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Modeling of Greenhouse Gas Reductions Options and Policies for California to 2050:

Analysis and Model Development Using the CA-TIMES Model

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1. INTRODUCTION

Energy system modeling has been used around the world to analyze how specific regions could make major shifts in the energy system to adopt low-carbon options and reduce the threat of anthropogenic climate change. Energy system modeling can help us understand the nature of the technological, resource and behavioral changes that are needed to limit emissions of greenhouse gases (GHGs).

CA-TIMES is a model of the California energy system that has been under development for almost a decade and was inspired by the ambitious targets that were put forward by the Governor of California in 2005 and 2006, and the passage of AB32. Governor Schwarzenegger laid out an extremely ambitious target of an 80% reduction in greenhouse gas (GHG) emissions from 1990 levels by 2050. This target laid out a grand challenge for the state of how to achieve a major transformation of the energy system to reduce the amount of energy the state and rely on low carbon energy sources. There is a significant amount of uncertainty about the evolution of the energy system many decades in the future, so the initial goal of analyses tasked with answering questions about meeting these targets was to understand what sorts of possible futures might conceivably meet the GHG goals. Among these possible futures, a next step was to identify the lowest-cost way (or relatively inexpensive ways) to achieve these goals. A number of modeling and system analyses have been performed over the years with the goal of improving our understanding of the mitigation options for California (e.g. Morrison et al 2014, Mahone et al. 2015, Greenblatt 2015, Roland-Holst 2015, Wei et al 2013, Greenblatt and Long 2012).

The work and analysis described in this report is the third stage of development of the CA-TIMES model, an energy system optimization model for analyzing technology and resource investments and utilization to meet these GHG targets. The first stage, described in McCollum et al (2012), provided the foundation of the energy system model of CA-TIMES, but with simple representation of all end-use sectors except for transportation. The second iteration of CA-TIMES, described in Yang et al (2015), extended the model to include detailed representation of energy services and end-use technologies in the residential and commercial sectors as well better representation of several aspects of the electric sector, including spatial and temporal representation of intermittent renewable (wind and solar) resources.

This report describes the third stage, which includes three types of improvements to the analyses that can be performed by CA-TIMES. The first type describes improvements to the **core model structure** of CA-TIMES, including incorporating heterogeneity and consumer choice, technology learning-by-doing, energy storage, and demand response. The second type of improvement is focused on the specific **types of analyses** that the CA-TIMES model can be used to analyze rather than changes to the model, per se. These improvements allow for many more model scenarios to be developed and run, analyzing new policies, as well as combinations of policies and uncertainty analysis focused on parameter uncertainty. The third model improvement focuses on **improving modeling outputs** and presentation of results, including improved sector and technology level reporting, analysis of sector and technology level abatement costs, and reporting of results with different combinations and interactions of policies and Monte Carlo parameter uncertainty.

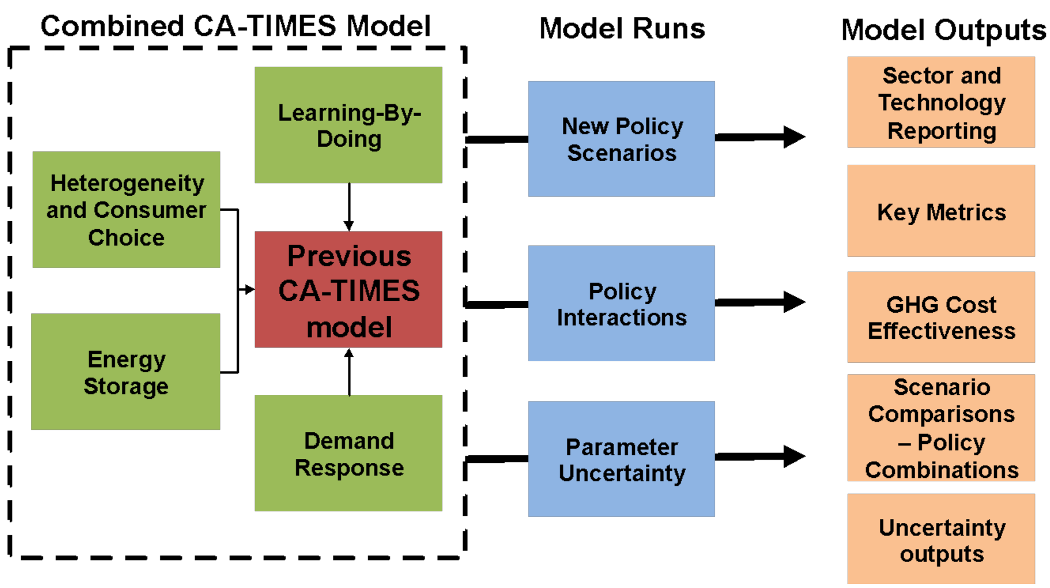

Figure 1. Schematic of the model improvements made to CA-TIMES from earlier versions of the model

2. METHODOLOGY AND MODELING IMPROVEMENTS

This report is not meant to be full documentation of the CA-TIMES model but rather to provide an update to the last full CA-TIMES report (2014). This section will provide a brief description of the model and describe the major modeling changes and approaches to new scenario analyses performed in analyzing California's GHG emissions reduction options to 2050. For a more detailed description of the structure and assumptions of the previous CA-TIMES model see (Yang et al 2014, Yang et al 2015).

2.1 Brief description of modeling framework

The CA-TIMES model is a linear optimization model that seeks to build an energy system (by investing in technologies and processes) that can meet projections for future energy service demands in a least cost manner. It is a bottom-up, technologically-rich, integrated economic optimization model that is based upon the MARKAL/TIMES framework (Loulou 2005). The model represents all of the main sectors of the energy system in the state including energy supply (energy resources, energy imports/exports, fuel production, conversion and delivery, and electricity production) and energy demands (residential, commercial, transportation, industrial and agricultural end-use sectors). In each of these parts of the energy system, the demand for end-use energy services must be supplied by flows of energy and energy commodities that are mediated and/or transformed by various technologies, such as vehicles, appliances, transmission and distribution systems, power plants, fuel production facilities and resource extraction. The model chooses the appropriate mix of these technologies in order to ultimately meet the demand for energy services that also yield the lowest discounted system cost, and subject to any specific system constraints such as limits on resource availability, technology growth limits and/or policy constraints (e.g. limits on emissions).

The structure of the CA-TIMES model is laid out across numerous energy sectors. Figure 2 shows the structure of the model as broken into various stages of the energy system. On the left side of the figure shows the demands that drive the need for energy production/conversion/delivery processes. Projected service demands to 2050 are described exogenously as input assumptions for the residential, commercial and transport sectors, and projected fuel demands are specified for the industrial and agricultural sectors. The specification of energy service demands (e.g. heating, cooling, lighting, water heating, etc in the residential and commercial sectors and vehicle miles traveled (VMT) across different transportation sectors (light-duty, heavy-duty, aviation, marine, etc)) means that the model has the flexibility to meet these demands from a set of technologies (appliances and vehicles) that can differ in the fuel type, energy efficiency and capital and operating costs. As a result, the model has the flexibility to trade off higher costs for these technologies for greater emissions reductions and choose the appropriate mix of these technologies. In two other demand sectors, industry and agriculture, these end-use demands are not specified, and an assumption about the fuel demanded by the entire sector is used. This limits the ability of the model to alter emissions reductions in these sectors only to changes in carbon intensity of the input fuels (electricity, natural gas, liquid fuels).

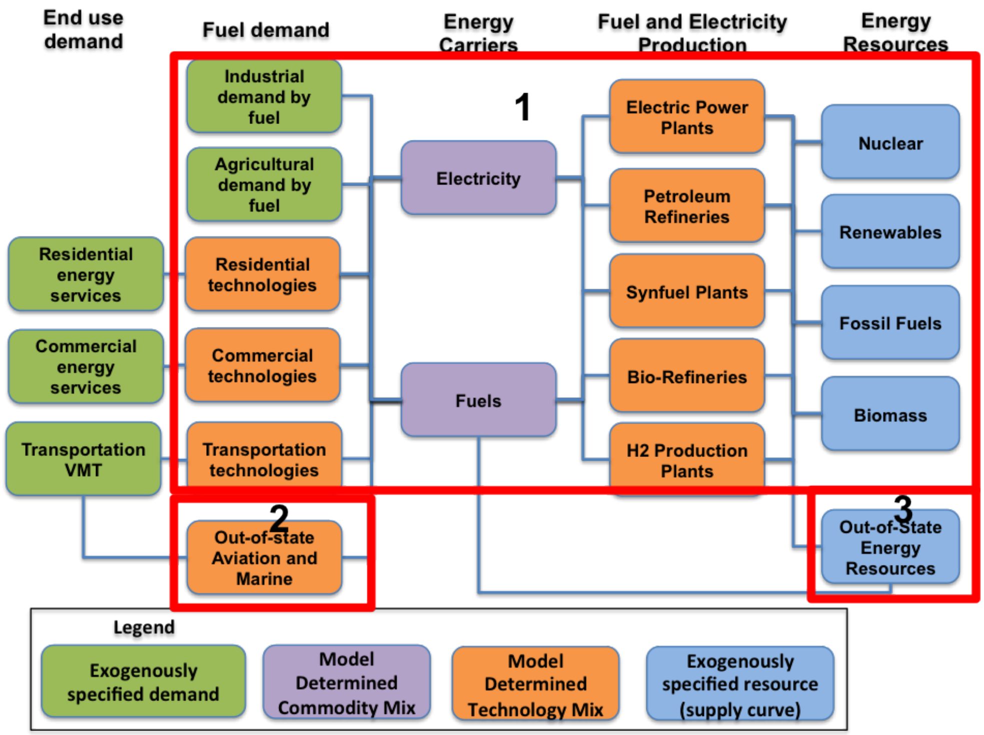

Figure 2. High-level CA-TIMES model structure describing demands for end use services and fuels and the energy conversion technologies and energy resources that are used to meet these demands. This figure also includes the emissions accounting categories (1) emissions regulated under a statewide cap (2) emissions from CA that are not included in the cap and (3) out-of-state emissions from energy resources brought into California.

The choice of technologies and fuels that are used to supply these sectoral demands need to be supplied requires the existence of an energy supply infrastructure to provide these energy flows. The CA-TIMES model must invest in technologies to extract and transport primary energy resources to California and plants and facilities that convert these primary energy resources into electricity and the finished fuels that are demanded. Each of these choices have a direct economic cost, related to the investment, installation and operation of the supply infrastructure and demand technologies. Because CA-TIMES is an optimization model, all of the economic costs of these choices are summed and discounted to present value in order to find the mix of resource usage and technologies that meet the energy demands while minimizing the overall system cost. The same process can be used to analyze scenarios for meeting GHG emissions targets; the model will find the exact mix of technologies and resource utilization that minimizes the combined economic costs of all parts of the energy system that both meets the specified energy demands and GHG targets.

Also included in Figure 2 is a categorization of the emissions categories tracked in the model. Emissions from the energy system that fall under the emission cap are all fuel combustion activities occurring solely within the state **and** *imported* electricity emissions

California tracks emissions from categories 1 and 2 in their official inventory, though only category 1 (*Included Instate emissions*) emissions are included in the cap for the purposes of meeting California's current climate change law for 2020 (AB32) and presumably the 2050 target.

2.2 Key updates in latest version

2.2.1 Consumer choice

The CA-TIMES model framework has detailed input datasets containing projections for future end-use energy demands, technology performance characteristics, and capital and operating costs. However, CA-TIMES and other similar models are not generally equipped to represent how consumer markets might actually respond to policy or technology changes. The default decisions of the model yield unrealistic, 'all-or-nothing' technology choices, because heterogeneity of decision-maker preferences and motivations are not represented. Often models such as these invoke ad-hoc approaches to model more "real-world" behavior, such as constraints on the share of specific technologies, on rates of growth and adoption and high discount rates to represent non-monetary factors that may affect utility for some technologies. Representing consumer behavior realistically becomes particularly important when it comes to light-duty vehicles in the transportation sector: they are the source of a substantial percentage of emissions that are difficult to reduce, and consumer choice plays an important role in their adoption. An alternative methodology that incorporates theory-based behavioral factors directly into a frequently used energy systems modeling framework called COCHIN-TIMES (COnsumer CHoice INtegration in TIMES) is developed. This modification incorporates multiple types of factors related to consumer utility/preference for vehicles, namely the inclusion of non-monetary factors that influence consumer utility for vehicles and also inclusion of consumer segmentation. The version incorporated into the CA-TIMES model uses MA^3T vehicle choice model developed by Oak Ridge National Laboratory as the primary data source (Lin and Greene 2011), but the approach can be implemented more generally. The end-use demands of light-duty cars and light-duty trucks are divided into diverse set of consumer segments differentiated by driving profiles (annual VMT), and attitude toward risk. For each consumer segment, disutility costs are included based on their perception towards various vehicle technologies, such as, the range limitation cost to represent the limited vehicle range of battery electric vehicles, refueling inconvenience cost to capture the coverage of fueling infrastructure, risk premium and so on. These "additional costs" influence the optimal technology for each consumer segment in a given model year, in the framework of a cost-minimization model. The technology investment results are then aggregated for all the consumer groups.

2.2.2 Learning-by-doing

Many of the climate policies adopted in California can be considered technology-forcing policies, such as the ZEV program, LCFS, and the AB2514/CPUC energy storage mandate. These policies were intended to elicit advancements in technology and/or technology cost reductions by forcing firms to commit resources to R&D and/or technology deployment. We implement a version of technology cost learning into the CA-TIMES model where future values of technology costs are no longer a function of time alone but depend on the cumulative investment decisions given policies specified, the level of stringency of policies, and the ultimate "learned out" costs of technology compared with other incumbent/competitive technologies. We implement this process for important components in light-duty vehicles, batteries, electric motors and fuel cells, which can be found across a range of vehicle types (hybrids, plug-in hybrids, battery electric vehicles and fuel cell hybrid vehicles).

2.2.3 Energy storage

Earlier versions of the CA-TIMES models included existing pumped hydro as the only electricity storage option. This version of the model incorporates a simplified lithium ion battery-based storage system as another storage option.

2.2.4 Demand response

In CA-TIMES, all of the residential and commercial service demands have a specified load profile over 48 sub-annual timeslices (6 "seasons" per year and 8 slices per day), which are used to characterize electricity generation and usage in the electricity sector.
These load profiles for specific residential and commercial end-uses are fixed and without demand response (DR), electricity consumption would follow these same load profiles. Including DR allows for electricity consumption to vary slightly from these service demand profiles.
In order to model demand response (DR) in CA-TIMES, we define a DR technology that can store electricity whenever the price of electricity is low (and constraints are met). Then DR technology discharges in the appropriate timeslice to match the service demand load profile (with satisfying the defined constraints). For example, we can model a technology which represents thermal systems where you can pre-cool a building so that demand is lessened during the peak hour and shifted before and after the peak hour.
We implement DR in our model to 2050, and expect it will be used to deal with variability associated with high levels of intermittent renewable generation.

2.2.5 Parameter uncertainty

In an economic optimization model such as CA-TIMES, technology costs are among the most critical parameters for determining which resources and technologies are adopted to fulfill the energy demands. Most energy system models choose a specific set of technology costs as well as other important parameter values for their modeling runs. However, because of the inherent uncertainty in forecasting the value of these parameters out into the future, the probability that all of the parameter value chosen will end up being correct is essentially zero. As a result, we run a Monte Carlo simulation varying the parameter values across a reasonable range of values in order to understand the impact of the parameter values on the final results and also to understand the possible range of outcomes possible.

Some of the most important parameters that we have investigated in our modeling include population, biomass and hydro availability, availability of nuclear power and carbon capture and sequestration, methane leakage, availability of demand response, level of emissions offsets, battery and fuel cell costs, oil and natural gas prices, light-duty VMT demands, and solar PV costs.

2.2.6 Other updates: Commercial sector (behavior)

Space heating, space cooling and water heating are the most heterogeneous end-uses in the commercial sector. We adopt the behavior rules used in the NEMS model by breaking these end-uses into three segments based on three behavioral rules including "same technology", "same fuel" and "least cost". These segments show how different consumers behave in choosing a new technology when he/she wants to replace the existing technology. For example, changing the technology type for space cooling in a commercial building can have numerous barriers which limit technology changes, such as requiring additional utility work, plumbing, lack of information about alternatives, and so forth; as a result, consumers with a certain type of cooling system will often buy the same or a similar technology. Similarly, some consumers will choose a technology that consumes the same type of fuel type due to the associated transitioning costs. And, some other consumers always buy a least cost technology, even if it means switching to a new technology type, despite of these challenges. It is necessary to note that all consumers choose the least-cost technology associated with their behavioral rule.

2.2.7 Computational requirements of new combination model

Each of these new modeling features were incorporated into the previous version of the CA-TIMES model. The integration of all of these features created a number of computational issues that we had to solve. Ultimately, we were able to get each of these elements incorporated into the model in order to run our primary and policy combination scenarios. We are able to run individual scenarios of our model on a conventional desktop PC (Windows, Intel Core i7 with 16GB RAM), using GAMS optimization software and CPLEX solver.

In order to run the many thousands of model scenario instances for our policy combinations and parameter uncertainty analysis, we were able to utilize the National Energy Research Scientific Computing Center (NERSC) computing cluster at the Lawrence Berkeley National Lab, part of the US Department of Energy. This enables the running of many parallel model scenario instances in order to dramatically speed up the total computational time required to complete thousands of CA-TIMES runs.

2.3 Descriptions of scenarios and policies

One of the main values of the CA-TIMES model is to run the model with varying sets of technology, resource and policy-related inputs and analyze the results to understand which options the model chooses as the optimal solution to satisfy the energy service demands.

There has recently been significant discussion about the next phase of policies that will be needed to continue to reduce emissions beyond the 2020 target. 2030 is the next big milestone year and Governor Brown recently announced a number of key targets for that year, some of which were signed into law. SB350 codifies that 50% of electricity generation should come from renewable sources, i.e. the 50% Renewable Portfolio Standard (RPS), and a doubling of energy efficiency in California buildings. Other targets that have not yet been passed include a 50% reduction in petroleum consumption and a 40% reduction in GHG emissions below 1990 levels.

2.3.1 Greenhouse Gas Cap Policies

We investigate several GHG cap trajectories in our scenarios. A cap trajectory (which is used interchangeably with cap) is specified upper limit on GHG emissions from 2020 until 2050. Current law (AB32) has a binding GHG cap that total included emissions should be at 1990 levels (431 MMTCO2e) in the year 2020. CA-TIMES only tracks energy system emissions, so subtracting out emissions from non-energy sources and sinks, the 2020 including GHG emissions limit used in CA-TIMES policy modeling is 391 MMTCO2e (see Figure 2). The 2020 GHG cap scenario assumes that the 2020 limit is in effect until 2050 (i.e. included energy system emissions cannot exceed 391 MMTCO2e between 2020 and 2050). In addition to this existing policy, several other GHG cap policies are investigated. We also investigated the Governor's new 2030 GHG target of 40% below 1990 levels (2030 cap) and assumed that this target emissions level would be held constant until 2050. Another cap scenario includes both the 2030 target and the 2050 target of GHG reduction of 80% below 1990 levels (2030 and 2050 cap), with interpolated values in intermediate years. Finally, we looked at two 2050 cap scenarios, one with a linear interpolation for cap levels between 2020 and 2050 (2050 line) and one where the 2020 target is held constant until 2050 (2050 step).

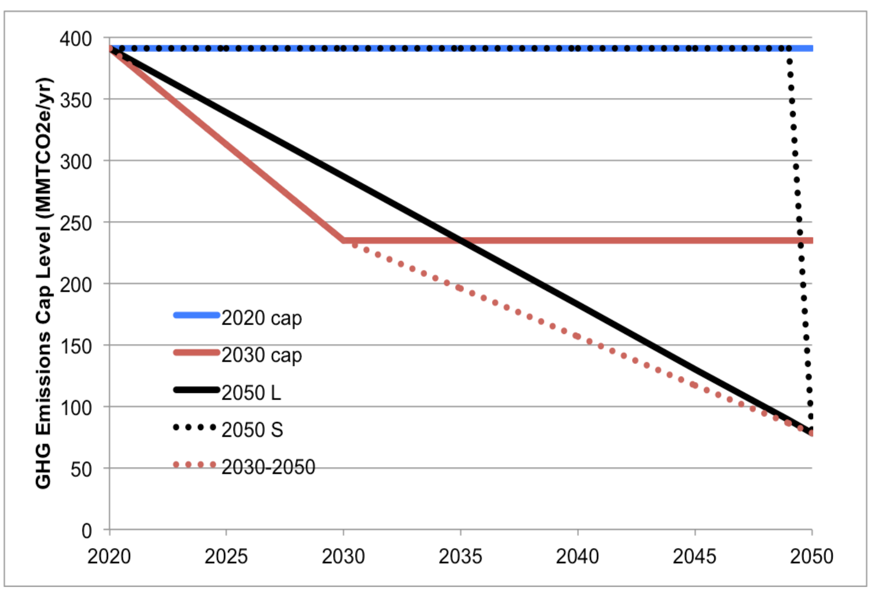

Figure 3. GHG cap trajectories that are investigated in this report.

2.3.2 Fuel Economy (CAFE) Policies

We investigate several fuel economy (CAFE) policies in our scenarios. In our primary scenarios, we use the existing policy, which approximately achieves 54 mpg (test-cycle) for cars and 40 mpg for light-trucks by 2025. Other CAFE policy variations include no fuel economy policy and an extension of CAFE, in which cars achieve 101 mpg (test-cycle) and light-trucks achieve 68 mpg in 2050.

2.3.3 Renewable Portfolio Standards

We investigate several renewable portfolio standard (RPS) policies for California. The state recently enacted legislation, which set the RPS target at 50% by 2030, which is an increase over the previous policy of 33% by 2020. Other variations of this policy include no RPS policy and an extension of an 80% RPS policy to 2050. We use the older 33% policy in our primary scenarios but analyze the impact of the new 2030 50% RPS on the model results.

2.3.4 Low Carbon Fuel Standard (LCFS)

The low carbon fuel standard (LCFS) regulates the carbon intensity of transportation fuels in California. The main policy in our primary scenarios is the existing policy of a 10% reduction in fuel carbon intensity by 2020. We also investigate several variations, including no LCFS policy and a 50% reduction in fuel carbon intensity by 2050.

2.3.5 Zero Emission Vehicle Mandate (ZEV)

The primary scenarios use the current policy ZEV policy of 22%[1] ZEV requirement by 2025. Variations on this policy include a no-ZEV policy and also a 60% ZEV requirement by 2050.

2.3.6 Petroleum Reduction

The governor recently announced a reduction target of 50% for on-road petroleum usage, but this policy has not been enacted yet in a regulatory framework. As a result, our primary scenarios do not include any targets for petroleum reduction, though we investigate variations including a 50% reduction in on-road transportation petroleum usage in 2030 and an 80% reduction by 2050.

2.4 CA-TIMES Limitations to Policy Analysis

Because these policy discussions have importance to the legislative and regulatory process, analysis of these and other policies can be performed using CA-TIMES. However, it is important to note that CA-TIMES is one type of tool that can help inform researchers, analysts and stakeholders about the impacts of policy. The model does not simulate the collective

[1] This requirement should not to be interpreted as 22% of vehicles sold in 2025 must be a ZEV vehicle (such as a hydrogen fuel cell vehicle or plug-in electric vehicle), since vehicle characteristics such as range and refueling time can affect how each vehicle is counted.

behavior and decisions of individual decision makers (businesses and consumers), but rather assumes a single global decision-maker that makes decisions across all parts of the energy system and can trade off costs and benefits irrespective of where they occur in the entire system. Thus, the results can be viewed as the least-cost outcome from the perspective of the entire system, which can diverge from the results that could come about from the cumulative impact of millions of individual decision-makers, even assuming that the input assumptions are correct.

As a result, CA-TIMES outputs should not be taken as a forecast of what will happen as a result of specific policies or conditions on the system, but rather an estimate of the energy system investment and operation decisions that lead to the lowest overall cost under these policies or conditions. The model results are useful as a tool to understand a subset of the types of changes that could be implemented to achieve GHG reduction and other policy goals, but it does not account for all aspects of feasibility.

3. COMPARISON OF SCENARIO RESULTS

These scenario results look primarily at the changes in the GHG caps as described in section 2.3.1, with some analysis of newer policies that are of interest, including the petroleum reduction target and the updated 2030 RPS. These primary policies, unless stated otherwise, will use the base set of current policies, including the 33% RPS, CAFE policy to 2025, ZEV mandate to 2025, LCFS to 2020, and no petroleum reduction target.

We present selected results from each of these scenarios. Given the large number of sectors, service demands, technologies, resources and energy pathways present in the model, it is difficult to report on every aspect of the modeling results. We focus on the sectors and technologies with the largest impact on energy use and emissions: electricity, transportation technologies and fuels, and buildings.

3.1 New Policy Scenarios

3.1.1 2020 only cap (Reference scenario)

Our reference scenario for this primary set of results assumes that the existing set of policies are present, described above, as well as the 2020 GHG cap. Note that all other cap scenarios described in this section will also include the 2020 GHG cap, though this is not explicitly stated in the description of these scenarios.

Greenhouse gas emissions in the *Reference* scenario decline from 2010 levels (420 MMTCO2e) decline to around 280 MMTCO2e by 2050. This 27% reduction in GHG emissions below 1990 levels results from a variety of changes to the energy system such as growth in renewable electricity generation, increased efficiency in end use appliances and vehicles, and growth in the use of natural gas and biofuels for transportation. These changes are driven, in part, by policies in place to 2030 (e.g. RPS, ZEV mandate, CAFE, LCFS and others) and, in part, by cost reductions for renewable generation, and efficient appliances. Each of these sector specific changes will be discussed in more detail.

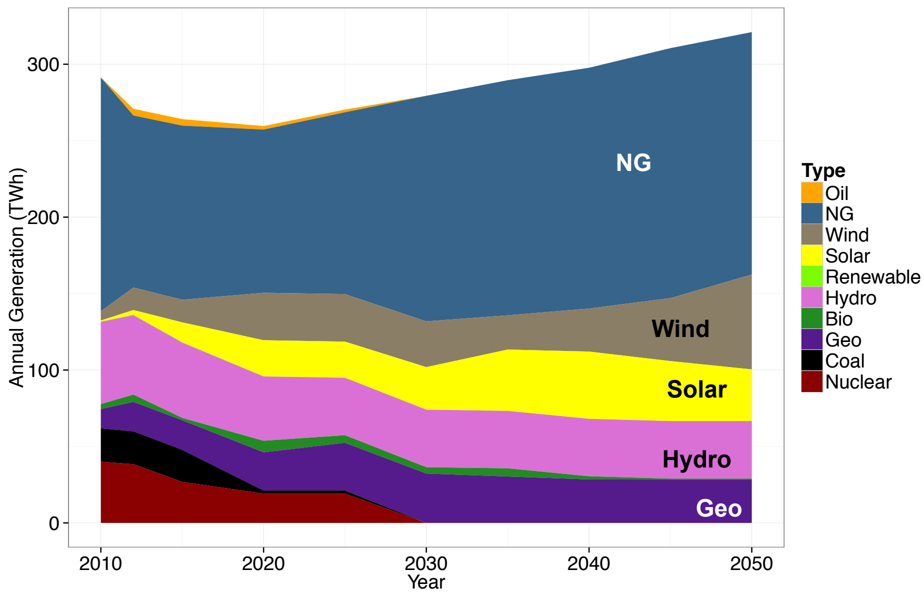

Figure 1. Electricity generation by resource in the 2020 GHG cap (reference) scenario.

