Research Report – UCD-ITS-RR-14-04

Modeling Optimal Transition Pathways to a Low Carbon Economy in California: California TIMES (CA-TIMES) Model

Appendices and Supplemental Material

April 2014

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Contract # 09-346

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APPENDICES AND SUPPLEMENTAL MATERIAL

for California TIMES (CA-TIMES) Model

Prepared for the California Air Resources Board and the California Environmental Protection Agency

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April 2014

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CA-TIMES APPENDICES AND SUPPLEMENTAL MATERIAL

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APPENDIX A. COST OF ELECTRICITY GENERATION TECHNOLOGIES

A number of cost analyses and modeling studies from well-known and respected sources have different assumptions about the current and future costs of electricity generation technologies. These cost assumptions were compiled as a point of comparison to better understand the range of potential future costs. Given that CA-TIMES chooses the generation mix based upon minimizing system cost, these ranges can also provide reasonable set of assumptions for sensitivity analyses of electricity mix under uncertainty about future plant capital costs.

The major studies/sources that are used are a 2012 Black and Veatch study for NREL (which is used as input to the NREL ReEDs and UC Berkeley SWITCH model), NREL's Renewable Energy Future's study, NEMS/AEO for 2012 and 2013.

Each power plant type is compared in a graph of future capital costs projections. It is important to note that costs are all in 2010$ and cost in CA-TIMES are inflated with capital cost multipliers for the California region based upon cost multipliers from NEMS (2013).

Cost multipliers for California Power Plants

Power Plant	Cost Adjustment
Coal w/ CCS	1.12
Conv. NGCT	1.24
Adv. NGCT	1.29
Conv. NGCC	1.25
Adv. NGCC	1.24
Adv. NGCC w/CCS	1.15
Fuel Cell	1.03
Nuclear	1
Biomass	1.08
MSW	1.06
On-shore Wind	1.12
Off-shore Wind	1.05
Solar Thermal	1.13
Solar PV	1.11

Cost multipliers for wind, solar PV and solar thermal in other regions

	Solar PV	Solar Thermal	Wind
Southwest (AZ/NW)	0.99	0.99	1.03
Northwest (BC/ID,NV, OR,UT,WA,WY)	0.99	0.99	1.05

Thermal Power Plants

Nuclear

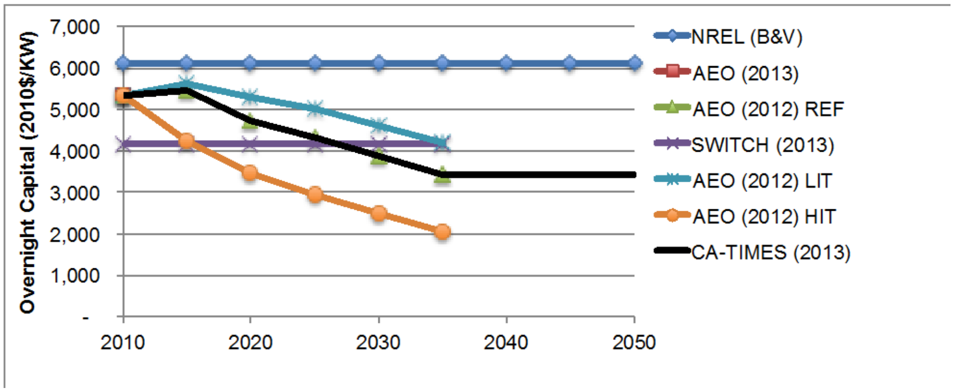

Figure A1. Cost comparison for Nuclear Light Water Reactor (LWR) Power Plants for CA-TIMES and other studies

Natural Gas Power Plants

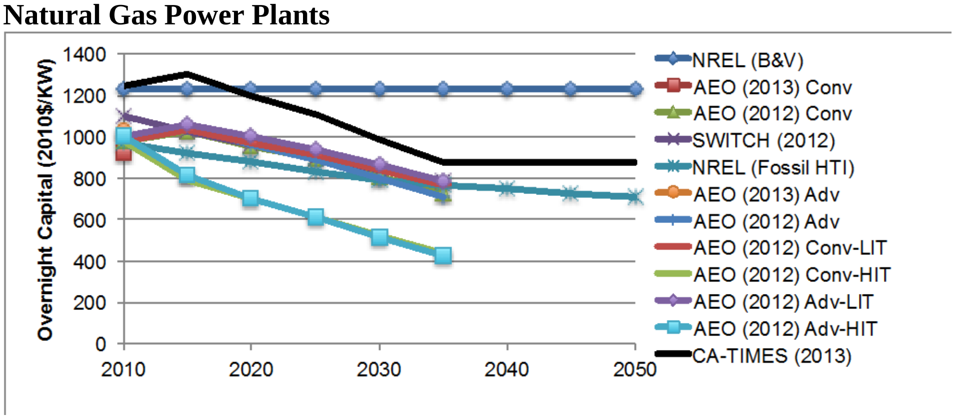

Figure A2. Cost comparison for Natural Gas Combined Cycle (NGCC) Power Plants for CA-TIMES and other studies

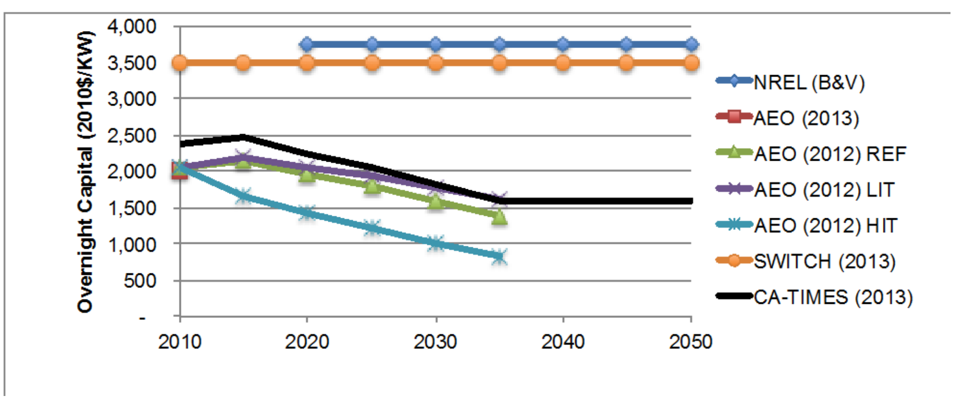

Figure A3. Cost comparison for Natural Gas Combined Cycle Power Plants with CCS (NGCC w/ CCS) for CA-TIMES and other studies

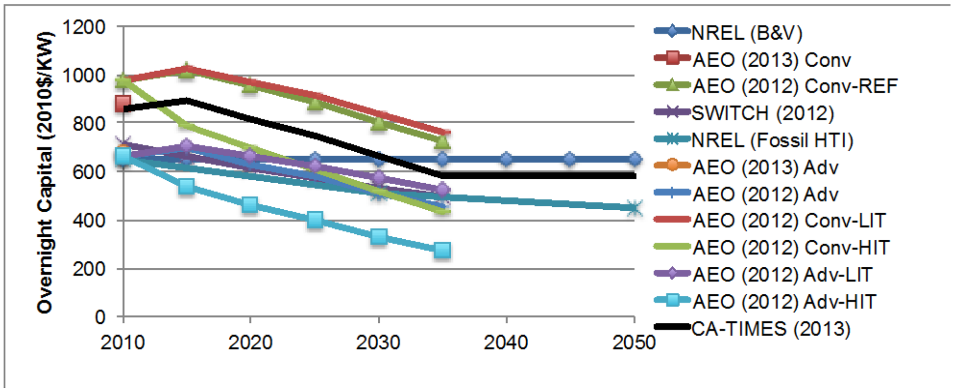

Figure A4. Cost comparison for Natural Gas Combustion Turbine (NGCT) Power Plants for CA-TIMES and other studies

Renewable Power Plants

Biogas Power Plants

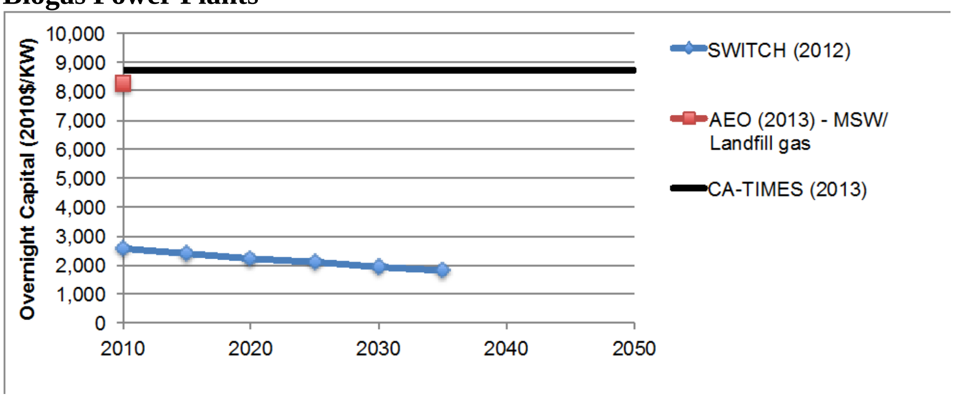

Figure A5. Cost comparison for Biogas Power Plants for CA-TIMES and other studies

Biomass Combined Cycle Power Plants

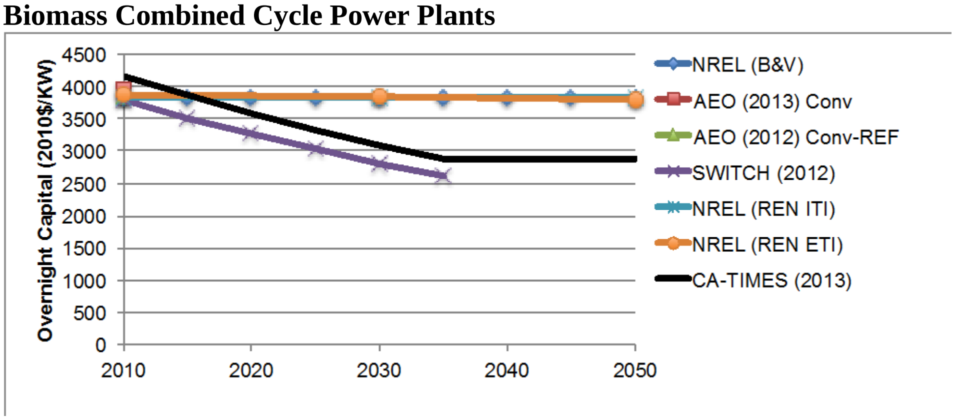

Figure A6. Cost comparison for Biomass Integrated Gasification Combined Cycle (Biomass IGCC) Power Plants for CA-TIMES and other studies

Hydroelectric Power Plants

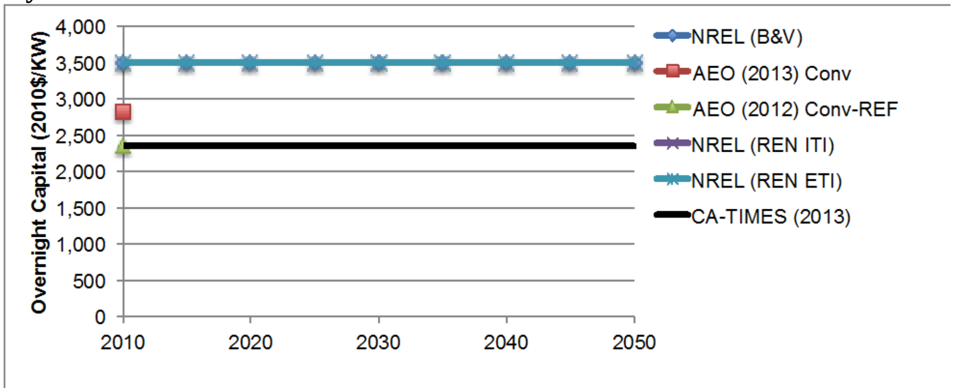

Figure A7. Cost comparison for Hydropower Power Plants for CA-TIMES and other studies

