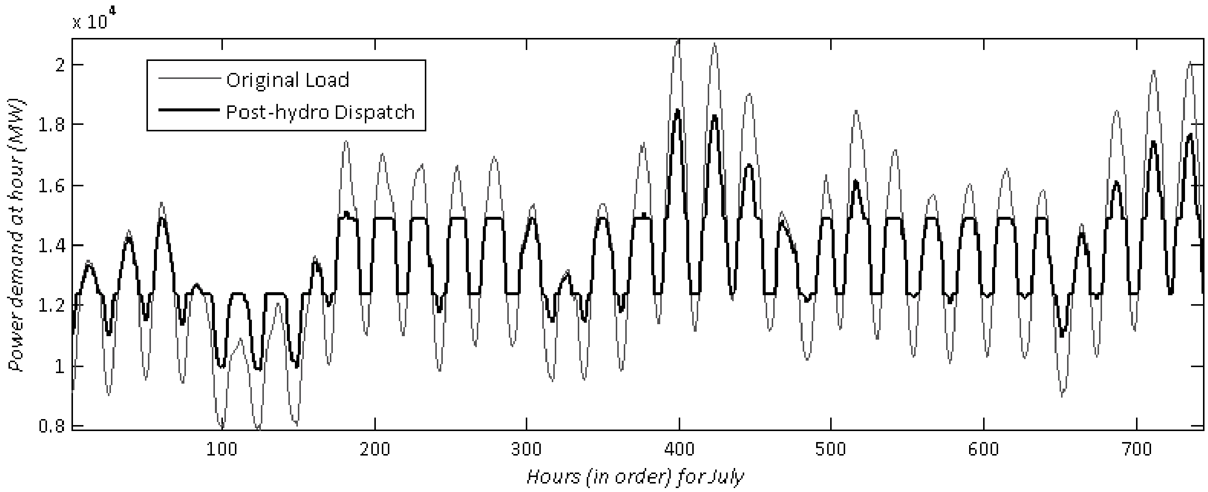

Figure 28. Unsorted original and post-hydro dispatch demand curve

3.4.3 Capacity Factor Dispatch

Capacity Factor Dispatch is based on each power plant's capacity factor for a given year, which implies the amount of electricity generated by that plant is known. In MEFEM, Capacity Factor Dispatch is accomplished using each plant's historical generation from 2005 [25] coupled with historical system electricity demand for that year [37]. The power plant stacking order is determined by capacity factor in descending order. The power bands calculated for 2005 are the basis for power bands in all other years, and are sized such that the power plant's yearly energy output exactly matches the historical amount:

$$P_{N,NPC} \cdot f_N \cdot t_y = \int_0^{t_y} P_N(t)\,dt \qquad \textbf{Equation 16}$$

Where f_N is the asset's historical capacity factor and $P_{N,NPC}$ is the plant's nameplate capacity.

Equation 16 and Equation 9 form the mathematical basis for the development of the power bands. The Capacity Factor Dispatch algorithm is written such that the size of each plant's power band meets both equations. An initial guess for power band size is made by:

$$P_{N,min} = \begin{cases} 0 & for\ N = 1 \\ P_{N-1,max} & for\ N > 1 \end{cases}$$

$$P_{N,max} = \begin{cases} P_{N,NPC} \cdot f_N & for\ N = 1 \\ P_{N,NPC} \cdot f_N + P_{N-1,max} & for\ N > 1 \end{cases} \qquad \textbf{Equation 17}$$

In Figure 29, a portion of a load duration curve focused on the lowest point is shown. This point is referred to as the minimum demand level. For all power plants whose upper power band limit is less than the minimum electric demand level, the size of their power band will be exactly as predicted in Equation 17, since they are running all year. However, for plants whose power band levels are located above the minimum electric demand level, the electric demand level dips below their maximum for some hours, and the plant's net energy output will be less than required (Equation 16 is not met). Figure 29, left, shows that plant A, at the initial guess of power band, will have a deficit in energy generation. The Capacity Factor Dispatch algorithm iteratively increases the size of the power bands, as shown in Figure 29 (right), until Equation 16 is met for all plants in the dispatch order. The increase in the power band shown in Figure 29 has been exaggerated for clarity.

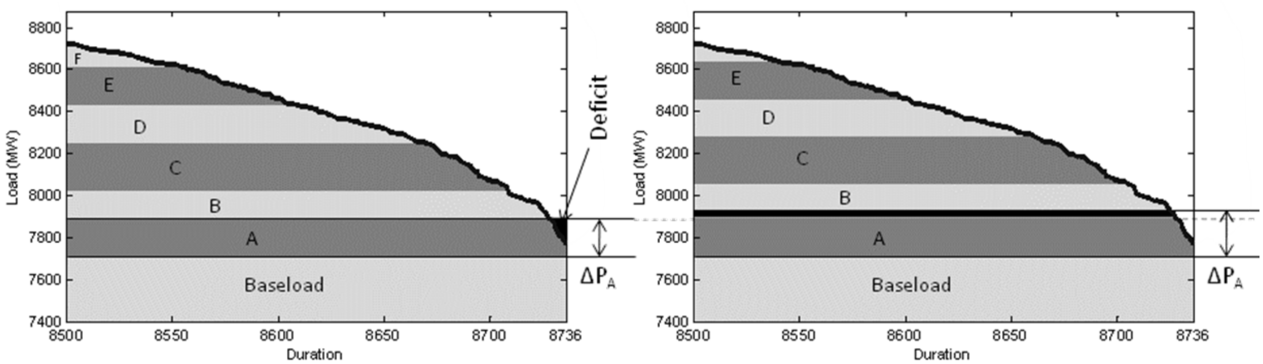

Figure 29. (Left) Original plant stack (Right) Increased plant A power band.

This iterative process is done for all plants in the stack. After calculating the power band for the last plant in the dispatch stacking order there remains a system energy deficit, which is assumed to be met by imported energy from the MISO system. The percentage of imported energy is calculated only once, in the base year 2005. It is then kept constant for all simulation years. This process is known as the initial stack and the resulting modeled capacity factors are exactly equal to the input capacity factors.

After the initial stack and imported energy percentage calculations are complete, the Capacity Factor Dispatch begins dispatching for all the simulation years; however, it must have a way to handle new power plants and changes to electric demand from year to year. New assets are given an assumed capacity factor in the capacity decisions module, which will determine their required output energy and their placement in the stack. The assets are once again sorted by capacity factor. The size of power bands from the previous year are used (in the case of 2009, the first simulation year, the previous year refers to 2005), but their placement changes since new plants push up plants that have a lower capacity factor. The area fit done for the base year is repeated on all new power plants such that Equation 16 is met with the new electric demand. Figure 30 illustrates a new plant added to the stack.

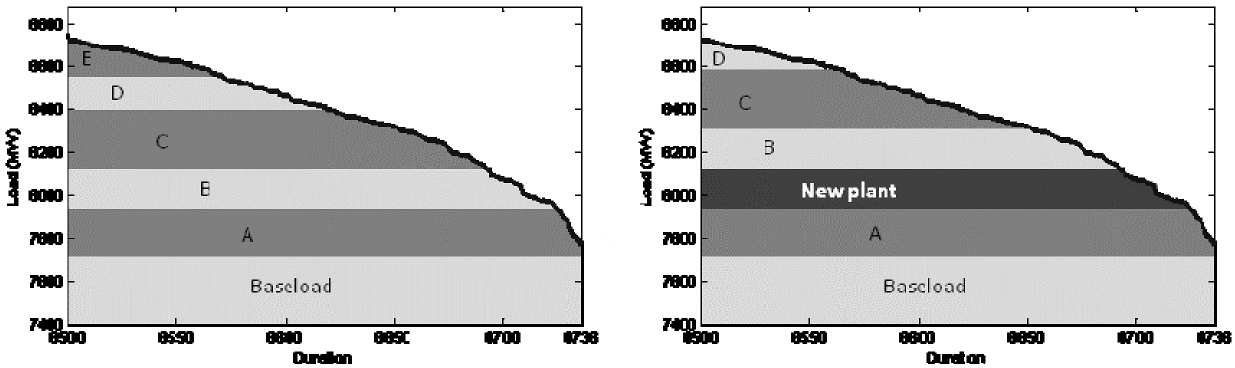

Figure 30. New power plant is added to the stack.

At this point, the percentage of imported energy will not be the same as before, since the electric demand levels have changed and the system's generating mix has changed (due to both new plants and retirements). The algorithm now determines the difference between the energy that would be imported if the current cumulative power bands were used and the amount of energy imported based on the imported percent. This difference in energy can translate into a difference in power using similar methods described in previous stacking functions. Once that difference in power is discovered, the power bands of all assets that are deployed at demand levels greater than the minimum hourly demand are multiplied by a single factor such that the imported energy calculated either of the two ways described above are equal. Figure 31 below shows this process of "squeezing" power bands for peaking plants. The power bands for all plants above minimum demand are either increased or decreased. The figure on the right, below, illustrates the case where their power bands have to decrease, either to accommodate newly built plants, or as a response to a decrease in overall system electric demand.

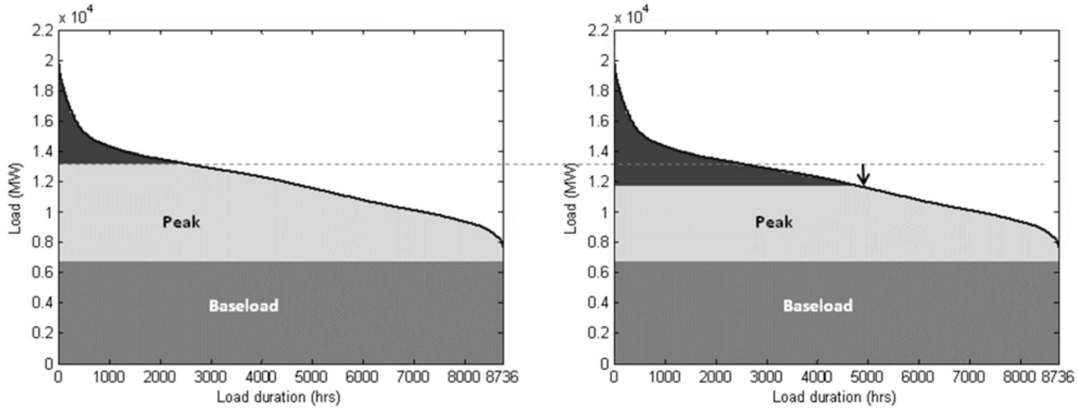

Figure 31. Changes in power bands to meet required imported energy percentage

3.4.4 Economic Dispatch

The economic dispatch algorithm creates a stacked dispatch order of generating assets based on their cost of generation. Cost is calculated for each power plant, the power plants are sorted from cheapest to most expensive to generate electricity, and then the power bands assigned are:

$$P_{N,min} = \begin{cases} 0 & for\ N = 1 \\ P_{N-1,max} & for\ N > 1 \end{cases}$$

$$P_{N,max} = \begin{cases} P_{N,NPC} \cdot a_N & for\ N = 1 \\ P_{N,NPC} \cdot a_N + P_{N-1,max} & for\ N > 1 \end{cases}$$

Equation 18

Where a_N is the plant's availability factor. No further refinement of power band size is required (as opposed to Capacity Factor Dispatch, where the requirements for power bands were different). Cost is calculated on a \$/MWh basis. The total cost of generation is the sum of fuel cost and emissions related costs. Fuel costs are calculated by:

$$\frac{C_{fuel}}{E_{gen}} = HR\left(\frac{C_{fuel}}{E_{fuel}}\right)$$

Equation 19

Where HR is the power plants heat rate, the ratio of fuel energy consumed per electrical energy produced; C_{fuel} is the total cost of fuel, and E_{gen} and E_{fuel} are the amounts of electricity generated and fuel energy consumed, respectively. Carbon dioxide cost is calculated by taking eGRID specific emission factors and applying global warming potentials from the IPCC 4th Assessment Report[38] to methane and nitrous oxide:

$$\frac{C_{GHG}}{E_{gen}} = \frac{C_{GHG}}{m_{GHG}}\left[\frac{m_{CO2}}{E_{gen}} + 25\frac{m_{CH4}}{E_{gen}} + 298\frac{m_{N2O}}{E_{gen}}\right] \qquad \text{Equation 20}$$

Finally, the total generating cost is:

$$\hat{C} = \frac{C_{CO2eq}}{E_{gen}} + \frac{C_{fuel}}{E_{gen}} \qquad \text{Equation 21}$$

The only exception to Equation 21 is the total generating cost of nuclear power plants. These costs are assumed to remain constant throughout the simulation and include operation and maintenance. All renewable plants are assumed to have no cost, thereby ensuring they are always dispatched. Units for cost are in $2008/MWh generated. Fuel prices can be found in Appendix D.

Source List

Heat Rates	EPA eGRID 2005 [25]
Emission Factors	EPA eGRID 2005 [25]
Fuel Costs	EIA Annual Energy Outook 2010 [39]
CO_2 Costs	American Clean Energy and Security Act of 2009 - *H.R. 2454 [40]*

3.5 Emissions & Life Cycle Metrics

The outputs of MEFEM are life cycle emissions and energy use for both vehicle liquid fuel consumption and electricity generation. The model tracks criteria pollutants: CO, NO_X, Pb, PM_{10}, SO_X and VOCs, and greenhouse gases: CO_2, CH_4, and N_2O. It aggregates GHGs using the most recent Global Warming Potentials[38] identified by the IPCC. It also tracks total fuel cycle energy for stationary and mobile energy generation sources. MEFEM applies emissions factors (kg/kWh of electricity or kg/gal of fuel) or a upstream energy factor (MJ/mmBtu of fuel input for electricity or MJ/gal of fuel) to the energy produced from each power plant and its heat rate or to the gallons of gasoline consumed to determine the total fuel cycle energy usage and emissions. Emissions factors are separated into both their upstream and combustion components so that they may be tracked separately.

3.5.1 Electricity Generation Energy and Emissions

The electricity system's total fuel cycle is described in Figure 32, where 'm' denotes atmospheric emissions and 'E' denotes energy flow. E_{User} refers to the site energy for electricity, consumer's actual meter reading. A constant transmission and distribution loss factor is applied of 1.09 ([24]), and this is treated as the electricity that power plants must generate, $D(t)$ from subsection 3.4. Note that manufacturing of plants is not included in this accounting.

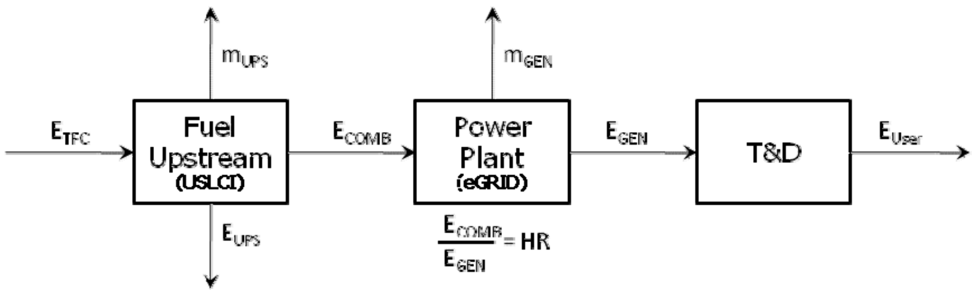

Figure 32. Total fuel cycle diagram for electricity production.

Emissions Factors

The total emissions from electricity generation are comprised of both combustion emissions and upstream emissions, as denoted in Figure 32. Combustion refers to the emissions released when the fuel is burned, while upstream refers to the emissions released while mining, drilling, refining the fuel, and transportation of the fuel from the extraction site to point of combustion. Upstream emissions factors for electricity are from the USLCI database [41] examined using the SimaPro software. Each of the eleven emissions types were determined in SimaPro by subtracting the "electricity, at power plant" process emissions from the sum of all life cycle emissions for these processes. The USLCI database does not specify a difference between PM2.5 and PM10, so all particulates are assumed to be PM10. Some emissions data was not reported in the same categories (for example, sulfur dioxide was reported by some processes as SO_2, and some as SO_X). To compensate for this, these datasets were summed to get a total for each emission factor. Combustion emissions factors associated with the generation of electricity are from two sources: eGRID and USLCI. The emission types provided by eGRID are NO_X, SO_X, CO_2, CH_4, and N_2O. These emissions were specific to each generating asset and are thus believed to be more representative than using average emissions data. National averages for CO, Pb, PM, and VOCs by source fuel type were used from the USLCI database using the same methodology as the upstream emissions because plant specific information was not available. It is assumed that national average upstream emissions for sub-bituminous coal are the same as those for bituminous coal. See Appendix G for a list of the ten emission factors used for existing plants averaged by fuel type.

Total Fuel Cycle Energy Factors

The factors for total fuel cycle energy were determined in SimaPro, using the USLCI database and Eco-Indicator 95 reporting methods. These factors include upstream energy from all coal, natural gas, crude oil, and uranium ore used in the entire fuel cycle of each power plant type. This upstream energy total was translated into a ratio of upstream energy to either combustion energy or generation energy. This ratio represents the national average for a total fuel cycle energy factor for each plant type. This factor, multiplied by a power plant's combustion or generation and added to the combustion energy gives that plant's total fuel cycle energy consumption. Wind, water and landfill gas generation are assumed to consume zero MJ of total fuel cycle energy, as facility manufacturing energy is not included in this model. Table 3 shows these upstream factors. Biomass and nuclear plants are based on generation energy, while fossil fuel plants are based on combustion energy.

Table 3. Upstream factors for power plants

	Coal	Natural Gas	Oil	Biomass	Nuclear
E_{UPS} / E_{COMB}	0.0217	0.05	0.027	N/A	N/A
E_{UPS} / E_{GEN}	N/A	N/A	N/A	0.0492	0.0207

Emissions Calculation

To calculate emissions, MEFEM applies the combustion and upstream emissions factors to the energy generation output from the electricity dispatch algorithm. MEFEM generates emissions for each power plant using eGRID emissions factors (for NO_X, SO_2, CO_2, CH_4, N_2O), its fuel type and the amount of energy usage representing hourly electricity generation for the entire simulation year. It applies the eGRID and national average emissions factors for each fuel type, both upstream and combustion, to the electricity generated for each power plant at each hour. The outputs are the annual and hourly upstream and combustion emissions for each power plant.

3.5.2 On-Road Vehicle Energy and Emissions

Gasoline's total fuel cycle is described in Figure 33, where 'm' denotes atmospheric emissions and 'E' denotes energy flow. Note that this fuel cycle diagram is simpler than that of electricity. Vehicle manufacturing emissions and energy are not included.

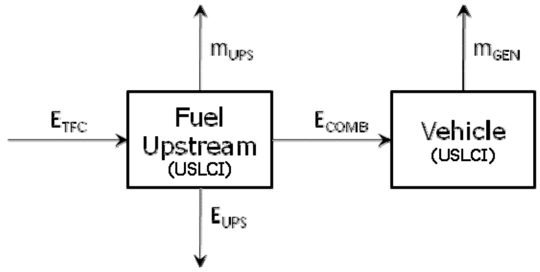

Figure 33. Total Fuel Cycle diagram for gasoline.

The total fuel cycle emissions from vehicular gasoline consumption are also comprised of both combustion and upstream emissions. The gasoline emission factors for both combustion and upstream activities used in this model are taken directly from GREET1.8c [42]. GREET does not capture lead emissions. Similarly, the total fuel cycle energy factors for gasoline are also derived from GREET1.8c using the default inputs. These factors are recorded in MJ/gal consumed.

Table 4. Emission factors for *one gallon of gasoline* for both upstream and combustion processes.

	CO (g)	NO_X (g)	PM_{10} (g)	SO_X (g)	VOC (g)	CO_2 (kg)	CH_4 (g)	N_2O (g)	GHGs (kg)
Combustion	87.6	3.30	0.679	0.140	4.21	8.82	0.351	0.281	8.92
Upstream	1.62	5.45	1.26	2.738	3.14	1.94	12.5	0.131	2.27

3.5.3 Allocation Methods

Vehicle consumption of gasoline fuel is a precise and unambiguous output. However, attributing electricity emissions and fuel cycle energy to vehicles is more complex. Once PHEV electric demand is quantified and added to the regular baseload demand, the dispatch and capacity additions model have no inherent way to allocate emissions to demand sources. This begs the question: given a source of large amounts of energy (i.e., the Michigan electric system) using multiple fuels, how does one allocate emissions to a small consumer (the PHEV users)?

In this study, two emission allocation methods are employed. In the first method, *Average Emissions*, the model tracks the electric power generation mix that exists in each hour of every simulation year. Then emissions associated with the specific hourly generation mix are calculated, normalized and applied to the hourly PHEV demand. Once each hour of a simulation year has been allocated, the total PHEV emissions from electricity generation are calculated. The second method, *Marginal Emissions,* compares the total electrical system emissions from baseline MI and PHEV electricity demand to the total electrical system emissions with only the baseline MI demand, allocating the difference to PHEVs.

Average Emissions

As previously stated, the system tracks the power output of each power plant at each simulation hour. Therefore, it is possible to calculate the total electricity system emissions for each simulation hour:

$$\dot{m}(t) = \sum_{N=1}^{all\ plants} \left(\frac{m}{E}\right)_N P_N(t) \qquad \text{Equation 22}$$

Where $\frac{m}{E}$ is the emission factor for the nth power plant, $P_N(t)$ is the hourly nth power plant output, and $\dot{m}$ is the total electricity emission rate. The units for the emissions rate, $\dot{m}$, are mass per hour. The PHEV load is also tracked on an hourly basis. The emissions assigned to PHEVs are calculated as follows:

$$\dot{m}_{PHEV}(t) = \frac{\dot{m}(t)}{\sum P_N(t)} P_{PHEV}(t) \qquad \text{Equation 23}$$

Total annual emissions for PHEVs, m_{PHEV}, are simply the sum of the emissions rate for all hours of the simulation year:

$$m_{PHEV} = \sum_{t=1}^{last\ hour} \dot{m}_{PHEV}(t) \qquad \text{Equation 24}$$

The effect of this allocation method is that a portion of the emissions of every power plant in the stack at that given hour are 'assigned' to PHEVs based on the proportion of PHEV to total load.

Marginal Emissions

In its simplest form, 'marginal emissions' refers to the difference between the emissions rates of two scenarios. Given the emissions for two separate model runs, Equation 25 would be used to calculate the marginal emissions for PHEVs:

$$m_{PHEV}(t) = m_1(t) - m_2(t)$$ **Equation 25**

Where m_1 has to be the total electric system emissions calculated in a scenario *with* PHEVs and m_2 is the total electric emissions calculated in a scenario *without* PHEVs. The effect of this allocation method is that the emissions of only the additional power plants that had to be 'turned-on' to provide power for charging are assigned to PHEVs.

4. Scenarios

As discussed in the methodology section, both the PECM and MEFEM models have many input parameters that are to be explored through scenario analysis. Each portion of the model has several inputs, such as the infiltration level, charging parameters, or new capacity grid mix, and the possible combinations of these are very large. Appendix C describes the forecasts of future baseline electricity demand with Michigan. In this section, a fixed set of inputs will be defined to create a small set of scenarios pertaining to 4 different aspects of the model: PHEV Fleet Infiltration, Electricity Generating Capacity, PHEV Charging, and Electricity Dispatch. Then combinations of these scenarios will be used to characterize the different model simulations for comparison of their results.

In order to define a model simulation, a code system will indicate the changed input examined. Each type of scenario is given a prefix, FI for fleet infiltration scenarios (subsection 4.1), EG for electricity generating capacity scenarios (subsection 4.2), CH for charging scenarios (subsection 4.3) and DM for electric dispatch method (subsection 4.4). After each prefix a number will be used to denote that particular scenario's set of input parameters which will be defined in their respective subsections. Subsection 4.5 will define the groups of simulations that will be analyzed and discussed in the results in Section 5.

4.1 PHEV Fleet Infiltration Scenarios

The magnitude of PHEV electrical demand depends on the number of PHEVs on the road. As mentioned in the Section 3.2, the number of PHEVs is determined by the number of vehicle sales each year which in turn is defined by the infiltration scenario selected for simulation. The annual new PHEV sales for each size, (N_{PHEV}) class is a function of the number of new vehicles sold in 2009 (S_{2009})[22], a sales growth multiplier (G)[20] and the proportion of sales that are PHEVs (termed PHEV infiltration rate, I). Equation 26 describes this relationship.

$$N_{PHEV}(y) = S_{2009}\, G(y)\, I(y) \qquad \text{Equation 26}$$

Each parameter is size class dependent, and the algorithm repeats this calculation for each of the seven size classes. Both the sales multiplier and the infiltration rate vary for each year of the simulation. The infiltration rates are what vary between scenarios. There are five infiltration scenarios, labeled zero, low, medium, high, and max PHEV Infiltration, shown in Table 5. While the infiltration curves for each size class are based on the same data sources, PHEVs can be purchased for some size classes earlier than others, based on the expected availability of commercial PHEVs to the public. Figure 34 displays a visualization of the different scenario's infiltration rates with time for the compact and midsize classes, where the first PHEVs are sold in 2010. For other size classes, the same curve is applied, but shifted so that the first PHEVs are sold in the appropriate year.

Table 5. Fleet Infiltration (FI) scenario inputs

Shorthand Title	Scenario Number	Infiltration equation	2030 Sales percent
Zero infiltration	FI1	Zero throughout	0%
Low infiltration	FI2	Directly from AEO data	3%
Medium infiltration	FI3	Equation 27	22%
High infiltration	FI4	Equation 28	58%
Max infiltration	FI5	Equation 29	100%

Note that Figure 34 shows only sales percentage, not on-road vehicle percentage. On-road PHEVs are shown in subsection 5.2.

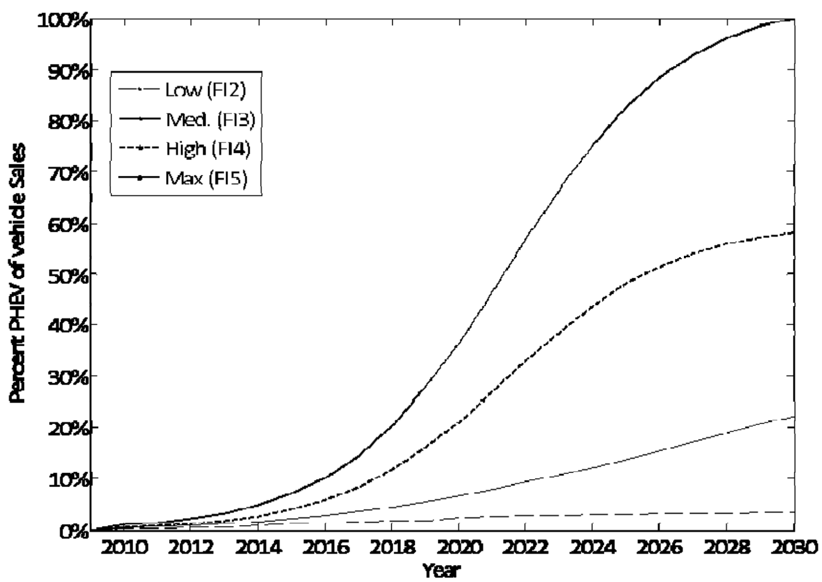

Figure 34. PHEV sales infiltration scenarios

The Zero PHEV infiltration scenario does not allow any PHEVs to be sold in the state over the length of the simulation. All vehicles in the light duty fleet are conventional, gasoline driven vehicles. This scenario is used as a baseline scenario containing the business as usual gasoline and electricity consumption and emissions.

The Low PHEV infiltration scenario is taken from the EIA's AEO 2009 projections for PHEV infiltration[20]. It is a conservative estimate that reaches a maximum of about 3% of new vehicle sales by 2030.

The Medium PHEV infiltration scenario is based on historical and projected conventional hybrid sales[43]. These projections are fitted to a logit market curve, reaching a maximum of about 20% of sales in 2030. Equation 27 describes the fitted curve, infiltration at year time 'y', where 0.6, or 60%, is the absolute maximum infiltration, which is not achieved in the model timeframe (60% in the medium scenario would occur in roughly 2090). The constant of 0.08 is a fitted slope parameter and the constant of 1.74 indicates an inflection point in which the inner sum becomes negative after 22 years causing a shift in the sales trend from exponential growth to arriving asymptotically to the maximum value of 0.6, which is not reached in the simulation:

$$I(y) = 0.6exp[-exp(-0.08y + 1.74)]$$ **Equation 27**

The High PHEV infiltration scenario is based on a scenario taken from a 2009 research report about PHEV potential for reduction of petroleum use[44]. The 2005 American Housing survey[45] states that in the Midwest, about 75% of homes are single family which would have plug-in availability. According to the NHTS, about 80% of households drive less than 55 miles a day [46], and thus would see a substantial decrease in fueling costs with a PHEV. Therefore, without taking into account the greater upfront costs for a PHEV, it would be rational for about 60% of the population to select a PHEV as their next vehicle purchase. Again, a logit model was created to mimic the technology adoption in the vehicle market, but with a dramatically faster ramp up to a roughly 60% market share achieved by 2030. Equation 28 describes the infiltration level 'I' for time at year 'y' in the High Scenario:

$$I(y) = \frac{0.6}{1 + 100exp(-0.4y)}$$ **Equation 28**

The Maximum PHEV infiltration scenario has the same rate of increase to maximum infiltration as the High scenario, but the maximum infiltration is increased to 100% (see Equation 29). While this is a highly unlikely scenario, the fast introduction of PHEVs to such a high proportion of sales brings many plug-in vehicles online within the model timeframe. This allows for clearer examinations of the interaction of PHEVs with the electrical system and the impact of very high PHEV infiltration.

$$I(y) = \frac{1}{1 + 100\,exp(-0.4y)} \qquad \text{Equation 29}$$

4.2 Electricity Generating Capacity Scenarios

Each year of the simulation, MEFEM checks to see if new electricity generating assets are required to satisfy RPS or reserve margin requirements as outlined in subsection 3.3. This change in the mix of assets in the system can affect the generators used to meet load due to PHEV demand. The size and type of the assets created to meet these requirements are dictated by the electricity generating capacity scenario being explored. Four scenarios are examined that influence the fuel mix of new generating capacity by altering the RPS and the mix of generating capacity used to meet the reserve margin.

A Renewable Portfolio Standard (RPS) is state legislation that mandates a specified portion of electricity generation to be met from renewable sources. In MEFEM, there are two possible RPS cases, one based on an extended Michigan RPS and one that is based on the California RPS. In the Michigan based RPS, the current legislation is used up to 2015, with targets for renewable generation being 2% by 2012, 5% by 2014, and 10% by 2015 [47]. In addition, the RPS is expanded in the model to include the proposed 20% of generation by 2025 due to the push for renewable energy jobs in the state [28]. An even more aggressive RPS scenario is loosely based off of the proportions and timing of the California standard, with 20% by 2016, 29% by 2025 and 33% by 2026. For years without a concrete target, the standards are interpolated between the two nearest goals. The percent of annual energy generation that is required to be from renewable sources is shown in Figure 35 for both scenarios. A set of scenarios investigating higher percentages of biomass electricity can be found in Appendix N.

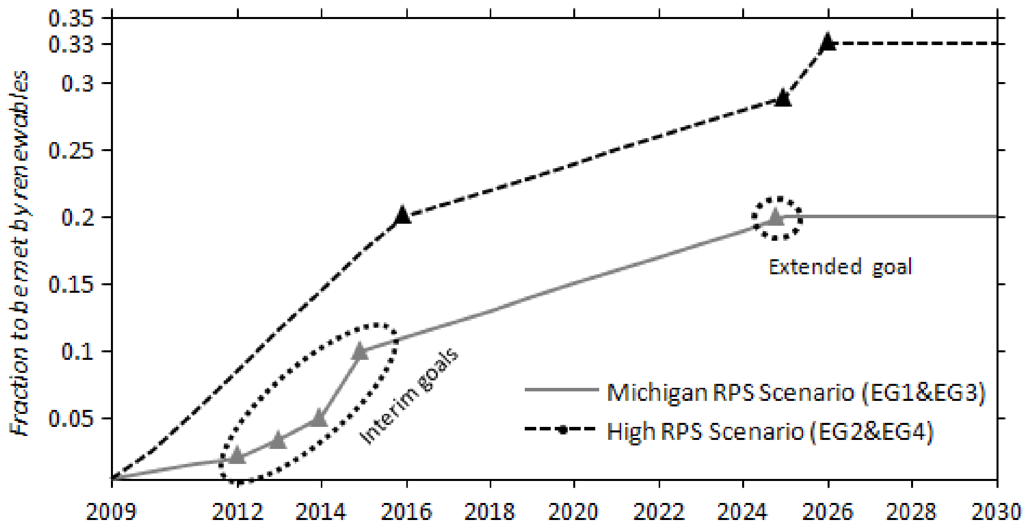

Figure 35. Renewable portfolio standard scenarios

New generating assets must be added to the grid to meet growth in peak electricity demand. The methodology discussed in section 3.3 outlines how much new capacity is added each ear. The fuel types of new plants are determined by the grid mix scenario. MEFEM has two possible grid mix scenarios. One option is based on the national trends in new generating capacity creation as reported by the EIA [20] and is labeled as the baseline grid mix scenario. The EIA only supplies data for the next few years for new capacity, so everything after 2012 is assumed to have the same proportional new capacity grid mix as 2012. The other grid mix option, named the high nuclear scenario, is identical to the baseline grid mix except that all new coal generation is replaced with nuclear capacity after the year 2018. In order to make a significant impact on the availability of nuclear generation, this scenario employs more rapid retirements of the existing coal plants in Michigan, as discussed in Section 3.3. Figure 36 shows the two scenarios' capacity mix by fuel type as a function of the simulation year. These values are input into the model to determine the proportional fuel mix of new generating capacity to meet peak demand.

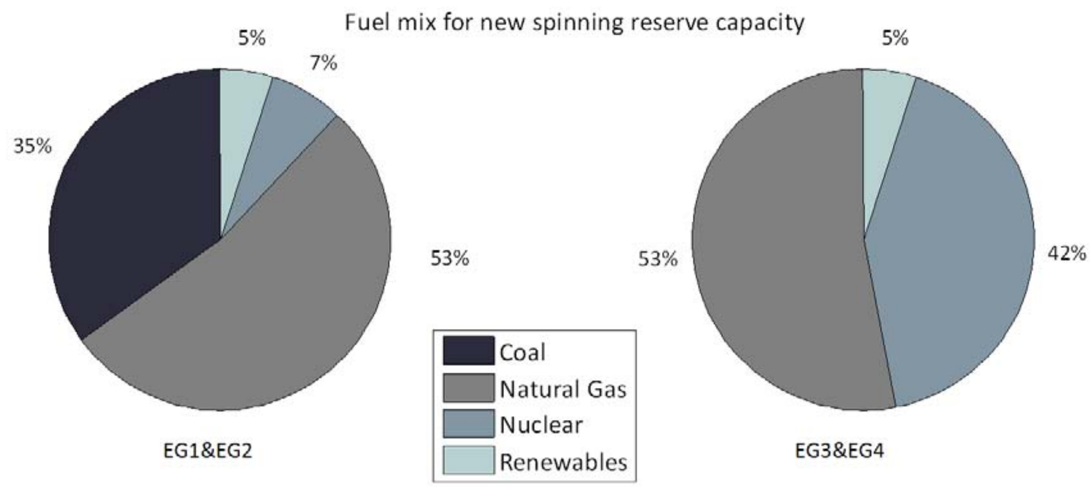

Figure 36. Grid mix scenarios

MEFEM has two possible RPS scenarios and two possible grid mix scenarios. Combinations of these two option sets define the electricity generating capacity scenarios. Table 6 identifies the four possible scenarios that are used in the model.

Table 6. Electricity generation capacity (EG) scenario inputs

Shorthand Title	Scenario Number	RPS	Grid Mix
Baseline	EG1	Michigan	Baseline
High RPS	EG2	California	Baseline
High Nuke	EG3	Michigan	High Nuclear
High RPS/High Nuke	EG4	California	High Nuclear

4.3 Charging Scenarios

While the magnitude of the aggregated PHEV demand is determined by the selected PHEV infiltration scenario, the shape of that demand is determined by the set of PECM inputs used to create the hourly normalized PHEV load. Eight charging scenarios were developed to focus on the differences in time and magnitude of PHEV charging demand due to changes in driver behavior, available charging infrastructure and proposed utility imposed charging restrictions or price incentives. As outlined in the methodology for PECM (subsection 3.1), the trip data is a set of actual trip schedules detailing when and where a person travels. A charging scenario is comprised of a set of nine values, one for each of the nine input parameters to PECM, each affecting the time, rate, and duration of the charging of an average vehicle. Those parameters are charging location (CL), battery size (BS), charging current (CI) and voltage

(CV), charge onset delay (CD), minimum dwell time (MD), lower (NL) and upper (NU) bound of the no charge window, and last minute charging.

The baseline charging scenario (CH1) represents the case in which a vehicle owner charges only at home and begins charging as soon as they arrive. Charging occurs at the standard household wall outlet rate of 12A, 120V. The battery size is loosely based on that of a Chevrolet Volt with a 65% eSOC swing, yielding a usable battery size of 10.4 kWh. This scenario is considered the baseline because it requires no adjustments, at home or at the utility, to infrastructure, and charging is only available to drivers at home. Table 7 details the PECM model input parameters for every scenario.

Table 7. Charging (CH) scenario inputs to PECM

Scenario Name and Number		PECM Inputs								
		CL	BS (kWh)	CI (Amp)	CV (Volt)	CD	MD	NL	NU	LM
Baseline	CH1	Home	10.4	12	120	0	0	None	None	No
Last Minute	CH2	Home	10.4	12	120	0	0	None	None	*Yes*
Home & Work	CH3	*Home & Work*	10.4	12	120	0	0	None	None	No
Window	CH4	Home	10.4	12	120	0	0	*1pm*	*7pm*	No
Slow	CH5	Home	10.4	*8*	*120*	0	0	None	None	No
Fast	CH6	Home	10.4	*16*	*240*	0	0	None	None	No
Fast, H & W	CH7	*Home & Work*	10.4	*16*	*240*	0	0	None	None	No
1/2 Battery	CH8	Home	*5.2*	12	120	0	0	None	None	No

The last minute charging scenario (CH2) uses the same inputs as the baseline charging scenario, but shifts the charging load to the last possible minute while ensuring a vehicle's battery will reach its maximum eSOC before the vehicle leaves on a trip. This requires that vehicle owners know a priori when they will leave for a trip and that the vehicles have the capability to hold off charging until that moment. Last minute charging has been identified as an effective way to reduce battery degradation for some chemistries [19], and also may provide more of a demand leveling service to utilities (also generally known as valley-filling).

The home and work charging scenario (CH3) allows a vehicle owner to charge their vehicle at work as well as home. The rate of charging and the battery size remain the same as the baseline, and no extra constraints are added to the system. While it may not be widely available as yet, employers may add charging stations to communal lots, increasing charging opportunities. With more charging opportunities, a greater proportion of miles can be driven electrically, but with greater load on the system.

The no-charge window scenario (CH4) specifies a period, between 1pm and 7pm, in which PHEVs are not allowed to charge their battery. This scenario is meant to represent a utility enforced period in which vehicles are not allowed to charge to avoid times of peak electricity demand. This might also lend some insight into situations where utilities use price incentives to force demand out of a peak periods.

The slow charging scenario (CH5) adjusts the charging rate of the baseline scenario to 8A at 120V. This is meant to represent a charge rate that is compatible with older homes or a faulty residential electric system and is one of the selectable charge settings on the Chevrolet Volt [17]. This will should also reduce the peak of the charging load but make an average vehicle charge for more of the day.

The fast charging scenario (CH6) increases the rate of charging from the baseline scenario to 16A at 240V. This represents a homeowner who has installed a fast charging station at their residence and is also one of the selectable charging rates of the Chevrolet Volt[17] . This scenario is expected to increase the magnitude of peak charging but reduce its duration.

The seventh charging scenario combines fast charging with home and work charging. This assumes that employers would have higher voltage charging available to their employees, and that homeowners would also install these types of charge stations. This scenario represents the highest amount of electricity consumption possible for the baseline battery size, using the parameter values examined in this model.

The last charging scenario, CH8, halves the baseline usable battery size to gauge the effect that a smaller battery has. This means that a given vehicle would have half the electric range, roughly 20 miles for a compact car. However, this may not significantly alter the total percentage of electric miles driven, since many of the trip schedules in the NHTS do not use the entire 10.4 kWh presented in the baseline scenario. A half-size battery would also make the purchase price of a PHEV more economical and would lower the vehicle's weight. Additional charging scenarios can be found in Appendix K.

4.4 Electricity Dispatch Scenarios

The electricity dispatch scenarios examine the effect of the dispatch algorithm used and, if economic dispatch is chosen, changes to a price-based model of electricity generation. Three scenarios are examined to test the models sensitivity to the dispatch algorithm employed. Table 8 describes the four scenarios employed.

Table 8. Electricity dispatch scenario inputs

Scenario Name and Number		Dispatch Method	Fuel Price Source	GHG Tax
Capacity Factor	DM1	Capacity Factor	-	No
BAU Economic	DM2	Economic	AEO 2010	No
GHG Tax	DM3	Economic	AEO 2010	Yes

The baseline scenario (DM1) uses capacity factor dispatch. As detailed in the dispatch methodology section 3.4, capacity factor dispatch uses historical data to predict future behavior, with the premise that those plants that were previously heavily utilized will continue to be used at roughly the same rates. However, with new legislation pending to implement carbon taxes along with projected changes in fuel prices, this assumption is not likely to remain accurate in the future. The economic dispatch scenarios are designed to try and account for these future changes in generating costs.

The business as usual (BAU) economic dispatch scenario (DM2) sources the fuel costs from the reference case of the AEO 2010 [39]. This scenario incorporates varying fuel costs, but does not include any carbon legislation.

The GHG tax scenario (DM3) adds a cost in 2008$/ton CO_2e to the emissions of greenhouse gases to the fuel costs from the BAU economic dispatch case. Greenhouse gas emission rates are determined using global warming potentials as described in subsection 3.5, and an emissions cost, based on the EPA's analysis of HR2454, is added to the fuel cost to get a total cost of generation. Figure 37 shows all the generation costs used by the scenarios.

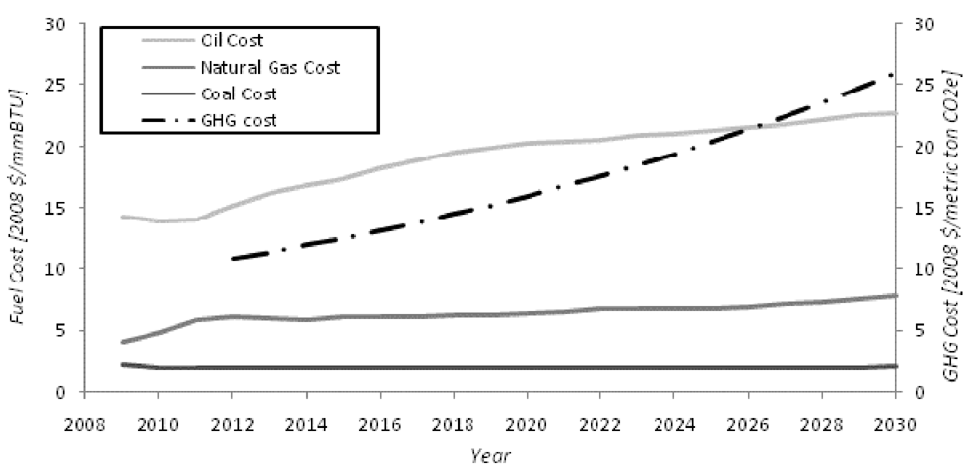

Figure 37 Generation cost curves over simulation timeframe – all scenarios.

4.5 Simulations Analyzed

Table 9 below identifies the combinations of scenarios that are simulated and discussed in the results section, Section 5. In addition, any simulation where marginal emissions of PHEVs are considered requires an additional FI1 simulation to be run to see the interaction of the scenario parameters with PHEV infiltration. For instance, calculation of marginal emissions in the FI4-EG3-CH1-DM1 simulation also requires there to be a FI1-EG3-CH1-DM1 simulation, but these complimentary scenarios were not explicitly listed in the table below for simplicity purposes. While Table 9 is not an exhaustive list of potential simulations, these specific scenario combinations were selected to isolate scenario groups and examine the effect of manipulating one parameter at a time.

Table 9. Full list of investigated simulations

Simulation Group	Name	Fleet Infiltration	Electricity Grid	Charging	Electricity Dispatch
Fleet Infiltration	Baseline Zero	***FI1***	EG1	CH1	DM1
	Low	***FI2***	EG1	CH1	DM1
	Medium	***FI3***	EG1	CH1	DM1
	High	***FI4***	EG1	CH1	DM1
	Maximum	***FI5***	EG1	CH1	DM1
Electric Grid Mix	Baseline Generation Capacity	FI4	***EG1***	CH1	DM1
	High RPS	FI4	***EG2***	CH1	DM1
	High Nuclear Capacity	FI4	***EG3***	CH1	DM1
	High RPS/High Nuclear	FI4	***EG4***	CH1	DM1
Charging	Baseline Charging	FI4	EG1	***CH1***	DM1
	Last-minute Charging	FI4	EG1	***CH2***	DM1
	Home-Work Charging	FI4	EG1	***CH3***	DM1
	No-Charge Window	FI4	EG1	***CH4***	DM1
	Slow Charge	FI4	EG1	***CH5***	DM1
	Fast Charge	FI4	EG1	***CH6***	DM1
	Fast Charge at Home and Work	FI4	EG1	***CH7***	DM1
	Smaller Battery	FI4	EG1	***CH8***	DM1
Electric Dispatch	Capacity Factor Dispatch	FI4	EG1	CH1	***DM1***
	BAU Economic	FI4	EG1	CH1	***DM2***
	GHG Tax	FI4	EG1	CH1	***DM3***

Source list

Trip Data	NHTS[46]
New vehicle sales	MI MVR[22]
Vehicle sales growth	AEO2009[20]

Low infiltration	AEO2009[20]
Medium infiltration	Lemoine 2008[43]
Historical HEV sales	U.S. D.O.E, Alternative Fuels & Advanced Vehicles Data Center, HEV Sales by Model[48]
High infiltration scenario	Vyas2009[44]
Daily driving range to suit PHEV ownership	Shiau Samaras 2009[49-50]
Household statistics	2005 American housing survey[45]
Michigan RPS	2008 Clean renewable and efficient energy act[27]
High RPS	CA RPS[51]
New capacity fuel mix proportions	AEO2009[20]
Projected fuel costs	AEO2009[20]

5. Results and Discussion

While the major results of the simulations are the total fuel cycle energy, greenhouse gas, criteria pollutant emissions, and the gasoline displacement by PHEVs, to properly examine these results many interim outputs of the model also must be presented. The PHEV Energy Consumption Model (PECM) results are independent of the Michigan Electricity, Fleet and Emissions Model (MEFEM). PECM uses nationwide travel survey data and its primary output is a weekly vehicle demand curve. For this reason, PECM can be treated as a separate result and can be used for analyzing the response of PHEV infiltration in any region. The following discussion in subsection 5.1 pertains solely to Michigan independent results from the PECM simulations. The PECM results are input into MEFEM to assess the changes in greenhouse gases (subsection 5.2), air criteria pollutants (subsection 5.3), total fuel cycle energy (subsection 5.4), and gasoline displacement (subsection 5.5) for the Michigan system.

5.1 PHEV Energy Consumption Model Results

The outputs of PECM are primarily electricity usage and gasoline consumption for PHEVs. These results will help to explain the emissions impacts of the charging scenarios examined later in Section 5.4. For a more complete discussion of the PECM results see Appendix H.

While the outputs of PECM are size class specific, the following figures and results are based on a light duty PHEV fleet with the size class distribution shown in Table 10. This distribution corresponds to the PHEV distribution observed in the high fleet infiltration scenario, FI4, for the year 2030. Using a weighted average result based on this distribution rather than all results for the individual size class allows for a clearer presentation of PECM results.

Table 10. PHEV Fleet Distribution (based on 2030 High Fleet Infiltration Scenario)

Sub-Compact	Compact	Midsize	Large	Van	SUV	Pickup
7.5%	19.5%	25.7%	10.6%	5.7%	21.8%	9.1%

5.1.1 Daily Variation in PHEV Consumption

In PECM, each day of the week is treated separately and the individual daily loads are strung together to form weekly PHEV charging loads on the electric system. This subsection outlines some of the results of this daily variation under baseline (CH1) charging conditions. Table 11 defines the inputs for the PECM outputs discussed in this subsection. Different consumption parameters are explored using naturalistic drive cycles in Appendix O, and a Chevrolet Volt specific analysis is conducted in Appendix Q.

Table 11. Input Parameters to PECM for Baseline Charging Scenario

Input Type [units]	Code	Baseline Value
Charging Location	CL	Home
Battery Size [kWh]	BS	10.4
Charge Current [A]	CI	12
Charge Voltage [V]	CV	120
Charge Delay [min]	CD	0
Minimum Dwell [min]	MD	0
No-Charge Lower Bound [hour]	NL	0
No-Charge Upper Bound [hour]	NU	0
Last Minute Charging Flag	LM	0

A seven day charging load for an average vehicle is shown below in Figure 38. The one week time period represented along the horizontal axis begins on Sunday at midnight. The vertical axis spans a charging rate of 0 kW to 1.44 kW, which is the maximum charge rate of a single vehicle in the baseline scenario (CH1). The highest peak in charging occurs at 8PM on most days. Wednesday evening shows the highest charge rate, 0.708kW, which is 49% of the maximum possible charge rate, or 49% of vehicles in the NHTS were charging at that time. Saturday evening, at 9PM, has the lowest peak, 0.512kW, which represents 36% of the maximum charge rate. In this model charging load never drops to zero because there are always vehicles charging at any time. The shape of the weekend loads differ from the weekday loads with a wider bell shape and a more gradual peak. An anomaly occurs each evening between midnight and 1AM due to the fact that disparate days are strung together. This discontinuity is most noticeable in the transition from Sunday to Monday. The model uses Monday data to create the midnight hour between Sunday and Monday, thus the magnitude of charging is higher because it actually represents the charging carried over from Monday night loads.

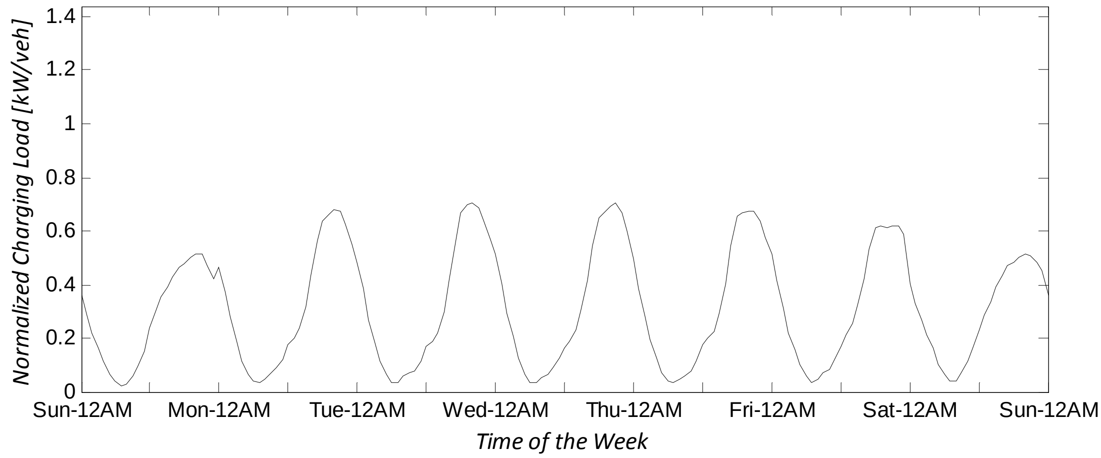

Figure 38. Weekly charging load for the baseline scenario under a 2030 high fleet scenario distribution

Figure 39 displays the percent of electrically driven miles for each day in a one week time period. The results display a fluctuation by day of the week in the percentage of driving propelled by electric power ranging from 55.4% on Sunday to 64.7% on Tuesday.

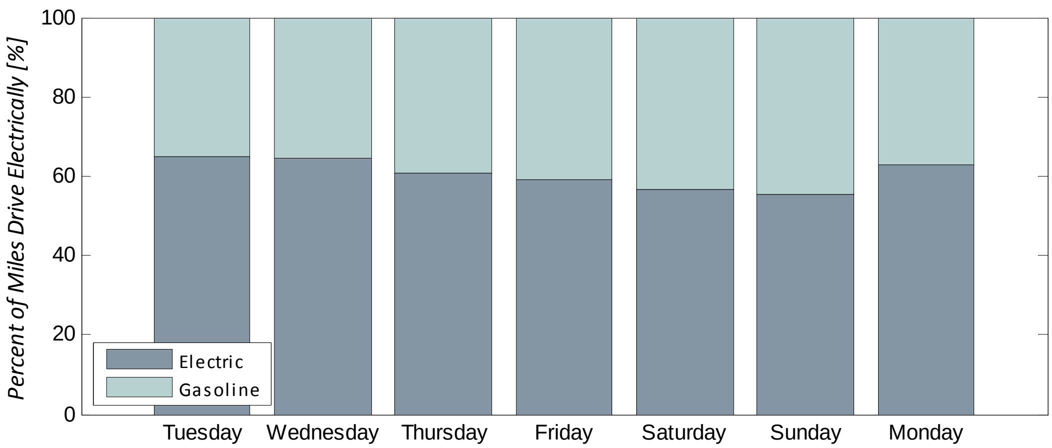

Figure 39. Variation of the percentage of miles driven electrically by day of the week

5.1.2 Charging Scenario Analysis

The main output of PECM, used by MEFEM to evaluate impacts on emissions, is an hourly load curve with PHEV electricity demand in kW per vehicle for every hour of the year. PECM generates seven sets of normalized load curves, one for each vehicle size class, similar to the graph in Figure 38. These charging load profiles are heavily influenced by the inputs to PECM. Table 7, in Section 4.4, indicates the inputs into each of the eight charging scenarios. In order to understand their impacts on emissions, we must first understand the impacts of the different charging scenarios on vehicle energy use. The graphs in Figure 40 display the average electricity and gasoline consumption per vehicle for each charging scenario. Comparison of the two figures reinforces the intuitive inverse relationship between electricity consumed and gasoline consumed, showing that as more electricity is consumed, less gasoline is combusted. Energy consumption for all scenarios fluctuate around 50 kWh of electricity and roughly four gallons of gasoline per week.

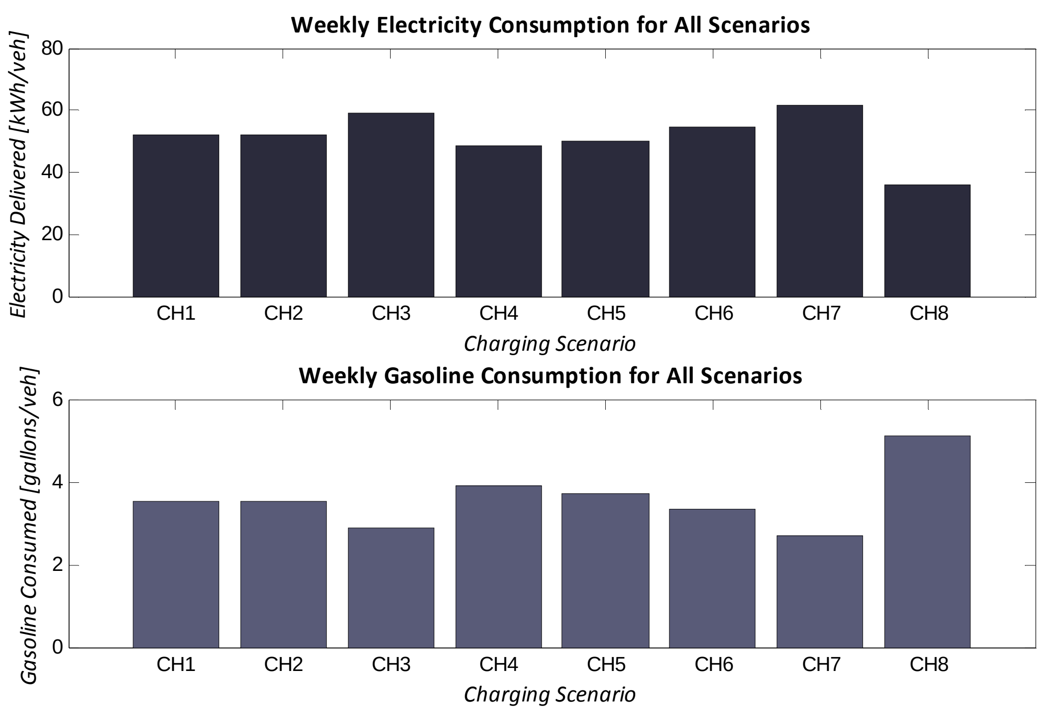

Figure 40. Energy consumption by charging scenario

The values of PHEV electricity consumption shown in Figure 40 are listed below in Table 12. The electricity consumption rates for each scenario are also listed as a percentage change from the baseline. The last minute charging scenario (CH2) shows no change in vehicle kWh consumption rates over baseline charging (CH1) conditions, as last minute charging only shifts the time of charging and does not affect the amount of charging that occurs. The scenarios that reduce electricity consumption are: enforcing a no-charge window (CH4), slow charging (CH5) and decreasing battery size (CH8). The smaller battery size causes the greatest decrease in electricity consumption per vehicle and has the largest impact on charging of any single parameter manipulation. On the other hand, the charging scenarios responsible for an increase over baseline levels are: home and work charging (CH3), fast charging (CH6) and the combination of the two, a fast charge home and work case, responsible for the sharpest rise in vehicle energy consumption. The results show that the most important single parameter that effects electricity consumption is battery size, followed by allowing vehicles to charge at work as well as home and then enforcing a no charge window.

Table 12. PHEV electricity consumption for all scenarios and percentage deviation from baseline with a 2030 High infiltration PHEV distribution.

Charging Scenario	CH1	CH2	CH3	CH4	CH5	CH6	CH7	CH8
Average Electricity Consumed [kWh/week]	52.3	52.3	58.9	48.3	50.3	54.5	61.4	36
Percent deviation from baseline (CH1)	-	0%	+12.6%	-7.6%	-3.8%	+4.4%	+17.4%	-31.2%

Table 13 and Figure 41 summarize the impact of the charging scenarios on the mode driven, charge depleting or charge sustaining. In every scenario with the exception of the smaller battery size scenario (CH8), the majority of driving is done in charge depleting mode in which the vehicle is operating on electric power. Miles driven electrically range from 109 to 182, while miles powered by gasoline combustion, the charge sustaining mode of operation, range from 152 to 79. This means that depending upon scenario, a vehicle will be driving anywhere from 42% to 70% of its miles on electric power.