Figure 1 shows the electricity generation by resource type in the reference scenario. Overall demand for electricity grows slightly from 2010 to 2050, declining in early years due to efficiency improvements and then increasing again due to population growth. Approximately 34% of generation is from renewable resources in 2020 and 2030 (exceeding the 33% RPS target), and about 39% in 2050. The carbon intensity of electricity declines from 325 gCO_2/kWh to around 210 g/kWh in 2030 and 167 g/kWh in 2050.

Transportation fuel usage, shown in Figure 2, shows that overall transportation fuel demand declines slightly (~9%) from 2010 to 2050. Gasoline and diesel fuel usage declines from 71% of all fuel usage in 2010 to only 24% in 2050 and all fossil-based transportation fuels declines from 95% of fuel usage in 2010 to 53% in 2050. Biofuels and natural gas fuels rise to 35% and 13% of total fuel demand respectively by 2050, driven by cost reductions and the rising price of petroleum.

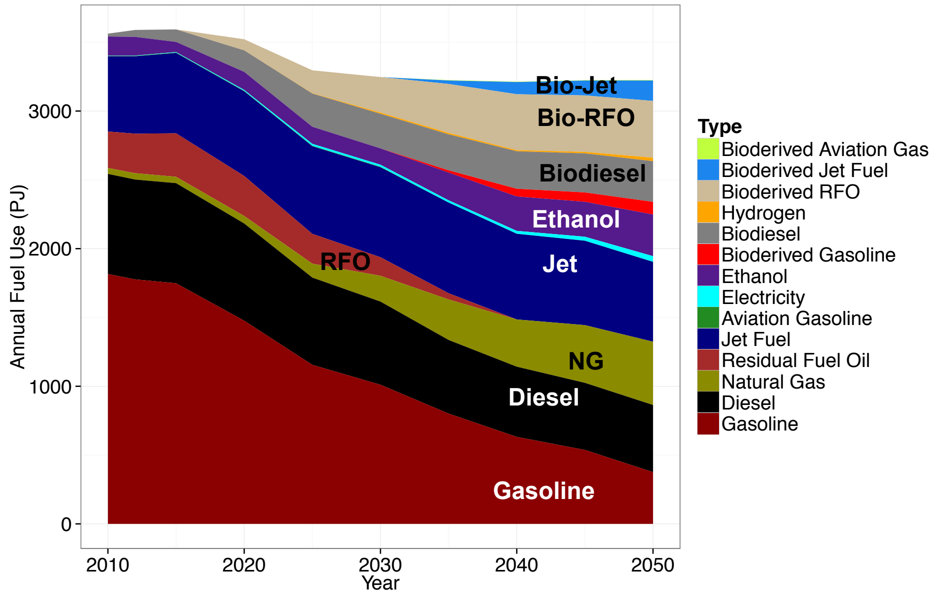

Figure 2. Transportation fuel demand by fuel type in the 2020 GHG cap (reference) scenario.

Light-duty vehicles (LDVs) account for the largest share of transportation energy usage, making up approximately half of total transportation fuel demand in 2010 (about 14.6 billion gallons of gasoline equivalent (GGE)). On-road fleet average vehicle efficiency in the light duty sector increases substantially achieving 66 miles per gallon of gasoline equivalent (mpgge) by 2050, an increase of 180% over 2010 levels (23 mpgge). This efficiency improvement reduces LDV fuel consumption to about 5.7 billion GGE in 2050 or about 21% of 2050 total transportation fuel demand, because of greater growth in heavy-duty and aviation activity and greater increase in LDV efficiency relative to other sectors.

The LDV vehicle mix in this *Reference* scenario continues to be dominated by combustion vehicles to 2050, though an increasingly large proportion of those combustion vehicles are hybrids (see Figure 3). ZEV and partial ZEV technologies (battery electric vehicles (BEVs), plug-in hybrid vehicles (PHEVs) and fuel cell vehicles (FCVs)) make up approximately 11% (2.4 million) of the light-duty fleet in 2030 and 26% of the fleet (6.5 million) in 2050. BEVs make up the majority of these vehicles, accounting for 20% of the fleet (5 million) in 2050 though only about 12% of fleet VMT. This discrepancy is due to the presence of three consumer groups with varied average driving behavior and BEVs are preferentially adopted by low VMT consumers driving fewer miles, due to range limitations for these vehicles. Hybrids are chosen preferentially among consumers with longer driving distance, accounting for 64% of vehicles in 2050 but 76% of VMT.

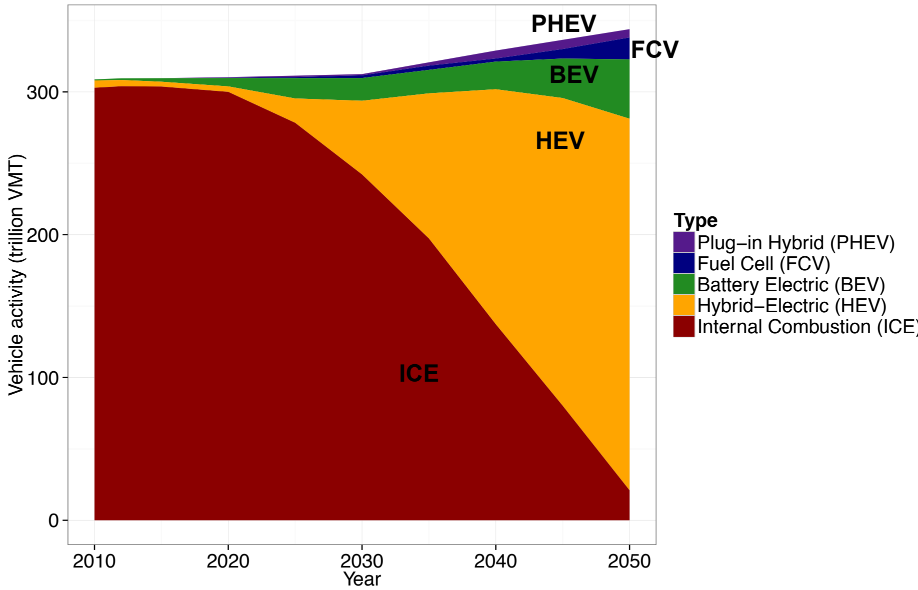

Figure 3. Light-duty vehicle miles traveled by vehicle category in *Reference* scenario.

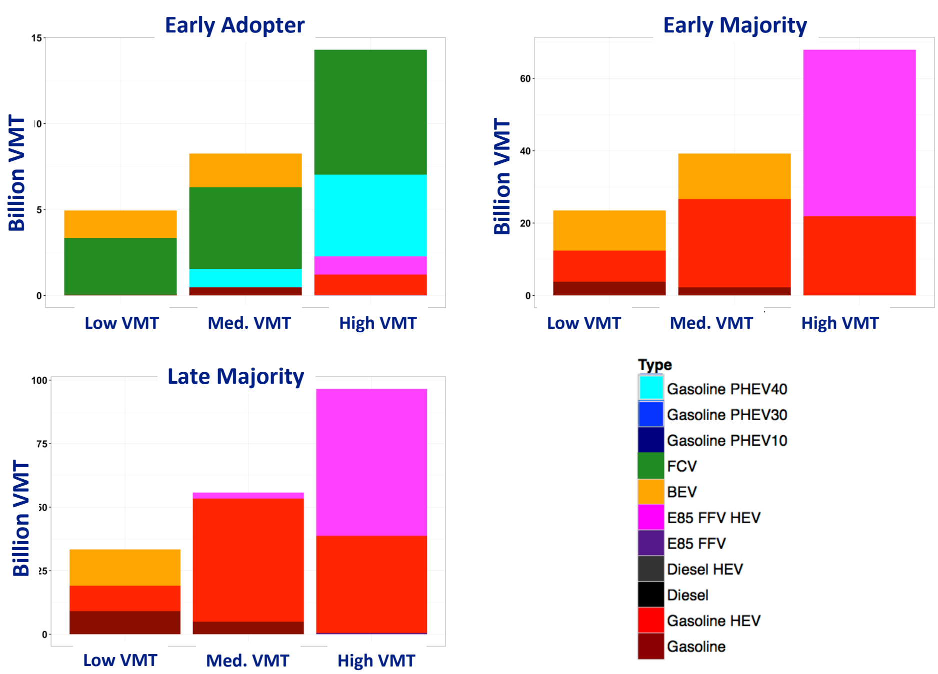

Figure 4. Breakdown of vehicle activity in 2050, *Reference (*2020 cap) scenario

Figure 4 shows how the disaggregation of consumers into different types impacts the fleet of light-duty vehicles in 2050. Splitting consumers into groups based upon risk preference and daily driving distance enables diversification of vehicle adoption and usage. These results are more realistic than previous CA-TIMES results because they reflect differences in the way consumers perceive utility and also use their vehicles. Among advanced vehicles, BEVs are purchased primarily by consumers who drive fewer miles, while PHEVs and FCVs are used by consumers who drive more miles. Risk- averse consumers (late majority) tend to buy more conventional vehicles like hybrids rather than electric or hydrogen powered vehicles.

Overall primary energy usage for the *Reference* scenario (shown in Figure 5) shows a slight decrease (2%) over the modeling period with growth in natural gas and biomass usage over the modeling period (34% and 11-fold increase respectively). Petroleum demand declines from 60% to 21% of primary energy use over the modeling period.

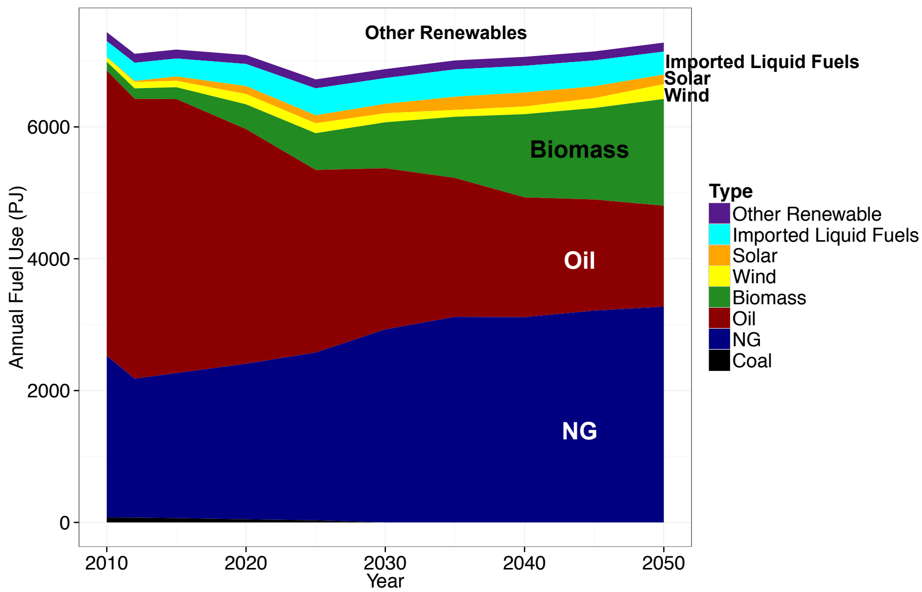

Figure 5. Primary energy resource contributions in the *Reference* scenario.

Building and appliance efficiency in the residential and commercial sectors increases fairly significantly in the *Reference* scenario. This efficiency comes about due to incremental improvements in efficiency across service demands as well as changes to new technologies (i.e. CFL and LED lighting). Overall efficiency across all sector services increased by approximately 50% in the residential sector and 90% in the commercial sector. The larger increase in efficiency for commercial is due in part to the fact that lighting makes up a larger fraction of service demand in the commercial sector than in residential (25% vs 8%). Residential energy use continues to be dominated by natural gas fuel for space heating and water heating, while cooling, refrigeration, televisions, and other are the primary demands for electricity. Lighting moves from being one of the largest sources of residential electricity usage to a small contributor to electricity demand due to the substantial increase in lighting efficiency. The largest energy uses in the commercial sector are for heating and cooling as well as lighting and miscellaneous.

3.1.2 Stringent GHG Emissions Cap Scenarios

Beyond the 2020 GHG emissions cap that is embedded into state law, the State of California has two additional targets that have been identified by the current and previous executive branches: the 80% GHG reduction target below 1990 levels by 2050 (first announced in 2005) and a 40%

GHG reduction target by 2030 (announced in 2015) (Brown 2015). The 80% reduction target has been studied more extensively (e.g. Morrison et al 2014, Wei et al 2013, Greenblatt and Long 2012), including previous iterations of the CA-TIMES model (Yang et al 2015).

In this paper, we analyze three different additional GHG reduction trajectories beyond the 2020 target. The first is the 40% GHG reduction by 2030 (2030 cap), the second is the 80% reduction by 2050 (2050 cap) and the third is the combination of these two policies, 40% reduction by 2030 and an 80% reduction by 2050 (2030-50 cap).

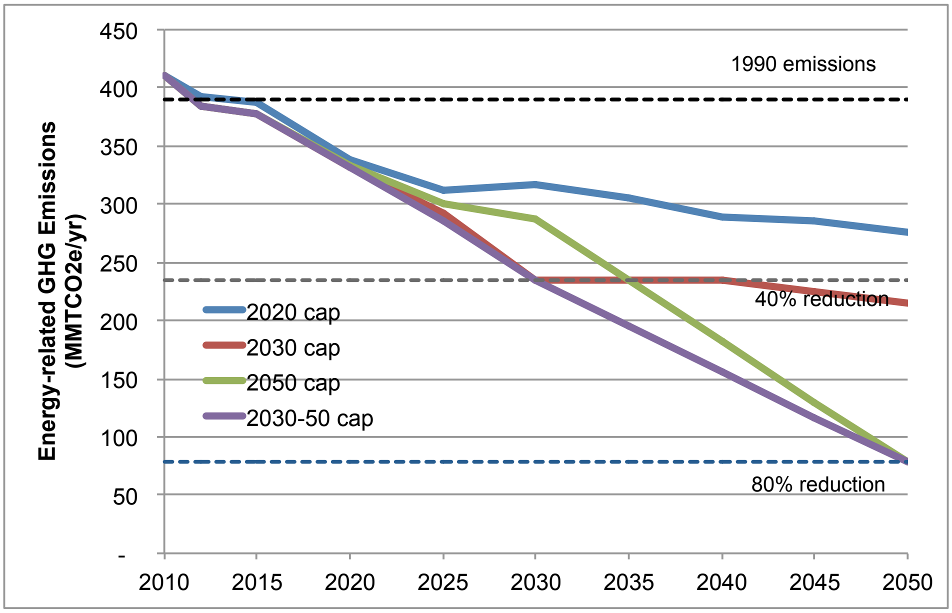

Figure 6. Greenhouse gas emissions (million metric tonnes of CO_2-equivalent, MMTCO2e) in the four primary cap scenarios.

Figure 6 shows the greenhouse gas emissions trajectories for the four different carbon cap scenarios discussed in this section. Each of the scenario runs has very similar emissions trajectory to 2020. This is due to slow adoption and turnover for existing vehicles and other appliances and also to the fact that each of these scenarios has an equivalent set of policies to 2025-2030. Emissions diverge significantly by 2030 because of the various stringency levels of these scenarios[2]. After 2030, emissions in the three additional GHG policy scenarios meet the additional GHG caps, though the 2030 cap scenario exceeds this level in the 2045-2050 timeframe.

The rest of this section will discuss the technology and resource adoption for each of these scenarios and compare to the 2020 cap scenario.

For electricity generation, the generation mix or total generation does not vary significantly between scenarios in 2020 (see Figure 7). Total generation in 2030 is fairly similar as well, though the generation mix can be quite different depending on the stringency of the cap in 2030. Scenarios achieving a 40% GHG reduction in 2030 see significantly higher levels of wind and

[2] The 2030 reduction level in the 2050 cap scenario is 26.7% below 1990 levels (or 280 MMTCO2e).

solar generation (76% renewable (including hydro) in the 2030 cap scenario vs 68% renewable in the 2030-50 cap scenario vs 47% in the 2020 cap scenario and 48% in the 2050 cap scenario). This is due primarily to wind and solar renewable generation as fairly low cost options for decarbonization to meet this stringent target in a short timeframe. The 2050 electricity generation is where we see the largest differences, with the scenarios with the 80% reduction target in 2050 having nearly twice as much electricity generation as the other scenarios. This is due to major electrification and electrolytic hydrogen production in transportation but also including electricity growth across many different sectors and end-uses (including industrial processes and building space and water heating).

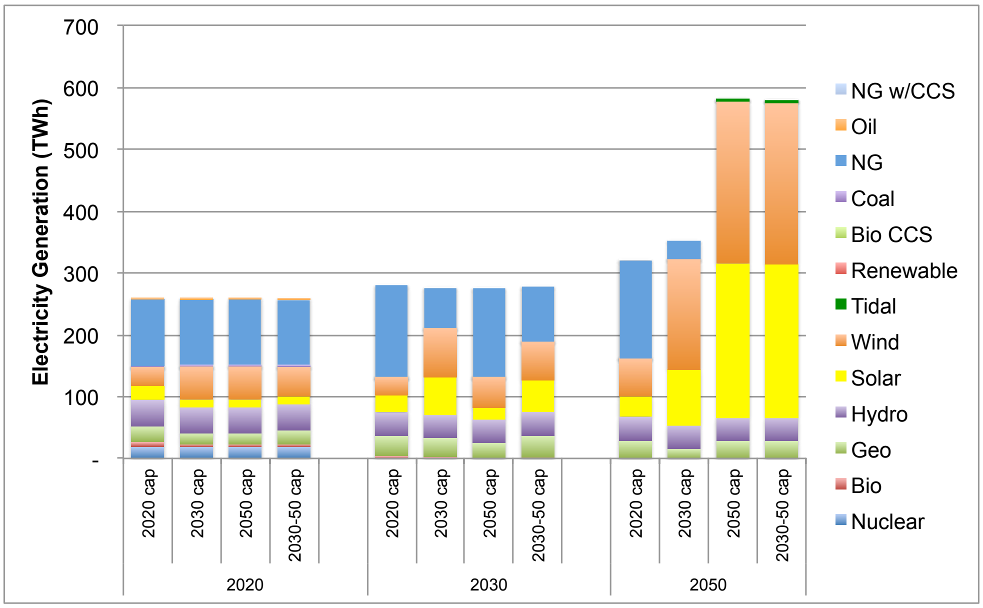

Figure 7. Electricity generation mix for the four primary cap scenarios.

The generation mix in 2050 is essentially 100% renewable for the two scenarios with 80% reduction. The very large contribution of intermittent renewables is managed by several mechanisms for balancing supply and demand that are modeled in CA-TIMES. These include demand response for buildings, electric vehicle charging, electricity storage technologies and flexible generation of H_2 for transportation purposes. Flexible hydrogen production accounts for approximately 12% of total electricity demand in 2050 (~69 TWh). These grid management strategies lead enable balancing of electricity supply and demand at these very high levels of intermittent generation.[3]

Figure 8 shows demands for electricity by sector for the four primary scenarios. In the 2050 cap and 2030-50 cap scenarios (those with the 80% GHG reduction requirement), we see the very large increase in demand for electricity in 2050 and this growth occurs across all sectors but especially prominent in transportation, fuel production (primarily hydrogen), and residential.

[3] This model does not have the temporal or spatial resolution to do a complete analysis of the operation of the electric grid and supply demand balance. However, based upon the simplified model temporal resolution, which can capture the broad changes in electricity supply and demand seasonally and diurnally, the model appears to build sufficient balancing capacity in terms of energy storage, and flexible loads.

Electrification of these sectors enables significant improvements in efficiency associated with electrification as well as the zero-carbon electricity.

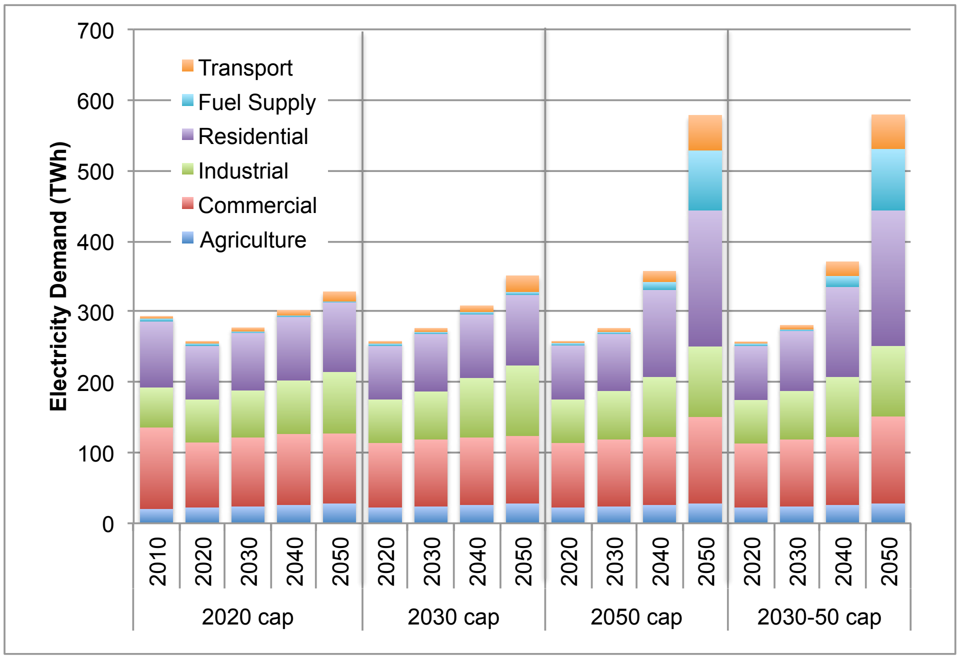

Figure 8. Electricity demand by sector across four primary scenarios.

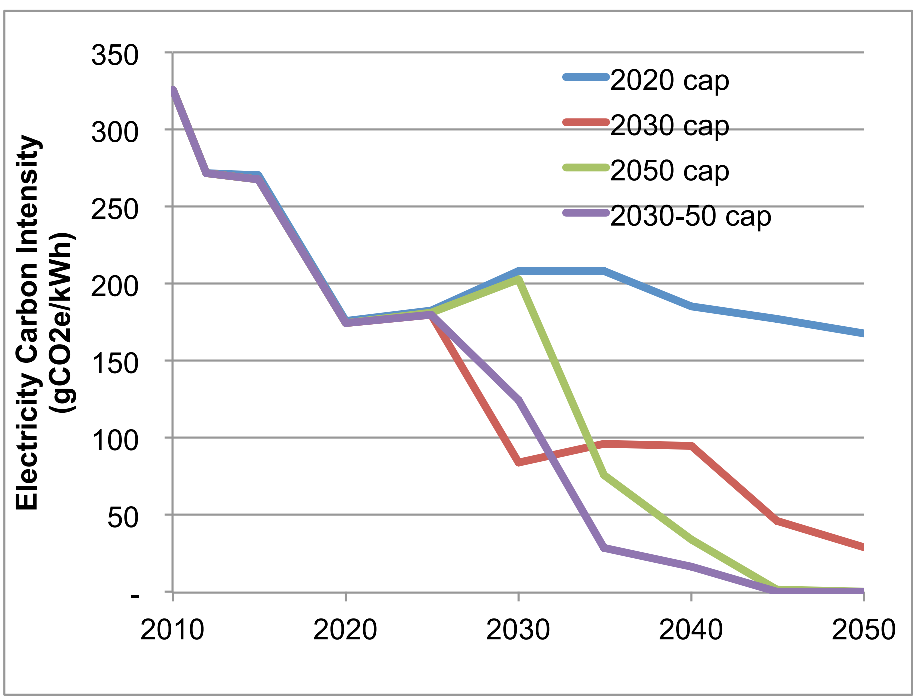

Figure 9. Electricity carbon intensity for the four primary scenarios.

Figure 9 shows how the carbon intensity of electricity generation changes over time. Through 2025, the generation mix and carbon intensity are the same across scenarios, but in 2030 there are significant differences in order to meet the more stringent 2030 cap for some scenarios. The 2030 cap scenario has the lowest carbon intensity at around 84 gCO2e/kWh, while the 2030-50 cap scenario has a CI of 125/kWh. Electricity CI in the 2020 and 2050 cap scenarios remains at around 200/kWh. The two scenarios with an 80% reduction cap achieve 0g/kWh by 2045.

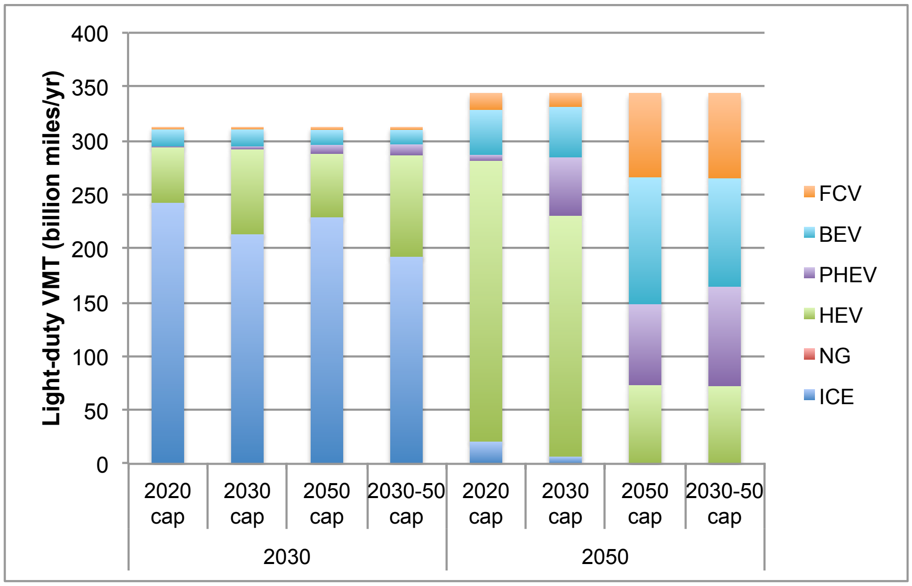

Figure 10. Light-duty vehicle for the four primary cap scenarios.

Figure 10 shows the mix of light-duty vehicle activity in billions of VMT per year for the primary scenarios. We see that ZEV activity across each of the scenarios (BEVs, FCVs and PHEVs) in 2030 is very similar at 6-8% (primarily due to presence of the ZEV mandate through 2025). ZEV stock (not shown in the figure) is 11-12% in 2030 (2.4 to 2.6 million vehicles). 2050 vehicle activity is quite different across the four scenarios, except for the two scenarios with the 2050 80% GHG reduction target. These scenarios have around 18 million ZEVs in 2050, accounting for 79% of LDV VMT. HEVs make up the remainder of LDV miles in these stringent cap scenarios. HEVs make up the vast majority of VMT while FCVs are 4% and BEVs contribute 12-14% in the 2020 and 2030 cap scenarios. However, PHEVs are more much more prevalent in the 2030 cap scenario than in the 2020 cap scenario.

Figure 11 shows how the mix of aggregate transportation fuel usage varies across the different cap scenarios. Total fuel consumption is fairly similar in 2030 across cap scenarios, though the use of gasoline and diesel fuels is about 20-25% lower in scenarios with a stringent 2030 cap relative to the *Reference* scenario. Biofuels makes up a growing proportion of the fuel mix in 2030 (19-27%) and 2050 (31-39%). The biggest change occurs in the 2050 timeframe where gasoline and diesel usage are dramatically lower in the scenarios with the 80% reduction cap in 2050 (82% below 2010 levels). Hydrogen and electricity are also prominently used is these scenarios accounting for 8% and 6% of total fuel demand respectively in 2050. Natural gas is more prominently used as a transportation fuel in scenarios that do not have the stringent 80% reduction target in 2050, because of its modest GHG reduction potential.