Ocean Tidal Power Plants

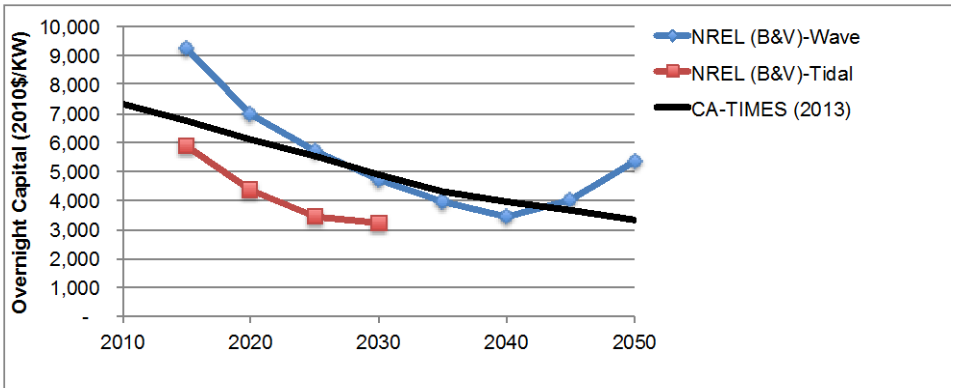

Figure A8. Cost comparison for Ocean Tidal Power Plants for CA-TIMES and other studies

Geothermal Power Plants

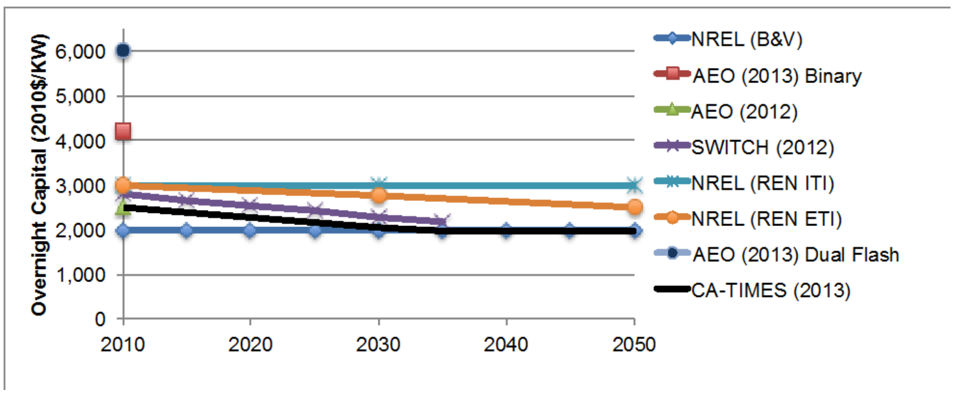

Figure A9. Cost comparison for Geothermal Power Plants for CA-TIMES and other studies

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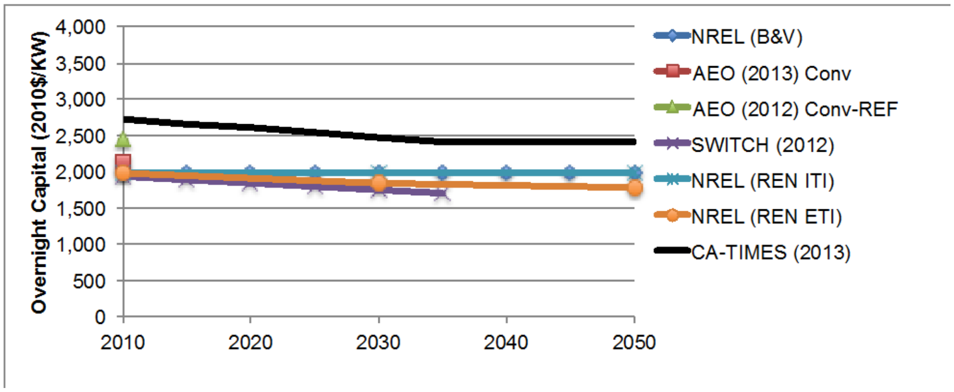


Figure A10. Cost comparison for Onshore Wind Turbines for CA-TIMES and other studies

Solar Power Plants

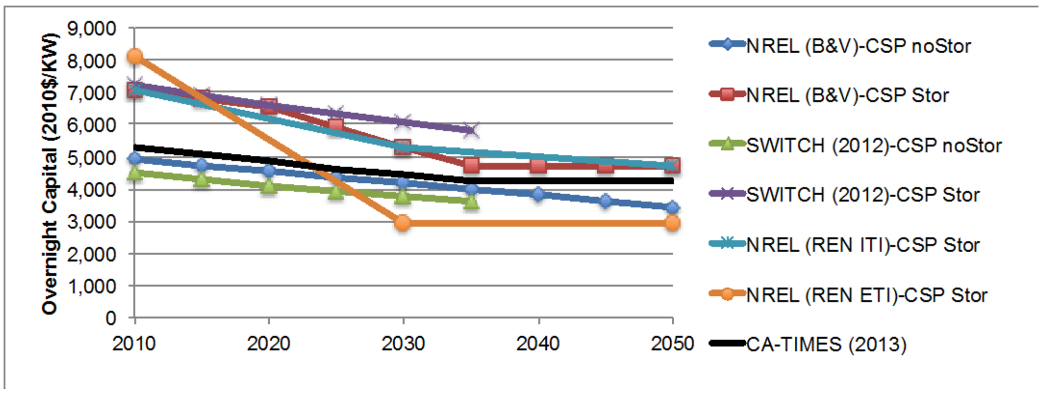


Figure A11. Cost comparison for Concentrating Solar Thermal Power Plants for CA-TIMES and other studies

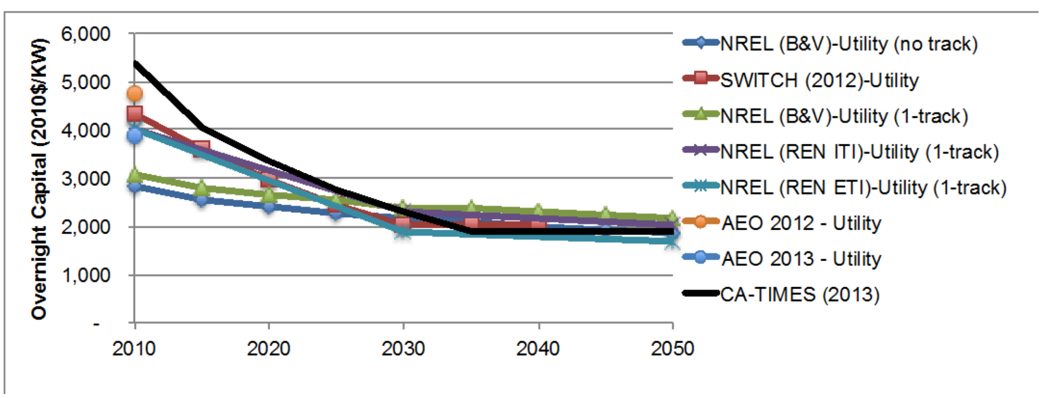


Figure A12. Cost comparison for Utility Scale Solar Photovoltaic Power Plants for CA-TIMES and other studies

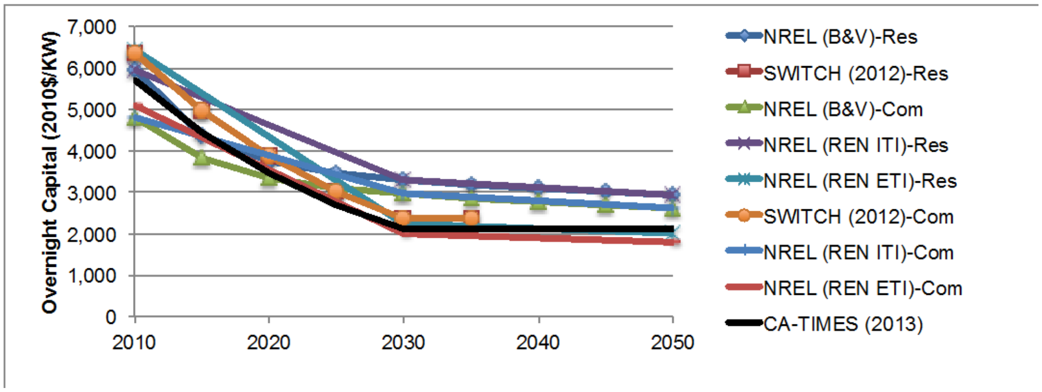


Figure A13. Cost comparison for Distributed (Residential and Commercial) Solar Photovoltaic Installations for CA-TIMES and other studies

Hurdle Rates and Growth Constraints

Electric power plants also have hurdle rates associated with them to represent the monetary and non-monetary effects of risk, uncertainty and other barriers to adoption of new technologies. The base hurdle rate for all mature technologies is 15%. Hurdle rates are assumed to decline for some advanced technologies in 2030. Hurdle rates are taken from EPA's 9-region MARKAL model (U.S. EPA 2008). Electric power plant capacity additions are limited by the absolute amount of capacity that can be added in each five-year time period.

	Hurdle Rate (2010)	Hurdle Rate (2030)	Max Capacity Growth (GW/yr)
Natural Gas Combustion Turbine (NGCT)	15%	15%	None
Natural Gas Combined Cycle (NGCC)	15%	15%	None
Natural Gas Combined Cycle with CCS	30%	25%	None
Biomass Gasification Combined Cycle (IGCC)	25%	15%	0.3 to 0.5
Coal Steam	15%	15%	None
Coal Gasification Combined Cycle (IGCC)	25%	25%	None
Coal Gasification Combined Cycle (IGCC) w CCS	30%	25%	None
Nuclear Conventional Light Water Reactor	25%	25%	0.4 to 0.6*
Nuclear Pebble Bed Modular Reactor	44%	30%	0.4 to 0.6*
Nuclear Modular Helium Reactor	44%	30%	0.4 to 0.6*
Geothermal	15%	15%	0.3 to 0.5
Hydropower	15%	15%	None
Solar Photovoltaic (Residential)	15%	15%	1 to 1.2
Biogas	25%	15%	0.6
Molten Carbonate Fuel Cell	25%	20%	0.2 to 0.4
Tidal	45%	30%	0.2 to 0.4
Wind Turbine	15%	15%	3 to 4.4
Utility Solar Thermal	25%	15%	2.4 to 3*
Utility Solar Photovoltaic	25%	15%	2.4 to 3*
Electricity Transmission Line	15%	15%	None

*Limits on capacity additions of nuclear and utility solar apply to all types collectively not individually

APPENDIX B. ASSUMPTIONS OF TRANSPORTATION TECHNOLOGY COSTS, EFFICIENCIES, HURDLE RATES, ELASTICITIES, AND GROWTH/CAPACITY CONSTRAINTS

The costs and efficiencies of vehicle technologies are mainly taken from the Annual Energy Outlook (AEO 2012; AEO 2013). The major criteria for the data source being: (a) they should have both light-duty car and light-duty truck data for consistency, as the model analysis involves both, (b) the data source should have a base year gasoline price, so that the incremental cost comparison is done between different studies, as an example shown in this Appendix for electric vehicle with 100 mile range. The cost values are compared between different scenarios, and only if, the vehicle cost is significantly away from the range of the incremental cost values, it is adjusted. Annual Energy Outlook does not have all the vehicle technologies present in the CA-TIMES model. So, the following table presents the cost and efficiency assumptions for those. The fuel cell vehicle technology cost specified in the AEO lies outside of the cost comparison study range, so it is adjusted, as an exception.

Technology	Cost Assumptions	Efficiency Assumptions
Moderate midsize fuel efficient vehicle technology	The cost of the vehicle is assumed to be approximately 20% higher than their standard midsize vehicle technology.	Typically assumed to be about 15% higher than their standard midsize vehicle technology.
Advanced midsize fuel efficient vehicle technology	The cost of the vehicle is assumed to be approximately 20% higher than their standard midsize vehicle technology.	Typically assumed to be about 30% higher than their standard midsize vehicle technology.
Plug-in vehicles	Obtained from Annual Energy Outlook data.	The fuel efficiencies are specified separately for the charge-sustaining and charge-depleting modes. For the charge-sustaining modes, the efficiency is assumed to be equal to the comparable hybrid vehicles (gasoline/diesel/ethanol). The charge-depleting (CD) efficiency of the plug-in vehicle is calculated based on the ‘utility factors’ assigned for different mile ranges. Utility factor is the fraction of total annual VMT that is performed by electricity (CD mode). The utility factor is assumed to be 0.20 for 10-mile range vehicles, 0.40 for 20-mile range vehicles, 0.59 for 40-mile range vehicles, and 0.72 for 60-mile range vehicles.
Fuel Cell Vehicle	From the incremental cost comparison, the AEO cost data for fuel cell vehicles seem to be significantly higher than most studies. So, it is adjusted to be in line with the rest of the cost studies. The detailed cost data is summarized in the CA-TIMES cost assumptions table.	
Motorcycles	The fuel economies and costs vary widely by motorcycle type and model. The averages were obtained from the CEC IEPR and Caltrans MVSTAFF data.	
Bus	The costs and efficiencies of the bus technologies, such as diesel, hybrid and natural gas buses are obtained from various sources (U.S. EPA 2003; EESI 2007; INFORM 2007; UCS 2007).	
Passenger rail	The costs are obtained from the EPA US9r model database for the year 2005 and they are then converted to 2010 dollars (U.S. EPA 2006).	The efficiencies of the passenger rail are obtained from the National Transit Database (NTD 2005; NTD 2010). It is assumed to be the same for the year 2010. For the future years, they are scaled by the externally calculated growth rates.