Table 13. Weekly Average Driven Miles based on 2030 Fleet Distribution

Scenario	CH1	CH2	CH3	CH4	CH5	CH6	CH7	CH8
Electric Miles [mi/veh/wk]	157.0	157.0	176.4	145.6	151.4	162.4	182.3	108.5
Gasoline Miles [mi/veh/wk]	103.8	103.8	84.4	115.3	109.5	98.4	78.6	152.4
Percent Electric [%]	60%	60%	68%	56%	58%	63%	70%	42%

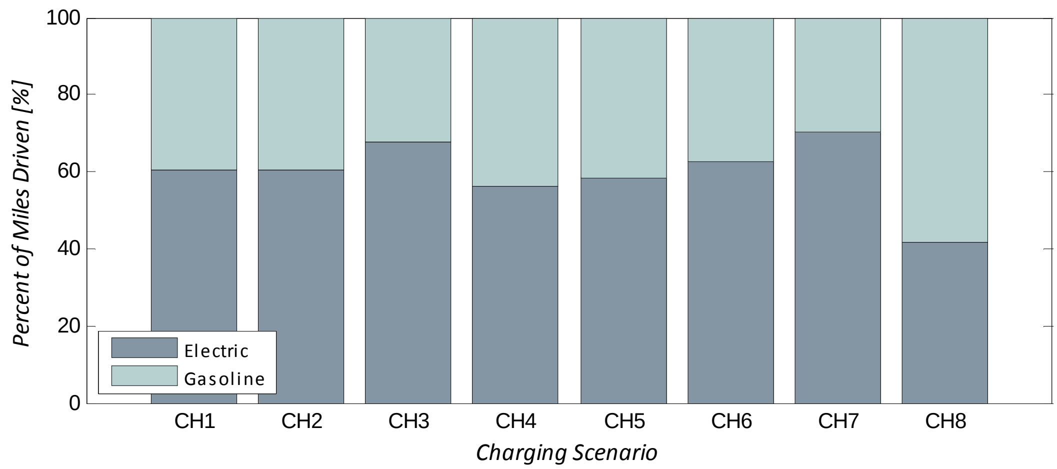

Figure 41. Percentage of travel driven electrically by charging scenario

While the total amount of energy consumption is important, it is expected that the time at which charging occurs may have a large impact on the emissions produced due to the type of generation dispatched to meet that demand. Figure 42 displays the changes to the electric load profile (over a 24-hour period) with the addition of PHEV load for each PHEV charging scenario. The results shown in Figure 42 are from the high infiltration simulation for the year 2030. In all eight subplots, the darker shaded region represents the non-PHEV base electrical load in Michigan in 2030 on a Tuesday in July, chosen to represent a typical summer, high demand load. The lighter shaded region is the PHEV load in 2030 added to the non-PHEV load. The light colored line plotted on top of the darker shaded region represents the PHEV charging load profile independent of the base electric load. The load displayed represents approximately 3,224,000 PHEVs on the road with the size class distribution described in Table 10.

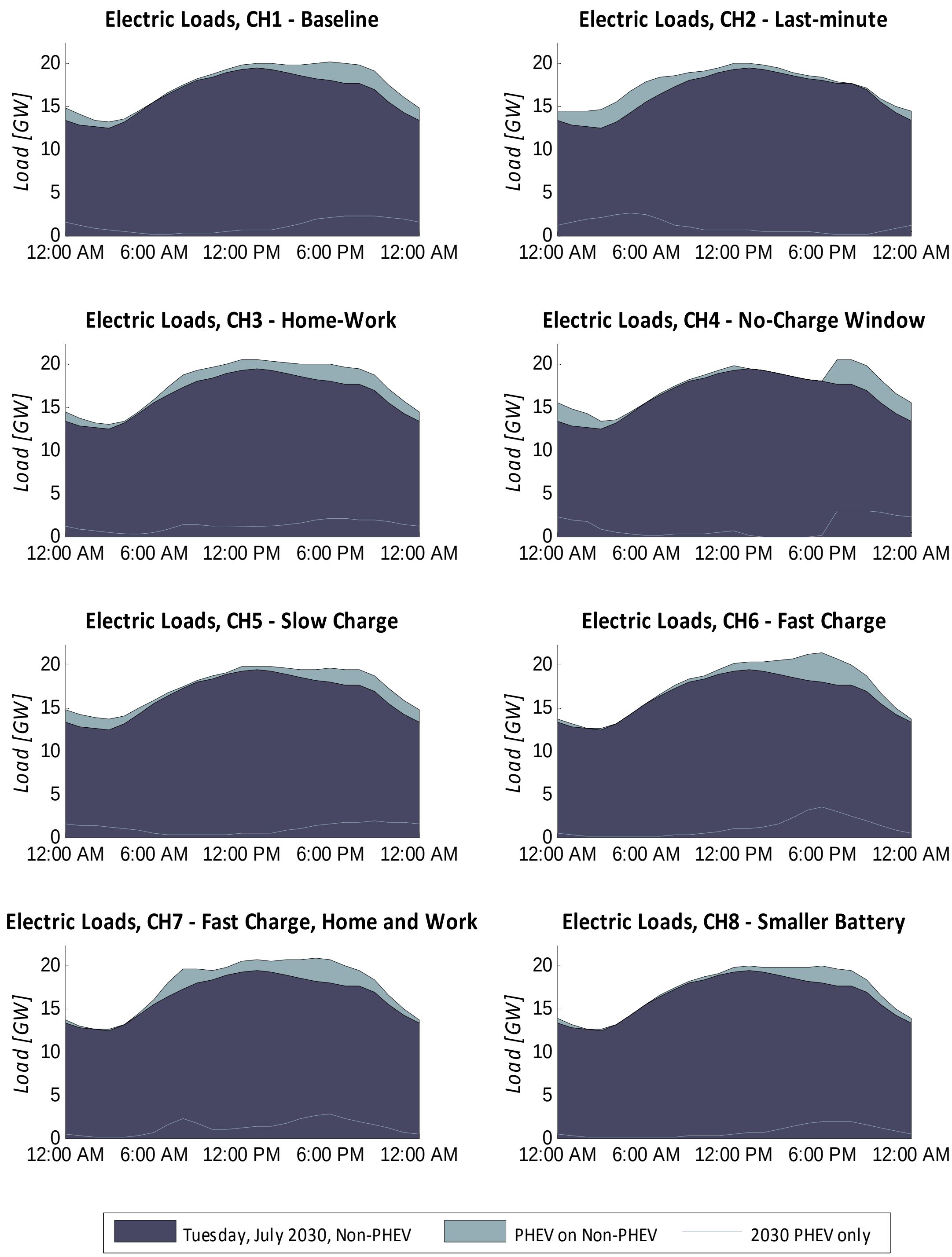

Figure 42. Aggregate PHEV load added to non-PHEV load for a Tuesday in July 2030

In the baseline charging scenario (CH1), the majority of charging takes place after the summertime peak occurs in the intermediate load level range. This has the effect of slightly increasing the peak load while forcing the system to near peak capacity for an extended duration of the day. Last minute charging (CH2) shifts most of the load into the times of least demand and in the morning hours with only a slight increase in peak load. It has the effect of leveling out the load curve, which would allow for more baseload capacity into the electric system. Home and work charging (CH3) increases total energy consumption but distributes the PHEV load across the summertime peak demand. It increases the peak slightly more than the baseline scenario and creates an extended peak period around the existing one. Enforcing a no-charge window (CH4) shifts a significant portion of the charging load into off-peak hours, but creates a new spike in load at 7PM that is larger than the original peak seen under baseline charging conditions. This effect is due to PHEVs essentially queuing up to charge as soon as they are allowed, and may be an undesirable effect of the this type of policy. The slow charging scenario (CH5) flattens and spreads the charging load out over more of the day, avoiding much addition to the peak but again extending the duration of peak loading. Fast charging (CH6) creates a large new peak around 7PM. With PHEVs able to charge quickly, most of the load is occurring in the early evening hours when many people come home from work, contributing to this new peak. Fast charging at home and work (CH7) appears to reduce the size of the new peak observed in CH6 and distributes the charging load over the summertime peak period. Almost no load is being added to the times of minimum demand in this scenario. This implies that a fast charge scenario that employs last minute charging (not examined here) may be the most efficient charging behavior at reducing the fluctuation in grid load. In the smaller battery size scenario (CH8) there is a decrease in the magnitude of the charging load over the baseline profile with most charging occurring in the evening hours.

The relative impact of PHEV charging loads on the electric system demand curve depends on two factors: the number of PHEVS plugging-in to the grid and the charging behavior. The graphs in Figure 42 provide insight into the impact of PHEVs on the overall system load curve. Those of concern to electric utilities are reductions in demand peaks, increases in off-peak usage and shifts in demand from peak to off-peak times. The results of the charging scenarios demonstrate that, on a weekly basis, the baseline charging (CH1), home and work charging (CH3), fast charging (CH6) and home and work fast charging (CH7) cases require a large fraction of PHEV charging to occur during times of high peak or moderate to high peak loads. The last minute (CH2) and slow charging scenarios show a more evenly spread distribution of additional PHEV demand over the weekly load curve. Enforcing a no-charge window (CH4), from 1pm to 7pm, increases the minimum load but also creates a sharp new peak at 7pm when the black-out period ends.

5.1.3 Minimum Dwell time and Charge Onset Delay

The scenarios used in the MEFEM emissions analysis do not examine two of the possible inputs to PECM, minimum dwell time and charge onset delay. This was done because the impact of the inputs on the energy consumption and percent of miles driven electrically was too minimal to merit inclusion. PECM was run with minimum dwell times of 30, 60, 90 and 120 minutes. In every case, the difference in electricity consumed compared to baseline was less than 2% and there was almost no visible difference in the shape of the charging curve. This slight change was not enough to expect to see any significant changes in emissions results.

PECM was also run with 30 and 60 minute charge onset delays. This had a less than 1% difference in the total amount of electricity consumed compared to the baseline scenario and simply shifted the charging curve over by about one hour. This slight shift should not have a significant impact on emissions results and, thus, was not included in the present analysis. A much larger charge onset delay, causing a larger shift in the load curve, may have a significant emissions impact. However, since the charge onset delay is meant to represent a period in which the vehicle hardware cools down, a much larger delay seemed unreasonable.

5.2 Greenhouse Gas Emissions

The results from the PECM model described in 5.1 are used as inputs to MEFEM. To assess the impact of PHEVs on greenhouse gas emissions, three greenhouse gases are tracked: Carbon Dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O). All the results are presented in CO_2 equivalents using global warming potentials as defined by IPCC Fourth Assessment Report over the 100 year time horizon[38]. The specific scenarios analyzed to quantify greenhouse gas emissions are listed in tables at the beginning of each of the following subsections.

5.2.1 Fleet Infiltration Implications

Table 14. List of simulations discussed for PHEV Fleet Infiltration

Simulations	Fleet Infiltration	Electric Generation Capacity	Charging	Electricity Dispatch
Zero infiltration	*FI1*	EG1	CH1	DM1
Low infiltration	*FI2*	EG1	CH1	DM1
Medium infiltration	*FI3*	EG1	CH1	DM1
High infiltration	*FI4*	EG1	CH1	DM1
Max infiltration	*FI5*	EG1	CH1	DM1

The number of PHEVs on the road has a significant influence on total fleet emission results. The degree of this effect was investigated by running the simulations listed in Table 14, varying the infiltration scenarios while holding the baseline charging (CH1), baseline electricity generating capacity (EG1), and capacity factor dispatch methodology (DM1) scenarios constant.

The sales infiltration scenarios defined in Section 4.2 determine the number of PHEVs in the light duty vehicle fleet. Figure 43 displays the number of PHEVs in the light duty vehicle fleet with respect to simulation year for all sales infiltration scenarios. The inset plot shows the number of PHEVs, in single units not millions, for the years 2014 through 2016. If approximately 3.3% of the U.S. population resides in Michigan [52], one million PHEVs in the United States would translate to roughly thirty thousand PHEVs in the state of Michigan. Under this assumption, the results of the medium infiltration scenario align with the Obama administration's goal for one million PHEVs on the road by 2015[1]. This same scenario has 13.3% of light duty vehicles as PHEVs in the final simulation year, 2030. In the low infiltration scenario, PHEVs comprise 3.2% of the fleet in 2030. For the high and maximum scenarios these percentages are 42.6 and 73.3, respectively.

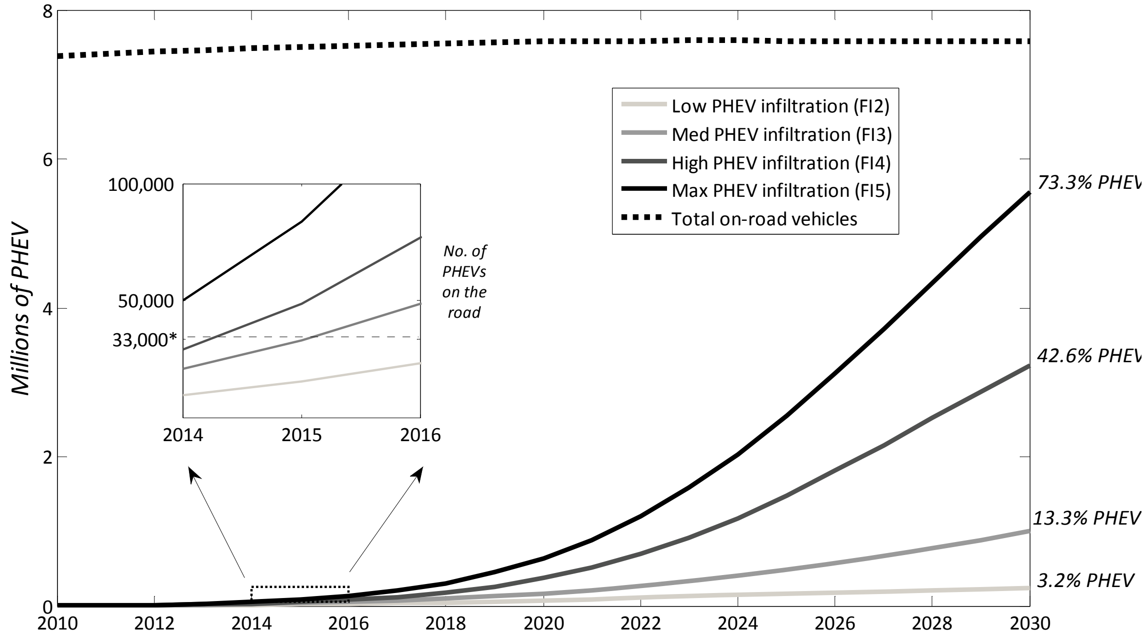

Figure 43. Number of PHEVs on the road, 2010 - 2030

Table 15 below shows the additional electricity (MWh) demand from PHEV addition to the grid in the year 2030 for each infiltration scenario. These values are for PHEV infiltration under the baseline charging (CH1) and baseline electric grid (EG1) scenarios.

Table 15. Additional electricity demand from PHEV infiltration, 2030 (CH1, EG1)

	FI2	FI3	FI4	FI5
Total PHEV additional Demand (MWh)	716,000	2,986,000	9,548,000	16,446,000
Percent change from FI1 electricity demand (%)	0.6 %	2.5 %	7.9 %	13.6 %

In a fleet of purely conventional vehicles, transportation emissions are the sum of gasoline combustion and upstream emissions. The addition of PHEVs to the fleet reduces total fuel cycle gasoline emissions by displacing conventional vehicle gasoline use, but results in an increase in combustion and upstream emissions from electricity generation. It is important to re-emphasize the issue of emissions allocation mentioned in previous sections. Note that total electricity emissions will be the same for a given pathway regardless of the allocation method; However, the portion of emissions that should be allotted to each demand source (i.e., lighting, HVAC, or, for the purposes of this study, PHEV batteries) is under question. The simplest results to present, as they bypass this issue of allocation, are system wide emissions which are defined as all transportation related emissions and all electricity related emissions combined. Figure 44 and Table 16 provide system wide GHG emissions in the year 2030 for all fleet infiltration scenarios.

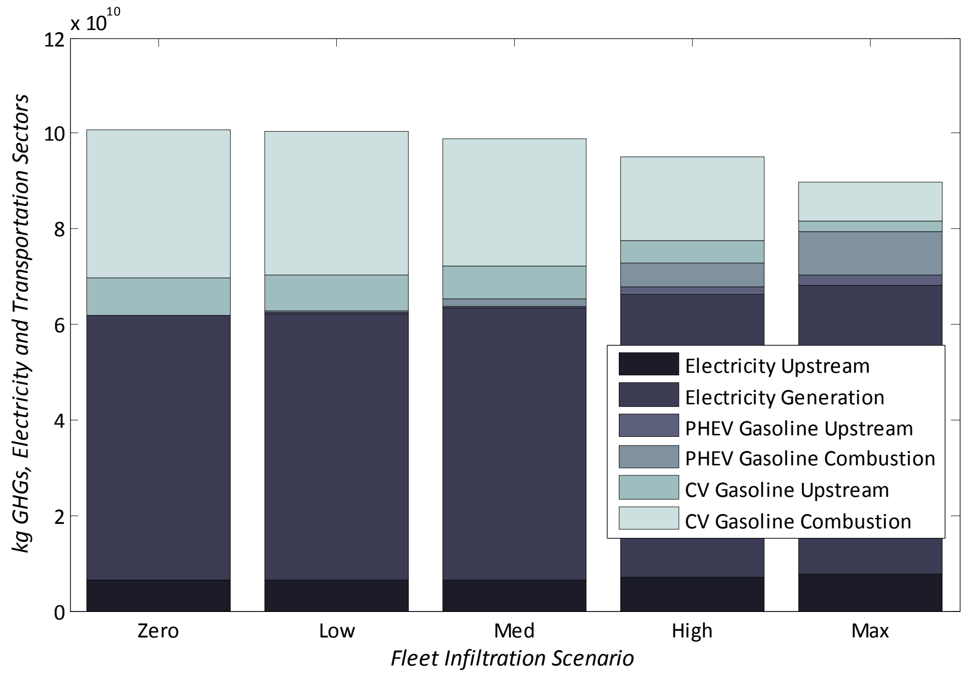

Figure 44. Total GHG emissions for the year 2030 for all infiltration scenarios (EG1, CH1)

Table 16. Change in 2030 GHG Emissions due to PHEV addition (base grid scenario)

Change in Emissions	PHEV Scenario			
	Low	Medium	High	Max
Total Δ Electricity (billion kgCO2e)	0.35	1.42	4.37	6.14
Total Δ Gasoline (billion kgCO2e)	-0.74	-3.12	-9.95	-17.15
Net Change (billion kgCO2e)	-0.40	-1.70	-5.58	-11.01
Deviation from Zero PHEV Scenario (%)	-0.39%	-1.68%	-5.54%	-10.93%

Table 16 and Figure 44 illustrate the simultaneous increase in electricity emissions and decrease in gasoline emissions for the year 2030. The resultant total emissions are lower in all infiltration scenarios, with the difference from the zero PHEV simulation increasing with increasing infiltration.

Table 17 shows the size of the total emissions reduction created for the entire timeframe explored, in which the summed emission totals for every year are compared. Here, the percent reduction in emissions is much smaller due to the relatively slow PHEV infiltration for the first several years.

Table 17. Change in full timeframe GHG Emissions due to PHEV addition.

	Zero	Low	Med.	High	Max
Total Emissions 2009-2030 (billion $kgCO_2e$)	2566	2565	2563	2557	2546
Total difference from Zero (billion $kgCO_2e$)	-	-0.72	-2.70	-8.85	-20.03
Deviation from Zero PHEV Scenario (%)	-	-0.03%	-0.10%	-0.34%	-0.78%

The next step is to allocate a portion of the emissions generated by electricity to the transportation sector, and examine only transportation related emissions using the methodology outlined in Section 3.5. Ascribing the net reduction seen in Table 16 to PHEVs is an example of marginal emissions allocation.

In the marginal allocation method, emissions are assigned to PHEVs by comparing the emissions from the PHEV scenario to the emissions in the base, zero PHEV scenario. In the PHEV scenario, additional demand is placed on the system due to PHEV charging. To meet this demand, existing plants are either utilized more, or new plants are built. The size of the new plants needed to meet RPS and spinning reserve requirements is dependent on the number of PHEVs and the outputs of PECM. In addition to the additional renewable generation due to the increase in electricity demand, more new capacity will be added for reserve margin to accommodate PHEV load distributed over the annual peak demand. New plants are given the characteristics of those found in Appendix B, which are cleaner and more efficient than the initial assets in 2010. As per the stacking methodology, these plants will be utilized before many of the older plants, and typically have lower emissions than older plants, as seen in Appendix G. The majority of the difference in emissions due to the additional PHEV load will typically come from these new plants. If the PHEV load is added to off-peak demand, or 'valley-filling', then while the excess electricity requires more renewable energy to meet RPS, no new capacity will be necessary for spinning reserve, and the demand for PHEVs will be met by existing, dirtier plants. This implies that the marginal emissions of PHEVs will be lower if PHEV load is added to peak periods rather than off-peak.

Average emissions allocation analyzes the plants used to satisfy load at every hour, and develops an average emission per kW for each hour. These hourly average emissions factors are then applied to the PHEV load. The hourly average takes into account the entire generation mix. Adding new, cleaner capacity reduces the average emission factor, but, unlike the marginal allocation methodology, the dirtier, existing grid has a significant impact on this average. For this reason, average allocation typically results in higher emissions allocated to PHEVs than marginal emissions. See Appendix G for a more in depth discussion of the changes in the electricity mix and effects of allocation methodology. In Figure 45 a graph of the 2030 grid mix under the EG1 scenario shows the proportion of the fuel mix emissions for average and marginal allocation.

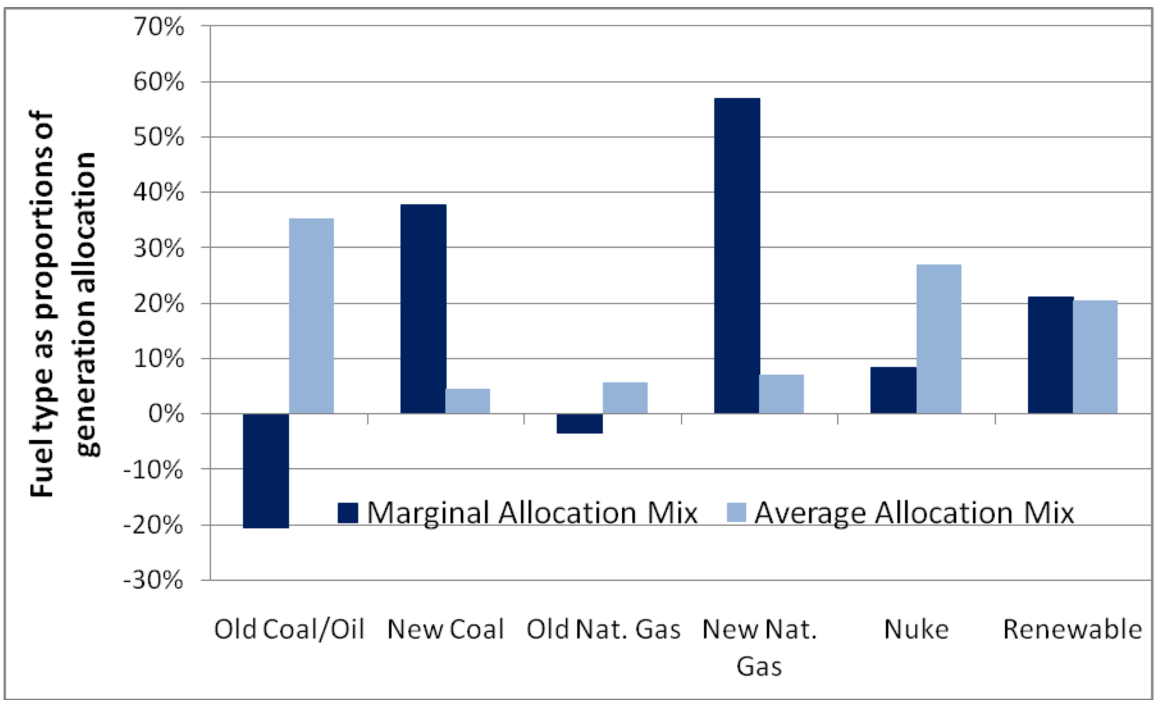

Figure 45. 2030 Marginal & Average Grid Mixes for PHEVs

Figure 44 shows the total system greenhouse gas emissions in the year 2030 for both the electricity and transportation sectors. Figure 46, below, shows the greenhouse gas emissions for the transportation sector alone, under the high PHEV scenario, using both allocation methods. These graphs also show total greenhouse gas emissions under the zero PHEV scenario for comparison. In Figure 46, the total GHG emissions displaced over the 20-year timeframe are represented by the area labeled 'avoided emissions', or the size of the 'wedge' between the zero PHEV scenarios and the top of the scenario emissions curve. Electricity emissions increase in both allocation methods as total gasoline emissions decrease over time due to the increase in PHEVs on the road. In Figure 46 below, the average allocation emission method (shown on the right) typically ascribes a greater portion of the electricity emissions to PHEVs, again because the baseload coal-fired generation emissions are taken into account. Both allocation methods show that it takes a substantial amount of time before plug-in vehicles comprise enough of the fleet to create an appreciable difference.

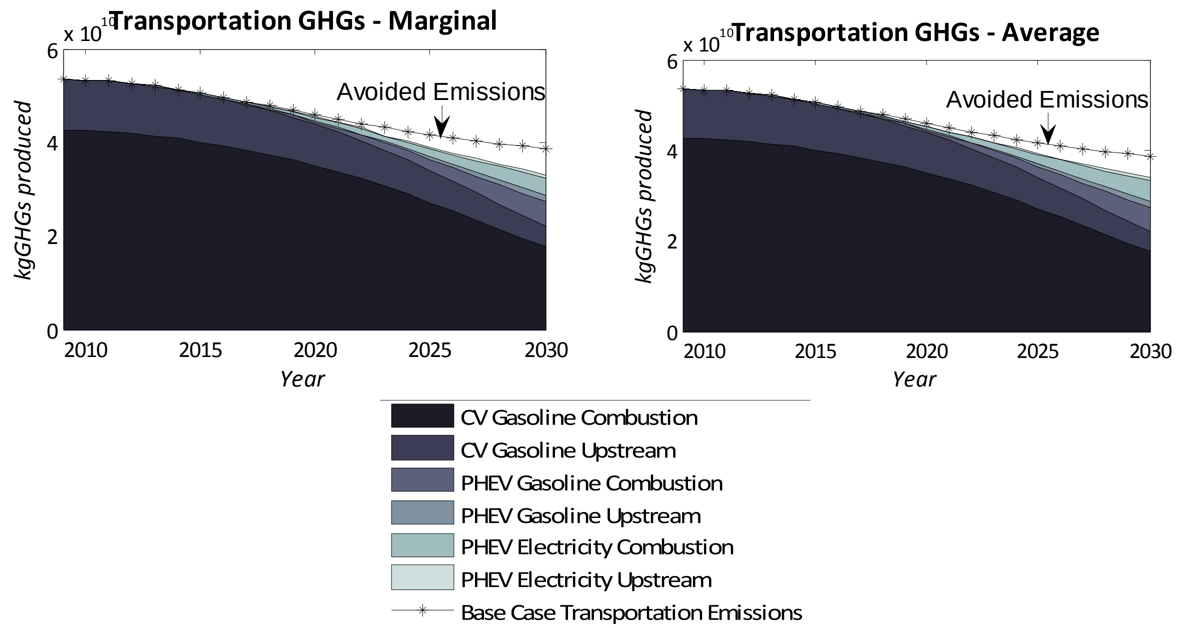

Figure 46. Transportation sector marginal and average emissions under high PHEV infiltration.

Figure 47 and Table 18 below, show the same trend of decreasing transportation sector emissions due to the increase of plug-in vehicles in the fleet, as well as the difference in emissions between the allocation methods.

Table 18. Total fuel cycle GHG emissions (billion kg), transportation sector, 2030 (data for Figure 46)

FI Scenario	Total Transportation Emissions (billion kg)		Percent Change	
	Average Allocation	Marginal Allocation	Average Allocation	Marginal Allocation
FI1 (Zero)	38.7	38.7	0.00%	0.00%
FI2 (Low)	38.4	38.3	-0.93%	-1.02%
FI3 (Med)	37.2	37.0	-3.95%	-4.38%
FI4 (High)	33.8	33.1	-12.64%	-14.41%
FI5 (Max)	30.1	27.7	-22.16%	-28.43%

These results are produced under baseline charging (CH1) conditions where the additional PHEV demand increases the system peak load (reference Figure 37 in subsection 5.1.1). The model builds new generation capacity to meet the additional demand when PHEVs are charged in the evening. These new plants will have a higher capacity factor than some of the older plants of the same type and thus will be used more often.

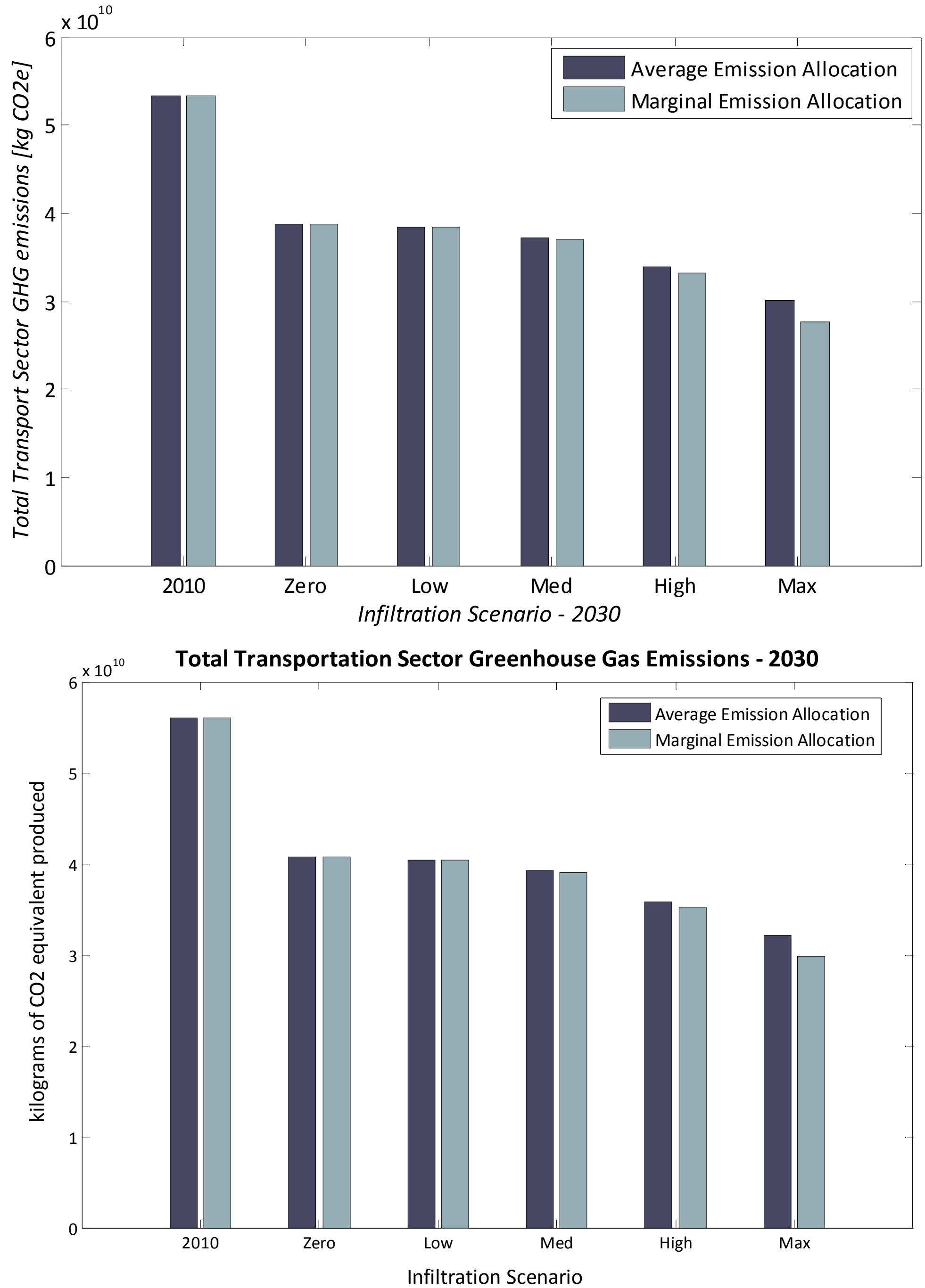

Figure 47. Total transportation sector greenhouse gas emissions, both allocation factors

Figure 48, below, displays the electric load profile, dispatched generation by fuel type and the emissions from this generation attributable to PHEV demand as a function of time over a 48 hour period in July 2030. The electricity generation PHEV emissions are shown for both allocation methods. The comparison of these graphs side by side provides insight into which fuel sources are being used to meet electricity demand as it varies with time and the resulting impact on emissions. This is particularly important when considering average emissions allocation methods, as fuel type is an indicator of the magnitude of emissions rates that are typically seen in electricity generation (See Appendix G). The marginal emissions are dependent on the marginal fuel mix of the supplied electricity in any given hour. The marginal fuel mix, shown in Figure 45 for 2030, is what the fuel supply mix would look like if, at every hour, the electricity supply without PHEV levels, graph 2 in Figure 48, were subtracted from those in graph 3, Figure 48. This plant fuel types that supply this marginal grid mix would dictate the marginally assigned emissions to PHEVs shown in graph 4 of Figure 48. During the dip in marginal emission levels observed in the hours around 18 – 20, there is a decrease in imported energy, the majority of which is supplied by coal fired plants. The marginal emissions appear to take on a negative trajectory while average emissions stay fairly constant.

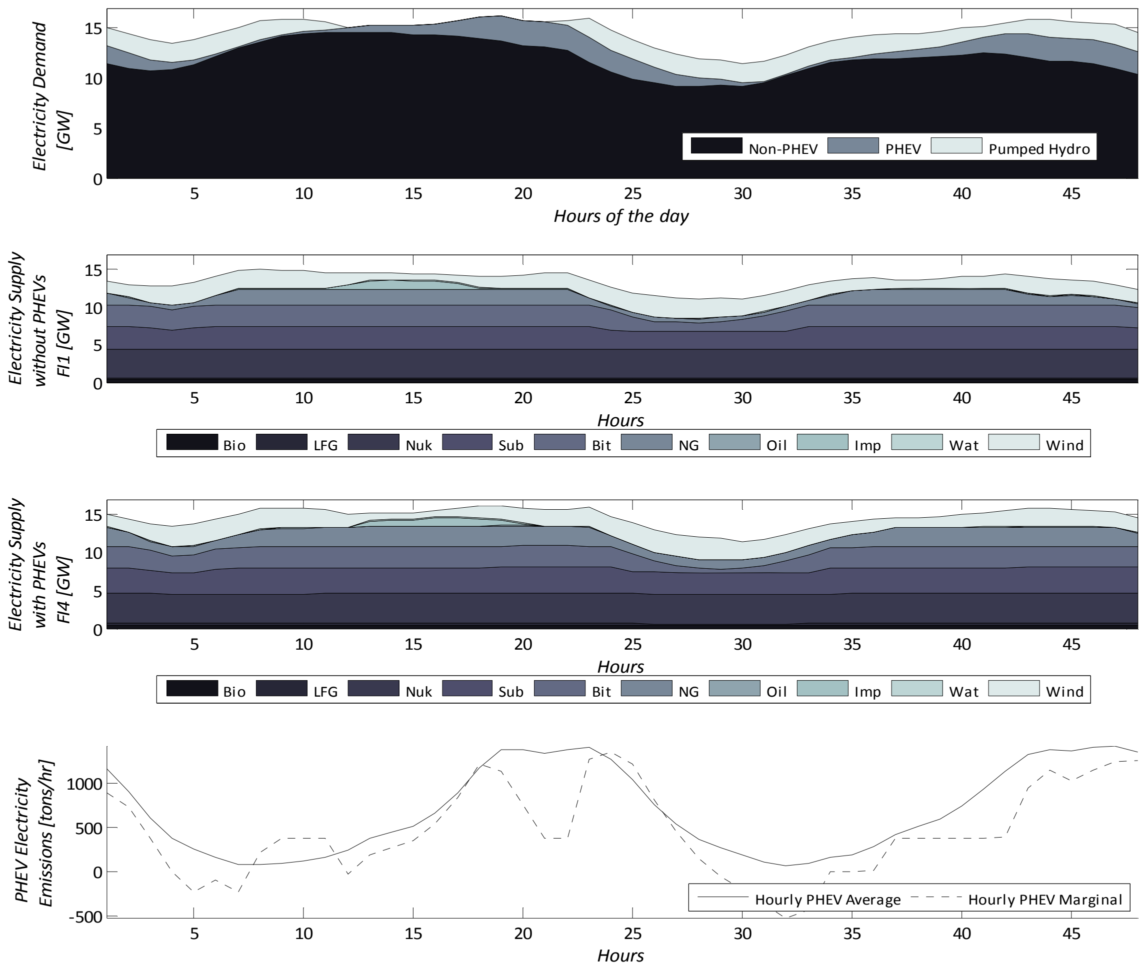

Figure 48. Load, fuel mix and emissions, 2 days in July 2030 (base grid and charging, high PHEV)

5.2.2 Electricity Generation Capacity Implications

Table 19. List of scenarios discussed in Section 5.2.2.

Scenarios	Electric Generation Capacity	Fleet Infiltration	Charging	Electricity Dispatch
Baseline (MI RPS)	*EG1*	FI1 & FI4	CH1	DM1
High RPS	*EG2*	FI1 & FI4	CH1	DM1
High Nuclear	*EG3*	FI1 & FI4	CH1	DM1
High RPS/High Nuclear	*EG4*	FI1 & FI4	CH1	DM1

The previous subsections discuss how both the timing and total amount of PHEV energy demand affect the emissions. Another important factor is the effect of changes in the generating capacity fuel mix on these pathways and in turn how the new vehicle related grid demands impact power generation requirements. Note that in the scenario table, Table 19, FI1 scenarios are listed to account for new baseline scenarios. The results are the impact of PHEVs on a grid type, not the impact of different grid types. The increase in electricity consumption from PHEV battery recharging under every grid scenario for the high PHEV infiltration is 9,220,000MWh.

The electricity generation capacity scenarios heavily influence the generation fuel mix of the future grid. In Figure 49, below, the larger pie chart on the left displays the fuel mix of the Michigan grid in the year 2009, the first year of simulation. The four pie charts on the right represent the fuel mixes for the year 2030 under each of the four electricity generation capacity scenarios discussed in Section 4.3. The results show that the implementation of a more aggressive RPS, like the one in the EG2 scenario, results in fewer additions of coal and natural gas generating units, than the more modest RPS case of EG1. This happens because building renewable plants to meet renewable requirements takes priority.

Under the EG3 (nuclear) and EG4 (high renewable and nuclear) scenarios, there is growth in natural gas generation but a significant decrease in coal generation. This is caused by the generating unit retirement schedule employed in these two scenarios. In EG3 and EG4, accelerated decommissioning of units retires a substantial amount of coal capacity to allow for the addition of nuclear power. Only coal plants are retired at an accelerated place in this retirement schedule, all other scheduled decommissioning remain the same as EG1 and EG2.

All four scenarios result in a decrease of fossil fuel use in power generation over time, at varying degrees compared to the 2009 fuel mix. This decrease is due mostly to the RPS scenarios employed, as even the base case scenario assumes that the Michigan legislature will extend the current RPS from 10% by 2015 to 20% by 2025, which is a substantially cleaner generation mix than the present.

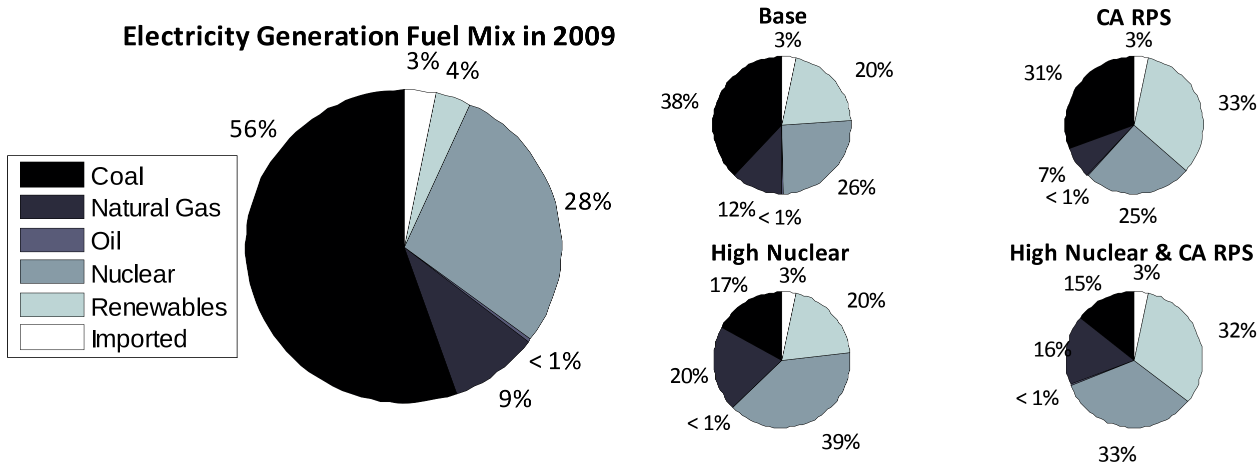

Figure 49. 2030 Fuel mix for the four grid scenarios

Table 20 below shows the full fuel cycle emissions (thousand tons) from electricity generation in 2030 under each electric grid scenario. The fourth column in Table 20, difference in total system GHG emissions, shows the percent increase in total fuel cycle GHG emissions from total system electricity generation over the entire year of 2030 between the zero and high PHEV infiltration scenarios. The aggressive renewable scenario, EG2, shows the greatest percent increase in total system emissions from the addition of PHEVs to the grid. In the no PHEV case for this scenario a large amount of new renewable generation capacity is built to satisfy the RPS requirements. These renewable additions provide enough system capacity to meet the marginal capacity reserve requirement resulting in zero non-renewable plant additions. Since all new capacity has zero emissions, the total system capacity is kept low. In the high infiltration case of the EG2 scenario, the additional PHEV load causes new plant additions for the marginal capacity reserve requirement. In this case, the new capacity needs are met with roughly 670 MW of natural gas and 440 MW of coal capacity. These changes are responsible for the high percent change in system GHG emissions between the infiltration cases of the high renewable scenario.

Table 20. GHG (kgCO_2e) emissions comparison, 2030 Electric Sector

EG Scenario	Total System GHG emissions (FI1) (thous. ton)	Total System GHG emissions (FI4) (thous. ton)	Percent Change (FI4 – FI1) (%)
EG1	61,971	66,346	7.06%
EG2	49,184	53,051	7.86%
EG3	41,824	43,465	3.92%
EG4	35,690	37,133	4.04%

As the grid mix becomes successively cleaner, from electricity generation capacity scenarios EG1 through EG4, PHEV greenhouse gas emissions per mile (kgCO_2e/mile) driven in the year 2030 are reduced, as seen in Figure 50. Figure 50 along with Table 21 also displays the difference in emission allocations methods, with greater reductions in marginal emissions than in average emissions. The error bars indicate PHEVs driven in charge sustaining and charge depleting modes using both the nominal marginal and average factors. The positive errors are the GHG emissions attributed to purely gasoline consumption where as the negative error bars are those as if solely electricity was consumed to propel PHEVs.

The difference in kilograms per mile between the average and marginal allocation methods is small in EG2 compared to the other three electric grid scenarios. In EG2, the high RPS requirements result in a large quantity of zero emission renewable capacity added to the system, the majority of which is wind (90%). The addition of wind affects both marginal and average allocation because it is applied to the system as a negative load. In the EG3 and EG4 scenarios, there are greater numbers of generating asset retirements, necessitating the addition of more capacity to meet the MISO regulation. The new capacity additions to meet reserve requirements do not include any renewable sources except for a very small percentage (5 %) of LFG/biomass. The observed improvements in the CV fleet from 2010 to 2030, which are not present in the PHEV fleet, are due to the fact that fuel economy improvement factors are applied to CVs. Therefore the kilograms per mile emission factors of PHEVs do not change over the 20 year period like the CV fleet.

Table 21. Total fuel cycle GHG emissions per mile, 2030 (data for Figure 42)

	kg / mile
CV, 2010	0.5298
CV, 2030	0.3754

EG Scenario	**GHG (kgCO_2e) / mile**		
	Average	Marginal	Difference
EG1	0.262	0.252	0.010
EG2	0.241	0.240	0.001
EG3	0.225	0.189	0.036
EG4	0.215	0.185	0.031

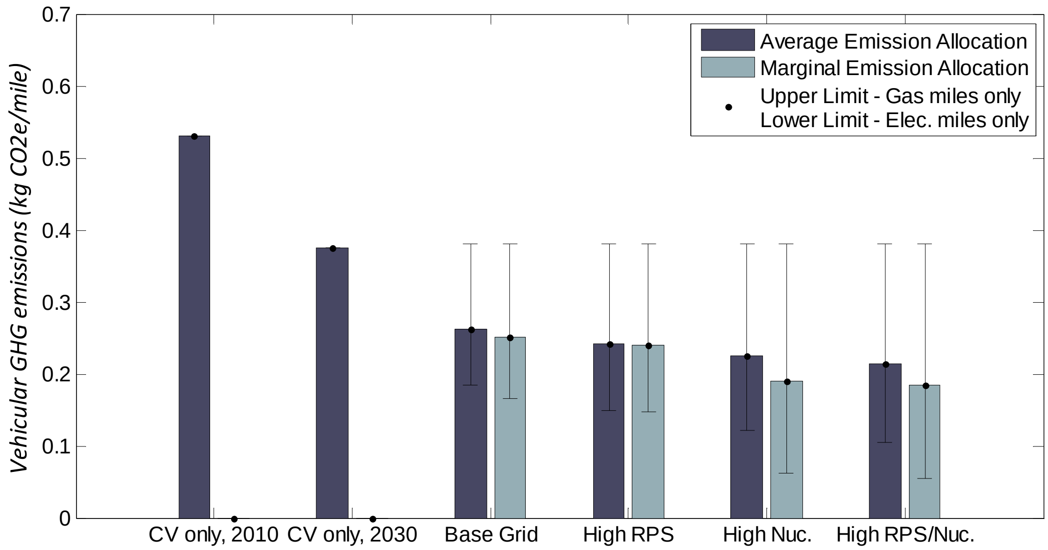

Figure 50. Per mile GHG emissions, 2030

The impact of each grid mix scenario on power generation greenhouse gas emissions are provided in Table 22 below. The middle column represents the net change in emissions over the 20-year time period under all four scenarios for both the zero PHEV and high PHEV infiltration cases. The column on the right displays the difference between the fleet infiltration cases under each grid mix scenario. This column is the change in emissions from electricity generation attributable to PHEV energy consumption; namely the impact of these new marginal demands on the grid.

Table 22. Percent change in electric sector GHG emissions, 2010 to 2030

Scenarios	Change in GHG emissions	Impact of PHEV additional demand
Base(EG1), FI1	-22.99%	5.44%
Base(EG1), FI4	-17.56%	
High RPS(EG2), FI1	-38.88%	4.80%
High RPS(EG2), FI4	-34.08%	
High Nuclear(EG3), FI1	-48.03%	2.04%
High Nuclear(EG3), FI4	-45.99%	
High RPS/High Nuclear(EG4), FI1	-55.65%	1.79%
High RPS/High Nuclear(EG4), FI4	-53.86%	

In the base case, greenhouse gas emissions from electric power generation decrease by 23% over the projection period, due to the imposed RPS standards. Adding PHEVs to the grid increases electricity use, increasing electricity sector emissions, decreasing the net reduction from the baseline scenario by about 5%. The results of the other scenarios demonstrate how cleaning up the grid's predominately coal-fired baseload assets produce a considerable decrease in associated greenhouse gas emissions, of up to 56% in this study's optimal scenario. Overall, these results indicate that policy-imposed constraints can command significant decreases in electricity generated greenhouse gas emissions by forcing electric sector transitions to low CO_2 generation. Furthermore, it supports the replacement of dated and dirty coal plants with cleaner generation technologies to promote significant emission improvements (per MWh generated), regardless of the size of PHEV charging load. If older plants are taken off sooner and cleaner baseload generation is brought online, total emissions for the grid will be greatly reduced over time, reducing the emissions allocated to PHEV. A higher RPS does improve the grid, but increasing PHEV loads require the additions of "dispatchable" generation sources. Dispatchable refers to those plants that are added to meet capacity marginal reserve requirements, or in other words plants with high availability factors.

5.2.3 PHEV Charging Behavior Implications

Table 23. List of scenarios discussed in Section 5.2.3.

Scenarios	Charging	Fleet Infiltration	Electric Generation Capacity	Electricity Dispatch
Base	*CH1*	FI4	EG1	DM1
Last Minute	*CH2*	FI4	EG1	DM1
Home & Work	*CH3*	FI4	EG1	DM1
Blackout Window	*CH4*	FI4	EG1	DM1
Slow Charge	*CH5*	FI4	EG1	DM1
Fast Charge	*CH6*	FI4	EG1	DM1
Fast Home & Work	*CH7*	FI4	EG1	DM1
Smaller Battery	*CH8*	FI4	EG1	DM1

As noted previously in Subsection 5.1, the charging habits of drivers affect the demand on the grid. As this load changes, the assets which are dispatched to serve this demand will also change. Restrictions on charging can also influence the amount electricity versus gasoline consumed by a PHEV driver. Figure 51 depicts the greenhouse gas emissions, in $kgCO_2e$/mile, under different charging scenarios, for a high PHEV infiltration, baseline electricity generation capacity, and capacity factor dispatch condition. Note the differences amongst all eight charge cases between marginal and average allocation methods, especially for the fast charge scenarios (CH6 and CH7). The pronounced differences for the fast charging scenarios are due to high spikes in peak demand, as discussed in Section 5.1.2, which require a larger amount of new capacity to be added to the system. Again, much of the affect to emissions from the grid are tied to the amount of new capacity that is necessary. 'Valley filling' scenarios, such as last minute charging or blackout periods do not increase the peak load, and therefore new capacity to meet spinning reserve is not needed. Since these new, cleaner energy sources are not brought online, the emissions associated are higher. Fast charging scenarios, CH6 and CH7, create a sharp spike in demand near peak hours, and require the highest amount of new capacity. Since the new installed capacity includes technology improvements, and as such is cleaner in than the existing generation, these scenarios result in the lowest emissions.

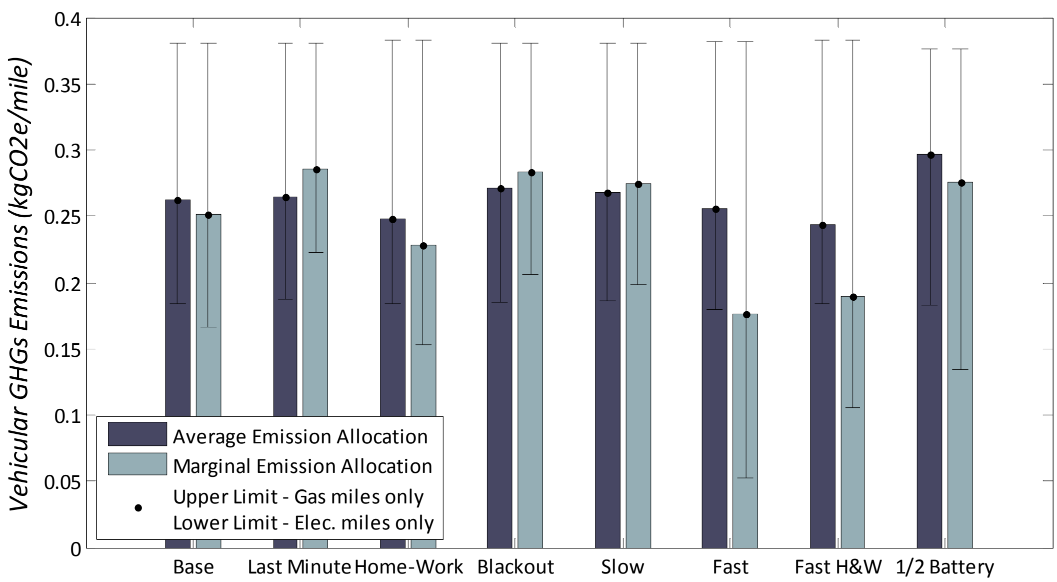

Figure 51. Per mile greenhouse gas emissions for each charging scenario in 2030

5.2.4 Electricity Dispatch Method

Table 24. List of scenarios discussed in section 5.6.

Dispatch Scenarios	DM	FI	EG	CH
Capacity Factor Dispatch	*1*	4	1	1
BAU Economic Dispatch	*2*	4	1	1
GHG Tax Econ. Dispatch	*3*	4	1	1

PHEV emissions vary between different electricity dispatch algorithms. This study used two methods to simulate power plant dispatch: capacity factor dispatch, described in subsection 3.4.3, and a stacked economic dispatch, subsection 3.4.4. In stacked economic dispatch, the dispatch order is based on fuel prices ($/mmbtu) and GHG emission costs ($/ton$CO_2$e). This Economic Dispatch model uses the plants with the cheapest fuel for energy price first, up to the availability factor adjusted power associated with each plant's fuel type. The results presented up to this point have been based on Capacity Factor Dispatch. However, several simulations were also run under the Economic Dispatch methodology. The results from the Economic Dispatch model shown in this subsection are GHG emissions per mile and grid fuel mix changes.

One difference between the Capacity Factor and Economic Dispatch methods is visible through comparison of the grid fuel mixes in the year 2030 displayed below in Figure 52. The most significant differences exist between the percentages of coal and natural gas in the fuel mix. Economic dispatch utilizes much more coal than natural gas due to the high costs of natural gas compared to those of coal. The economic dispatch method assigns power bands up to maximum proportion of the time the plant would be available based on availability factor. Capacity factor dispatch assigns power bands based on plant *capacity factor*, and caps maximum generation based on to the proportion of the actual unit's generation to the maximum theoretical energy the plant could provide on an annual basis.

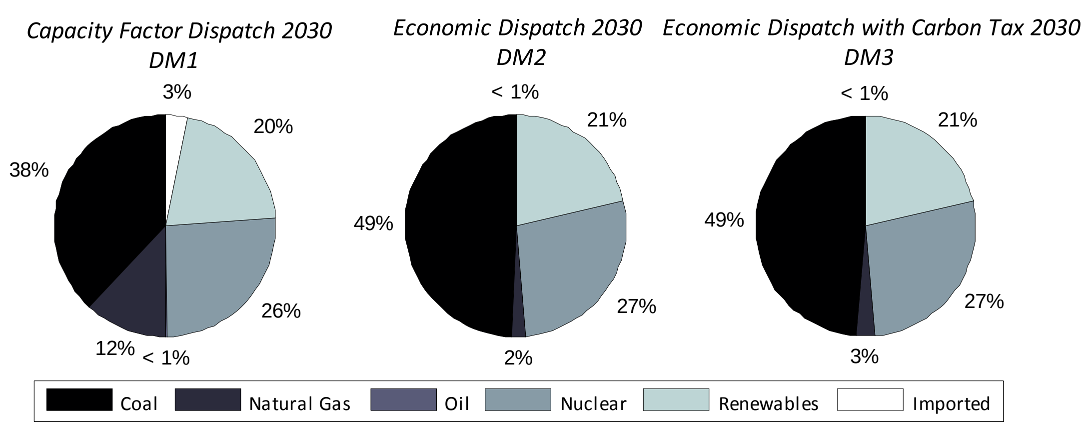

Figure 52. Electric Fuel mix for 2030 for all three dispatch scenarios

The Michigan grid has a large amount of coal with an initial nameplate capacity of coal assets of approximately 9,900 MW. If these coal assets were dispatched to their availability factors, the generation would be roughly 50% greater than the actual output these plants produced according to their historical capacity factors. Michigan is home to the second-oldest fleet of baseload coal plants in the nation with an average age of 49 years ([53]). The costs associated with dispatching older plants are greater than those of newer plants. As plants age they require more maintenance. Over time, these units will experience losses in thermal efficiency thereby requiring more fuel input per unit of energy generated. The Economic Dispatch model dispatches coal to its availability factor adjusted power because coal is a relatively cheap fuel source, and heat rates, which determine how much fuel a plant consumes, remain unchanged throughout the years, as do emissions factors. Aside from fuel and emissions prices, operational costs are not considered in dispatch decisions, which, due to the age of the Michigan's coal fleet, are not trivial. Since availability factors within the model are based on fuel type averages, the output of older plants may be overestimated.

In the baseline scenario for economic dispatch, the model only considers the cost of fuel when deciding how to dispatch the generating assets. In addition to fuel prices, the economic dispatch model is designed to respond to greenhouse gas emissions costs which were modeled after those in the Environmental Protection Agency (EPA) analysis of the American Clean Energy and Security Act, H.R. 2454 – GHG emissions and economic costs. However, as the results in Figure 52 show, a GHG emissions tax at the level proposed in H.R. 2454 is not high enough to reduce coal-fired electricity generation within the state.

Another limitation of the Economic Dispatch model is the absence of seasonal variation in natural gas prices, which may be one reason for the lack of natural gas generation present in the results. This deficiency in natural gas generation has significant effects on the emissions attributed to PHEVs between the two allocation methods. Both dispatch methodologies are stacked power dispatches; the difference is the order and size of the stacks. As such, operating limitations or competitive market considerations, such as minimum load levels, minimum stable operating levels, minimum run times, generation efficiency decline, ramping rates, operation and maintenance costs, plant construction costs, T&D costs, etc. are not modeled. These modeling assumptions have the greatest effect on generation and dispatch results under the economic dispatch method. The ability of a plant to ramp up and down (increasing or reducing output to meet fluctuations in demand) in response to changes in electricity demand can vary with the fuel used to generate the electricity. For example coal plants have long ramp up times. Therefore, they are predominately used as baseload or intermediate plants. Alternatively, natural gas generators have fairly short ramp up times and thus are used to meet peak demands. Based on these dispatch characteristics, baseload and intermediate plants that operate on a continuous basis are generally coal fired generators while peaking plants that operate in an intermittent dispatch mode are typically natural gas turbines. In real market conditions, natural gas turbines are dispatched to meet peak demands despite their high fuel costs per MWh generated. See Appendix R for a comparison of the generation of the different dispatch models to results obtained from a commercially available electricity dispatch modeling software package, Ventyx's PROMOD®.

Table 25 shows the GHG emissions per mile for the PHEV fleet as it varies with electricity dispatch and emissions allocation methods. The PHEV emissions under the average allocation method vary less than 1% between the Capacity Factor Dispatch and Economic Dispatch under carbon cost constraints scenario suggesting that during times when PHEVs are charging the instantaneous fuel mix of the electricity grid is similar in both dispatch methodologies. Note that these results are for the baseline charging scenario (CH1) where PHEVs charging predominately takes place during early evening hours. On the other hand, under the marginal emission allocation method more extreme variations occur between Capacity Factor Dispatch and Economic Dispatch under carbon costs constraints with a 17% increase in the DM3 scenario over Capacity Factor Dispatch. This difference between allocation methods is due to the absence of natural gas in marginal generation supply in the Economic Dispatch method. In the Economic dispatch simulations, marginal electricity demand is met by coal plants the consequence of which is the assignment of a larger amount of coal emissions to the PHEVs. Marginally assigned PHEV emissions are lower than those under the average allocation method in the case of Capacity Factor Dispatch, but are higher in the Economic Dispatch method due to the differences in intermediate and peaking generation fuel mixes.

Table 25. Comparison of PHEV per mile CO_2eq emissions in 2030

PHEV fleet emissions rate (g CO_2e/mile)	Dispatch Method		
	DM1	DM2	DM3
Average Allocation	267	265	264
Marginal Allocation	252	303	296

Marginally assigned PHEV emissions are lower than those under the average allocation method in the case of capacity factor dispatch, but are higher in the economic dispatch method due to the differences in intermediate and peaking generation fuel mixes between the methods. Under the average emissions allocation method PHEVs are being assigned an average GHG emissions rate based on the carbon intensity of all electricity generation in each hour. This remains relatively constant under the two dispatch methods due to a high proportion of the generation, largely both the baseload and renewable generation, being from nearly the same sources for each method. Under the marginal allocation method, PHEVs are assigned the incremental GHG emissions from power plants operating during battery recharging which would not be operating if PHEVs were not present, termed here as the 'marginal mix'. Because the cost of generation of natural gas is much higher than that of coal, the economic dispatch uses almost exclusively coal power in its marginal mix. In the capacity factor dispatch, the marginal mix is largely the existing natural gas peaking plants and new, cleaner generation. This difference in fuel mix accounts for the high variation in marginal results between the two methods. Other studies have used similar methods to the economic model employed in the present analysis, and a similar tendency to allocate high emissions on the margin was observed in the results of the study by Axsena, Kurania, McCarthy and Yang at University of California, Davis[54]. These high emissions in marginal allocation suggest that simplified economic dispatch methods should not be used with marginal allocation methods as they do not account for many of the complexities inherent to the electricity dispatch. These complexities include generator ramping constraints (coal-fired generation is much slower to ramp up to full power than natural gas turbines), transmission congestion, and seasonal variability in fuel prices. A capacity factor dispatch may be more suited to marginal allocation methodologies because it is inferred that these complexities are inherent to capacity factor, a quantity based on historical generation, despite its limited ability to adjust to changing market environments.