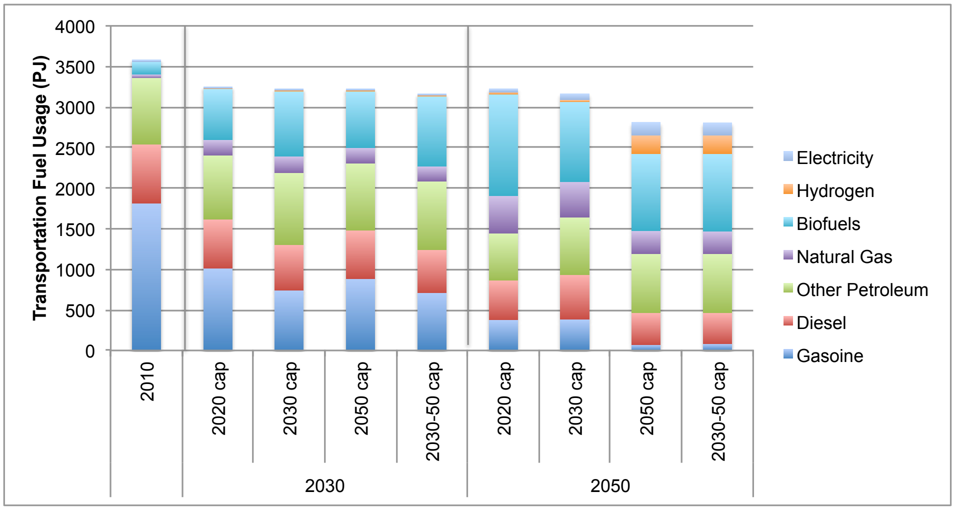

Figure 11. Transportation Fuel Usage by year for the four primary cap scenarios.

It is important to realize that approximately 800PJ (23%) of fuel usage in 2010 and between 900-1100PJ (32-36%) of fuel usage in 2030 and 2050 are in the aviation and marine sectors where most of activity crosses state boundaries and does not contribute to the emissions being regulated under the emissions cap. These fuels are primarily found in the "Other Petroleum" category as well as some contribution to biofuels usage.

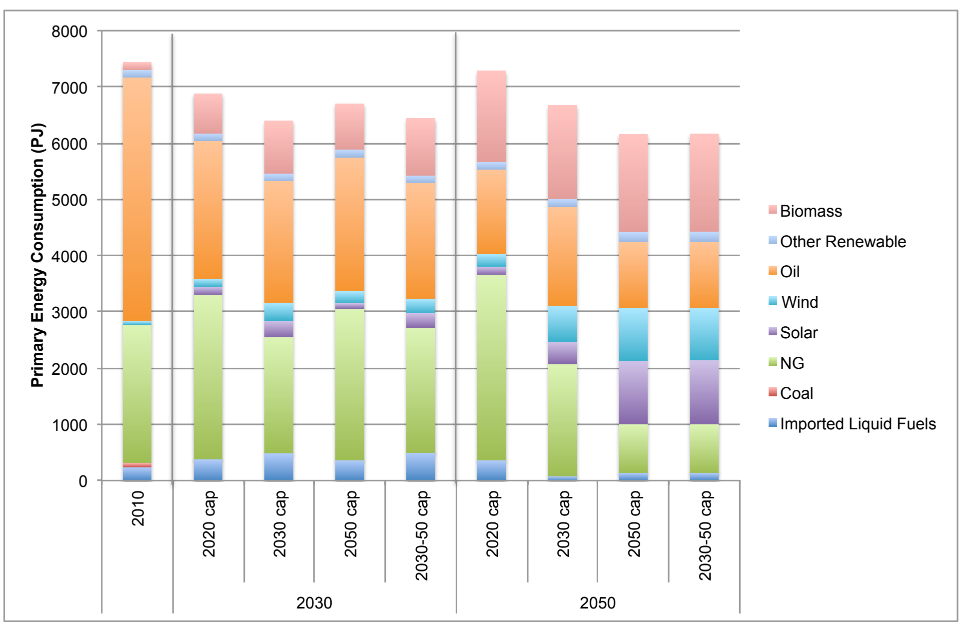

Figure 12. Primary energy resource consumption across the four primary cap scenarios.

Figure 12 shows the primary energy resource consumption over the four scenarios. In 2030 scenarios with the 40% GHG reduction target, show a shift away from natural gas towards wind and solar (as mentioned in discussion about changes to electricity generation). The primary energy consumption is 15% lower in scenarios with an 80% GHG cap in 2050 relative to the *Reference* scenario and the contribution of wind and solar displaces a great deal of natural gas resource usage. Oil consumption is also about 22% lower in these stringent 2050 scenarios relative to the *Reference* scenario.

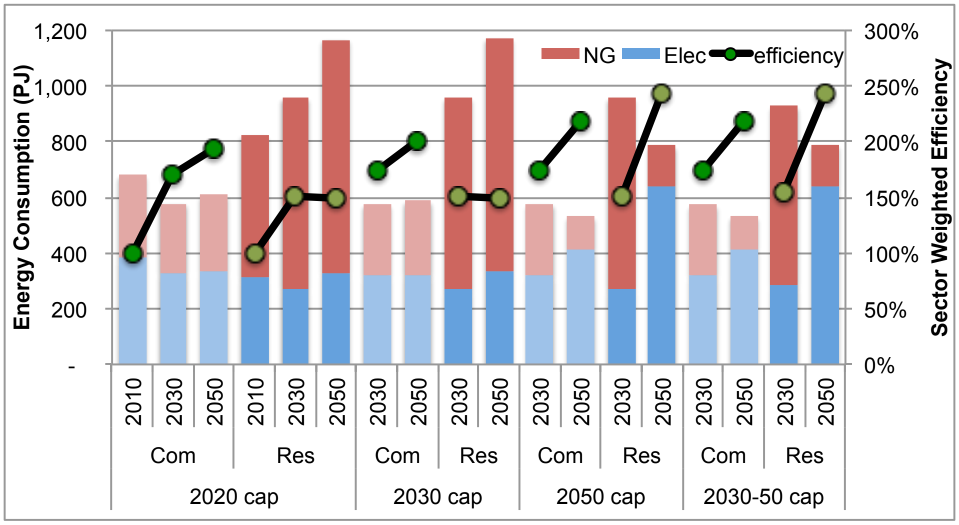

Figure 13. Residential and commercial fuel use and sector efficiency for the four primary scenarios

Figure 13 shows the fuel consumption and efficiency changes across the buildings sectors (residential and commercial) for the different scenarios. As previously stated, even in the *Reference* scenario, efficiency improvements are seen in these two sectors (93% improvement in commercial and 49% in residential in 2050, relative to 2010). Overall fuel demands decline for the commercial sector while demand for fuel (primarily natural gas) rises in residential due to water heating and space heating activity increases. These patterns are exactly the same in the 2030 cap scenario as well. The 2050 cap and 2030-50 cap scenarios show substantial increases in efficiency in 2050 beyond the *Reference* scenario, with commercial efficiency improving by 120% and residential efficiency improving by 140%. In addition, electrification of appliances increases the share of electricity used in these sectors. In the reference scenario, electricity makes up 36% and 57% of residential and commercial energy use respectively in 2010 and 28% and 55% in 2050. Residential electricity use declines because of the growing demand for water and space heating. However, in the scenarios with an 80% GHG reduction target, the share of electricity climbs significantly in these sectors. Electricity makes up 80% and 78% of residential and commercial energy use respectively in 2050, in order to reduce emissions from natural gas combustion.

3.1.3 Alternative Policies (50% RPS and 50% Petroleum Reduction)

This section focuses on understanding how changes in the specific policies can affect the technology choices in the GHG reduction scenarios. Two relatively newly proposed/enacted policies, the 50% RPS policy and the 50% petroleum reduction target[4], are analyzed in this section. The renewable percentage and petroleum reduction levels for 2030 (below 2010 levels), can be calculated for the four primary scenarios.

As previously shown in Figure 7 and discussed in the previous section, the 2030 RPS renewable percentage[5] is 34%, 63%, 34% and 55% for the 2020 cap, 2030 cap, 2050 cap and 2030-50 cap scenarios respectively. So the two scenarios with the 40% GHG cap in 2030 could achieve 50% renewable generation even without implementing the RPS policy. For the 2020 cap and 2050 cap scenarios, implementing the 50% RPS would increase the adoption of renewable generation in 2030 by approximately 50%. For the 2050 cap scenario, the GHG cap is binding, meaning that the 26.7% GHG reduction target is just met (but not exceeded), in order to minimize the system cost. As a result, when a 50% RPS is implemented, lowering the GHG emissions from the electricity sector, emissions from other sectors will rise if they can help lower system costs. GHG emissions in 2030 from the electric sector are reduced by nearly 18 MtCO2e with the implementation of the 50% RPS for the 2050 cap scenario, but transportation emissions rise by about 6 MtCO2e, leading to a net difference of around 12 MtCO2e (287 MtCO2e vs 275 MtCO2e). Because the GHG cap in the 2020 cap scenario is not binding in 2030, the implementation of a more stringent RPS impacts the emissions from the electric sector, but does not have a significant impact on emissions from other sectors. The 2050 RPS percentage in the regular 2020 cap scenario is 39% with the 33% RPS and 52% with the more stringent 50% RPS.

Petroleum consumption of on-road vehicles (from 2010 levels) is entirely gasoline and diesel consumption[6].

Table 1. On-road petroleum reduction levels for four primary scenarios in 2030 and 2050.

	2030	2050
2020 cap	41%	68%
2030 cap	50%	66%
2050 cap	41%	97%
2030-50 cap	52%	96%

Shown in Table 1 are the petroleum reduction levels for the four primary cap scenarios (without the petroleum reduction policy applied). Even without the petroleum reduction policy, both the 2030 cap and 2030-50 cap scenarios meet the 50% petroleum reduction target. The two scenarios without a 40% GHG target in 2030 are further from this goal (at 41% reduction). All scenarios achieve greater than 50% reduction in petroleum usage in 2050, even the 2020 cap scenario (primarily owing to the high cost of crude oil). The scenarios with an 80% GHG

[4] The 50% renewable portfolio standard was implemented in SB350, passed in late 2015, while the 50% petroleum reduction was not included in the final bill.

[5] We assume that the definition of renewables for RPS purposes continues to exclude existing and new large hydroelectric power.

[6] Petroleum consumption for this policy is counted as gasoline and diesel consumption in the light-duty, medium-duty, heavy-duty truck categories, excluding gasoline and diesel consumption for off-road and agricultural vehicles.

reduction cap, reduce their petroleum consumption in the on-road transport sectors almost entirely (96-97% reduction).

Applying a 50% petroleum reduction target to these scenarios in 2030, increases all the 2030 levels to at least a 50% petroleum reduction. Because all of these scenarios show substantial usage of natural gas and biofuels in non-road transportation sectors in 2030, much of these non-petroleum fuels can be shifted towards the on-road sectors and increase the petroleum reduction levels in the 2020 cap and 2050 cap scenarios from 41% to 50% without too much additional alternative fuel usage. Total transportation alternative fuel usage increases from ~24% to 27% when the petroleum reduction policy is applied to the 2020 cap scenario, leading to a slight reduction in transportation emissions (~8MtCO2e in 2030). Total alternative transportation fuel usage stays constant at 26% when applied to the 2050 cap scenario. Switching fuels around is sufficient to reduce on-road petroleum usage to the target level because of higher alternative fuel usage in the 2050 cap scenario. The emissions cap is binding in 2030 in the 2050 cap scenario, and this small change to transportation fuels does not reduce overall transportation emissions or total emissions.

3.1.4 GHG reductions and mitigation costs

We have briefly described the major technology, fuel and resource changes for each of the scenarios described in the previous sections. Accompanying these changes to the energy technologies used in the energy supply and end-use sectors are changes in investment and operating costs[7]. These incremental cost changes for the GHG cap scenarios are calculated with respect to the *Reference* scenario. Cumulative GHG emissions are also calculated relative to the *Reference* scenario, enabling a calculation of the average abatement cost for a given GHG cap scenario.

$$Mitigation\ cost = \frac{Total\ incremental\ cost}{GHG\ reduction} = \frac{(C_{GHG} - C_{Ref})}{(E_{Ref} - E_{GHG})} \qquad [1]$$

Equation 1 shows the calculation for mitigation cost used in this analysis and it is important to note that costs and emissions differences can be calculated across many different time periods, such as on an annual basis or over the entire modeling period. We report these values on for the entire modeling period.

[7] It is important to remember that the costs associated with technology changes in the industrial and agricultural sectors are not included in the cost calculations because we do not explicitly model technology adoption in these sectors. The only costs associated with these sectors relates to the fuel and electricity requirements needed to satisfy the exogenous fuel demand scenarios specified for these sectors.

Table 2. Incremental cost, GHG and mitigation cost for three GHG cap scenarios (2010 to 2050).

	2030 cap	***2050 cap***	***2030-50 cap***
Cumulative GHG difference (MMTCO2e)	1,722	2,566	3,297
Cost difference ($Millions, undisc)	-77,234	15,250	32,553
Mitigation Cost Avg. ($/tonne CO_2, cumulative undiscounted, 2010-2050)	-$44.9	$5.9	$9.9
Marginal Mitigation Cost ($/tonne CO_2, undiscounted, 2050 only)	N/A	$714	$813

Results for the incremental cost and emissions for these GHG cap scenarios are shown in Table 2. For the 2030 cap scenario, the requirement for a 40% reduction in emissions below 1990 levels by 2030 leads to approximately 1.7 $GtCO_2$ reduction in cumulative emissions relative to the *Reference* scenario (which has a cumulative emissions of 13.2$GtCO_2$, a savings of about 13%). Most interesting about this scenario is the negative incremental cost relative to the *Reference* scenario (~$77 billion), indicating that this scenario is actually lower cost than the *Reference* scenario.

The major changes in cost between the *Reference* scenario and the 2030 cap scenario relate to the major changes outlined earlier: in the electric sector, significantly higher renewable generation leads to higher investment costs, but slightly higher efficiency in transportation, a shift towards biofuels and reduction in natural gas generation leads to significant savings in fuel. A key assumption underlying this cost reduction is the use of the AEO2015 Reference case oil and gas prices, which grow significantly to 2050 (to ~$150/bbl for oil and $8.80/MMBTU for gas). The savings from this reduction in oil and gas usage exceed the additional investment costs needed to achieve the 2030 target. This leads to an average mitigation cost of around *negative* $45/tonne.

One important point is that some may be confused by the fact that the policy scenario is lower cost than the *Reference* scenario. CA-TIMES is an optimization model so it should find the lowest cost solution for all scenarios, including the *Reference* scenario, and adding another GHG constraint onto the model (as is the case in the 2030 cap scenario) should not lead to a lower cost solution. This unusual result is a product of the difference in how we calculate our incremental costs and how the model calculates the costs that make up the objective function used for the model optimization. The CA-TIMES model makes use technology specific hurdle rates as well as “disutility costs” to more adequately simulate real-world behavior, by inflating the cost of some options relative to others and influencing which technologies are chosen in the optimization. The hurdle rates are meant to represent consumer discounting of future costs such that technologies with higher initial capital costs, but with lower operating costs and ultimately, lower lifecycle costs may not be chosen (the so-called “efficiency gap”). Disutility costs are included to represent non-economic factors such as differences in utility and convenience for vehicle technologies. These factors are included in the objective function, which affects the technology investment decisions in the model, but these extra “costs” are not monetary costs and, as a result, they are removed when we calculate the economic costs of emissions reductions. The difference between the costs included in the optimization and the costs included in the incremental cost assessment can lead to this result of a lower cost GHG reduction scenario relative to the *Reference* scenario.

One final important factor that also contributes to the reduction in cost for a GHG reduction scenario is that our model includes investment cost reductions for some vehicle technologies (mainly battery and fuel cell powered vehicles) related to technological learning. In scenarios where the adoption of these technologies is higher (i.e. GHG reduction scenarios), the cost of these vehicles is lower owing to learning from greater production and economies of scale.

Also shown on Table 2 are the costs associated with the 2050 cap and 2030-50 cap scenarios. These two scenarios have positive incremental costs, indicating that emissions reductions lead to higher costs than the *Reference* scenario. However, these incremental costs are relatively small, $15 billion for the 2050 cap scenario and $33 billion for the 2030-50 cap scenario for the entire modeling period from 2010-2050. Given the large cumulative GHG reduction from these two scenarios, we calculate an average GHG abatement cost of around $6/tonne and $10/tonne for 2050 cap and 2030-50 cap respectively.

3.2 Policy interactions

3.2.1 Descriptions of combinations of complementary policies and carbon caps

The policy scenario analysis examines a number of policies that can be implemented in California across several different sectors and are described in detail in Section 2.3. The objective of this analysis is to understand the effect of these policies in the framework of CA-TIMES and how they affect the energy production/usage and technology adoption in California. More specifically, the analysis is a comprehensive examination of all combinations of possible policy scenarios among the six different sets of policies. The different policy categories and their affiliated levels of implementation lead to a rich set of policy suites for examination. These policy combinations form a total of 1,512 scenario runs of the CA-TIMES model, which are then run on the Department of Energy's National Energy Research Scientific Computing Center (NERSC), a supercomputing cluster that provides computational power that allows for the full set of scenarios to be examined. The results of each individual run is parsed and then aggregated at different levels to allow for visualization among different metrics.

3.2.2 Visualization of results re: technology mix, system costs and cumulative emissions

An individual run of CA-TIMES provides a rich output that allows us to examine many different aspects of California energy system. However, due to the large number of policy scenarios that were run, the results are aggregated in various ways in order to for visualizations to be possible across a number of important factors. An overview of the overall policy effect on cumulative emissions and total system cost through 2050 is shown in Figure 14. Each point represents a single model run of CA-TIMES corresponding to a specific combination of implemented policies. The points are clustered by color representing the five different emission cap scenarios. From an emissions perspective, the fact that there is almost no overlap between clusters indicates that there are very few combinations of policies that reduces emissions to the same degree as an emissions cap scenario. Even the most stringent set of policies with regards to emissions (the lowest point in a particular cluster) results in higher cumulative emissions than the next cluster of emissions corresponding to a cap scenario. For total system cost, generally reducing emissions results in higher costs. However, the trend is clearly not perfectly linear and has variance even at a single cumulative emission outcome. This indicates that certain policy instruments, for the purposes of emission reduction, are more efficient than others. Two policy interactions are shown in Figure 15 and Figure 16, a more comprehensive set of results can be found in the Appendix.

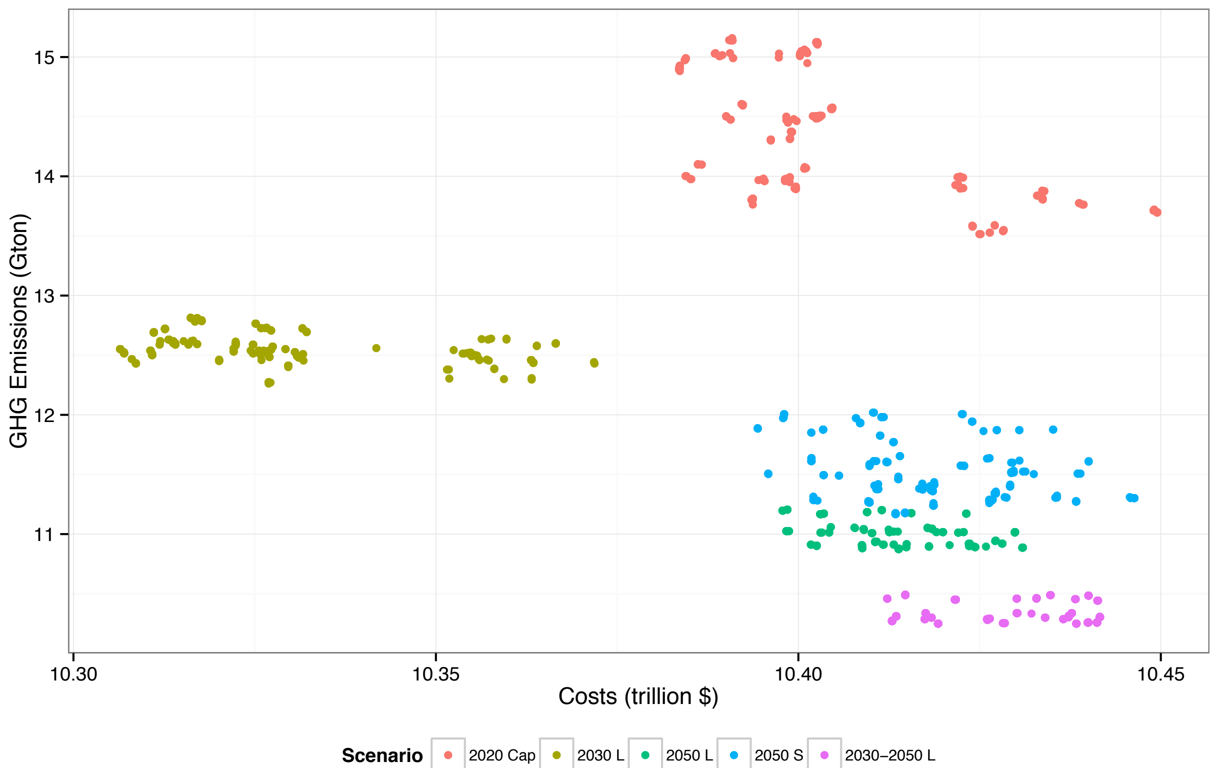

Figure 14: Overview of 1,512 policy scenario outcomes arranged by comparing each individual run's cost (trillions of $) versus greenhouse gas emissions (gigatons of CO2eq). The results are grouped by colors representing different emission cap scenarios.

The effect of the RPS policy on cumulative emissions can be seen in Figure 15. The different emission levels shown in each of the boxplots represent the full set of 1000+ policy scenarios. Each box represents the full range of emissions in a particular cap scenario (represented by the panel), a particular RPS stringency (represented by the x-axis), and across all the remaining policies (i.e. every stringency level of ZEV, LCFS, petroleum reduction, and CAFE). The red triangle represents the "base" set of policies with the exception of the ones being varied. In Figure 15, each triangle represents the fixed set of policies with ZEV through 2025, LCFS through 2025, no petroleum reduction requirements, and CAFE through 2025 but varied across the different stringency levels of RPS and the different cap scenarios. Since renewables are often the lowest hanging fruit for emissions reduction, any substantial measures to reduce emissions will often employ the use of renewables with or without RPS policies. As a result, changes in the RPS policy do not have as a dramatic effect on emissions in higher cap scenarios due to the fact that renewable generation is employed regardless of the policy in order to meet the emission requirements. The largest decreases in emissions are seen in the 2020 cap scenario, with a decrease in overall emissions by over a gigaton through 2025. However, while the effect is not as pronounced in the 2030 and 2050 cap scenarios, a slight decrease in cumulative emissions is observed as the stringency of the RPS is increased. This is likely due to the fact that while in the later periods renewables are added, the RPS may introduce renewable generation earlier than would otherwise have been adopted and therefore lead to lower overall cumulative emissions in California. In addition, the span of the boxplots indicates the range of emissions resulting from other policies. Due to the relatively small variance in emissions ranges, the interaction with other policies does not lead to large differences in emission levels. This is confirmed when we construct similar boxplots across other policies rather than just RPS, the cumulative emissions decrease is very small in all other groups of policies relative to the decreases seen when implementing the RPS.

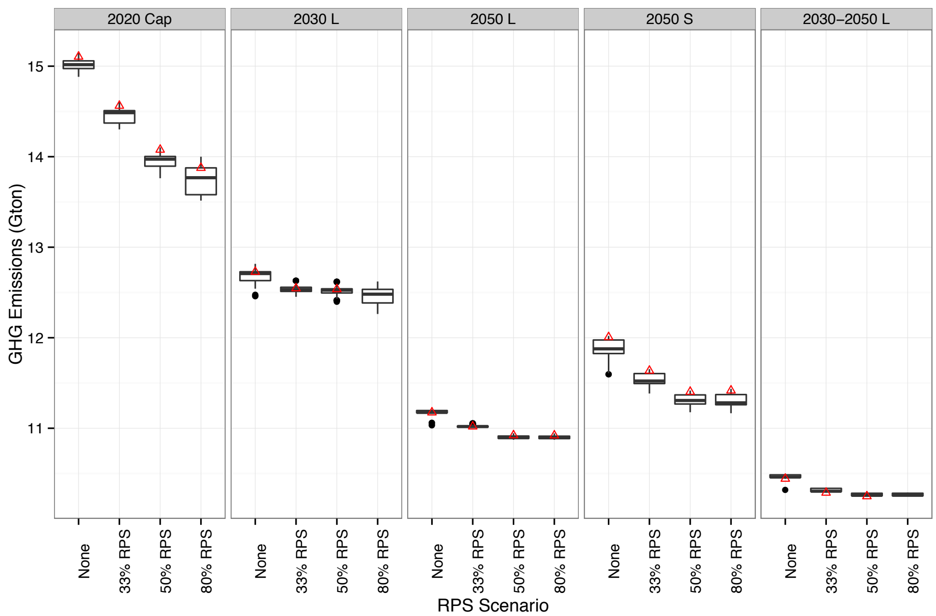

Figure 15: Cumulative emission distributions in 2050 across all policy scenario combinations. The emissions are grouped both by the five emission cap scenarios as well as different renewable portfolio standards. The boxplot of costs captures the variance resulting from other policies, whiskers are 95th percentile of the data and dots are outliers beyond the 95th percentile. The red triangles indicate our baseline policy scenarios.

For the adoption of different alternative fuel vehicle technologies, a focus was placed on analyzing the effects of the ZEV mandate across different levels of the cap scenarios (Figure 16). The mandate itself varied between having no mandate, a 22% requirement by 2025, and a 60% requirement by 2050. The results of the policy scenarios reveal that the ZEV policy has a large impact on several technologies under certain cap scenarios. In the baseline 2020 cap scenario as well as the 2030 cap scenario, there is higher adoption of both BEVs and FCVs as the stringency of the ZEV mandate increases. However, there is no effect for PHEV20 technology except in the 2030 cap scenario. In the higher 2050 cap scenarios, the variation in technology adoption is much smaller. An increase can be seen in FCVs and BEVs, the PHEV20s stay the same, and the longer range PHEV40s exhibit a slight decrease in adoption. One additional observation can be made on the relatively large range of adoption values for FCV technologies in the 2030 cap scenario. The variance in results indicates that the adoption of hydrogen vehicles is sensitive to other policies besides the ZEV mandate. A closer examination of the FCV adoption in the 2030 cap scenario across the remaining non-ZEV policies reveals that the remaining variation is almost entirely due to the LCFS policy. The increased requirement for low carbon fuel sources leads to the promotion of hydrogen as a transportation fuel source. The ZEV and LCFS policies interaction explains most of the variation seen among different FCV adoption levels in the 2030 cap scenario.