Cost assumptions for midsize cars in CA-TIMES v1.5:

2010$/vehicle	2010	2015	2020	2025	2030	2035	2040	2045	2050
Gasoline Car	23,661	23,732	24,423	25,789	25,897	25,910	25,910	25,910	25,910
Diesel Car	27,274	25,711	25,966	26,627	26,686	26,701	26,701	26,701	26,701
Gasoline Hybrid Car	27,823	26,912	27,214	28,069	28,014	27,950	27,950	27,950	27,950
Ethanol Flex Fuel Car	23,759	23,829	24,523	25,898	26,005	26,018	26,018	26,018	26,018
Gasoline Plugin 10-mile range	28,480	28,480	28,415	29,041	28,892	28,828	28,828	28,828	28,828
Gasoline Plugin 30-mile range	33,512	33,512	32,274	32,162	31,712	31,647	31,647	31,647	31,647
Gasoline Plugin 40-mile range	36,029	36,029	34,203	33,722	33,121	33,057	33,057	33,057	33,057
Diesel Hybrid Car		30,830	30,830	29,306	29,208	29,145	29,145	29,145	29,145
Diesel Plugin 10-mile range	32,031	32,031	32,031	30,278	30,086	30,023	30,023	30,023	30,023
Diesel Plugin 40-mile range	37,819	37,819	37,819	34,959	34,315	34,252	34,252	34,252	34,252
Fuel Cell Car			62,641	40,453	35,532	31,616	31,616	31,616	31,616
Electric Vehicle (100 mile range)		35,617	35,617	33,223	31,954	31,095	31,095	31,095	31,095
Electric Vehicle (200 mile range)			54,798	54,798	50,114	46,934	46,934	46,934	46,934

Cost assumptions for midsize cars from the AEO (U.S. EIA 2013), Kromer and Heywood (Matthew Kromer 2007), and Argonne study (Argonne 2009), $2010/Vehicle:

	AEO 2013			Kromer and Heywood		Argonne's Multi-path Study		
Vehicle Technologies	2015	2030	2040	BAU (2030)	Optimistic (2030)	2015	2030	2045
Gasoline Car	23,732	25,897	25,923	23,112	23,112	26,036	27,040	26,993
Diesel Car	25,711	26,686	26,714	24,931		29,148	29,663	29,498
Gasoline Hybrid Car	26,912	28,014	27,913	25,145	24,931	28,458	28,889	28,555
Ethanol Flex Fuel Car	23,829	26,005	26,031					
Gasoline Plugin 10-mile range		28,892	28,695	26,322	26,001	29,971	29,998	29,361
Gasoline Plugin 30-mile range				27,713	27,071			
Gasoline Plugin 40-mile range	36,741	33,121	32,259			36,497	34,347	32,665
Diesel Hybrid Car		29,208	29,109			31,340	31,255	31,005
Diesel Plugin 10-mile range						32,544	31,991	31,474
Diesel Plugin 40-mile range						39,177	36,504	34,921
Fuel Cell Car		50,532	43,533	28,569	26,964	36,269	33,471	32,366
Fuel Cell Plugin 10-mile range						35,713	33,107	31,614
Fuel Cell Plugin 40-mile range						44,554	38,612	35,582
Electric Vehicle (100 mile range)		31,954	30,662	34,026	30,495	55,552	44,746	39,020

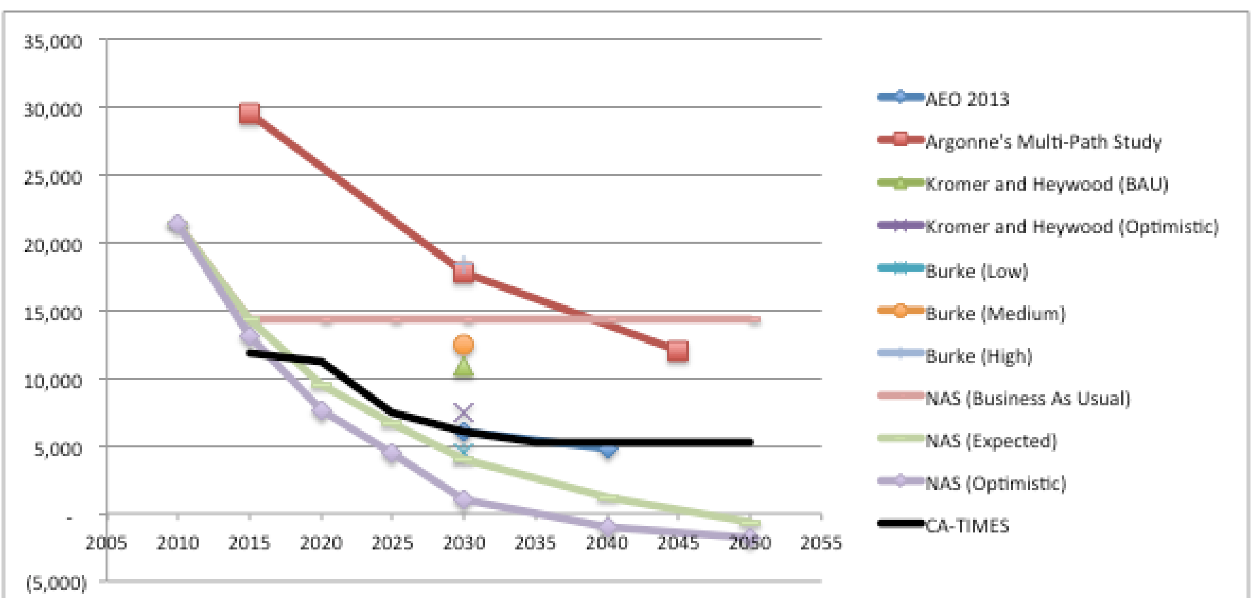
Cost assumptions for midsize cars from the NAS study (2013):

	NAS (Expected)						NAS (Optimistic)					
	2015	2020	2025	2030	2040	2050	2015	2020	2025	2030	2040	2050
Gasoline Car	28,976	29,504	30,395	31,440	32,143	3,078	28,880	29,344	30,155	31,120	31,813	32,737
Gasoline Hybrid Car	32,734	32,182	32,220	32,572	33,051	33,998	32,329	31,508	31,649	31,883	32,554	33,482
Gasoline Plugin 40-mile range	37,491	36,356	35,749	35,536	35,162	35,513	36,883	35,342	34,655	33,997	34,047	34,718
Fuel Cell Car	37,059	35,347	34,271	33,196	32,662	32,573	35,989	33,565	32,301	31,038	30,635	30,807
Electric Vehicle (100 mile range)	43,249	39,045	37,107	35,408	33,396	32,444	41,971	36,914	34,686	32,092	30,865	30,927

Incremental cost assumptions for midsize cars from the AEO (U.S. EIA 2013), Kromer and Heywood (Matthew Kromer 2007), and Argonne study (Argonne 2009), $2010/Vehicle:

Vehicle Technologies	AEO 2013			Argonne's Multi-path Study			Kromer & Heywood BAU	Kromer & Heywood Optimistic
	2015	2030	2040	2015	2030	2045	2030	2030
Gasoline Car	-	-	-	-	-	-	-	-
Diesel Car	$1,979	$790	$791	$3,112	$2,624	$2,505	$1,819	-
Gasoline Hybrid Car	$3,181	$2,117	$1,990	$2,422	$1,849	$1,562	$2,033	$1,819
Ethanol Flex Fuel Car	$98	$109	$108	-	-	-	-	-
Gasoline Plugin 10-mile range	-	$2,996	$2,772	$3,935	$2,958	$2,368	$3,210	$2,889
Gasoline Plugin 20-mile range	-	-	-	-	-	-	-	-
Gasoline Plugin 30-mile range	-	-	-	-	-	-	$4,601	$3,959
Gasoline Plugin 40-mile range	$13,009	$7,225	$6,336	$10,461	$7,308	$5,672	-	-
Diesel Hybrid Car	-	$3,311	$3,186	$5,304	$4,215	$4,012	-	-
Diesel Plugin 10-mile range	-	-	-	$6,508	$4,952	$4,481	-	-
Diesel Plugin 40-mile range	-	-	-	$13,142	$9,464	$7,928	-	-
Fuel Cell Car	-	$24,636	$17,610	$10,234	$6,431	$5,373	$5,457	$3,852
Fuel Cell Plugin 10-mile range	-	-	-	$9,677	$6,067	$4,622	-	-
Fuel Cell Plugin 40-mile range	-	-	-	$18,518	$11,572	$8,589	-	-
Electric Vehicle (100 mile range)	-	$6,057	$4,739	$29,516	$17,706	$12,027	$10,914	$7,383
Electric Vehicle (200 mile range)	-	-	-	-	-	-	-	-

Incremental cost comparisons of electric vehicles (100-mile range), $2010/vehicle:



Efficiency assumptions for midsize cars from the AEO (U.S. EIA 2013), MIT study (2007) , and Argonne study (Argonne 2009), MVMT/PJ:

	AEO 2013			Argonne's Multipath Study			Kromer & Heywood
Vehicle Technology	**2015**	**2030**	**2040**	**2015**	**2030**	**2045**	**2030**
Gasoline Car	276.6	403.1	401.8	199.1	205.2	228.7	369.8
Diesel Car	343.9	427.4	426.2	253.6	264.0	302.3	431.5
Ethanol Flex Fuel Car	274.6	407.9	407.1				
Gasoline Hybrid Car	393.8	561.0		339.5	388.3	438.7	661.0
Gasoline Plugin 10-mile Range	441.5	629.1	627.4	896.9	1035.9	1107.7	786.5
Gasoline Plugin 30-mile Range							927.3
Gasoline Plugin 40-mile Range	531.0	747.7	745.3	914.2	1040.5	1144.1	
Gasoline Plugin 60-mile Range							1018.5
Natural Gas Car	286.7	433.5	433.4				
Natural Gas Bi-Fuel Car	264.8	401.0	401.1				
Diesel Hybrid Car				361.5	404.9	465.2	
Diesel Plugin 10-mile Range				934.1	1024.3	1141.4	
Diesel Plugin 40-mile Range				913.9	1060.4	1135.5	
Fuel Cell Car	363.2	420.9	420.7	407.6	460.6	545.9	839.6
Fuel Cell Plugin 10-mile Range				800.6	930.1	1049.3	
Fuel Cell Plugin 40-mile Range				797.7	932.2	1050.9	
Battery Electric Vehicle (100 mile)	1293.0	1418.1	1441.7	739.9	862.9	990.2	1150.6
Battery Electric Vehicle (200 mile)	662.3	1093.5	1127.7				

Efficiency assumptions for midsize cars from UCD Study for different drive cycles (Burke et al, 2011), MVMT/PJ:

	UCD Study (Burke)								
	2015			2030			2045		
Vehicle Technology	**FUDS**	**FHWDS**	**US06**	**FUDS**	**FHWDS**	**US06**	**FUDS**	**FHWDS**	**US06**
Gasoline Car	318.5	479.2	288.5	364.6	563.8	338.5	376.2	593.1	354.6
Gasoline Hybrid Car	563.8	570.0	357.7	659.2	646.2	413.1	676.2	686.2	429.2
Fuel Cell Car	635.4	698.5	471.5	790.8	857.7	586.2	837.7	919.2	633.1

*FUDS: Federal Urban Driving Schedule
**FHWDS: Federal Highway Driving Schedule
+US06: US06 Driving Schedule