Since the Capacity Factor Dispatch method is based on historical power plant capacity factors, it more accurately simulates the split between baseload power plants and peaking generators. In contrast, the Economic Dispatch model uses the cheapest power supply source to meet electricity demands, regardless of whether this generation is for base, intermediate or peaking load. Despite the many shortcomings of this study's Economic Dispatch model relative to its Capacity Factor Dispatch method, it does have the ability to simulate a future market where carbon intensive electricity is less utilized, and cleaner fuels such as natural gas constitute a greater portion of the generation mix. The GHG emissions tax scenario, based on H.R. 2454, does not cause a significant turnover in generation mix. The capacity decision model can already simulate a significant change in the fuel mix from input guidelines such as accelerated retirement scheduling, aggressive RPS and high nuclear scenarios, but those changes are through pre-defined parameters, rather than on real time price-based conditions. In theory, economic dispatch represents the most accurate simulation of real world conditions. However, in order to mimic the behavior of the competitive electricity market, the model would need to be able to perform asset valuations on a spatially and temporally nodal basis. As the limitations of the current Economic Dispatch model dictate the results, this report has focused on the Capacity Factor Dispatch model results. Economic dispatch results can be found in Appendix P.

5.3 Criteria Air Pollutant Emissions

Table 26. List of scenarios discussed in subsection 5.3

Simulations	FI	EG	CH	DM
Baseline electricity generation PHEV (5.3.1)	1 & 4	1	1	1
Cleanest electricity generation PHEV (5.3.2)	1 & 4	4	1	1

In the previous subsections, the environmental consequences of PHEV infiltration have only been presented as changes in greenhouse gas emissions. Implications to Michigan air quality involve the examination of other atmospheric emissions. Six common air pollutants, defined as criteria pollutants by the EPA and regulated under the Clean Air Act [55], are as follows: Carbon Monoxide (CO), Lead (Pb), Nitrogen Oxides (NO_X), Particulate Matter (PM_{10}), Ozone (which is created at ground-level via chemical reaction between NO_X and volatile organic compounds, VOCs), and Sulfur Dioxide (SO_X). The Michigan Electricity, Fleet and Emissions Model (MEFEM) calculates the emissions for CO, Pb, NO_X, PM_{10}, VOC, and SO_X. Note this study does not account for any potential new emission controls required in future regulations.

5.3.1 Total system air pollutant emissions

In the following discussion, total system emissions in 2030 are compared for simulations with and without PHEVs under the baseline electricity generation capacity scenario (EG1) and simulations with and without PHEVs under the cleanest electricity generation scenario (EG4). The results are presented as a percent change from the zero PHEV case (FI1). The results in Figure 53 are for EG1 conditions and those displayed in Figure 54 are for the EG4 case. These figures are shown to demonstrate the net effect of PHEV infiltration on the entire Michigan system and how these effects change depending on two potential cases for the Michigan 2030 generation capacity fuel mix. A complete table of fuel specific, per mile emissions factors for electricity generation and gasoline usage can be found in Appendix I and Appendix J.

Total system emissions results display increases in SO_X for both electric grid cases and increases in Pb pollutant levels for the EG1 scenario. The increases seen are related to the shift towards electrically driven miles, in which case the electric sector is a more prominent source of pollution than gasoline on a per mile basis. Total system emissions include all electricity generation and transportation sector emissions. Since oil plays such a small role in electricity generation in the initial year, and is not considered an option for new capacity generation, oil electric generation effects are omitted from the following discussion of criteria pollutant emissions. Between the FI1 and FI4 simulations for EG1 oil is the only generation fuel that experiences a net decrease. A net decrease as used here would indicate that more plants of this fuel type are retired or have their power bands decreased than are added as new generation capacity to the system. A net increase would indicate the opposite effect. In the EG4 simulations, there is a net decrease in oil and coal.

In both figures there is an observed decrease in CO emissions when PHEVs are added to the fleet because gasoline has significantly higher total fuel cycle CO emission rates than electricity generation from any fuel type.

The increase in Pb emissions shown in Figure 53 is due to the fact that electricity demands for PHEV recharging causes additional generation capacity. The data source used for gasoline use does not track Pb emissions, despite the fact that it may be present in upstream processes, and therefore a reduction in gasoline consumption cannot decrease Pb emissions. Under EG1 new capacity needs are met mainly by new natural gas and coal generation both of which have Pb emissions. The decrease in Pb emissions under EG4 shown in Figure 54 is caused by the replacement of coal generation with nuclear generation between grid scenarios in addition to the accelerated retirements of coal assets in EG4.

NO_X emission levels decrease in the base grid scenario because all electricity generation fuels have lower NO_X emission rates than gasoline. The total change in electricity generated NO_X emissions due to PHEV infiltration is a net decrease in coal power generated and a net increase in natural gas electricity. Natural gas electricity has the lowest NO_X emissions rate outside of nuclear generation and renewables. The further decrease of NO_X in EG4 is due to the reduction of coal generation because coal has the highest NO_X emission rates of all electricity fuel sources.

PM_{10} remains about the same as the zero PHEV case. Although coal, the predominant energy source in the grid mix, has a greater PM_{10} emission levels than gasoline, the other fuel types used in this study for electricity generation are lower than both gasoline and coal. New power plants have the same PM_{10} emission rates as existing assets of the same fuel type. In the clean grid case these emissions decrease as nuclear replaces coal in the fuel mix. The emissions levels of PM_{10} are less because more coal assets are retired in this scenario.

VOC levels decrease in both generation scenarios due to the displacement of gasoline by PHEV infiltration. Gasoline has higher VOC emission rates than any electricity generation source, even though within the model, new power plants are modeled with the same VOC emission rates as old plants of the same fuel type. Although VOC levels increase due to increased electricity demand from PHEVs, the majority of which is from increased natural gas generation, the corresponding decrease in VOC emissions from gasoline displacement results in a net decrease in total system full fuel cycle emissions.

Total SO_X emissions increase in both generation scenarios when PHEVs are added. New coal plants, built to serve the additional load, have much lower SO_X emissions rates than existing plants. However, because the majority of SO_X emissions for natural gas occur in the upstream phase, the technology improvements applied to new plants do not have as large an effect on total natural gas emissions rates. The technology characteristics for new and existing (averages) plants can be found in Appendix J. While gasoline displacement, especially counting the avoided upstream gasoline emissions, reduces the overall SO_X emitted in the system, the prevalence of natural gas and coal generation within the system results in a net increase in SO_X emissions. It should also be noted that SOX emissions caps are not taken into account in the model and therefore generation emissions from existing plants may be inflated.

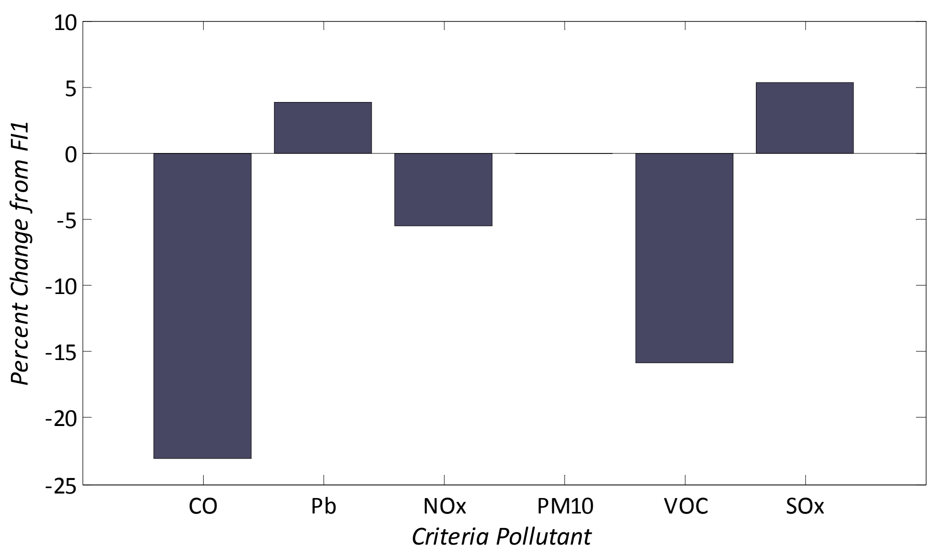

Figure 53. Change in total system emissions between FI1 and FI4 (EG1, CH1, 2030)

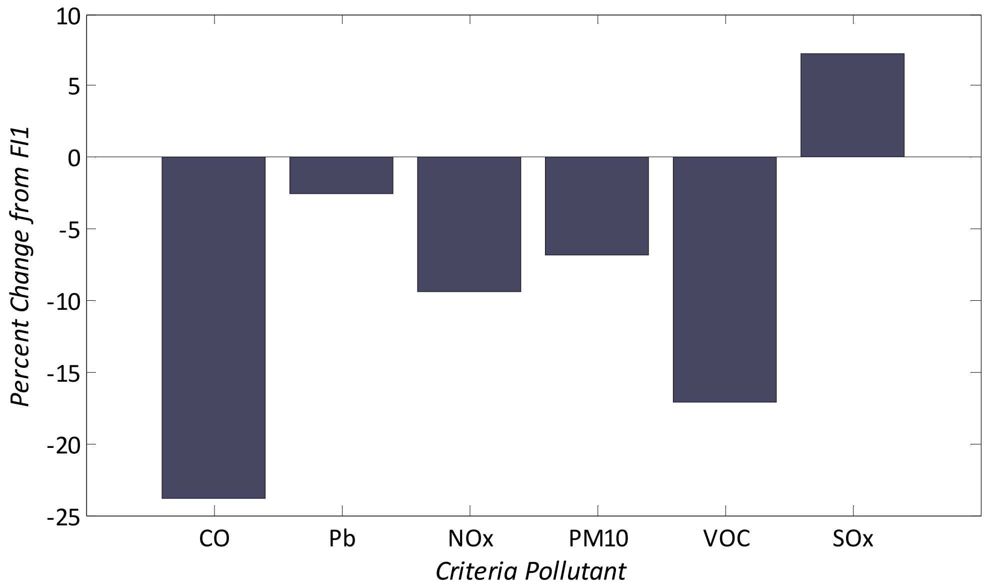

Figure 54. Change in total system emissions between FI1 and FI4 (EG4, CH1, 2030)

The well-to-wheel changes in system wide criteria air pollutant emissions with the addition of PHEVs to the fleet are summarized below in Table 27.

Table 27. Percent change in total system criteria air pollutants.

	CO	Pb	NO_X	PM_{10}	VOC	SO_X
Percent change EG1	-23%	*+4%*	-5%	*-0.1%*	*-16%*	*+5%*
Percent change EG4	-24%	-2%	-9%	-7%	*-17%*	*+7%*

5.3.2 Transportation sector air pollutant emissions

In this subsection, transportation sector emissions in 2030 are broken out from total system emissions and examined by each emission allocation method. They are compared for simulations with high PHEV infiltration between the baseline electricity generation capacity scenario (EG1) and the cleanest electricity generation scenario (EG4) for both emission allocation methods. The results are presented as a percent change from the zero PHEV case (FI1), with Figure 55 displaying emission levels under EG1 conditions and Figure 56 showing these same emissions under the EG4 case.

In both grid scenarios, CO and VOC emission levels all decreased by roughly the same magnitude between marginal and average allocation methods. The reason there is no discrepancy in between allocation methods for these pollutants is because it is the displacement of gasoline that is responsible for the majority of the change in emissions rather than electricity generation changes. Although lead increased in the system due to added electricity demand, it is not displayed in the figures because the base FI1 scenario has zero lead emissions and therefore a percent increase could not be calculated.

NO_X emissions increase about 1% in the case of average emissions because natural gas represents a larger proportion of the fuel mix with PHEVs than without them, while coal and nuclear, both of which have lower NO_X emission rates than natural gas, represent a slightly smaller portion of the fuel mix in FI4 than they did in FI1. However, in the case of marginal allocation, NO_X emissions decrease because marginal emissions are more closely associated with new capacity additions in the system to meet the added PHEV demand. This is because the addition of PHEV charging loads causes existing plants to be used less while new plants meet the new load. In the case of NO_X, new power plants have greatly improved emissions rates over their existing counterparts. In EG4, the same reasoning stands for the decrease in marginal NO_X emissions. In the case of average emissions, NO_X levels decrease because of overall grid improvements.

While marginal emissions of PM_{10} decrease the EG1 scenario, there is an increase in average PM_{10} emissions. Even though coal is reduced in the grid, new plants are modeled with the same PM_{10} emission rates as old plants and coal electricity generation is a very heavy emitter of PM_{10}. In EG4, PM_{10} levels decrease under both allocation methods. This is due to the accelerated coal retirements under this scenario as well as the greater proportion of nuclear (a cleaner burning fuel in terms of PM_{10}) than coal in EG4.

In both grid scenarios, SO_X levels increase because electricity generation emits more SO_X than gasoline. In EG1, marginally allocated emissions are lower than those on the average because the added generation to serve PHEV load are power plants with improvements in SO_X emission rates. Marginal emissions are closely associated with new capacity additions. In EG4, emissions are reduced compared to EG1. However the marginally allocated emissions do not decrease as much because in EG4 there are accelerated retirements of existing coal assets along with fewer new coal plants added to the system. Coal powered generating units have the greatest technology improvements, vastly reducing the SO_X emission rates of new coal generation. In EG1, the addition of PHEVs requires the addition of new generating assets, including new coal, making marginally allocated SO_X levels lower than the average grid, which is influenced by existing coal at 40% of total generation. However in EG4, existing coal is removed in greater numbers than EG1 but not replaced with any new coal generation so while the entire grid does in fact improve with respect to SO_X as shown by the decrease in average emissions, the marginally allocated emissions in EG4 do not receive the same “benefit” as in EG1 from the coal technology improvements.

While an increase in SO_x emissions is not desirable, it should not be cause for alarm. Historically, Michigan has not had trouble meeting the EPA’s SO_2 standards. The entire state of Michigan has been in attainment with the National Ambient Air Quality Standards for SO_2 since 1982 [56]. The measured SO_2 levels have consistently been at about one third or less than the 30 ppb average annual SO_2 standard at each of the monitoring sites throughout the state. However, the EPA adopted a new 1-hour standard of 75 ppb in June of 2010 [57]. Based on air quality measurements from 2007 to 2009, it is expected that Wayne County will be in violation of the standard initially, but EPA models predict it will be in compliance by 2020 [58]. It is unclear if the additional demand for electricity from PHEVs will prevent Wayne or other counties from complying with the new standard.

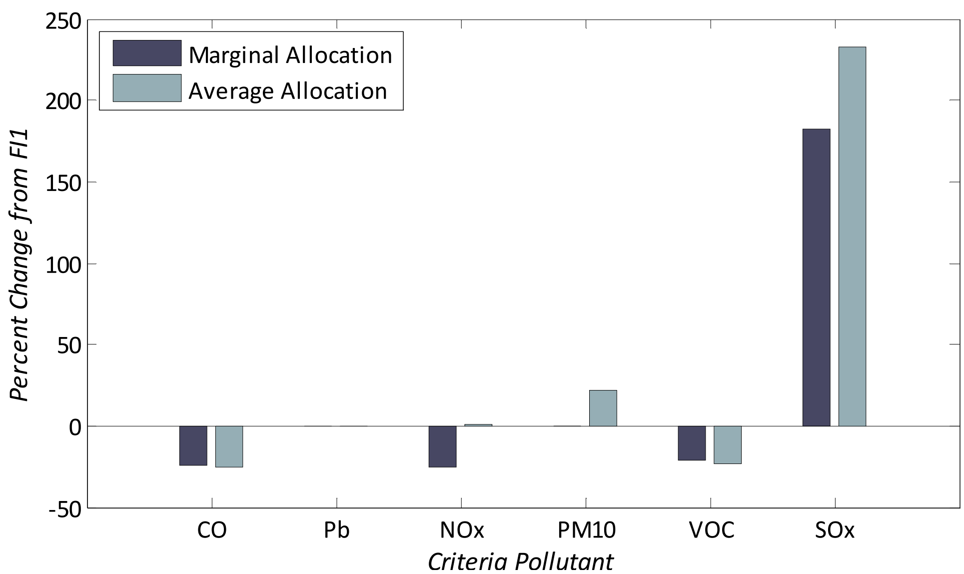

Figure 55. Change in transportation emissions between allocation methods (FI4, EG1, CH1, 2030)

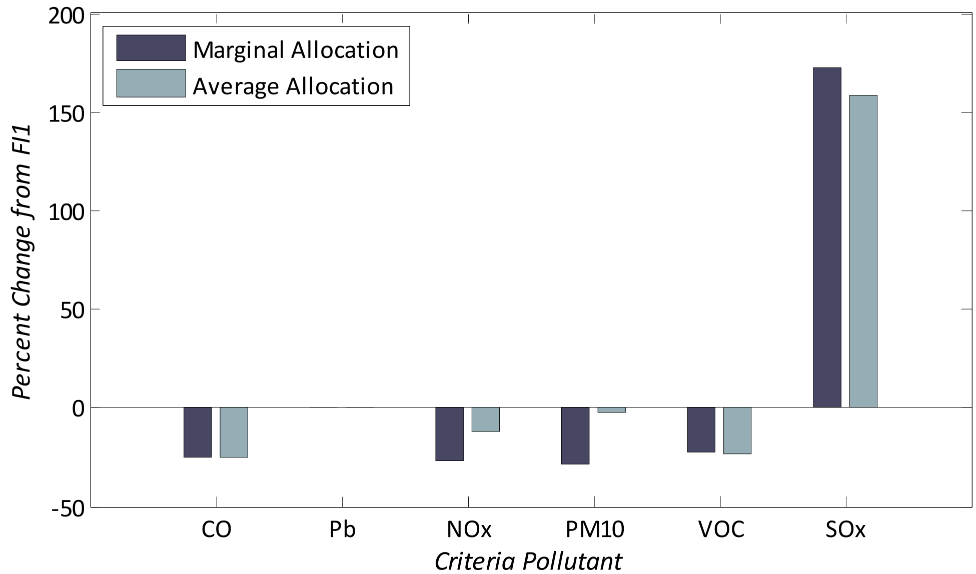

Figure 56. Change in transportation emissions between allocation methods (FI4, EG4, CH1, 2030)

The well-to-wheel changes in transportation sector criteria air pollutant emissions under high PHEV infiltration between allocation methods and grid fuel scenarios are summarized below in Table 28.

Table 28. Percent change in transportation sector criteria air pollutants.

		CO	Pb	NO_X	PM_{10}	VOC	SO_X
Percent change EG1	Average Allocation	*-25%*	*N/A*	*1%*	*22%*	*-23%*	*232%*
	Marginal Allocation	*-25%*	*N/A*	*-25%*	*-0.4%*	*-21%*	*182%*
Percent change EG4	Average Allocation	*-25%*	*N/A*	*-12%*	*-2.3%*	*-23%*	*158%*
	Marginal Allocation	*-25%*	*N/A*	*-27%*	*-29%*	*-22%*	*172%*

Table 29 shows the per mile emissions for all the criteria air pollutants, shown under both EG1 and EG4 scenarios. Values larger than those of the 2030 CV per mile emissions are bolded. Per mile emissions for EG4 are lower than those observed in EG1 for all tracked criteria pollutants. The negative value for lead emissions under the EG4 simulation marginal allocation method does not indicate that the total Pb emissions without PHEVs are higher than the total Pb emissions with PHEVs. This would be impossible due to the fact that gasoline does not have any associated lead emissions. It is caused by the allocation methodology of assigning marginal emissions to PHEVs. In EG4 the marginal mix of generation used to meet the additional PHEV demands are mainly natural gas and nuclear power (Appendix G). Although the 2030 grid mix under scenario EG4 is fairly devoid of coal fired generation, it is still present.

Coal generated electricity has lead emission rates roughly 50% higher than the average lead emissions from nuclear and natural gas. Therefore when PHEVs are assigned the marginal lead emissions it results in a negative value because the mix of the PHEV electricity fuel sources have lower lead emissions than do those power plants supplying the total system baseline electricity demand.

Table 29. Per mile criteria air pollutant emissions.

		CO g/mile	Pb µg/mile	NO_X mg/mile	PM_{10} mg/mile	VOC mg/mile	SO_X mg/mile
EG1	PHEV Average	1.25	**8.58**	**301**	**100**	115	**627**
	PHEV Marginal	1.28	**4.35**	122	65	128	**513**
EG4	PHEV Average	1.24	**3.84**	215	62	114	**459**
	PHEV Marginal	1.25	-1.31	110	22	120	**491**
	2030 CV	3.00	0.00	294	65	247	97

5.3.3 Criteria air pollutants (comparison with GHGs)

Since the Clean Air Act [59], power-plant criteria pollutants have been decreasing despite increasing electricity demands. As shown in the results of this study, PHEVs reduce total fuel cycle greenhouse gas emissions compared with CVs because most CO_2 is emitted from the burning of gasoline. While GHG emissions are global emissions, interpretation of criteria pollutant results is more complex as the impacts of criteria pollutants are location and time dependent. Therefore, criteria air pollutant emissions from mobile tailpipe cannot be considered equally to emissions from stationary power sources. PHEVs produce emissions at both sources.

The results imply that a switch from a conventional vehicle to a PHEV operating in charge depleting mode (all electrical miles) will reduce overall air pollution (except sulfur emissions), and this net benefit is even more pronounced under a less carbon intensive grid. However, the model does not categorize the emissions as point sources. The model looks at the total emission at only state-level resolution. The PHEV CD mode of operation displaces emissions from where more vehicles are driven to where power plants are located. These effects are not accounted for, and as a result, some places will experience a reduction in emissions while some will see air pollutants increasing, as seen in the PHEV study by Thompson, Webber and Allen[12]. However, it may be simpler to regulate emissions from hundreds of stationary power plants than from millions of vehicle tailpipes.

5.4 Total Fuel Cycle Energy

Figure 57 displays the per mile total fuel cycle energy for electric-driven miles. The total fuel cycle energy, or well-to-wheels energy, includes all life cycle energy used to drive the vehicle, from mining, processing and transporting fuels to vehicle propulsion. The black dotted line represents the average energy per mile need to propel the vehicle. This value, 0.30 kWh/mile (1.06 MJ/mile), is marked off to serve as a reference point, the electrical energy needed solely for vehicle propulsion while in charge depleting mode. In general, energy consumed above this line can be ascribed to electricity generation and upstream energy. Again, note the discrepancy between emission allocation methods in the fast charge scenarios, where the grid has experienced a greater number of clean capacity additions.

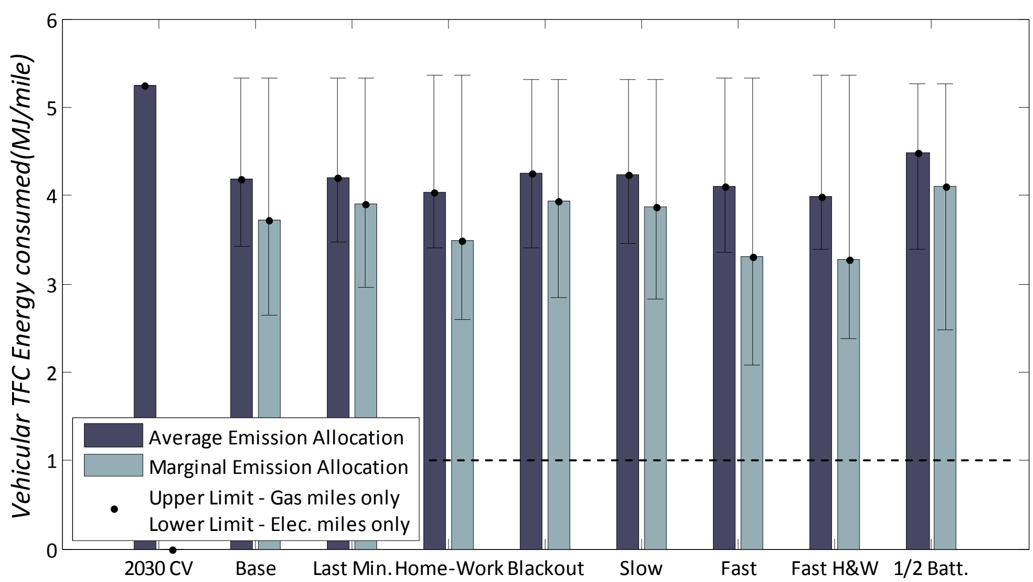

Figure 57. Per mile primary energy for each charging scenario.

All the charging simulations are based on the base future grid mix scenario. When comparing across different generation mixes in Figure 58, the high nuclear scenarios had an increase in per mile energy for PHEVs, while the High RPS scenario reduced the total fuel cycle energy, likely as facility production energy was omitted and electricity supplied by wind, hydro, or LFG had zero associated total fuel cycle energy.

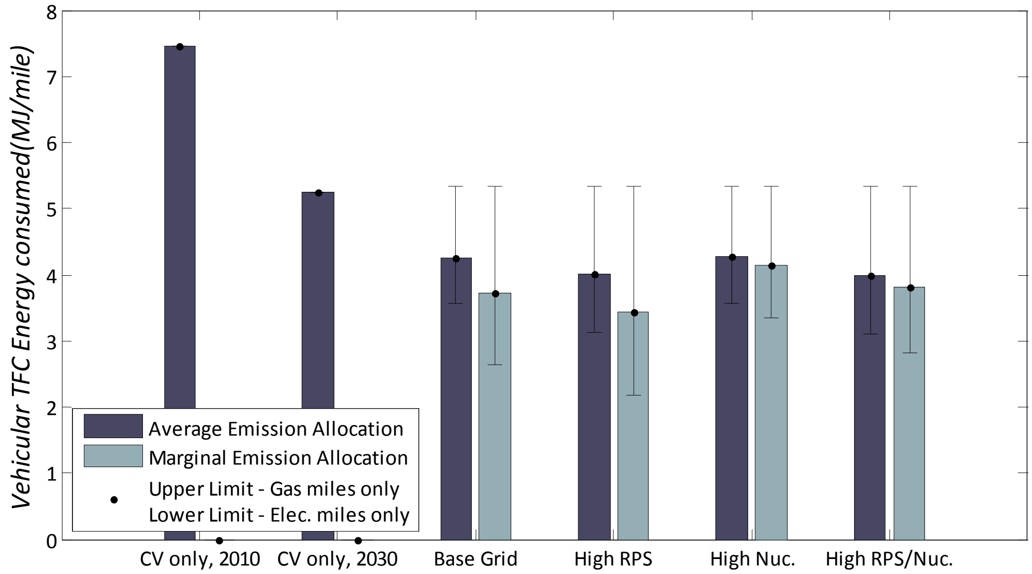

Figure 58. Per mile primary energy for each grid mix scenario.

5.5 Gasoline Displacement

The volume of gasoline displaced by electrically driven miles is calculated for each scenario. The amount of gasoline consumed on a per-vehicle basis is a direct output of the PHEV Energy Consumption Model (PECM). These values are applied to each infiltration scenario, with each PHEV displacing a conventional vehicle in the same size class. This vehicle substitution results in a net reduction of gasoline. The volume of gasoline displaced over each PHEV infiltration scenario, under the base charging (CH1) and base grid mix, is shown in Table 30, along with the proportion of gasoline used in year 2030 compared to the year 2009. That is, due to improvements in the CV fleet alone, Michigan will only use 73% of the gasoline in 2030 as it did in 2009. Bringing many PHEVs online can reduce the state's use to less than half that.

Table 30. Gasoline displacement (millions of gallons) by PHEV fleet infiltration scenario, 2010 - 2030

PHEV Fleet Infiltration Scenario	FI1 (Zero)	FI2 (Low)	FI3 (Med.)	FI4 (High)	FI5 (Max)
TFC gasoline displacement from PHEV infiltration (M gal)	0	569	1,768	5,236	9,019
Percent of total consumption avoided	0	0.6%	2%	6%	10%
Percent of yearly use from 2009	73%	71%	67%	54%	40%

As Table 15 shows, PHEVs increase electricity use. Table 30 shows that increasing the number of on-road PHEVs decreases the state's gasoline needs. Table 31 displays the gallons of gasoline displaced for each PHEV charging scenario under the high PHEV infiltration and base grid mix scenarios.

Table 31. Gasoline displacement (millions of gallons) by PHEV charging scenario, 2010 - 2030

Charging Scenario	CH1 (Base)	CH2 (LM)	CH3 (H&W)	CH4 (Window)	CH5 (Slow)	CH6 (Fast)	CH7 (Fast H&W)	CH8 ($^1/_2$ Batt.)
Gasoline Displacement (Mgal)	5,236	5,236	5,845	4,874	5,060	5,407	6,030	3,728
Deviation from baseline (%)	0%	0%	+11.6%	-6.9%	-3.4%	+3.3%	+15.2%	-28.8%
% of yearly use from 2009	54%	54%	52%	55%	55%	53%	51%	59%

The displaced gasoline volumes shown in Table 31 are dependent on the results of the PECM model, specifically the gasoline/electric miles split seen in Table 13 in subsection 5.1.2. For each PHEV, a greater proportion of miles driven in electric mode translates into a larger displacement of gasoline. Each charging scenario was conducted under a high PHEV infiltration rate; each simulation has the same number of PHEVs. However, comparing Table 30 and Table 31, it can also be seen that while the timing and amount of charging has an effect, increasing the number of vehicles on the road would have a larger cumulative effect on reducing the state's gasoline needs. Many PHEVs are better than few PHEVs, but for a single PHEV, more gasoline is displaced in earlier years than in later years because of the CV improvements seen in Table 30. These gasoline reduction figures do not account for the petroleum used to generate electricity as energy from oil constitutes a negligible fraction of the total Michigan electrical energy supply. The fuel mix of generated electricity does not contribute to any of the reductions in gasoline consumption seen in these results.

5.6 Comparison to other studies

As mentioned in the literature review (subsection 2.1), many previous studies have examined the per mile emissions of PHEVs. Figure 59 shows a collection of per mile greenhouse gas (GHG) intensities for PHEVs (grams of CO_2e per mile) in several of the studies discussed in subsection 2.1, with varying color bars signifying the range of results reported in those studies. The darkest shaded portions represent the values of GHG intensity found in studies that report only a singular emissions level or the lowest value found in studies that present a range of per mile GHG results. The lightest shaded bars symbolize the upper limit of GHG per mile intensities that pertain to studies which reported a range of results. The results from MEFEM are displayed on the right most side of the graph for comparison.

The wide range of per mile emissions stems from the methodology used by the research groups.

For example, the two bars furthest to the left that represent studies by Keoleian and Sullivan, used the same energy consumption factors for PHEVs but assumed different grid CO_2 intensities to achieve different results. EPRI, which has the lowest, studied PHEV emissions from a 2050 electricity generation grid. Overall per mile emissions ranged from 125 to 477 gCO_2e/mile.

The range of MEFEM results, from 215 to 296 gCO_2e/mile, is based on the highest and the lowest average emissions from all scenario sets studied under high PHEV infiltration. The highest PHEV emissions in 2030 were found from the ½ battery charging simulation (FI4 EG1 CH8, Figure 51). The lowest emissions were seen in the High RPS, High Nuclear Electricity simulation (FI4 EG4 CH1, Figure 50), which had the lowest GHG grid intensity. Scenarios such as ½ battery charging in a High RPS, High Nuclear grid would probably have lower emissions per mile from coupling the high electric-to-gasoline miles ratio with at cleaner grid, but this simulation was not investigated in depth, and was not included in creating this grid. Again, the difference in scope of the various studies makes it difficult to compare results. However, the fact that the results of this study are within the range of previous, similar studies adds credibility to the assumptions and methodology used.

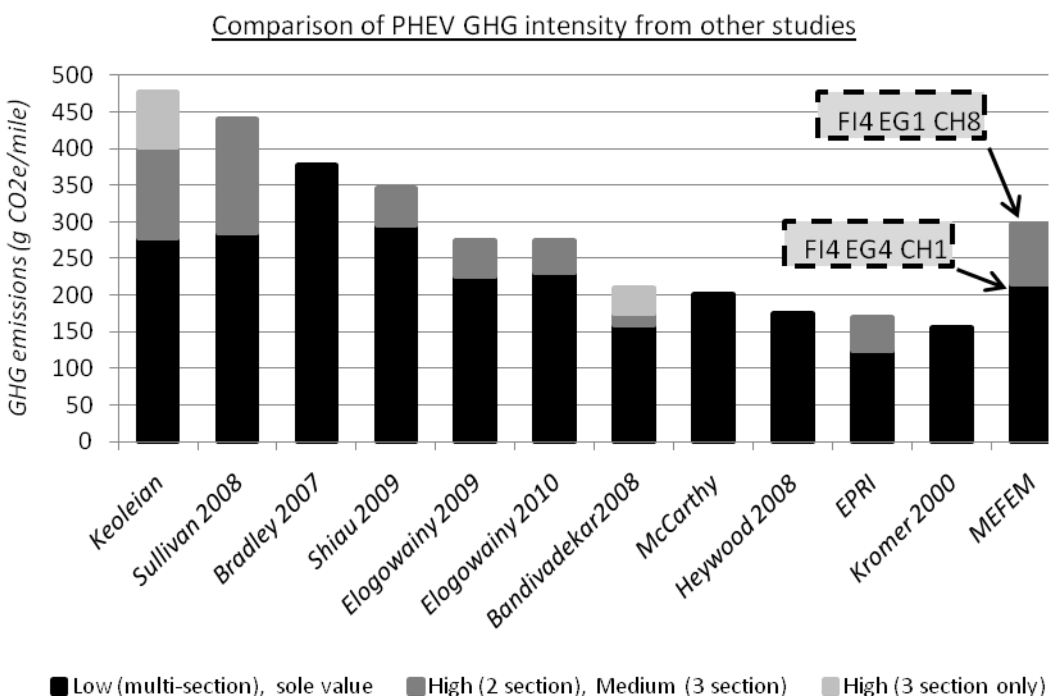

Figure 59. GHG emissions results comparison with other studies

6. Conclusions and Recommendations

The objectives of this study were to determine and evaluate the environmental impacts of widespread PHEV adoption in the state of Michigan from 2010 to 2030.

Two models were developed to examine the effect of emissions from potential future pathways for PHEV battery charging, fleet infiltration, and changes to electricity generation that PHEV introduction may create. The first model, the *PHEV Energy Consumption Model*, begins by determining the individual PHEV electricity demand profiles and gasoline use under a range of vehicle charging assumptions and actual trip patterns from a national daily travel database. In the *Michigan Electricity, Fleet and Emissions Model,* these demand profiles are scaled by the number of PHEVs on the road as defined in the selected infiltration scenario. The total electricity demand for PHEVs is added to the state's baseline electric load and modeled as a single node using average transmission line loss without any further considerations of the system's nodal constraints. New electricity generating capacity is added to the system to meet RPS and spinning reserve requirements when necessary. Plants are dispatched to meet hourly demand based on Michigan specific historical plant capacity factors or the cost of generation. The final results are total fuel cycle energy consumed and emissions of greenhouse gases and criteria air pollutants. These are reported as a system total or allocated to the transportation sector using both marginal and average methodologies. Total transportation sector gasoline displacement is also reported.

While increasing PHEVs reduces gasoline consumption, the extent to which PHEVs can decrease emissions will depend mainly on the impacts to the electric grid from an increasing number of these vehicles in the fleet. A set of scenarios were constructed to explore key variables including market infiltration rates, PHEV user charging and driving behavior, vehicle design characteristics such as battery size and efficiency, and future mixes of electricity generating capacity technologies and their dispatch order. Based on the analysis of simulation results, the team has developed a number of conclusions, recommendations and suggestions for future work which are summarized below.

6.1 Key Findings

Increasing the number of PHEVs in the Michigan fleet reduced net greenhouse gas emissions at every infiltration level (Subsection 5.2)

The shift from gasoline- to electricity-fueled travel yielded a net reduction in total fuel cycle greenhouse gas emissions in every explored simulation, despite the additional emissions from electricity generation. This reduction in total statewide greenhouse gases from electricity and transportation, under the baseline charging and electricity grid mix, ranged from 0.4 to 11.0 billion $kgCO_2e$ in 2030, a 0.4% to 10.9% reduction, depending on the infiltration level. Over the course of the 20 year timeframe, infiltration of PHEVs reduced total GHG emissions by 0.7 to 20 billion $kgCO_2e$, depending on the infiltration level. The relationship between PHEV infiltration and GHG emissions reductions was not linear, with higher infiltration levels having a disproportionately greater impact on GHG emissions reduction. Total fuel cycle emissions of a PHEV, assuming baseline grids and charging methods, ranged from 262 to 252 gCO_2e per mile in 2030 depending upon the allocation method. For reference, an average conventional vehicle in 2010 emitted 530 gCO_2e per mile and in 2030 it was expected to emit 375 gCO_2e per mile. PHEVs in 2010 emitted 265 gCO2e per mile (average allocation) in the model.

PHEV infiltration caused a decrease in the level of certain criteria air pollutants but an increase in others (Subsection 5.3)

CO, NO_X, $PM_{10,}$ and VOC total system emission levels were reduced as a result of PHEV infiltration under both grid mix scenarios. However, total system SO_X emissions increased at each level of PHEV infiltration in all electricity generation scenarios. In the baseline electricity generating capacity case, Pb emissions also increased (4%) in addition to SO_X emissions (increase of 5%). In the high nuclear and high RPS generating capacity case, only SO_X increased. The especially high SO_X is largely due to the fuels consumed for electricity generation versus gasoline, but the results may be inflated because the dispatch model used in this study did not take sulfur caps into account nor advances in SO_X 'scrubbing' into account.

However, while some emissions did increase, these are local emissions at a limited number of power plants. An air quality model of the region is needed to understand the potential impacts of these local emissions, but it should be noted that the benefit of emitting from a small number of sources, compared to distributed emissions among a vehicle fleet, is that it may be much cheaper and easier to mitigate said emissions.

When transportation sector emissions were isolated from total system emissions, the same general trends were observed, but in the cases of particulate matter, SO_X and NO_X large discrepancies existed between marginal and average allocation methods because emissions from new capacity and older natural gas-fired power plants were weighted more heavily toward PHEVs in the marginal allocation method than the average allocation method. The average allocation method assigned a higher percentage of coal generation, which had higher emissions rates than the new capacity and natural gas plants (with SO_X being the only exception), giving the average allocation method higher emissions than the marginal.

PHEVs have lower total fuel cycle energy use than conventional vehicles (Subsection 5.4)

Total fuel cycle energy, or well-to-wheels energy use for PHEVs, under the baseline charging and electric grid mix scenarios was lower than that of the average per mile rate of the CV fleet. In MEFEM, conventional vehicles in 2030 had a fuel economy of 30 miles per gallon. These vehicles consumed 5.2 MJ per mile, accounting for both upstream and combustion energy. Depending on the allocation method, the CH1 scenario on road PHEVs consumption ranged from 3.7 to 4.2 MJ per mile in the base grid scenario. Since the per mile total fuel cycle consumption is lower for PHEVs, increasing the number of PHEVs in the fleet reduces the total transportation sector energy use.

PHEVs can significantly reduce the state's gasoline consumption (Subsection 5.5)

Gasoline displacement increased as the number of PHEVs increased in the simulation. High infiltration reduces gasoline consumption by 26% in 2030 compared to a completely conventional vehicle fleet. By the year 2030, between 569 and 9019 million gallons of gasoline were displaced when compared to the scenario without PHEVs. Within the model, the consumption rates of conventional vehicles improved annually, but the consumption rates of PHEVs did not. Because PHEV technology does not improve, the benefits of a single PHEV are reduced over time. Therefore, the actual gasoline displacement as infiltration increases may increase if PHEV technology improvements were included in the model.

Total system greenhouse gas emissions were modestly affected by the shape and magnitude of the PHEV charging load (Subsection 5.2.3)

The total fuel cycle system greenhouse gas emissions were affected by charging assumptions in the high PHEV scenario. In 2030, the charging scenarios examined in this report showed between a 3.5% reduction (fast charging) and a 1.6% increase (last minute charging) in GHG emissions when compared to the baseline charging scenario. The two fast charging scenarios showed the greatest reduction in most emissions, largely due to the increase in the annual peak load. This increase resulted in a need for more new generating capacity within the model to meet spinning reserve requirements.

New capacity was assumed to be cleaner than existing generators, having the characteristics displayed in Appendix B. The last minute charging scenario posted the greatest increase in emissions because most of the load was added in the hours of least demand, which was largely coal-fired generation and reduces the amount of new capacity needed to meet demand.

The shape of the normalized charging curve for a single PHEV is significantly affected by changes to charging behavior. A fast charge can create a large spike in the aggregate behavior; a larger battery will increase the magnitude and duration of charging; last minute charging will shift the load to the times of least demand; and instituting periods in which a vehicle cannot charge creates an instantaneous peak when the window ends.

While these differences in the shape of the charging curve are not significant until there are a large number of PHEVs in the LDV fleet, for any number of PHEVs, greater proportions of miles driven in electric mode tend to decrease GHG emissions.

Imposing a period of time in which vehicles cannot charge to avoid additional peak demand seems to have less desirable results than intended. Enforcing this makes all PHEV consumers in the model simply wait until the no-charge window is lifted to plug in, creating a very significant peak in a later hour. The no-charge window scenario had among the highest per mile greenhouse gas emissions of any charging scenario examined with a 1.5% increase over the baseline scenario. One way to mitigate this peak may be to stagger the start time of PHEVs through demand side management controlled by the utility's smart grid.

Last minute charging was the most effective strategy to shift load into off peak hours. In order to implement last minute charging, vehicles will have to come equipped with software that allows users to set the time they expect to leave in the morning such that the vehicle can estimate the latest possible time to begin charging. However, last minute charging increased emissions in most categories as less new capacity is brought online and it allows more generation to be met by existing baseload coal-fired plants.

The greatest GHG emissions and energy use of any charging scenario occurred in the smaller battery scenario, due to the decrease in electrically driven miles. An examination of continually increasing battery size, found in Appendix H, revealed a strong coupling of battery size to the percentage of electrically driven miles. However, it also showed that the rate of increase diminished as battery size grew. This suggests an interesting trade-off: while larger batteries allow for more electrically driven miles, smaller batteries will be more economical and many consumers may opt for smaller battery sizes if their commute does not require larger range. This suggests that an optimization of battery size, GHG reductions, and cost may be an interesting direction for further research.

Renewable generation and accelerating the retirement of coal-fired power plants improve transportation sector greenhouse gas emissions (Subsection 5.2)

By simulating a high RPS, nearly 33% of Michigan's electricity needs could be provided by clean, renewable sources. However, because of the nature of our dispatch model, the large addition of renewable sources had the effect of replacing natural gas generation. This is not a realistic result since peaking plants will be required to even out these intermittent power sources. If the model correctly accounted for ramping constraints, more natural gas utilization would be observed. As more natural gas generation is added to the system to complement renewable intermittent generation, a larger decrease in GHG emissions may be seen as less coal-fired generation will be utilized.

Other simulations showed that retiring older coal plants to bring nuclear baseload generation online resulted in much lower emissions both overall and due to PHEVs. In the base grid scenario, PHEVs increased greenhouse gas emissions related to electricity by 5.4% from 2010 to 2030. The high RPS scenario decreased this to 4.8%. The high nuclear simulation, which accelerates the retirement of coal-fired baseload and builds more nuclear generation, served the PHEV load with only a 2.0% increase in greenhouse gas emissions, while reducing the overall grid GHG emissions to 54% of the original 2009 grid. In this high nuclear scenario in 2030, coal generation drops substantially from the baseline grid mix scenario, going from 38% of total generation to 17%, and nuclear generation increases from 26% to 39% of total generation.

When examining the effects of a changing grid, removing older plants and increasing new, cleaner generation decreases criteria air pollutant emissions compared to a baseline grid scenario, but SO_X emissions still increase with PHEV infiltration (Subsection 5.3)

Higher PHEV infiltrations increase the need for new generation, and by bringing cleaner sources of generation online, emissions are reduced. However, the sulfur content of the fuels used to generate electricity, especially the upstream SO_X emissions of natural gas generation, is much higher than the intensity of SO_X in the avoided gasoline. Therefore, while cleaning the grid reduces the total emissions in the electricity generation sector, more PHEVs increase SO_X emissions in the transportation sector.

The addition of renewable generation can reduce total fuel cycle energy (Subsection 5.4)

Since renewable generation was modeled without any manufacturing energy, it has no associated total fuel cycle energy. Thus, increasing the amount of renewable generation in the system has a significant impact on the PHEV's total fuel cycle energy. By retiring coal plants and increasing nuclear and natural gas generation, the high nuclear scenario had a greater effect on emissions than the high RPS scenario. However, PHEVs within the high RPS scenario had the lowest energy consumption per mile travelled, at 3.4 MJ/mile using a marginal allocation method, while the high nuclear scenario increased PHEV energy use per mile to above the base scenario rates. For all the grid scenarios, PHEV energy use per mile was still lower than CV energy use.

6.2 Recommendations

PHEV adoption should be encouraged within the state

In every scenario extrapolating a future Michigan grid, increasing the infiltration of PHEVs decreased greenhouse gases, transportation energy, and most criteria pollutants. Increasing PHEVs also reduced the state's petroleum use.

To avoid creating new peaks in electricity demand, more charging locations and last minute charging are the best strategies

Utilities may be interested in avoiding new peaks in electrical demand to minimize the need for new peaking capacity in the future. The goal is then to both spread out the PHEV demand and to move it to off peak hours, which is best simulated by the last minute charging and the home-work scenario. Fast charging would force new, cleaner generation into the grid; however, this would come about by creating new peaks in the system electrical demand that, in this model, creates the need for new cleaner generating capacity. Home and work charging provides a similar electric-to-gasoline miles ratio as fast charging, and home and work charging produces similar reductions in GHG emissions to fast charging without creating such large peaks in demand using the average allocation method. If the goal is to avoid creating large peaks while still increasing total electric miles driven, then investments in work charge infrastructure will work better than investments in fast charge infrastructure.

To bring about the greatest environmental improvements, Michigan's aging coal-fired power plant fleet should be retired and replaced with cleaner generating sources

While adding renewable generation does improve the grid, simulations in which coal plants that were retired at age 60 and replaced with cleaner sources showed significant decreases in greenhouse gas emissions. When the grid was improved, the additional emissions attributed to PHEVs were also reduced.

A standardized methodology for assigning electricity generation emissions due to PHEV charging is needed

The method of assigning electricity generation emissions to PHEVs needs to be standardized. The marginal allocation methodology only attributes the emission from generation units that are brought online to meet the additional load to PHEVs which in this model are typically new plants in the later years. However, under the average allocation method, the existing generation also comprises a large component of emissions assigned to PHEV loads. To definitively quantify the environmental effects of PHEVs, an allocation method must be chosen.

6.3 Future Work

The study identifies some of the complexities associated with analyzing an integrated system of transportation and electric sectors. Depending on the power level, timing, and duration of the PHEV connection to the grid, there could be a wide variety of impacts on grid constraints, capacity needs, fuel consumed, and emissions generated. Some areas that could be more fully explored include:

Incorporating other alternative fueling strategies for light duty vehicles

Within this study, vehicles were modeled as either plug-in electric hybrid or conventional gasoline fueled vehicles. The emissions factors for gasoline include a small amount of blended ethanol, but this ratio is fixed within the model. Appendix M explores a fleet of 85% ethanol PHEVs. In the future, vehicles may use alternative fuels such as biodiesel, petroleum diesel, natural gas, or other biofuels. Further work could investigate the effects on emissions and gasoline displacement from the incorporation of these fuels into the model.

Developing PHEV technology improvements within PECM

PHEVs in the model have the fuel consumption characteristics listed in Appendix F which are based on pre-production and academic sources in 2009. While conventional vehicles have continually improving fuel economies, PHEV characteristics do not change in the model. PHEVs are also expected to improve over time, and modeling this would improve emissions results.

Employing blended charging strategies

All PHEVs will not be charging under the same conditions. It is likely that actual PHEVs in the fleet will employ many of the different scenarios outlined and combinations of some of the parameters in those scenarios. The scenarios provided represent the bounds of the actual energy consumption patterns of PHEVs: i.e. it is unlikely that all PHEV owners will have access to fast charge infrastructure (CH6). Development of a blended energy consumption representation that is a weighted average of the different charging scenario results may provide a more accurate picture of what will be seen at large fleet infiltration levels. In addition, these weighted averages could be used to determine optimal scenarios for specific utility needs, such as filling in the valley in daily demand curves.

Developing the electricity generation and dispatch further

Capacity factor dispatch is employed with the underlying assumption that future dispatch will be similar to the dispatch of the previous year. Outside factors that change the economics of electricity generation, such as new taxes or regulations, would skew the dispatch order in real life but would not be captured by the capacity factor dispatch methodology. Also, the ratio of imported power was held constant and used only to serve peak demand, but this is not necessarily the case for the Michigan grid.

Other power dispatch characteristics not captured in the current model include minimum run times for facilities, minimum load levels, and physical constraints on ramping rates and associated ramping emissions.

While a large fleet of PHEVs could theoretically be accommodated within Michigan at current capacity levels, depending on when or where vehicles are plugged in load transmission and distribution constraints could arise at local or regional levels. The model's current treatment of demand and generation as point sources is a great simplification. The current economic dispatch model also assumes that fuel prices are constant all year, which is not accurate for natural gas. A further developed economic dispatch would allow better research into the effects of emissions pricing, especially with a more sophisticated transmission and distribution methodology and more time variability in fuel prices.

Appendix A. Initial assets matrix

This appendix provides information about the quality of power plant data presented in this report. The list of generating assets is presented first, followed by a discussion of sources. The initial Assets Matrix contains 186 existing plants from the state of Michigan, and spans several pages. A summary of generation information can be found at the end.

Table 32. Assets Matrix

Plant Name	Main Fuel	Nameplate Capacity (MW)	Capacity Factor	Heat Rate (Btu/kWh)
491 E 48th Street	Nat Gas	161.7	0.01	11,614
Ada Cogeneration LP	Nat Gas	33.1	0.71	8,500
Ada Dam	Hydro	1.4	0.4	0
Adrian Energy Associates LLC	LFG	2.4	0.89	8,500
Alcona	Hydro	8	0.35	0
Allegan Dam	Hydro	2.6	0.52	0
Arbor Hills	LFG	30.3	0.47	14,022
B C Cobb-Coal	Sub Coal	312.6	0.75	11,080
B C Cobb-NG	Nat Gas	207	0.02	15,858
B E Morrow	Nat Gas	36	0	17,310
Bay Windpower I	Wind	1.8	0.12	0
Belle River-Coal	Sub Coal	1395	0.67	10,315
Belle River-NG	Nat Gas	255.9	0.06	13,095
Berrien Springs	Hydro	7.2	0.48	0
Big Quinnesec 61	Hydro	4.4	0.05	0
Big Quinnesec 92	Hydro	17.8	0.6	0
Boardman	Hydro	1	0.58	0
Brent Run Generating Station	LFG	1.6	0.94	9,069
Buchanan	Hydro	4.4	0.36	0
C & C Electric	LFG	5.7	0.42	13,648
C W Tippy	Hydro	20.1	0.31	0
Cadillac Renewable Energy	Biomass	44	0.57	9,458
Cargill Salt	Bit Coal	2	0.65	9,894
Caro	Oil	9.4	0	11,743
Cascade Dam	Hydro	1.6	0.44	0
Cataract	Hydro	2	0.19	0
Central Michigan University	Biomass	4.8	0.07	12,071
Chalk Hill	Hydro	9.9	0.32	0
Cheboygan	Hydro	1.5	0.43	0
Claude Vandyke	Nat Gas	47.8	0.02	12,915
Coldwater	Nat Gas	12	0.01	12,616
Conners Creek	Nat Gas	275.4	0.03	16,820
Constantine	Hydro	1.2	0.38	0
Cooke	Hydro	9	0.3	0
Covert Generating Project	Nat Gas	1176	0.09	7,335
Croswell	Oil	5.1	0	11,443
Croton	Hydro	8.9	0.48	0
Crystal Falls	Hydro	1	0.53	0
Dafter	Oil	9	0	18,726
Dan E Karn-Coal	Sub Coal	544	0.79	10,680
Dan E Karn-NG	Nat Gas	1402.3	0.04	16,892
Dayton	Oil	10	0	22,667
Dearborn Industrial Generation	Nat Gas	760	0.29	5,048
Decorative Panels Intl	Bit Coal	7.5	0.71	6,117
Delray	Nat Gas	142.2	0.05	13,246

Detour	Oil	6	0.01	19,396
Diesel Plant NG	Nat Gas	10	0	20,365
Diesel Plant Oil	Oil	20.9	0.01	10,872
Donald C Cook	Nuke	2285.3	0.87	0
DTE East China LLC	Nat Gas	357.6	0.03	12,296
Eckert Station	Sub Coal	375	0.46	13,764
Edenville	Hydro	4.8	0.35	0
Edison Sault	Hydro	41.8	0.58	0
Endicott Station	Bit Coal	58.2	0.74	16,717
EQ Waste Energy Services	LFG	1.4	0.81	8,500
Erickson Station	Sub Coal	154.7	0.72	12,152
Escanaba	Bit Coal	49.8	0.41	12,510
Escanaba Paper Company	Biomass	103.3	0.76	14,353
Fermi	Nuke	1281	0.78	2
Five Channels	Hydro	6	0.42	0
Foote	Hydro	9	0.34	0
Four Mile Hydropower Project	Hydro	2	0.48	0
Frank Jenkins	Nat Gas	3.8	0	8,357
French Landing Dam	Hydro	1.6	0.44	0
French Paper Hydro	Hydro	1.3	0.74	0
Gaylord 1	Nat Gas	80	0.02	16,784
Gaylord 2	Nat Gas	70.2	0.01	16,545
Genesee Power Station LP	Biomass	39.5	0.68	16,643
George Johnson	Nat Gas	73	0.05	11,711
Gladstone	Oil	22.6	0.03	19,491
GM WFG Pontiac Site Power Plant	Bit Coal	28.9	0	6,859
Grand Blanc Generating Station	LFG	4	0.9	11,594
Grand Rapids	Hydro	7.5	0.5	0
Granger Electric Generating Station #1	LFG	3.2	0.94	11,836
Granger Electric Generating Station #2	LFG	4	0.78	12,771
Graphic Packaging	Oil	11.8	0.09	17,392
Grayling Generating Station	Biomass	38	0.76	15,975
Greater Detroit Resource Recovery	Biomass	68.4	0.44	7,050
Greenwood	Nat Gas	1071.3	0.08	12,143
Hancock	Nat Gas	160.2	0.01	13,382
Harbor Beach	Bit Coal	125	0.33	10,658
Hardy	Hydro	30	0.34	0
Hemlock Falls	Hydro	3.1	0.33	0
Henry Station	Nat Gas	15.4	0.01	8,997
Hillman Power LLC	Biomass	20	0.77	15,812
Hillsdale	Nat Gas	21.9	0.01	11,279
Hodenpyl	Hydro	19	0.18	0
Hoist	Hydro	4.4	0.32	0
Hydro Plant	Hydro	2.2	0.36	0
J B Sims	Bit Coal	65	0.77	10,390
J C Weadock	Sub Coal	331.2	0.71	11,079
J H Campbell	Sub Coal	1558.7	0.73	10,211
J R Whiting	Sub Coal	364	0.73	11,765
James De Young	Bit Coal	62.8	0.55	14,874
James R. Smith	Hydro	3.2	0.4	0
Kalamazoo River Generating Station	Nat Gas	73.1	0.02	13,945
Kalkaska CT #1	Nat Gas	75	0.01	11,102
Kent County Waste to Energy Facility	Biomass	18	0.64	20,422
Kinder Morgan Power Jackson Facility	Nat Gas	649	0.04	8,788
Kingsford	Hydro	9	0.32	0
LaFarge Alpena	Oil	47.2	0.68	9,659
Livingston Generating Station	Nat Gas	170.1	0.01	16,000

Loud	Hydro	4	0.47	0
Lowell	Nat Gas	3.6	0.01	4,377
Ludington	Hydro	1978.8	-0.1	0
Lyon Development	LFG	5	0.46	17,491
Main Street	Nat Gas	6	0	9,077
Manistique	Oil	4.8	0.01	16,469
Marshall	Nat Gas	11.8	0.01	10,763
McClure	Hydro	8	0.48	0
Menominee Acquisition	Bit Coal	4	0.21	8,066
Menominee Mill Marinette	Hydro	1.8	0.95	0
Michigamme Falls	Hydro	10.6	0.3	0
Michigan Power LP	Nat Gas	154.1	0.78	8,476
Midland Cogeneration Venture	Nat Gas	1853.8	0.38	7,289
Mio	Hydro	5	0.3	0
Mistersky	Nat Gas	189	0.15	14,955
Modular Power LLC	Oil	14.8	0	10,745
Monroe	Bit Coal	3293.1	0.65	9,436
Mottville	Hydro	1.6	0.42	0
Neenah Paper Munising Mill	Bit Coal	6.2	0.7	10,271
Newberry	Oil	5.5	0.01	11,119
Ninth Street Hydropower Project	Hydro	1.2	0.56	0
Northeast	Nat Gas	129.8	0	15,592
Norway	Hydro	5.6	0.45	0
Norway Point Hydropower Project	Hydro	4	0.34	0
Otsego Mill Power Plant	Nat Gas	21.2	0.46	9,454
Ottawa Generating Station	LFG	4.8	0.94	11,165
Palisades	Nuke	811.8	0.93	0
Parkedale Pharmaceuticals	Nat Gas	2.8	0.9	14,783
Peavy Falls	Hydro	15	0.34	0
Peoples Generating Station	LFG	3.2	0.95	7,037
Pine Street	Nat Gas	7	0	8,956
Pine Tree Acres	LFG	5.6	0.97	10,686
Plant Four	Oil	24	0.02	15,454
Portage	Oil	22.6	0.08	16,570
Powertrain Warren General Motors	Nat Gas	4	0.45	5,421
Presque Isle	Bit Coal	624.7	0.63	11,815
Prickett	Hydro	2.2	0.45	0
Putnam	Oil	13.5	0	18,085
Quinnesec Mich Mill	Biomass	28	0.86	14,106
Renaissance Power LLC	Nat Gas	680	0.08	10,879
River Rouge-Coal	Sub Coal	650.6	0.52	9,589
River Rouge-NG	Nat Gas	282.6	0	9,957
Riverview Energy Systems	LFG	6.6	0.62	10,886
Rogers	Hydro	6.8	0.44	0
Romulus Operations Powertrain	Nat Gas	10.7	0	40,790
S D Warren Muskegon	Bit Coal	50.9	0.45	6,427
Saint Marys Falls	Hydro	18.4	1.05	0
Sanford	Hydro	3.6	0.23	0
Saxon Falls	Hydro	1.2	1.05	0
Secord	Hydro	1.2	0.33	0
Shiras	Sub Coal	77.5	0.45	13,751
Smallwood	Hydro	1.2	0.28	0
St Clair	Sub Coal	1570.9	0.54	10,309
St Louis	Oil	6.9	0.01	9,725
State St Generating	Oil	16.2	0.01	8,499
Stone Container Ontonagon Mill	Bit Coal	15.6	0.75	5,640
Straits	Nat Gas	20	0.01	17,927

Sumpter	Nat Gas	340	0.04	13,107
Sumpter Energy Associates	LFG	12	0.83	14,189
Superior Falls	Hydro	1.2	1.17	0
T B Simon Power Plant	Bit Coal	99.3	0.28	6,618
TES Filer City Station	Bit Coal	70	0.73	12,310
Thetford	Nat Gas	222.4	0.02	17,327
Tower	Oil	25.2	0	18,829
Trenton Channel	Bit Coal	775.5	0.62	10,442
Twin Falls	Hydro	7.6	0.47	0
Ubly	Oil	12.4	0	19,219
University of Michigan	Nat Gas	44.5	0.41	12,392
Venice Resources Gas Recovery	LFG	1.6	0.66	15,890
Vestaburg	Nat Gas	31.4	0.01	18,002
Victoria	Hydro	12	0.49	0
Viking Energy of Lincoln	Biomass	18	0.92	9,698
Viking Energy of McBain	Biomass	18	0.88	13,743
Voss Lantz	Nat Gas	1	0.47	8,500
Voss Taylor	Nat Gas	1	0.43	8,500
Warner Lambert	Nat Gas	12.4	0.24	8,500
Water Street Station	Nat Gas	12.6	0.01	15,613
Way Dam	Hydro	1.8	0.3	0
Webber	Hydro	4.3	0.26	0
White Pine Electric Power	Bit Coal	60	0.24	15,886
White Rapids	Hydro	9.1	0.36	0
Wyandotte	Bit Coal	78.4	0.46	14,812
Zeeland	Nat Gas	22.3	0.01	13,658
Zeeland Plant	Nat Gas	968.1	0.07	8,852

Table 33. Summary of Generation Details

Summary of Generation Details:	
Sum of generation	121,328 GWh
Sum of generation excluding wind and hydro	120,999 GWh
2005 total electric demand	125,165 GWh
Imported percentage	3.33%

As noted previously in this report, the source for the initial set of power plants and their generation details is the EPA's eGRID database. The specific version of this database used was published in 2007 and contains generation data for the year 2005. The information provided in eGRID includes fuel consumption, emissions and emission rates, and generation and resource mix; along with plant identification, location, and structural information for Michigan power plants. These eGRID files represented the most comprehensive power generation data source for the purposes of this study. However, certain data quality issues were identified within eGRID that required special attention. Some of these disparities could be ameliorated from changes within the dataset itself while other discrepancies necessitated input from separate sources. In addition to eGRID, values for certain categories were derived from two principal sources: EIA 2005 906/920 electricity database files and the

Michigan Air Emissions Reporting System [60]. The original eGRID database contained a total 193 plants. The final list of generating assets as displayed above and utilized in this analysis totals 186. This procedure had 6 steps: (1) re-labeling of duplicate plants, (2) elimination of plants with capacity factor < zero, (3) correction of primary fuel type discrepancies, (4) break-out of specific plants to generator level detail, (5) correction of inconsistent heat rates, and (6) substitution of irrational emission factors. Details for each step are defined in greater detail as follows:

1. From the original set of eGRID data, there two separate plants that were both named 'Diesel Plant' and two separate plants that were both named 'Gaylord'. Both sets of duplicate plant names were broken out into the following: Diesel Plant Oil, Diesel Plant NG, Gaylord 1 and Gaylord 2. The total number of plants did not change; only plant names were altered.
2. All plants listed with negative capacity factors, aside from the Ludington pumped hydro unit, were removed from the assets list. Eleven plants fit this description, all of which were small (in terms of nameplate capacity) fossil fuel generators.
3. The 'Fermi' plant, confirmed by DTE Energy to be a nuclear generation unit, was listed in eGRID as an oil plant. The primary fuel type for Fermi was changed to nuclear.
4. The eGRID workbook, for the year 2005, includes spreadsheets for boilers, generators and plants. Information from the plant-level sheet was used for the majority of the analysis. However there were a few plants that required generator break-outs based on the discrepancy between the plants listed primary fuel type and percentage of plant generation from that fuel type. Plants were broken down to generator unit level if they met the following criteria: (1) the discrepancy just described was greater than one percent, (2) it was a fossil fuel plant that provided at least one percent of the total power generation. If a plant met these criteria, it was broken into generating units based on distinct fuel types. For example, Dan E. Karn is a plant that is comprised of five generators, three natural gas and two coal generators. It is sufficiently large in terms of generation, and therefore was split into two separate "plants" named Dan E. Karn-NG and Dan E. Karn-Coal, with nameplate and capacity factors characterized by the appropriate group of the generators. These steps were necessary for four plants in the model: Dan E. Karn, B.C. Cobb, River Rouge and Belle River. Emissions and heat input for each fuel type was calculated by mapping the boilers to the generating units within the eGRID workbook. This step brings the total number of plants to 186.
5. Heat rate improvement measures were taken for fossil fuel assets whose heat rates were

greater than 17,000 or less than 9000 (in the case of coal) or less than 7000 (in the case of natural gas or oil), deemed 'unreasonable'. This was true of 34 plants in the database. The new heat rates that were assigned to these plants came from the EIA-906/920 electricity database files for 2005.