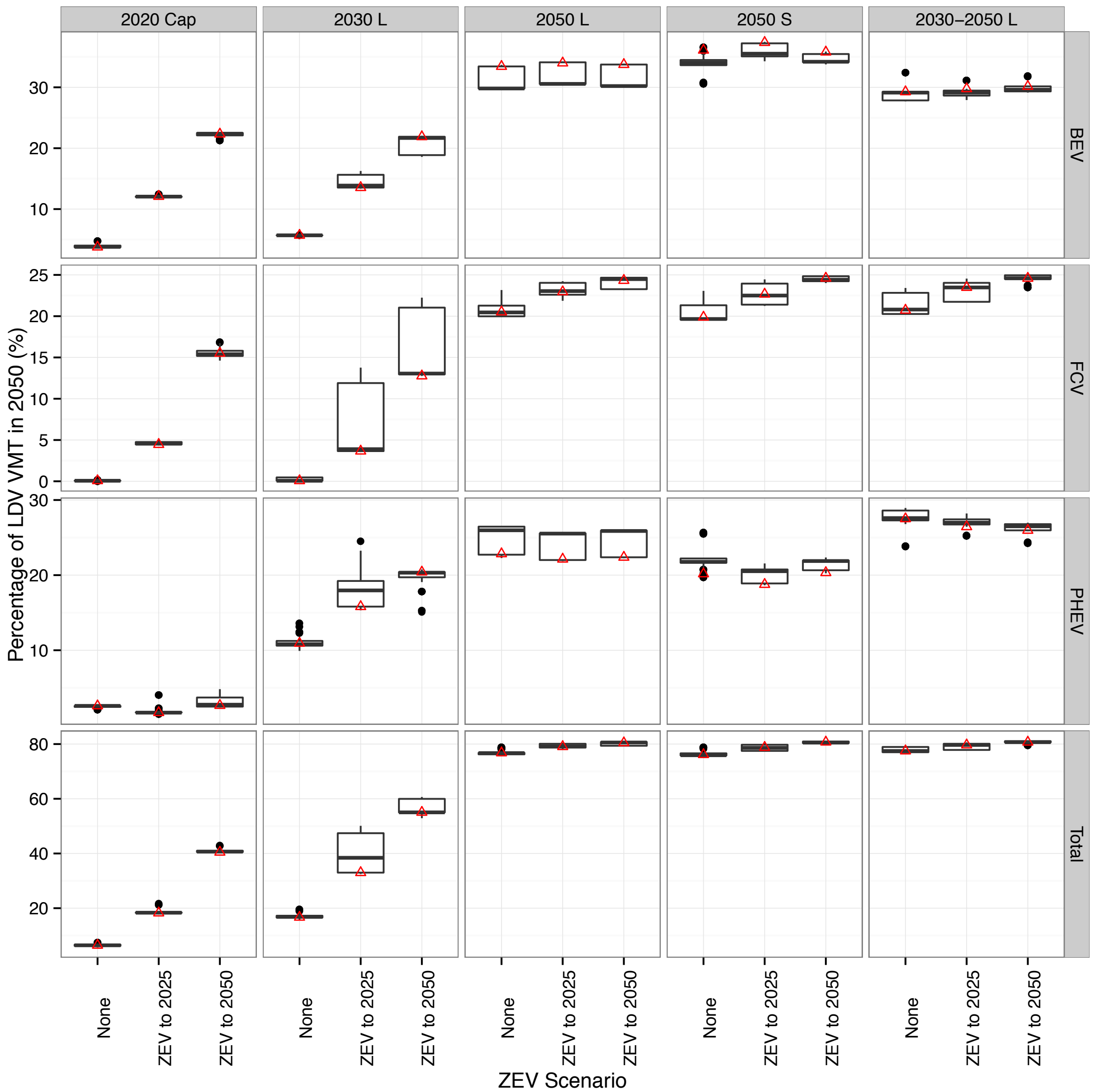

Figure 16: Percentage of light-duty vehicle miles travelled by different vehicle technologies (battery electric vehicles, fuel-cell vehicles, plug-in hybrids and all ZEV technologies) across different ZEV mandates and emission cap scenarios. The boxplot of costs captures the variance resulting from other policies, whiskers are 95th percentile of the data and dots are outliers beyond the 95th percentile. The red triangles indicate our baseline policy scenarios.

3.3 Uncertainty analysis

3.3.1 Describing uncertain parameters input ranges

The CA-TIMES model is designed to make projections of California's energy system far into the future till 2050 in order to investigate how the state can meet its long-term emission goals. However, many assumptions and inputs of the model are inherently unknown or uncertain. A sensitivity analysis across a number of parameters is conducted in order to examine the robustness of the model. The parameters varied in the uncertainty analysis are shown in Table 3. They consist of three primary categories: demand parameters, technology/resource availability, and technology/resource costs. We also examine the parameters of methane leakage rates, the availability of emission offsets, and industrial sector electrification.

Table 3: Parameters varied for uncertainty analysis

	Minimum decrease	Baseline	Maximum increase
Demand parameters			
Population (million people in 2050)	-10%	50.3	+10%
VMT/capita	-10%	same per capita	+10%
Technology and resource availabilities			
Peak hydro availability (PJ/yr)	17.0	85.4	139
Biomass availability	-25%	+0%	25%
Maximum nuclear activity (PJ)	0	0.0	284.6
CCS sequestration capacity (kT/yr)	0	0	70000
CCS start date	2025	2030	2040
Demand response availability	5%	10%	25%
EV charger availability (Home/Work)	40%	52%	70%
Technology and resource costs			
Oil prices in 2050 ($/barrel)	75	149.66	200
NG Costs in 2050 ($/MMBTU)	6	8.8	12
Batteries cost parameter	-30%	+0%	+50%
Fuel cells cost parameter	-20%	+0%	+50%
Solar costs	-20%	+0%	+25%
CCS costs	-10%	+0%	+50%
Other			
CH_4 leakage rates	0.55%	1.10%	3.30%
Emissions offsets allowable	0%	0%	8%
Industrial sector electrification	-25%	+0%	+25%

Two approaches are taken in order to conduct the uncertainty analysis. The first is a pure sensitivity analysis varying each parameter individually to the minimum and maximum values in Table 3. This sensitivity analysis allows us to observe the isolated effect of varying a single parameter on specific outcomes of interest. The second approach we take is to vary all the parameters simultaneously using a Monte Carlo simulation. The distributions of the parameters are defined such that half of the distribution lies above the median and half of the distribution lies below the median. In each half, the distribution is defined such that the probability of selecting the median value is twice that of the maximum and minimum in each respective half. The parameter values between the minimum/maximum and median are proportionally linearly connected. The Monte Carlo method allows us to observe any non-linear effects resulting from varying the parameters, as well as any potential interactions between the parameters as they change. For both approaches, we run the analyses for both a baseline scenario with no emissions cap and a GHG scenario, the 2050 cap (linear) scenario achieving an 80% reduction in GHG emissions by 2050.

3.3.2 Visualization of results with regards to ranges of key metrics

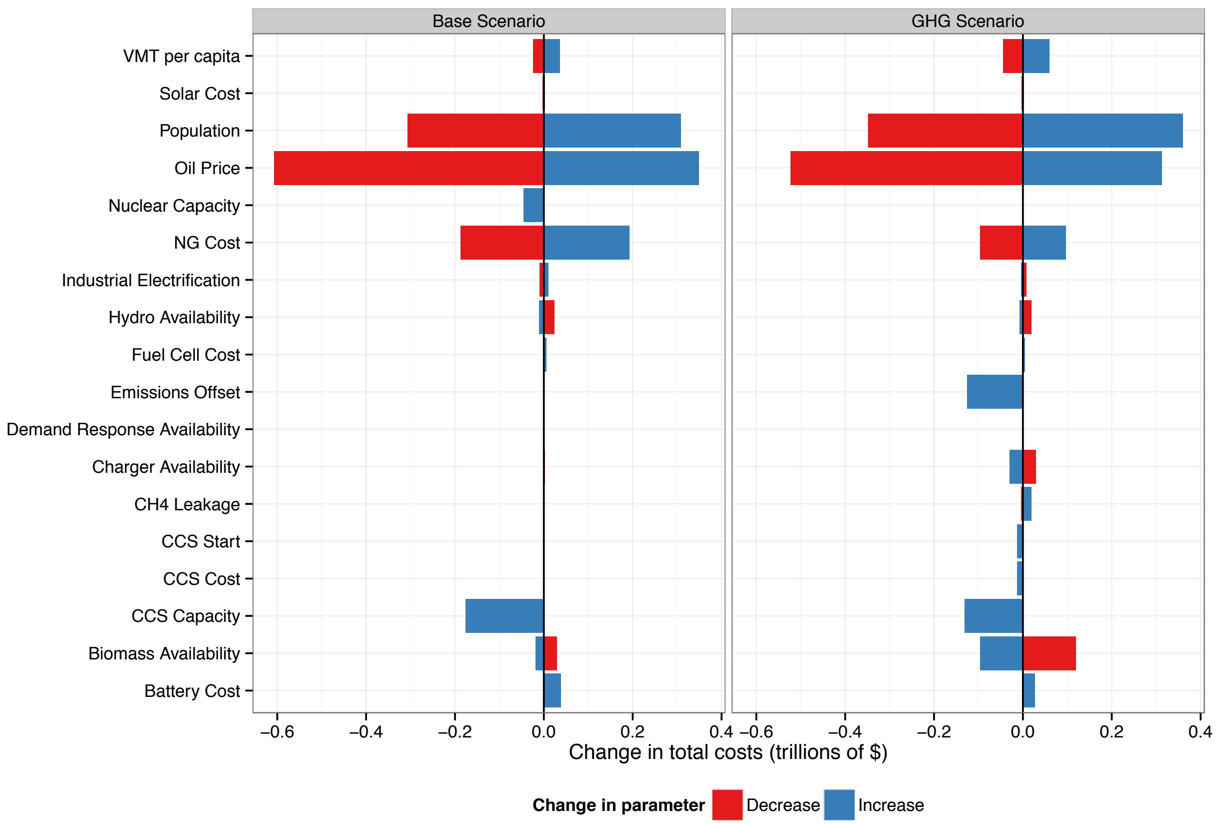

Figure 17: Tornado diagram of uncertainty parameters varied across their full range versus the total system cost differenced against the median value

A small sample of outcomes is displayed in the main report, a comprehensive set of figures are provided in the appendices. Two tornado diagrams are shown in Figure 17 and Figure 18, as the parameters in Table 3 are each individually varied from their minimum to maximum respective values. The tornado diagrams show the effect of setting an individual parameter to the minimum or maximum of the parameter range on the total system cost (2010-2050) and cumulative emissions (2010-2050) relative to a median BAU (2020 cap) or GHG (2050 line) scenario. In the base scenario, the largest effects on costs are oil prices, population, and natural gas costs and can change the total system costs from the baseline as much as -$600 to $300 billion. For the remaining parameters, the change in total cost ranges from less than $50 billion difference from the baseline. However, in the GHG scenario several additional parameters have an observable effect on the total costs. These include VMT per capita, emissions offset availability, CCS capacity, and biomass availability, all of which lead to differences from the baseline on the order of $100 billion.

The tornado diagram in Figure 18 displays the effect of the uncertain parameters on the cumulative emissions output of CA-TIMES. There is a noticeable difference between the scenarios: in the base scenario the cumulative emissions are much more sensitive to the varied parameters while in the GHG scenario the variance in parameters does not lead to large changes in the emissions totals. Similar to the total costs, the parameters of oil price and population have the largest effect on cumulative emissions in the baseline scenario. In addition, methane leakage, CCS capacity, nuclear capacity, biomass availability, and hydro peak availability also lead to noticeable changes on cumulative emissions. The magnitude of effect on the largest parameter (oil price) is a range from -350 to 1100 Mtons of cumulative CO_2 emissions. Interestingly enough, none of the parameters that lead to substantial changes in the baseline scenario result in any changes to emissions in the GHG scenario with the exception of methane leakage. The availability of emissions offset is the largest affecter of cumulative emissions, though the range is only a 500 MTon change.

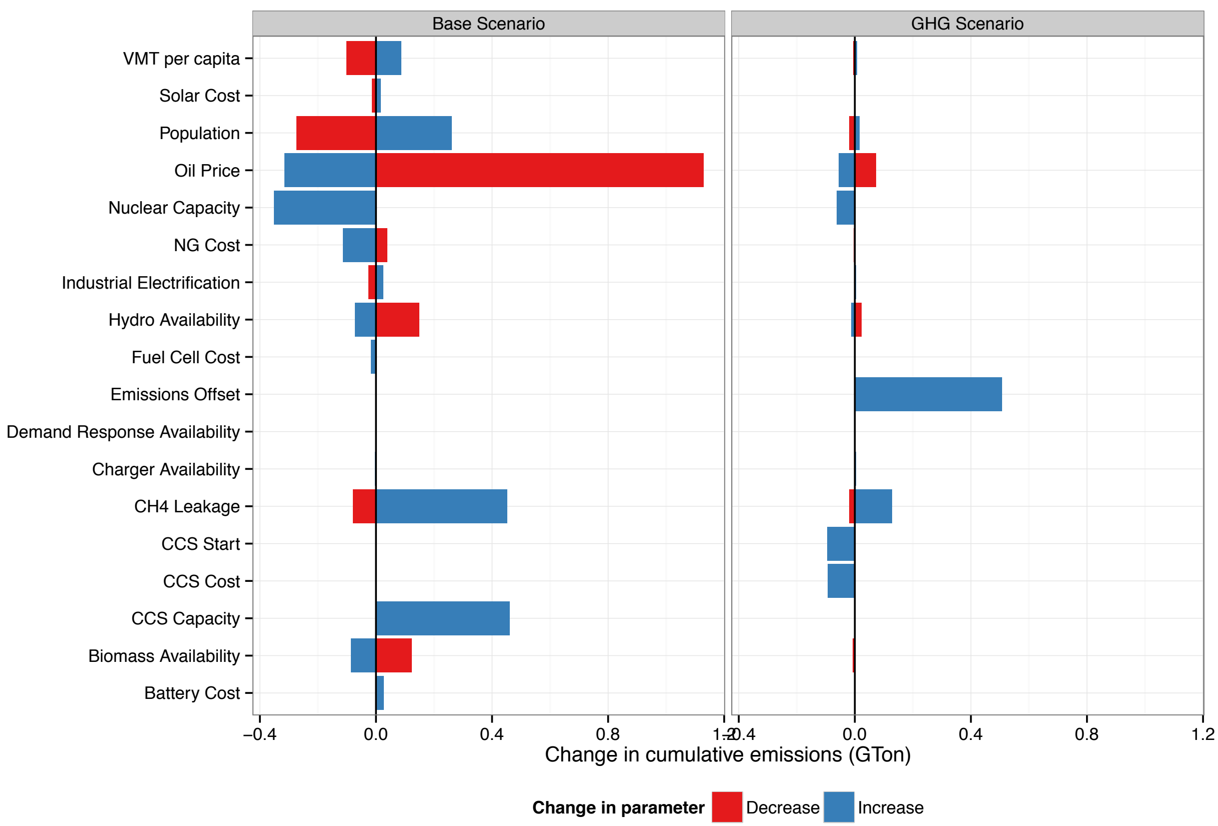

Figure 18: Tornado diagram of uncertainty parameters varied across their full range versus the cumulative emissions differenced against the median value

In Figure 19, we demonstrate one of the outcomes of the Monte Carlo analysis. The proportion of four vehicle technologies is shown as a function of a changing battery cost. The direct effect on BEV technologies can be seen in the lower left quadrant: a decrease in the battery cost does not have a substantial effect on adoption but an increase in the cost up to a 50% increase leads to a steady decrease in adoption in both the baseline and GHG scenarios. There is no observable change in the PHEV technologies resulting from a change in battery price. The Monte Carlo runs also allows for us to observe the indirect effects of the changing adoption levels: there is a slight substitution towards hybrids and more noticeably towards FCVs as the battery price increases in order to compensate for the lower adoption of BEVs.

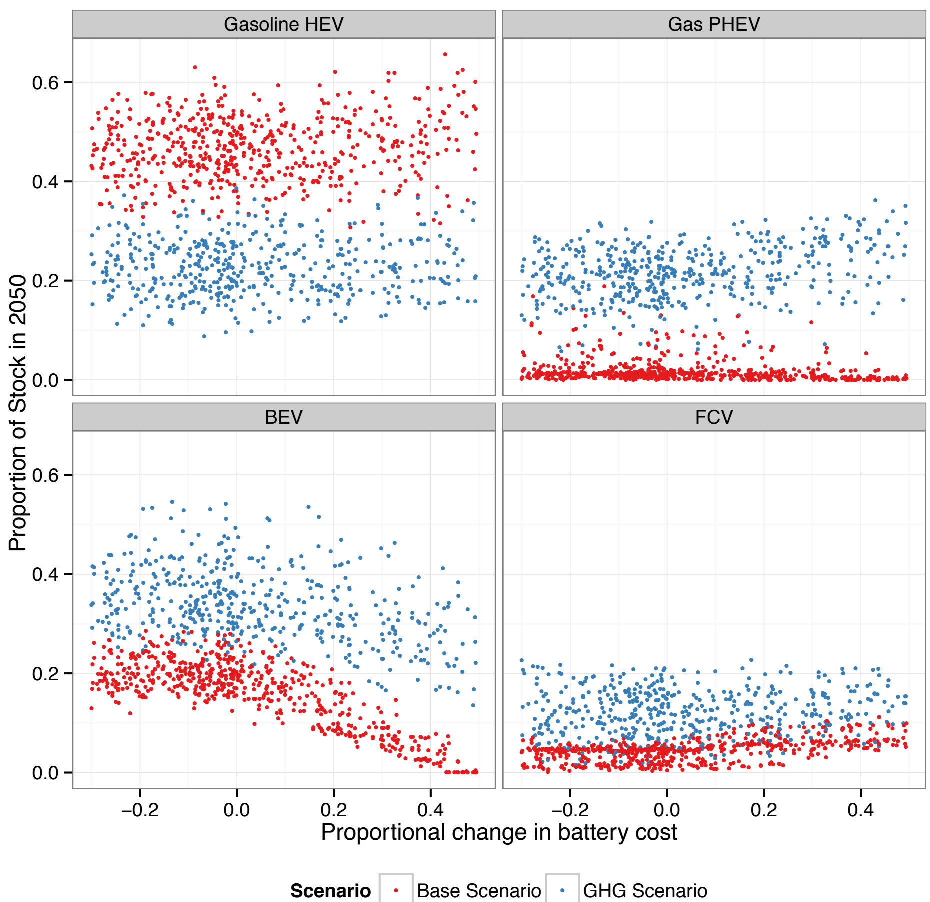

Figure 19: Proportion of vehicle technologies as a function of battery cost

The Monte Carlo analysis provides insight into how parameters affect the different sources of primary energy into the energy system. The direct effect of oil price changes can be observed in the "Oil" panel of Figure 20. Importantly, the decrease in oil usage is non-linear in the base scenario as the price increases, an effect that is not observable in the sensitivity analysis tornado diagrams. As with the vehicle technologies, the substitution patterns are readily observable among the other primary energy sources. The renewable sources of wind and solar do not change perceptibly in response to oil price changes, though other fossil fuel sources increase in response: imported liquid fuels in a linear stepwise fashion up until $25/PJ before levelling off.

The change in both natural gas and coal is imperceptible though there is a large amount of variance in their respective adoption levels. Most noticeably, the biomass usage increases to a large extent in the baseline scenario but remains mostly flat for the GHG scenario.

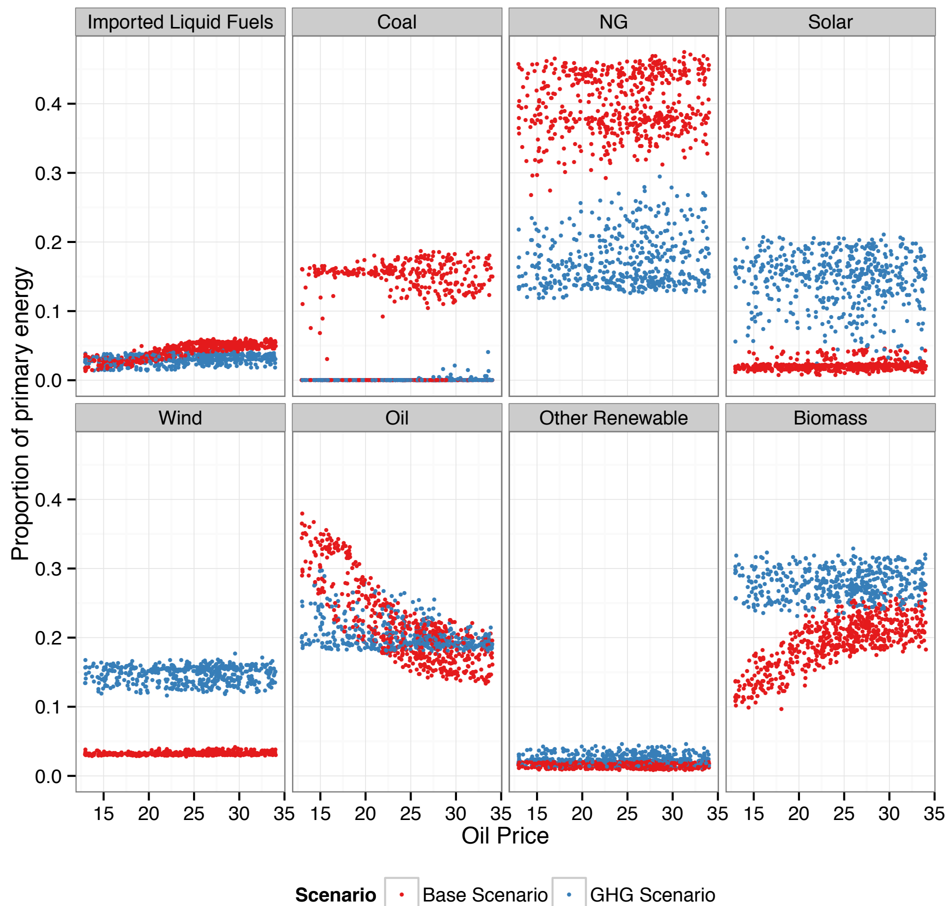

Figure 20: Primary energy usage by type as a function of oil price ($/PJ)

4. DISCUSSION AND CONCLUSIONS

This report describes a number of modeling updates for the CA-TIMES energy system model. These updates span a range of additions:

(1) Structural changes to the model to enable an improved representation of the different aspects/sectors of the energy system:
   a. Inclusion of consumer heterogeneity and preferences in the light-duty vehicle sector
   b. Inclusion of technology cost reductions via learning-by-doing
   c. Inclusion of a representation of demand response in residential and commercial service demands

(2) Analytical improvements that enable greater numbers of model scenarios to be developed, run and analyzed
   a. Policy combinations
   b. Uncertainty analysis

(3) Additional modeling outputs and presentation of results
   a. Mitigation cost assessment
   b. Scenario comparisons of policy combinations
   c. Scenario comparisons of uncertainty runs

These changes entailed a great deal of work and lead to a more realistic and robust model of California's energy system. This improved model was used to generate a number of new scenarios and combinations of scenarios that lead to additional insight into the technology investments and cost implications of meeting different policy and emissions targets across a range of policy combinations and uncertain input parameters.

Four main policy scenarios were analyzed (2020 cap, 2030 cap, 2050 cap and 2030-50 cap) and the 2030 cap scenario had the lowest overall system cost of any of these scenarios. Relative to the baseline (2020 cap) scenario, the 2030 cap scenario reduced overall cost by about $77 billion from 2010 to 2050 while reducing emissions by 1.7 GtCO2e. This leads to a negative mitigation cost of -$45/tCO2e. This is a slightly counter-intuitive result that a policy scenario leads to a lower cost result than the Reference scenario, but can be explained by discount rates used in the model to simulate the same myopic, real-world purchase behavior that leads to the "efficiency gap". The two scenarios with 80% reduction targets (2050 cap and 2030-50 cap) both have slightly higher costs than the Reference scenario ($15 billion to $33 billion higher) and cumulative GHG savings of 2.5 and 3.3 GtCO2e. These scenarios have relatively low average mitigation costs of $6/tCO2e and $10/tCO2e, though the marginal cost of abatement in 2050 are on the order of $700-800/tCO2e.

The 2030 cap scenario achieves the 40% GHG reduction target in 2030 primarily through renewable generation in the electric sector, achieving 63% RPS generation in 2030 and 80% in 2050. This significantly reduces natural gas usage in the electric sector as a result and leads to significant cost savings relative to the Reference scenario. ZEV adoption in this scenario is not significantly different from the Reference scenario. The 2030-50 cap scenario also relies heavily on renewables to meet the 2030 GHG target though not as strongly as the 2030 cap scenario, as transportation plays a slightly larger role in decarbonizing the 2030-50 scenario. The 2050 cap (linear) scenario has a much less stringent GHG target for 2030 (26.66% reduction vs 40% reduction), and as a result, has more modest changes in 2030, though the mix of technologies, fuels and electricity generation are very similar between the two 80% reduction scenarios.

Because of relatively high oil and gas prices in our scenarios, biomass becomes a large contributor to transportation fuel mix across all scenarios. Renewable electricity generation from wind and solar is much more variable across scenarios, depending on the level of the emissions cap. Total electricity demand increases significantly to meet the 80% GHG reduction target due to a shift to electrification across a number of sectors, though the largest increase in demand is associated with transportation (for charging electric vehicles and producing electrolytic hydrogen for fuel cell vehicles).

The policy combination analysis showed that there was little overlap between any of groups of scenarios with different GHG caps. Different combinations of policies could affect the cumulative emissions and total system cost for a given GHG cap trajectory, though the effects that policies could have diminished as the cap became more stringent. This is due to fewer available options for technology and resource mixes that still satisfy the emissions targets. An example of policies that interact with one another are the ZEV mandate and the LCFS. Increasing the stringency of the ZEV mandate and of the LCFS tend to cause significant changes in the adoption of fuel cell vehicles and battery electric vehicles. However, these policies have the largest effect when the cap is less stringent (i.e. in the 2020 and 2030 cap scenarios). As the cap gets more stringent, changes in these policies have a much smaller impact on the mix of vehicles. Overall, the share of ZEV technologies (PHEVs, BEVs and FCVs) is relatively constant in 2050 in the scenarios with an 80% reduction cap, regardless of other policy combinations. However, for the less stringent cap scenarios, the share of LDV ZEV technologies can vary quite a bit depending on the presence of the ZEV mandate and the LCFS.

The uncertainty analysis enables the better understanding of the sensitivity of the model to changes in model input parameters. This was done as single parameter sensitivity as well as a Monte Carlo analysis varying all the parameters simultaneously. The main drivers for changes in system cost and emissions were population and oil price. For the most part, emissions in the GHG scenario don’t change significantly because of the stringency of the GHG cap, changes in the model due to a change in one parameter tend to lead to changes in other sectors, in order to minimize cost while meeting the constraint. Among the parameters we analyzed were changes in oil price, which affects the share of energy resources used in the model, and battery price, which affect the mix of vehicle technologies used to meet transportation demand.

5. ACKNOWLEDGEMENTS

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CA-TIMES REPORT APPENDICES

1. CONSUMER HETEROGENEITY AND CHOICE (COCHIN)

COCHIN component uses MA^3T vehicle choice model to obtain the behavioral characteristics capturing the perceptions of various consumer groups for different vehicle technologies. MA^3T (Market Allocation of Advanced Automotive Technologies) is a nested multinomial-logit model developed by Oak Ridge National Laboratory (Lin and Greene 2011) for projecting the penetration rates of advanced vehicle technologies in the US, based on several projected inputs such as vehicle attributes, regional market segmentation, energy prices and policies. The model has 1458 consumer segments throughout the country divided based on regions (nine aggregated census regions), settlement levels (urban, suburban or rural), driving behavior, risk attitude towards technology, home and work charging availability.

The model uses vehicle prices, fuel costs as well as an estimate of the value of non-monetary factors (will be referred to as 'disutility costs') to determine the purchase probability of a vehicle technology for a particular consumer group. The disutility costs are assessed based on the vehicle technology and fuel infrastructure attributes, and behavioral parameters of each consumer group. Though, the direct costs (vehicle and fuel costs) are the same across all consumer groups for a given vehicle technology, the disutility costs can differ, often markedly, depending on a particular consumer group's perception of those attributes. Table 1 shows the different components of the disutility costs and how they are determined in the MA^3T model.