Technology-specific hurdle rates: transportation sector

Vehicle Technology	Hurdle Rate	Vehicle Technology	Hurdle Rate	Vehicle Technology	Hurdle Rate
Gasoline Car	18%	Gasoline Hybrid	25%	Diesel Plug-in 30 mile	47%
Diesel Car	30%	Hydrogen Fuel Cell	45%	E85 Plug-in 30 mile	35%
Gasoline Plug-in 10 mile	35%	Adv. Gasoline Car	25%	Gasoline Plug-in 40 mile	35%
E85 Flex Fuel Car	18%	Adv. Flex Fuel Car	25%	Diesel Plug-in 40 mile	47%
Natural Gas Car	45%	E85 Hybrid Car	25%	E85 Plug-in 40 mile	35%
Natural Gas Bi-Fuel Car	45%	E85 Plug-in 10 mile	35%	Gasoline Plug-in 60 mile	35%
LPG Bi-Fuel Car	45%	Diesel Plug-in 10 mile	47%	Diesel Plug-in 60 mile	47%
Battery Electric Car	45%	Gasoline Plug-in 30 mile	35%	E85 Plug-in 60 mile	35%
Diesel Hybrid	37%				

Energy service demand elasticity for the transport sector

Energy service demand	Low (inelastic)	High (elastic)	Representative	Source
Light-duty Passenger Travel	-0.034	-0.213	-0.1	Low from Hughes et al. (2008), High from Barker et al. (2009), Rep. is a mid value that is a little higher than Hughes et al.'s high value.
Motorcycles and Motorscooters Travel	-0.034	-0.213	-0.1	Low from Hughes et al. (2008), High from Barker et al. (2009), Rep. is a mid value that is a little higher than Hughes et al.'s high value. Assume motorcycles are similar to light-duty vehicles.
Light-duty Truck Travel	-0.034	-0.213	-0.1	Low from Hughes et al. (2008), High from Barker et al. (2009), Rep. is a mid value that is a little higher than Hughes et al.'s high value.
Heavy-duty Truck Travel	--	--	-0.213	Only one value found in Barker et al. Road transport category is used.
Medium-duty Travel	--	--	-0.213	
Transit Bus Travel	--	--	-0.213	
School Bus Travel	--	--	-0.213	
Intercity and Other Buses Travel	--	--	-0.213	
Commuter Rail Travel	--	--	-0.311	Only one value found in Barker et al. Rail transport category is used.
Heavy Rail Travel	--	--	-0.311	
Light Rail Travel	--	--	-0.311	
Intercity Rail Travel	--	--	-0.311	
Freight Rail Travel	--	--	-0.311	

Market growth rate constraint

The equation for the capacity investment in the model, for a given time-period ‘t’, and growth rate ‘r’ is,

$CAP(t) = CAP(t-1) * r + CAP_{START}$

For any new investment, CAP(t-1) is zero. If the starting capacity, $CAP_{START,}$ were not specified, then there would be no increase in the capacity of the commodity.

All growth rates are annual and they are 1.50 from the year 2010 till 2030, and 1.10 for the year 2030 and beyond.

Capacity constraints

Starting value for capacity build-up for light-duty cars (LDC) and light-duty trucks (LDT)(thousands of vehicles)

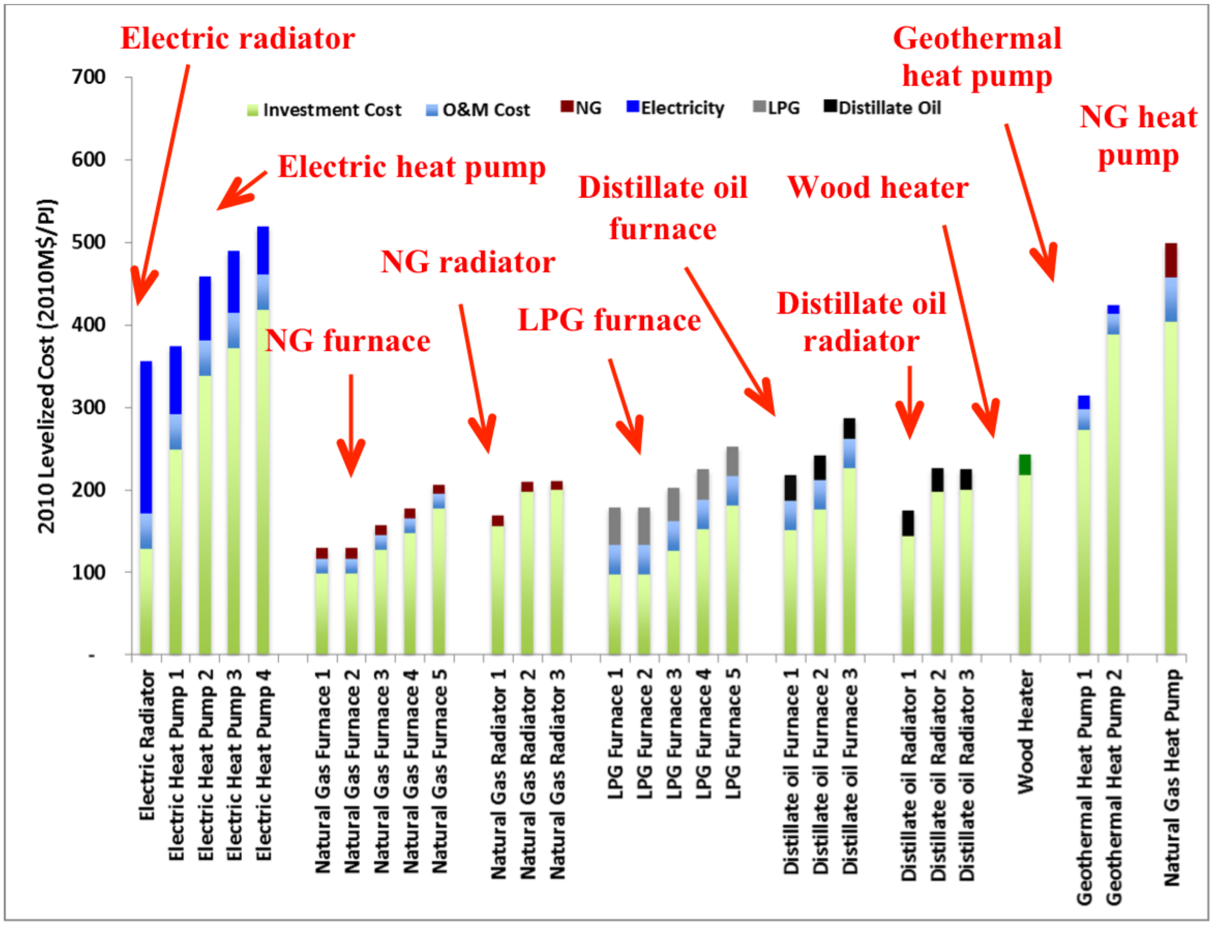
Vehicle Technology	LDC	LDT	Source
Diesel	100	175	There were roughly 275,000 diesel ICE vehicles in CA in 2005. LD Cars made up less than half of this quantity, while LD Trucks made up a bit more than half.
Diesel Hybrid	20	20	
Plug-in vehicle	20	20	California Sales of all PEVs (PHEVs and BEVs) has been about 60,000 from 2011 to 2013.
Battery electric	20	20	Assumed same as for PHEVs
Fuel Cell	10	10	
Flex Fuel (E85)	300	300	There were 107,789 ethanol FFVs in CA in 2005. In 2010, there are roughly 299,146. (source: Leighty et al. 80in50 PATH stock turnover model)
Flex Fuel Hybrid (E85)	200	200	
Gasoline Hybrid	200	200	There were 103,193 gasoline HEVs in CA in 2005. In 2010, there are roughly 348,495. New LD Car and Truck sales in California are about 1 million each annually. If automakers had to, they could ramp up production pretty quickly and supply a substantial fraction of these 1 million vehicles (in each class) with gasoline HEVs.

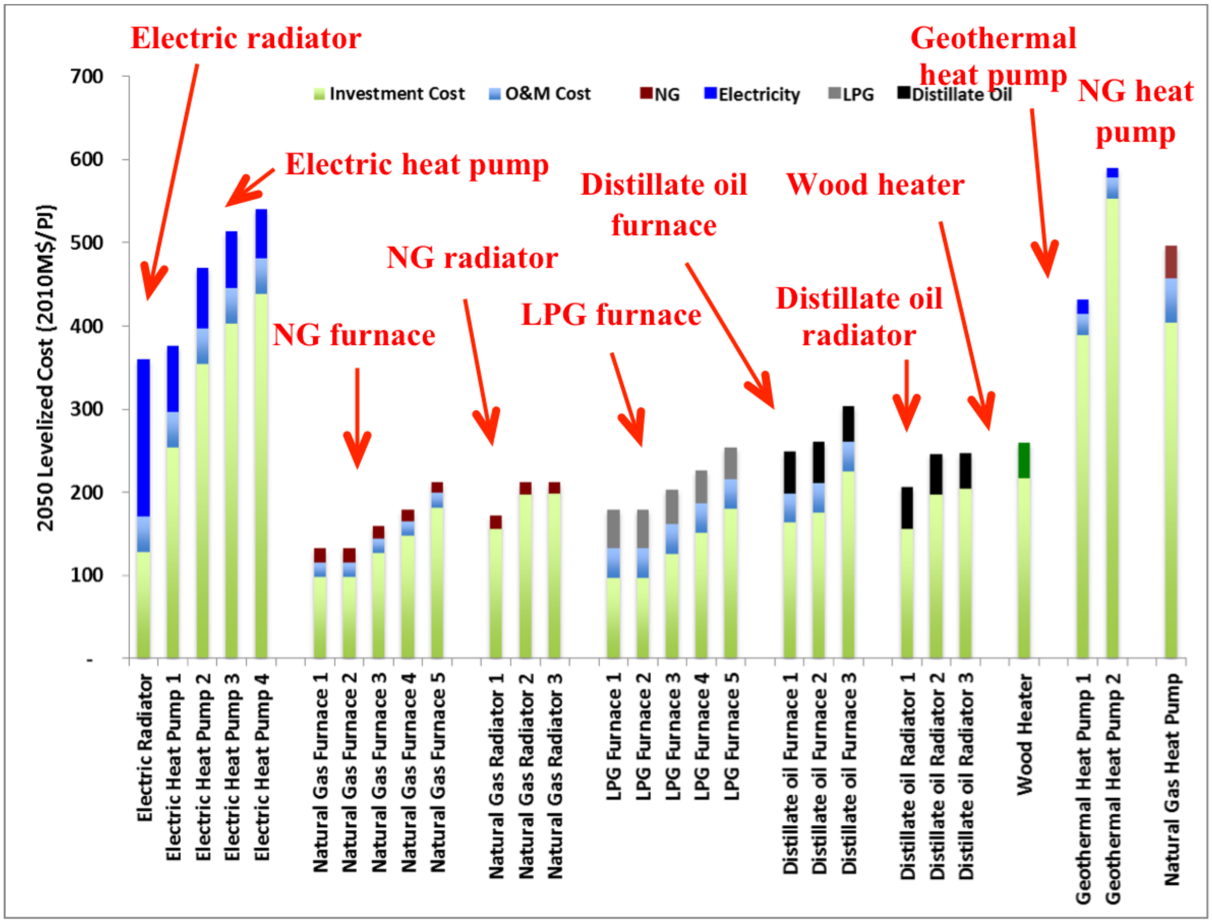
Moderate Gasoline Car	750	750	There were 11,289,000 gasoline ICE light trucks in CA in 2005. Assume that moderate and advanced gasoline vehicles start at a capacity level that is a reasonable fraction of this number. New LD Car and Truck sales in California are about 1 million each annually. If automakers had to, they could ramp up production pretty quickly and supply a substantial fraction of these 1 million vehicles (in each class) with gasoline HEVs.
Advanced Gasoline Car	750	750	
Advanced E85	200	200	There were 156,585 ethanol FFVs in CA in 2005. In 2010, there are roughly 303,203. (source: Leighty et al. 80in50 PATH stock turnover model) Assume that moderate and advanced E85 vehicles start at a capacity level that is a reasonable fraction of this number.
Natural Gas Car	1	0.5	There were roughly 1,358 natural gas vehicles in CA in 2005.