6. Finally, there were two plants, Midland Cogeneration Venture and Dearborn Industrial Generation, with unreasonably low NO_X, SO_2 and CO_2 emission rates, rates near zero. These values were corrected by substituting NO_X and SO_2 rates from MAERS and CO_2 rates from EPRI 2007 TAG for next generation natural gas plants. CO_2 rates for these plants could not be found in either the MAERS or EIA 906/920 documents. The value from EPRIs TAG was deemed a prudent choice as both of these plants a relatively new co-generation units and therefore should theoretically have lower CO2 emission rates compared to their conventional counterparts

Appendix B. Scripted fleet retirements and additions

Given the time span of this study, it is probable that plants in operation will not continue to provide electricity for the entire twenty year span. This is due in part to the fact that plant efficiency decreases with increasing age, a relationship excluded from the present model. Taking plants offline within the model is termed 'retirement,', and two sets of retirement matrices are used in the model. Within the baseline list are plants specified per the Michigan Capacity Need Forum – Report to the Michigan Public Service Commission (Appendices) in 2006[26]. The accelerated retirements is based on the age of the generation unit. Generator units of power plants are be retired once they reach the age 60. Tables of both plant retirement schedules are below:

Table 34. Baseline retirements list

Plant Name	Year	MW	Plant Name	Year	MW	Plant Name	Year	MW
B.C. Cobb-NG	2013	68	**Northeast**	2018	124	**B C Cobb-Coal**	2022	160
B.C. Cobb-NG	2013	61	**Northeast**	2018	153	**River Rouge-Coal**	2022	155
B.C. Cobb-NG	2015	52	**J R Whiting**	2018	162	**J C Weadock**	2022	247
491 E 48th Street	2015	39	**Eckert Station**	2019	46	**Wyandotte**	2022	22
Trenton Channel	2015	210	**St Clair**	2019	171	**Eckert Station**	2023	47
Conners Creek	2016	11	**St Clair**	2019	158	**Escanaba**	2023	47
James De Young	2016	215	**Presque Isle**	2020	155	**Mistersky**	2023	280
J R Whiting	2017	102	**J C Weadock**	2020	25	**River Rouge-Coal**	2023	26
J R Whiting	2017	102	**B C Cobb-Coal**	2021	160	**Dan E Karn-Coal**	2024	255
			River Rouge-NG	2021	242	**Dan E Karn-Coal**	2024	260

Table 35. Accelerated Retirements list

Plant Name	**Year**	**MW**	**Plant Name**	**Year**	**MW**	**Plant Name**	**Year**	**MW**
Trenton Channel	2010	120	**J C Weadock**	2015	156.3	**Fermi**	2026	16
Trenton Channel	2010	120	**Presque Isle**	2015	25	**Hancock**	2026	41.8
Mistersky	2010	44	**Dafter**	2015	1	**Northeast**	2026	16
Diesel Plant Oil	2010	2.7	**Dafter**	2015	1	**Northeast**	2026	16
Diesel Plant Oil	2010	2.7	**Dafter**	2015	1	**Northeast**	2026	16
Hillsdale	2010	2.7	**LaFarge Alpena**	2015	10	**Presque Isle**	2026	57.8
Marshall	2010	1	**Lowell**	2016	1.1	**Main Street**	2026	1.1
Marshall	2010	1.7	**B C Cobb-Coal**	2016	156.3	**Main Street**	2026	1.3
Newberry	2010	0.7	**River Rouge-NG**	2016	282.6	**Zeeland**	2026	1.4
Frank Jenkins	2010	0.8	**Zeeland**	2017	2	**T B Simon Power**	2026	12.5
St Louis	2010	0.6	**Decorative**	2017	7.5	**Stone Container**	2026	15.6
Main Street	2010	0.9	**B C Cobb-Coal**	2017	156.3	**J H Campbell**	2027	403.9
Diesel Plant NG	2010	1	**River Rouge-Coal**	2017	292.5	**Hancock**	2027	19
Diesel Plant NG	2010	1	**J C Weadock**	2018	156.3	**Hancock**	2027	19
Diesel Plant NG	2010	1	**Escanaba**	2018	11.5	**Hancock**	2027	19
Diesel Plant NG	2010	1	**Escanaba**	2018	11.5	**Harbor Beach**	2027	2
Wyandotte	2010	11.5	**Mistersky**	2018	50	**Harbor Beach**	2027	2
Tower	2010	1.3	**Eckert Station**	2018	44	**Northeast**	2027	16
Tower	2010	1.3	**St Louis**	2018	1.3	**Shiras**	2027	12.5
Caro	2010	1.3	**Wyandotte**	2018	22	**Main Street**	2027	0.6

Caro	2010	1.3	**River Rouge-Coal**	2018	358.1	**Zeeland**	2027	1.1
Ubly	2010	0.6	**Vestaburg**	2019	3	**Claude Vandyke**	2027	23
Ubly	2010	0.7	**Graphic**	2019	10	**B E Morrow**	2028	18
Ubly	2010	0.7	**Dan E Karn-Coal**	2019	136	**Gaylord 1**	2028	16
Ubly	2010	0.9	**Dan E Karn-Coal**	2019	136	**J H Campbell**	2028	18.6
Vestaburg	2010	0.3	**Manistique**	2020	2	**J C Weadock**	2028	18.6
Vestaburg	2010	0.7	**Hillsdale**	2020	4.1	**J R Whiting**	2028	18.6
Vestaburg	2010	0.7	**Eckert Station**	2020	47	**Harbor Beach**	2028	121
B C Cobb-NG	2010	69	**Dafter**	2020	3	**St Clair**	2028	18.5
B C Cobb-NG	2010	69	**Dafter**	2020	3	**Trenton Channel**	2028	535.5
B C Cobb-NG	2010	69	**Vestaburg**	2020	3	**Eckert Station**	2028	80
S D Warren	2010	3.5	**St Clair**	2021	352.7	**S D Warren**	2028	19.1
Menominee	2010	2.5	**Main Street**	2021	1	**Cargill Salt**	2028	2
Neenah Paper	2010	6.2	**Dan E Karn-Coal**	2021	136	**B E Morrow**	2029	18
Conners Creek	2011	135	**Dan E Karn-Coal**	2021	136	**Straits**	2029	20
Conners Creek	2011	135	**J H Campbell**	2022	265.2	**Hancock**	2029	19.6
James De Young	2011	11.5	**Presque Isle**	2022	37.5	**Monroe**	2029	2.7
St Louis	2011	0.9	**James De Young**	2022	22	**Monroe**	2029	2.7
Tower	2011	1.3	**Menominee**	2022	1.5	**Monroe**	2029	2.7
J R Whiting	2012	106.3	**Zeeland**	2023	1.7	**Monroe**	2029	2.7
J R Whiting	2012	106.3	**Presque Isle**	2024	54.4	**Monroe**	2029	2.7
Diesel Plant Oil	2012	5.5	**Eckert Station**	2024	80	**St Clair**	2029	544.5
Caro	2012	1.3	**Lowell**	2025	1.1	**Coldwater**	2029	3.5
LaFarge Alpena	2012	12	**T B Simon Power**	2025	12.5	**James De Young**	2029	29.3
J R Whiting	2013	132.8	**Gaylord 1**	2026	16	**Wyandotte**	2029	7.5
St Clair	2013	168.7	**Gaylord 1**	2026	16	**Pine Street**	2029	1.1
St Clair	2013	156.2	**Gaylord 1**	2026	16	**Pine Street**	2029	1.1
Marshall	2013	1.1	**Gaylord 1**	2026	16	**Escanaba Paper**	2029	27.2
St Clair	2014	156.2	**Dayton**	2026	2	**Thetford**	2030	33.6
St Clair	2014	168.7	**Dayton**	2026	2	**Thetford**	2030	33.6
Diesel Plant Oil	2014	3	**Dayton**	2026	2	**Thetford**	2030	33.6
Hillsdale	2014	3.5	**Dayton**	2026	2	**Thetford**	2030	33.6
Eckert Station	2014	44	**Dayton**	2026	2	**Hancock**	2030	41.8
White Pine Electric	2014	20	**Fermi**	2026	16	**St Clair**	2030	2.7
White Pine Electric	2014	20	**Fermi**	2026	16	**St Clair**	2030	2.7
White Pine Electric	2014	20	**Fermi**	2026	16	**Eckert Station**	2030	80

In order to replace the capacity retired, new plants must be built in accordance to the methodology in subsection 3.3. Table 36 highlights their attributes.

Table 36. New Capacity Technology Characteristics

	Capacity Factor	Availability Factor	NO_X emission rate (lb/MWh)	SO_2 emission rate (lb/MWh)	CO_2 emission rate (lb/MWh)	CH_4 emission rate (lb/**GWh**)	N_2**O emission rate (lb/GWh**)	Heat Rate (Btu/kWh)
Coal	0.80	0.87	0.7075	0.1539	1922.81	21.995	32.336	8844
Oil	0.18	0.80	14.7	0.0147	1289.13	37.706	6.161	9800
Natural Gas	0.80	0.87	0.1285	0.00428	951.376	18.618	1.862	7139
Nuclear	0.90	0.90	-	-	-	-	-	9502
Biomass	0.80	0.85	1.485	0.2997	0	102.171	13.623	10607
Wind	0.29	0.13	-	-	-	-	-	-
LFG	0.90	0.90	-	-	-	-	-	-

To determine the values for each entry in this New Capacity matrix we use the following sources.

Capacity Factor:

	CF	**Source**
Bituminous Coal	0.80	EPRI – Generation Options under a carbon Constrained Future
Sub - bituminous Coal	0.80	NERC GADS (Coal)
Residual Oil	0.18	NERC GADS (Petroleum)
Natural Gas	0.80	EPRI – Generation Options under a carbon Constrained Future (Natural Gas Combined Cycle) (NERC says 0.32 for NGCC, EIA says 0.42, but these are current averages)
Nuclear	0.90	NERC GADS (Nuclear)
Biomass	0.80	NRDC Renewable Energy for America: Biomass
Hydro	0.41	NERC GADS (Hydro)
Wind	0.31	NREL (From modeled wind power data in MI)
LFG and Other Renewable	0.90	eGRID (average for LFG)

SO_2 Emissions Factors:

	SO_2 EF [lb/MWh]	Source
Bituminous Coal	0.1539	EPRI Volume 2 (98% of sulfur content for post 2010 Coal plants) & CNF (Powder River Basin Coal for MI)
Sub - bituminous Coal	0.1539	EPRI Volume 2 (98% of sulfur content for post 2010 Coal plants) & CNF (Powder River Basin Coal for MI)
Residual Fuel Oil	0.0147	Uses Emissions/mmBtu from Consumer's permit application to MDEQ and HR from EPRI V1 (Petroleum)
Natural Gas	0.00428	Uses Emissions/mmBtu from Consumer's permit application to MDEQ and HR from EPRI V2 (Nat Gas CC)
Nuclear	0	MPSC CNF / USLCI - Zero Combustion emissions
Biomass	0.2997	Scaling eGRID emissions factors (for Cadillac Renewable Energy Plant) by HR from EPRI V1 (Biomass)
Hydro	0	USLCI - Zero Combustion emissions
Wind	0	USLCI - Zero Combustion emissions
LFG and Other Renewable	0	USLCI - Zero Combustion emissions

NO_X Emissions Factors:

	NO_X EF [lb/MWh]	Source
Bituminous Coal	0.7075	MPSC's CNF using EPRI HR
Sub - bituminous Coal	0.7075	MPSC's CNF using EPRI HR
Residual Fuel Oil	14.7	Uses Emissions/mmBtu from Consumer's permit application to MDEQ and HR from EPRI V1 (Petroleum)
Natural Gas	0.1285	Uses Emissions/mmBtu from Consumer's permit application to MDEQ and HR from EPRI V2 (Nat Gas CC)
Nuclear	0	MPSC CNF / USLCI - Zero Combustion emissions
Biomass	1.4850	Scaling eGRID emissions factors (for Cadillac Renewable Energy Plant) by HR from EPRI V1 (Biomass)
Hydro	0	USLCI - Zero Combustion emissions
Wind	0	USLCI - Zero Combustion emissions
LFG and Other Renewable	0	USLCI - Zero Combustion emissions

CO_2 Emissions Factors:

	CO_2 EF [lb/MWh]	Source
Bituminous Coal	1922.81	EPRI Volume 2 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Sub - bituminous Coal	1922.81	EPRI Volume 2 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Residual Fuel Oil	1289.13	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Graphic Packaging)
Natural Gas	951.376	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Covert Generating Project)
Nuclear	0	MPSC CNF / USLCI - Zero Combustion emissions
Biomass	0	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Cadillac Renewable Energy)
Hydro	0	USLCI - Zero Combustion emissions
Wind	0	USLCI - Zero Combustion emissions
LFG and Other Renewable	0	USLCI - Zero Combustion emissions

CH_4 Emissions Factors:

	CH_4 EF [lb/GWh]	Source
Bituminous Coal	21.995	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Sub - bituminous Coal	21.995	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Residual Fuel Oil	37.706	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Graphic Packaging)
Natural Gas	18.618	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Covert Generating Project)
Nuclear	0	MPSC CNF / USLCI - Zero Combustion emissions
Biomass	102.171	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Cadillac Renewable Energy)
Hydro	0	USLCI - Zero Combustion emissions
Wind	0	USLCI - Zero Combustion emissions
LFG and Other Renewable	0	USLCI - Zero Combustion emissions

N_2O Emissions Factors:

	N_2O EF [lb/GWh]	Source
Bituminous Coal	32.336	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Sub - bituminous Coal	32.336	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Belle River)
Residual Fuel Oil	6.161	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Graphic Packaging)
Natural Gas	1.862	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Covert Generating Project)
Nuclear	0	MPSC CNF / USLCI - Zero Combustion emissions
Biomass	13.623	EPRI Volume 1 GHG Emissions factors broken up by eGRID GHG percents from a sample plant (Cadillac Renewable Energy)
Hydro	0	USLCI - Zero Combustion emissions
Wind	0	USLCI - Zero Combustion emissions
LFG and Other Renewable	0	USLCI - Zero Combustion emissions

Heat Rate:

	HR	Source
Bituminous Coal	8844	EPRI Volume 2 (Post 2010 Coal plants)
Sub - bituminous Coal	8844	EPRI Volume 2 (Post 2010 Coal plants)
Residual Oil	9800	EPRI Volume 1 (Petroleum, never added to mix)
Natural Gas	7139	EPRI Volume 2 (Post 2010 Natural Gas Combined Cycle)
Nuclear	9502	EPRI Volume 1 (Average New Nuclear)
Biomass	10607	EPRI Volume 1 (Average New Biomass)
Hydro	-	N/A
Wind	-	N/A
LFG and Other Renewable	-	N/A

Equivalent Availability Factor:

	eAF	Source
Bituminous Coal	0.87	NERC GADS (Coal)
Sub - bituminous Coal	0.87	NERC GADS (Coal)
Residual Oil	0.8	NERC GADS (Petroleum)
Natural Gas	0.87	NERC GADS (Natural Gas Combined Cycle)
Nuclear	0.90	NERC GADS (Nuclear)
Biomass	0.85	NERC GADS (Fossil Fuels)
Hydro	0.85	NERC GADS (Hydro)
Wind	0.125	MPSC's CNF
LFG and Other Renewable	0.90	Used CF from eGRID (average for LFG)

Appendix C. Future baseline consumer demand

To develop an hourly load profile from 2009-2030, we used a scaled version of the load reported in Michigan for 2008. The hourly load profile for 2008 was determined by summing up the reported demand [37] for the following utilities:

- DTE Energy
- Consumers Energy
- Upper Peninsula Power Company
- Wolverine Power Cooperative

This demand profile was scaled to represent all Michigan utility sales based on data reported by the MPSC for 2008 [61]. If sales data provided is summed, it reports 94,793,015 MWh sold by the four utilities above and 105,475,262 MWh sold in Michigan. This disagrees slightly with the hourly load data from FERC. If that is summed, the total load provided for by the four utilities was 97,159,607 MWh. To determine the hourly load for all of Michigan, the FERC hourly load is multiplied by the ratio of total Michigan sales to the sales in the listed utilities. This gives us a total of 108,108,546 MWh of load satisfied in Michigan. The hourly values that sum up to this load will be what is used to extrapolate out a forecast for Michigan growth assuming relative load profiles do not change from year to year.

The FERC filings and sales information represent the electricity demanded of the utilities in Michigan by their customers, and thus do not include transmission and distribution losses in the system. Approximately 9% of electricity generated is lost in its transmission and distribution from power plants to end-use consumers[62]. To turn this demand into a load at the generator, the base year demand is multiplied by a factor of 1.09 to represent these losses.

To forecast Michigan load growth over the length of a simulation, two sources are used. First, the EIA's Annual Energy Outlook [63] provides forecasts of electricity usage and generation up until 2030. This is coupled with forecasts provided in FERC Form 714 filings by the 4 utilities mentioned, which forecast out ten years from 2008 – 2018. To determine the annual percentage change in electricity generation in Michigan. The forecasts for the four utilities are summed together to determine an annual percentage growth rate for the state.

$$R_k = \frac{E_k}{E_{k-1}}$$

Where R_k is the growth rate in MI for a given year, k, and E_k is the sum of electricity demand forecasted by the four utilities for that year. The Michigan specific data only goes out to 2018, but forecasts to 2030 are needed, so the rate of growth for the rest of the country is scaled to a Michigan growth rate for the last 12 years. To do this we use the same equation with the forecasted national "net generation available to the grid" to get a growth rate, r_k, for the nation for every year to 2030. To scale demand, we examine the ratios of expected national to Michigan yearly growth from 2009 to 2018 and determine the average ratio, D.

$$D = \left(\sum_{k=2009}^{2018} D_k\right) / 10 = \left(\sum_{k=2009}^{2018} \frac{R_k}{r_k}\right) / 10$$

This average ratio is then multiplied into the national electricity rate of change from years 2019-2030 to get a Michigan specific demand change for those years. This outputs a vector of yearly growth factors for Michigan loads that can be coupled with the adjusted load from 2008 to forecast hourly load profiles for every year between 2009 and 2030. Below is a graph showing the growth rates used. It shows the EIA, the reported growth rates by MI Utilities, and the rates that were generated using the calculations discussed.

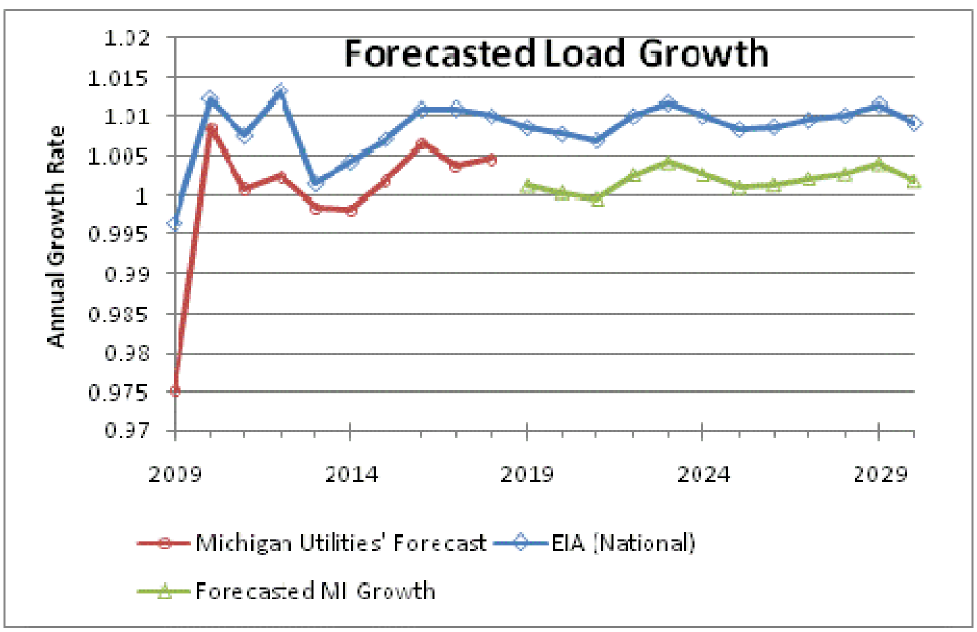

Figure 60: Forecasted annual load growth rate for MI and the USA

Appendix D. Fuel prices for Economic Dispatch

While Figure 34 shows the fuel prices visually, fuel prices in dollars per mmBtu each year are presented in the table below. Prices are in $/mmBtu for fuel costs (in 2008 dollars), and tax is $/metric ton CO2e. Fuel prices are EIA predictions [39].

Table 37. Fuel costs used in the economic dispatch model

	Sub-bituminous Coal	Bituminous Coal	Oil	Natural Gas	CO2 tax
2009	2.15	2.15	14.24	4.14	0
2010	1.99	1.99	13.91	4.85	0
2011	1.98	1.98	14.06	5.82	0
2012	1.99	1.99	15.2	6.17	10.8
2013	1.99	1.99	16.21	5.94	11.34
2014	1.99	1.99	16.89	5.9	11.91
2015	2.01	2.01	17.36	6.08	12.5
2016	1.99	1.99	18.22	6.16	13.13
2017	2	2	18.88	6.17	13.78
2018	1.99	1.99	19.51	6.22	14.47
2019	1.99	1.99	19.92	6.29	15.19
2020	1.98	1.98	20.25	6.42	15.95
2021	1.98	1.98	20.4	6.52	16.75
2022	1.99	1.99	20.58	6.69	17.59
2023	1.99	1.99	20.89	6.74	18.47
2024	1.99	1.99	21.07	6.7	19.39
2025	1.99	1.99	21.35	6.75	20.36
2026	2	2	21.6	6.91	21.38
2027	2	2	21.83	7.05	22.45
2028	2.01	2.01	22.14	7.27	23.57
2029	2.02	2.02	22.54	7.51	24.75
2030	2.03	2.03	22.71	7.73	25.99

Appendix E. Vehicle size class mapping

Within the PECM and MEFEM models, vehicles are handled by size class. The size classes used are subcompact, compact, midsize, and large 'car classes', as well as the van, SUV, and pickup 'truck classes.' While this nomenclature is consistent through the model, in developing various parameters different naming schema were used by different sources. In this appendix, the names used to create the parameters within the original sources are mapped to the size classes used in the model.

Table 38. List of parameters and sources for mapping size classes

Parameter	Source
Trip Data for PECM	2009 NHTS[14]
Initial Vehicles Sales	MI Motor Vehicle Registrations[22]
% of new vehicle sales	AEO 2009[20]
New Conventional equivalent fuel economy (mpg)	AEO 2009[20]

Table 39. Mapping size classes to source classes

Size Class	Trip Data	Initial Vehicle Sales	% new Vehicle sales	New CV equivalent mpg
Subcompact	Car	40% of 2 door	Subcompact	Subcompact
Compact	Car	60% of 2 door	Compact	Compact
Midsize	Car	75% of 4 door, roadster	Midsize	Midsize
Large	Car	25% of 4 door, roadster	Large	Large
Van	Van	Van	Small/Large Van	Small/Large Van
SUV	SUV	Station Wagon	Small/Large Utility	Small/Large Utility
Pickup	Pickup	Pickup	Small/Large Pickup	Small/Large Pickup

Appendix F. Plug-in electric hybrid vehicle characteristics

Table 40. PHEV energy consumption rates for all size classes

		Charge Depleting Electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (mpg)
PHEV	Subcompact	0.240	50
	Compact	0.246	43.5
	Midsize	0.274	32.8
	Large	0.3	26
	Van	0.346	26.14
	SUV	0.330	26.14
	Pickup	0.372	21

Within the PECM model, plug-in hybrids complete daily trips using some combination of electricity stored in the battery and gasoline combustion. The consumption parameters used in the model vary by size class and are listed in the table above. This appendix lists consumption parameters based on OEM press releases and academic sources used to compile the table above. Typically for a size class, an average of all electricity consumption parameters were taken, and a 55/45% city highway inverse average for 2009 model year hybrids was used to find gasoline consumption parameters. However, as data was sometimes unavailable, this is not the case for all size classes. Note that EV range and usable battery size are listed for reference, and was not available for many academic sources.

Subcompact

A pre-production electric vehicle, plug-in electric hybrid, and a hybrid electric vehicle were reviewed. The plug-ins report similar charge depleting electricity consumptions, whereas there is a large difference between the charge sustaining gasoline consumption parameters, and an inverse average was taken.

Table 41. Subcompact PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (mpg)
OEM	Mitsubishi i-MiEV	60	16	0.24	--
	Audi A1 e-tron plug-in	30	7.2	0.24	39.2
	Honda Fit Hybrid				70

Compact

Two pre-production plug in sources were used, as well as parameters from the Electric Power Research Institute's (EPRI's) Hybrid Electric Working Group [Duvall, 2002, 2003, and 2004], to obtain the electric charge depleting parameter used in the model. The charge sustaining fuel economy rating was determined through a 55%/45% comparison of compact hybrids.

Table 42. Compact PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (city/hwy mpg)
OEM	Toyota Plug-in Prius	15	3.64	0.243	
	VW Golf	93	21.2	0.228	
	Toyota Prius Hybrid				48/45
	Honda Civic Hybrid				40/45
	Honda Insight Hybrid				40/43
Academic	EPRI [6]	33	8.6	0.260	

Midsize

The midsize class electric consumption was determined from two pre production vehicles characteristics as well as many academic references. Fuel consumption was determined from a 55%/45% split of hybrid vehicles in that class.

Table 43. Midsize PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (city/hwy mpg)
OEM	Chevy Volt	40	10.4	0.26	
	Fisker Karma	50	13.5	0.27	
	Ford Fusion Hybrid				36/41
	Chevy Malibu Hybrid				26/34
	Nissan Altima Hybrid				35/33
	Toyota Camry Hybrid				33/34
	Saturn Aura Hybrid				24/32
Academic	[6]	33	9.9	0.30	
	[3]	10	3.6	0.22	
	[3]	30	8.2	0.24	
	[3]	60	16.5	0.28	
	[64]	20	4.8	0.24	
	[65]			0.25	
	[66]			0.25	

Large car

At the time of writing, there were no pre-production plans for large passenger car sized PHEV or EV, and the fuel consumption parameters were estimated to be larger than the Midsize class, but smaller than any of the truck classes.

Van

Two vans, a passenger and a cargo van were examined to determine electric consumption. Note that the Sprinter Van used a NiMH battery, and a general estimation comparable of Li-Ion consumption, based on Prius NiMH and Li-Ion conversion characteristics. The SUV charge sustaining gasoline consumption was used.

Table 44. Van PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (city/hwy mpg)
OEM	Luxgen MPV EV	120 miles	41.5	0.345	
	Daimler Sprinter	18.6 miles	9.8	0.346	

SUV

The SUV size class within the model encompasses full size, midsize, and small/compact SUV, and as such within the group the actual consumption parameters may vary. While the Ford Escape PHEV is off-schedule for production, specifications for the test models were used. Also, two publications investigated the consumption parameters for various SUV sizes. Seven hybrid SUV of various sizes were also viewed for the gasoline consumption parameter.

Table 45. SUV PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (city/hwy mpg)
OEM	Ford Escape PHEV	30	7.2	0.20	
	Ford Escape Hybrid				34/31
	Toyota Highlander Hybrid				27/25
	Chevy Tahoe Hybrid				21/22
	Cadillac Escalade Hybrid				20/21
	Mercury Mariner Hybrid				34/31
	Saturn Vue Hybrid				25/32
	GMC Yukon Hybrid				21/22
Academic	[6] (Midsize SUV)	33	12.5	0.38	
	[6] (Fullsize SUV)	33	15.2	0.46	
	[3] (Crossover SUV)			0.28	
	[3] (Midsize SUV)			0.33	

Pickup

There are no current production pickups planned at the time the report was written. Fuel consumption parameters for a converted F-150, as well as one academic source were used. Five hybrids were examined to estimate PHEV gasoline fuel economy.

Table 46. Pickup PHEV characteristics

		EV Range (miles)	Usable Battery (kWh)	Charge Depleting electricity consumption (kWh/mi)	Charge Sustaining Gasoline consumption (city/hwy mpg)
OEM	Ford F-150 Converted by Enviva	38	12	0.316	
	[66]			0.429	
	Chevy Silverado Hybrid (2WD)				21/22
	Chevy Silverado Hybrid (4WD)				20/20
	GMC Sierra hybrid				21/22
	Dodge Durango hybrid				20/22
	Chrysler Aspen Hybrid				20/22

Table 47. Source list for PHEV characteristics

Hybrid fuel economies		http://www.fueleconomy.gov/
Plug in specifications	Mitsubishi i-MiEV	http://www.mitsubishi-motors.com/special/ev/index.html
	Audi A1 e-tron	http://www.audi.com/com/brand/en/experience/audi_e-tron/audi_a1_e-tron.tab_0002.html
	Toyota Plug-in Prius	http://www2.toyota.co.jp/en/news/09/12/1214.html
	VW Golf Plug-in	http://www.autoweek.com/article/20100503/GREEN/100509981
	Chevy Volt	http://www.chevrolet.com/pages/open/default/future/volt.do
	Fisker Karma	http://www.fiskerautomotive.com/
	Luxgen MPV EV	http://www.luxgen-motor.com/cars/EV/
	Daimler Sprinter PHEV	http://www.calcars.org/calcars-news/83.html (repost of press release from former daimlerchrysler)
	Ford Escape PHEV	http://media.ford.com/article_display.cfm?article_id=27333
	Ford F-150 Converted by Enviva	http://www.prlog.org/10119559-envia-announces-rev-plug-in-ford-series-truck-conversion-gets-43-mpg-plug-in-your-tru.html

Appendix G. Emissions allocation example from MEFEM

Subsection 3.5.3 showed in simple terms how the emissions from the electricity generation sector are allocated to the transportation sector to account for PHEV charging. Within the model, changes to the generation mix also play a role, and this appendix describes how marginal and average allocation methods are affected by changes in the grid.

Table 48. Changes in baseline scenario generation (MWh) from 2009 to 2030

	From Existing	From New	Total
Sub-bituminous	(14,045,043)	2,330,605	(11,714,437)
Bituminous	(4,449,802)	0	(4,449,802)
Oil	(24,280)	0	(24,280)
Natural gas	(3,156,053)	3,529,202	373,149
Nuclear	0	524,386	524,386
Biomass	(105,627)	1,055,559	949,931
Hydro	(190)	0	(190)
Wind	(0)	18,400,760	18,400,760
Other Renewable	0	1,359,370	1,359,370
TOTAL	(21,780,995)	27,199,882	5,418,887

Table 48 outlines the changes in the grid from 2009 to 2030 for the zero PHEV, baseline simulation by generation type. Overall, the amount of electricity needed to be generated increased by 5,400 GWh, but the current existing plants provide roughly 22,000 GWh less electricity to meet demand, with the greatest reductions coming from coal generation, probably due to retirements in the system. New capacity is added in many fuel types, however overall in the system coal and oil is reduced, while natural gas, nuclear, biomass and wind generation is increased. The 190 MWh reduction of hydro is an artifact of system dispatch, and changes slightly from year to year- hydro generation is neither reduced nor added in the system. Note that all new coal is assumed sub-bituminous.

Table 49 shows the average emissions factors for 2030 generation by fuel type. It can be seen that oil has very high factors, but it comprises a very small proportion of generation. Aside from oil, and that natural gas has high SO_X factors (which is largely from upstream processing of natural gas), coal remains the highest pollutant per generation in the categories. Existing biomass also has high NO_X factors. While all new coal is assumed to be sub-bituminous, it can be seen that the emissions do not vary significantly between the two coal types. Hydro and wind generation do not have emissions factors.

Table 49. Average emissions factors (g/kWh) for existing plants, by fuel type

	Sub-Bit. Coal	Bit. Coal	Oil	Natural Gas	Nuclear	Biomass	LFG
CO	0.30	0.30	3.74	0.49	0.01	0.09	0
Pb (g/Wh)	0.0949	0.0949	0.0517	0.0035	0.00088	0	0
NO_X	1.58	2.07	12.63	0.49	0.07	1.19	0.81
PM_{10}	0.78	0.78	0.16	0.05	0.06	0.04	0
VOC	6.90	6.90	2.42	5.68	0.23	0.30	0
SO_X	3.57	5.33	94.68	6.04	0.23	1.54	0
CO_2	1009.05	958.96	4033.69	551.85	10.84	163.99	0.01
CH_4	1.84	1.84	1.22	3.31	0.03	0.31	0
N_2O	0.02	0.02	0.06	0.00	0.00	0.04	0
GHGs	1060.05	1009.75	4082.60	635.11	11.54	185.21	0.01

Taking generation offline only to replace it with new capacity of the same fuel type does not seem like much of a gain, but the characteristics of the new generating assets are 'cleaner' in many pollutant categories than the existing power plants, especially in the NO_X, SO_X and greenhouse gas pollutant categories. Average reduction in emissions by fuel type when deploying a new plant rather than an older plant can be seen in Table 50 (emissions that are unchanged are not represented). Note that Hydro and wind generation has no associated emissions, nor do new LFG plants, while existing LFG do emit some NO_x and CO_2. There is a slight increase in methane emissions in the new generation; however, this change is negligible, and overall GHG emissions are reduced.

Table 50. New v. Existing capacity, emissions improvements by fuel type

	NO_X	SO_X	CO_2	CH_4	N_2O	GHGs
Coal	59%	94%	10%	0.06%	10%	9%
Natural Gas	67%	6%	13%	-0.10%	30%	11%
Nuclear	0%	0%	0.31%	0.004%	0%	0.29%
Biomass	42%	91%	99%	84%	86%	97%
LFG	100%	0%	100%	0%	0%	100%

Marginal emissions assigned to a simulation depend on the change in generation from baseload to the PHEV scenario.

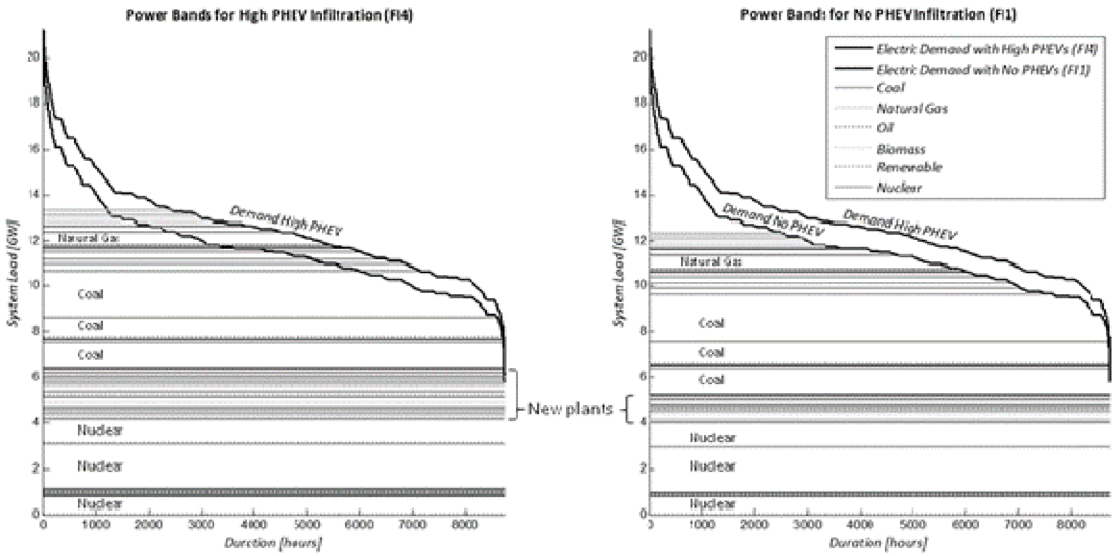

Figure 61. Load duration curves with power bands, 2030 (EG1, CH1, FI1 & FI4)

Figure 61 shows the stacking dispatch results for the FI4 and FI1, base generation case scenarios. It can be seen that much of the new load is served by a growth in the number of new plants. Table 51 shows the difference in generation by fuel type between the base case and the high fleet infiltration scenario for the year 2030.

Table 51. Change in generation (MWh) from baseline to FI4 (High PHEV) in 2030

	From Existing	From New	Total
Sub-bituminous	(783,568)	3,472,033	2,688,465
Bituminous	(1,111,694)	0	(1,111,694)
Oil	(11,839)	0	(11,839)
Natural gas	(312,642)	5,257,650	4,945,008
Nuclear	0	781,207	781,207
Biomass	(55,964)	121,724	65,759
Hydro	0	0	0
Wind	(0)	1,298,215	1,298,215
LFG	0	574,328	574,328
TOTAL Difference	(2,275,708)	11,505,157	9,229,448

The table shows that adding PHEVs necessitates an increase in electricity generation of about 9,300GWh in the base scenario. This is met by decreasing the use of existing plants and increasing the use of plants added through capacity reserve or renewable needs. Also, the majority of the new generation is done by natural gas plants, although coal and wind do contribute as well. Because natural gas is cleaner than coal and that new plants are cleaner than old plants, the emissions associated with the marginal 9,300GWh of generation are less than would be expected by using an average of the emissions generated at each hour. Average emissions include the emissions generated by both the old and the new plants. The more new capacity added to the system as a result of increasing PHEV load, the better the marginal emissions will look.

Table 52. Changes in High RPS/Nuclear scenario generation (MWh) from 2009 to 2030 (FI1)

	From Existing	From New	Total
Sub-bituminous	(27,444,278)	631,111	(26,813,166)
Bituminous	(17,552,665)	0	(17,552,665)
Oil	(202,964)	0	(202,964)
Natural gas	(6,430,670)	13,450,832	7,020,162
Nuclear	(5,147,634)	12,518,421	7,370,787
Biomass	(883,658)	1,518,453	634,795
Hydro	3,131	0	3,131
Wind	(0)	31,933,561	31,933,561
LFG	(71,526)	3,100,477	3,028,951
TOTAL	(57,730,265)	63,152,856	5,422,591

In the High RPS, High Nuclear scenario, the same additional 5,400GWh are added, but there are much greater reductions and additions compared to the base generation scenario due to the accelerated retirement of coal plants.

Table 53. Change in High RPS/Nuclear scenario generation (MWh) (FI1 to FI4)

	From Existing	From New	Total
Sub-bituminous	(655,547)	117,322	(538,226)
Bituminous	(493,184)	0	(493,184)
Oil	(8,316)	0	(8,316)
Natural gas	(115,194)	4,103,006	3,987,812
Nuclear	(187,877)	3,844,608	3,656,730
Biomass	(45,028)	111,156	66,128
Hydro	(3,321)	0	(3,321)
Wind	0	2,104,291	2,104,291
LFG	(4,372)	453,801	449,429
TOTAL Difference	(1,512,840)	10,734,183	9,221,343

Adding PHEVs again requires 9,300 GWh of generation for 2030, but the grid makeup in this scenario brings on much less coal and more wind, to meet the new RPS requirements, and new nuclear generation in place of coal. This results in even lower marginal emissions, stemming from new natural gas, nuclear, and wind, while even with the accelerated retirements, existing coal plants still provide about a quarter of the total generation within the state, skewing the average emissions reported.

Appendix H. Additional PECM Results

The PHEV energy consumption model (PECM) is a standalone model that analyzes the trip data within the NHTS and simulates PHEV driving and charging. While certain scenarios and results were presented in the main document, additional results specific to PECM are presented here.

Effect of Battery size

As the battery size increased, the electricity demand also increased. This also had the effect of 'shifting' the peak usage hour later and later, although the power at any given hour was increased as battery size increased.

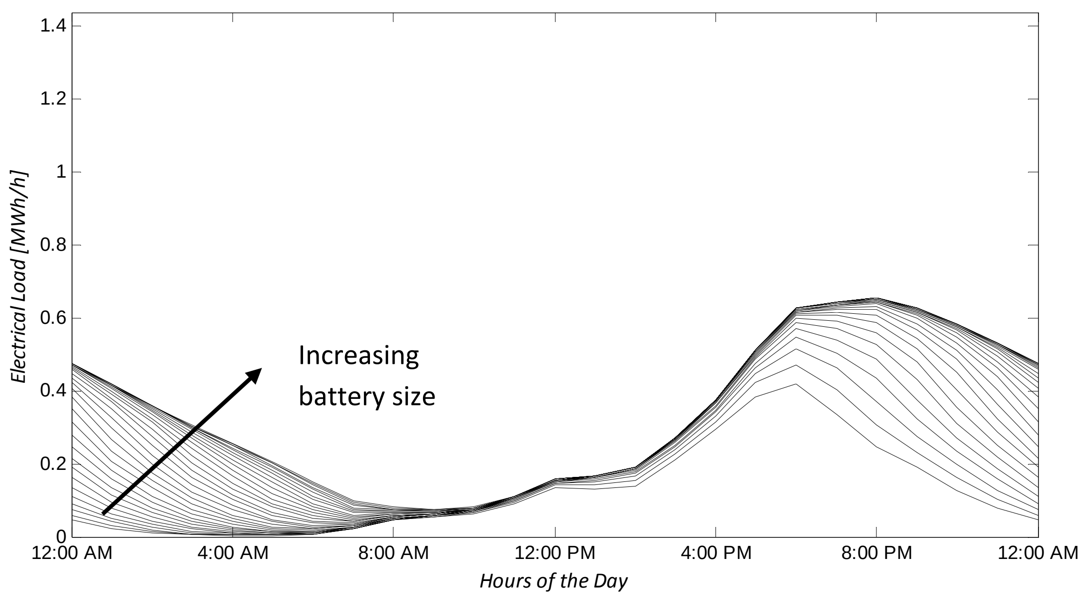

Figure 62. Effect of battery size on normalized PHEV charging load

Electricity use and percentage of electric miles increased as battery size increased, although the relationship was non-linear. Charging speed was shown to have a greater effect on these parameters as battery size increased.

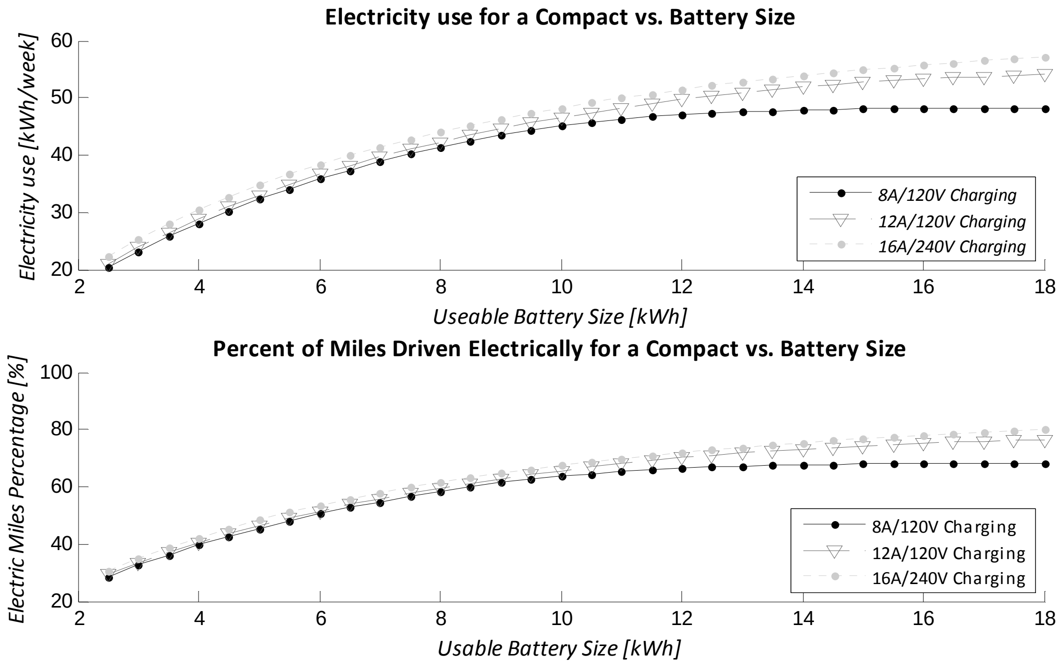

Figure 63. Battery size effect on electricity consumption and percent of electric miles

Effect of Size class

Within PECM and MEFEM, there are seven vehicle size classes: sub-compact, compact, midsize, large, van, SUV, and pickup. Each of these classes have different associated parameters for consumption, and while the sub-compact, compact, midsize, and large car classes share NHTS trip data, the van, SUV, and pickup classes each have a separate NHTS dataset. Appendix E shows the datasets used for each size class.

The following figures are a daily and a weekly load curve with all seven size classes represented. The larger classes, van, SUV, and pickup, typically draw more power. The car classes have similar curves due to the shared data set, while the van class is noticeably more jagged, as the van data subset was the smallest.

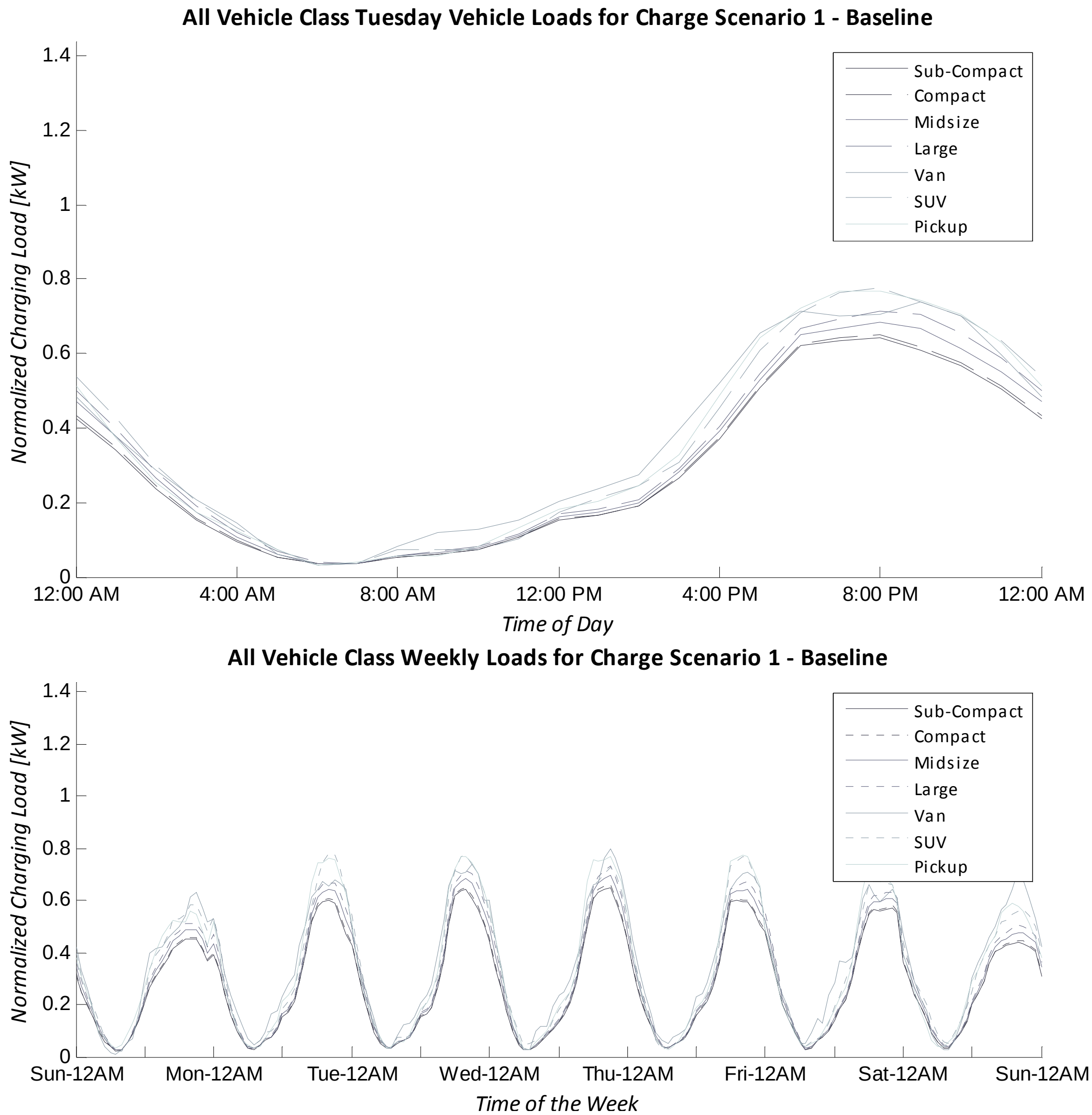

Figure 64. Load curves, daily and weekly, showing difference by size class

Again, the larger classes consumed more electricity, and in the following figure, it can be seen that more gasoline was consumed as well.

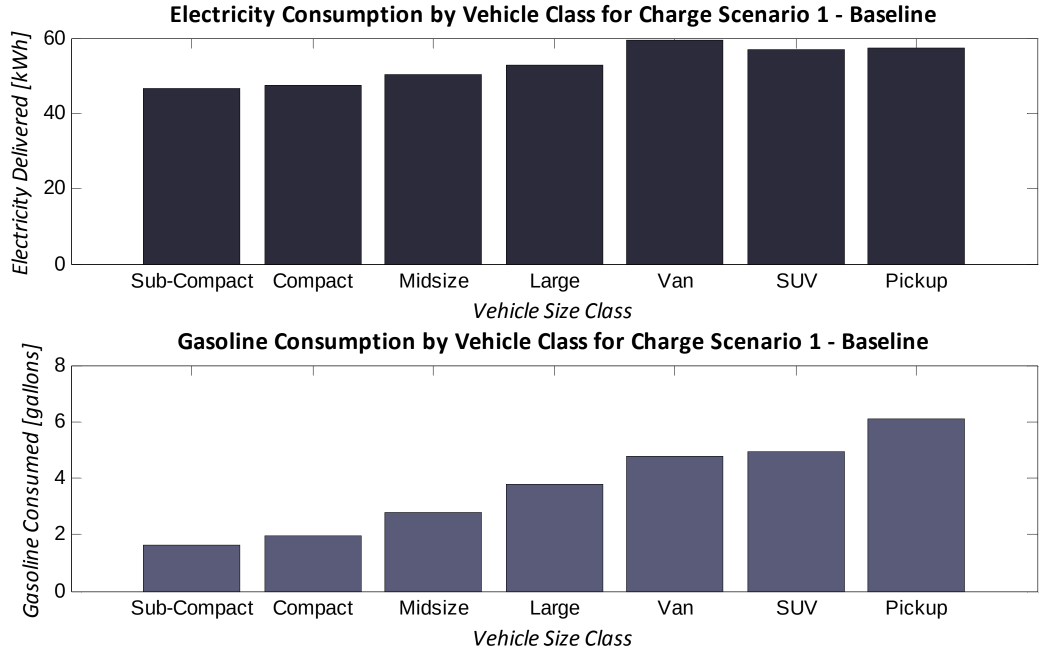

Figure 65. Energy consumption per week by size class

The smaller car size classes had a greater proportion of electrically driven miles, but for all vehicle size classes ranged between 50 to 60%.

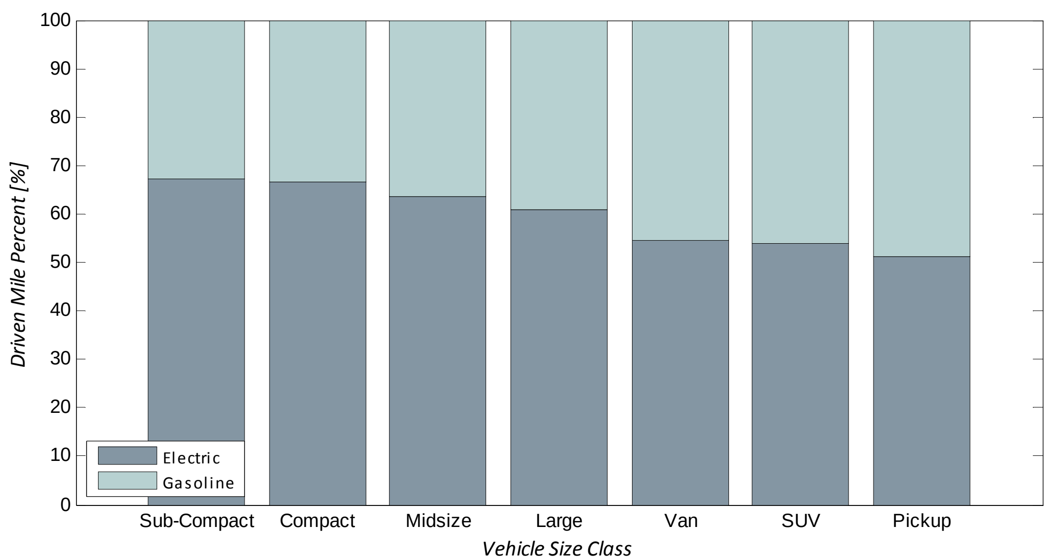

Figure 66. Percent of miles driven electrically by vehicle size class in the baseline charging scenario

Additional Load lineups

While the loads are shown in Figure 42 overlaid on a July day's demand, each scenario is reproduced here with the normalized load, and the resulting load for high PHEV infiltration overlaid on a January and July demand.