Table 1. Disutility Cost Components

Disutility Cost Component	Description	Dependent Characteristics
Refueling Inconvenience Cost	The combined time and inconvenience cost to refuel a vehicle	Annual miles driven, fuel economy, vehicle storage, station availability, value of time
Range Limitation Cost (BEVs)	The estimated generalized cost incurred by a BEV owner due to limited range of battery electric vehicles in conjunction with the owner's VMT pattern	Daily VMT, annual miles driven, infrastructure availability, anxiety cost (consumer-specific, based on their risk attitude)
Model Availability Cost	The expected level of generalized cost perceived by the consumer as a function of the number of available number of makes and models for a given vehicle technology	Previous 5-year sales number of the vehicle technology, same for all the consumer groups
Risk Premium	The risk premium perceived	Cumulative stock value of the

	by the consumer based on their ability to take risk	vehicle technology, risk premium coefficients (differs based on their attitude towards risk)
Home Charger Installation Cost	The consumer incurs this cost to install a charger if he/she chooses to buy a PHEV or BEV and has the ability to charge at home	Home recharging infrastructure availability
Towing Capability	This is a negative cost or utility that the consumer gains from the towing capacity of the vehicle	Vehicle technology
Cargo Space Availability	This is a negative cost or utility that the consumer gains from the availability of luggage space. Trucks have a higher utility than cars in terms of cargo space availability	Vehicle class (car or truck)

The modification of the standard TIMES model to incorporate COCHIN component is done in two steps: disaggregating the end-use demand into different consumer groups, and including disutility costs to capture the perceptions of consumers for various vehicle technologies. The integrated CA-TIMES-COCHIN model represents twelve vehicle technologies in light-duty car and truck sectors. The technologies include conventional vehicles (gasoline, diesel, E85), hybrid vehicles (gasoline hybrid, diesel hybrid, E85 hybrid), plugin-hybrid vehicles (10-mile, 20-mile and 40-mile charge depletion ranges), fuel cell vehicles, and battery electric vehicles (100-mile and 200-mile ranges). The end-use segment divisions for each vehicle class (light-duty car/ light-duty truck) include driving profile and risk attitude differences of consumers. The model assumes that there are three categories of drivers: low annual VMT (6925 annual miles) consisting of 36% of the population, medium annual VMT (12,855 annual miles), and high annual VMT (22,630 annual miles) drivers, each consisting of 32% of the total population. And, there are three categories of consumers based on their attitude towards risk: early adopters (8%), and early majority (38%) and late majority (54%) groups. In this version of the model, about 52% of the consumer groups are assumed to have access to home and work recharging, i.e. they live in a household where they can invest in a dedicated home charger if they are purchasing a PEV. The rest of the population (48%) do not have access to home or work charging, and they are assumed to get all their charging done in public chargers. The public charger availability, defined as the probability of getting access to a charger, increases over time, reaching 10% in the year 2050 as shown in Figure 1.

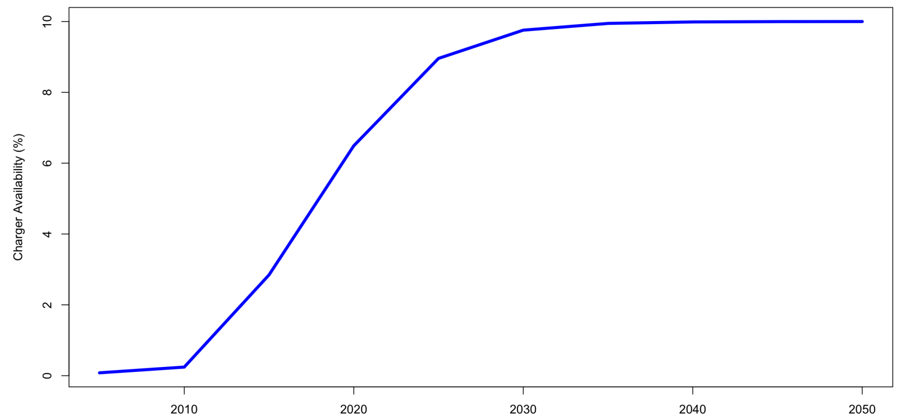
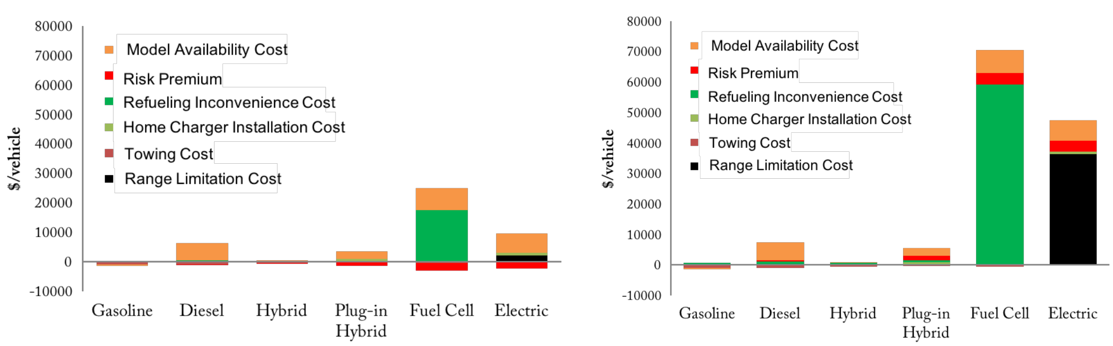


Figure 1. Public Charger Availability Representation in the model

In order to describe the differences consumer perception can have on the disutility costs, two extreme consumer groups are chosen to illustrate the disutility cost components. Figure 2(a) shows the cost components of various vehicle technologies for a consumer who belongs to early adopter, low annual VMT category, and Figure 2(b) shows the cost components of vehicle technologies for a consumer who belongs to late majority, high annual VMT category. We can observe that, the low annual VMT drive has a substantially low refueling inconvenience and range limitation costs, compared to the high annual VMT driver. Moreover, the risk premium is a negative cost for early adopter indicating this consumer perceives the newness of a vehicle as a novelty or a positive quality, compared to the late majority consumer, who perceives newness as a liability.



(a) Early Adopter, Low Annual VMT (b) Late Majority, High Annual VMT

Figure 2. Illustrative Disutility Cost Components

Figure 3 and Figure 4 show the disaggregated LDV activity of the baseline scenario (2020 cap scenario) and an 80% GHG reduction scenario in the year 2050 divided across consumer groups (the aggregated activity outcome of these scenarios are shown in Figure 3 and Figure 10 in the Main Report). It can be observed that, gasoline hybrid form a significant share irrespective of the risk categories. Advanced vehicle technologies, such as, plugin-hybrid, battery electric and fuel cell vehicles are adopted in larger shares by early adopter category, and as the consumers get risk averse (early majority and late majority), hybrids dominate their purchases. For the same scenario, while looking at the adoption of technologies based on VMT differences, it can be observed that higher VMT groups tend to purchase more fuel efficient technologies, with the exception of battery electric vehicles (due to their range limitation). And, overall, more diversity of vehicle technology adoption comes from early adopter category.

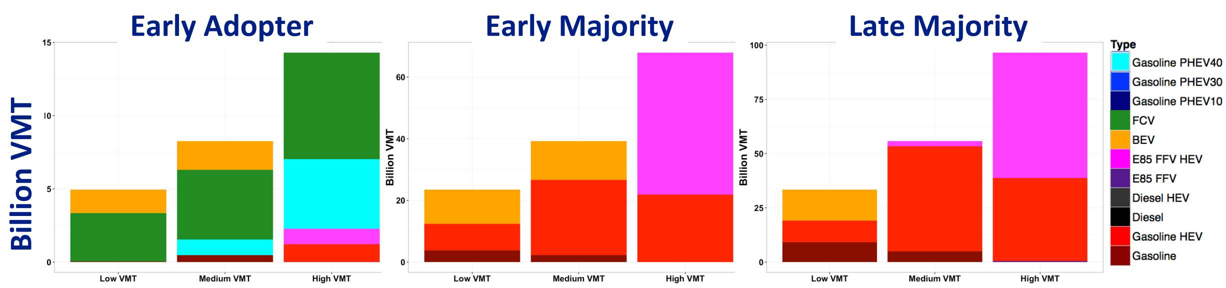


Figure 3. LDV Activity across consumer groups in the year 2050 (baseline scenario)

In the GHG scenario, due to the stringent carbon cap, advanced vehicle technologies are adopted by all the consumer groups by the year 2050. Similar to the BAU scenario, early adopters tend to be the pioneers in adopting advanced vehicle technologies. In this case, the early adopters do not invest in gasoline hybrid technologies, and prefer plugin-hybrid, fuel cell and battery electric vehicles. In the early majority category, most VMT is mostly supplied by fuel cell vehicles and battery electrics with some VMT supplied by plug-in hybrids and a few conventional hybrids. The late majority drivers rely a bit more on conventional hybrids and plug-in hybrids, though a sizeable fraction of VMT comes from fuel cells and ZEVs. In each of these risk categories, fuel cells tend to be prominently used by the high VMT drivers while battery electrics make up a greater proportion of the low VMT drivers.

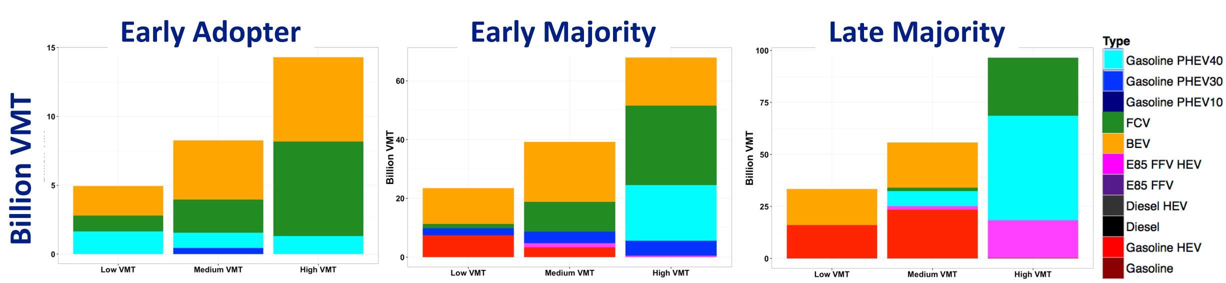


Figure 4. LDV Activity across consumer groups in the year 2050 (GHG scenario)

1.1 Learning-by-doing

In linear optimization models such as TIMES, the total discounted system costs are minimized (or total welfare surplus is maximized). These models choose the cheapest available technologies to satisfy the given demand until their use is limited by technical, economic, or user constraints. Then, the second cheapest available technologies are used until their use is restrained again by a constraint, and so on. Since the improvement of technology based on experience requires the use of technology as a trigger that contradicts with the original paradigm of TIMES (selecting least-cost technology), methods have been developed to treat the description of technological process of technologies endogenously, which are called Endogenous Technological Learning (ETL).

ETL improves internal consistency of the energy models, and can be more appropriate for analysis attempting to assess the relative importance of different technologies (Grubb, Köhler et al. 2002). Models with ETL can also help us with the analysis of policies with the target of supporting emerging technologies. The insight from these models can help us determine the effectiveness of these kinds of policies (e.g., ZEV mandate and subsidies for electric cars). Incorporating ETL and representing technology dynamics effectively in long-term energy systems and integrated assessment models is recognized as one of the greatest challenges in energy modeling (Grubb, Köhler et al. 2002). Most of energy optimization models including TIMES are linear models, and it is required to change the modeling framework from a linear model to a mixed-integer linear model (MILP) in order to incorporate ETL in them. (Loulou, Remne et al. 2005). MILP models are computationally burdensome to solve, and they significantly increase the solution time, even if we have only one technology under learning. We propose a methodology which applies an iterative approach that can be used instead of solving a MILP problem. This approach includes the following steps:

1- We set the cost of learning technologies exogenously for all time periods and run the model.

2- The amount of investment in the learning technologies in all time periods is extracted (The market penetration of the new technology is estimated for the assumed costs), and the cumulative installed capacity is calculated for all time periods.

3- The new costs of technologies are calculated for all time periods (exogenously) based on the following learning curve formula and the calculated cumulative production of the new technology.

   $$C_t=C_0\times(\frac{Qt}{Q0})^{-b}$$

   Where the capital cost at time t (C_t) equals to the initial capital cost (C_0) to the ratio of cumulative installed capacity at time t (Q_t) and initial installed capacity (Q_0) raised to the power of $-b$. b is a constant, and it is called the experience parameter. The literature uses not b but progress ratio, PR, or learning rate, LR, to characterize the steepness of the learning curve. The learning rate can be defined as the relative reduction in price for each doubling of cumulative sales, and is typically around 10-20% for new energy technologies (Seebregts, Kram et al. 1998). The relation between b, PR and LR can be written as $PR=1-LR=2^{-b}$.

4- The new calculated cost trajectory for all time periods is entered as new input assumption into the model and another iteration of the model is run.

5- New investment in learning technologies are extracted from the results again (step 2), if this amount is different from the previous iteration, then we go to step 3, otherwise we reach the final result.

Since we are able to calculate new costs of learning technologies outside the model, we avoid MILP and approximation of learning curve, which saves a lot of computations. Therefore, we are able to include a lot of technologies in the learning process without any additional computational burden. Using the proposed methodology, we can study the role of technology-forcing policies and learning process in cost reduction and adoption of emerging technologies.

We use a cluster approach to endogenize learning of alternative fuel vehicles in CA-TIMES. As explained, in the cluster approach, a group of technologies share a common component –"key technology"– to which learning has been applied. E.g., car battery is an example of a key component technology, and members of the corresponding cluster of "shell" technologies in which the key component used are battery electric cars and buses, gasoline and diesel hybrid vehicles and buses, and gasoline and diesel plug-in hybrid cars and buses. In this study three key component key technologies, including fuel cell systems ($/kW), electric drivetrains ($/kW) and automotive battery systems ($/kWh), undergo learning in the model. These technologies are represented in the model as technologies by their own, in addition to the vehicle shell technologies in which they are deployed.

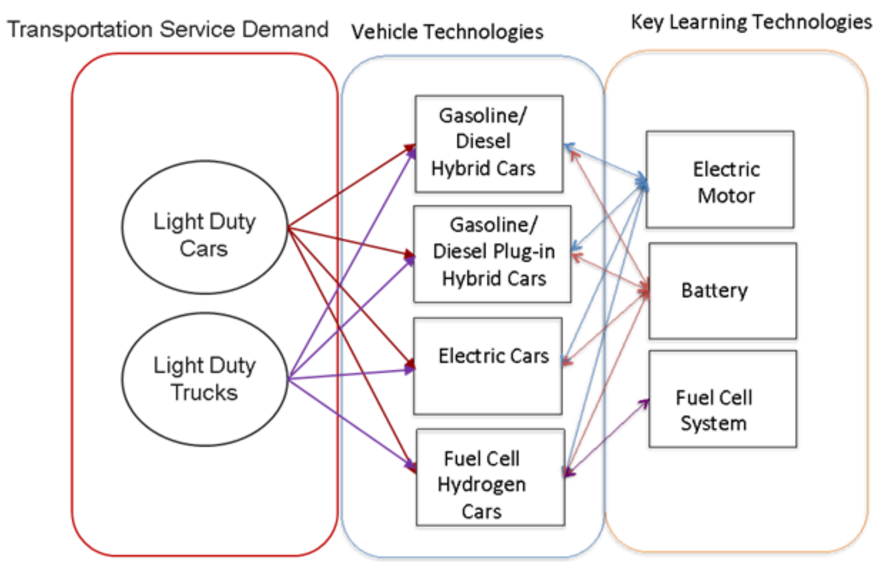


Figure X. Proposed cluster learning implementation in CA-TIMES

As shown in Figure X, each of key component technologies is embedded in vehicles that use them. E.g., battery electric vehicle uses electric drivetrain and battery, while fuel cell vehicle contains fuel cell system, electric drivetrain and battery. We assume that only the investment costs undergo the learning process. Therefore, we only attribute capital cost to key component technologies. O&M costs and efficiencies are linked to the vehicles (shells). Learning of a key component occurs regardless of the vehicle type in which it is deployed. i.e. cost reductions that happens from the utilization of battery in light-duty cars also apply to the battery for use in light-duty trucks. Lipman and Hwang (2003) argue that this is a realistic assumption by the car industry, and they see opportunities in hybrid vehicles to pave the way for electric vehicles (both battery electric vehicles and fuel cells vehicles). In the same way, Zaetta and Madden (2011) recommended that the plausible way for fuel-cell buses is through shared learning with car fuel cells; however, they mentioned that there exist different opinions in the industry about the degree of similarity between the fuel-cell system in buses and those in cars.

The following table shows the characteristics of representative light duty cars and trucks in our model. The vehicle architecture recommended below is based on NRC (2013).

Table 2. Characteristics of representative vehicles in CA-TIMES

Vehicle Type	Battery size (kWh)	Motor size (kW)	Fuel system Size (kW)
Hybrid Electric Car	1.3	25.6	0
Plug-in Hybrid Electric Car-10	10.4	76.7	0
Plug-in Hybrid Electric Car-20	12.5	79	0
Plug-in Hybrid Electric Car-40	13.9	115	0
Electric Car-100	37.6	110.8	0
Electric Car-200	78.96	138.5	0
Fuel Cell Car	2.1	110.8	88.7
Hybrid Electric Truck	1.7	33.5	0
Plug-in Hybrid Electric Truck-10	15.1	100.5	0
Plug-in Hybrid Electric Truck-20	18.27	125.6	0
Plug-in Hybrid Electric Truck-40	20.1	150.8	0
Electric Truck-100	54.5	142.7	0
Electric Truck-200	114.45	178.3	0
Fuel Cell Truck	3	142.7	125.6

The following table represents our assumptions regarding initial cumulative capacity, learning rate, initial price and annual cost reduction rate.

Table 3. Learning assumptions in CA-TIMES

Component	Learning Rate	Initial Cumulative Capacity	Initial price	Annual Cost Reduction	Floor Cost
Battery	7%	0.604 (GWh)	$600/kWh	0.7%	$150/kWh
Electric	10%	128 (GW)	$25/kW	1.2%	$5/kW

Drivetrain					
Fuel Cell System	4%	0.0887 (GW)	$216/kW	2.5%	$30/kW

It is assumed that the initial number of fuel cell cars is 1000 units (Navigant 2015) which is equivalent to 0.0887 GW. Data for fuel cell system is based on Fuel System Cost (DOE 2015) and McKinsey&Company (2009).

Cumulative installed capacity is assumed to be in line with the number of hybrid electric vehicles, since sales of BEVs and PHEVs are relatively small compared with hybrid electric vehicles. McDowall (2012) estimated the total global cumulative capacity of hybrid electric vehicles to be 5 million in 2010 and they assumed each vehicle has 25.6 kW electric motor; therefore, the total installed cumulative capacity would be 128 GW. The initial cumulative capacity of batteries is calculated based on estimation of having about 20,000 electric cars in 2010 according to Weiss et al. (2012). Other informations are adopted from Anandarajah et al. (2013).

Another important assumption that we should impose to our model is global adoption of alternative fuel vehicles (AFV). The learning process is not restricted to the adoption of AFVs in California, and it is a global phenomenon. Therefore, it is important to capture the AFVs adoption of rest of the world. We use a multiplication factor to capture this phenomenon: we assume rest of the world adoption is five time higher than California in 2012, and this multiplication factor increases linearly up to 20 times higher than California in 2050.

The following figure shows the aggregate activity of light duty cars and trucks in the baseline scenario with and without Zero Emissions Vehicle (ZEV) mandate up to 2025. It can be seen without having ZEV mandate we do not have any Plug-in Hybrid Electric Vehicle (PHEV), Battery Electric Vehicle (BEV) and Fuel Cell Vehicle (FCV). On the other hand, with imposing ZEV mandate, there will be ZEV adoption including BEVs and FCVs. ZEVs are adopted to satisfy ZEV mandate up to 2025, but there will be a decent adoption of ZEVs without having any constraint up to 2025.

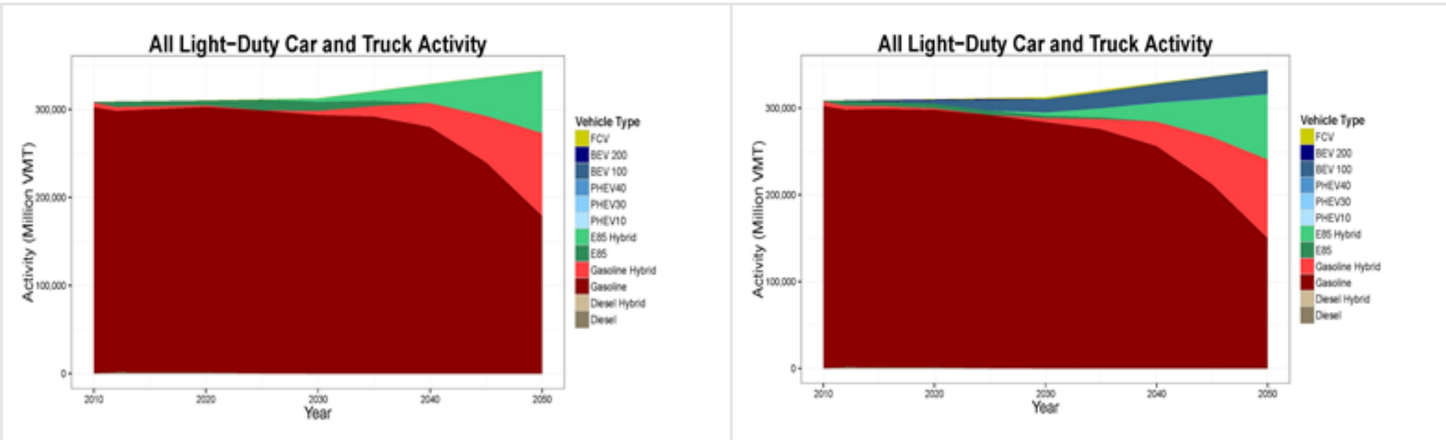
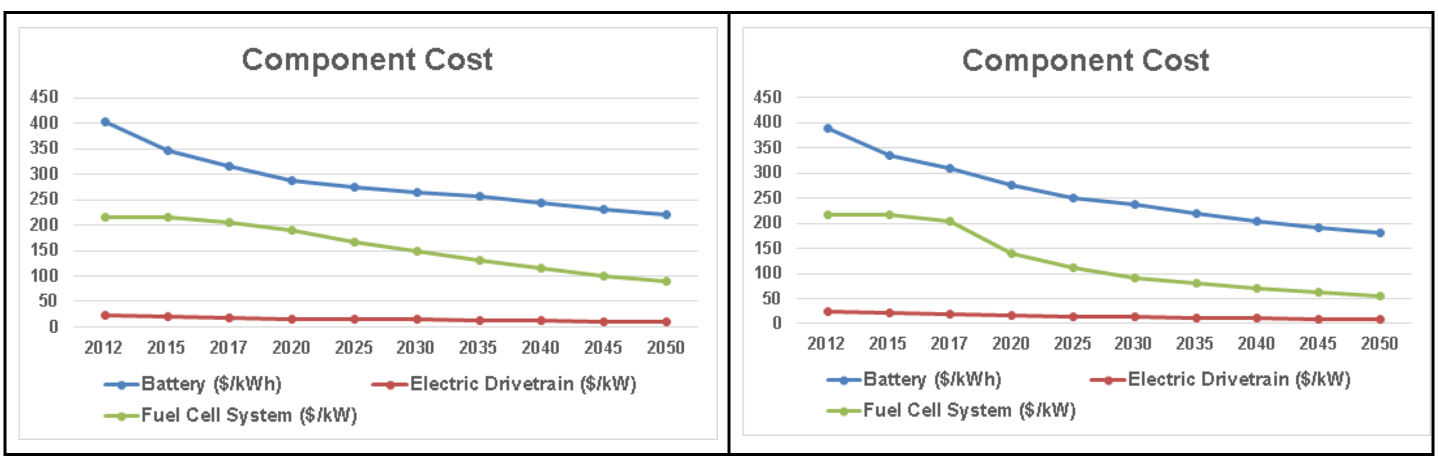


Figure 5. Activity of light duty cars and trucks in the BAU scenario without ZEV mandate (Left) and with ZEV mandate up to 2025 (Right).

In Figure 6, we can see how the cost of different components decline due to the learning process in the baseline scenario. There will be no learning by doing in the baseline scenario without having ZEV mandate since there is no ZEV adoption. However, the cost of these components decline due to annual cost reduction assumption. It can be seen cost of battery, fuel cell system and electric drivetrain would be \$220/kWh, \$89/kW and \$10/kW in this scenario in 2050, respectively. With having ZEV mandate, there will be learning by doing and cost of battery, fuel cell system and electric drivetrain reduce to \$180/kWh, \$55/kW and \$8/kW in 2050, respectively. Moreover, we can see the full cost of different vehicles in the bottom panel. The vehicle cost difference is relatively large between 2025 and 2035 since learning by doing plays an important role in this period, however, the cost difference becomes smaller in the later years since the annual cost reduction, which does not depend on



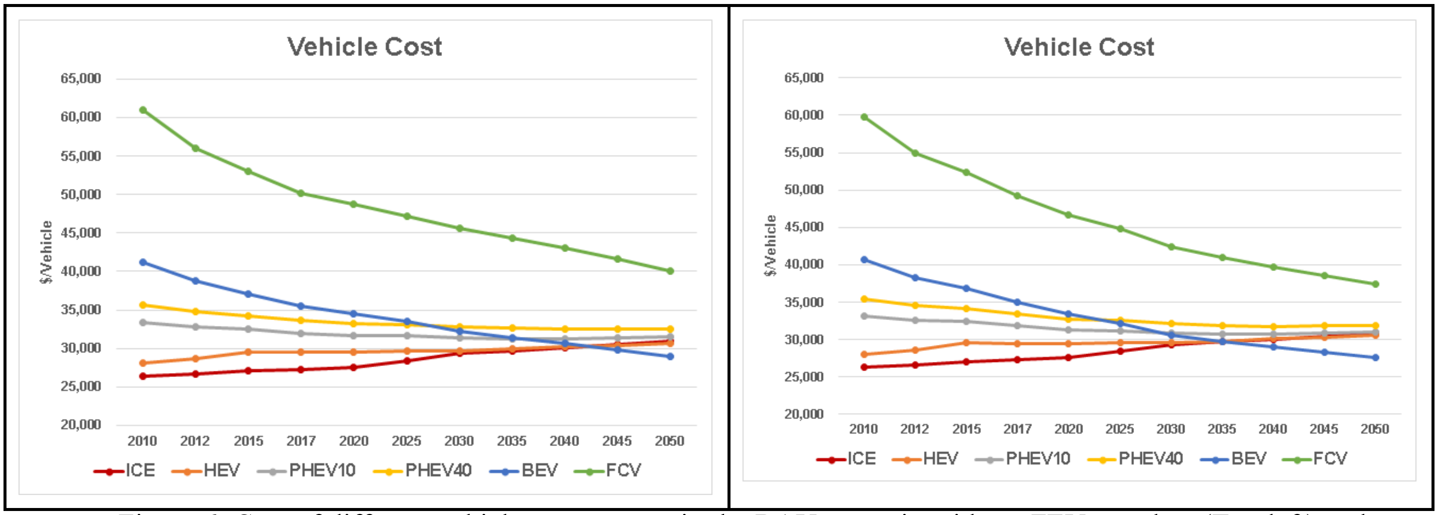


Figure 6. Cost of different vehicle components in the BAU scenario without ZEV mandate (Top left) and with ZEV mandate up to 2025 (Top right), and cost of different vehicles in the BAU scenario without ZEV mandate (Bottom right) and with ZEV mandate (Bottom left).

2. DEMAND RESPONSE

Demand reduction and demand response are one of the most important factors in reducing the cost of climate mitigation due to the savings in investments in infrastructure, vehicles, appliances and fuel use. In the electricity grid with a high penetration of renewable energy, demand management could also maximize the capacity factor of the electricity network and save a lot of investments in infrastructure. Demand side management (DSM) is a change of energy consumption of consumers due to various reasons, behavioral change and the price mechanism (Mohsenian-Rad, Wong et al. 2010) for example. DSM strategies have been used for many decades to promote a more efficient consumption. DSM strategies generally can benefit the energy system in various ways: they can allow a better management of available resources and help reduce the cost of system as well as avoid interruption of service.