APPENDIX C. ASSUMPTIONS OF RESIDENTIAL AND COMMERCIAL TECHNOLOGY COSTS, HURDLE RATES, ELASTICITIES, AND GROWTH/CAPACITY CONSTRAINTS

Levelized cost

1. Residential space heating





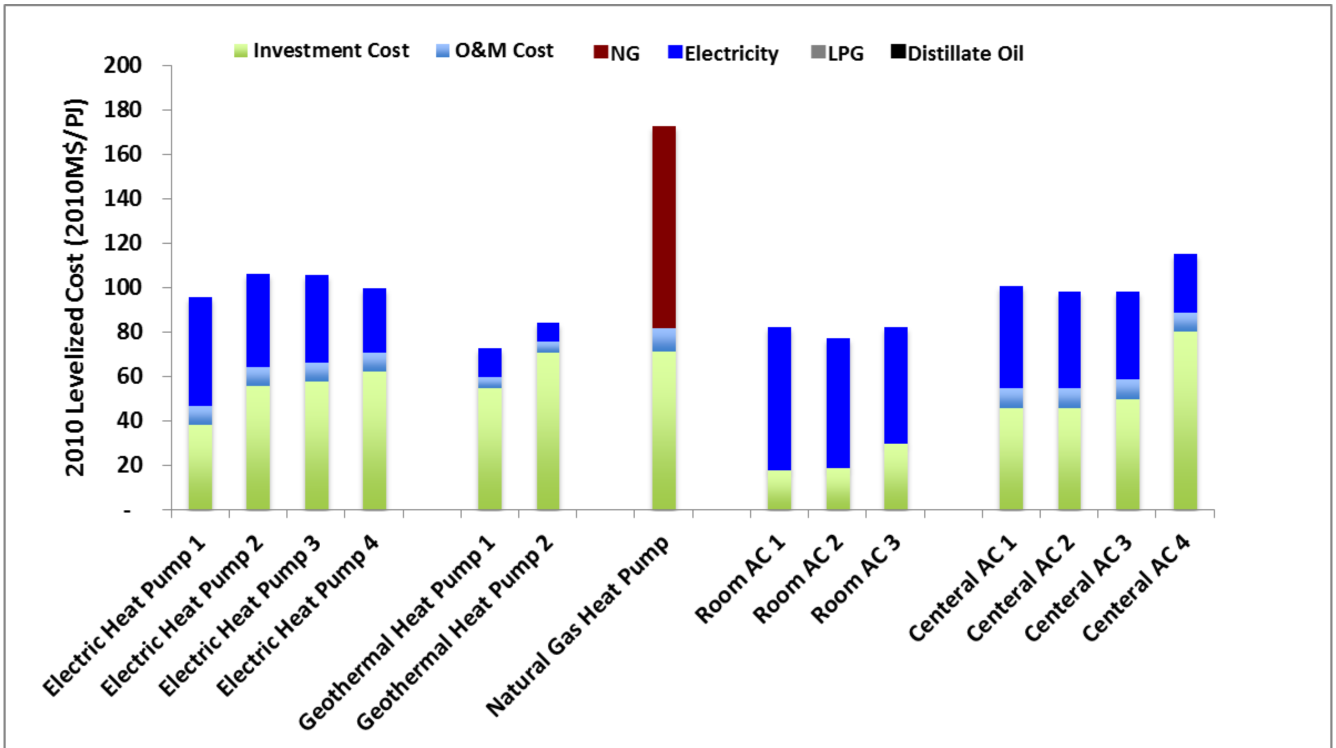
Levelized cost of residential space heating in 2010 (top) and 2050 (bottom) using fuel costs of 2010.
NGA: natural gas; LPG: liquid petroleum gas.

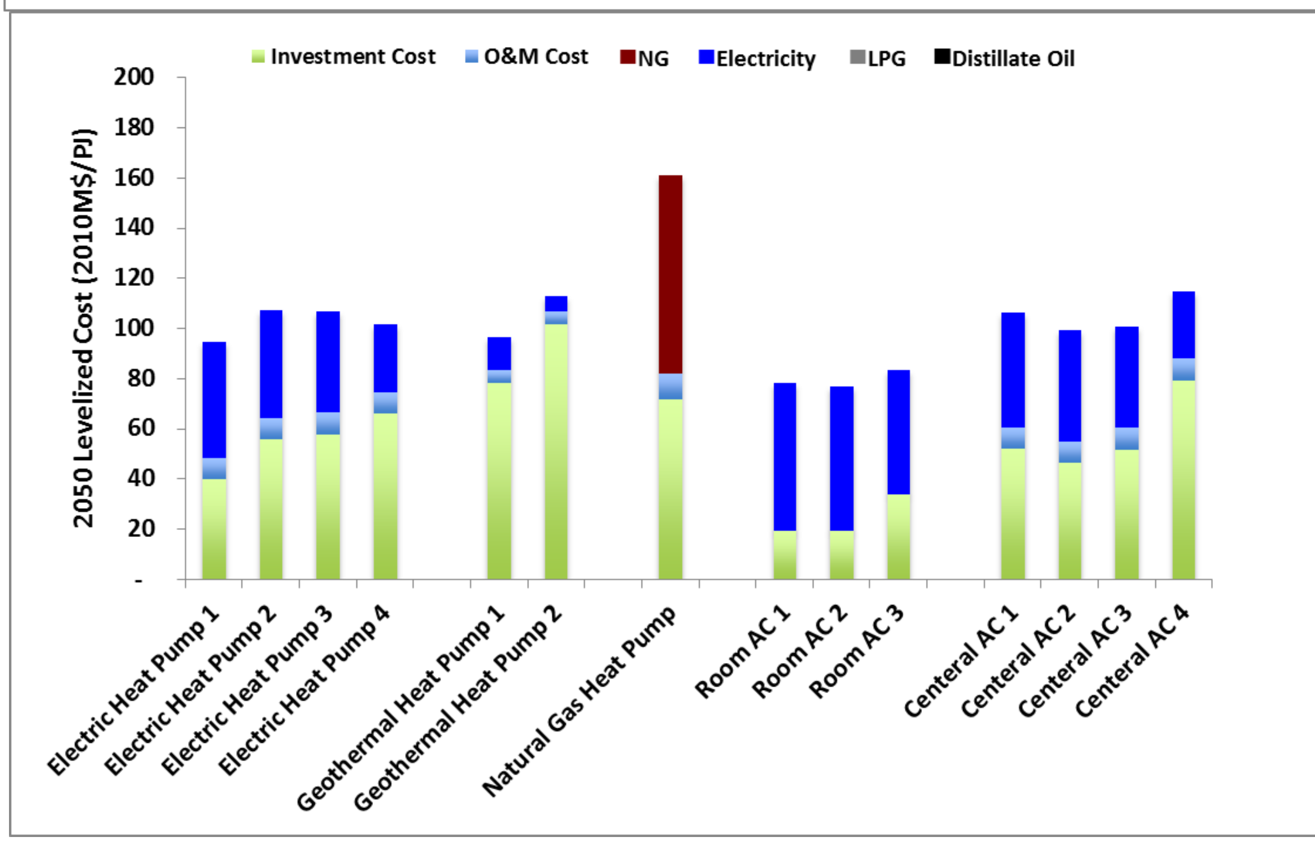
Figures above show the levelized cost of space heating technology in 2010 and 2050. Note that technology cost and efficiency improvement of each equipment over time is determined exogenously, though most of the changes over time are small compared to the variations between technologies. The overall efficiency of an end-use across technologies is determined endogenously by the model based on the investment decisions on the mix of technologies and fuel types to meet the overall demand each year.

Within the same type of technology (e.g. electric heat pump a-d), the capital costs of more efficient technologies are higher. The technology-specific hurdle rate for space heating technology range from 15-25% (U.S. EIA 2011).

Note that fuel costs shown below are the *annual average* fuel costs for 2010 from (EIA 2013). The actual fuel costs of fuel use are projected endogenously by the model, which can vary significantly based on the time of use (e.g. peak vs. off-peak or summer vs. winter) and scenarios.

2. Residential space cooling

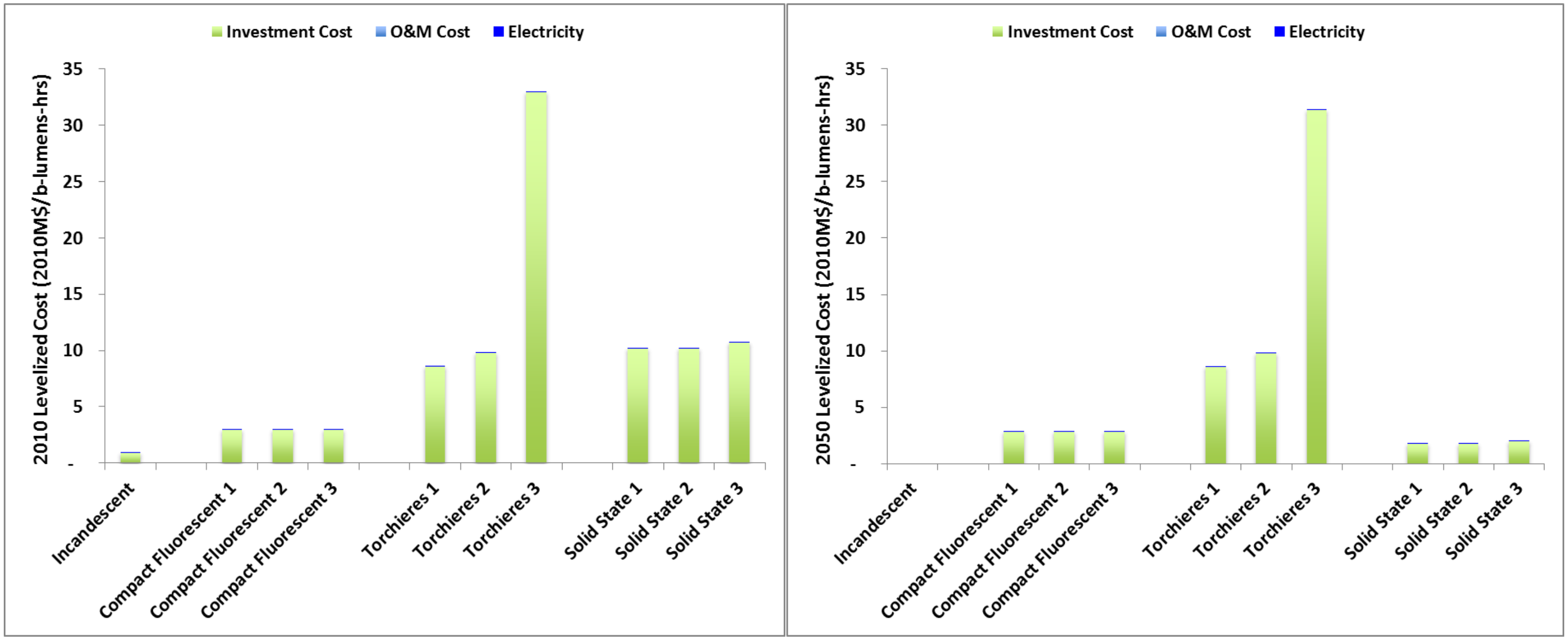




Levelized cost of residential space cooling in 2010 (top) and 2050 (bottom) using fuel costs of 2010.

Figures above show the levelized cost of space cooling for 2010 and 2050. Higher capital costs also translate into higher levelized cost within the same type of technology (e.g. electric heat pump a-d) due to the fact that fuel use cost is a much smaller portion of total levelized costs. Room ACs have the lowest investment cost but higher annual fuel cost, but overall they still have the lowest levelized cost among all cooling technologies.