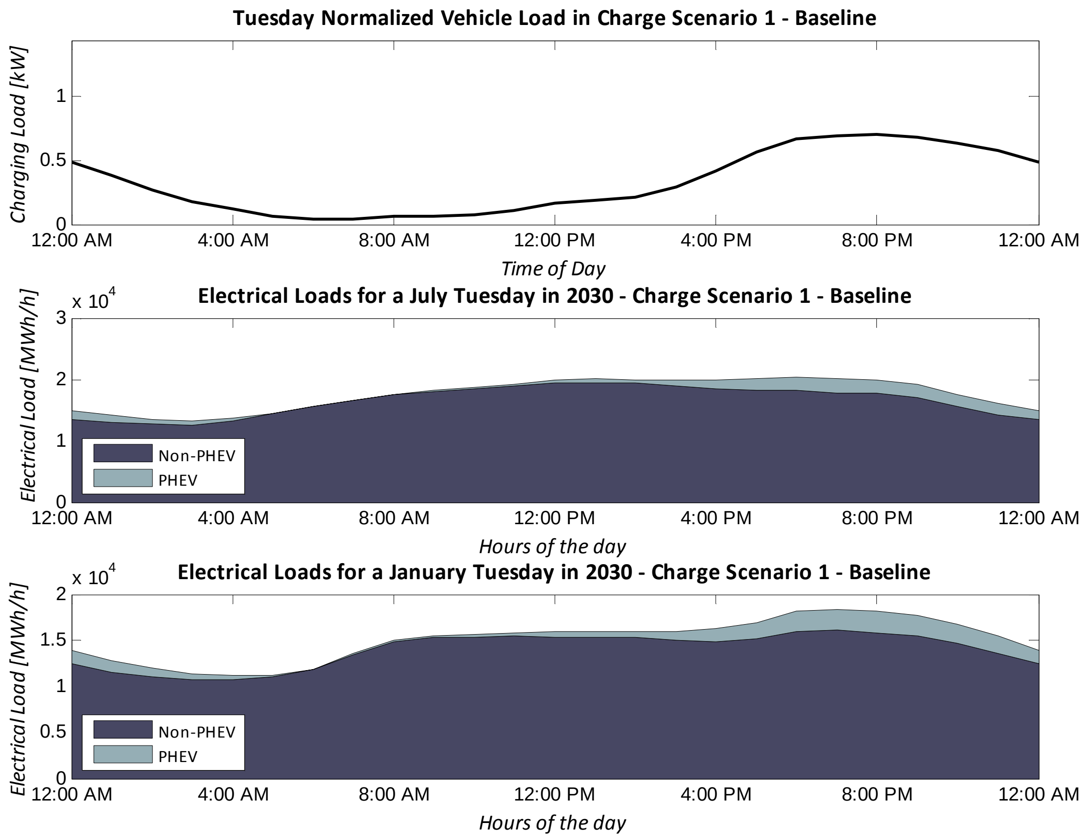

Figure 67. Baseline charging load profiles (High PHEV infiltration, 2030)

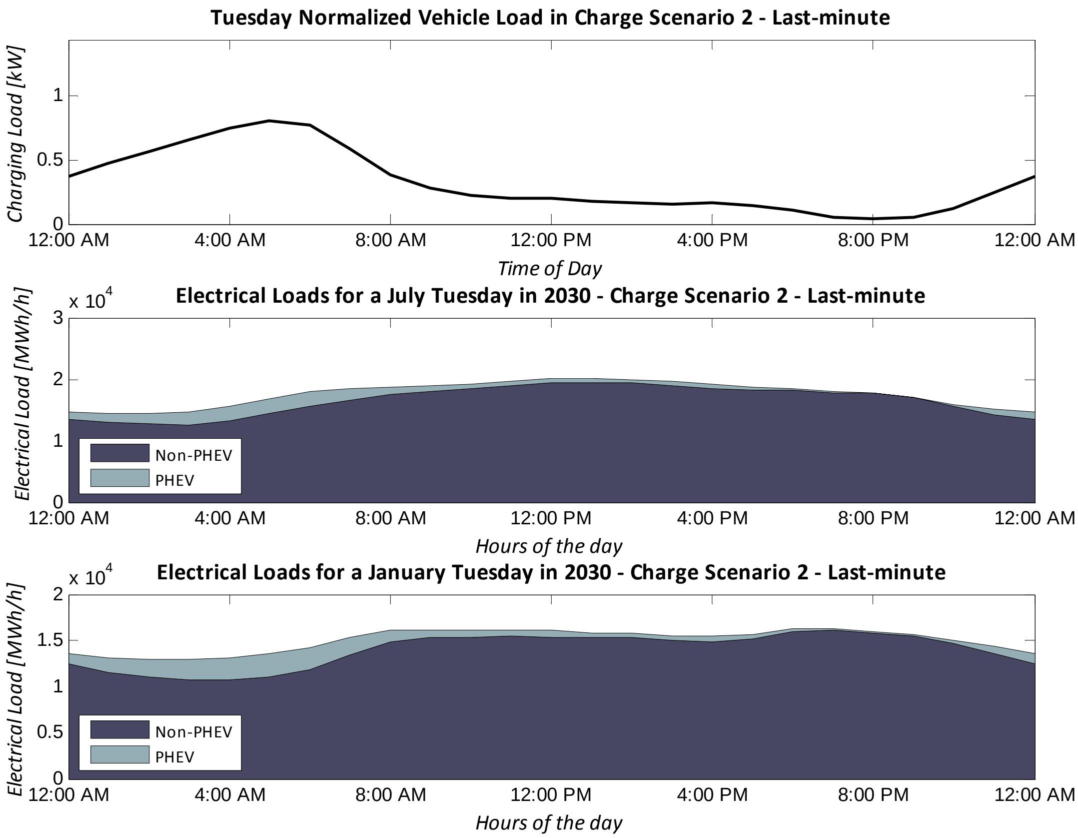

Figure 68. Last minute charging load profiles (High PHEV infiltration, 2030)

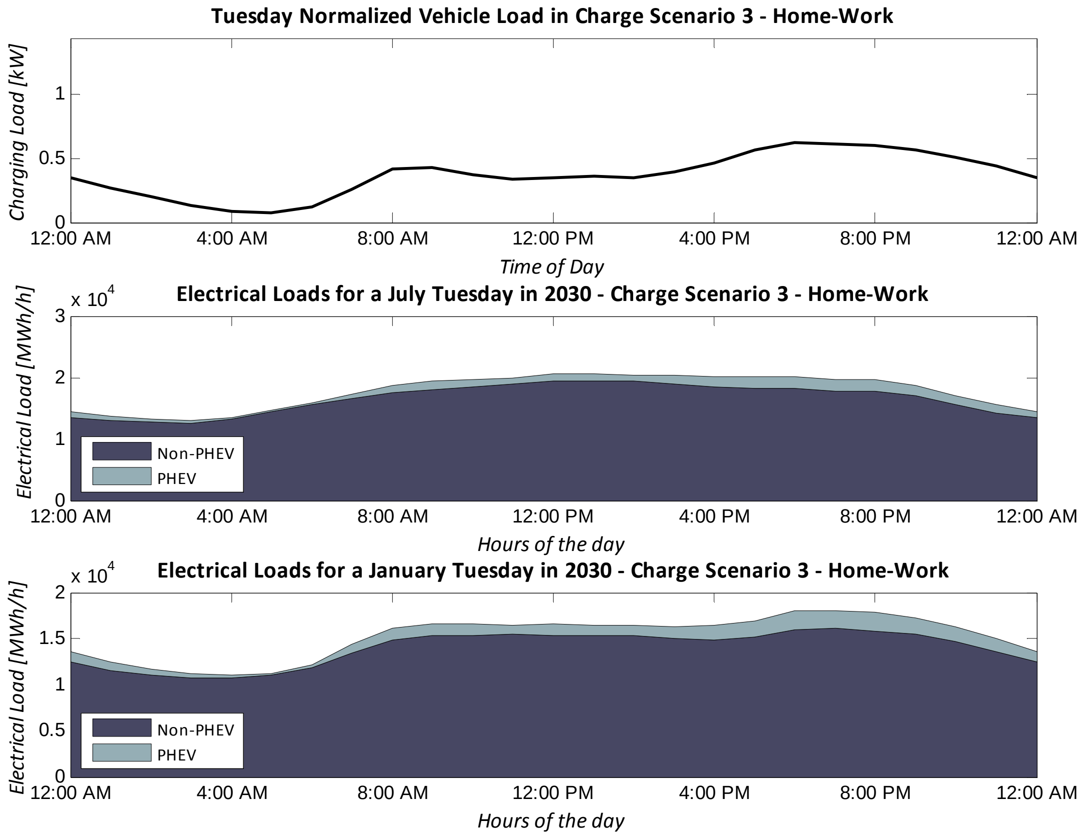

Figure 69. Home-work charging load profiles (High PHEV infiltration, 2030)

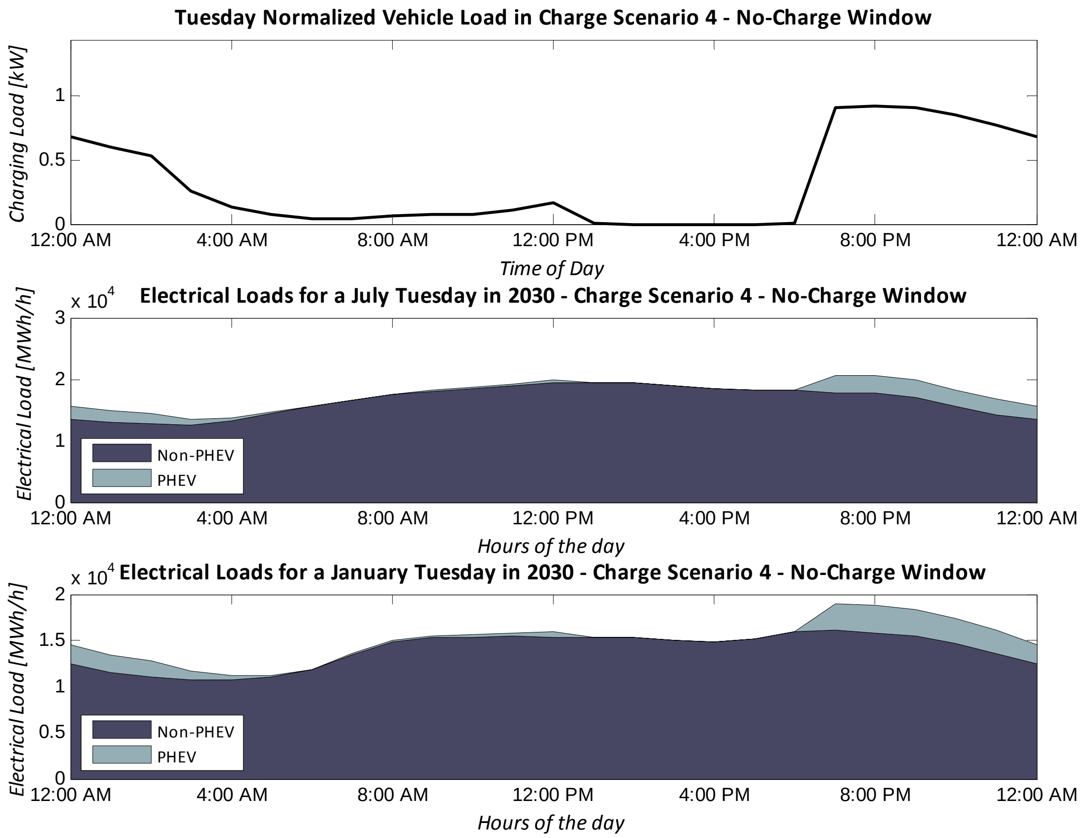

Figure 70. No-charge window charging load profiles (High PHEV infiltration, 2030)

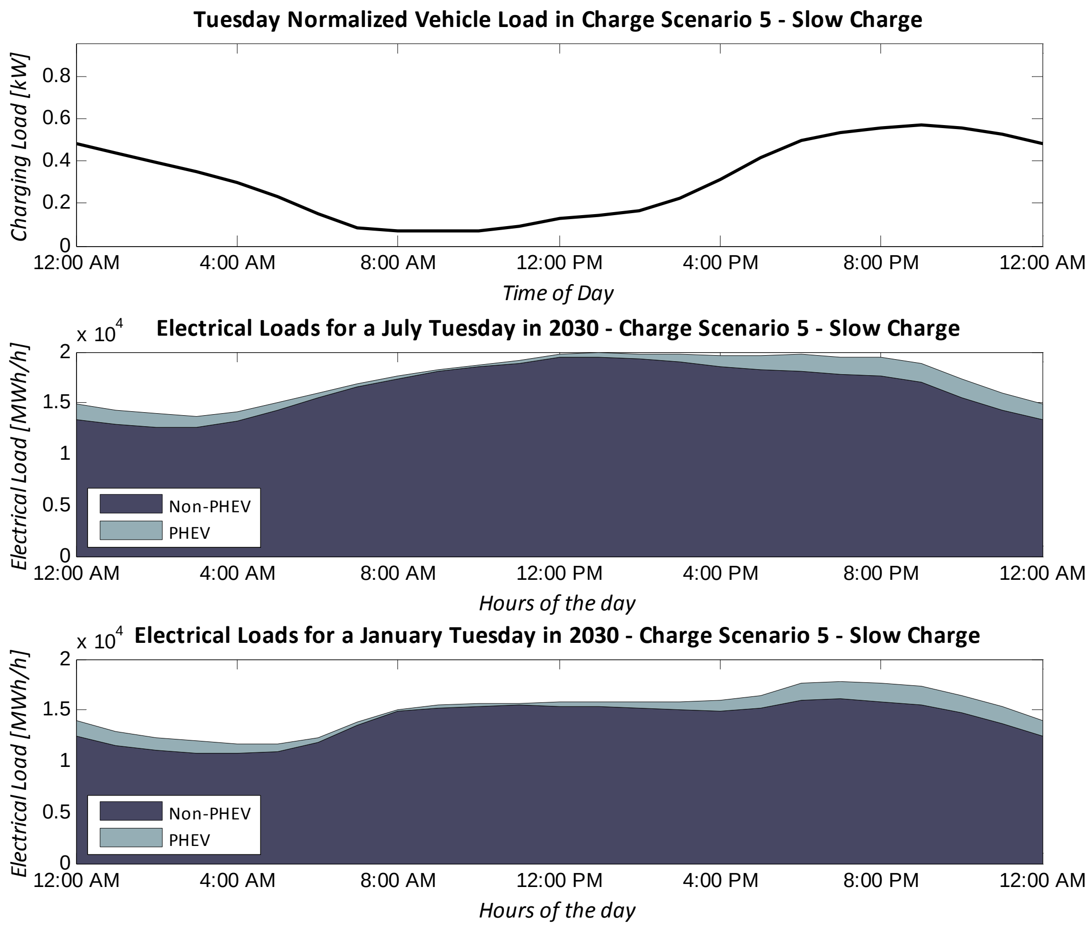

Figure 71. Slow charging load profiles (High PHEV infiltration, 2030)

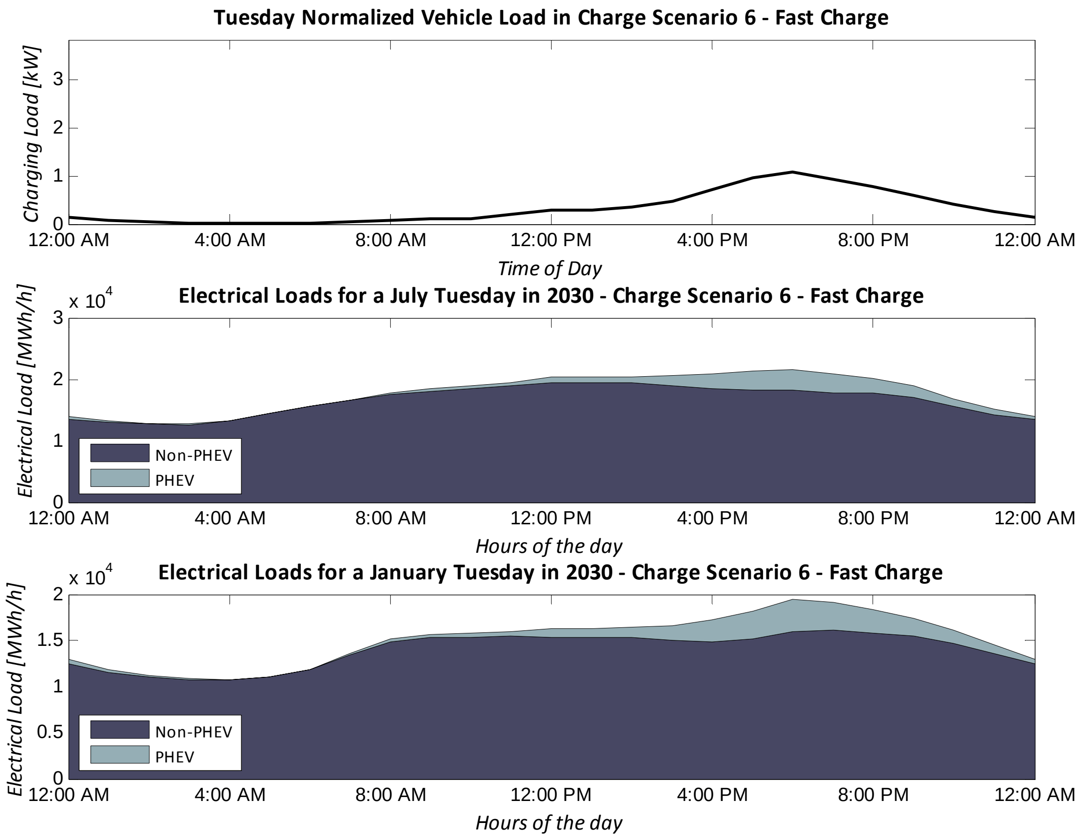

Figure 72. Fast charging load profiles (High PHEV infiltration, 2030)

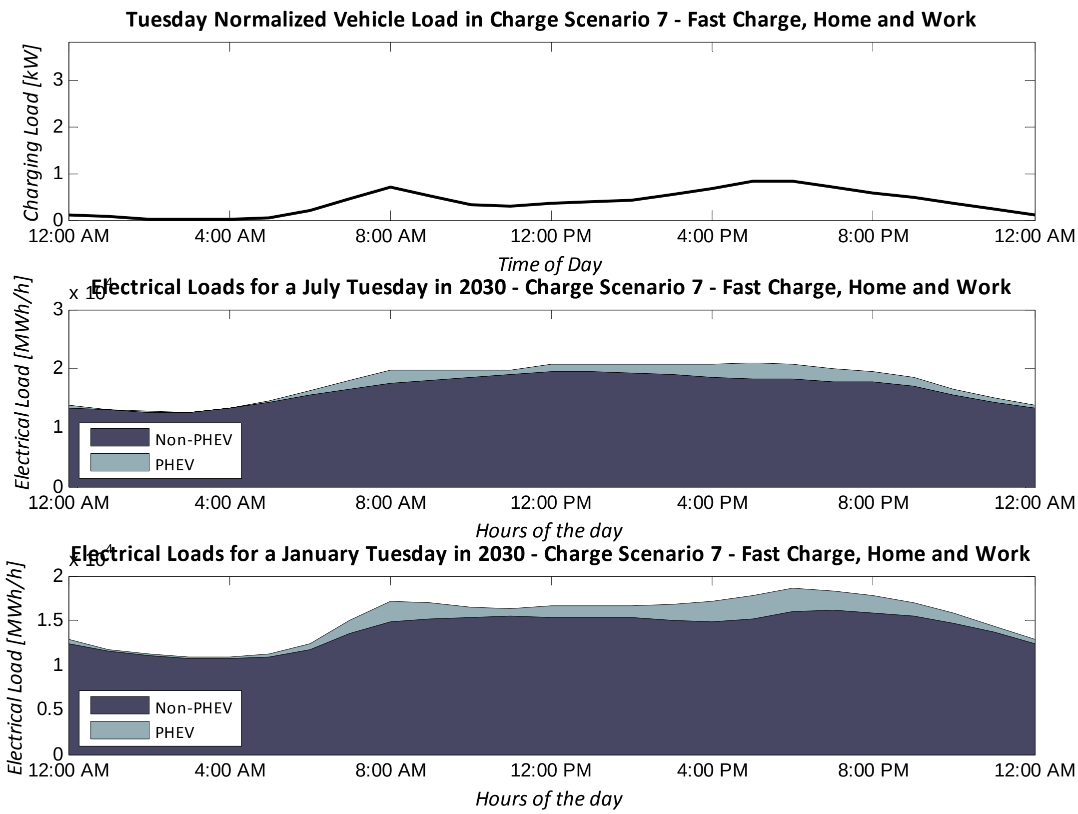

Figure 73. Fast, Home-work charging load profiles (High PHEV infiltration, 2030)

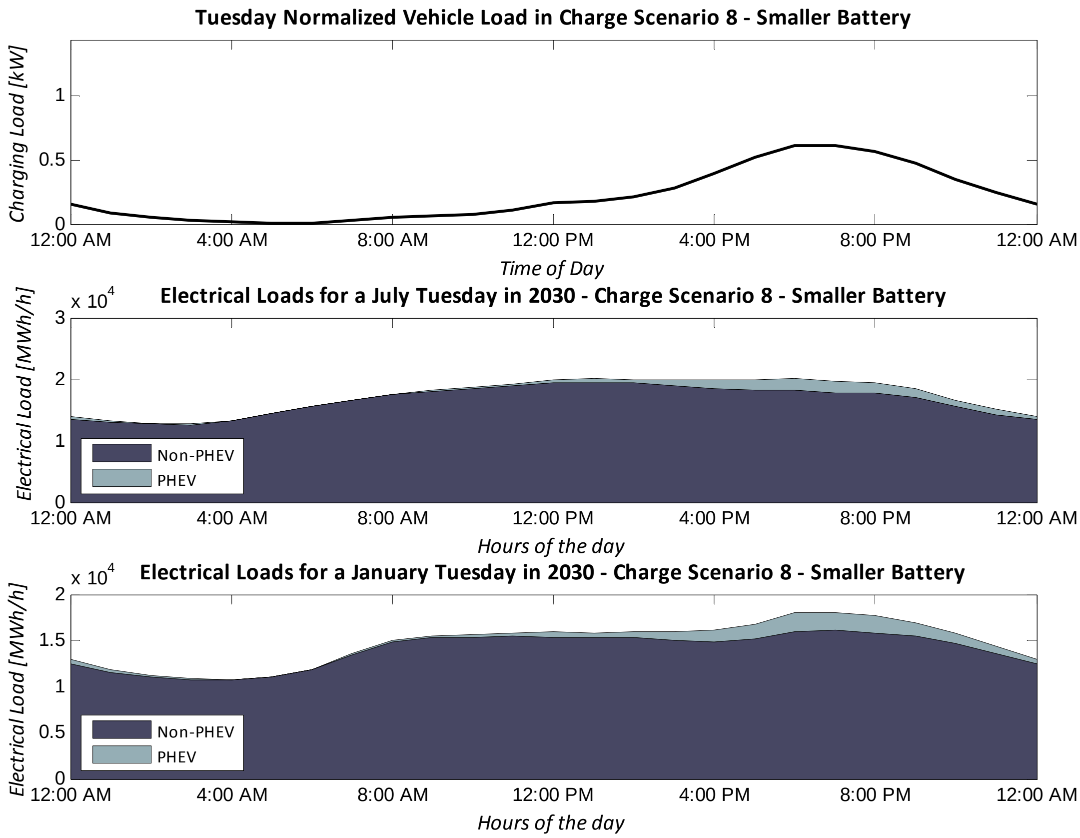

Figure 74. Smaller battery charging load profiles (High PHEV infiltration, 2030)

Appendix I. Additional Greenhouse Gas Emissions Results

The following figures show the total system greenhouse gas emissions in 2030 for the electricity grid mix simulations and for the charging simulations. Figure 75 shows results for the different electricity generation mix simulations. Figure 76 shows results for the different charging simulations.

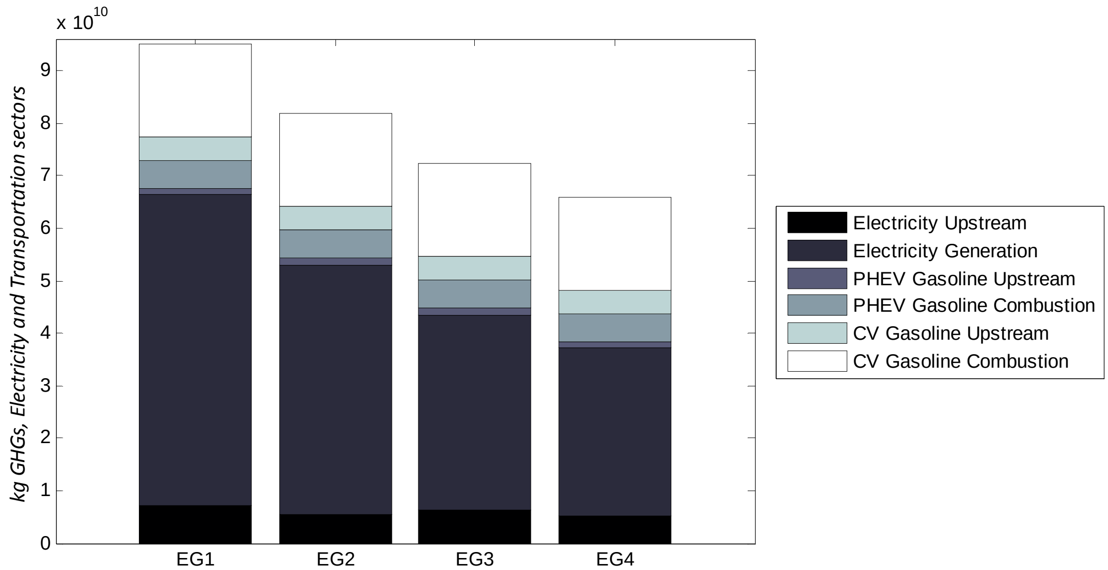

Figure 75. Total GHG for the year 2030 for all electricity grid mix simulations

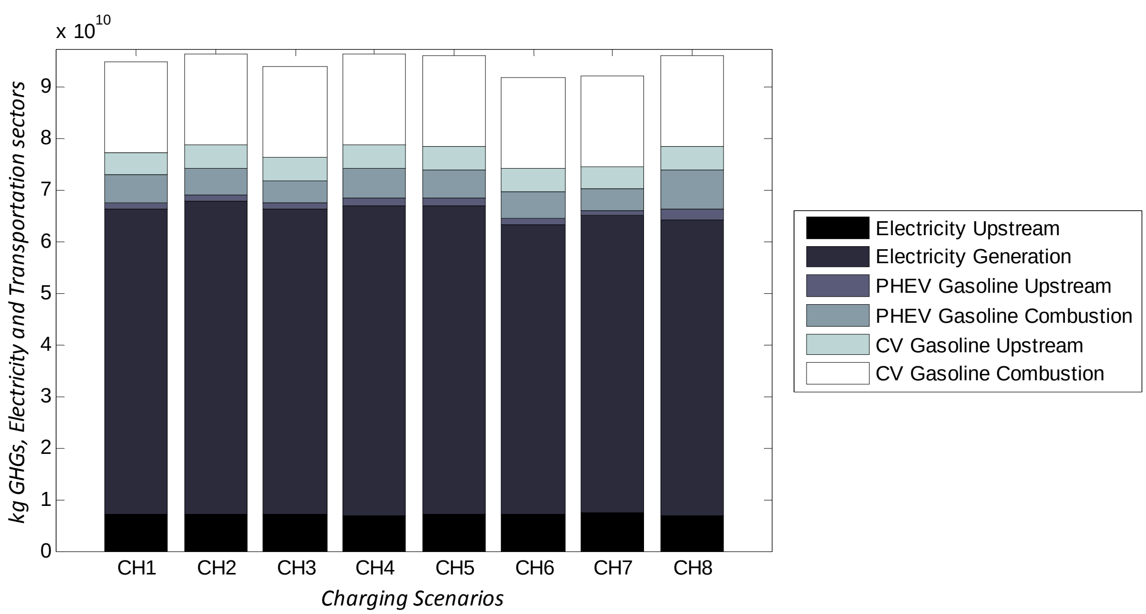

Figure 76. Total GHG for the year 2030 for all charging simulations

Appendix J. Additional Criteria Pollutant Results

The data tables below show the criteria air pollutant emission rates pertinent to the results discussion in this study's report.

Table 54. Criteria air pollutant emission rates, 2030, EG1

EG1 Simulation	CO	Pb	NO_X	PM_{10}	VOC	SO_X
	mil kg	kg	mil kg	mil kg	mil kg	mil kg
FI4 Total Emissions	255	5153	132	49	28	359
FI1 Total Emissions	331	4963	139	49	34	341
Percentage Change	**-23%**	**4%**	**-5%**	**-0.1%**	**-16%**	**5%**
FI4 CV&PHEV Emissions Average	231	375	30	8	20	33
FI4 CV&PHEV Emissions Marginal	233	190	23	7	20	28
FI1 CV Emissions	309	-	30	7	25	10
Percentage Change Average	**-25%**	**-**	**1%**	**22%**	**-23%**	**232%**
Percentage Change Marginal	**-25%**	**-**	**-25%**	**-0.4%**	**-21%**	**182%**

Table 55. Criteria air pollutant emission rates, 2030, EG4

EG4 Simulation	CO	Pb	NO_X	PM_{10}	VOC	SO_X
	mil kg	kg	mil kg	mil kg	mil kg	mil kg
FI4 Total Emissions	248	2248	79	26	27	256
FI1 Total Emissions	326	2305	87	28	33	238
Percentage Change	**-24%**	**-2%**	**-9%**	**-7%**	**-17%**	**7%**
FI4 CV&PHEV Emissions Average	231	168	27	7	20	26
FI4 CV&PHEV Emissions Marginal	231	-57	22	5	20	27
FI1 CV Emissions	309	-	30	7	25	10
Percentage Change Average	**-25%**	**N/A**	**-12%**	**-2.3%**	**-23%**	**158%**
Percentage Change Marginal	**-25%**	**N/A**	**-27%**	**-29%**	**-22%**	**172%**

Figure 77 through Figure 83 display the total system criteria pollutant emissions under the EG1 scenario for charging scenarios CH2 through CH8. The following remarks on the data represented in these figures is based on the difference in results shown from the results under the baseline charging scenario (CH1) discussed in detail in subsection 5.3. For each of the following figures, the emissions which displayed a significant change in emissions levels from those of CH1 are noted. Further detail on the cause of the observed trends is omitted. Specific explanations about the driving forces behind changes of each emissions level can be referenced in the criteria air pollutants results discussion section of the main report body (subsection 5.3).

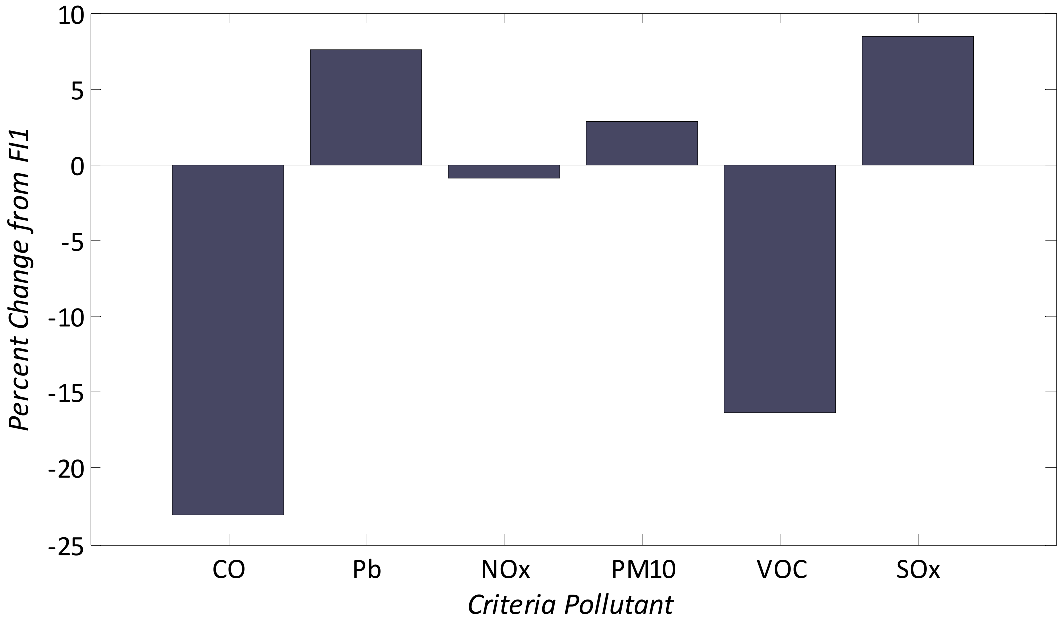

Figure 77. Change in total system criteria air pollutants, 2030 (CH2, EG1, FI4)

In the CH2 scenario, the most significant changes are the increase in lead, decrease in NO_X, increase in PM_{10} and increase in SO_X.

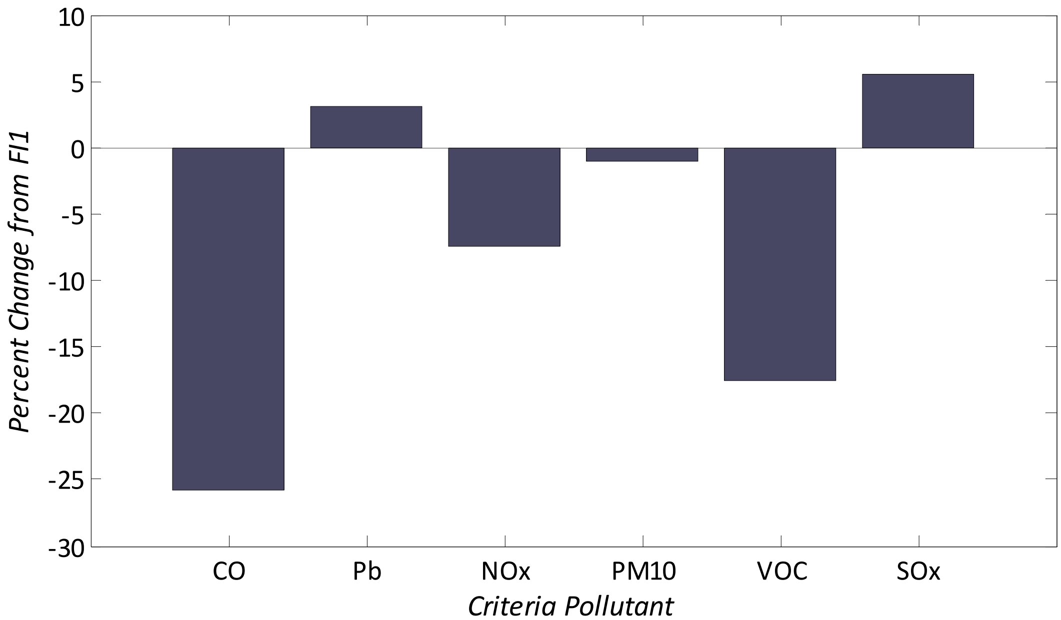

Figure 78. Change in total system criteria air pollutants, 2030 (CH3, EG1, FI4)

In CH3 scenario, the most significant changes are the decrease in NO_X and decrease in PM_{10}.

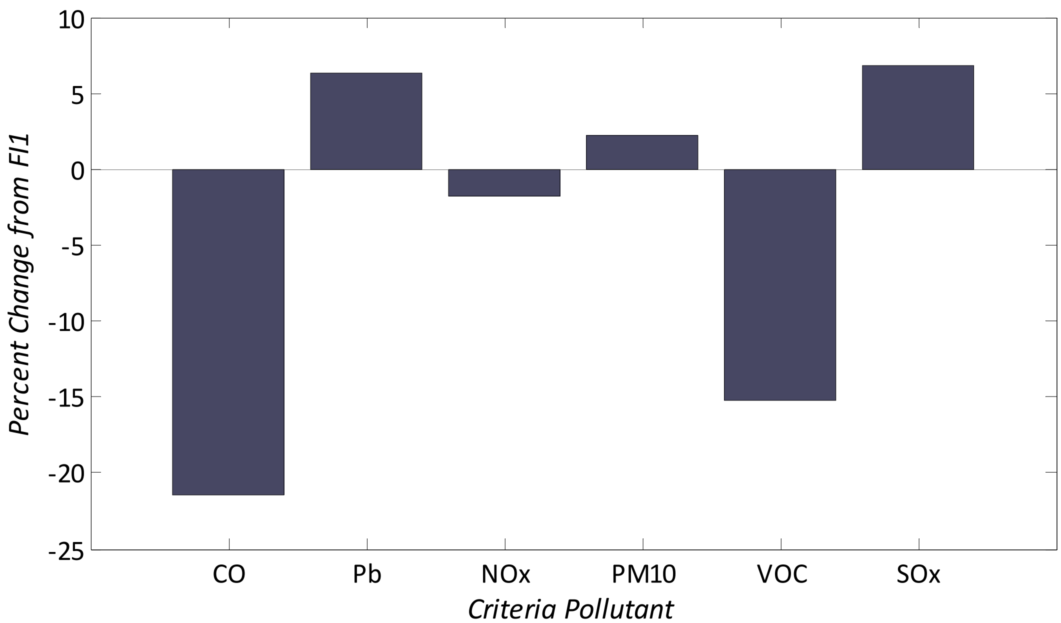

Figure 79. Change in total system criteria air pollutants, 2030 (CH4, EG1, FI4)

In CH4 scenario, the most significant changes are the increase in lead, increase in NO_X and decrease in PM_{10}.

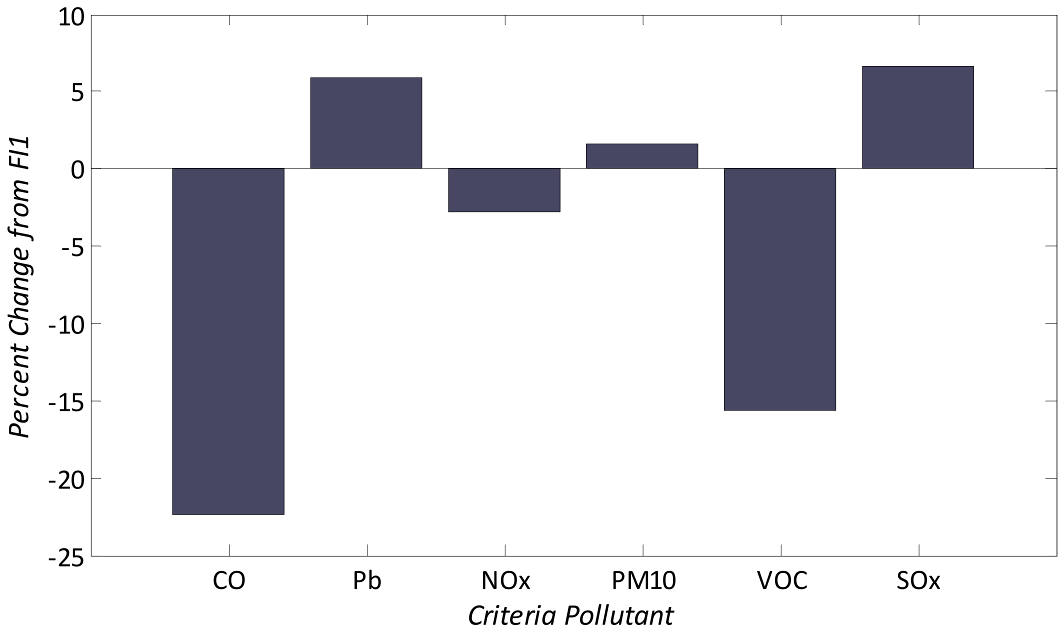

Figure 80. Change in total system criteria air pollutants, 2030 (CH5, EG1, FI4)

In CH5 scenario, the most significant changes are the increase in lead, increase in NO_X and increase in PM_{10}.

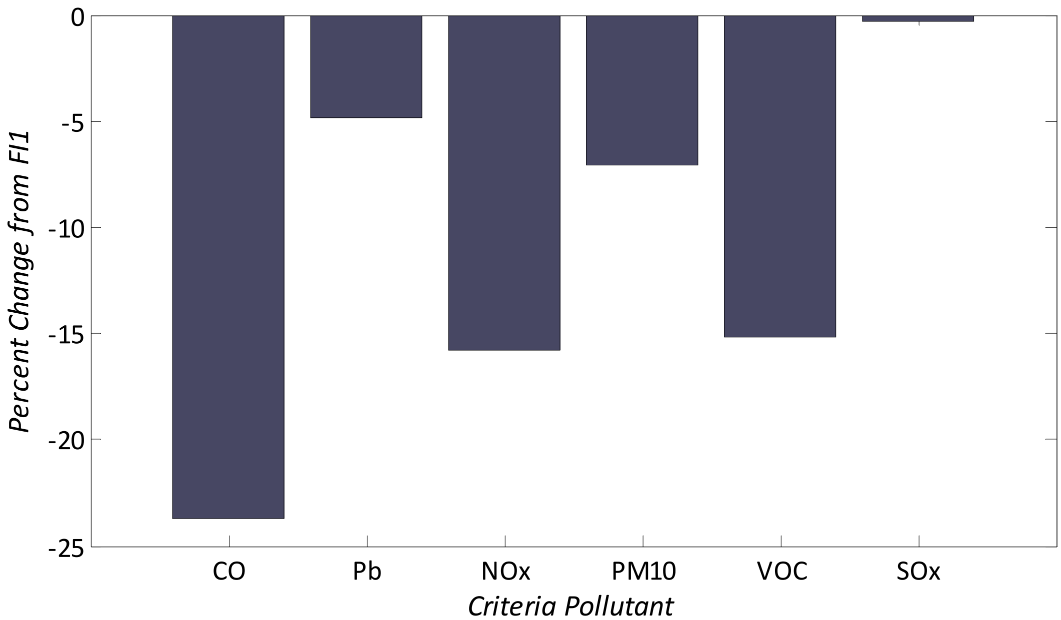

Figure 81. Change in total system criteria air pollutants, 2030 (CH6, EG1, FI4)

In CH6 scenario, the most significant changes are the decrease in lead, decrease in NO_X, decrease in PM_{10}, and decrease in SO_X.

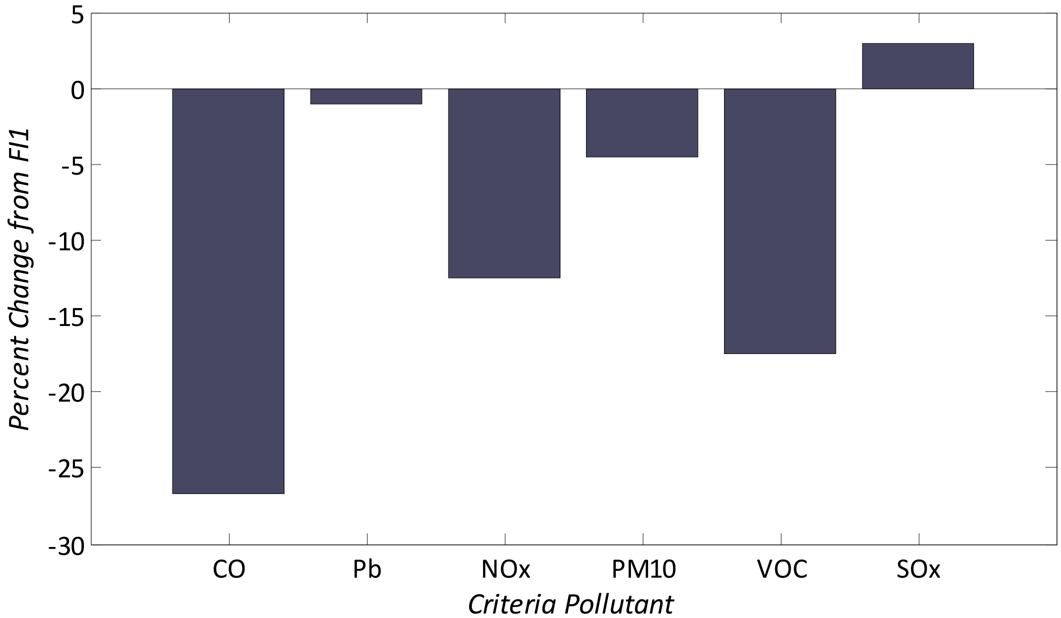

Figure 82. Change in total system criteria air pollutants, 2030 (CH7, EG1, FI4)

In CH7 scenario, the most significant changes are the decrease in lead, decrease in NO_X and decrease in PM_{10}.

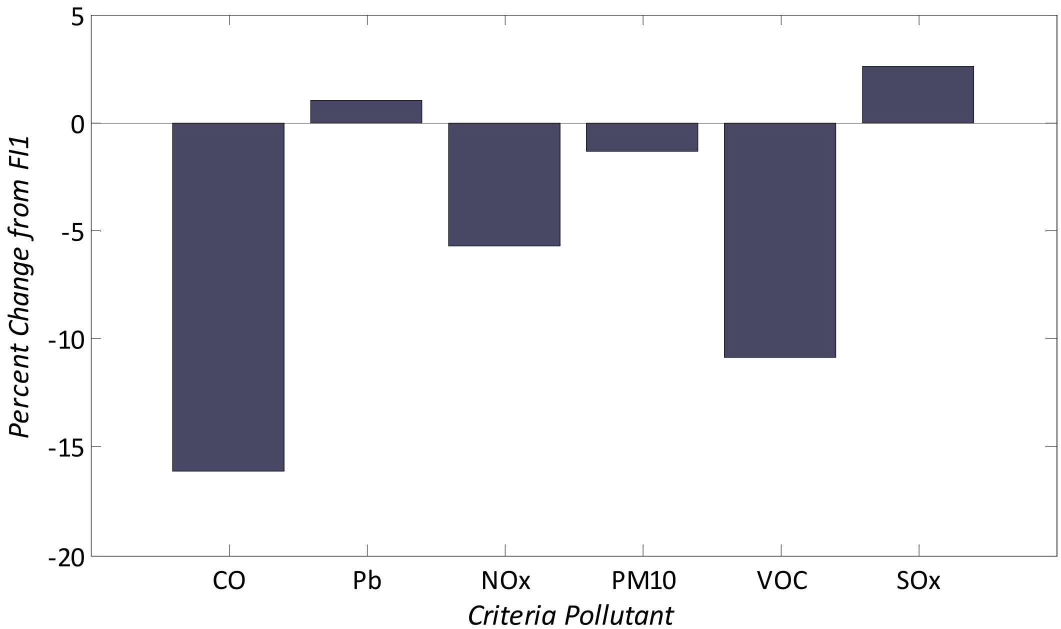

Figure 83. Change in total system criteria air pollutants, 2030 (CH8, EG1, FI4)

In CH8 scenario, all emission level trends are similar to those of CH1. However, the magnitude of these changes is less drastic.

Appendix K. Additional charging scenarios and NHTS location analysis

The PECM model considered many charging scenarios to determine the normalized electric demand for each type of vehicle. We know that even though the actual magnitude of the demand depends on the aggregated electric load due to the entire fleet, the shape of the demand curve depends entirely on the charging behavior of each vehicle in the fleet.

New charging scenarios that can level the peaks and "fill up" valleys in the load curve are considered and analyzed. Three new charging scenarios were considered:

1. Level 3 charging – In this scenario, vehicles charge at a very fast rate, namely 240 V and 80 A as recommended by SAE standards. This scenario assesses the maximum burden on the load curve assuming that all charging stations at home and elsewhere will be highly power dense. This would typically reduce gas miles driven and increase the load on the grid.
2. Staggered charging – A variable no-charge window is applied to different vehicles to mitigate queuing efforts. This assigns a unique no-charge window from a fixed set of random windows in an attempt to distribute the peak observed when applying a single no-charge window.
3. Charge everywhere – In this scenario, the assumption is that the PHEVs charge everywhere they stop provided the time for which it is parked exceeds a minimum dwell time of 30 minutes. This represents a maximum charging scenario as the vehicles are free to charge at any place they stop.

An investigation of these scenarios shows that the staggered charging scenario does indeed fill up the valleys and reduce the existing peaks. However, a peak is still formed after each no-charge window. This also decreases the overall load on the grid by restricting the time allowed for charging in the day. The level 3 charging has higher peaks and more deviation from a completely uniform load. Charging everywhere increases the area under the load curve and represents the maximum consumption case from the grid.

Also, a time-weighted analysis of the charging locations was conducted to identify the locations with the largest potential for charging infrastructure. It shows that grocery, clothing and hardware shops, restaurants, schools and sports centers are the most parked-at locations, after home and work. This gives us an insight on the locations that should have high priority for developing charging infrastructure, because vehicles will be parked at these locations both frequently and for long periods of time.

Motivation

Current load curves have "peaks" and "valleys". We know that the introduction of PHEVs will add new peaks to the current load. Our motivation here is to understand how the PHEV fleet changes the load curve and to try to flatten it by using different mechanisms like having no-charge windows, having staggered charging etc.

- Level 3 charging scenarios – These offer a fast charging option for users and have a high potential to implementation. It is important to understand its burden on the grid and subsequently the emissions associated with it.

- Staggered charging window scenario – As electric companies try to reduce their peaks and fill up the valleys in their load curve, they will need to force the vehicles to charge at non-peak hours. However, forcing all vehicles to shift to non peak hours by using a singularly defined no-charge window causes a new peak, which is undesirable. Hence different vehicles need to be encouraged to charge at different times. Utility companies are exploring no-charge policies to reduce this peak.
- Charging everywhere scenario – In the ideal future, PHEVs will infiltrate the market to such an extent that charging infrastructure is widely developed and vehicles have the option to charge everywhere. This represents the maximum load that the grid will see.

Considering new scenarios to modify the shape of the load curve and level it are necessary to assess the possible impacts that such scenarios will cause.

A study was also conducted to determine high value locations for the development of vehicle charging infrastructure. This was done using NHTS data to understand both where, and for how long, vehicles were parked.

Methodology

1. Charging scenario 1 is the case where vehicles charge at level 3. This can be simulated using the existing model by changing input variables CI (Charging current) and CV (Charging Voltage). The

variables CI and CV are changed to 80 and 240 respectively, in accordance with SAE standards. This simulates a case where all the vehicles charge at level 3, which is the highest rate allowed by the vehicle. Hence the PECM inputs remain the same except for CI and CV.

2. Charging scenario 2 is the case where vehicles are not allowed to charge at a particular window of time every day. A set of 24 no-charge windows of 10 hour durations were generated with start times between 1300 hours and 1875 hours, increasing in intervals of 15 minutes. 10 hour durations were picked because our base case simulations of PHEV infiltration showed that the average length of the high load period was around 10-12 hours. In order to reduce the burden on the grid during these times, a no-charge window of 10 hours was implemented during this time period in the day. One of these windows is randomly selected and assigned to each vehicle. Thus every vehicle has a different charging restriction upon it.
3. Charging scenario 3 is the case where a PHEV friendly infrastructure is assumed to be in place. Charging stations are available everywhere and vehicles charge if they are parked for more than the minimum dwell time. Thus, the only change in the PECM inputs for the model would be MD set to 30 minutes. Apart from this, the model had to be slightly modified to remove the charging location constraint (can charge only at home) applied in the base case. Table 56 and Table 57 give the inputs of the PECM model for these three new scenarios.
4. ‘High-value’ locations represent those locations where the time-weighted frequency of vehicles parked is highest. These are the locations that would need to be targeted for developing charging infrastructure. The Trip Index matrix or the TID matrix gives us the starting and ending times of the trip and the location code of where the vehicle parks. For each of these parking locations, the time parked was found by subtracting the end time from the next start time for the same vehicle. The total number of instances of every unique location was determined. This gives us the number of times a vehicle parked at every location. The total time parked at every location was then divided by the frequency of parking for the respective location. This calculated value for each location represents the time-weighted frequency of parking. The time-weighted frequency of a location gives us a more realistic idea of whether or not it is worth installing charging stations at that location.

Table 56. PECM inputs for the three new vehicle charging scenarios

Scenario name and number		PECM Inputs								
		CL	**BS (KWh)**	**CI (Amp)**	**CV (Volt)**	**CD**	**MD**	**NL**	**NU**	**LM**
Level 3	CH1	**Home**	10.4	**80**	**240**	0	0	none	none	no
Staggered	CH2	**Home**	10.4	12	120	0	0	**variable**	**variable**	no
Charge everywhere	CH3	**Everywhere**	10.4	12	120	0	**1800**	None	None	no

Table 57. Description of the three charging scenario names

Acronym	Full Name	Difference from baseline conditions
CH1	Level 3	Charge at the fastest rate compatible with the vehicle's design
CH2	Staggered no-charge windows	Different vehicles have different no-charge windows
CH3	Charge everywhere	Vehicles charge everywhere they park for more than the minimum dwell time

Findings

1. CH1 – Level 3 charging scenario:
2. Figure 84 shows us the load curve of the level 3 charging scenario described earlier. This curve shows us that the overall demand drastically increases. All the peaks are much higher than the baseline due to lower times needed to completely charge the vehicle at the higher charging rate. Figure 85 through Figure 87compare the base case scenario with the level 3 charging scenario for three vehicle classes: Sub-compact cars, large vehicles and pick-up trucks. Clearly, the peaks are higher and shift to the left due to faster charging rates which allow the vehicles to charge more in the same time.

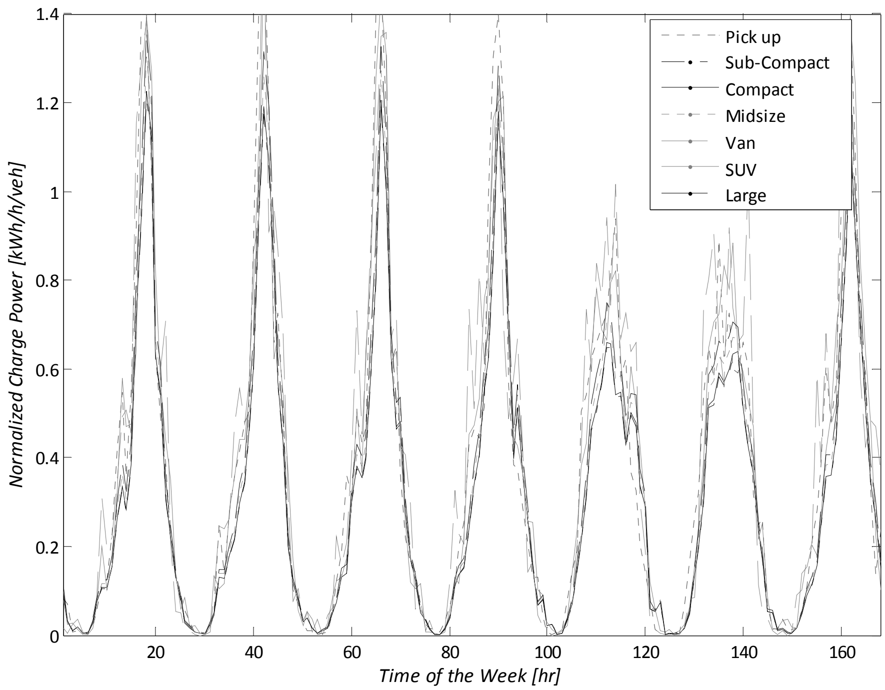

Figure 84. Level 3 charging scenario

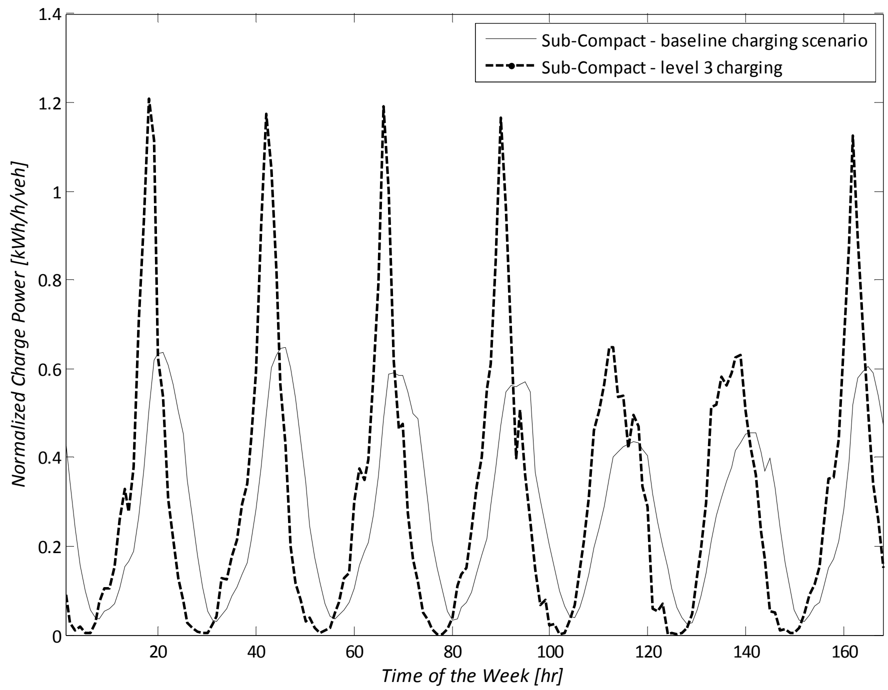

Figure 85. Comparison of baseline charging scenario with level 3 charging (sub-compact)

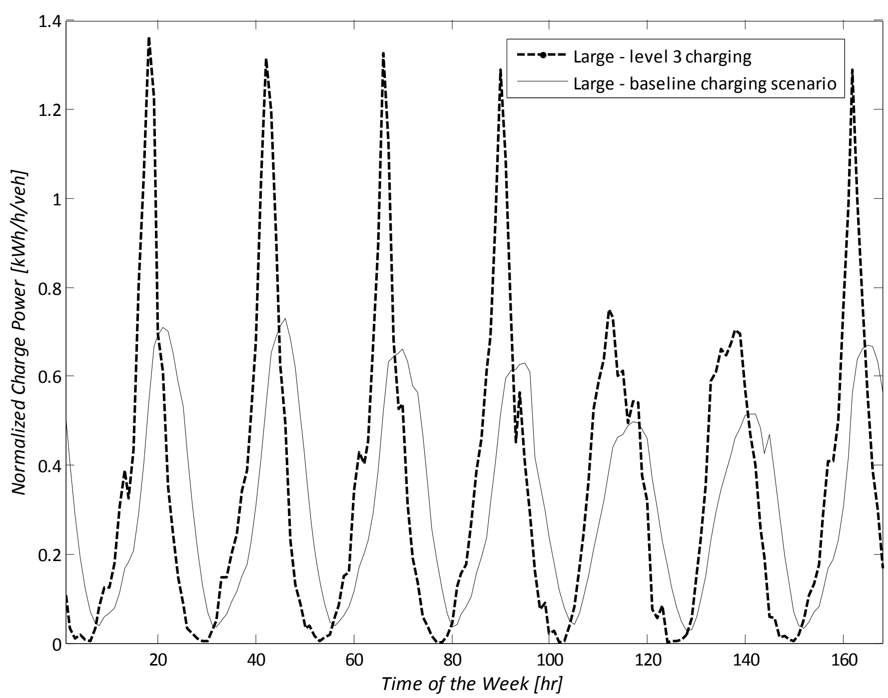

Figure 86. Comparison of baseline charging scenario with level 3 charging (large car)

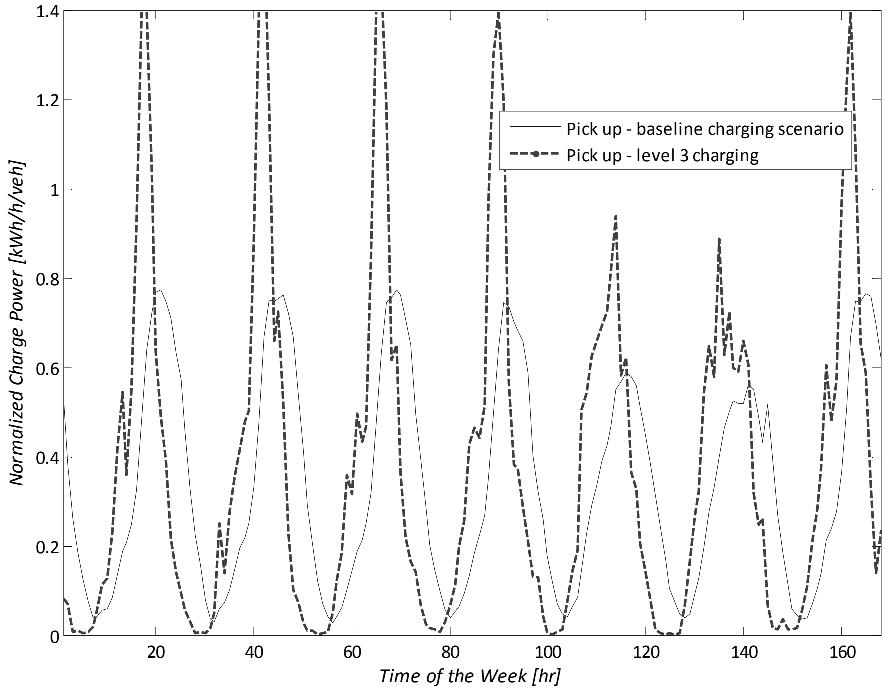

Figure 87. Comparison of baseline charging scenario with level 3 charging scenario (pick up)

3. CH2 – Staggered no-charge window charging scenario: Figure 88 shows us the load curve of the staggered no-charge window descried earlier. From the curve, we can see that the overall demand is lesser than the baseline curve. This is because of the constraint on charging placed on every vehicle. This reduces the amount of time for which the vehicles can charge. There are two peaks now. The new one appears after the no-charge window for each day of the week. Figure 89 through Figure 91 compare the base case scenario with the staggered no-charge window charging scenario for three vehicle classes: Sub-compact cars, large vehicles and pick-up trucks. A small portion of the load in the new scenario shifts from the peak period to the troughs or the 'valleys' of the original load curve.