While energy efficiency programs have a primary goal of decreasing energy consumption in the long/medium terms, dynamic demand response programs encourage consumers to shift their loads. In order to avoid over investment in the new generation capacity in the planning of electricity systems the DSM strategies are to be undertaken. Moreover, the effect of designing new DSM policies must be analyzed in detail as they can have a significant impact on the cost-benefit of the existing electricity network. Furthermore, by increasing penetration of renewables in the electricity network, the development of demand response programs can benefit the investment in the new generation capacity by enabling a better match between supply and demand (Pina, Silva et al. 2012).

Our results indicate California's electricity network should use significant amount of renewable electricity (more than 80% of the total electricity consumption) to meet 2050 emissions reduction target. Balancing a supply and demand of electricity grid with a high amount of renewable penetration is a complex and challenging task (Warren 2014). DSM strategies and developing energy storage technologies could be a solution to this challenge (Droste-Franke, Paal et al.

2012). Using the current status of CA-TIMES, we incorporate demand response in some commercial and residential service demands and study their impacts..

In CA-TIMES, all of the residential and commercial service demands have a specified load profile over 48 sub-annual timeslices (6 “seasons” per year and 8 slices per day), which are used to characterize electricity generation and usage in the electricity sector. These load profiles for specific residential and commercial end-uses are fixed and without demand response (DR), electricity consumption would follow these same load profiles. Including DR allows for electricity consumption to vary slightly from these service demand profiles. In order to model demand response (DR) in CA-TIMES, we define a DR technology that can store electricity whenever the price of electricity is low (and constraints are met). Then DR technology discharges in the appropriate timeslice to match the service demand load profile (with satisfying the defined constraints). For example, Figure 7 shows DR tech ts2 can store electricity from timeslices 1 and 3 and discharge it in timeslice 2 (demand is met in timeslice 2 but electricity consumption is in timeslice 1 and 3, i.e. demand reduction happens in timeslice 2). For example, this technology represents thermal systems where you can pre-cool a building so that demand is lessened during the peak hour (time slice 2) and shifted before and after the peak hour (timeslice 1 and 3). We implement DR in space heating and space cooling, and expect it will be used to deal with variability associated with high levels of intermittent renewable generation.

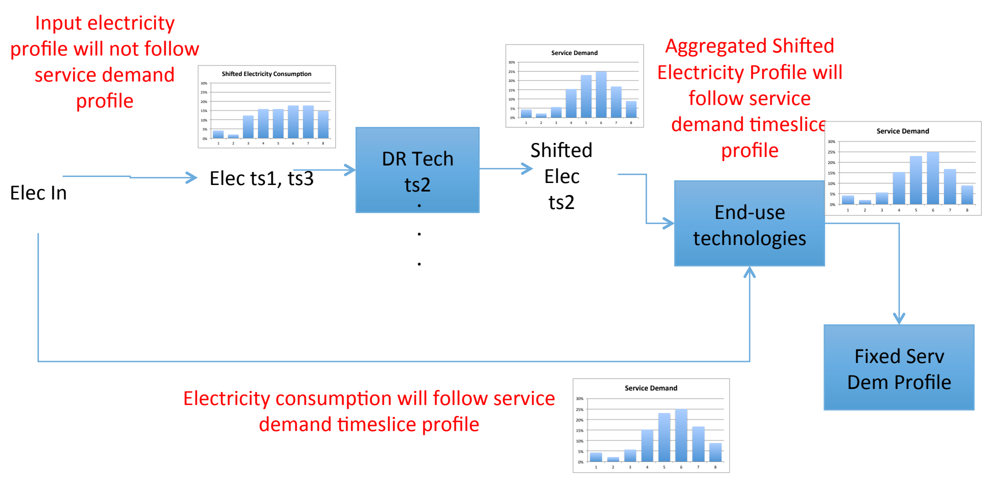


Figure 7. Demand response representation in CA-TIMES

Based on Gils (2014), there is a potential to shift space cooling demand by less than three hours and space heating demand by 12 hours. The smallest time slice in CA-TIMES is three hours, so space cooling demand can shift by one time slice and space heating demand can shift by four time slices. An important consideration is the cost associated with DR which is not captured using our model. These costs could be capital costs that are necessary to implement DR such as cold or hot air storages or welfare loss associated with the loss of convenience in shifting service demand. Moreover, all of customers are not able to implement DR technologies, however, as we increase the penetration of DR technologies among consumers the benefit of DR for the electricity network increases.

Figure 8 shows how electricity input for meeting residential space cooling service demand in different time periods of July/August season would shift in the presence of DR in 2050.

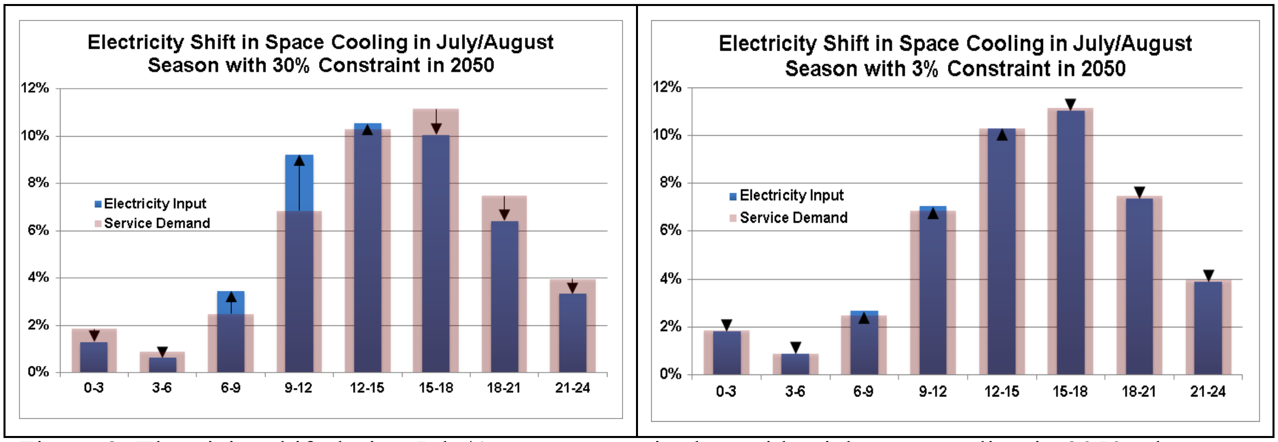


Figure 8. Electricity shift during July/August season in the residential space cooling in 2050 when up to 30% of service demand can be shifted to adjacent timeslice (left) and when up to 3% of service demand can be shifted (right)

It can be seen that electricity consumption reduces during late afternoon and evening (15-24) when the consumption of electricity is high and it shifts to morning and early afternoon (6-15) when there is less electricity demand. This process helps a grid to shift the peak load and decrease the investment cost in the peaking power plants which generally run during high demand periods. Moreover, our results show the only non-renewable electricity power plant that is used in 2050 is natural gas combined cycle power plant. The model has to invest in this type of power plant to make up the peak demands that cannot be met by available renewables. Therefore, DR technologies can smoothen the electricity demand by reducing peak demands which leads to saving in investment cost as well as emissions reduction.

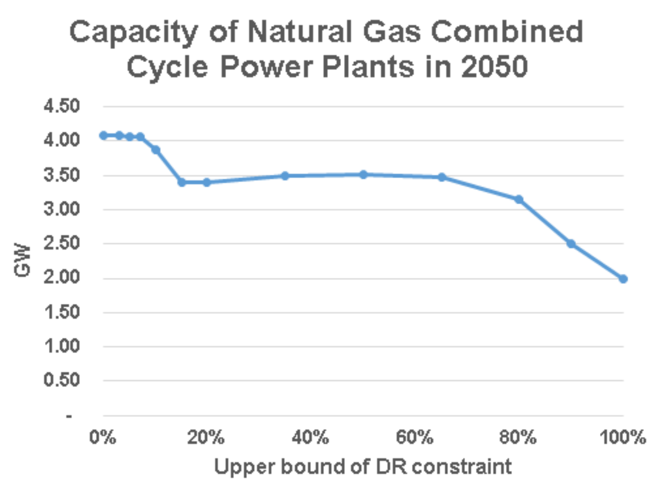


Figure 9. Capacity of natural gas combined cycle power plant in the system under different level of constraint for shifting service demand in the residential and commercial space heating and cooling in 2050

Figure 9 shows as the constraint on the percentage of service demand that can be shifted using DR technologies in the commercial and residential space heating and cooling relaxes the capacity of installed natural gas combined cycle power plants decreases, and it would be equal to almost 50% of the installed capacity without implementing DR when it is possible to implement DR for all of the commercial and residential space heating and cooling service demands.

3. MARGINAL COST CURVES

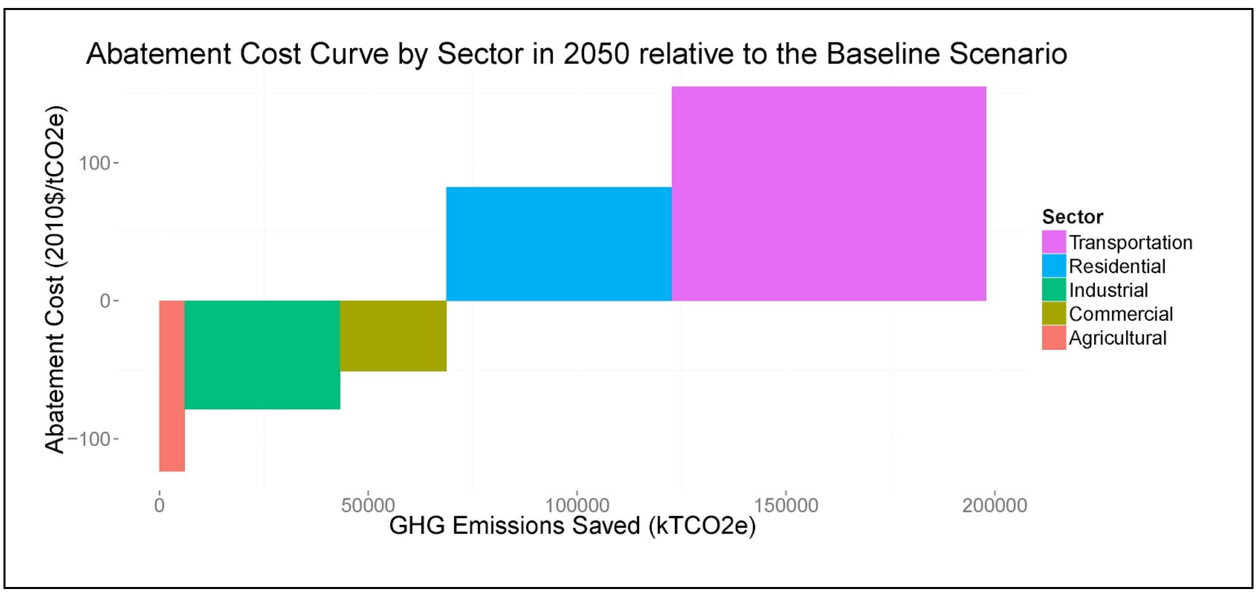
The best way to reduce GHG emissions cost-effectively is a very important policy question. In this section we build different types of abatement cost curves based on the results from CA-TIMES model. The obtained curves in this research show cost-effectiveness of various technology and policy options considering system-wide behavioral, technological, and intertemporal interactions.

Marginal abatement cost (MAC) curves have become a very popular tool in the policy world to answer this question, since they can represent the complex issue of cost-effective emissions reduction in a simple manner. A marginal abatement cost (MAC) curve is a graph that shows the cost, usually in $ per tCO2, associated with the different emissions mitigation options and the level of emissions reduction. Therefore, these curves plot the marginal abatement cost on the y-axis and the emission abatement level on the x-axis. MAC curves not only indicate the marginal cost of emission abatement for varying amounts of emission reduction, but they can also be used to calculate the total abatement costs as well as average abatement costs by calculating the integral of the curve. Moreover, MAC curves can be plotted for the various GHG mitigation measures: ordering all GHG mitigation measures from the lowest individual cost to the highest individual one. Each measure is also associated with an amount of GHG reduction and a cost per tonne of GHG emissions reduction (cost per tonne) to achieve those reductions. The cost per tonne for each measure shows the average cost per tonne of achieving the given amount of reductions for that measure. Therefore, within each GHG mitigation measure some of the reductions may be more expensive than others.

There are not many MAC curves that are developed for California that show the cost-effectiveness of mitigation options and their potential to reduce GHG emissions. Sweeney, Weyant et al. (2008) developed the only expert-based MAC curves in California to help policy makers identify cost-effective mitigation measures to achieve AB32 mitigation target in 2020. However, they did not consider interactions between different sectors and different policies, inter-temporal interactions and behavioral aspects. Currently, the state does not have any model-based MAC curve that shows the cost-effectiveness of mitigation options in 2030 and 2050 for California. Using CA-TIMES, we are able to generate MAC curves at different detail levels including end-use and technology detail, considering inter-temporal, behavioral, technological and economic interactions. CA-TIMES is able to simultaneously optimize the economic costs of meeting GHG reduction target as well as other policy measures, while explicitly accounting for technology feasibility and cost-effectiveness of GHG reductions across the whole economy.

Figure 10 illustrates the abatement cost curves in the GHG reduction scenario with linear cap up to 2050 (2050 cap scenario) relative to the baseline scenario (2020 cap scenario) in 2050. The transportation sector is the most expensive sector on average to mitigate GHG emissions at $157/tCO2e, however, the residential sector is the next most expensive at $82/tCO2. Due to the commercial sector behavioral rules which limit fuel switching in the Reference (2020 cap) scenario but allows allows more service demands to choose the least-cost available option in GHG scenario (especially for space cooling, heating and water heating), abatement cost in the commercial sector is -$50/tCO2e. The representation of the agricultural and industrial sector is very simple in the CA-TIMES and we do not have any technology representation in these sectors. However, we assume an exogenous efficiency improvement in the industrial sector, which leads to the significant emissions saving in this sector. Savings in the agricultural sector are only coming from electricity decarbonization.

By looking at the abatement cost curve at end-use level in 2050, the most expensive end-use to save emissions is marine while the cheapest one is buses. Decarbonization of the bio-derived residual oil is the main reason of expensive saving in this end-use, and the cost-saving opportunity to shift from gasoline and diesel buses to plug-in hybrid buses in 2050 leads to a significant cost saving in this end-use. It can be seen that the most expensive end-use to mitigate GHG emissions in the residential sector is the space heating which is caused by the electrification of this sector and adoption of efficient electric heater. The average mitigation cost of light-duty cars is $168/tCO2e, which is due to the adoption of alternative fuel vehicles including fuel cell vehicles and electric vehicles. At the same time, GHG emissions abatement from light-duty trucks is $69/tCO2 in 2050 ,which is lower than cars due to greater savings in the fuel costs. It is also important to keep in mind that these curves reflects the life-cycle economic costs that consumers incurred, and many consumers would not choose the cheapest option due to different reasons such as high capital cost and risk aversion which is known as efficiency gap.



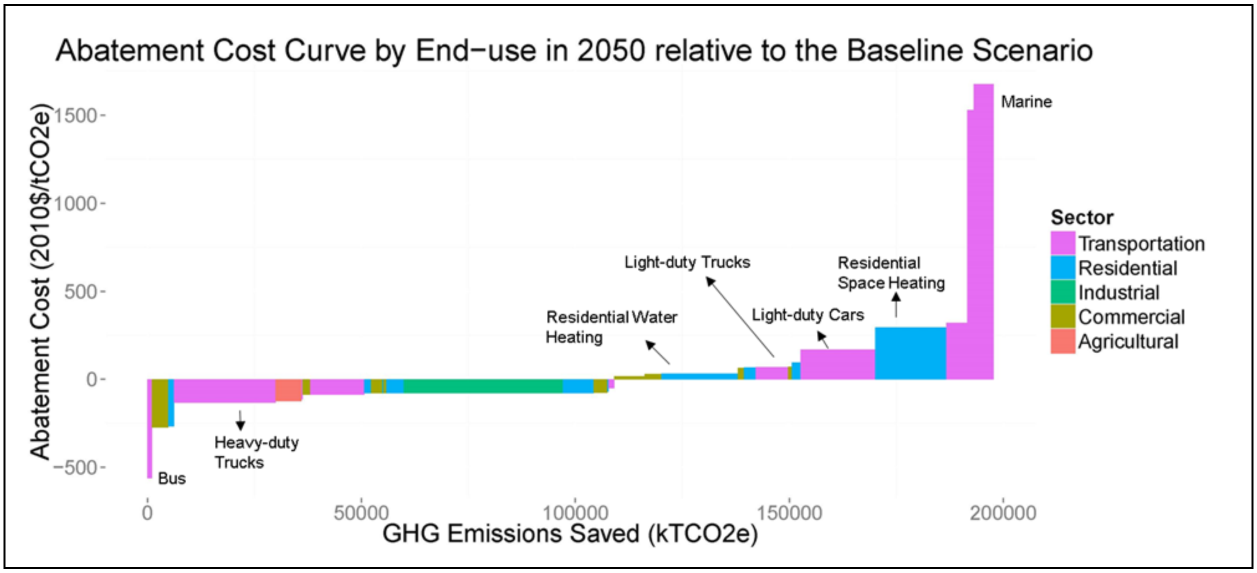
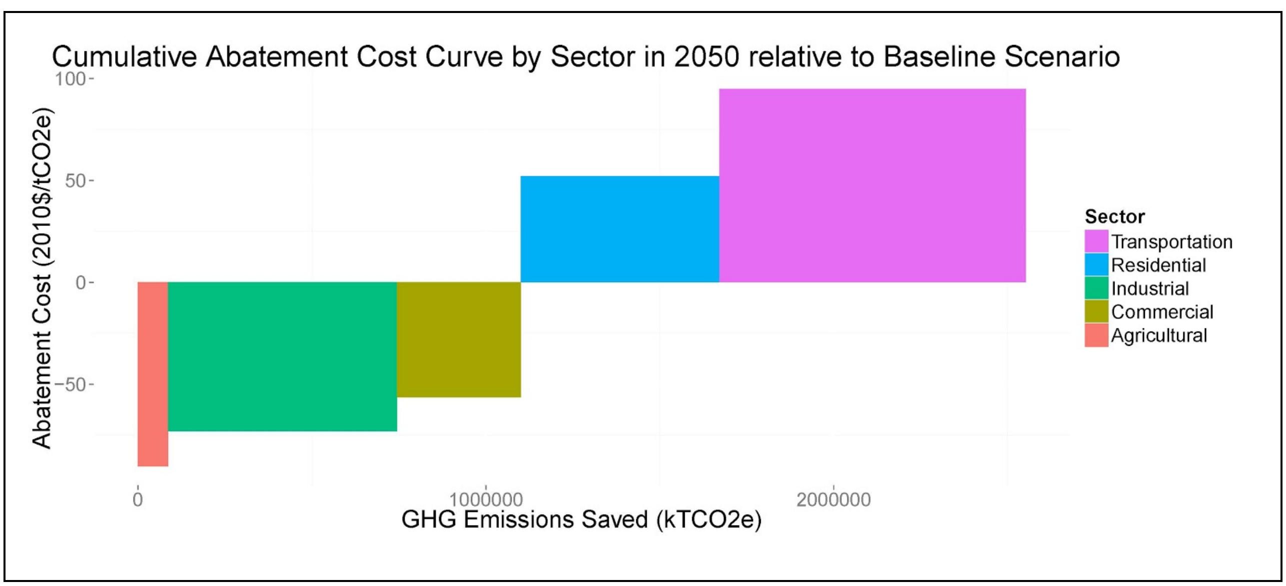


Figure 10. Abatement cost curve in the GHG reduction scenario (GHG Line) relative to the baseline in 2050 by sector (top) and by end-use (bottom)

Figure 11 depicts the average cumulative abatement cost curves between 2010 and 2050. Similar to abatement cost curves by sector in 2050, transportation sector is the most expensive sector for GHG emissions mitigation between 2010 and 2050 with an abatement cost of $95/tCO2e. However, the largest source of emissions savings are coming from the transportation sector during this period. GHG emissions saving from the commercial sector is negative cost (i.e. emissions reductions save money relative to the baseline scenario) due to the relaxed behavioral rules in the GHG policy scenario, which allow consumers to choose the most cost-effective technology, even if it means switching fuels and technology types (i.e. natural gas furnace to an electric heat pump).



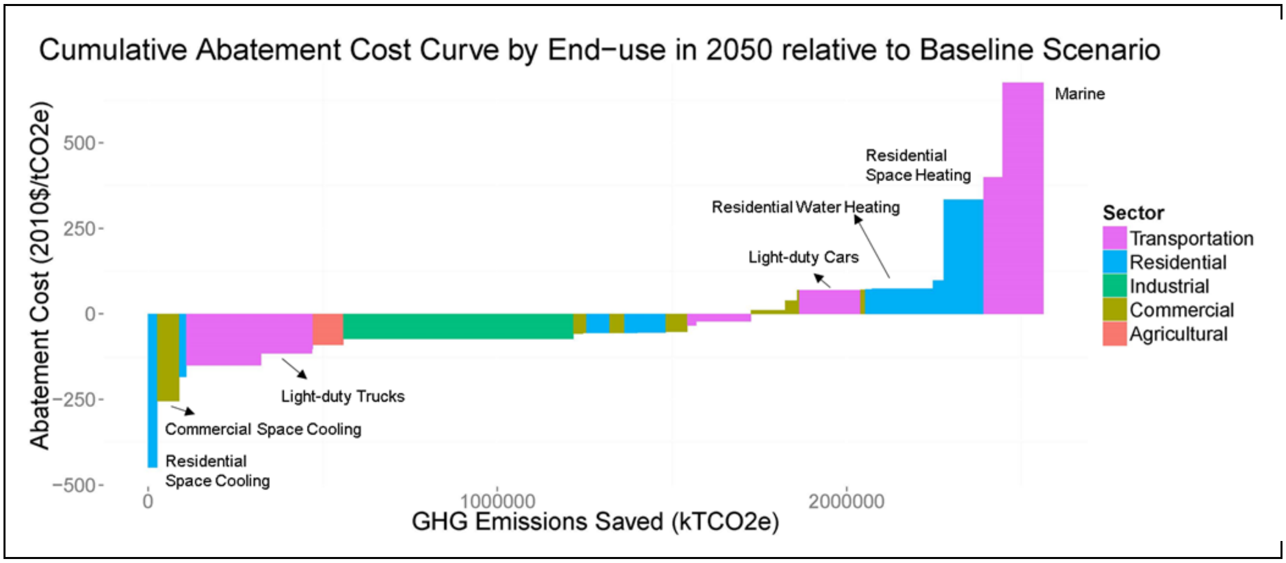


Figure 11. Cumulative abatement cost curve in the GHG reduction scenario (GHG Line) relative to the baseline between 2010 and 2050 by sector (top) and by end-use (bottom)

Marine is the most expensive end-use to mitigate GHG emissions from cumulatively during 2010 and 2050[1]. Residential space heating is the most expensive end-use in the residential sector due to the electrification. Average cumulative mitigation costs of light-duty cars and trucks are $69/tCO2e and -$22/tCO2e, respectively. The negative cost of mitigation in light-duty sector means shifting to alternative fuel vehicles is cost saving and it is important to implement policies that overcome existing barriers such as high capital cost.

[1] The marine and aviation sectors include GHG emissions that are outside the cap and thus not included in this emissions reduction calculation, however, all the costs from these sectors are included in the cost calculation which can lead to higher mitigation costs.

4. POLICY SCENARIOS

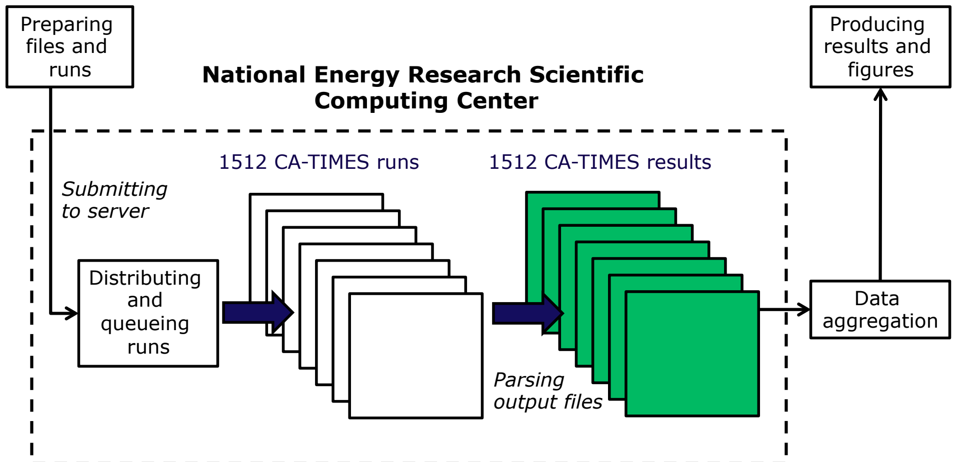


Figure 12: Procedure for running policy scenarios on NERSC supercomputing cluster.

Figure 12 shows the procedure we used to run over 1500 CA-TIMES runs on a distributed supercomputing cluster at the Department of Energy's National Energy Research Scientific Computing Center (NERSC). The separate model specifications are set for each individual run and then can be run in parallel among the various computing nodes on the cluster. This enables us to quickly run hundreds of runs simultaneously and several thousand runs in a matter of minutes to hours instead of months. Once all of this data is generated from each of the scenarios, the results are parsed and aggregated in order to make sense of the data.

We supplement the figures in the main report with additional visualizations of interest. We examine policy impacts on system costs, emissions, power generation, efficiency gains in the residential and commercial sector, fuel usage, and vehicle fuel efficiency.

Policy impact on system costs

The largest variation in system cost results from the different cost scenarios but we also observe some variation in costs resulting from other policies as well. The full range of costs we find is between $10.3 trillion up to $10.5 trillion cumulatively, with a total range across all scenarios of less than $200 billion. In Figure 13-Figure 15, we display costs for LCFS policy, RPS, and the ZEV mandate respectively. In the LCFS scenario (note that we run specific an LCFS scenario specific to the cap scenarios and do not include a 2050 LCFS baseline scenario) we observe consistent increases in cost as LCFS is introduced and as it is extended through 2050. One note of interest is that even in the 2050 cap scenarios, the presence of a cost increase due to LCFS indicates that the cap scenarios do not employ all of the measures required by LCFS in order to comply with the emission reduction requirements. However, in the 2030 L scenario, the variation is significantly larger in range than in the 2050 cap scenarios. This indicates that there are likely some interactions between LCFS and other policies we varied in our scenario analysis. In addition, the lack of smaller variation range in stringent cap scenarios also indicates that the cap scenarios overlap slightly with LCFS policy.