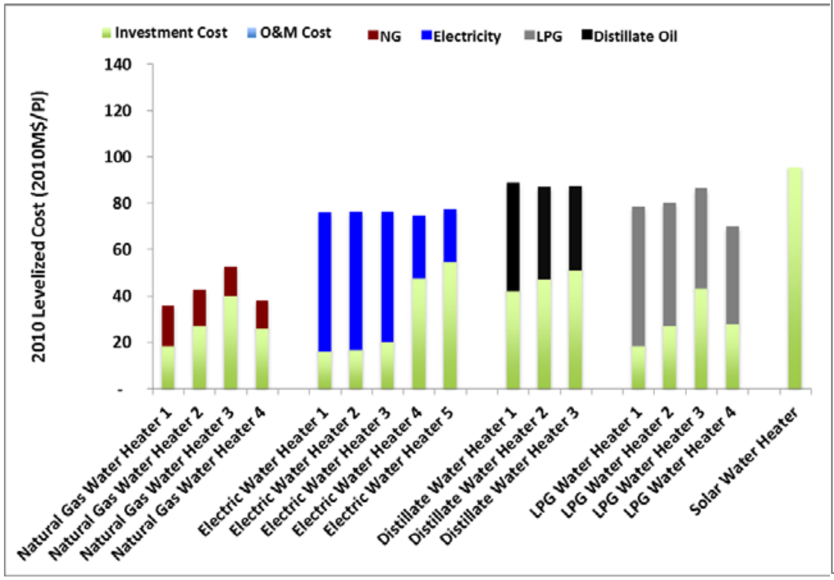
3. Residential lighting

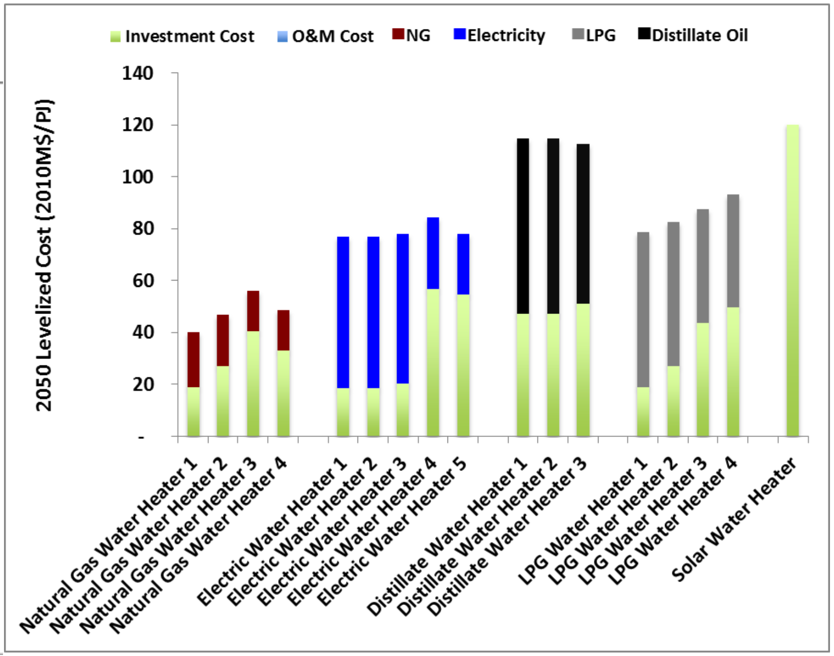


Levelized cost of residential lighting in 2010 (top) and 2050 (bottom) using fuel costs of 2010.

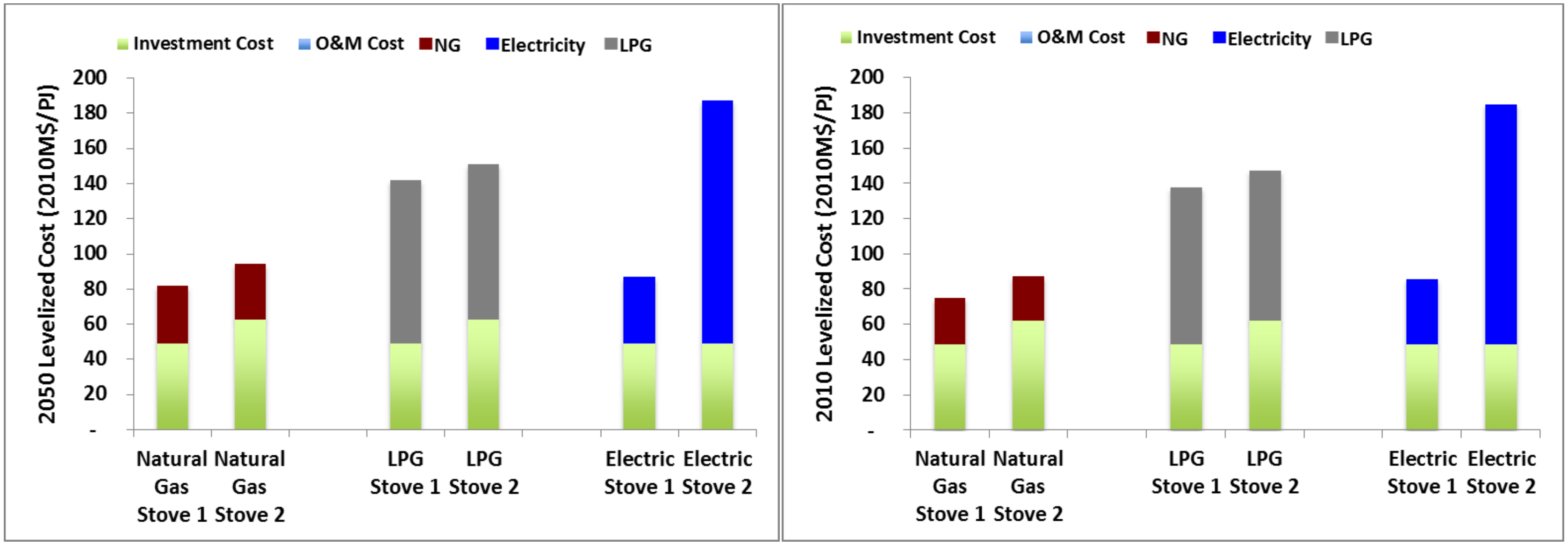
Compact fluorescent lighting (CLF) already has very favorable levelized cost today. Other more advanced lighting technologies are very expensive today, but become cost-effective in the future. In the following the levelized costs of other residential and commercial technologies can be seen.

4. Other residential end uses

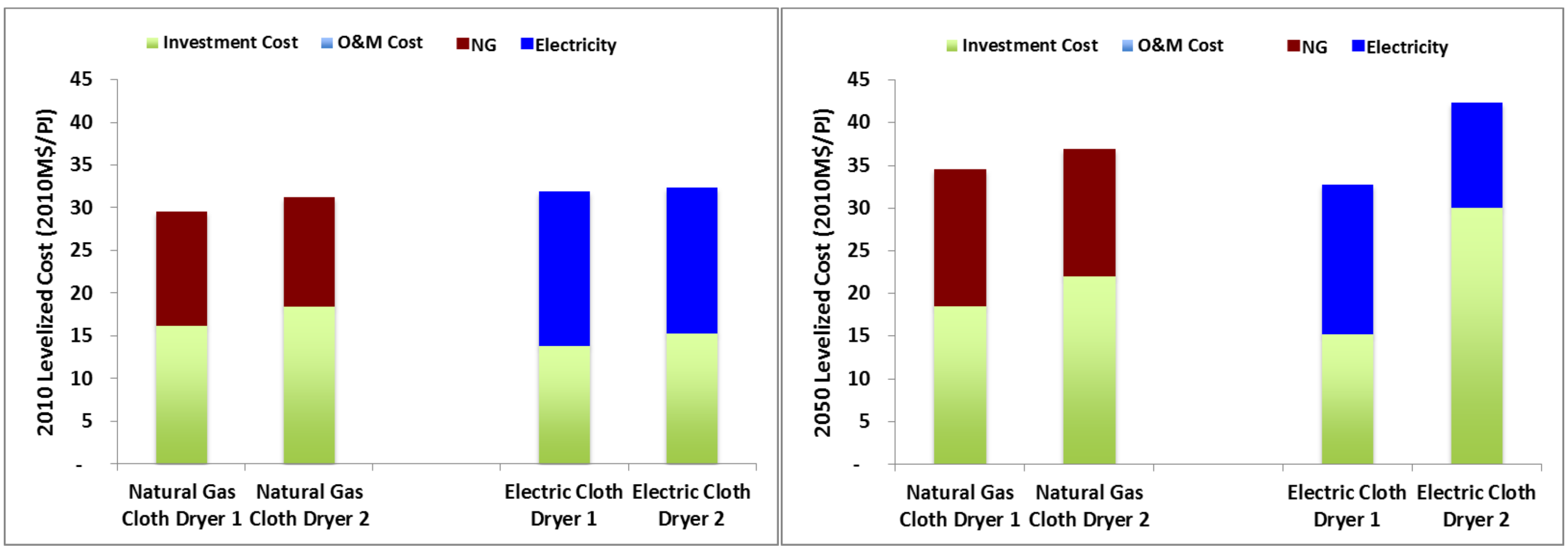




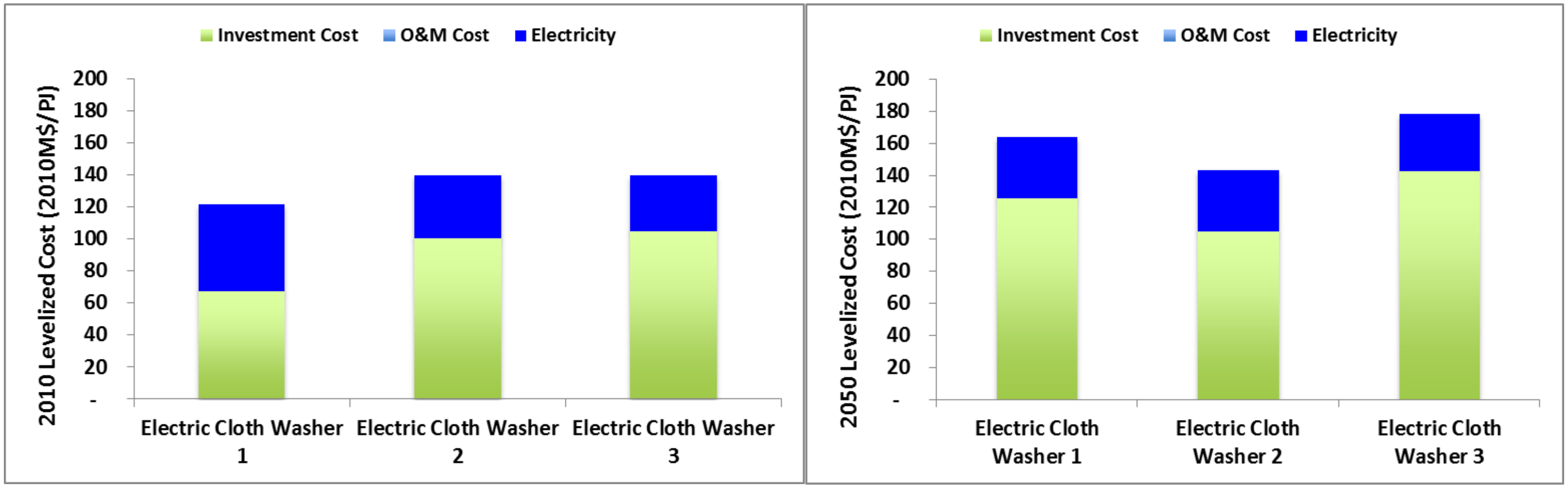
Levelized cost of residential water heating in 2010 (top) and 2050 (bottom) using fuel costs of 2010.



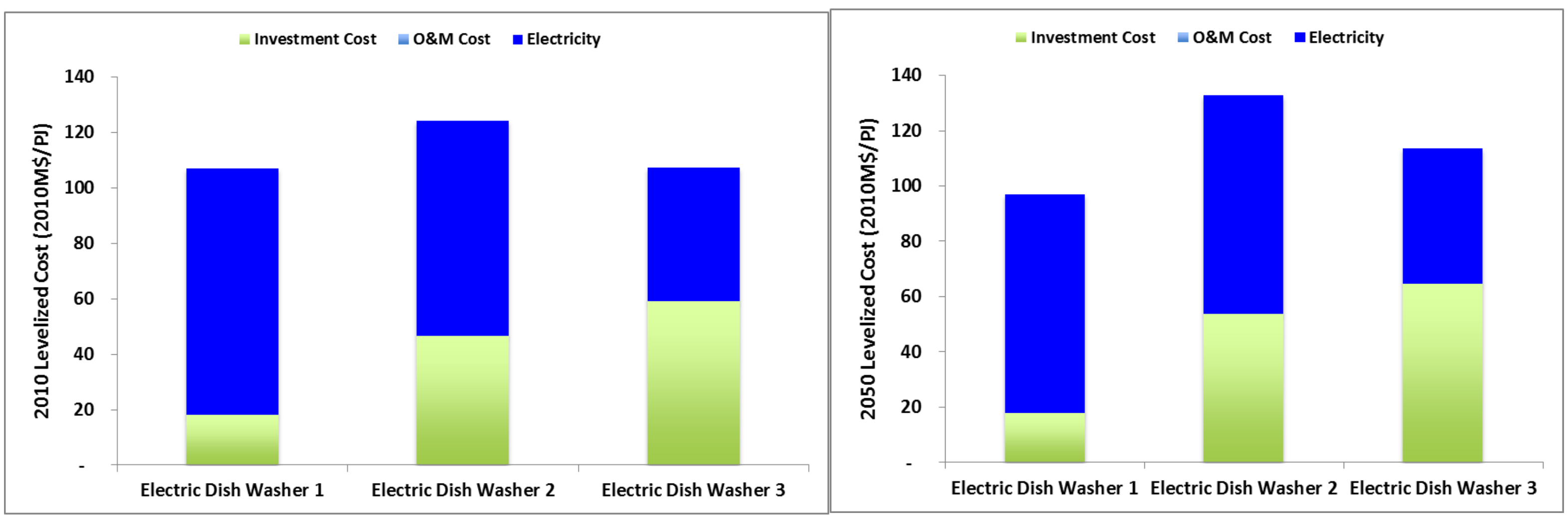
Levelized cost of residential cooking in 2010 (top) and 2050 (bottom) using fuel costs of 2010.