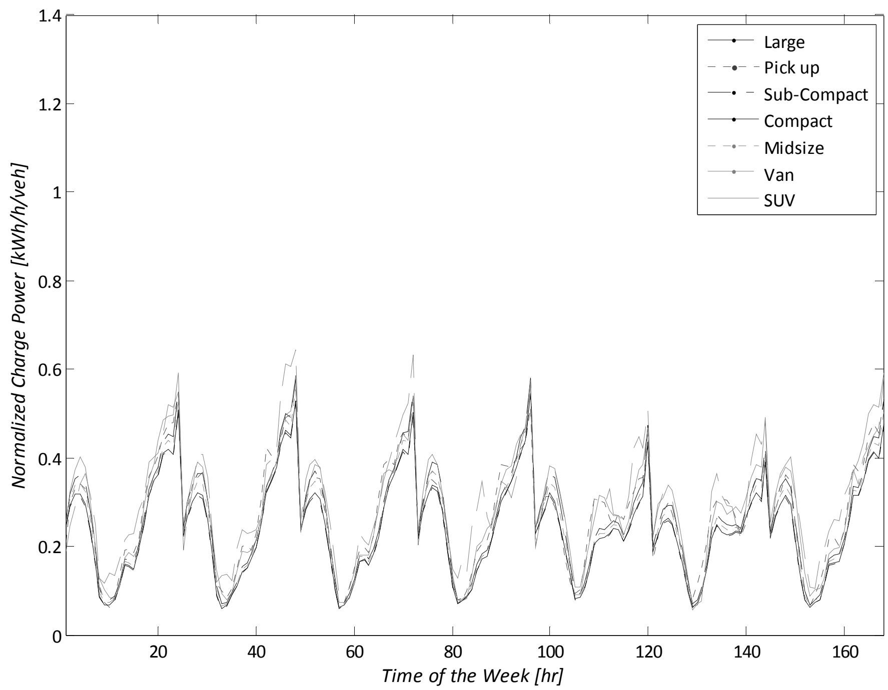

Figure 88. Staggered no-charge window scenario

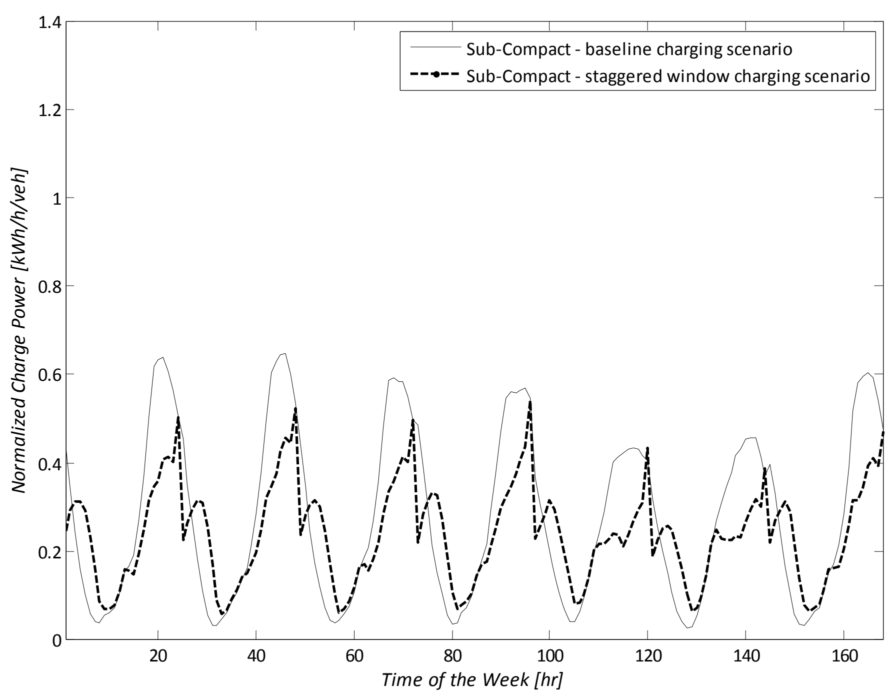

Figure 89. Comparison of baseline charging scenario with staggered window charging (sub-compact)

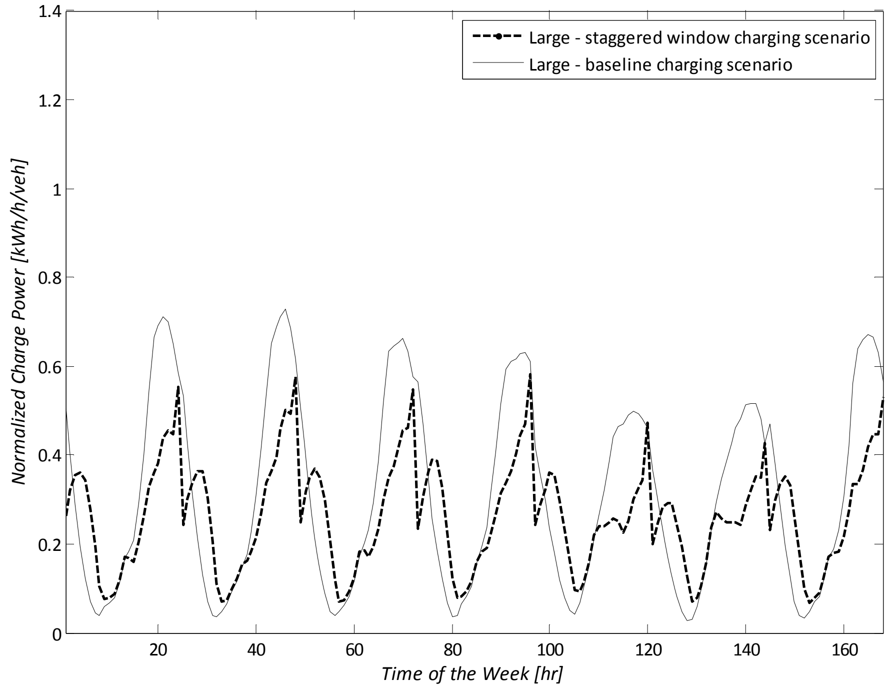

Figure 90. Comparison of baseline charging scenario with staggered window charging (large car)

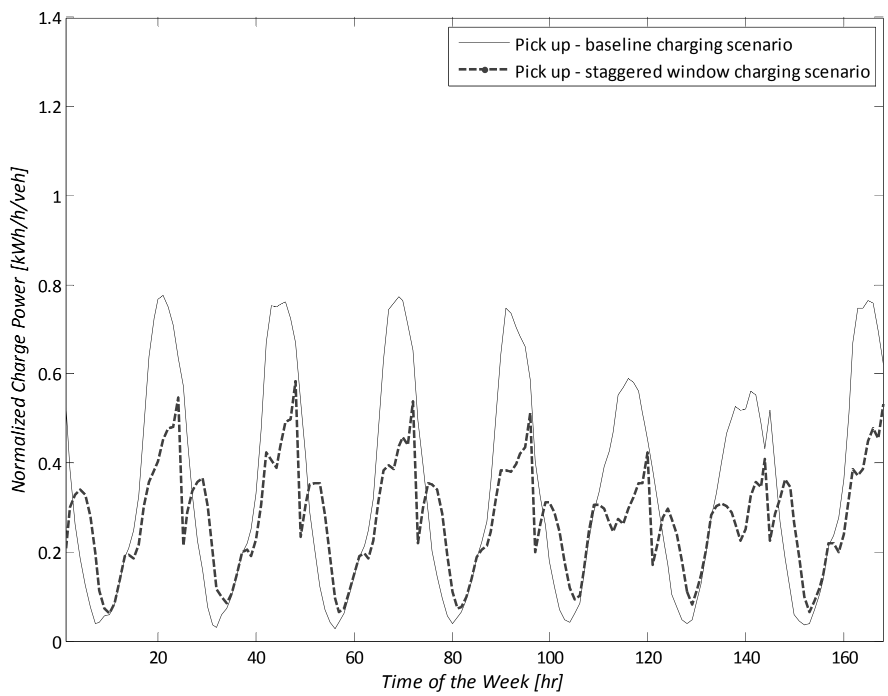

Figure 91. Comparison of baseline charging scenario with staggered window charging (pick up)

No-charge windows are helpful to level the load curve and operate the power plants at base load. A strict no-charge window is difficult to achieve in practice. But providing incentives like lowering electricity tariff during certain times can encourage people to charge at other non-peak times of the day and reduce the need to run peaking plants for the utility company.

4. CH3 – Charge everywhere scenario: Figure 92 shows us the load curve of the charge everywhere scenario descried earlier. From the curve, we can see that the overall demand is comparable to the baseline curve. This is because, even though vehicles are allowed to charge everywhere, the minimum dwell time of 30 minutes reduces the amount of charging significantly preventing them from charging at home and work for short stopovers. The baseline case assumed that vehicles could charge at home if they stopped for any amount of time Figure 93 through Figure 95 compare the base case scenario with the charge everywhere scenario for three vehicle classes: Sub-compact cars, large vehicles and pick-up trucks. We see that the peaks form at the same times each day, but the 'valleys' in the baseline curve are filled up effectively. The new curve is flatter during the day but like the baseline curve, has a valley in the night.

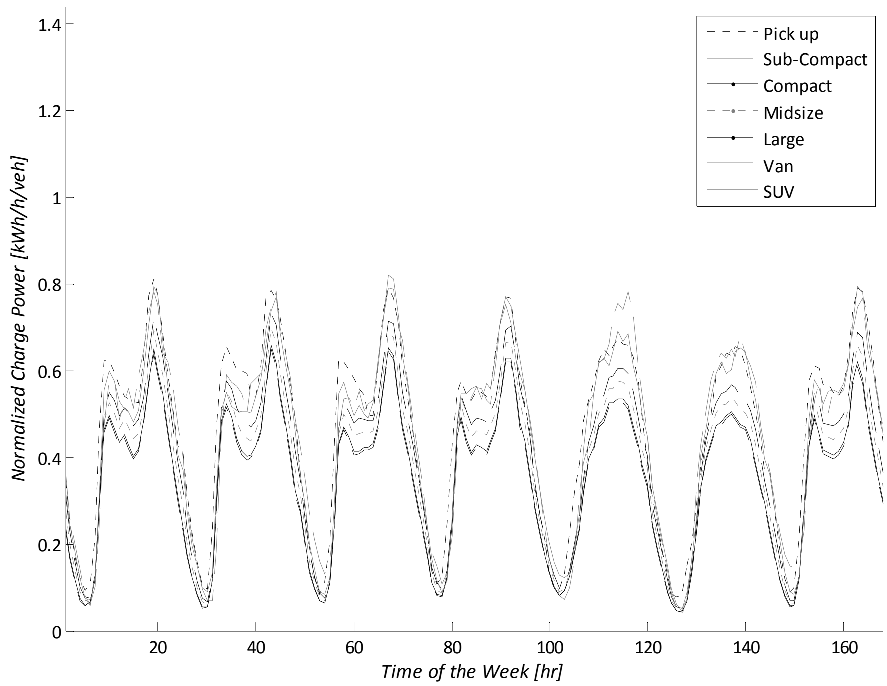

Figure 92. Charging everywhere scenario

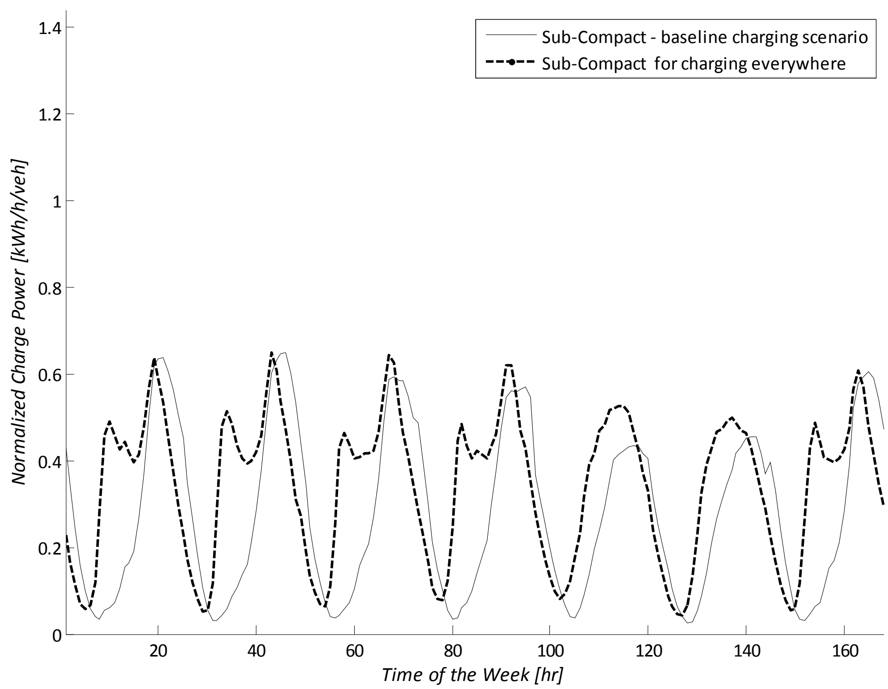

Figure 93. Comparison of baseline charging scenario with charging everywhere (sub-compact)

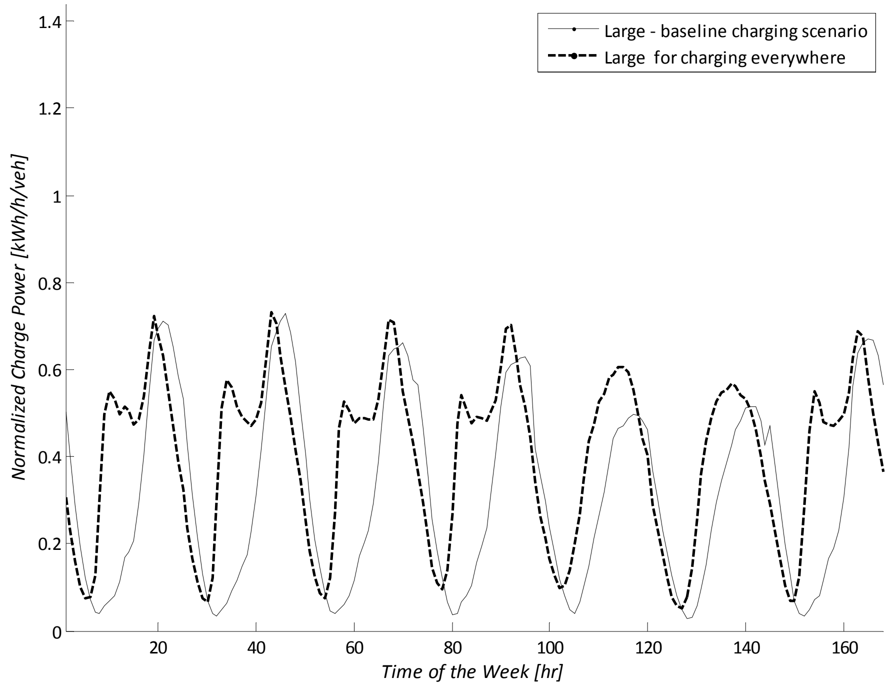

Figure 94. Comparison of baseline charging scenario with charging everywhere (large car)

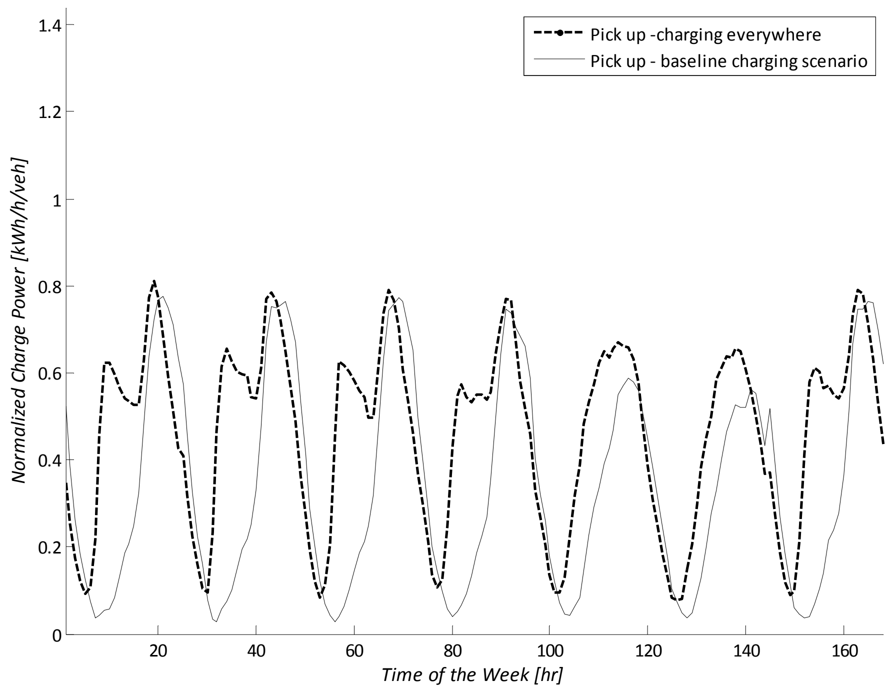

Figure 95. Comparison of baseline charging scenario with charging everywhere (pick up)

5. An analysis of parking times per stop at every location in the NHTS trip data showed that after home and work, the five most parked locations were relatives' residence, grocery, clothing and hardware shops, restaurants, schools and sports centers. Friends' and relatives' house are homes too and we can assume that charging infrastructure exists in those places. Hence the locations of high priority to be considered for installing parking infrastructures are:
    a. Grocery, clothing and hardware shops
    b. Restaurants
    c. Schools (for students)
    d. Sports centers

    Table 58 below, taken from the National Household Travel Survey User Guide, defines the location codes that were used for the analysis.

    Table 59 below shows the results of the analysis to determine these "high-value" locations. The locations in green are the ones with highest time-weighted values after home and work (which are 1, 11, 12 and 14). Location code -1 denotes the option where the users who filled the survey decided to skip answering the 'purpose of trip' question.

Table 58. Description of location as per NHTS User guide for trip data

Location Code	Description of location
1	Home
11	Go to Work
53	Visit Friends/ Relatives
22	Go to religious activity
41	Buy goods: groceries/clothing/hardware store
12	Return to Work
-1	Appropriate Skip
82	Get/eat meal
14	Other work related
21	Go to school as student
51	Go to gym/exercise/play sports

Table 59. High value location findings

Total			
Location code	**Frequency of parking**	**Time parked for (in minutes)**	**Average time for which vehicle parks for per stop**
1	243904	964456669417	10592895.0
11	64555	46994827252	1980507.3
53	24590	2882466491	**302847.3**
22	12178	1554860775	**301478.4**
41	97102	9741090174	**257517.5**
12	10989	693515891	182573.1
-1	2772	124612242	131219.4
82	36233	1734124821	**123951.1**
14	14413	551286427	122720.6
21	4430	227434749	**108601.3**
51	14688	604162140	**106894.7**
54	8164	296719671	99963.8
30	14862	556275586	91004.1
52	3111	77635157	83507.0
50	6084	165601753	79731.6
42	29310	788557178	68043.0
40	15435	302637495	59558.5
60	9109	181830104	57887.6
71	22445	404734114	52441.1
81	4118	78036765	50782.7
73	23442	322479776	41228.4
65	3869	44336123	30821.3
13	2151	24682780	30599.1
97	1156	12800439	27439.0
63	4428	38986323	19689.8
20	1530	9608046	16395.0
55	2747	16666433	15897.0
43	12939	73319028	14959.4
72	2303	11714763	13500.0
83	5372	19467060	10156.2
61	2686	8440492	8807.2
62	877	2671639	7432.8
64	2228	5811682	7185.7
80	1422	2909837	5351.7
70	491	503294	2946.6
23	334	346055	2820.7
10	1	1235	1235.0
24	314	119337	1218.3

Appendix L. Cost analysis of PHEV versus CV

Introduction

Vehicle affordability is an important factor in deciding which car to buy. When comparing a conventional vehicle (CV) and a plug-in hybrid electric vehicle (PHEV), ideally, consumers would like to recover the increased upfront cost of the vehicle in gasoline savings over the lifetime of their vehicle. If consumers cannot at least breakeven during the lifetime of their vehicle, then it would not make economic sense to purchase a PHEV. This analysis identifies factors such as daily driving distance, battery price, fuel price, and government incentives that may make the PHEV more affordable relative to a CV and evaluates how sensitive the breakeven point is to these factors.

Methodology

In order to model the costs of a CV and a PHEV, the Chevrolet Malibu LTZ and the Chevrolet Volt were chosen to gather information and evaluate differences between the CV and PHEV platforms. It was assumed that all else would be equal between the two vehicles other than initial cost and fuel costs. The warranty for the Chevrolet Volt insures the battery for 8 years, so any damage or battery degradation would likely be a cost to the manufacturer rather than the consumer. The warranty for the rest of the vehicle is very similar to that of a conventional vehicle, so it was also assumed that maintenance costs would be similar for a CV and a PHEV.

In order to estimate lifetime ownership costs for both vehicles, the first consideration was the initial cost of buying the CV and PHEV.

Battery Cost

Cost estimates ranged from \$700/kWh to \$1220/kWh [67] for batteries. An average value of \$990/kWh was chosen as the representative battery cost. Three different battery sizes were evaluated based on their electric mile range. Batteries of a 40 mile, 20mile, and 10 mile range were considered, corresponding to usable battery capacities of 10.4 kWh, 5.2 kWh, and 2.6 kWh. These values are 65% of the total battery capacity, so they correspond to battery sizes of 16 kWh, 8 kWh, and 4 kWh respectively. These values were input into the following equation to determine Battery Cost.

$$Battery\ Cost = \frac{\$990}{kWh} \times Battery\ Size\ (kWh) \quad \text{Equation 30}$$

Initial Vehicle Cost

Conventional Vehicle cost was estimated to be equivalent to the 2011 Chevrolet Malibu LTZ MSRP rating of approximately $27,000 [68]. The PHEV cost was estimated to be the MSRP rating of the 2011 Chevrolet Volt at $40,280. This value was used for our base case, 40 mile electric range vehicle with a 16 kWh battery. Using the “Battery Cost” equation shown above, a price for the 16 kWh battery was determined. This price was then subtracted from the MSRP rating of the 2011 Chevrolet Volt in order to determine the cost of the PHEV without a battery. PHEV cost for vehicles with a 10 mile or 20 mile electric range was then estimated using the Battery Cost equation and the PHEV cost without a battery, illustrated by the following equation:

$$Initial\ PHEV\ Cost = 2011\ Chevrolet\ Volt\ MSRP - \frac{\$990}{kWh} \times 16\ kWh + Battery\ Cost$$ Equation 31

Tax Credit

In order to make the PHEV more competitive on the market, the US government has instituted a tax credit for vehicles with battery sizes greater 5 kWh [69]. The following equation was used to calculate the decrease in initial cost for the qualifying PHEVs:

$$Tax\ Credit = \$2500 + \$417 \times [Battery\ Size\ (kWh) - 5\ kWh]$$ Equation 32

Operational Costs

Next, operational costs of the CV and PHEV were considered. First, data on daily travel habits of individual Americans provided by the NHTS was filtered and used to produce four different profiles of electricity and fuel consumption. These profiles of energy consumption were then used to determine operational costs of the vehicles assuming negligible differences in maintenance costs. A discount rate of 5.0% was used to calculate the present value of future electricity and fuel costs. The following equation shows how the discount rate, r, was used to calculate a Discount Factor for each year, t, over the lifetime of the vehicle:

$$Discount\ Factor = DF = \frac{1}{(1+r)^{t-1}}$$ Equation 33

Vehicle Miles Traveled

Four scenarios of daily driving distance were considered. Discrete sets of NHTS data were created to account for drivers travelling between 0-40 miles/day, 0-60 miles/day, and 0-80 miles/day. The fourth scenario considered all drivers, regardless of their daily driving distance. Using the PECM model, described earlier in this report, the daily miles travelled by gasoline and electricity were calculated for each driver profile. The daily miles travelled were then aggregated to determine the average yearly miles travelled by gasoline and electricity for each driver profile.

Yearly Fuel Cost

For each driver profile, the average yearly miles travelled using gasoline was considered to be the Fuel Miles (mi/yr). Fuel Cost was estimated to be $2.92/gallon [70] and Vehicle Fuel Efficiency was estimated to be 33.3 mpg [71] for the PHEV and 27 mpg [72] for the CV. The following equation was used to calculate the yearly cost:

$$Yearly\ Fuel\ Cost = \frac{Fuel\ Miles\ \left(\frac{mi}{yr}\right) \times Fuel\ Cost\ \left(\frac{\$}{gallon}\right)}{Vehicle\ Fuel\ Efficiency\ \left(\frac{mi}{gallon}\right)} \times DF \qquad \text{Equation 34}$$

Yearly Electricity Cost

For each driver profile, the average yearly miles travelled using electricity was considered to be the Electricity Miles (mi/yr). Electricity Cost was estimated to be $0.10/kWh [73] and Consumption Rate was estimated at 3.85 mi/kWh. The Consumption Rate estimate is based on the 40 mile electric range [74] that a Chevrolet Volt can achieve, assuming that 65% of its 16 kWh battery is usable. A similar equation was used to calculate cost:

$$Yearly\ Electricity\ Cost = \frac{Electricity\ Miles\ \left(\frac{mi}{yr}\right) \times Electricity\ Cost\ \left(\frac{\$}{kWh}\right)}{Consumption\ Rate\ \left(\frac{mi}{kWh}\right)} \times DF \qquad \text{Equation 35}$$

Scenario Analysis

Effect of Filtered NHTS Data

For the three different battery sizes, daily miles traveled didn't have a pronounced effect on yearly electric miles until examining the 10.4 kWh PHEV. This is likely due to the fact that only the 10.4 kWh battery can travel 40 miles solely on electricity. For the smaller batteries, the user profiles are likely to reach their maximum amount of electric miles per day.

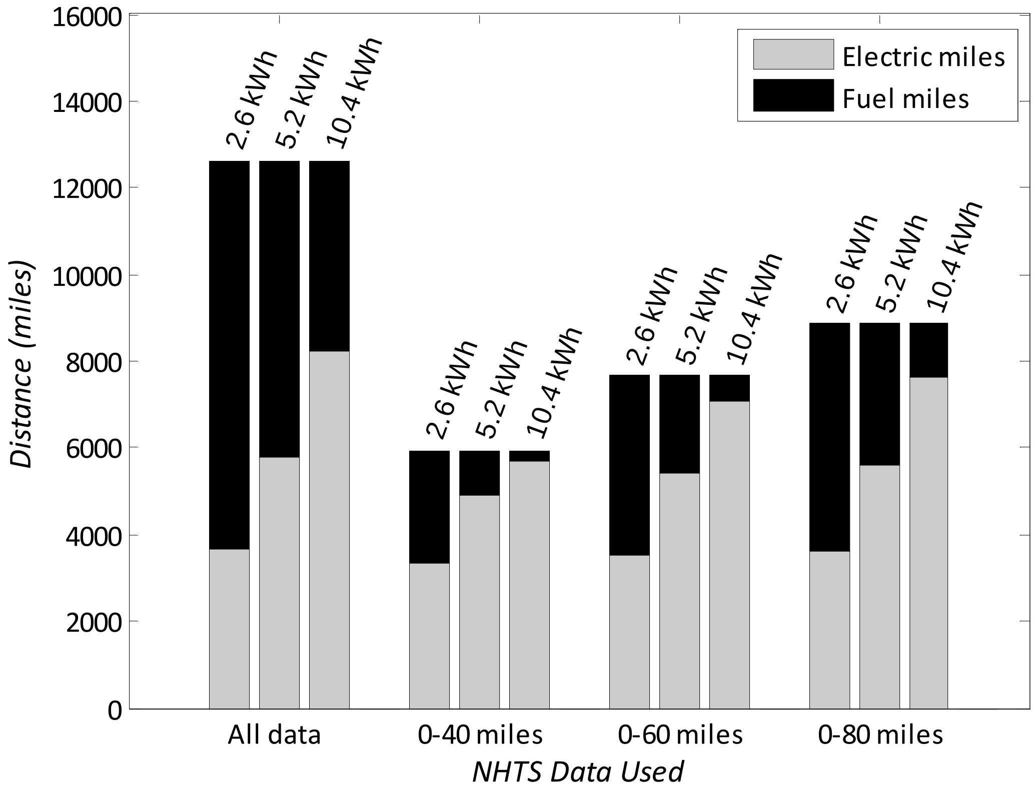

Figure 96. Ratio of miles driven on fuel and electricity.

On the other hand, yearly fuel miles show a more pronounced effect as the daily driving distance increases. Once again, this is likely due to the battery being drained completely during daily travel for the 2.6 and 5.2 kWh batteries.

Effect of Subsidies

The Plug-In Electric Vehicle Tax Credit enacted under the American Recovery and Reinvestment Act of 2009 decreases the cost of the 10.4 kWh PHEV by $7,500 and the 5.2 kWh PHEV by $3,751. This serves to make both vehicles more cost competitive. Considering the scenario using all driver profiles, the 5.2 kWh PHEV recovers its initial cost premium after approximately 2 years and the 10.4 kWh PHEV recovers its premium in approximately 8.5 years. Without the tax credit, the 10.4 kWh PHEV will not be able to breakeven until after 10 years and the 5.2 kWh PHEV will just barely breakeven in a 10 year time frame. The smaller 2.6 kWh PHEV will recover its initial cost premium in 2 years without a tax credit, which could justify the tax credit only applying to battery sizes greater than 5 kWh.

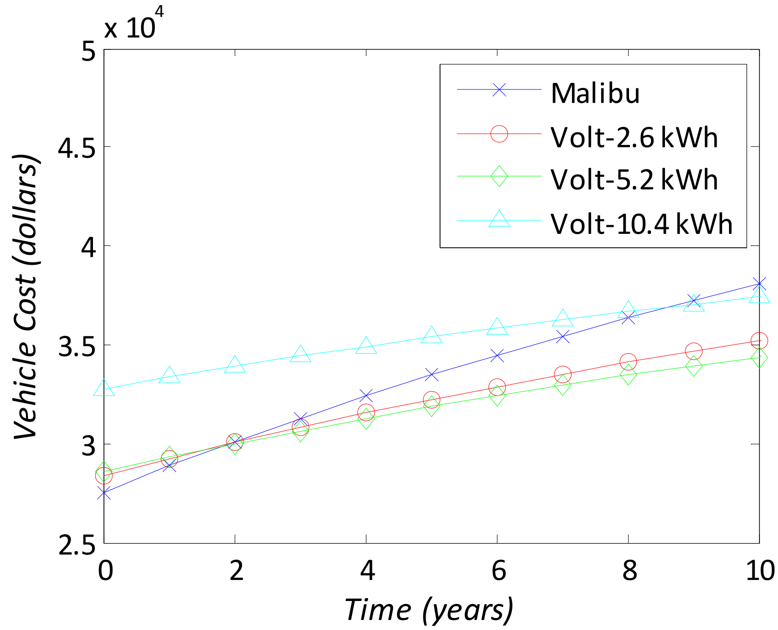

Figure 97. Tax Credit, $2.92/gallon, $0.10/kWh, All Drivers

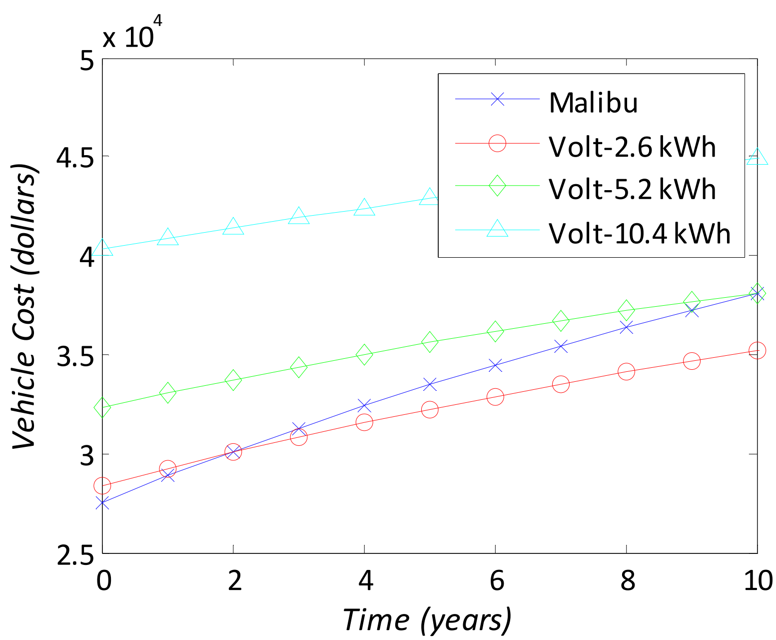

Figure 98. No Tax Credit, $2.92/gallon, $0.10/kWh, All Drivers

Effect of Fuel/Electric Prices

A doubling of fuel prices has a similar effect on the breakeven point(s) as the government subsidy. This seems largely driven by the increased slope of the CV cost curve. Increases in electricity prices have relatively little impact on the breakeven points. This is likely due to the relative magnitude of electricity prices to fuel prices and the fact that electricity prices have no effect on the CV cost, which seems to be the key variable in determining the breakeven point. (See Graphs 4-7)

Findings Summary

- A PHEV with a battery capacity of 10.4 kWh will not breakeven within the lifetime of the vehicle without a government subsidy to balance the cost premium of the battery.

- Breakeven points are progressively earlier with smaller batteries, suggesting that battery cost per kWh will need to decrease significantly to make economic sense without government incentives. The Boston Consulting Group study, *Batteries for Electric Cars – Challenges, Opportunities, and the Outlook to 2020*, suggests that this will not happen by 2020.
- The comparison of CV and PHEV costs is sensitive to fuel prices; at $6.50/gallon the PHEV will breakeven in about 8 years, similar to the effect of the government subsidy.
- After filtering the NHTS data to discriminate between users driving less than 40 miles/day, less than 60 mi/day, or less than 80 mi/day and observing the changes in vehicle costs, it becomes apparent that daily driving distance greatly affects the cost of PHEVs with a smaller battery. However, the cost difference of the 10.4 kWh PHEV and the CV remains relatively the same. This is likely due to the fact that significant gas savings are only achieved with a larger battery, but the battery premium balances these cost savings. (See Graphs 8-10)

Additional Figures

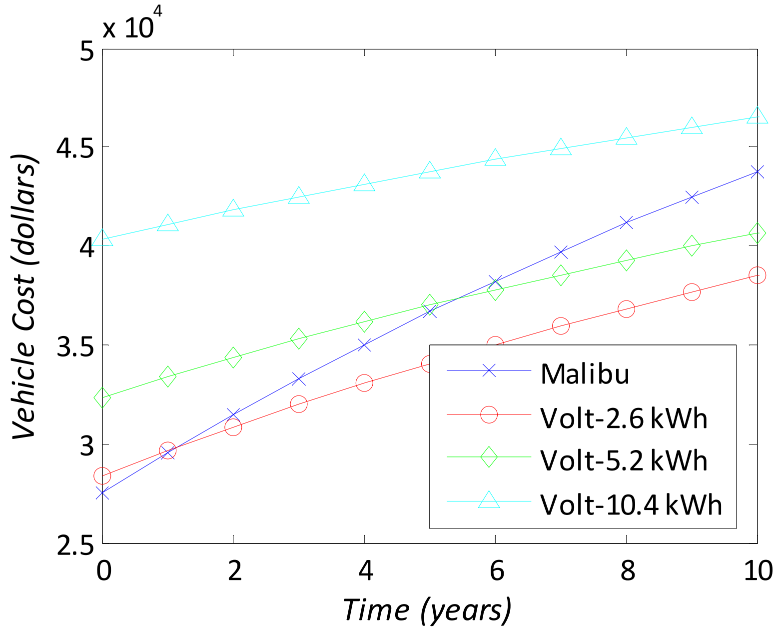

Figure 99. No Tax Credit, \$4.50/gallon, \$0.10/kWh, All Drivers

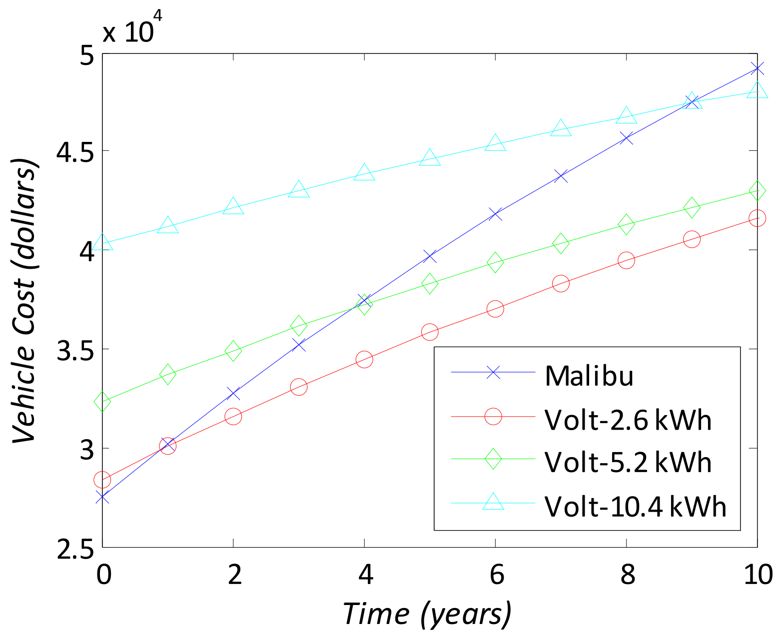

Figure 100. No Tax Credit, \$6.00/gallon, \$0.10/kWh, All Drivers

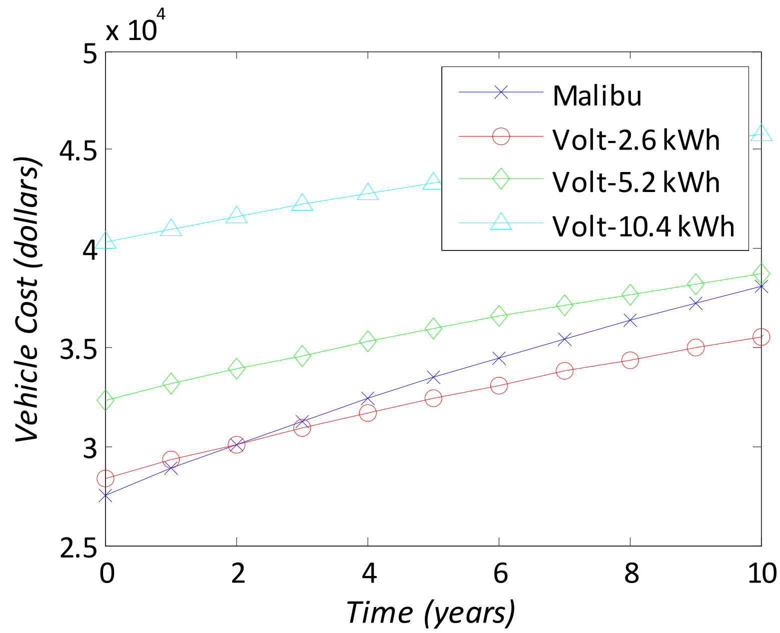

Figure 101. No Tax Credit, $2.92/gallon, $0.15/kWh, All Drivers

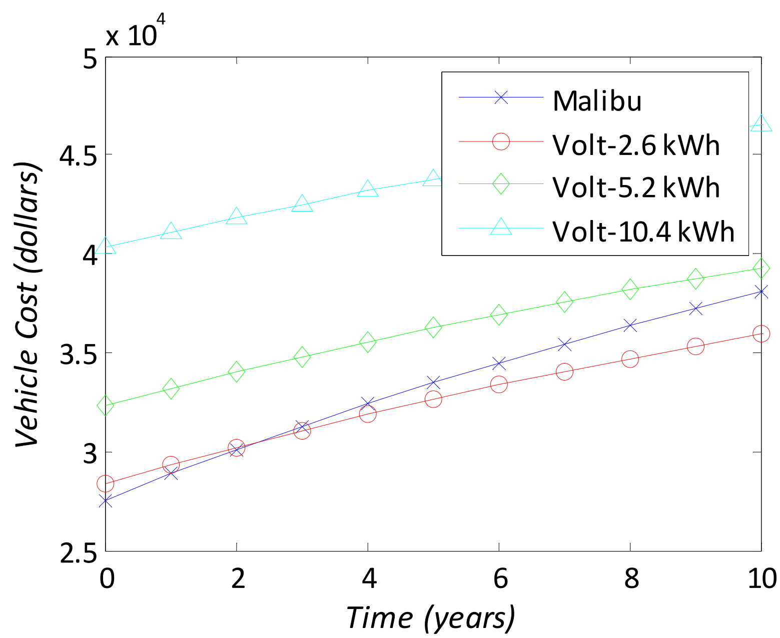

Figure 102. No Tax Credit, $2.92/gallon, $0.20/kWh, All Drivers

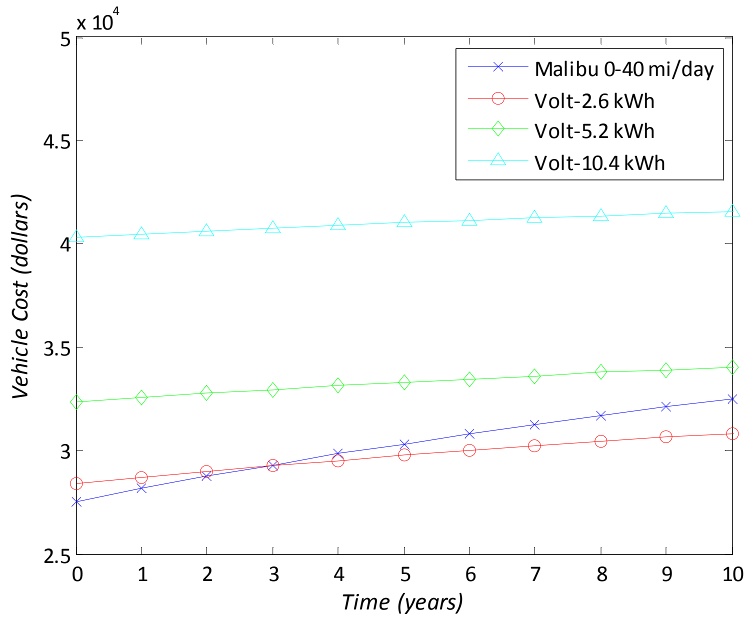

Figure 103. No Tax Credit, $2.92/gallon, $0.10/kWh, 0-40 miles/day

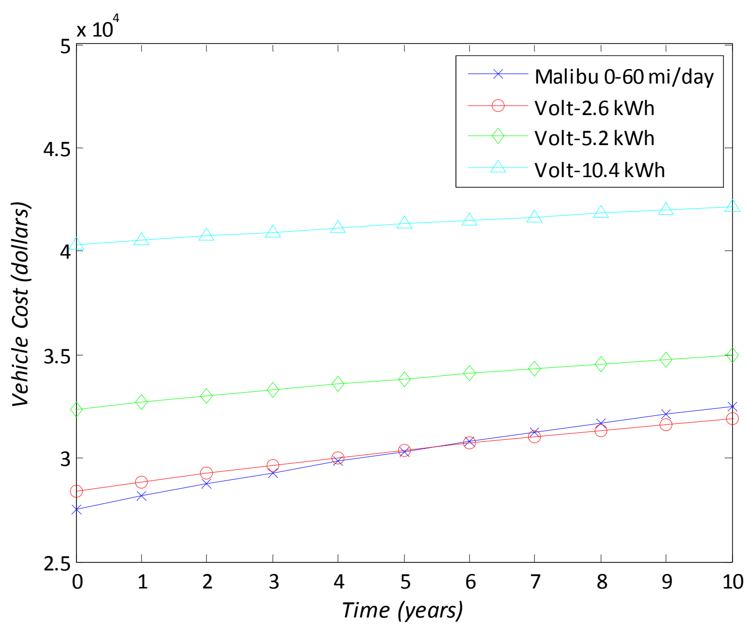

Figure 104. No Tax Credit, $2.92/gallon, $0.10/kWh, 0-60 miles/day

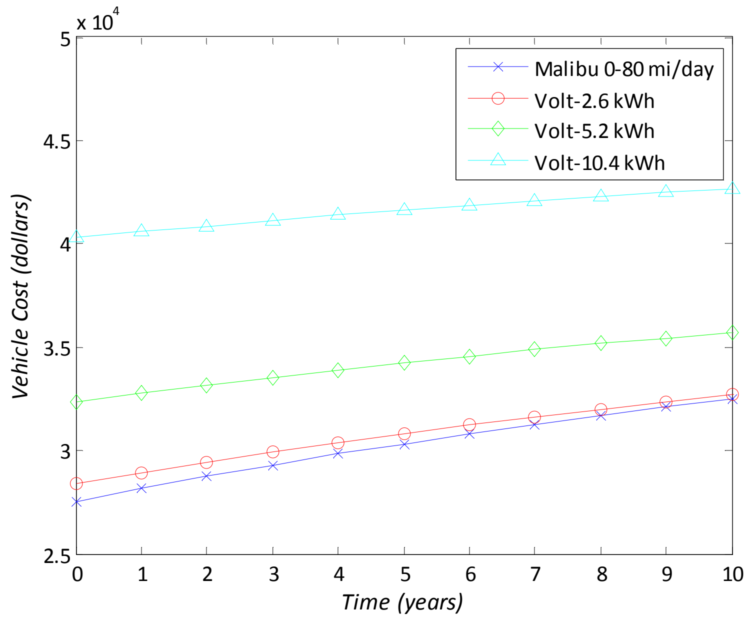

Figure 105. No Tax Credit, \$2.92/gallon, \$0.10/kWh, 0-80 miles/day

Appendix M. Use of E85 in PHEV fleet

Introduction

Although the majority of range extended PHEV's will be fueled by conventional gasoline during this study's timeframe, corn ethanol will be a significant fuel source that must be evaluated for its environmental effects and petroleum offset. Corn based ethanol fuel currently makes up 4% of the United States total transportation fuel use [75]. Almost all of the ethanol used for transportation fuel is used in low level blends such as E10. E10 is a blend of 10% of ethanol by volume, while the rest is made up of gasoline and additives. A second popular ethanol blend, available at an increasing number of fuel stations is E85, which is made up of a maximum 85% ethanol [76]. Currently, most of the ethanol used in transportation fuels is used in E10 blends, but the EIA expects that ethanol used in E85 blends will outpace E10 by 2020. This rise in E85 use is correlated with a predicted increase in sales of so called 'flex-fuel vehicles' (FFV's) which can run on both E10 and E85 blends. The EIA expects the number of FFV's to rise to 200,000 vehicles sold per year by 2015 as shown in Figure 106 below [77].

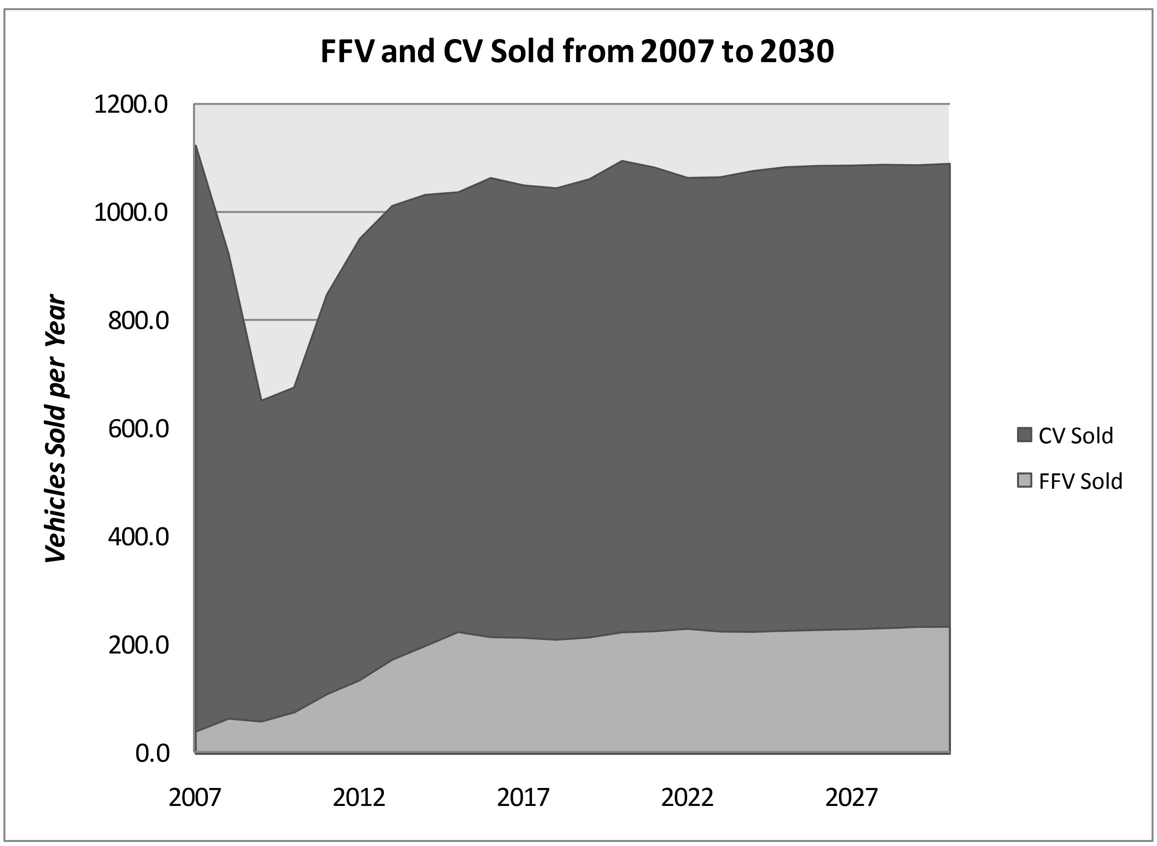

Figure 106. Shows the predicted number of flex-fuel vehicle and conventional vehicle sales per year

Corn ethanol is produced by two main methods; either by wet milling or dry milling. Both use the starch of the corn as the fermentable substance to produce the alcohol based fuel. The benefits of a dry milling over wet milling are: higher fuel yield, since the process does not filter out components; lower energy use, since grains do not need drying. Dry milling is more widely used in the corn ethanol production industry for these reasons. Table 60 presents the main differences in the processes.

Table 60. Properties of dry and wet milling for ethanol production [78]

	Dry milling	Wet milling
Plants using each type	88.6%	11.4%
Yield (gal/bushel)	2.8	2.6
Energy use (BTU/gal)	26,856	47,409
Plants using NG	92%	72.5%
Plants using Coal	8.0%	27.5%

The production of ethanol is expected to rise dramatically in the coming years as more cropland is converted and advanced sources of ethanol become available. These advanced sources include ‘generation 2 and 3’ biofuels. Generation 2 fuels are ones that use cellulosic sources for feedstock rather than the traditional corn based ethanol. The process to produce cellulosic ethanol is similar to that of producing corn based ethanol. The cellulose, must be converted to sugars before fermentation. There are a few promising methods to convert the cellulose including using sulfuric acid to break down the substance into sugars, but at the present time no processes are cost effective enough to justify large scale production [79]. Ethanol production from algae sources, generation 3 biofuels, are also considered to be an advanced source but are not expected to become a significant portion of the total ethanol production for some time [77].

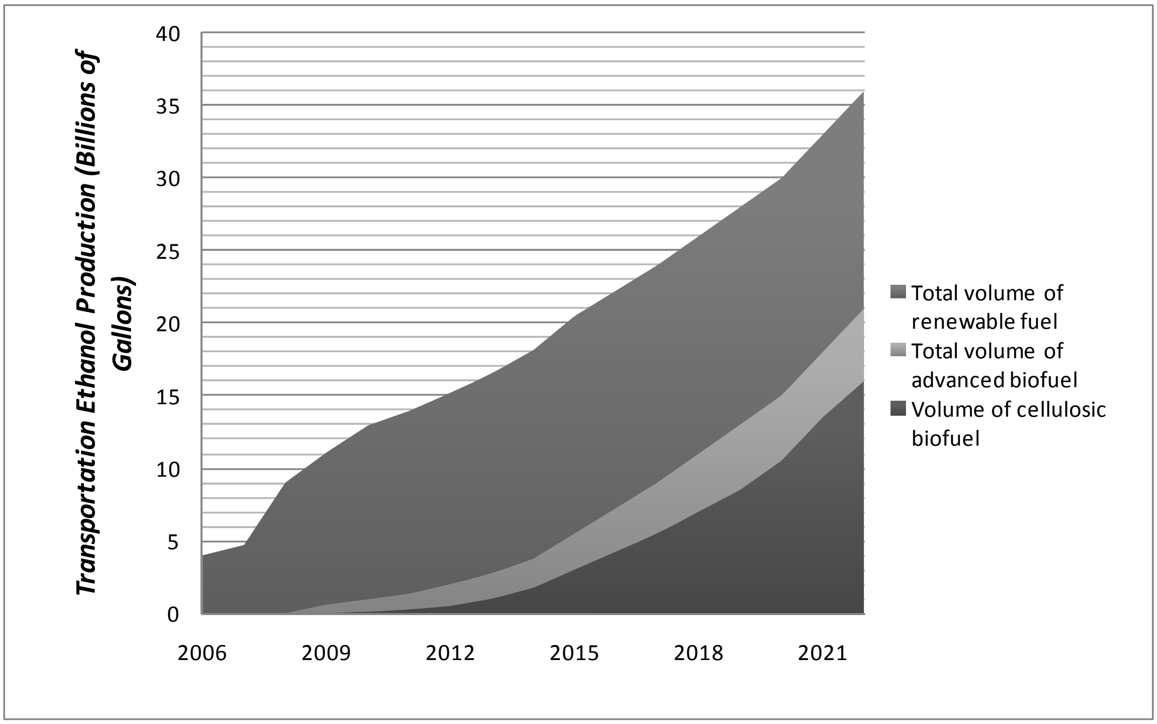

Figure 107. The predicted production of biofuels from advanced and current sources [80]

Corn based ethanol is added to the PHEV model to determine the associated emissions, and the avoided fossil fuel use from the fleet using a biofuel, compared to a conventional gasoline fueled fleet. Biofuel production is expected to rise dramatically between 2010 and the final year of the study, 2030. The effects of biofuel sources are analyzed on the combined emissions profile for both conventional and PHEVs.

Biofuel emissions in the transportation sector have both production and combustion components. The upstream emissions are comprised of corn farming and production while the downstream emissions are from the combustion of the fuel. Upstream emissions associated with corn farming come from the fossil fuel used in fertilizers, and farming equipment. The transportation of corn from the farm to the production facility also uses diesel, which is included in the emissions analysis. At the production site, fossil fuels are used to dry the corn and run the production equipment. Finally, the fuel needs to be transported to the fueling site, which uses diesel in fueling trucks [76]. These upstream fossil fuel uses account for almost 65% of the total fossil fuel used from a well to wheels analysis perspective [81].

Methodology

Several parameters were changed in the PHEV Energy Consumption Model to determine the emissions and total fuel use of a corn based ethanol PHEV fleet. The mile-per-gallon of the PHEV classes, and emissions per gallon of E85 were altered to change the fossil fuel source of the PHEV fleet from E10 to E85. Fuel economy data was originally sourced from the EPA's online database for flex fuel vehicles but did not contain enough vehicles to be statistically relevant for this report. Most of the vehicles with published ethanol consumption values were in the larger class size. The data for smaller vehicles and subcompacts, was either non-existent or did not have a large enough sample size.

Another issue with finding relevant fuel consumption data for ethanol fueled PHEV's was that only conventional, non-PHEV, vehicle data was published. Since the EPA-published fuel economy data for flex fuel vehicles was not sufficient for use in the model, another method was used to find more realistic values. A ratio of lower heating values (LHV) of the fuels was found using data from the GREET 1.8d database. Equation 36, below, shows how the lower heating value of the gasoline portion of E85 was calculated. GREET assumes that half of the gasoline is conventional (LHV_{CG}) while the other half is reformulated (LHV_{RG}).

$$LHV_{Gasoline} = 0.5 * LHV_{CG} + 0.5 * LHV_{RG} \quad \text{Equation 36}$$

Equation 37 shows the lower heating value calculation of E85. For this calculation, 80.8 percent of the E85 fuel is ethanol while the rest is gasoline. E85 is, in theory, 85 percent ethanol, (LHV_{EtOH}) but GREET publishes a lower value due to the denaturant added to the mixture [81].

$$LHV_{E85} = 0.808 * LHV_{EtOH} + 0.192 * LHV_{Gasoline} \quad \text{Equation 37}$$

Equation 38 then determines the ratio of the lower heating values of the two fuels. This ratio will be applied to the fuel consumption parameters used earlier in the model for the gasoline fueled PHEV's.

$$LHV_{ratio} = \frac{LHV_{E85}}{LHV_{Gasoline}} = 0.72 \quad \text{Equation 38}$$

Table 61 shows the results of scaling the gasoline fueled PHEV's to find the associated fuel consumption for each EPA class. The reduction in miles per gallon from switching from gasoline to E85 is consistent with the EPA fuel economy data on flex fueled vehicles with a large sample size [82]. For instance, the average fuel economies of the SUV class for flex fueled vehicles had a ratio of 0.729 between the E85 and gasoline consumption.

Table 61. Fuel consumption for gasoline and E85 PHEV

Class	Gas PHEV	Scaled E85 PHEV
	mile/gallon	mile/gallon
Subcompact	50.0	36.4
Compact	43.5	31.7
Midsize	32.8	23.9
Large	26.0	18.9
Van	26.1	19.0
SUV	26.1	19.0
Pickup	21.0	15.3

Emissions data was also sourced from the GREET 1.8d published data. The data is presented in grams-per-mile with an equivalent miles-per-gallon figure used in order to compare emissions of varying fuel sources on an energy equivalency basis. In order to use the emissions figures in the model an inverse of the lower heating value ratio was needed to scale the ethanol emissions accordingly, shown as equation 4 below.

$$Inverse\ LHV_{ratio} = \frac{1}{\frac{LHV_{E85}}{LHV_{Gasoline}}} = 1.37$$

Equation 39

The published emission values were multiplied by the inverse ratio and then multiplied by the equivalent miles-per-gallon used in GREET, which was listed as 23.4 (mpg). Table 62 summarizes these input values for both the upstream and combustion emissions. It is worth noting that the CO_2 emissions are given a credit for the amount of carbon contained in the burnt ethanol that is captured from the atmosphere [81]. This is one of the main benefits of biofuels compared to conventional fuels when viewed from an LCA perspective.

Table 62. The scaled emissions for E85 used in the model

Item	Scaled:	Scaled:
	g/gallon	g/gallon
	Total Upstream	Total Combustion
CO2 (w/ C in VOC & CO)	-716	6,311
CH_4	7.96	0.25
N_2O	2.66	0.20
GHGs	272	6,380
VOC: Total	4.29	2.92
CO: Total	2.32	63.88
NOx: Total	7.30	2.41
PM_{10}: Total	2.47	0.49
SOx: Total	4.52	0.03

The emissions and fuel consumption parameters for the biofuel fuel were used in the PECEM and MEFEM scenarios to determine the change between the baseline analysis and the E85 scenario. To compare the effect of E85 to these different scenarios a few infiltration rates were chosen, as well as different mixes between gasoline fueled and E85 fueled PHEV's within each infiltration rate. The infiltration rates chosen for comparison were the FI3, and FI5 rates. These are the medium and max rates used in the report.

Results and Findings

A comparison between the emissions from PHEV's running on E85 and those running on gasoline is made in Figure 108 and Figure 109 for the medium and maximum infiltration rate scenarios, respectively. The biggest difference between the two fuels is the increased N_2O emissions from upstream sources for ethanol. This can be attributed to the nitrogen in the fertilizers used to grow the corn [83]. All other emissions change by less than 5% using the medium FI3 scenario.