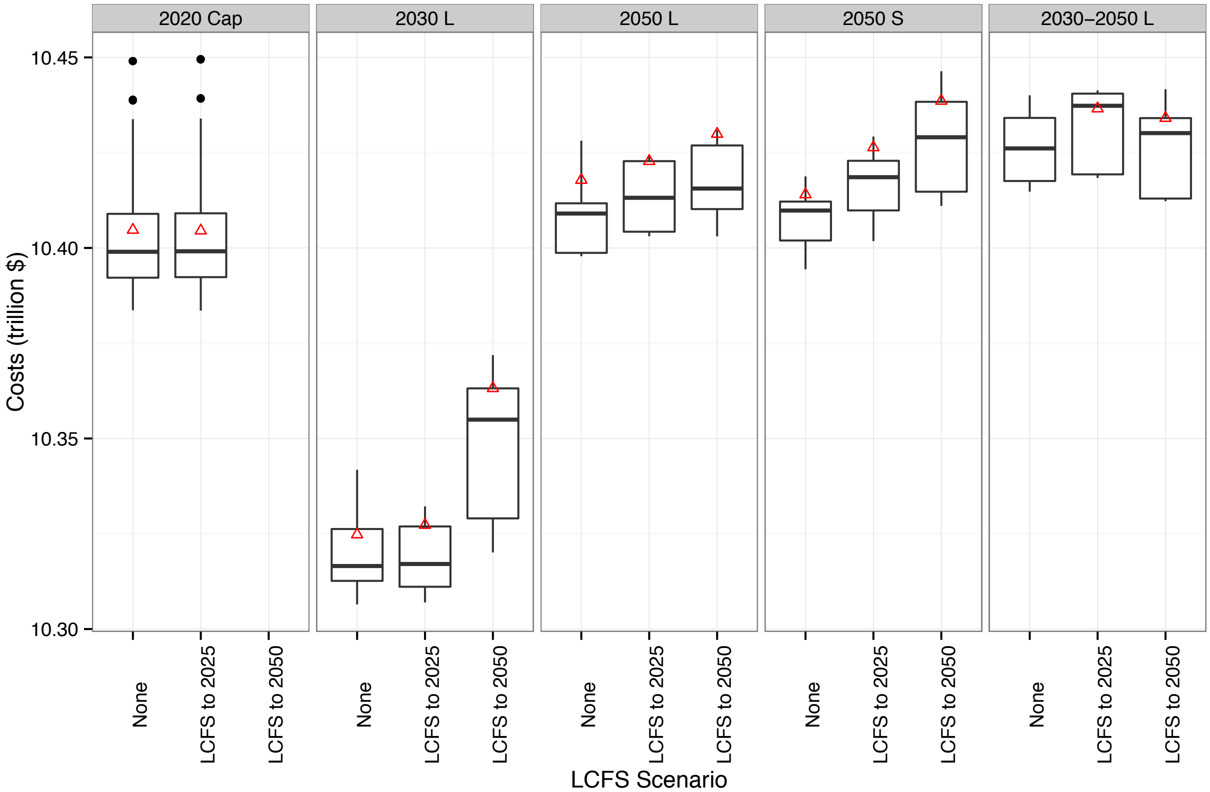


Figure 13: Total costs from CA-TIMES output, clustered by emission cap scenarios and LCFS policy levels. The boxplot of costs captures the variance resulting from other policies, the box itself represents the 25th and 75th percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

The effect of the renewable portfolio standards on system costs are shown in Figure 14. . The different emission levels shown in each of the boxplots represent the full set of 1000+ policy scenarios. Each box represents the full range of emissions in a particular cap scenario (represented by the panel), a particular RPS stringency (represented by the x-axis), and across all the remaining policies (i.e. every stringency level of ZEV, LCFS, petroleum reduction, and CAFE). The red triangle represents the "base" set of policies with the exception of the ones being varied. In Figure 13, each triangle represents the fixed set of policies with ZEV through 2025, LCFS through 2025, no petroleum reduction requirements, and CAFE through 2025 but varied across the different stringency levels of RPS and the different cap scenarios.

In almost all cases of RPS implementation, the costs do not increase significantly with the exception of the 80% requirement in the base case 2020 cap scenario. Since renewables are often the lowest hanging fruit for emissions reduction, any substantial measures to reduce emissions will often employ the use of renewables with or without RPS policies. Variation in the costs are likely due to changes induced by other policies. However, the relative uniformity of the size of the distributions (the range of values) indicates there is likely not a substantial interaction effect with other policies as RPS stringency increases (this does not discount direct interactions with other policies). In other words, the stringency of RPS does not magnify the changes in other costs from other policies.

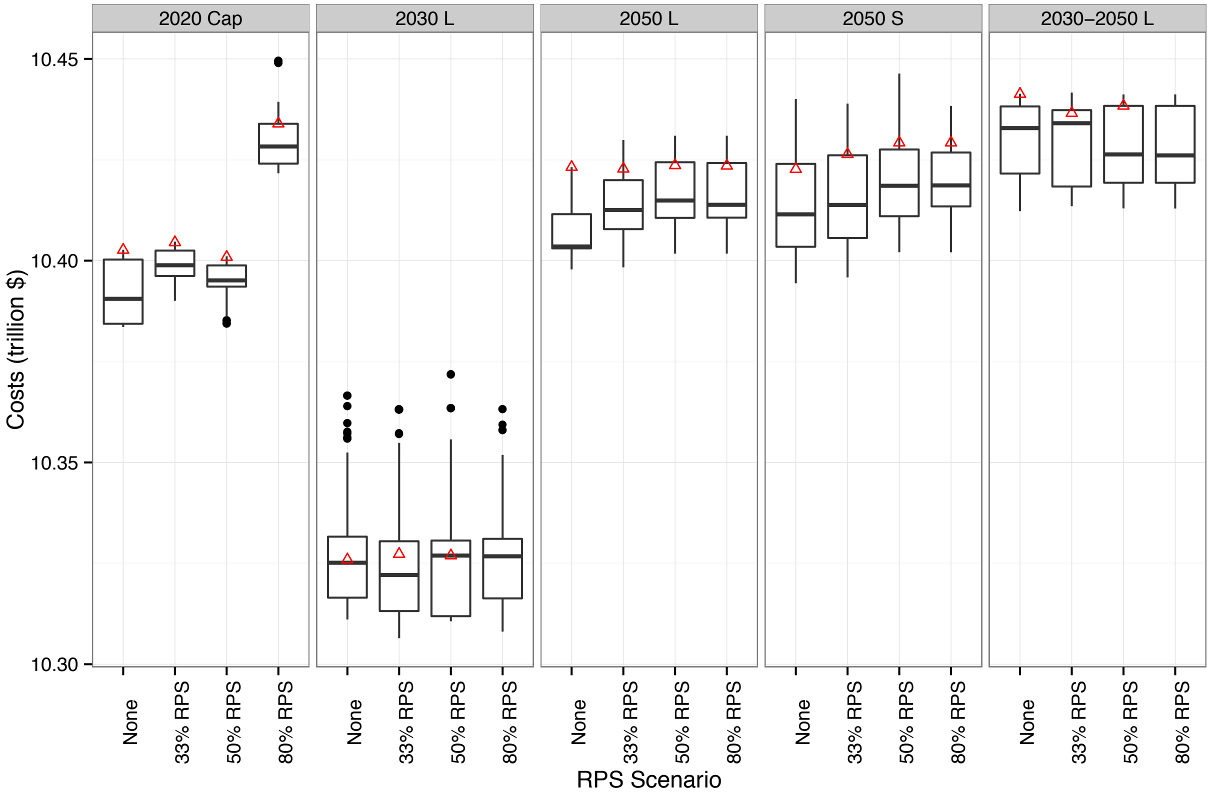


Figure 14: Total costs from CA-TIMES output, clustered by emission cap scenarios and RPS policy levels. The boxplot of costs captures the variance resulting from other policies, the box itself represents the 25th and 75th percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

In Figure 15 we display the effect of including the ZEV mandate across different cap scenarios. Interestingly enough, while the implementation of ZEV through 2025 increases total system cost as expected, the ZEV mandate through 2050 actually decreases costs in all cases. The trajectory of technology adoption finds a lower cost pathway when implementing the extensive ZEV program. The variation in the range of the distributions among different ZEV mandates and across cap scenarios are relatively large. In addition, the locations of the median values in the distributions are not consistent across different policy combinations, indicating that the presence of other policy initiatives may have an outcome on ZEV cost-efficacy. For example, the implementation of RPS may lead to a higher preference for electric vehicles, which would then be a cleaner alternative for the state. This interaction is not an unexpected effect due to the close ties that electric vehicles (and fuel cell vehicles) have with the electric power sector.

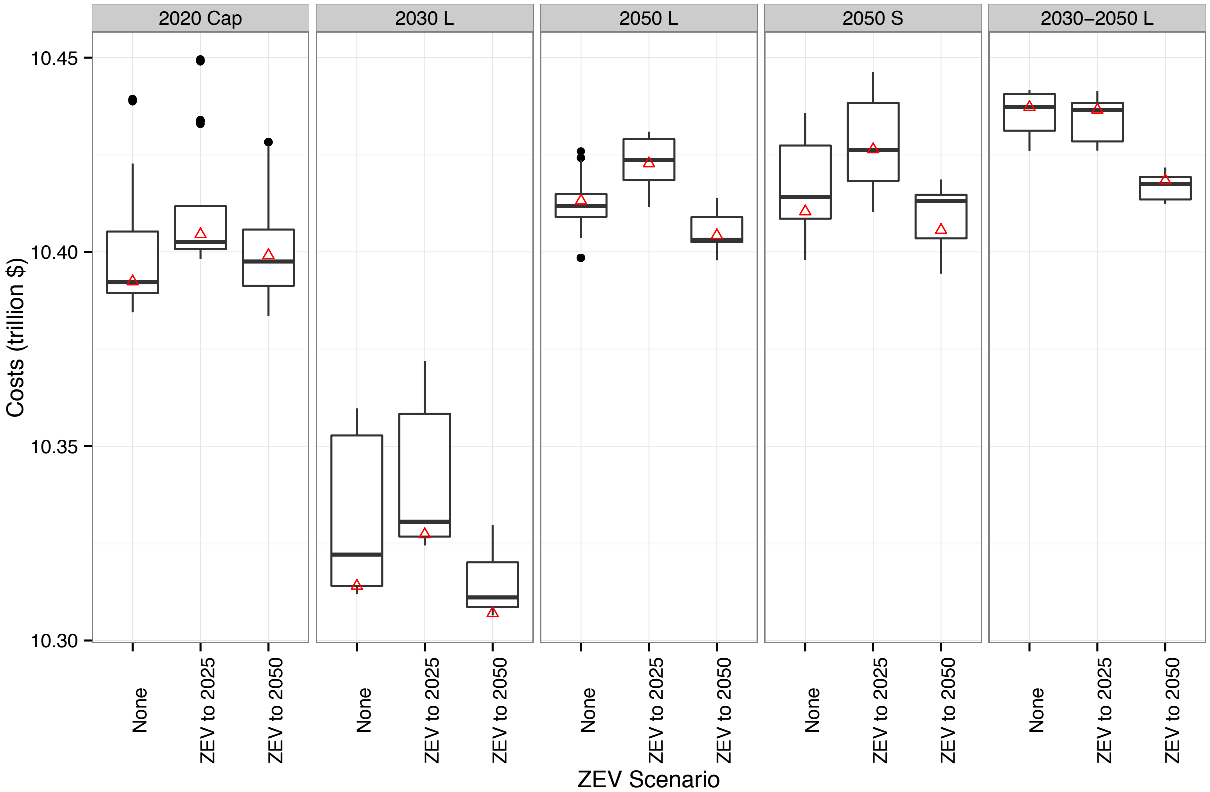


Figure 15: Total costs from CA-TIMES output, clustered by emission cap scenarios and ZEV policy levels. The boxplot of costs captures the variance resulting from other policies, the box itself represents the 25th and 75th percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied..

Policy impact on emissions

We display the overall range of emissions by the emission cap scenarios in Figure 16. As expected, the cumulative emissions decrease as the stringency of the caps increase. However, we note that the ranges of the distributions of emissions have essentially no overlap. While the ranges are relatively large, it is evident that no combination of policies will result in a reduction in emissions equivalent to increasing the stringency of the emissions cap. We note that while the emissions reduction requirement for 2050 is the same in all the 2050 scenarios, we observe variance in the cumulative emissions because leading up to the year 2050, the requirements are quite different. The full range of cumulative emissions over the 40 year time period is a total between 10 to just above 15 gigatons of CO_2.

The effect of the RPS policy on cumulative emissions can be seen in Figure 17. As pointed out earlier, the RPS does not have as a dramatic effect on emissions in higher cap scenarios due to the fact that renewable generation is employed regardless of the policy in order to meet the emission requirements. The most dramatic decreases in emissions are seen in the 2020 cap scenario, with a decrease in overall emissions by over a gigaton through 2025. While the effect is not as pronounced in the 2030 and 2050 cap scenarios, a slight decrease in cumulative emissions is observed as the stringency of the RPS is increased. This is likely due to the fact that while in the later periods renewables are added, the RPS may introduce renewable generation than would otherwise have been adopted and therefore lead to lower overall emissions in California.

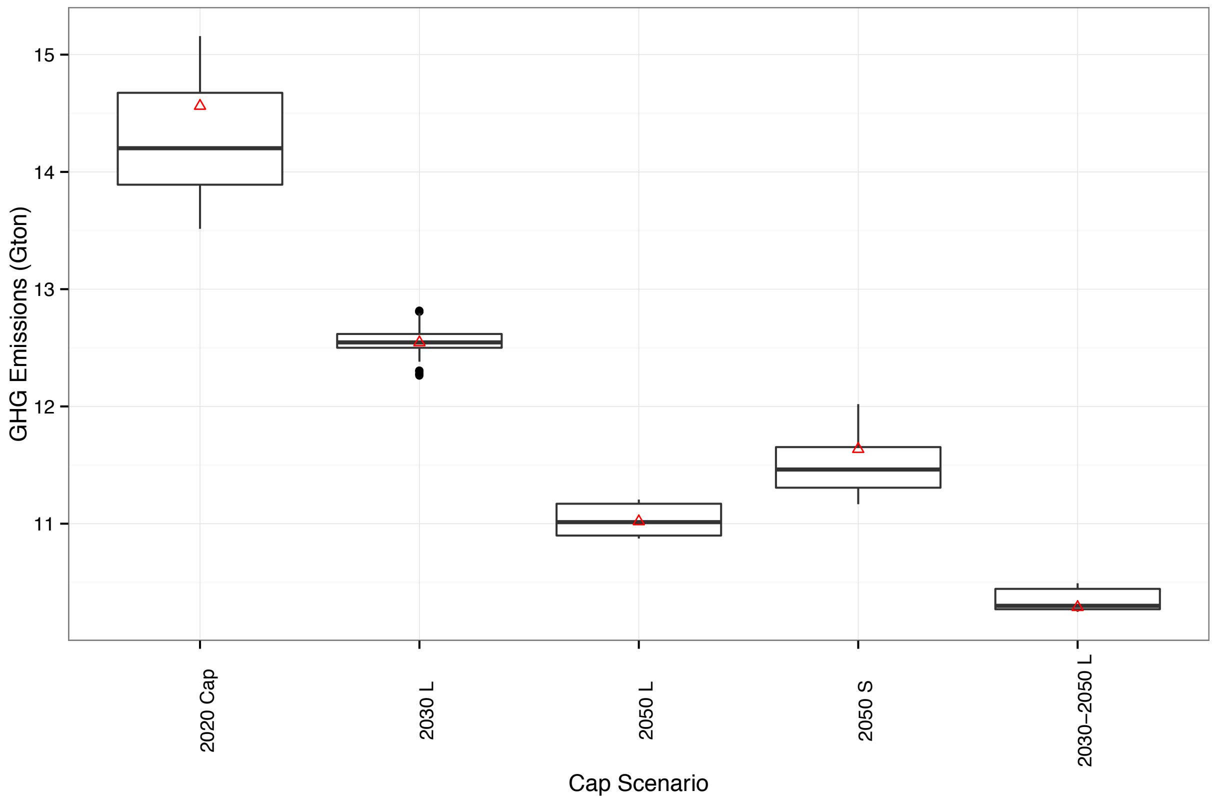


Figure 16: Cumulative emission distributions in 2050 across all policy scenario combinations. The emissions are grouped according to the five emission cap scenarios. The boxplot of emissions captures the variance resulting from other policies, the box itself represents the 25^{th} and 75^{th} percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

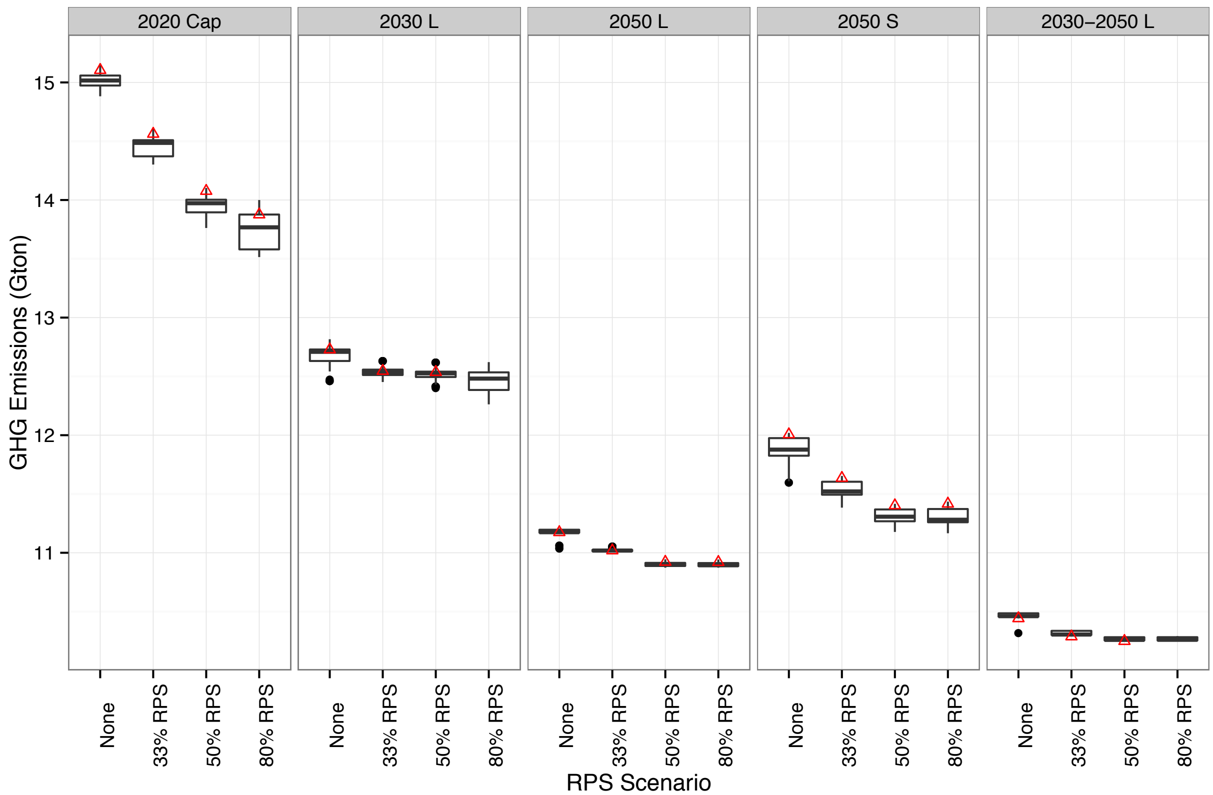


Figure 17: Cumulative emission distributions in 2050 across all policy scenario combinations. The emissions are grouped both by the five emission cap scenarios as well as different renewable portfolio standards. The boxplot of emissions captures the variance resulting from other policies, the box itself represents the 25^{th} and 75^{th} percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

Primary energy

Primary energy resource supplies are influenced strongly by greenhouse gas policies and the RPS policy. Figure 18, shows the decrease in the fraction of total energy system primary energy coming from fossil fuels. Fossil fuels as primary energy drop to about 35% in the most stringent scenarios. Given the range of the fossil fuel usage in scenario, it is clear that nearly the entire variation of fossil fuel usage is accounted for in the combination of the cap scenarios and the RPS requirements. While the decrease is noticeable in the 2020 cap across the different RPS policies, the difference is quite small in the 2030 cap and essentially non-existent in the 2050 cap scenarios.

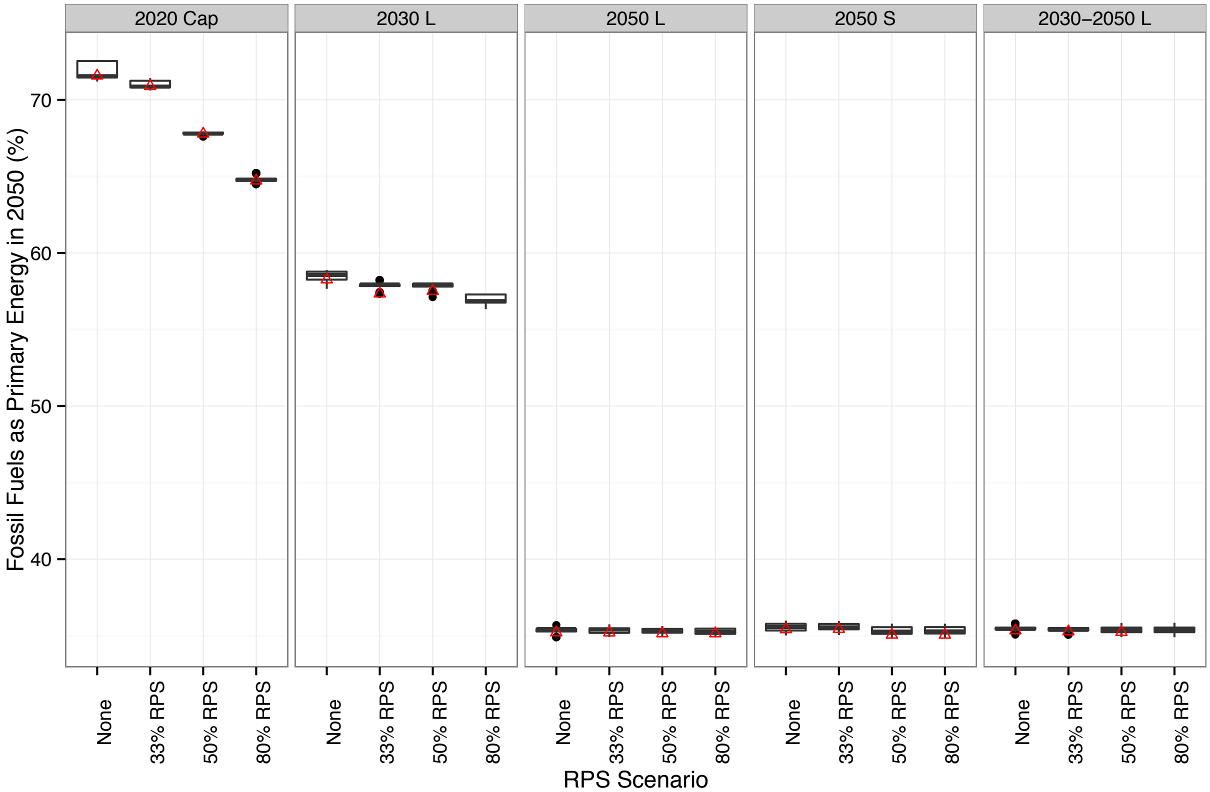


Figure 18: Percentage of energy system primary energy in 2050 supplied by fossil fuels across five emission cap scenarios and four different levels of renewable portfolio standards. The boxplot of primary energy usage captures the variance resulting from other policies, the box itself represents the 25th and 75th percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

Fuel usage

Biofuel usage in the transportation sector is shown in Figure 19; there is a marked increase relative to the 2010 biofuel usage baseline in the alternative fuel usage when comparing the 2020 and 2030 caps to the 2050 caps. While the higher compliance requirements in the more stringent LCFS policy through 2050 leads to a slight increase in the 2030 cap scenario, there is actually a slight decrease in biofuel usage when LCFS is introduced in the higher cap scenarios. This reduction appears to be balanced by an increase in hydrogen fuel usage in transportation. We note however, there is a significant amount of variation in the percentage of biofuels usage, particularly among the lower cap scenarios (which ranges from 20-60% increase). This indicates that the LCFS policy has large interactions with other policies that affect biofuel usage in the transportation sector.

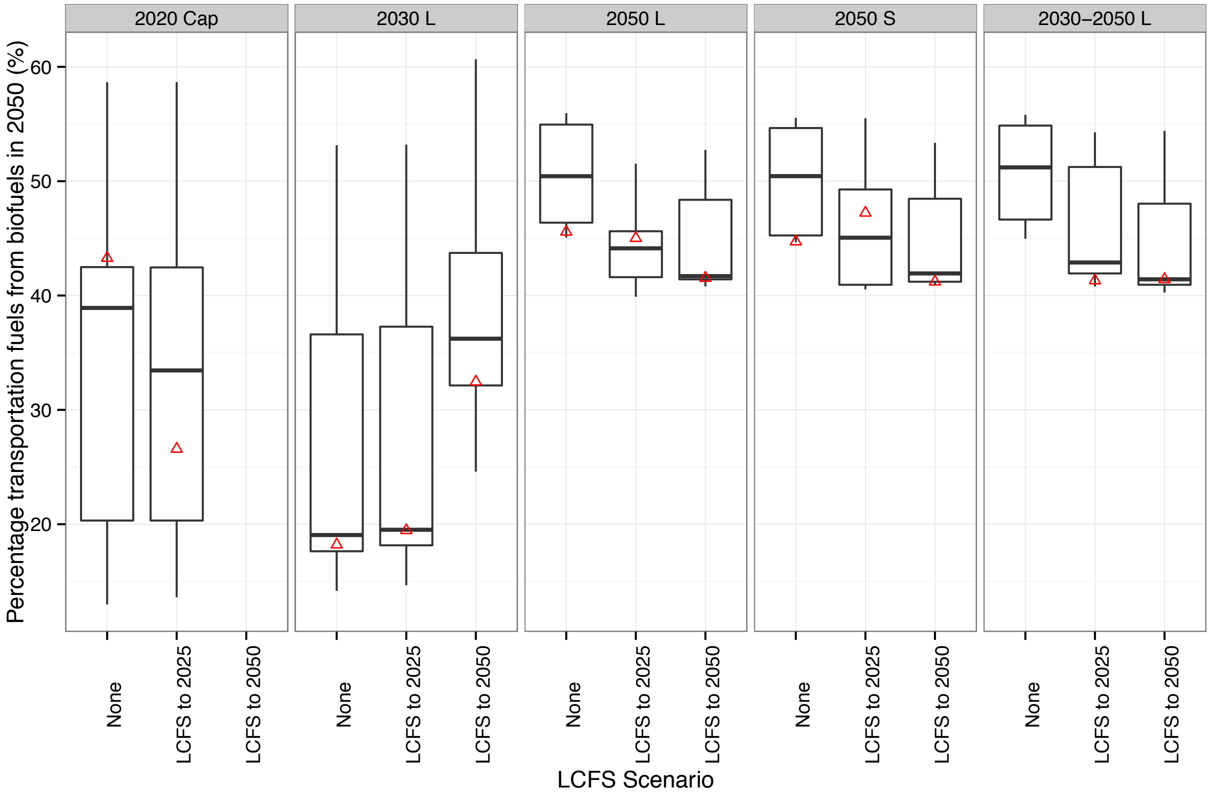


Figure 19: Percentage of biofuel use in the transportation sector in 2050. The data are grouped by both emission cap scenarios and LCFS policy levels. The boxplot of biofuel use captures the variance resulting from other policies, the box itself represents the 25th and 75th percentiles, the center line represent the median, the whiskers are 95th percentile of the data, and dots are outliers beyond the 95th percentile. The red triangles represent the base scenario where all other policies are varied.

Vehicle sector impacts

We calculate the test-cycle fuel efficiency for the light-duty vehicle transportation sector, the final fuel efficiencies in 2050 are displayed in Figure 20. We display the fuel efficiencies with respect to the cap scenarios and with the CAFE standards. Fuel economy increases with increasing stringency of the cap, but variation in the stringency of the CAFE standards does not appear to have much impact in within any given cap scenario, due to the fact that the policy is not binding (i.e. the fuel economy required by the policy is exceed). In the non-cap scenarios there is a significant amount of variance, likely resulting from other vehicle policies that influence fuel efficiency (such as ZEV or LCFS).