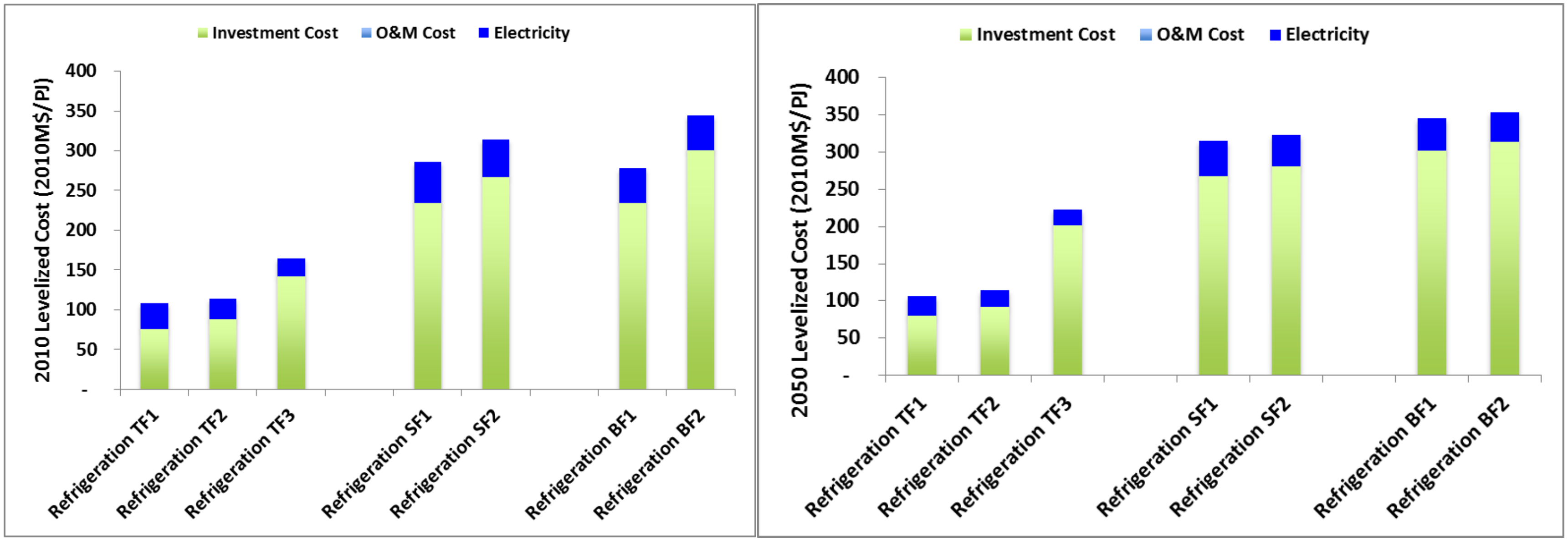
Levelized cost of residential clothes drying in 2010 (top) and 2050 (bottom) using fuel costs of 2010.



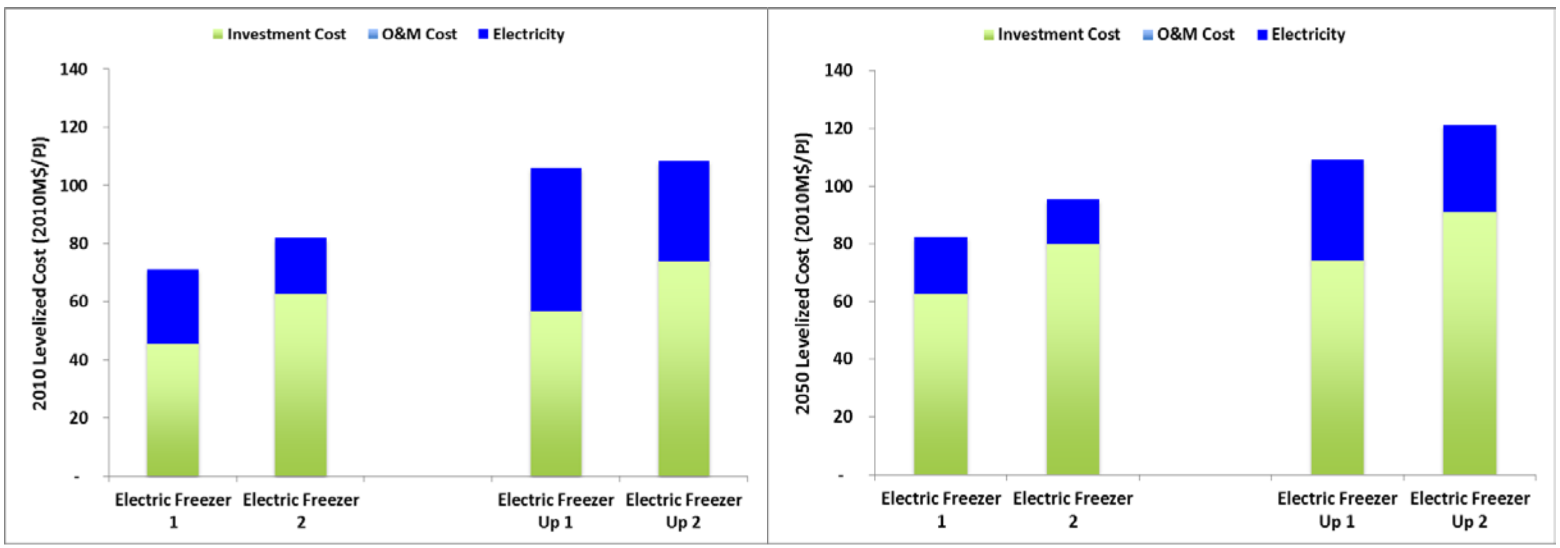
Levelized cost of residential clothes washing in 2010 (top) and 2050 (bottom) using fuel costs of 2010.



Levelized cost of residential dish washing in 2010 (top) and 2050 (bottom) using fuel costs of 2010.

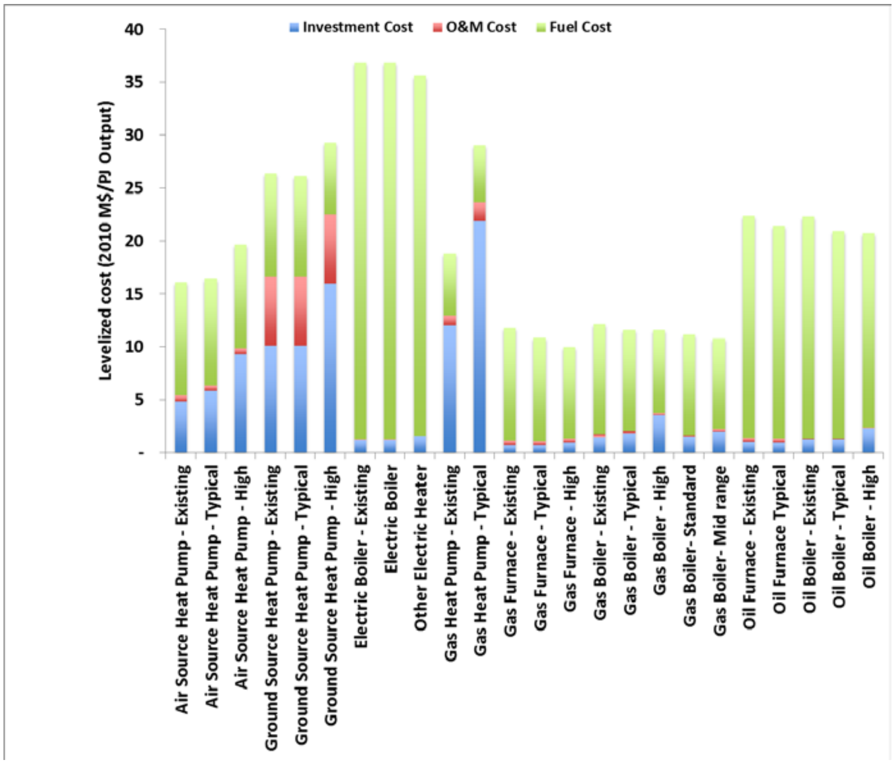


Levelized cost of residential refrigeration in 2010 (top) and 2050 (bottom) using fuel costs of 2010.



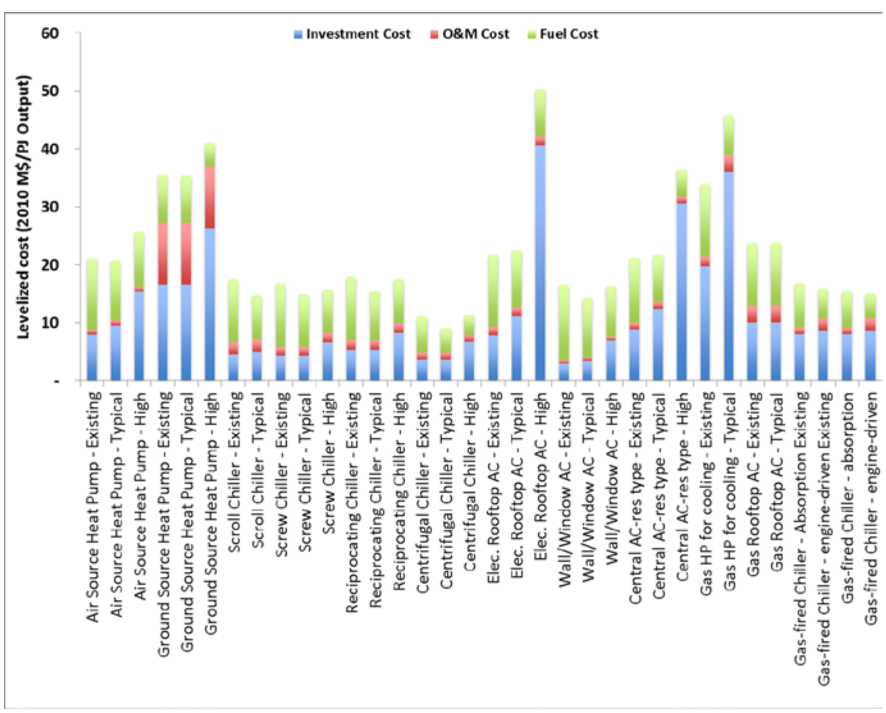
Levelized cost of residential freezer in 2010 (top) and 2050 (bottom) using fuel costs of 2010.