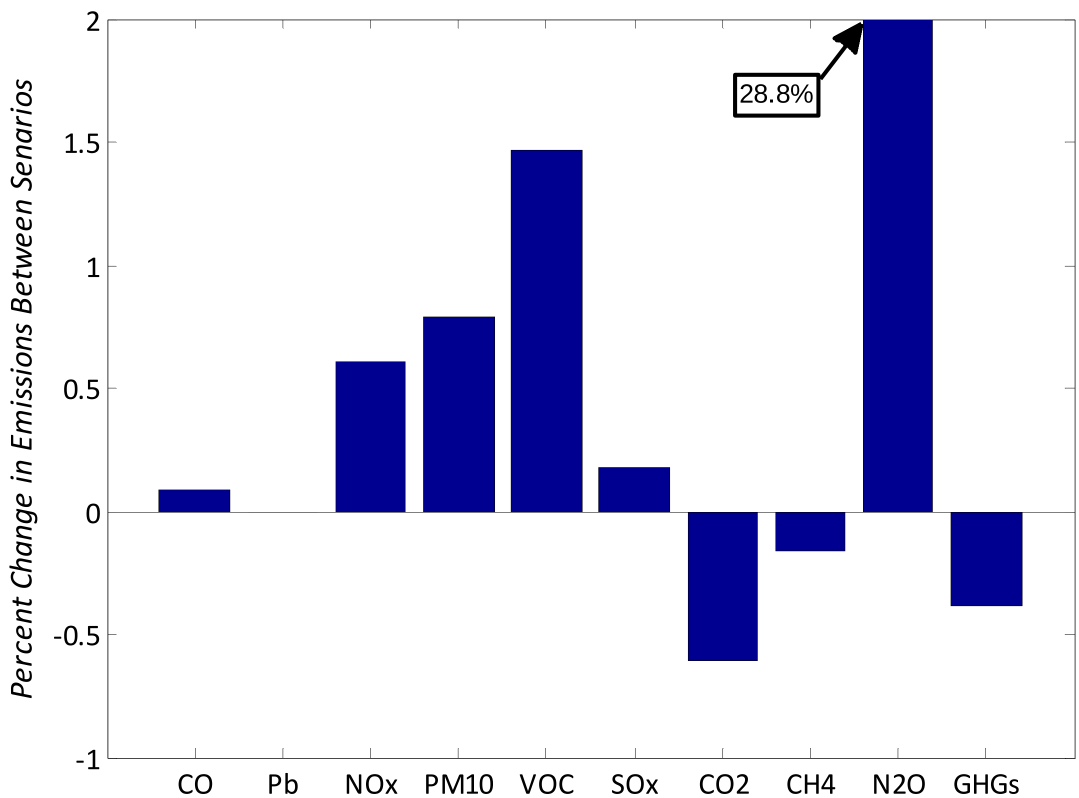

Figure 108. Change in emissions from the baseline case to a 100% E85 PHEV fleet using the FI3.

In Figure 109, the maximum PHEV infiltration scenario with all PHEV's running on E85 is compared to the same scenario with all PHEV's running on regular gasoline. The figure shows that N_2O emissions rise over 200% while other emissions, such as NO_X, PM_{10}, CO and SO_X change very little between E10 and E85 use. Carbon dioxide, methane and GHG's emissions all decrease slightly. The main reason for the relatively small changes among many of the particulate emissions is that the E85 fuel has to abide by the same emission standards as E10. Therefore, the main driver for a change in emissions between the two fuels is the difference in upstream rather than combustion emissions.

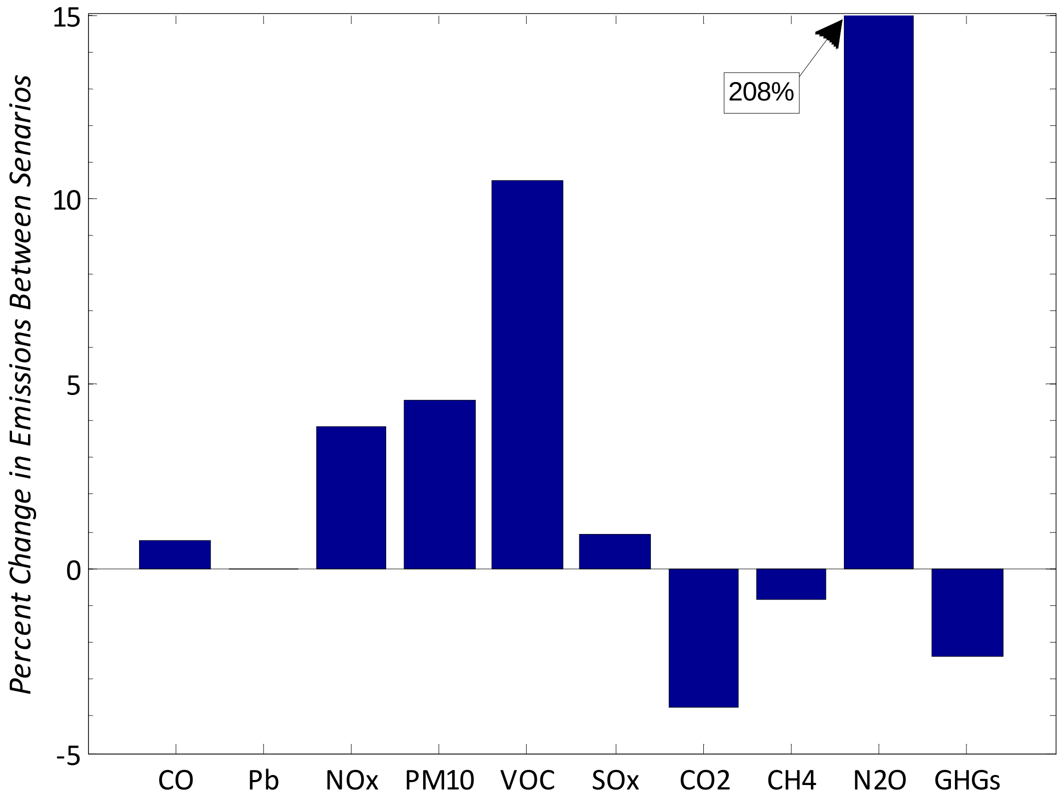

Figure 109. Change in emissions from the baseline case to a 100% E85 PHEV fleet using the FI5.

Figure 110 shows the total yearly GHG's-per-mile between 2009 and 2030 for the maximum PHEV infiltration case, with all PHEV's using E85. The top line represents the emissions from the conventional vehicles while the bottom lines represent the PHEV emissions-per-mile for both running on E85 and electric modes. During the final year of the simulation, year 2030, the conventional vehicle is emitting 0.375 kg GHG-per-mile while the PHEV is emitting 0.238, which is between the average electric and E85 emissions.

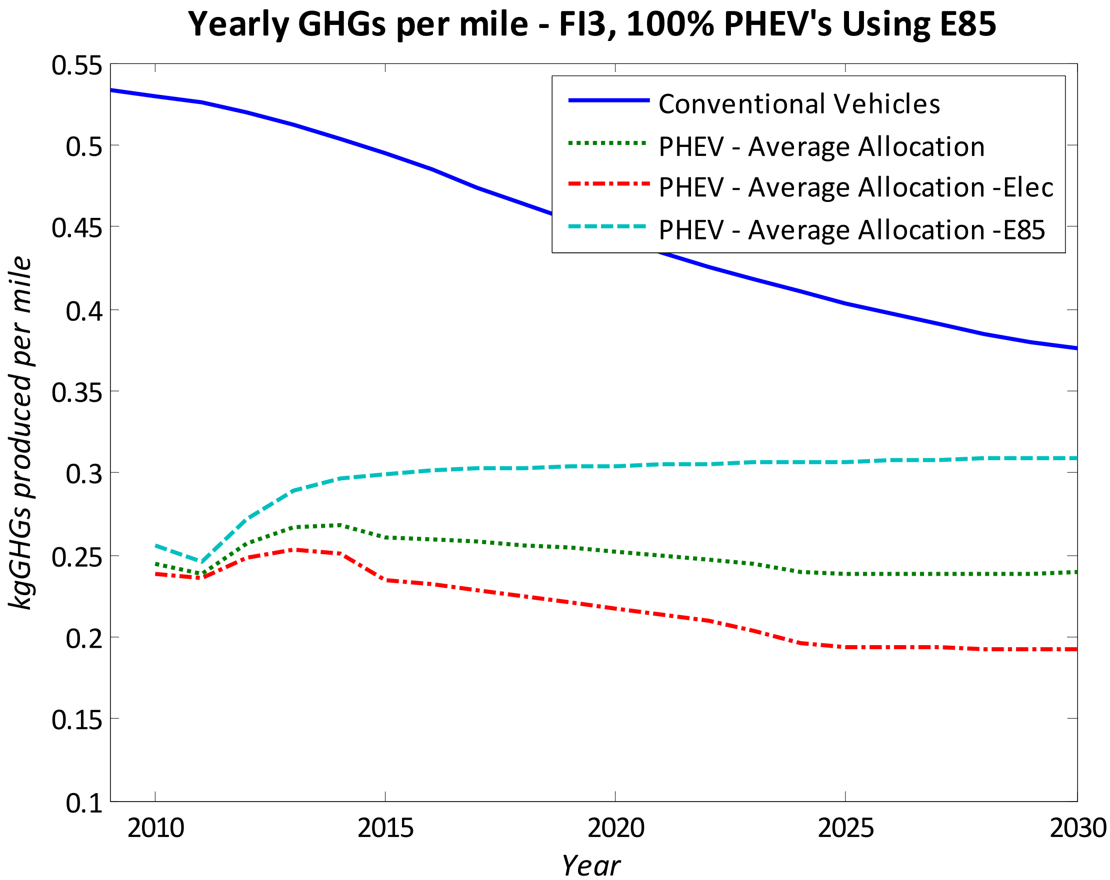

Figure 110. The yearly total GHG emissions for the PHEV using the FI5 infiltration rate scenario.

The total GHG emissions between the different scenarios analyzed in this report are shown in Figure 111 and Table 63. Summarized in Table 63, there is a small, but noticeable, 0.27% decline in GHG emissions when 50% of the PHEV fleet is running on E85 and the other 50% is running on gasoline in the medium penetration scenario. The decline from 100% of the PHEV fleet running on E85 yields an emissions decrease of 0.81% and almost 7.0% for the medium and maximum infiltration scenarios, respectively. Since any declines in GHG emissions is environmentally beneficial from an LCA perspective, even at the medium PHEV infiltration rate, utilizing generation 1 biofuels would make a difference, but to confirm this a net total vehicle LCA would need to be analyzed.

Table 63. Total GHG emissions and percent differences between different scenarios.

PHEV Infiltration Senario	Percentage of PHEV Fleet using E10	Percentage of PHEV Fleet using E10	Total kgGHGs (*10^{10})		
Medium	100%	0%	3.72		
Medium	50%	50%	3.71	**0.30%**	Percent Difference from '100% E10 Medium Senario'
Medium	0%	100%	3.68	**0.72%**	Percent Difference from '100% E10 Medium Senario'
Maximum	100%	0%	3.01		
Maximum	0%	100%	2.80	**7.02%**	Percent Difference from '100% E10 Maximum Senario'

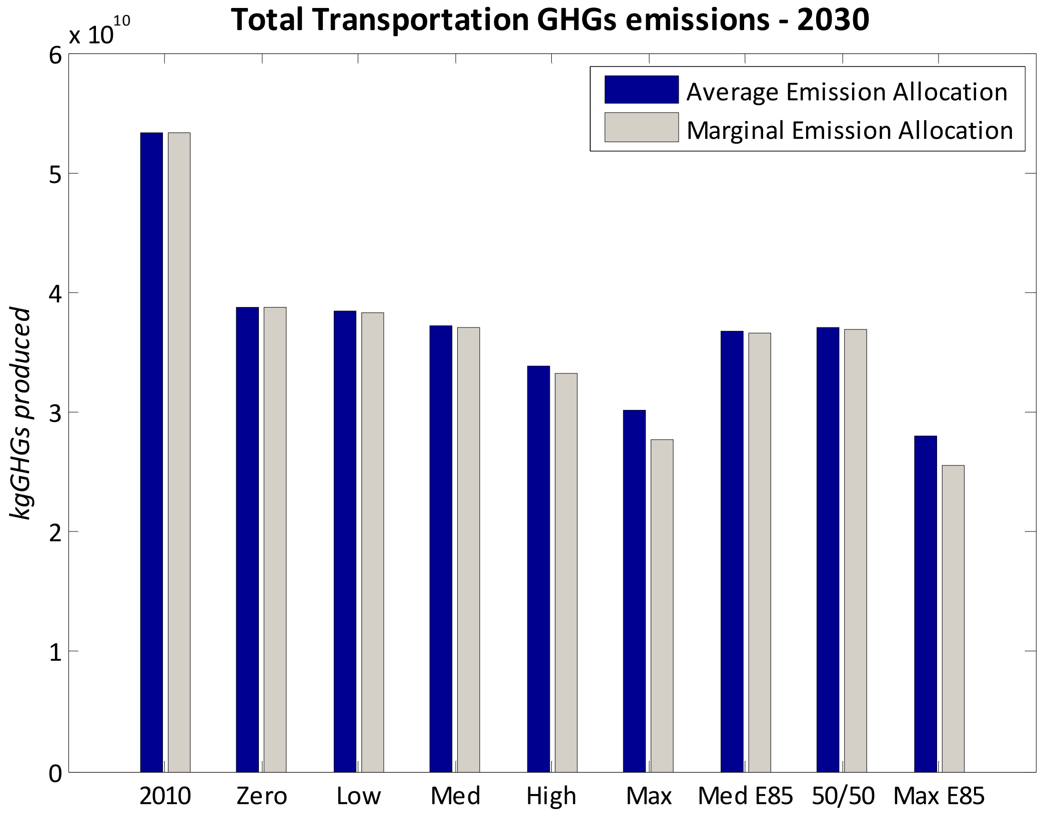

Figure 111. The total GHG emissions for all vehicles in 2030 under different scenarios.

Figure 50 in the main body of the report was utilized in order to compare the GHG emissions-per-mile produced by the PHEV fleet running on E85 to the conventional gasoline PHEV fleet. Shown here as Figure 112, the E85 PHEV fleet is shown stacked up against conventional vehicles from years 2010 and 2030, as well as the fleet under varying electric grid scenarios. The error bars represent charge sustaining and depleting mode of the PHEV's. Using the average emission allocation, there is an 11.9% decrease in GHG emissions, between the gasoline PHEV and E85 PHEV, and an 11.0% decrease using the marginal emissions allocation on the base grid scenario. There is a 24.4% decrease in GHG emissions during charge sustaining mode, between the high error bars, when using E85 in the fleet rather than conventional gasoline.

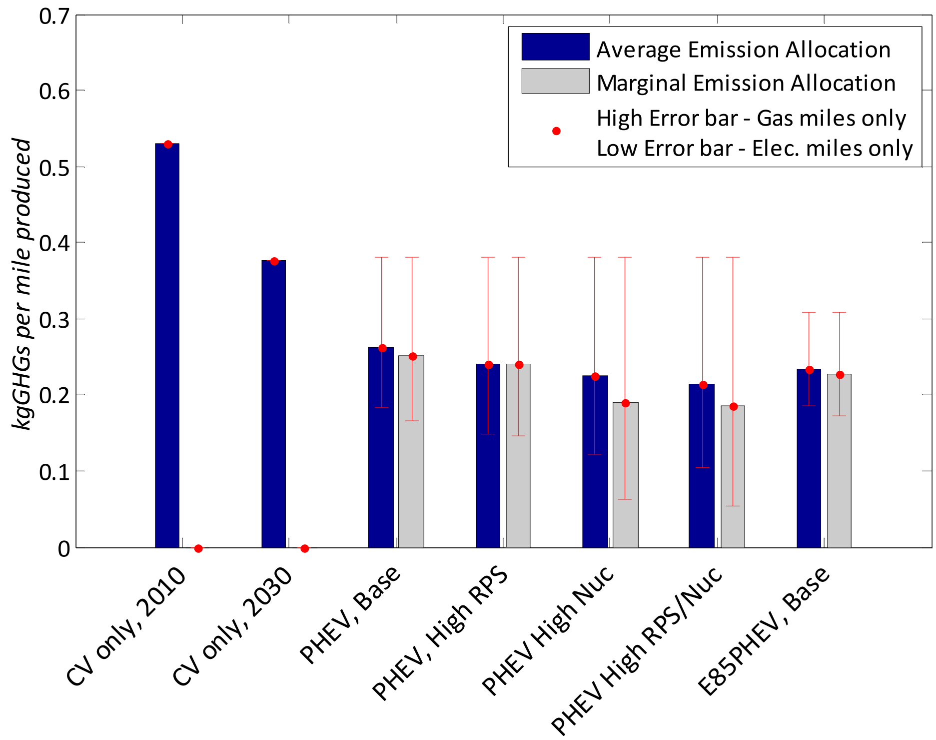

Figure 112. Per mile GHG emissions, 2030 including E85 PHEV's

There are definitely emissions tradeoffs to using corn based ethanol compared to conventional gasoline in any vehicle, PHEV or conventional ICE. As shown in the previous figures, emissions from NO_X, PM_{10}, CO and SO_X all slightly increase, to varying degrees depending on the PHEV infiltration rate. There are other land use and economic barriers to corn based ethanol that were no explored in this report but should be taken into account for any policy decision. There are definite emission benefits which come from a reduction in GHGs and CO_2 via the carbon credit gained from the corn in the upstream analysis. Other reports have stated that advanced biofuels, such as herbaceous biomass, can have a much larger effect on GHG reductions [84]. Until those advanced sources become widespread and commercially available, corn based ethanol is a relevant and important alternative fuel source for consideration to further reduce environmental impacts by the transportation sector.

Appendix N. Biomass electricity emissions

Introduction

Biomass electricity generation, or biopower, is an important source of renewable energy. In the State of Michigan, currently 1.1 percent of the state's total electricity is generated by biopower. Amongst renewable sources in the state, it is the second largest source of energy next only to hydropower, constituting 30 percent of the state's total renewable electricity mix in the year 2008 [36].

With the enactment of the 'Michigan Clean, Renewable and Efficient Energy Act (PA 295)' 2008, the Renewable Portfolio Standard (RPS) for the state of Michigan has been established. Electricity providers are to achieve retail supply that includes at least ten percent renewable electricity by 2015 [27]. Biomass, along with wind, is expected to play an important role in the state's future electricity production under stricter emission regulations and RPS [33],[85] . The plan published by DTE Energy [33] envisions a modest increase in biomass electricity, but the plan published by Consumers Energy [85] envisions a substantial increase in the renewable electricity generation from biopower between 2009 and 2030.

Estimates of biomass resources show that there are 10 million dry tonnes of biomass available in the state of Michigan on an annual basis, with 3 million dry tonnes (enough to supply about 350 MW of new generation capacity) available at a price of less than $40 / dry ton [86]. Biomass resources included in this estimate are urban wood waste, mill residues and forestry residues.

Biomass stocks are used to generate electricity using energy conversion processes like co-firing with coal, direct firing and gasification. The potential environmental impact of the biomass electricity generation system is assessed using a life cycle inventory. The emissions associated are dependent both on the biomass source and the technology being used. The common types of biomass electricity generation systems are as follows:

1. Direct-fired biomass power plant using biomass residue (woody residue, primarily)
2. Co-firing biomass residue with coal (15% biomass by heat input)
3. Biomass-fired integrated gasification combined cycle system using a biomass energy crop

The majority of the current biomass electricity generation assets use direct fire technology with waste woody residues as raw material [25]. Cofiring of biomass is the second most common method of using biomass. DTE's published plan for future expansion relies on this technology. The biomass- fired integrated gasification combined cycle technology which use energy crops, is the least deployed method at present, but can play a major role in the future with the advancement of gasification technology and development of supply chain mechanisms for dedicated energy crops.

In this report, direct firing of biomass in a power plant is investigated. Direct fired biomass plants are at present the most common biopower generation method at utility scale. This system is compared against the baseline case of a coal boiler with steam cycle, representing the emissions of average coal-fired power plants in the state of Michigan. Due to the RPS, renewable electricity must be generated, and if biomass electricity is used then it will likely function as baseload. This motivates the comparison with coal, which currently supplies a great deal of baseload.

Methodology

Biomass Electricity Generation and Emissions

For the calculation of the emissions from the biomass electricity systems the total fuel cycle is considered (as shown in Figure 113), where *m* denotes atmospheric emissions and *E* denotes energy flow. The emissions associated with the stage of biomass source procurement and transportation is denoted by *m1*. The combustion energy factor (MJ/dry ton of fuel input for electricity) and heat rate of biomass direct fired plants [25]are used to determine the total fuel cycle energy use and emissions. The emissions associated with power plant operations are denoted by m2. The total emissions from the fuel cycle are the sum of *m1* and *m2*. The greenhouse gases CO_2, CH_4 and N_2O and other pollutants are tracked at every stage. The total GHG emissions (CO_2equivalent) are aggregated using the global warming potentials (GWP) identified by IPCC [38]. The CO_2 is the baseline unit to which all other GHG are compared. The time horizon of 100 years is used. The GWP over 100 years for CH_4 is 25 and for N_2O is 298. The carbon dioxide equivalency is obtained by multiplying the mass and the GWP of the gases.

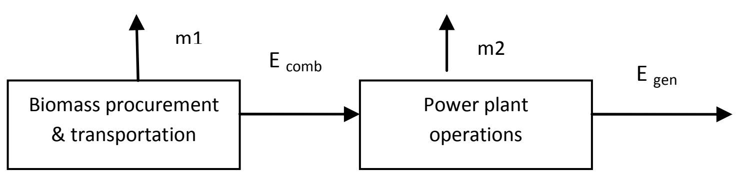

Figure 113. Fuel cycle diagram for biomass electricity

Direct-fired biomass power plant using biomass residue

In the state of Michigan, the most common method for biomass electricity generation is by direct combustion using conventional boilers [87]. In this, the boiler burns the waste wood products from the wood-processing industries. When burned, the wood produces heat that boils water and generates steam. Steam spins a turbine and activates the electricity generator. For the purpose of the calculation of the associated emissions the biomass fuel cycle process in subdivided into the stage of biomass feedstock procurement, transportation and power plant operations.

Biomass feedstock and avoided operations

Sources of biomass used for direct fire plants are sawdust and slabs produced by mills, and wood wastes generated in the manufacture of lumber, plywood and wooden products such as furniture, crates and pallets [87]. This wood residue is otherwise destined to be land filled leading to emissions of potent green house gases. Thus for the emissions calculation, the resource consumption and energy use that would have occurred during the alternative disposal of the biomass (landfill) are credited to the fuel cycle as avoided operations. The percentage of CO_2 and CH_4 avoided, by pre-empting the landfill operations, are calculated using Mann and Spath's proposed model [88]. Landfill operations assume 34.8% carbon in woody biomass. This carbon decomposes to a gas mixture approximately composed of 50% CO_2 and 50% CH_4. 10% of the landfill CH_4 is chemically oxidized or converted by bacteria to CO_2. The total CO_2 and CH_4 avoided per 100 kg of dry biomass are 111.7 kg and 6.5 kg, respectively. The original production and primary use of these woody residues are poorly characterized, therefore has not been included in the system boundary.

Assuming the combustion energy factor of 17 x 10^6 Btu/dry ton of wood [89] and taking the average heat rate of direct fired biomass plants [25], the emissions avoided per unit of electricity generated are as shown in Table 64. The net GHG emissions are aggregated using the global warming potentials identified by IPCC [38].

Table 64. Avoided emissions per unit of electricity generated using woody biomass N2O

	CO_2 (gm/kWh)	CH_4 (gm/kWh)	N_2O (gm/kWh)	Net GHG emission (gm CO_2 eq/ kWh)
Avoided emissions	(697)	(40)	-	(1697)

Biomass transportation

For woody residue transport it is assumed that the biomass origin would be within an 80 km (50 miles) radius of the power plant [90]. Average transportation distance can then be calculated by

$$D = \frac{2}{3}R_o\tau \quad \text{Equation 40}$$

Where, R_0 is the containing radius and τ the tortuosity factor (ratio of actual travel distance to line of sight). For a regular rectangular road grid , $\tau = 1.27$; for a broken landscape (hilly, lakes, swamps), $\tau = 3$ [91]. Assuming τ = 1.8 for the state of Michigan gives the average transportation distance of 96 km (60 miles). Fuel consumption for biomass transportation is 39 L per 100 km, assuming transportation by 40 short ton diesel truck and empty return [92]. Using emissions factors for a diesel truck from the GREET tool [78], the average combustion energy factor for biomass [89] and average heat rate of direct fired biomass plant [25], the emissions per unit of electricity generation using biomass are as shown in Table 65. The net GHG emissions are aggregated using the global warming potentials identified by IPCC [38]. Theoretically, the avoided transport emissions associated with not taking these wood residues to the landfill sites should be taken into total transport emissions associated with wood residue. But due to the poor characterization of the distance between residue and landfill site these emissions have not been included in the system boundary. Also, transport emissions contribute a small amount to the overall system emissions.

Table 65. Transport emissions for biomass used to generate electricity

	CO2 (gm/kWh)	CH4 (gm/kWh)	N2O (gm/kWh)	Net GHG emission (gm CO2 eq/ kWh)
Transportation	26.51918	0.00025	0.00099	26.81987

Emissions –Coal and biomass direct fired plant Table 66 indicates the average GHG emissions for the coal plants and the woody biomass direct fired plants. The average emissions for coal plants are established using emissions values from the Environmental Protection Agency's, eGRID database [78]. However, the eGRID study assigns zero CO_2 emissions to generation from the combustion of all biomass assuming these materials are subject to the natural carbon cycle. To account for the actual emissions from the biomass fired plants Argonne National Laboratory's GREET tool's average emissions values are taken.

Table 66. Average emissions factor (g/kWh) for coal and biomass direct fired plants

	CO_2 (gm/kWh)	CH_4 (gm/kWh)	N_2O (gm/kWh)	Net GHG emission (gm CO_2 eq/ kWh)
Coal only – eGRID	986.78	0.014	0.0167	992.19
Direct fired biomass plant-GREET	1087	0.041	0.117	1122.8

Biomass capacity addition 2009-2030

The biomass capacity is added to meet the Renewable Portfolio Standard (RPS) mandated by state legislation. In Michigan, the current RPS legislation has targets for renewable generation of 2% by 2012, 5% by 2014, and 10%by 2015 [27]. The RPS is expanded to include proposed 20% generation by 2025.

The contribution of biomass electricity to total RPS targets is based on generation percentages derived from renewable energy plans published by DTE Energy and Consumers Energy [33],[85]. Three cases are considered in this study with biomass contributing 5%, 15% and 25% to the total RPS. The remaining contribution for RPS fuel mix is from wind energy.

Results

Global warming potential:

Table 67 shows the fuel cycle emissions for the direct fired biomass electricity generation process. Net GHG emissions are calculated using the global warming potentials identified by the IPCC. Fuel cycle GHG emissions are the sum of the avoided emissions, transportation emissions and direct fired biomass plant operation emissions. For the woody biomass waste, the value of avoided emissions from landfill decomposition is greater than the emissions that occurred during transportation and combustion of the biomass to generate electricity. This results in a negative release of GHG gases. Figure 114 graphically shows the average greenhouse gas emissions for a biomass direct fired plant and the baseline case of the coal fired plant.

Table 67. Fuel cycle GHG emissions for direct fired biomass electricity

	CO_2 (gm/kWh)	CH_4 (gm/kWh)	N_2O (gm/kWh)	Net GHG emissions (gm CO_2 eq/ kWh)
Avoided	(697)	(40)	-	(1697)
Transportation	26.51918	0.00025	0.00099	26.81987
Direct fired biomass plant	1087	0.041	0.117	1122.8
Fuel cycle GHG emissions				(547.38)

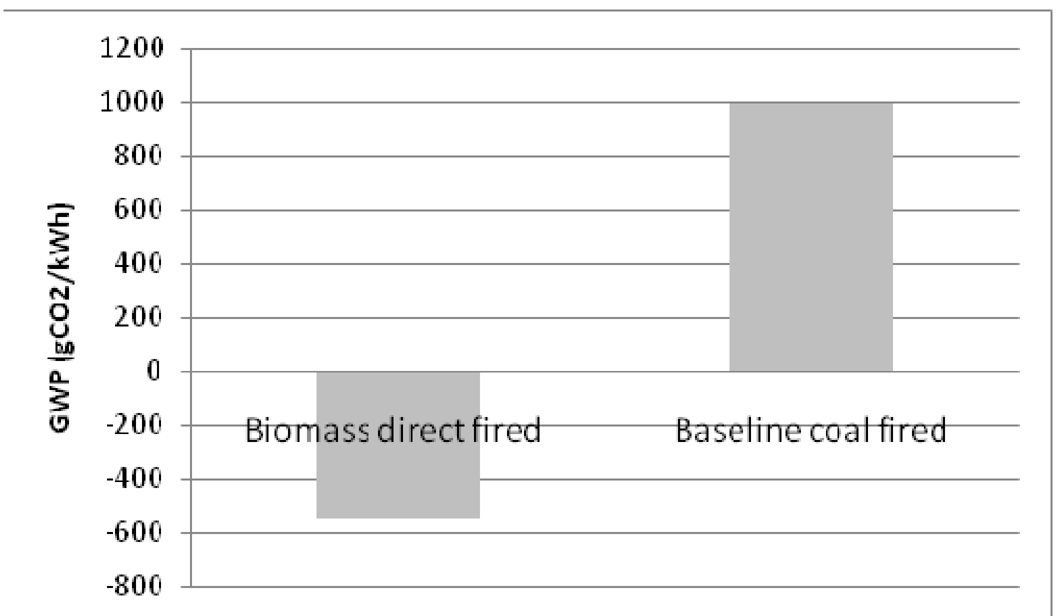

Figure 114. The greenhouse gas emmissions by biomass direct fired and coal fired palnt

Biomass direct fired vs coal plant emissions from 2009-2030

Figure 115 shows the projected biomass capacity addition in the state of Michigan from 2009 to 2030. The three scenarios considered are 5%, 15% and 25% biomass in the RPS fuel mix. The 5% biomass contribution to the RPS fuel mix requires the addition of 160 MW of biopower plants by the end of 2030. This capacity is close to the Consumers Energy plan of biopower capacity addition by 2030 [85]. The other two scenarios, 15% and 25% biomass in RPS fuel mix, indicates the addition of 500 and 800 MW of capacity of biomass electricity plants, respectively, by 2030.

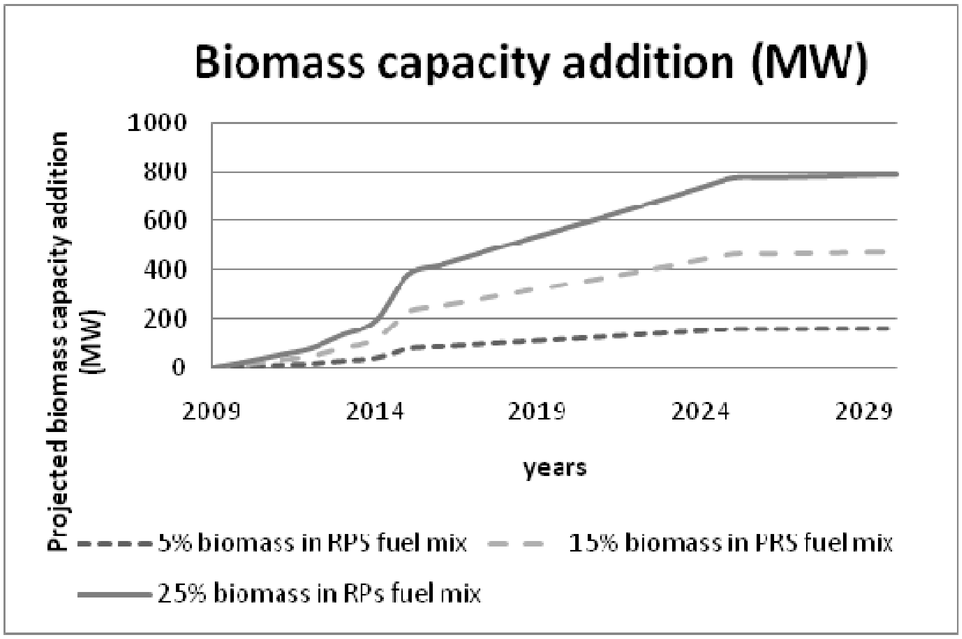

Figure 115. Projected biomass capacity addition in state of Michigan

Figure 116 through Figure 118 show the total avoided emissions from all the biomass direct fired plant per year and the emissions that would have occurred if coal fired plants were used instead of biomass. In Figure 116 5% biomass to RPS fuel mix is considered. In Figure 117 and Figure 118 15% and 25% biomass contribution to RPS fuel mix is considered, respectively. For the woody biomass waste, the value of avoided emissions from landfill decomposition is greater than the emissions that occurred during transportation and combustion of the biomass to generate electricity. This results in a negative release of GHG gases. Thus, with 5% biomass in the RPS, a total of $0.6*10^9$ kg of CO_2 eq emissions would be saved in the year 2030. If the same electricity is generated using the coal plant, there would be extra emissions of $1.2*10^9$ kg of CO_2 eq in the year 2030. Similarly, for 1 5% and 25 % biomass in RPS, total of $2.0*10^9$ kg of CO_2 eq and $3.2*10^9$ kg of CO_2 eq emissions, respectively, would be saved in the year 2030. If the same electricity is generated using the coal plant, there would be extra emissions of $3.8*10^9$ kg of CO_2 and $6.3*10^9$ kg of CO_2 eq in the year 2030, respectively.

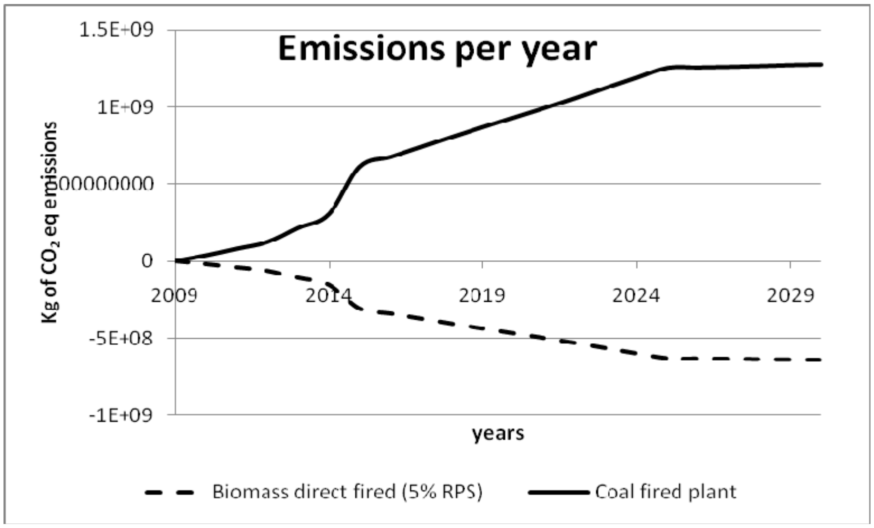

Figure 116. Emissions avoided per year by direct fired biomass electricity generation using 5% biomass in RPS fuel mix

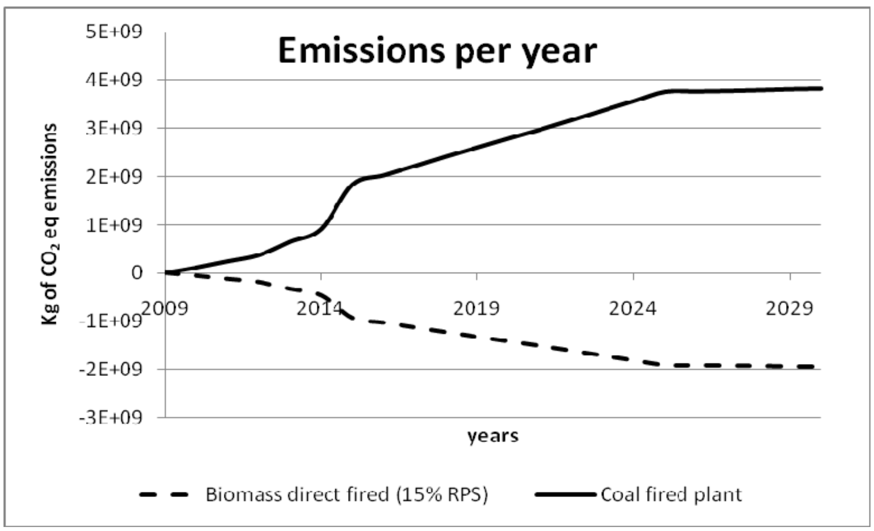

Figure 117. Emissions avoided per year by direct fired biomass electricity generation using 15% biomass in RPS fuel mix

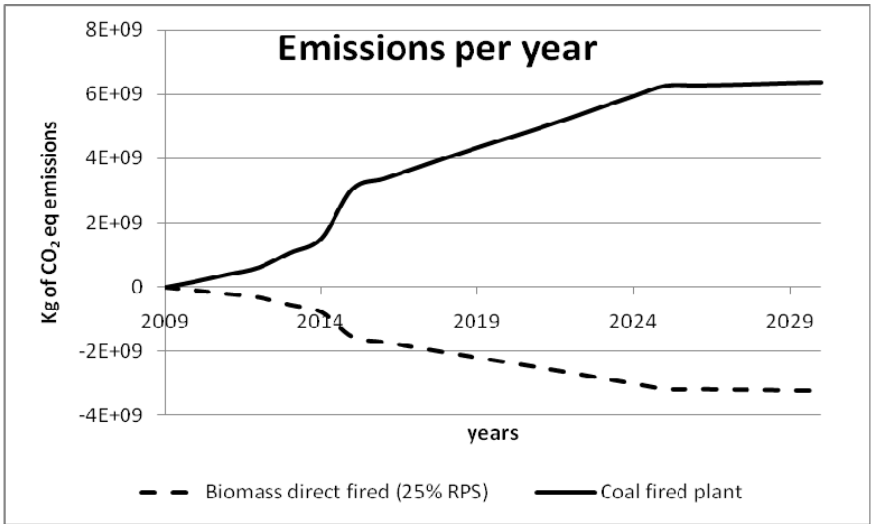

Figure 118. Emissions avoided per year by direct fired biomass electricity generation using 25% biomass in RPS fuel mix

Comparing with MEFEM model total grid emissions

Figure 119 shows the total grid emissions of the MEFEM base scenario. There is a decreasing trend in emissions over time because the old coal fired plants are retired over time and replaced with cleaner plants. In the base senario the biomass electricity contribution to the RPS fuel mix is 5%. The emissions values for biomass plants are assigned from the eGRID database.

Figure 120 through Figure 122 shows the decrease in total GHGs emissions if avoided emissions from biomass electricity plants are taken into account. In the year 2030,with 5 % biomass in RPS fuel mix, the total emissions are decreased by 2.3% from the baseline case . For the 15 % and 25% biomass in RPS fuel mix the total emissions are decreased by 3.9% and 5.5%, respectively, from the baseline case.

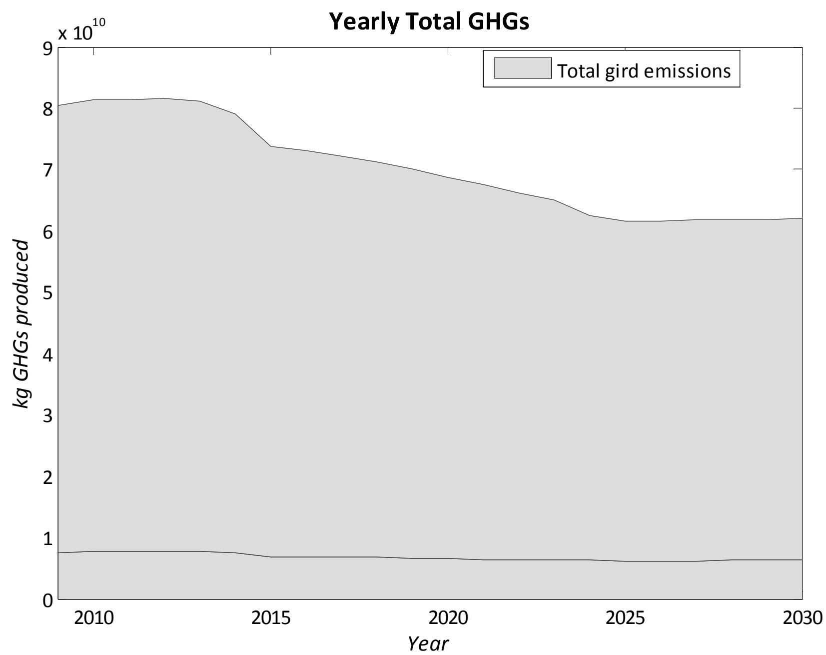

Figure 119. Total grid emissions from MEFEM model – baseline case

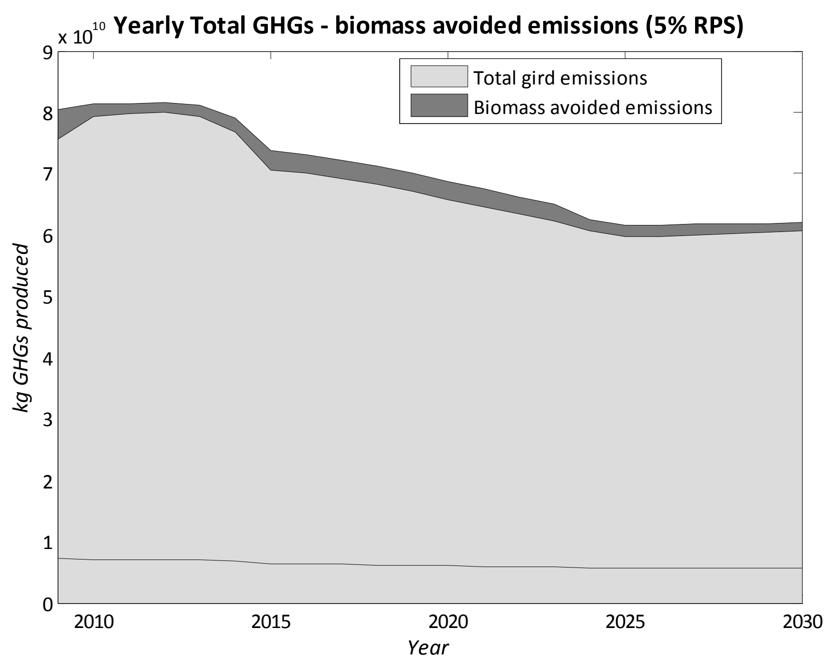

Figure 120. Total grid emissions with accoutning avoided emissions from biomass plants - MEFEM model 5% biomass in RPS fuel mix

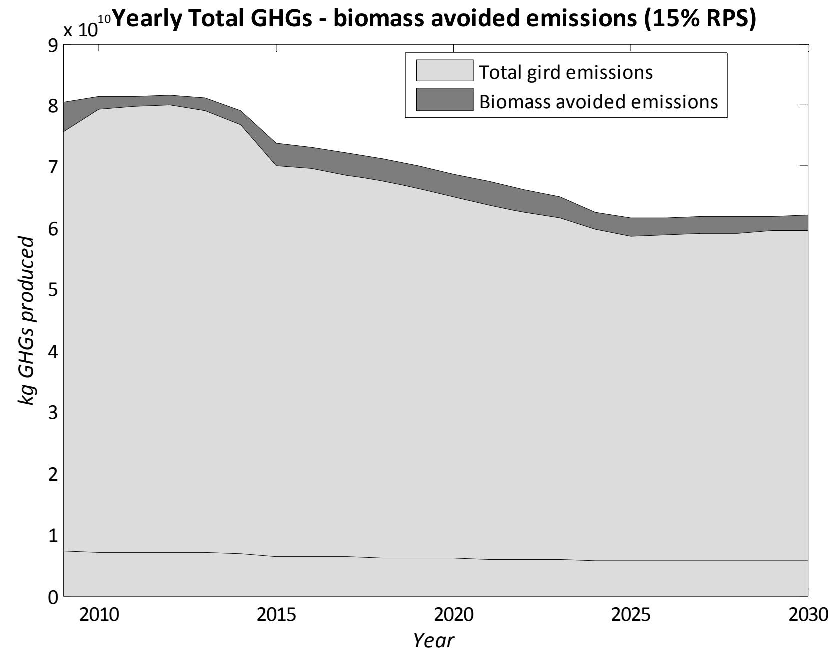

Figure 121. Total grid emissions with accoutning avoided emissions from biomass plants - MEFEM model 15% biomass in RPS fuel mix

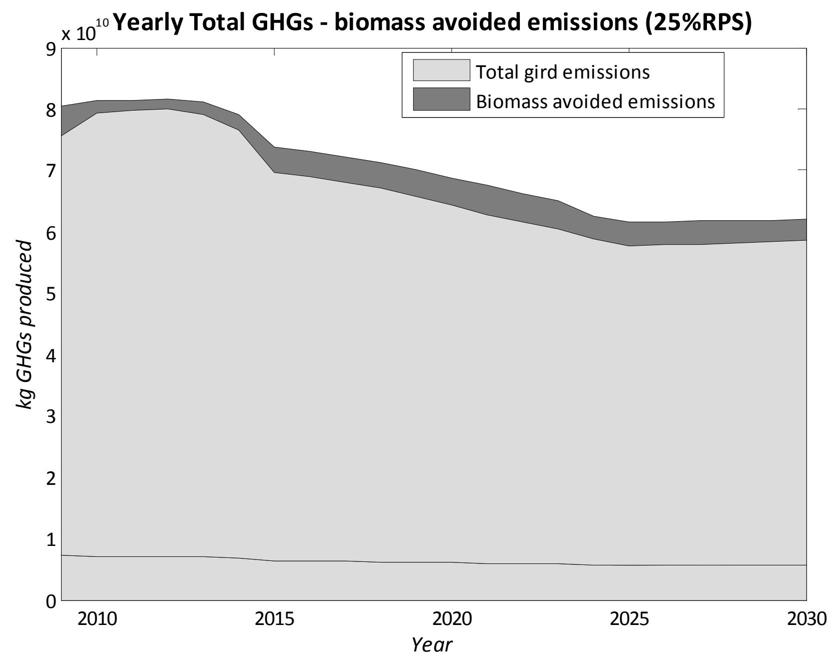

Figure 122. Total grid emissions with accounting avoided emissions from biomass plants - MEFEM model 25% biomass in RPS fuel mix

Discussion

Life cycle analysis demonstrates that electricity generation with wood residue in direct fired plants leads to considerable reductions in GHG gas emissions as compared to coal-based electricity production. However, the emissions results of direct fired biomass electricity plants are very sensitive to the system boundaries considered. The avoided emissions from the landfill decomposition are a major factor in determining the negative GHG emissions of the overall system.

Appendix O. Naturalistic drive cycle incorporation

Introduction

Vehicle manufacturers in the U.S. are directed by federal testing procedure to utilize chassis dynamometer driving schedules, developed by the US Environmental Protection Agency (EPA), for the collection of emissions data to satisfy Clean Air Act standards and to calculate fuel economy. Current testing procedures originated in 1972 with drive cycles developed to simulate urban (the Urban Dynamometer Driving Schedule or UDDS) and highway driving conditions (HWFET). The EPA adjusted the fuel economy estimates downward in 1984 – 10 percent for the urban drive cycle and 22 percent for highway – to better reflect real-world driving behavior and conditions. In 1996 it proposed adding new supplemental federal test procedures to address shortcomings of the UDDS drive cycle. These new test procedures were intended to capture the effects of cold weather operation; aggressive, high speed driving (US06); and the use of air conditioning (SC03). In late 2006, the EPA announced that it would begin using a new method for fuel economy calculations to capture these driving conditions for model year 2008, and manufacturers would be required to perform additional driving tests in 2011 for vehicles most sensitive to these conditions [93].

Many factors inform the life-cycle emissions and energy consumption of plug-in hybrid electric vehicles (PHEV). Beyond factors common to conventional internal combustion engine (ICE) vehicles such as weight and drag, PHEV energy consumption also has temporal and geographic dependencies related to battery charging and the source of electricity for charging. Such factors are captured in the Michigan Public Service Commission (MPSC) PHEV environmental impact assessment, but the designers of the PHEV energy consumption portion of the simulation model faced challenges in estimating PHEV fuel and battery energy usage without significant data from the measurement of actual PHEVs under real-world driving conditions. In order to establish an initial estimate of PHEV electricity and fuel consumption, average values for fuel economy and battery charge depletion rate were derived from academic papers, OEM publications, and EPA fuel economy statistics. Previous studies in PHEV power-train design [64, 94] and drive cycle fuel consumption[95-97] suggest that battery charge depletion rates are highly sensitive to acceleration events. This indicates an opportunity to enhance the MPSC PHEV environmental impact analysis by introducing a mechanism that captures the effects of real-world drive cycles on PHEV energy consumption. Knowledge of the energy consumption per mile as a function of actual driving patterns is a key input.

The MPSC PHEV analysis uses trip distances from actual vehicles collected in the 2009 National Highway Transportation Survey (NHTS). There is no indication of the drive cycle most relevant to a particular trip in the survey other than assumptions that can be made based on the trip distance, duration, and trip purpose (i.e. to work, to home, etc.). One might suggest equating energy usage from one of the federal drive cycles, based on trip distance, to energy usage of a PHEV on a trip of that distance. This poses two problems. First, federal drive cycles have proven rather lenient when estimating PHEV energy usage as mentioned above. Second, federal drive cycles for use in dynamometer testing assume a trip distance as given. The information in the NHTS data contains a range of trip distances. What is needed is energy consumption data from real-world driving behavior for any trip distance. Fortunately, that information is available via a statistical methodology developed to synthesize naturalistic drive cycles for an array of distances [98]. The following document discusses the integration of naturalistic drive cycle data into the MPSC PHEV environmental impact assessment and the comparison of the results to the original analysis.

Michigan Public Service Commission PHEV environmental impact assessment

Over the time period 2010 to 2030, the current PECM and MEFEM models are able to simulate total fuel cycle energy, greenhouse gas, and criteria air pollutant impacts for scenarios including different levels of PHEV fleet penetration and varied electrical grid generation portfolios. The simulation is comprised of two integrated MATLAB-based models. The PHEV Energy Consumption Model (PECM), which determines individual PHEV consumption patterns using 2009 NHTS data from Southwest Michigan drivers, develops an aggregated fuel and electrical energy consumption profile to inform the Michigan Electricity and Fleet Emissions Model (MEFEM) portion of the simulation. The MEFEM calculates hourly electricity demand and system wide emissions and fuel usage based on PHEV adoption. The PECM addresses the micro-effects of driving behavior on PHEV energy consumption, while the MEFEM captures the macro-effects on environment and electrical grid. To determine how real-world driving behavior affects the energy consumption of PHEVs in the MPSC study, the PECM is examined and modified in the current study.

The core functionality of the PECM is housed in a PHEV electrical load curve generation and fuel usage routine and its associated subroutines. It inputs NHTS daily trip data for seven vehicle classes and uses it to calculate aggregate weekly and annual PHEV electricity and fuel usage. There are several parameters, including charge time constraints, input to the PECM that are held constant in this comparison to isolate the effects of real-world drive cycles on PHEV energy consumption. Once vehicle data are loaded, the PECM iterates through daily trips resulting in battery state of charge (SOC) depletion and gasoline consumption based on average electricity and fuel consumption values taken from academic, OEM publications, and EPA fuel economy statistics. During trips with a battery SOC above the minimum value, PECM lowers the battery SOC at a constant charge depletion rate. Once the battery has reached the minimum, the model uses fuel as the consumed energy subject to the average fuel economy from the literature. This is, in a sense, strictly emulating a series PHEV platform where no fuel usage occurs (charge depleting mode) until the battery is entirely depleted, at which time the internal combustion engine becomes the source of motive power (charge sustaining mode).

The use of averages in the MPSC model for fuel economy and battery charge depletion rate limits the level of insight into actual trip behavior. For instance, suppose one PHEV driver has a short urban commute. The literature concerning real-world drive cycles suggests [95-97] that a daily trip of this category is characterized by high acceleration starts and stops. This information is unavailable when using average energy consumption rates, yet is critical in determining the actual vehicle consumption. Not only does this have implications for PHEV fleet electrical system loading and emissions projections - the main objectives of the MPSC PHEV model - it also affects determination of the PHEV all-electric range, component sizing, and related platform-specific parameters. It is the optimization of these variables, at the individual vehicle level, that provided the motivation to develop a methodology for characterizing naturalistic driving patterns for PHEVs.

Synthesized Real-World Driving Cycles

Alternatives to the federal drive cycles approach for simulating energy consumption in PHEVs are well documented. Carlson [95-97] examined vehicle speed and acceleration effects on fuel consumption, electrical energy consumption, and charge depletion rate of two Toyota Prius vehicles converted to PHEV test platforms. In that study, PHEV sensitivity to aggressive driver demand as compared to conventional vehicles is captured using a series of scaling factors, up to 1.4, applied to the federal urban drive cycle or UDDS. Overall energy consumption was shown to increase with increasing driving intensity. From work at the National Renewable Energy Laboratory [95-97], simulation results indicated that PHEV fuel efficiency was strongly associated with the daily distance traveled between charging events. In addition, a comparison between acceleration characteristics of real-world drive cycles from GPS travel data and federal drive cycles showed that even the more aggressive US06 drive cycle did not fully encompass the range of accelerations seen in the study's real-world driving sample [96]. Both studies arrived at improvements to estimates of both fuel economy and electric consumption but neither simulation was based on a series PHEV configuration. Perhaps more importantly, neither approach arrived at PHEV energy consumption as a function of trip distance. This is a key piece of information in a study such as the MPSC PHEV environmental impact assessment where real trip survey (NHTS) data is available. Once a relationship between vehicle trip distance and PHEV energy consumption is known, the PHEV model can be enhanced to leverage that knowledge.

Much of the previous research in PHEV design and control relies on the federal driving schedules discussed above, which were originally developed for emission certification tests of conventional vehicles [93]. To arrive at optimal levels of performance in areas such as vehicle all-electric range, acceleration, fuel consumption, and charging time, characterization of actual trips representative of typical commutes is essential. With the goal of establishing realistic forecasts of vehicle energy consumption, researchers analyzed naturalistic driving data from a database at the University of Michigan Transportation Research Institute (UMTRI). The data came from field operational tests in Southeast Michigan where 11 mid-size sedans were equipped with data acquisition systems. A sample of 221 trips was obtained covering a wide variety of driving distances and styles with a mix of urban, suburban, and highway driving. A proposed PHEV design optimization technique requires a drive cycle for a given distance, but using individual naturalistic driving schedules directly would lead to solutions that depend too much on personal driving style. Instead, a procedure was developed to create representative synthetic driving cycles suitable for implementation in the optimization framework [64, 94].

In order to synthesize drive cycles that match the characteristics of the naturalistic drive cycles from the UMTRI database, the researchers began by selecting representative drive cycles. These are drive cycles within a one mile window of eight target trip distances up to forty miles in length. Vehicle dynamics are represented using two states variables, vehicle velocity and acceleration. At each time step, t_k, along the real-world drive cycle, the value for velocity and acceleration at the next time step, t_{k+1}, is determined based on the probability of transitioning to that particular state as informed by the real-world driving data. In this manner, a transition probability matrix (TPM) is generated from the real-world velocity and acceleration measurements in the drive cycle data. With state variables selected, and the TPM defined, candidate schedules were synthesized stochastically using a Markov chain. Since the synthesis process is stochastic, the researchers introduced a technique to determine significant statistical criteria as a test of synthesized drive cycle fidelity to the original drive cycle data. Verification of the representativeness of synthetic cycles was performed by simulating PHEV performance in the Power-train Simulation and Analysis Toolkit (PSAT) and comparing the specific energy value to the average specific energy of the cycles falling within the same two mile wide trip distance window. Using this procedure, naturalistic drive cycles were synthesized for any trip distance.

Methodology

Although vehicle and engine control strategies play a role in determining the specific energy at the wheels, energy consumption is strongly affected by driving cycles[64, 94]. Once the response of a particular vehicle to naturalistic drive cycles is characterized at a sufficient number of trip distances along the vehicles commute, it becomes reasonable to suggest interpolation between these points to arrive at a continuum of energy consumption values so that consumption numbers are available for any vehicle trip distance. Then, given the trip distance and the vehicle's initial battery SOC, we can determine the gasoline consumption and battery SOC at the termination of each individual vehicle trip. Armed with this ability, we are able to assign energy usage values to any vehicle trip in the NHTS sample, thereby improving upon original PHEV energy consumption estimates used in the PECM.

The vehicle modeled in PSAT by the researchers is loosely based on the 2011 Chevrolet Volt, a series PHEV with a 16 kWh battery, 53 kW engine, and 120 kW electric motor. The energy use of a vehicle will change based on its architecture and size, but General Motors is pursuing production of this vehicle, or something similar, and it is deemed representative of the first generation of PHEVs [64, 94]. Recently published data on the Volt dimensions and weight suggest it will be placed in the Compact vehicle class [99], so this is the vehicle class it is compared to in the MPSC PHEV model. Other considerations were taken into account when translating the PSAT vehicle energy consumption data to a form usable by the model. The fuel and battery consumption values from PSAT ranged from trip distances of 4.7 miles up to 41 miles while trip distances in the NHTS sample range from 0.1 miles up to trips of hundreds of miles in length. In order to avoid data extrapolation beyond 41 miles, thereby creating a source of uncertainty in the comparison, NHTS trip distances are limited to those of 40.0 mile lengths or less. This implies that, for a series PHEV with a 40 mile all-electric range (the Chevrolet Volt is touted as such), no fuel consumption need occur during trip distances of 40 miles or less when starting out with a full battery. Two practical considerations point to why this will not be the case. First, the trips in the NHTS sample are one-way trips meaning drivers will often not have the opportunity or time to recharge the vehicle after a single trip. This behavior is already captured in the original MPSC PHEV model through logic informed by charging constraints. The second reason it is unlikely we will see zero fuel consumption for trip distances of 40 miles has to do with how actual PHEVs are designed to operate. The original MPSC model assumes a strictly series PHEV driving schedule where the two sources of motive power operate exclusively of one another. When the electric motor via battery power is on, the conventional gasoline engine is off, and vice versa. The researchers in the UM Auto Lab, in pursuing PHEV platform design and control optimization, are not limited to this condition. In the lab (and in the real world), the goal is to arrive at whatever blending of fuel and battery usage brings the highest overall vehicle efficiency. This results in regions of operation in the PSAT data where simultaneously the battery SOC is declining and fuel combustion is occurring. Not only is naturalistic driving behavior introduced to the MPSC PHEV model in this study, but also a greater detail of vehicle operation is modeled.

The naturalistic drive cycle and PSAT analysis leads to a more realistic characterization of driver/vehicle performance, effectively placing layers of functionality over one another. But, these detailed results presented challenges when adapting the data for use in the MPSC PHEV model. For instance, battery SOC in charge sustaining (CS) mode showed subtle fluctuations, or ripple, indicating that there was some battery charging within a small predefined SOC window to hold the battery SOC near the lower bound. In order to simplify the data translation from PSAT to MPSC PHEV model, these fluctuations were fixed at the lower bound of the usable battery SOC. In regions of the PSAT data where blended operation was significant, the same rippling appeared with higher amplitudes. Fluctuations in fuel consumption corresponded to inverse fluctuations in battery SOC leading to the conclusion that battery and ICE power were being substituted based on the control regime with the intention of maximizing overall vehicle efficiency. This posed a challenge in determining fuel economy of the vehicle. Upon further analysis of the data, extraneous points due to fluctuation were discarded. The fuel economy is described in three sections of trip distances: constant for trip distances of less than 8 miles, linearly decreasing from 8 to 30 miles, and constant again at a lower value from 30 to 40 miles. These three sections of fuel economy can be said to correspond to naturalistic drive cycles in urban, mixed, and highway driving.