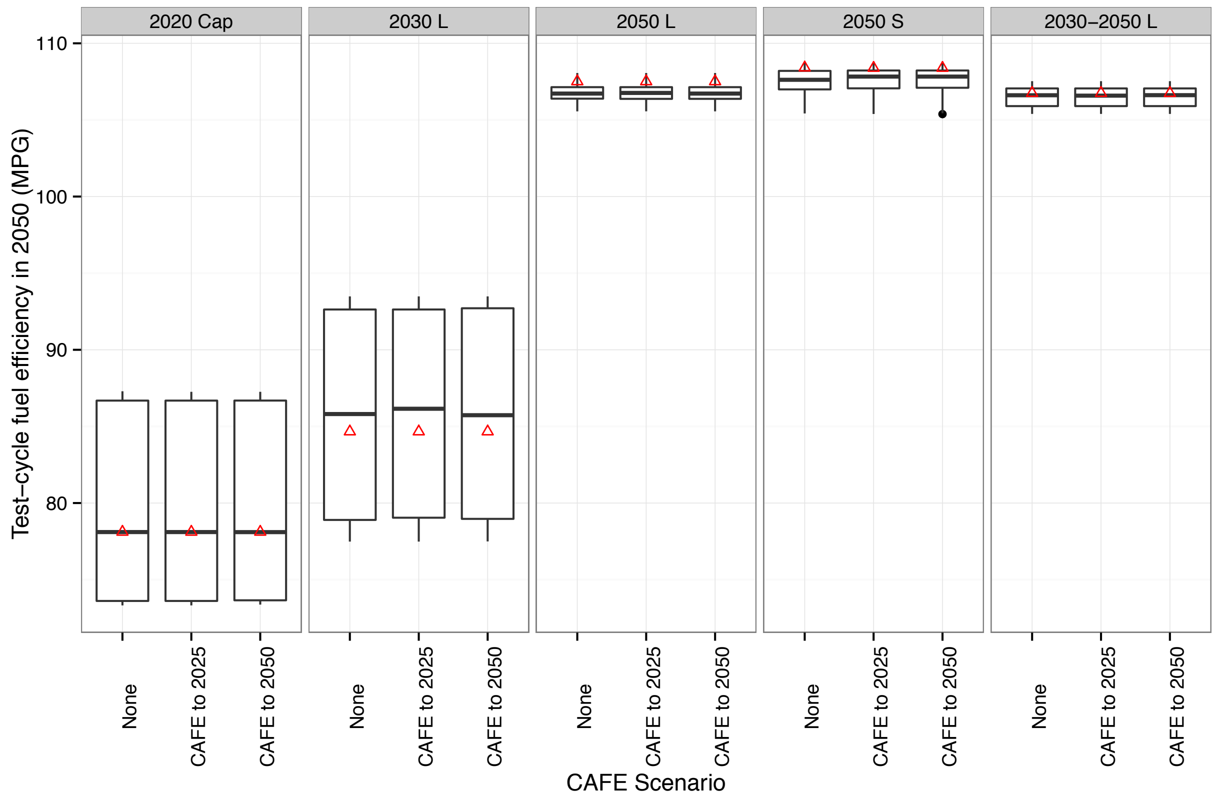


Figure 20: Average fuel efficiency across all passenger vehicles in California in 2050. The efficiencies are grouped by emission cap scenario and by different levels of the CAFE standard.

5. PARAMETER UNCERTAINTY

For every parameter, we assigned a distribution with the following rules:

- Probability of selection below the median and above the median value are both 50%
- The probability of selecting the minimum or maximum value are both half the probability of selecting the median value (equivalent to a truncated triangular distribution on each side of the median)
- The probability linearly interpolates between the min-median and between the median-max.

The shape displayed in Figure 21 is one example of what a typical parameter distribution may look like.

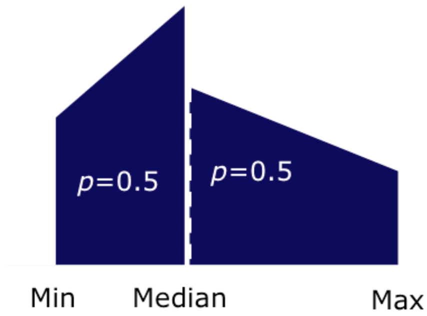


Figure 21: Assumed distribution assignment for all uncertainty scenarios

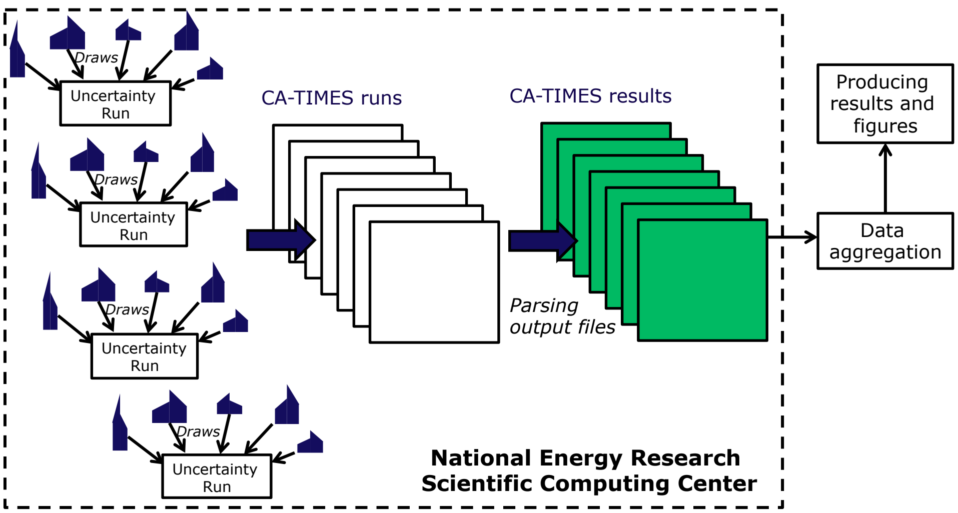


Figure 22: Procedure for conducting Monte Carlo uncertainty analysis through the National Energy Research Scientific Computing Center

The Monte Carlo procedure is conducted by creating a routine that can be executed in many simultaneous instances. We create an uncertainty run associated with a random seed that draws a value for each parameter being varied. The draws are recorded and the associated files are generated and tracked using the seed number corresponding to each run. The National Energy Research Scientific Computing Center is able to execute all of the requested uncertainty runs in parallel.

We supplement the material in the primary report with additional figures examining both overall effects of the parameters on a number of outcomes, as well as a closer examination of the effect of varying single parameters. In Figure 23, we display the average mitigation cost calculated as the difference in the GHG scenario cost and the baseline scenario cost divided by the difference in the GHG scenario emissions and the baseline scenario emissions. The noise in each graph is a result of the other parameters being varied simultaneously; any clear trends in the data indicate an isolated individual effect from the parameter being varied. We find that the majority of parameters do not have a clear effect on the average mitigation cost across the range of values in which they were drawn. The primary exceptions to this are the parameters of biomass availability and natural gas prices, both of whose increased availability/price respectively lead to higher average mitigation costs.

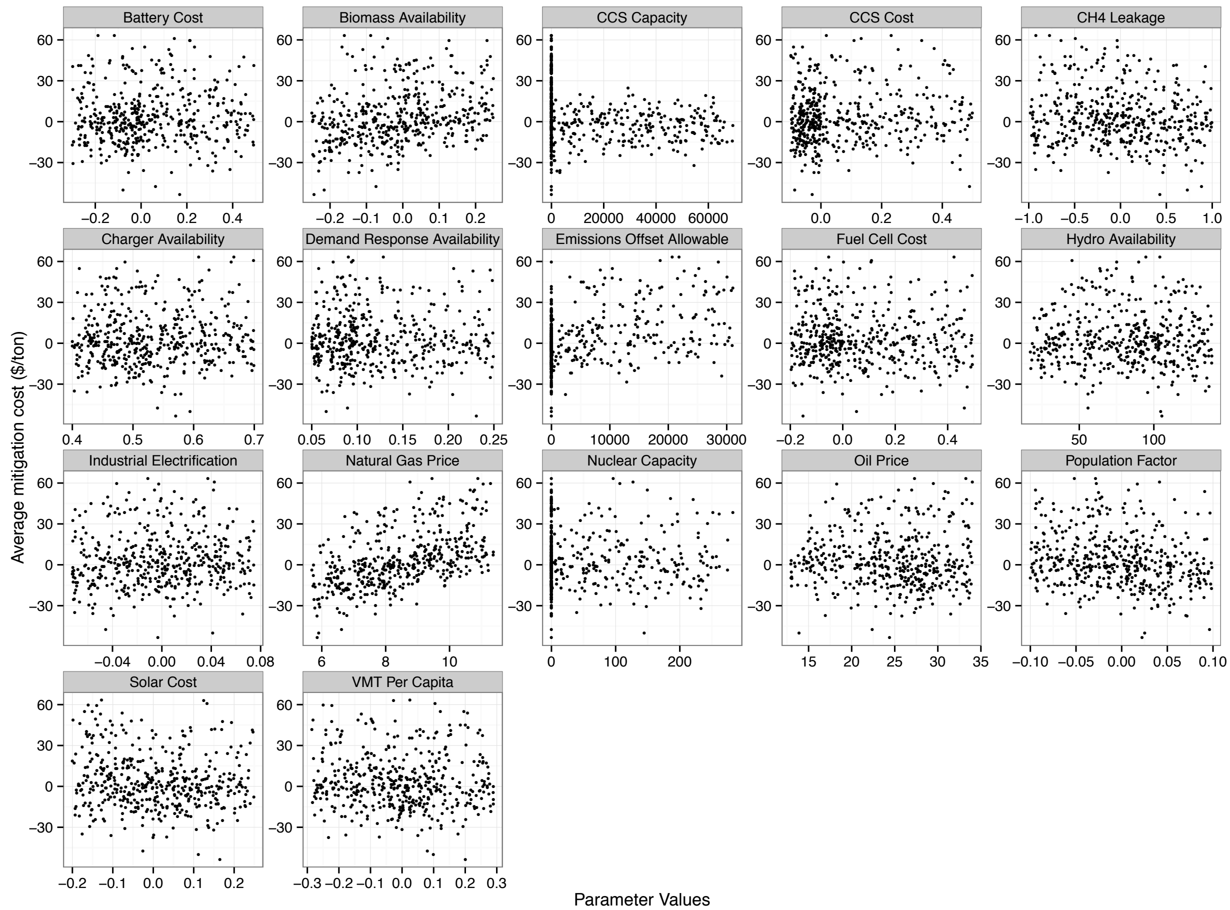


Figure 23: Average mitigation costs for uncertainty parameters

In Figure 24, we observe changes in primary energy use as the availability is altered -20% up to +20%. The direct effect on biomass use is observed to increase its proportion of primary energy usage from approximately 25% up to 35% in the GHG scenario. There is a similar increase in the baseline scenario up to 18-24% up from 15-19%, though there is higher variation in the baseline compared to GHG scenario. We are also able to observe indirect effects in other primary energy categories to understand the substitution patterns from the biomass availability changes. Imported liquid fuels, coal, natural gas, and other renewables do not seem to be impacted. However, both solar and wind decrease slightly in the GHG scenario (and remain relatively flat in the baseline scenario), and oil usage exhibits a very small decrease in both the GHG scenario and baseline scenario.

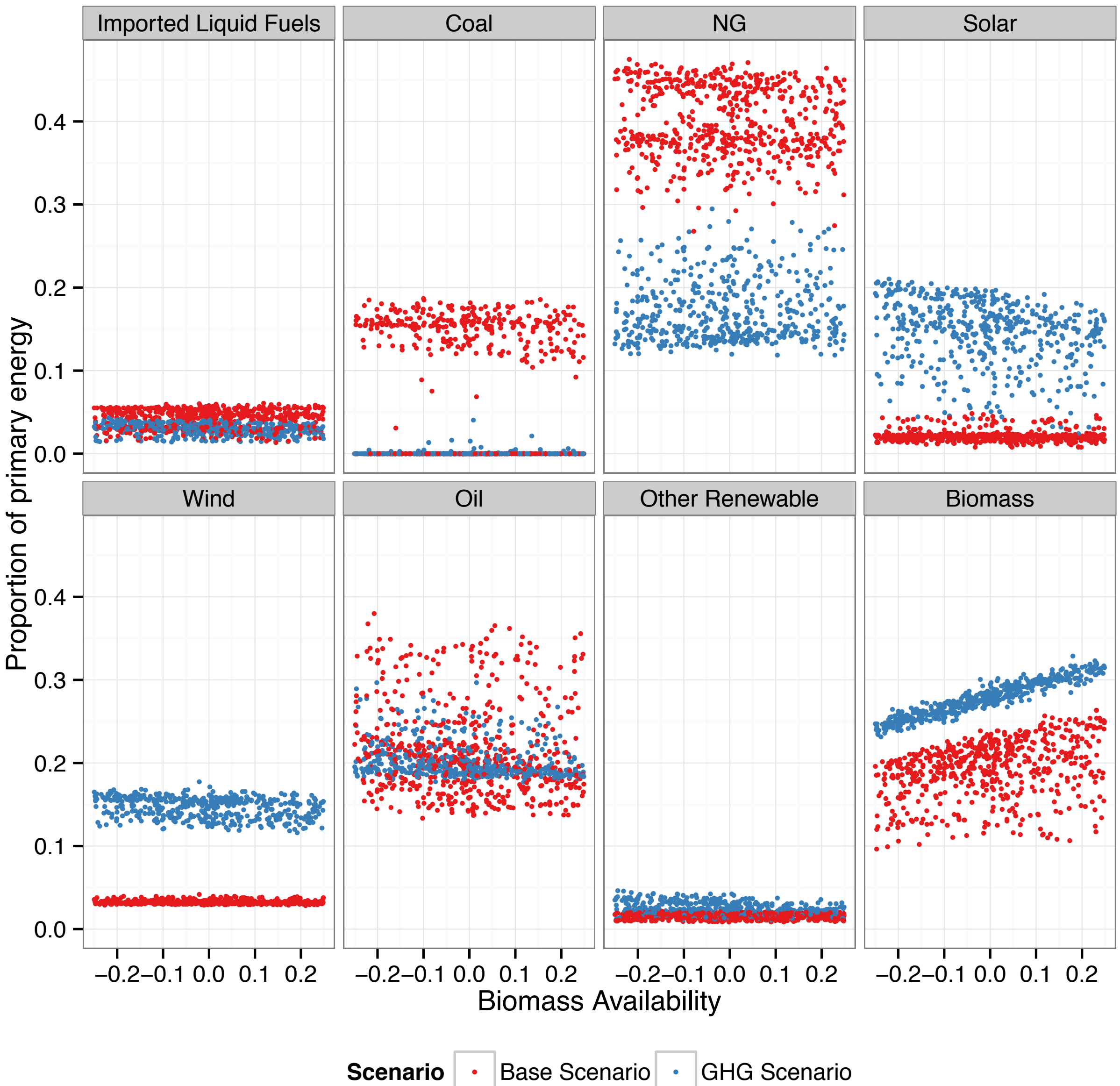


Figure 24: Primary energy usage by type as a function of biomass availability

In Figure 25 we observe the effect of varying natural gas prices on the different categories of primary energy. The direct effect on natural gas is sensible: an increase in price leads to a decrease in usage in both the baseline and GHG scenarios. However, the substitution across other primary energy sources remains relatively flat, there is only a small amount of variation seen with a slight increase in biomass usage in the baseline scenario both corresponding to higher natural gas prices.

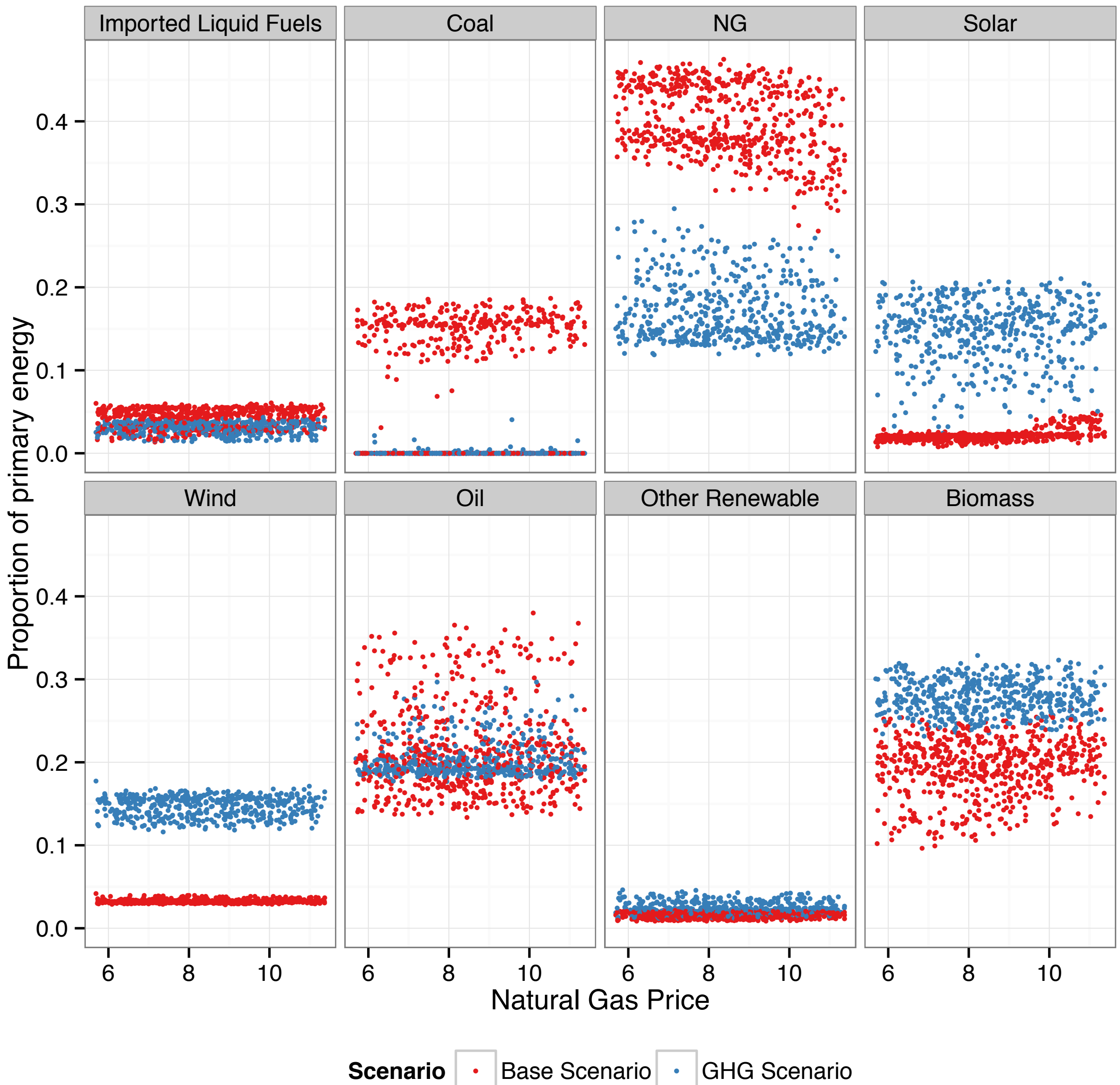


Figure 25: Primary energy usage by type as a function of natural gas price

In Figure 26, we examine the effect of electric vehicle charger availability (in terms of fraction of consumers who have home charging available, ranging from 40% to 70%) on the adoption of different vehicle technologies. There is a general trend of increase in BEVs in both the baseline (+10%) and GHG scenarios (+15%) when the EV chargers are more available, however for PHEVs only an increase is seen in the baseline scenario (+5-10%) and not the GHG scenario. We also observe a similar decrease in the gasoline HEV fleet as the chargers become more available, there is a substitution away from HEVs towards BEVs and PHEVs over the range of battery charger availability.

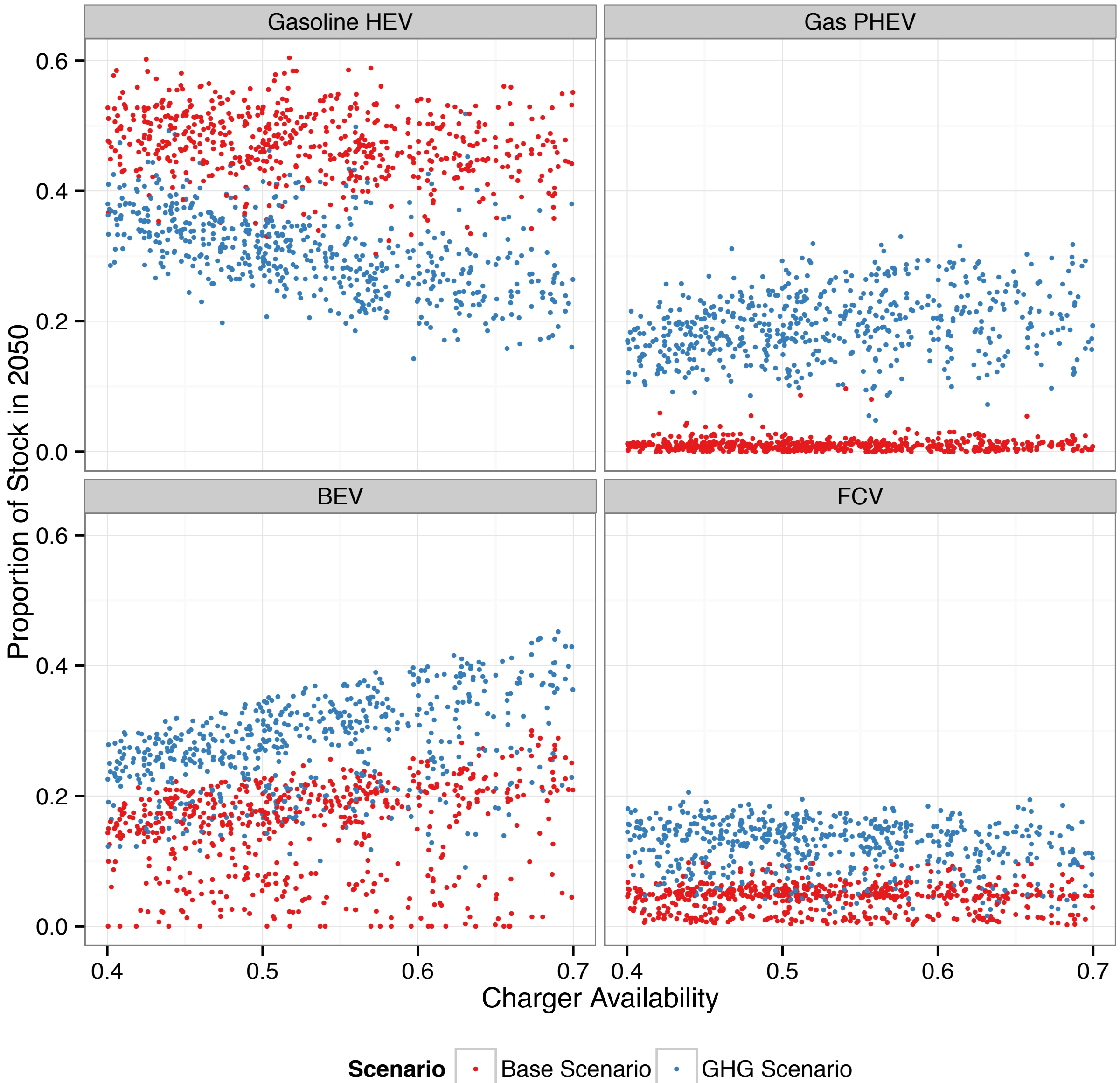


Figure 26: Proportion of vehicle technologies as a function of charger availability

In Figure 27, we vary the cost of fuel cells and observe the associated changes in the light-duty vehicle fleet by technology. As fuel cells increase in cost, there is a decrease in the proportion of fuel cell vehicles in the fleet in both scenarios. However, when fuel cell costs decrease below the baseline value, we do not observe much of a change in the proportion of fuel cell vehicles, thus indicating a saturation level of the FCV technology. There are not any clear substitution patterns in HEVs, PHEVs, and BEVs as the FCV technology changes in adoption levels as their cost changes.

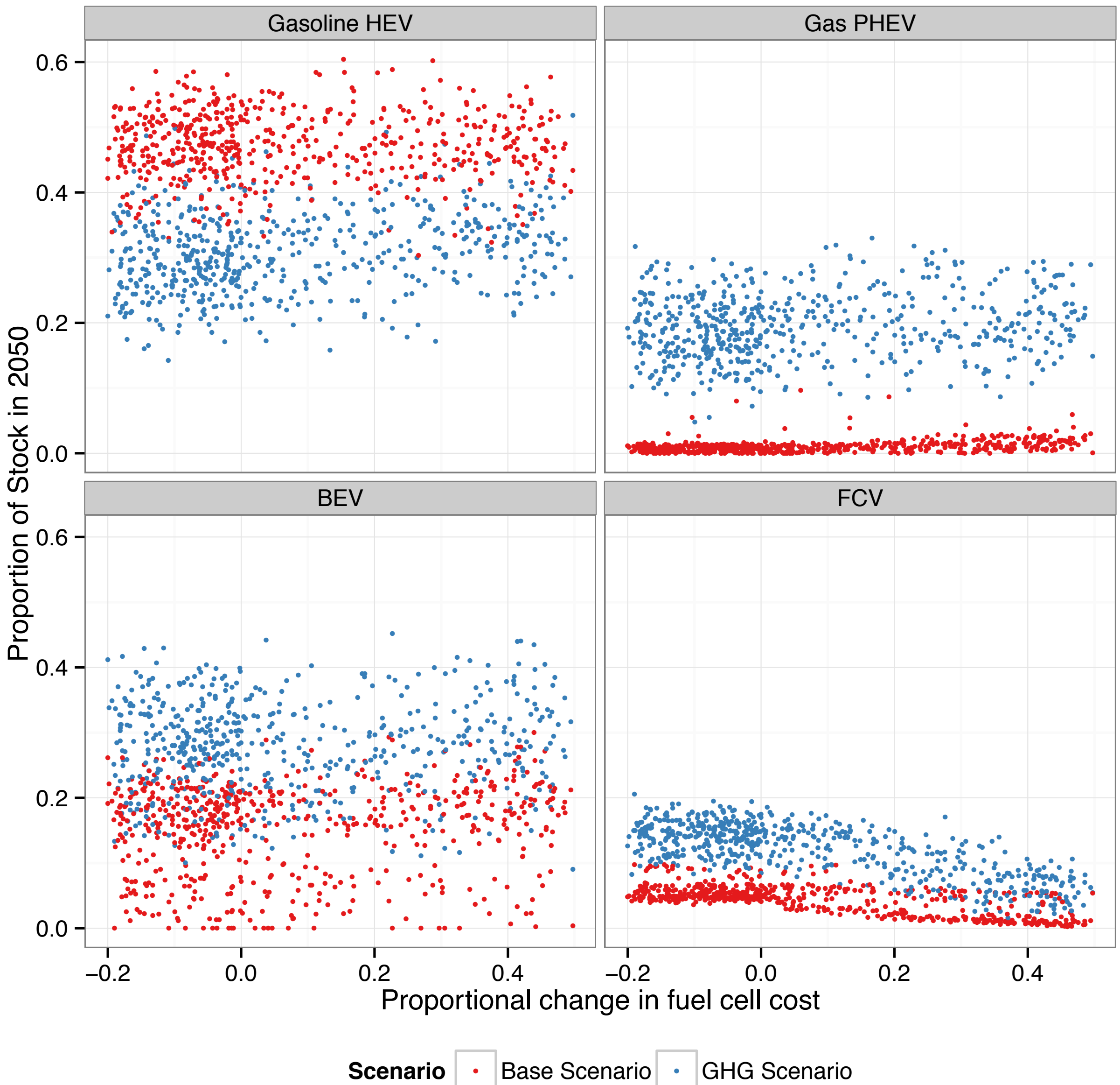


Figure 27: Proportion of vehicle technologies as a function of fuel cell cost

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