Before running the version of the MPSC PHEV model informed by naturalistic drive cycle data, an estimate of fuel economy is needed in order to calculate daily vehicle fuel miles. Since the vehicle modeled in PSAT by the UM Automotive Laboratory researchers is based on a vehicle similar to the

Chevrolet Volt series PHEV platform, we use recently published vehicle specifications for the Volt fuel tank (9.3 gallons) and extended range (approximately 310 miles with gasoline engine only) [71]. A simple calculation produces a fuel economy estimate of 33.3 mpg for the Volt. This is used as the average fuel economy. Now we look at how the fuel economy varies based on the trip distance. From the PSAT results informed by naturalistic drive cycles, fuel economy is seen to decline approximately 15% as trip distance increases from zero to forty miles. It is nearly constant at 36.1 mpg for trips of 8 miles or less, decreasing nearly linearly to 30.8 mpg for trip lengths of 30.1 miles and constant again until 40 mile trip lengths. This agrees with previous studies indicating higher energy densities for acceleration events at high velocities, such as occurs during high speed highway driving when a motorist accelerates to overtake another vehicle. Figure 123 shows representative drive cycles for the three sections of fuel economy. The average fuel economy of 33.3 mpg for the simulated Chevrolet Volt PHEV is shown as the dashed line. One can think of these three sections of trip distances as urban, mixed, and highway driving.

Table 68. Averages used in original MPSC PHEV energy consumption model and the Chevrolet Volt estimated fuel economy

Original MPSC PHEV model vehicle estimates		Fuel Economy estimate Chevrolet Volt
Electricity Consumption	Fuel Economy	
(kWh/mi)	(mpg)	(mpg)
0.246	43.5	33.3

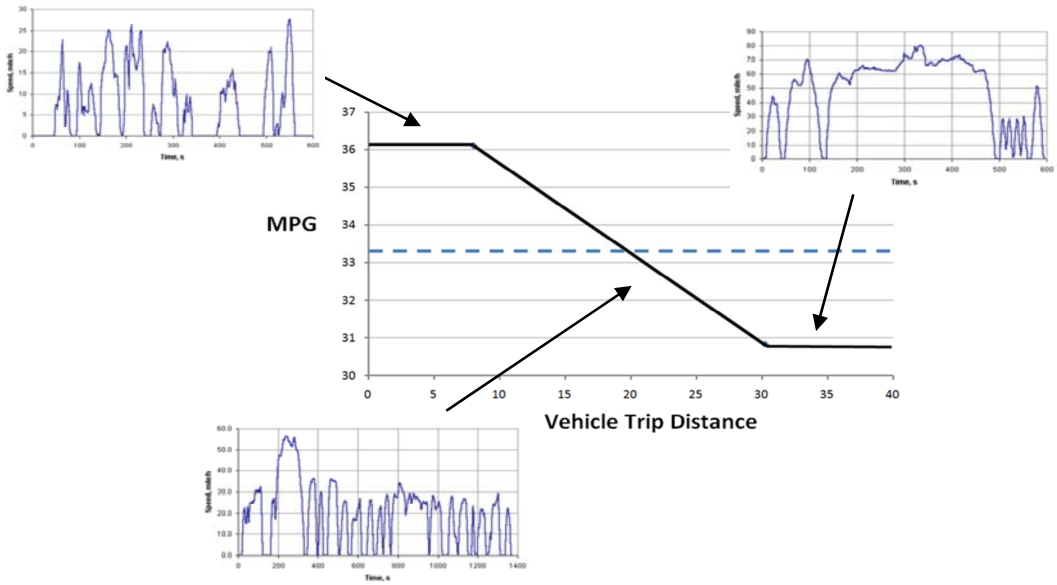

Figure 123. Fuel economy response to naturalistic drive cycles in urban, mixed, and highway driving

Results

The Michigan Public Service Commission (MPSC) PHEV environmental impact assessment model is designed for flexibility in order to provide a range of information for PHEV environmental and electrical system impacts. The original PECM is compared to a version modified to incorporate the PSAT simulation of naturalistic driving cycles in a vehicle similar in size and platform to the Chevrolet Volt. In the analysis, the focus is on fleet-wide electricity and gasoline use. These values are normalized to a single vehicle to identify energy consumption values for a typical PHEV in the Compact vehicle class. The results of the two simulations, shown Figure 124 through Figure 126, indicate that more battery electrical energy consumption and fuel consumption occur when naturalistic driving behavior is introduced to the model, as compared to energy consumption based on estimated fuel economy and charge depletion rate averages used in the original MPSC PHEV model. Higher electrical energy consumption results in fewer electric miles driven by the vehicle. With more realistic driving behavior, captured by synthesized naturalistic drive cycles, a larger percentage of the battery SOC is depleted over a given trip distance. This means fewer miles are driven in all-electric mode before the lower battery SOC limit is reached and fuel is consumed. Increased fuel consumption with naturalistic drive cycles, in comparison to the average fuel economy and charge depletion rate assumptions used in the previous study, occur for two reasons: the battery is depleted sooner under real-world driving conditions, thereby initiating fuel usage earlier in a trip; lower fuel economy under real-world driving conditions means that each additional mile uses more gasoline than was consumed with previous estimated averages.

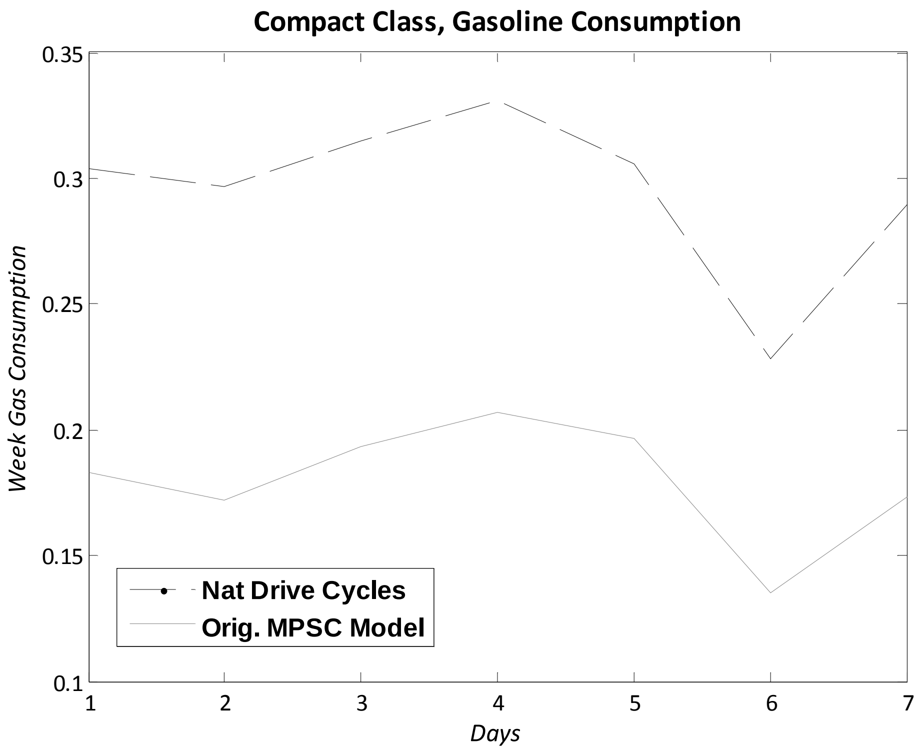

Figure 124. Comparison of gasoline consumption based on original MPSC PHEV model energy consumption averages and naturalistic drive cycle data.

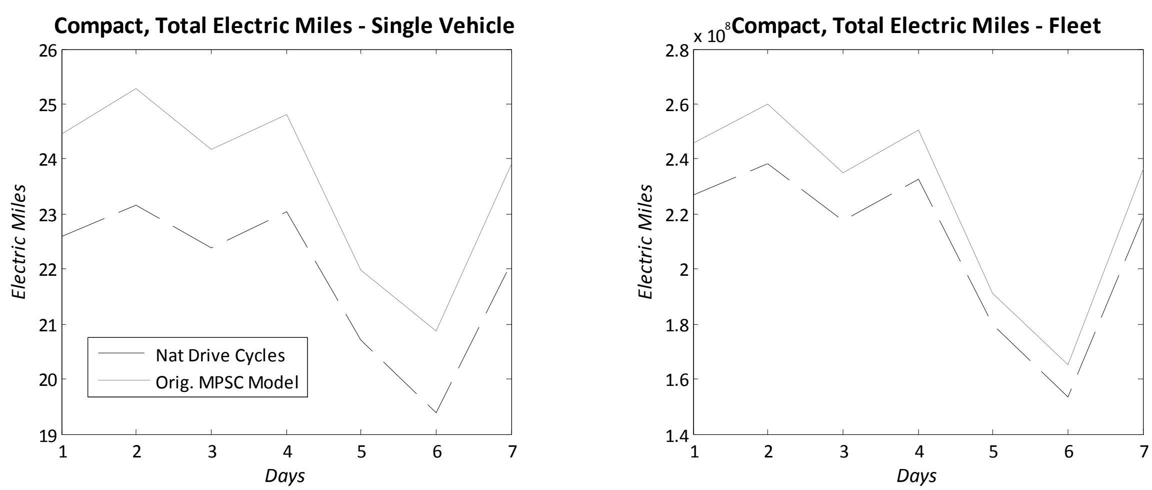

Figure 125. Comparison of total electric miles driven for original MPSC PHEV model using energy consumption averages and model using naturalistic drive cycle data (both single vehicle and fleet).

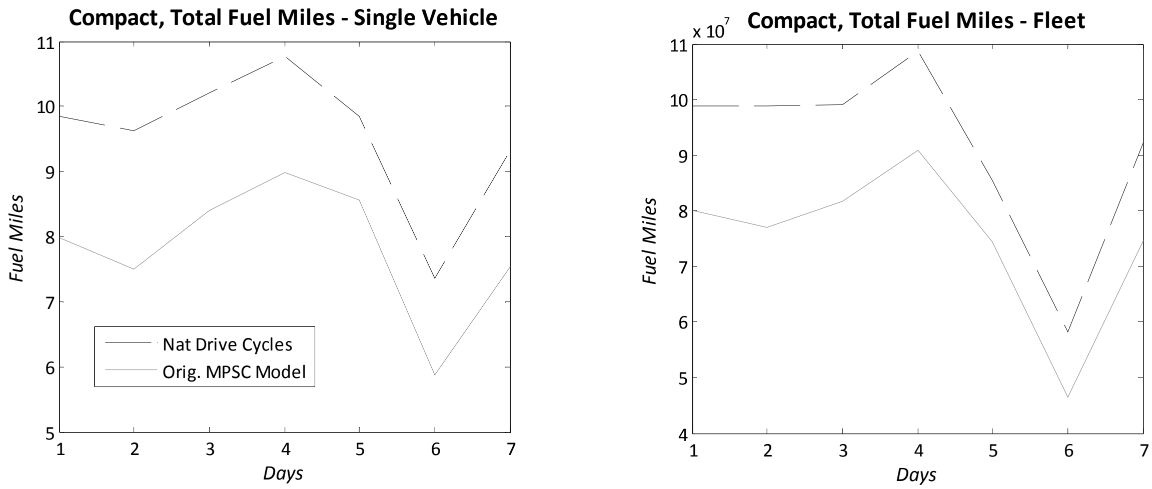

Figure 126. Comparison of total fuel miles driven for original MPSC PHEV model using energy consumption averages and model using naturalistic drive cycle data (both single vehicle and fleet).

In all driving conditions - urban, mixed, and highway - synthesized naturalistic drive cycles inform a more realistic fuel economy than the estimates used in the original MPSC PHEV energy consumption model. Forecasted use in electricity from the electric utility grid due to PHEV charging over the course of a week is shown in Figure 127. Normalized charging power (kWh/hour/vehicle) from the grid shows increases from 15 to 20% depending on the day of the week. Higher rates of battery discharge due to the naturalistic driving behavior lead to more electricity consumption from the grid.

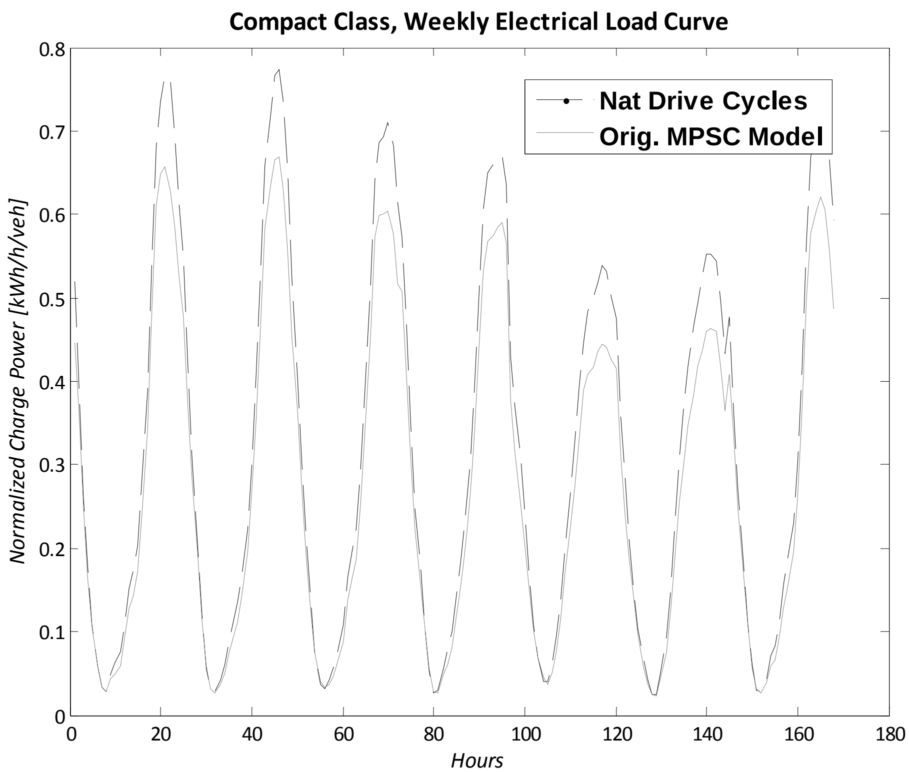

Figure 127. Comparison of weekly electrical load due to vehicle charging for original MPSC PHEV model using energy consumption averages and model using naturalistic drive cycle data

The original MPSC PHEV environmental impact assessment, which used static estimates for fuel economy and battery charge depletion rate based on the literature, shows conservative estimates of PHEV energy consumption when compared to the same vehicle simulation incorporating naturalistic driving behavior using a production PHEV in the same Compact vehicle class as reference. As noted in other studies [95-96], PHEV system performance is more sensitive to drive cycle selections than conventional vehicles. The results of the PHEV energy consumption simulation in this work reflect that finding by illustrating the PHEV-specific response to real-world driving behavior and comparing that response to estimates of energy consumption used in the original MPSC PHEV simulation. Higher levels of electrical system loading, due to higher battery charge depletion rates, and more vehicle fuel miles driven, due to lower fuel economies, suggests a higher environmental impact for PHEV infiltration than was indicated from the original MPSC PHEV model findings.

Appendix P. Emissions results from economic dispatch

The results presented in the main body of the report present the findings of the capacity factor dispatch approach. Here the findings from the economic dispatch are presented for completeness. The economic dispatch results are broken into two sections. First, a discussion of economic dispatch's impact on GHG emissions is provided. Second, the economic dispatch's results for criteria air pollutants are presented. All results and figures presented here have CF equivalents that are presented previously in the document.

Greenhouse gas results

Figure 128 provides system wide GHG emissions in the year 2030 for all fleet infiltration scenarios assuming the economic dispatch methodology. This figure can be compared with Figure 44 to observe the macro-level differences between the CF and economic dispatch models over both time horizon and fleet infiltration. The economic dispatch scenarios predict lower GHG emissions.

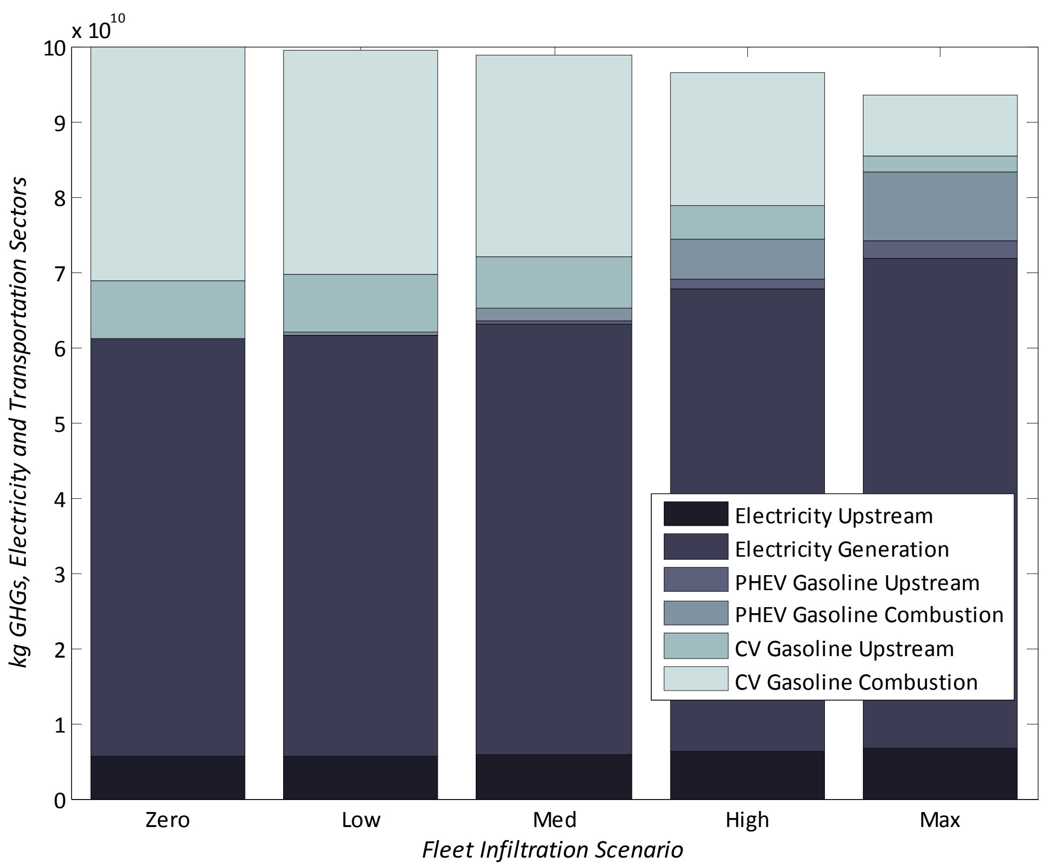

Figure 128 Total GHG emissions for the year 2030 for all infiltration scenarios (EG1, CH1)

Figure 128 shows the total system greenhouse gas emissions in the year 2030 for both the electricity and transportation sectors. Figure 129, below, shows the greenhouse gas emissions for the transportation sector alone, under the high PHEV scenario, using both allocation methods and the economic dispatch approach. These graphs also show total greenhouse gas emissions under the zero PHEV scenario for comparison (using the CF approach for consistency with Figure 46). In Figure 129, the total GHG emissions displaced over the 20-year timeframe are represented by the area labeled 'avoided emissions', or the size of the 'wedge' between the zero PHEV scenarios (using a CF approach) and the top of the scenario emissions curve. Electricity emissions increase in both allocation methods as total gasoline emissions decrease over time due to the increase in PHEVs on the road. Both allocation methods show that it takes a substantial amount of time before plug-in vehicles comprise enough of the fleet to create an appreciable difference.

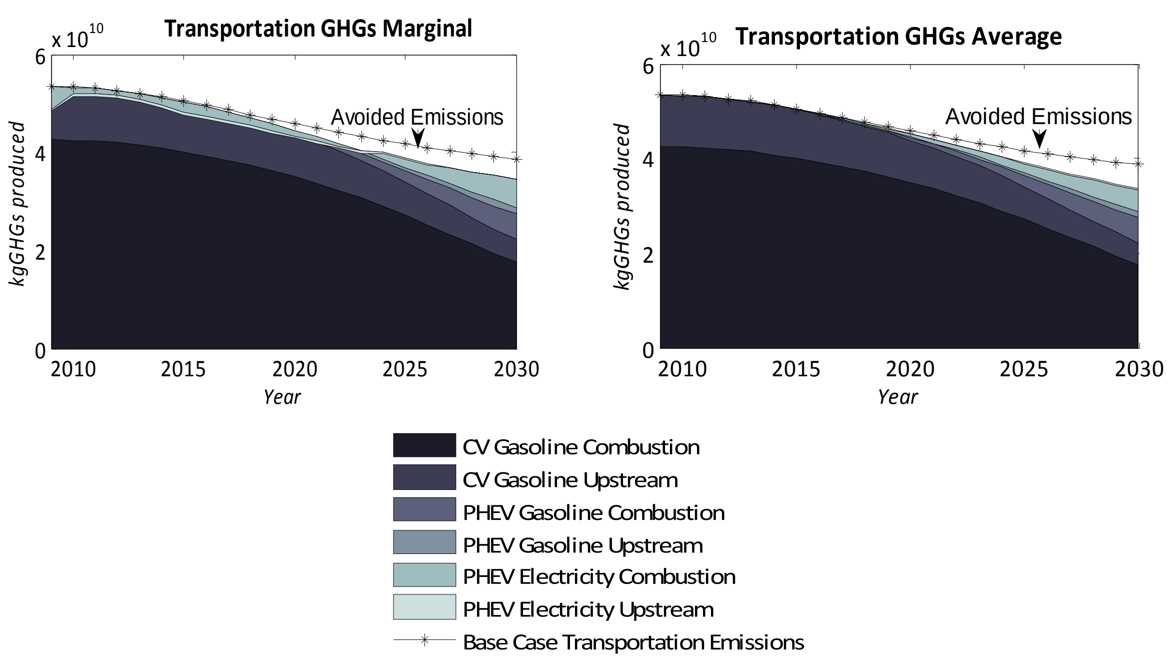

Figure 129. Transportation sector marginal and average emissions under high PHEV infiltration.

Figure 130 below, shows the same trend of decreasing transportation sector emissions due to the increase of plug-in vehicles in the fleet, as well as the difference in emissions between the allocation methods. This can be compared to Figure 47 to observe the difference from the CF model. These results are produced under baseline charging (CH1) conditions where the additional PHEV demand increases the system peak load (reference Figure 37 in subsection 5.1.1). The model builds new generation capacity to meet the additional demand when PHEVs are charged in the evening.

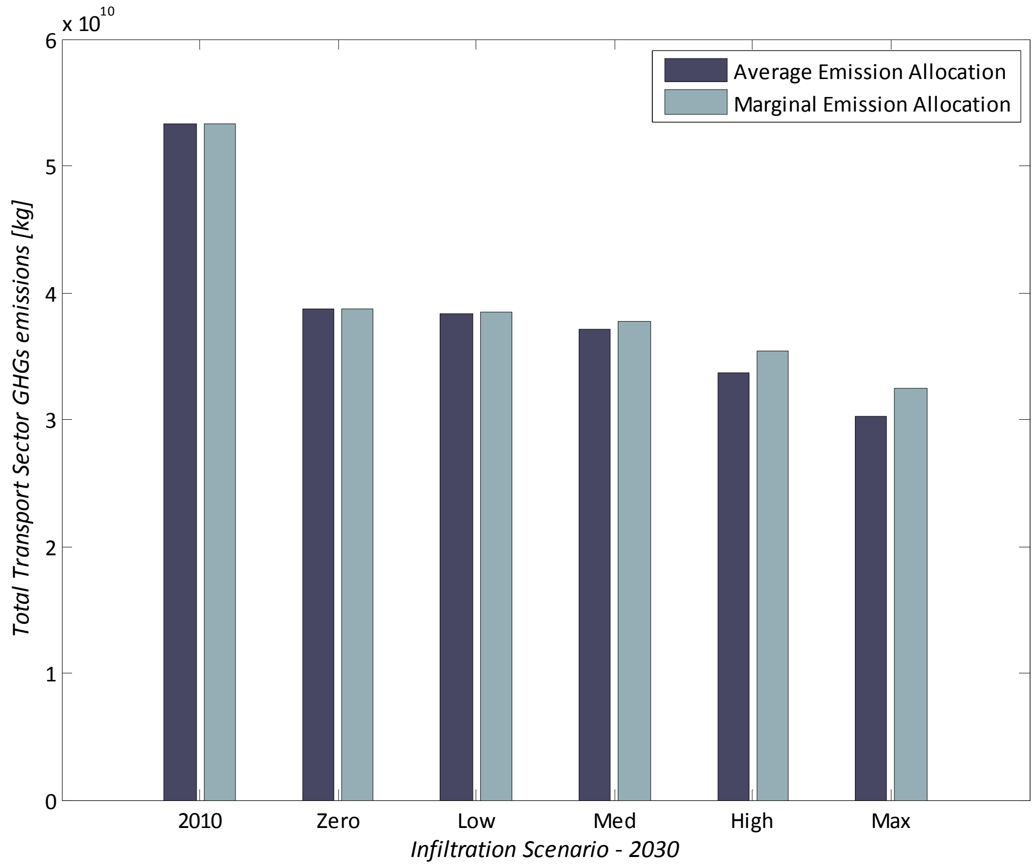

Figure 130. Total transportation sector greenhouse gas emissions, both allocation factors

Figure 131, below, displays the electric load profile, dispatched generation by fuel type and the emissions from this generation attributable to PHEV demand as a function of time over a 48 hour period in July 2030. The electricity generation PHEV emissions are shown for both allocation methods. The comparison of these graphs side by side provides insight into which fuel sources are being used to meet electricity demand as it varies with time and the resulting impact on emissions. Compared to Figure 48, the CF version of these results, this figure shows the same load pattern, but the marginal emissions allocation method here tends to be higher than that of Figure 48.

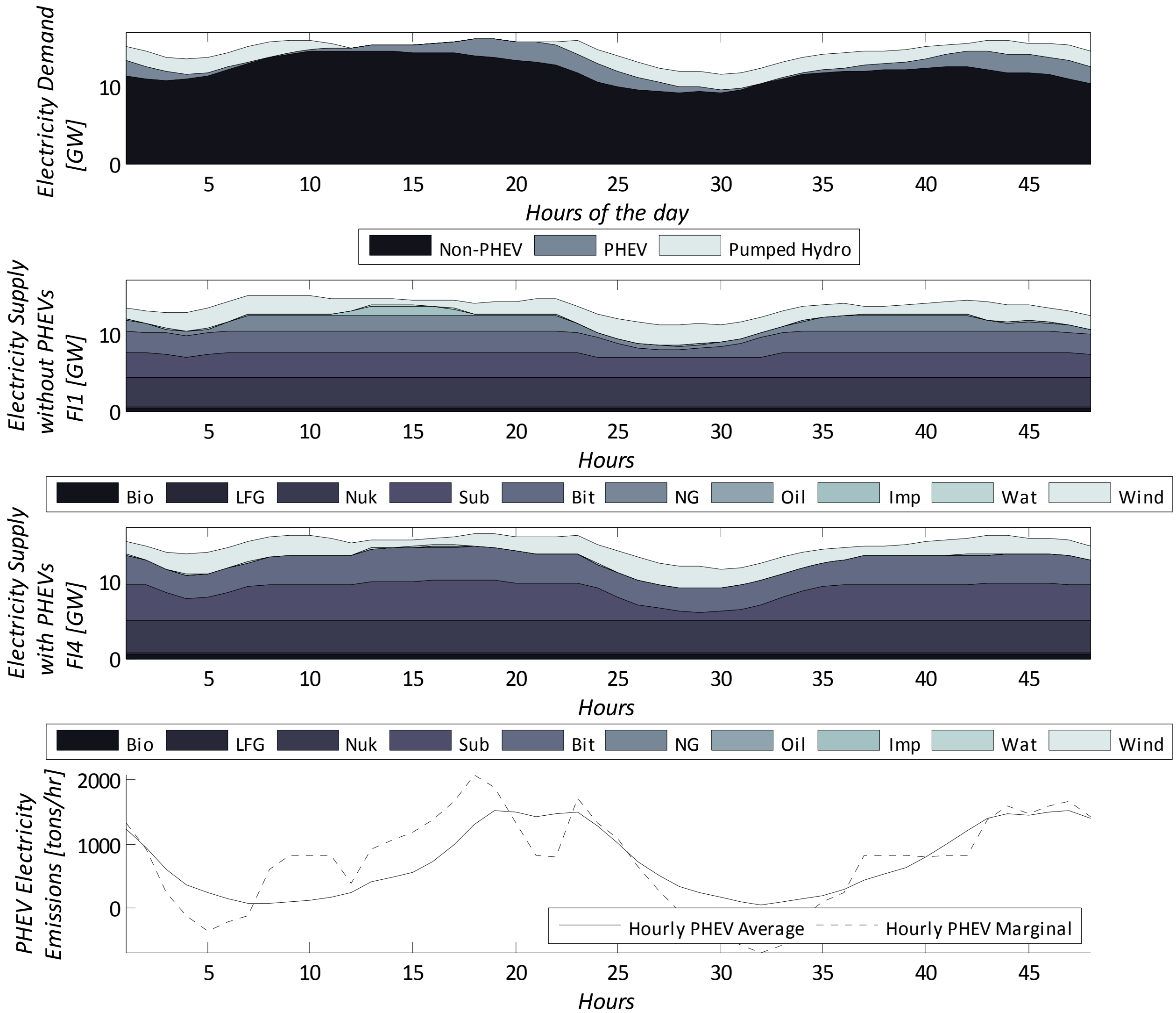

Figure 131. Load, fuel mix and emissions, 2 days in July 2030 (base grid and charging, high PHEV)

Figure 132 presents the per mile GHG emissions in 2030 using the economic dispatch model. Compared to Figure 51, this GHG prediction shows greater variation in the marginal emissions prediction, while showing a steadily decreasing trend in the average emissions allocation is the grid uses less GHG intense technology.

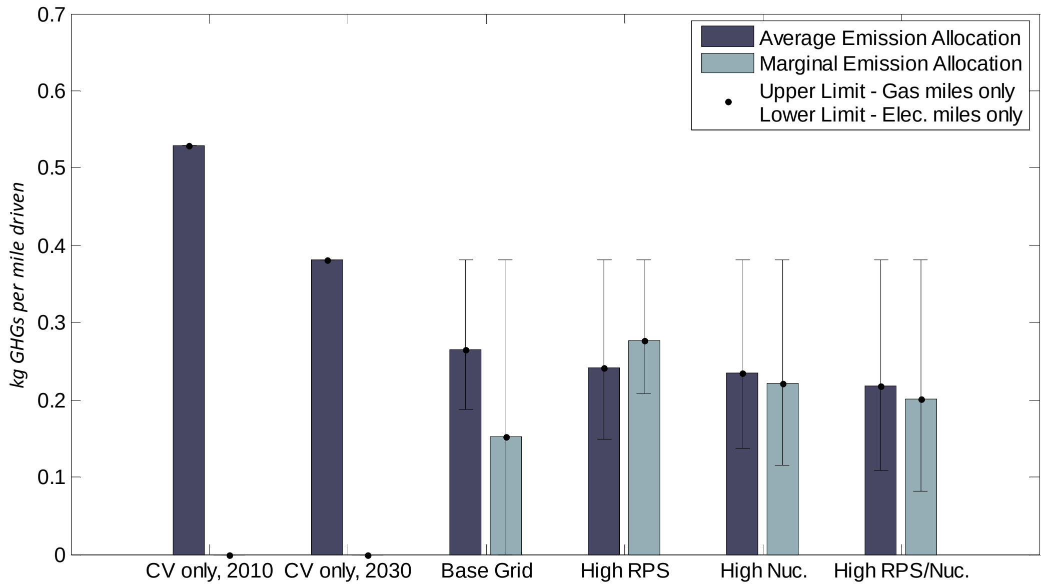

Figure 132. Per mile GHG emissions, 2030

The charging habits of drivers affect the demand on the grid. As this load changes, the assets which are dispatched to serve this demand will also change. Restrictions on charging can also influence the amount electricity versus gasoline consumed by a PHEV driver. Figure 133 depicts the greenhouse gas emissions, in kgCO_2e/mile, under different charging scenarios, for a high PHEV infiltration, baseline electricity generation capacity, and economic dispatch conditions.

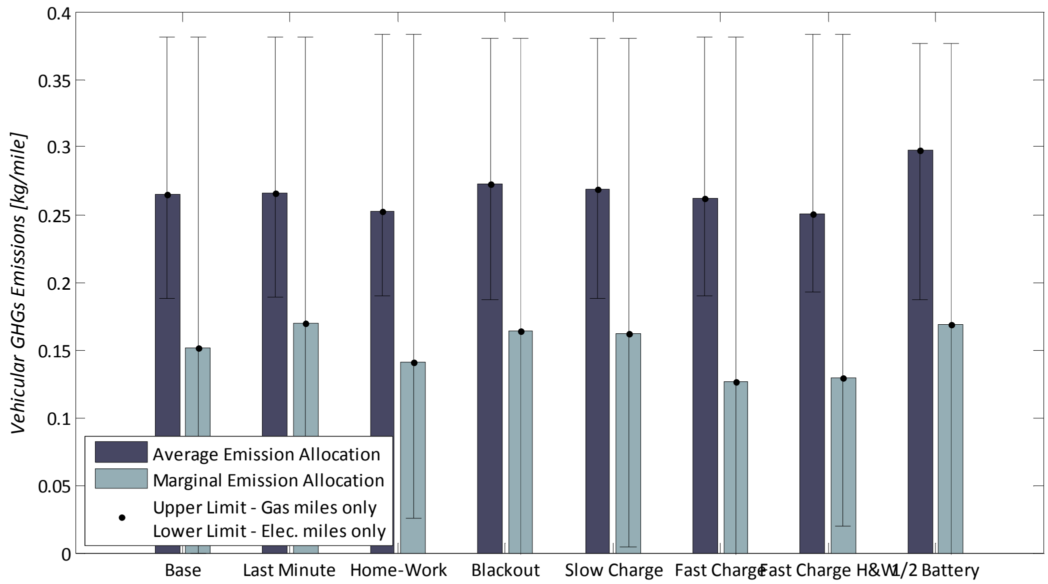

Figure 133. Per mile greenhouse gas emissions for each charging scenario

Criteria Pollutant Results

Criteria pollutant emissions are also highly influenced by dispatch methodology. In the following discussion, total system emissions in 2030 are compared for simulations with and without PHEVs under the baseline electricity generation capacity scenario (EG1) and simulations with and without PHEVs under the cleanest electricity generation scenario (EG4), using the economic dispatch method. The results are presented as a percent change from the zero PHEV case (FI1), using the CF method. This was done for consistency of comparison with the results that use the CF method. The results in Figure 134 are for EG1 conditions and those displayed in Figure 135 are for the EG4 case. These figures are shown to demonstrate the net effect of PHEV infiltration on the entire Michigan system and how these effects change depending on two potential cases for the Michigan 2030 generation capacity fuel mix.

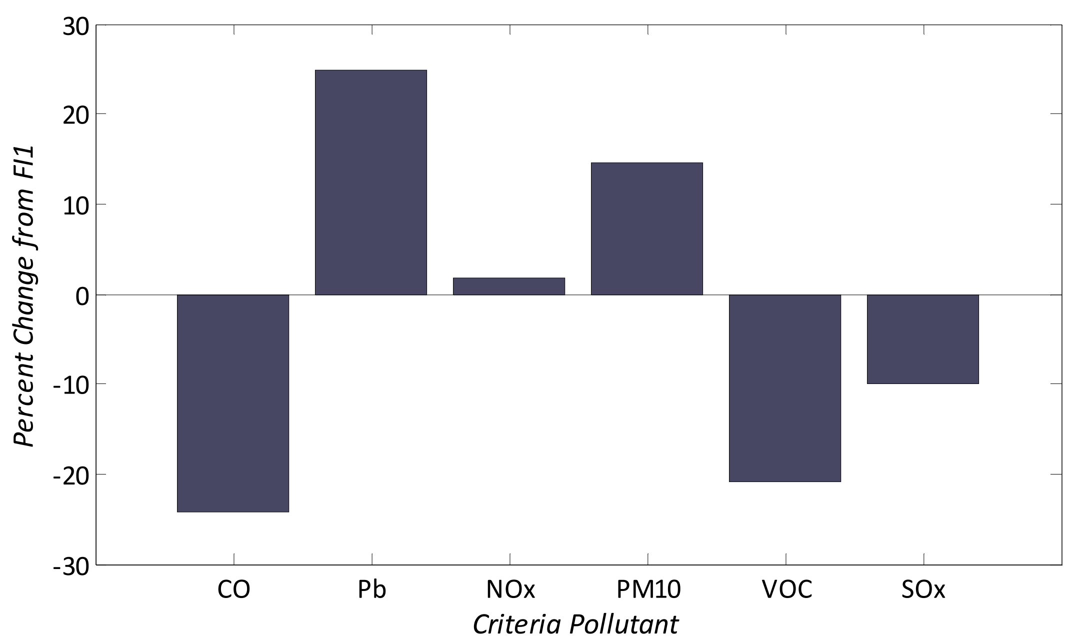

Figure 134. Change in total system emissions between FI1 (CF) and FI4 (economic) (EG1, CH1, 2030)

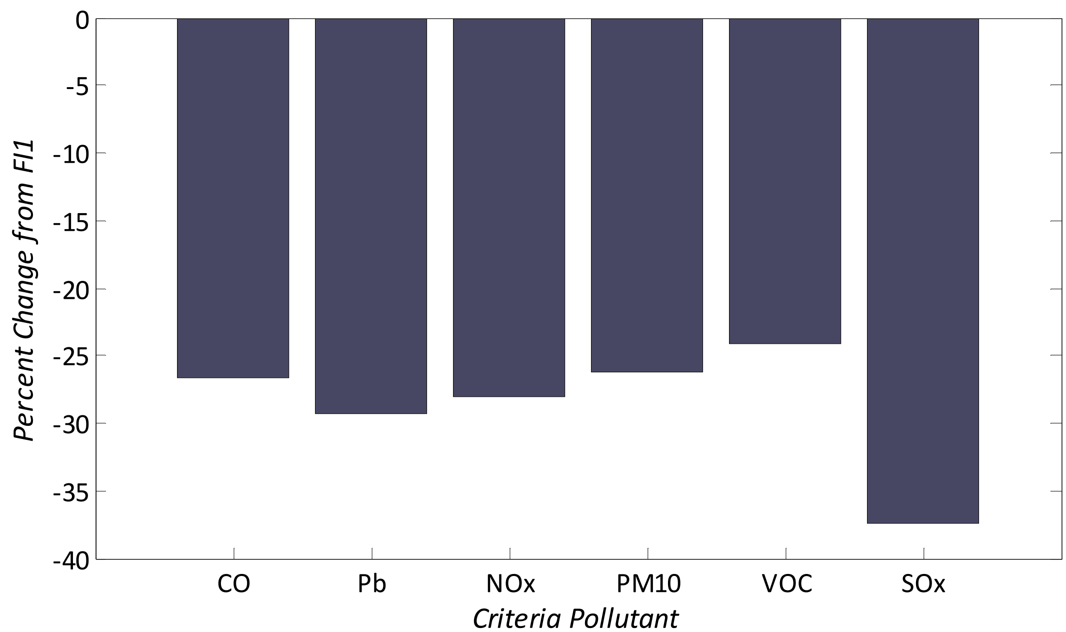

Figure 135. Change in total system emissions between FI1 (CF) and FI4 (economic) (EG4, CH1, 2030)

The results for the EG4 scenario are so drastically improved because of the usage of both renewable electricity and nuclear electricity. In the economic dispatch these assets will be deployed more than in the CF dispatch because the CF dispatch energetically limits the plants more than the economic dispatch, which follow economic rules.

Transportation sector emissions in 2030 are broken out from total system emissions and examined by each emission allocation method. They are compared for simulations with high PHEV infiltration between the baseline electricity generation capacity scenario (EG1) and the cleanest electricity generation scenario (EG4) for both emission allocation methods. The results are presented as a percent change from the zero PHEV case (FI1) (using CF dispatch), with Figure 136 displaying emission levels under EG1 conditions (using economic dispatch) and Figure 137 showing these same emissions under the EG4 case (using economic dispatch). The marginal emissions of SO_X are substantially reduced in both cases.

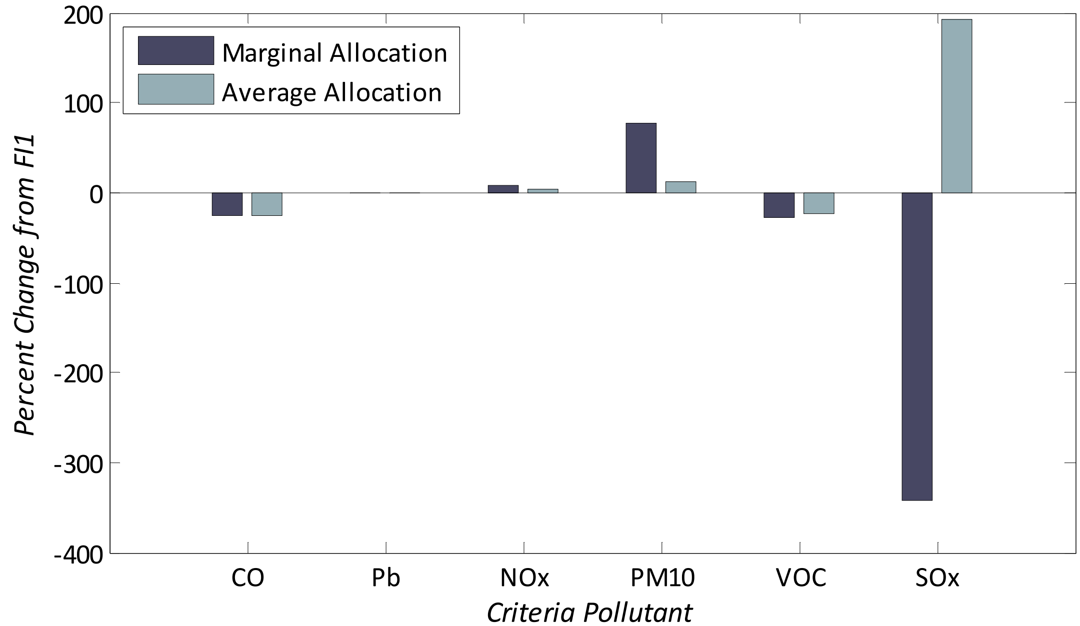

Figure 136. Change in transportation emissions between allocation methods (FI4, EG1, CH1, 2030)

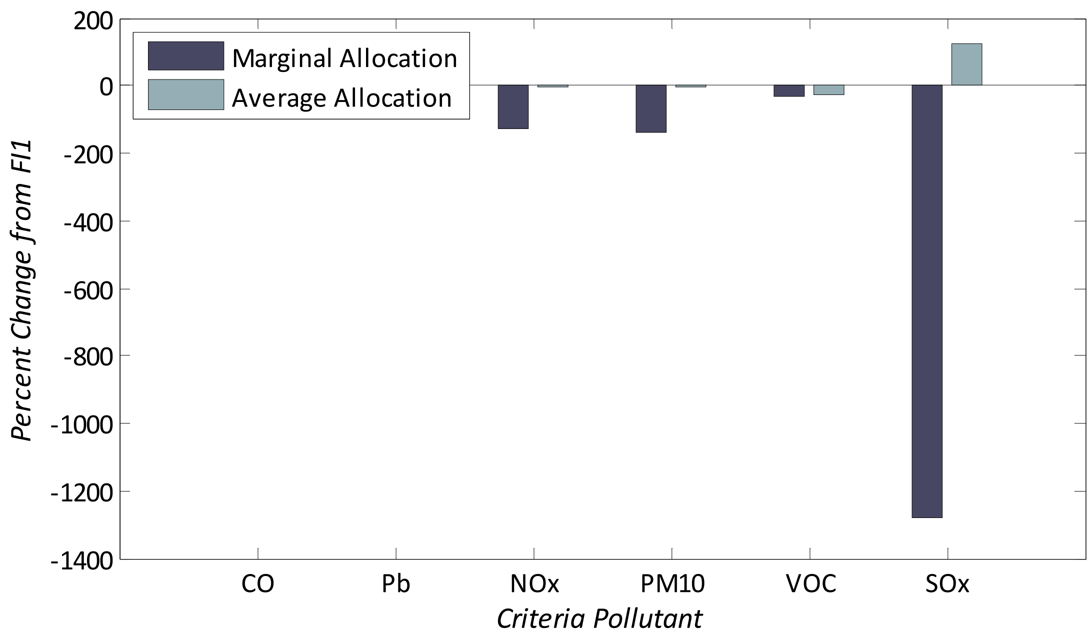

Figure 137. Change in transportation emissions between allocation methods (FI4, EG4, CH1, 2030)

Appendix Q. Case-study: The Chevy Volt

As the Chevrolet Volt is the only PHEV on the market at the time of this studies completion, the known information on the Volt is used to examine its impacts for the next couple of years using the models developed to simulate charging/fueling and driving in Michigan. The scenario parameters modeled are defined below (see Chevy Volt Modeling Inputs). These are short-term fuel cycle results and as the grid is transformed future environmental performance will improve significantly as indicated by the main findings presented in the body of this report (e.g., 2030 scenarios).

Chevy Volt Impacts

Emissions and Energy Impacts

The Chevy Volt has a much lower greenhouse gas emissions rate than an average on-road conventional vehicle. Figure 138 displays the Volt's GHG emissions rates under different charging scenarios in Michigan. There is a slight variation in the Volt's emission rate if the consumer's charging behavior changes, ranging from 252 g CO_2e /mile to 269 g CO_2e/mile using the average emissions allocation method and 278-352 g CO_2e/mile using marginal allocation. This is nearly half as carbon intense as the emissions rates predicted for an average on road conventional vehicle of that year at 520 g CO_2e /mile and approximately two thirds of that of a predicted average compact vehicle purchased in 2012.

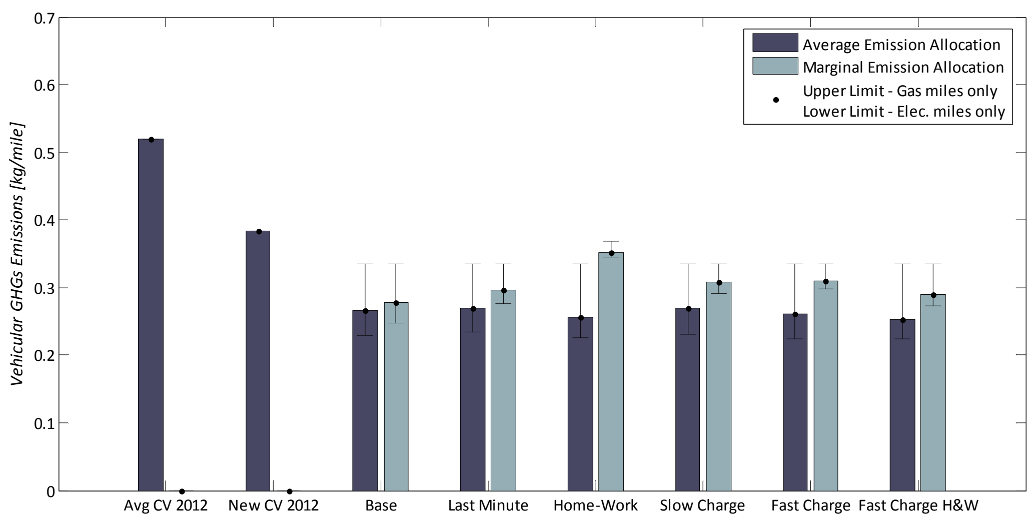

Figure 138: The Chevy Volt's greenhouse gas consumption rate for each charging behavior scenario in 2012 (EG1)

Criteria Pollutant emissions and total fuel cycle energy consumption rates are also shown in Table 69. In most categories, there is a reduction for driving the Chevy Volt; however, sulfur oxide, particulate matter, and lead emissions increase compared to conventional vehicles. The increase in lead emissions is likely somewhat smaller, as upstream lead emissions were not modeled for gasoline consumption. Additionally, NO_x emissions increase when compared to the new compact vehicle in 2012. While all these emissions do increase, this is due to shifting emissions sources from the vehicle tailpipe to the electricity power plant. These are far fewer emissions sources and are much easier to manage.

Table 69: Chevrolet Volt Emissions and TFC Energy Consumption for 2012 using Average Allocation

	Avg On-Road CV	New CV - Compact	Chevrolet Volt - Charging Scenarios					
			CH1	CH2	CH3	CH5	CH6	CH7
Greenhouse Gas Emissions [g CO_2e/mile]	520	383	266	269	256	269	261	252
NO_x Emisions [mg/mile]	406	300	351	357	358	350	350	359
SO_x Emisions [mg/mile]	133	99	804	815	881	783	819	903
CO Emisions [g/mile]	4.15	3.05	0.98	0.99	0.79	1.04	0.93	0.74
VOC Emisions [mg/mile]	341	252	93	93	78	97	89	74
Pariticulate Matter Emisions [mg PM_{10}/mile]	90	66	122	126	128	122	121	128
Lead Emisions [μg Pb/mile]	0	0	12	12.4	13.1	11.8	12	13.3
Total Fuel Cycle Energy [MJ/mile]	7.27	5.36	4.12	4.19	4.02	4.17	4.05	3.97

Gasoline Displacement

The gasoline displaced by the expected fleet of Chevy Volts was calculated and displayed below in Table 70. As the fleet more increases in size by 400% in 2012, the displacement is much greater. This displacement represents gasoline avoided by compact vehicles that would have been bought instead of the Chevy Volt.

Table 70: Estimated Gasoline Displaced (gallons) by the Chevy Volts introduction to MI

Year	Chevrolet Volt - Charging Scenarios					
	CH1	CH2	CH3	CH5	CH6	CH7
2011	579,000	579,000	550,000	587,000	571,000	543,000
2012	2,829,000	2,829,000	2,687,000	2,871,000	2,793,000	2,650,000

Chevy Volt Modeling Inputs

Table 71 summarizes the data used to modify the PECM and MEFEM models to get these results for the Chevy Volt.

Table 71: Chevy Volt characteristics for modeling

	Useable Battery Size	Electricity Consumption	Fuel Economy	2011 MI Vehicle Sales	2012 MI Vehicle Sales
Chevy Volt	10.4 kWh	0.26 kWh/mi	33.3 mpg	958	3832

Vehicle Characterization

With its release, the consumption parameters and actual useable battery size of the Chevrolet Volt are available to the general public. The Volt will allow a driver to deplete the battery by 10.4kWh before running in charge sustaining mode [100]. This implies an average electricity consumption rate from the battery of 0.26kWh per mile in order to meet the stated electric range. The Volt will also carry an additional 9.3 gallons of gasoline which can be used in charge sustaining mode to propel the vehicle an additional 310 miles [101], so the average fuel economy of the is estimated at 33.3 miles per gallon. These values allow an average Volt to be modeled in the PECM.

Fleet Infiltration

Once the Volt's energy consumption has been modeled, the fleet infiltration of Volts is required in MEFEM to determine the environmental impacts in the system. General Motors has released expected production numbers for 2011 and 2012. For the 2011 model year, GM expects to produce 15,000 Volts, of which 10,000 will be sold in the United States. For 2012, GM is anticipating ramping up production to 60,000 units [102]. If the same proportion is shipped overseas, 40,000 will be sold in the United States. GM is also limiting the markets they will be sold in for these two years to Michigan, California, New York, New Jersey, Connecticut, Texas and Washington, D.C. [102]. Based on the proportion of populations of this set [103], Michigan will receive 958 vehicles in 2011 and 3832 in 2010.

Appendix R. Dispatch Method Comparison to PROMOD Results

The present appendix discusses a comparison of the dispatch scenarios in the analysis to results obtained from the Ventyx's PROMOD® software. The results will be compared on the basis of generation by aggregate fuel type and at the power plant level. A discussion of the relevant differences in the inputs to PROMOD and the sources for those differences is provided to help illuminate the observed differences in electricity dispatch.

The Market Intelligence group of DTE Energy Resources, Inc. generated electricity dispatch results from the PROMOD software to validate the dispatch methodologies developed for MEFEM. The data from our model required to run PROMOD included hourly electricity load, generator information, fuel prices, and carbon tax prices corresponding to two scenario sets: a zero PHEV Infiltration (FI1), Baseline Charging (CH1), Baseline Grid (EG1) set; and a High PHEV Infiltration (FI4), Baseline Charging (CH1), Baseline Grid (EG1) set.

Figure 139 displays the aggregate generation mix by fuel type for all dispatch methodologies in 2030 for the zero PHEV scenario set. PROMOD dispatch results seem to dispatch slightly more nuclear than any other scenario, and dispatched coal and natural gas fired thermal plants somewhere between what MEFEM's capacity factor and economic dispatch methods.

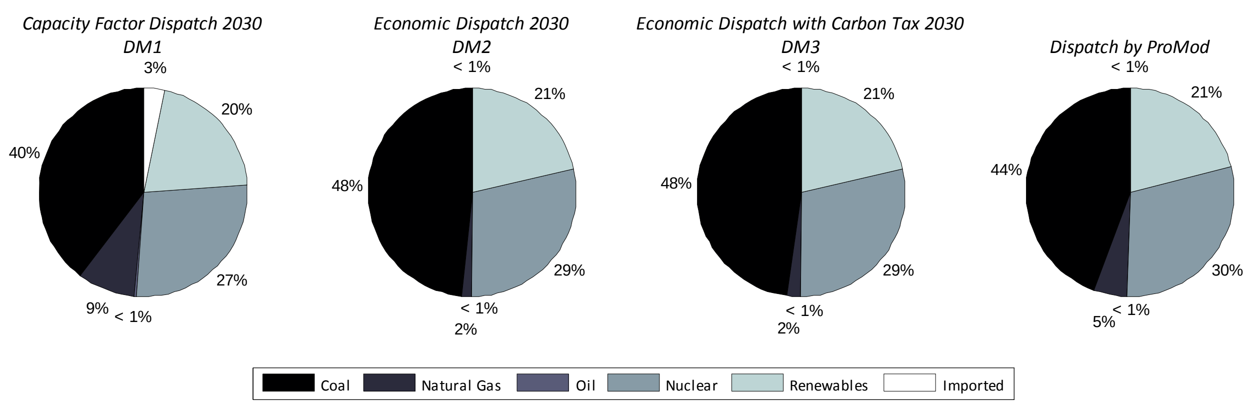

Figure 139. 2030 Fuel mixes for generation by dispatch mode (FI1-CH1-EG1)

We also examined this scenario set to determine the percentage of agreement in annual electricity generation of each asset on the grid. Table 72 describes the percent agreement between dispatch methodologies. Capacity Factor Dispatch hovers at about 83% unit generation agreement with all of the other dispatch methodologies, while the economic dispatch methodologies have approximately a 93% agreement with PROMOD results. Implementation of a carbon tax seems to have nearly zero effect (99% agreement) on which units are dispatched in MEFEM's economic method.

Table 72. Agreement of plant level dispatch for the Zero PHEV Scenario in 2030

		MEFEM Dispatch Method		
		Capacity Factor Dispatch	Economic Dispatch	Economic Dispatch with Carbon
Method for Comparison	PROMOD	83.1%	93.3%	92.8%
	CF Dispatch		83.0%	82.5%
	Economic Dispatch			99.0%

When adding PHEV load from a High PHEV scenario, the results of the comparison do not seems to change significantly. Figure 140 shows the 2030 generation by fuel type for each dispatch scenario with the additional load. There is more new capacity in the system, which is modeled predominantly as natural gas combined cycle units, so the percentages change somewhat. PROMOD continues to fall somewhere between the capacity factor and economic approaches in MEFEM.

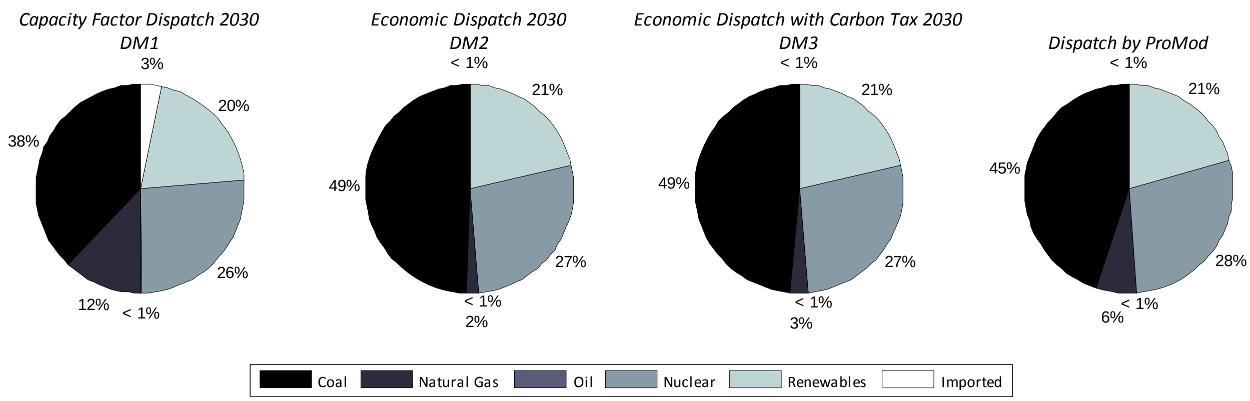

Figure 140. 2030 Fuel mixes for generation by dispatch mode (FI4-CH1-EG1)

The percent of unit generation agreement, shown in

Table 73, changes little between the four dispatch scenarios when PHEV load is added.

Table 73. Agreement of plant level dispatch for the High PHEV Scenario in 2030

		MEFEM Dispatch Method		
		Capacity Factor (CF) Dispatch	Economic Dispatch	Economic Dispatch with Carbon
Method for Comparison	PROMOD	84.0%	93.7%	93.4%
	CF Dispatch		83.7%	83.5%
	Economic Dispatch			99.2%

PROMOD employs an economic based dispatch model that is more sophisticated than the one used in MEFEM's economic dispatch algorithm. To run the PROMOD software, the modeler had to add information that was not used in MEFEM. This information is listed below; values and explanations are given when known:

- Minimum Capacity – This limits the minimum level at which a generating asset can run at and was set to 20% of the nameplate capacity.
- Forced Outage Downtime – When a generating asset has a forced outage, this value indicates how long it will be until the asset is operational again. For nuclear plants the value is 168 hours, for all others it is 48 hours.
- Forced Outage Rate – Set to 3.75, unclear as to what this value means in the context of PROMOD.
- Partial Availability Rate – Set to 96.25, unclear as to what this value means in the context of PROMOD.
- Monthly Variable Fuel Costs – In PROMOD, natural gas fuel costs varied stochastically by month.
- Minimum Downtime – Unclear as to what this value means in the context of PROMOD.
- Minimum Runtime – Unclear as to what this value means in the context of PROMOD.
- Ramp up rate – How fast a plant can increase its power output, generally in percent of capacity per min or MW/min.
- Ramp down rate – How fast a plant can decrease its power output, generally in percent of capacity per min or MW/min.
- Heat rates that fell below 8000 (from eGRID database) were changed to 8000.
- Scheduled Outages – Each asset had a value that indicated the number of weeks between scheduled outages and what time of year that the first outage occurs.

The values chosen for these inputs came from the personal experience of the modeler, and have not been verified by other sources. Some of the capability indicated by these additional inputs could be implemented into further iterations of the economic dispatch model in MEFEM. Outages, downtime, and runtime could replace the need to simplify unit availability with an availability factor, as the current iteration of MEFEM's model does. Additionally, seasonal fuel prices and constraints on asset power ramping could add more realism to the model.

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