5. Commercial heating



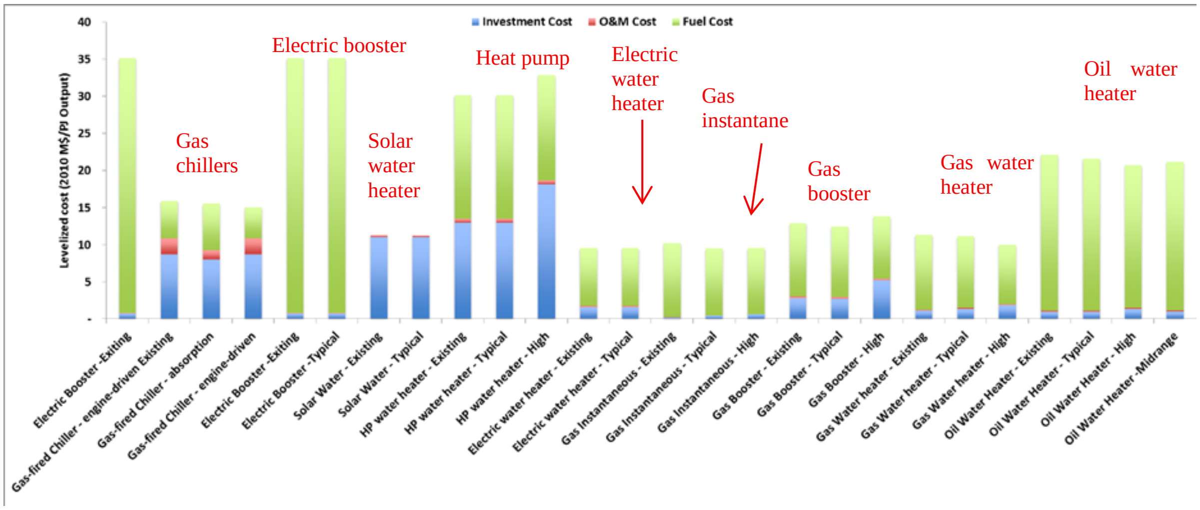
Levelized cost of commercial heating in 2010

6. Commercial cooling



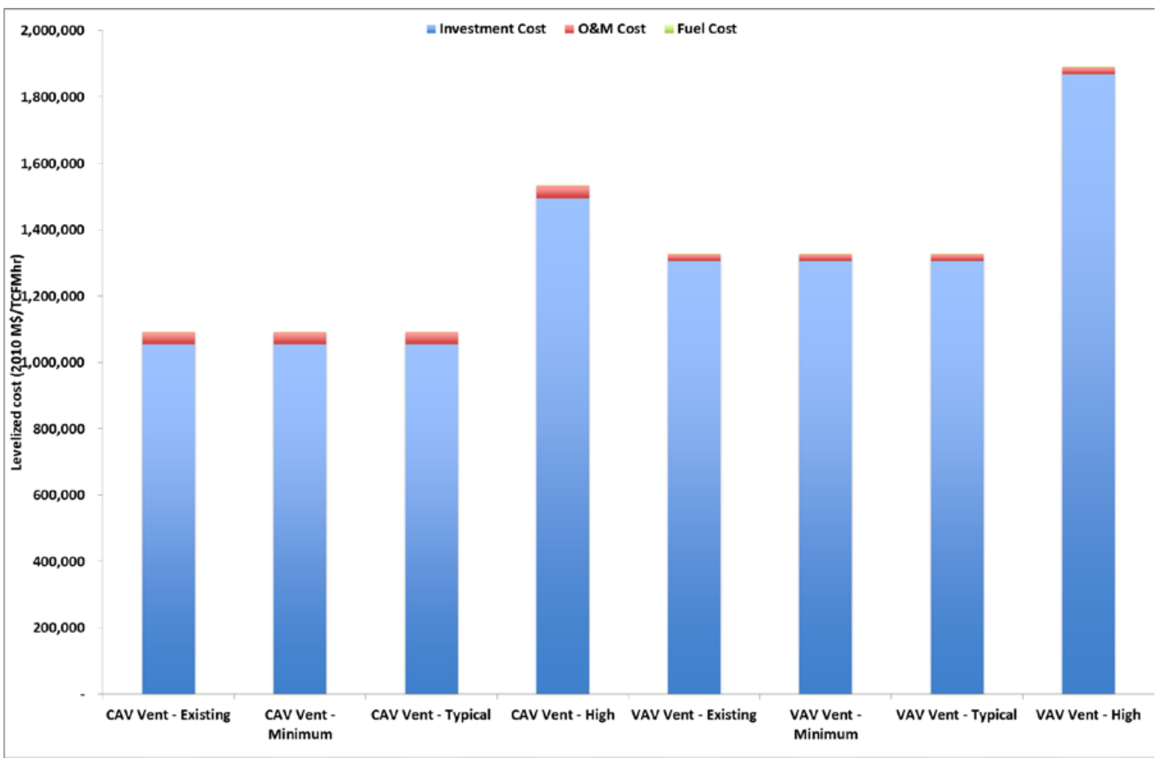
Levelized cost of commercial cooling in 2010

7. Commercial water heating



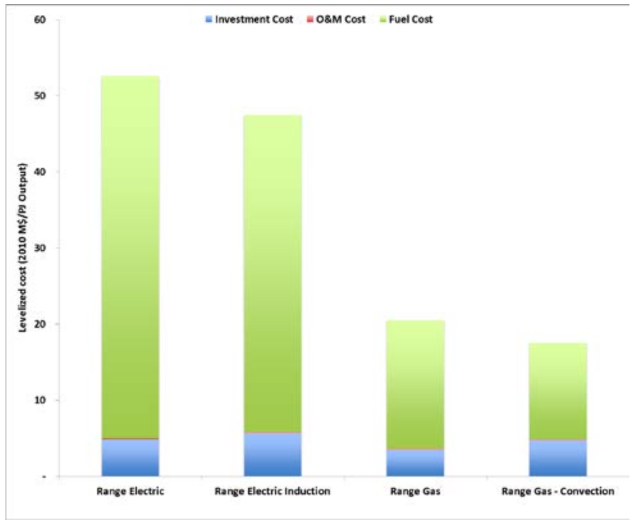
Levelized cost of commercial water heating in 2010

8. Commercial ventilation



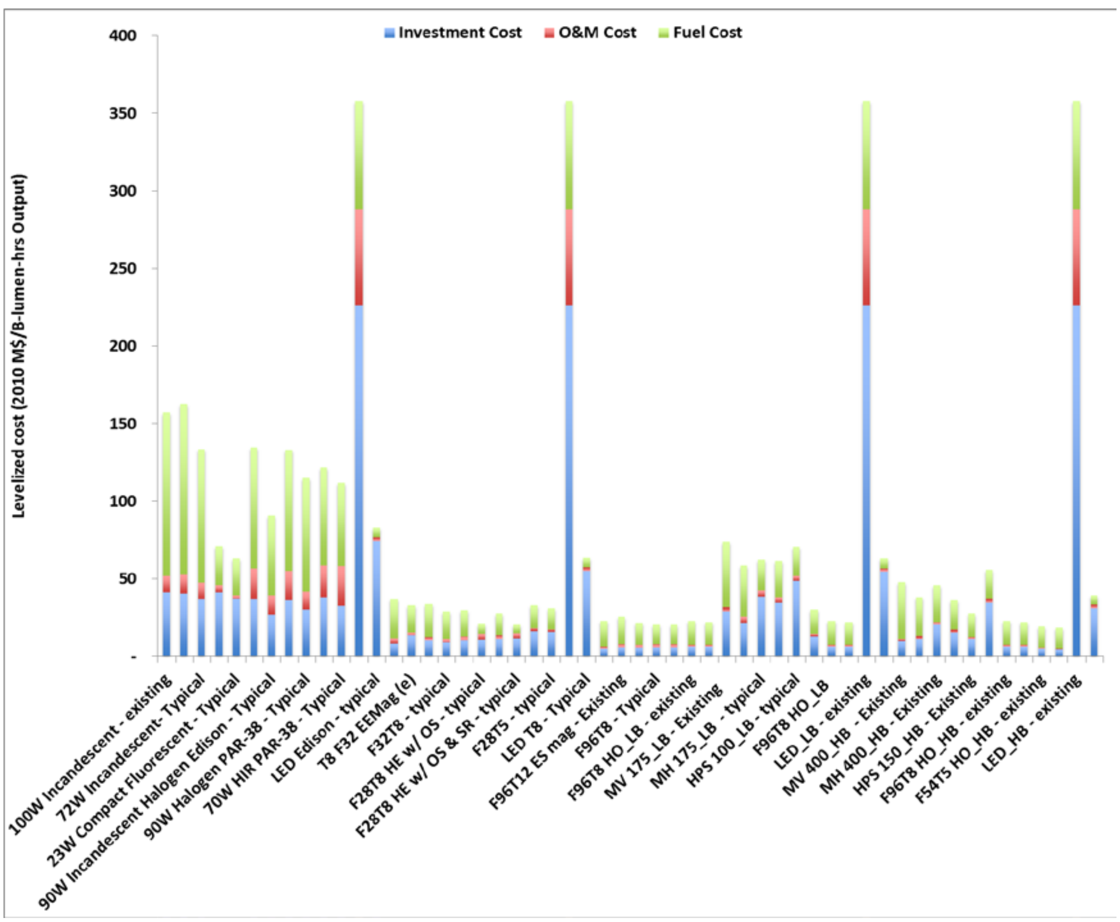
Levelized cost of commercial ventilation in 2010

9. Commercial cooking



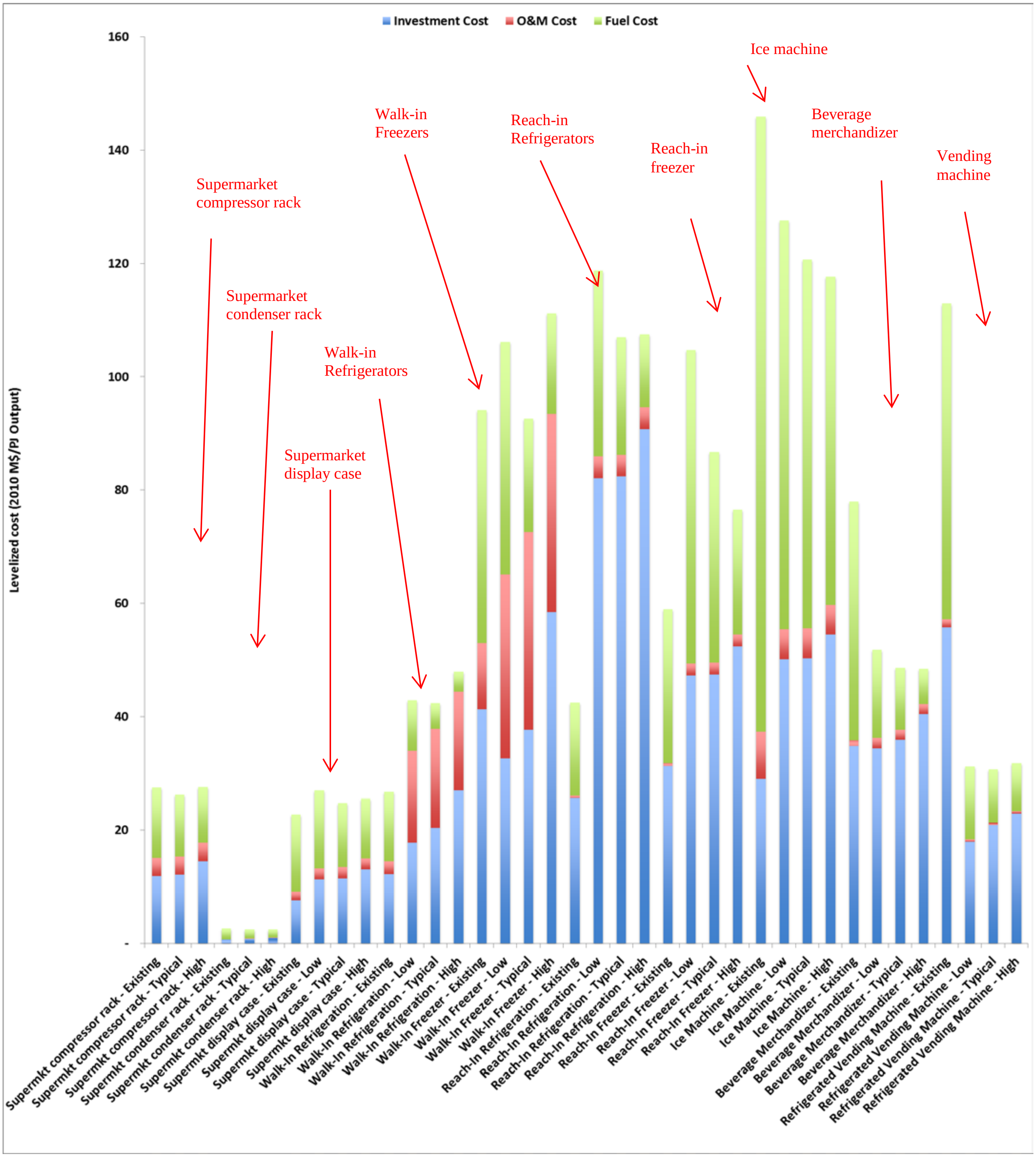
Levelized cost of commercial cooking in 2010

10. Commercial lighting



Levelized cost of commercial lighting in 2010

11. Commercial refrigeration



Levelized cost of commercial refrigeration in 2010

Hurdle rate

Residential

End-use	Technology	Hurdle rate
Space Heating	Electric radiator	15%
	Electric Heat Pump	25%
	Natural Gas Furnace	15%
	Natural Gas Radiator	15%
	LPG Furnace	15%
	Distillate Furnace	15%
	Distillate Radiator	15%
	Wood Heater	15%
	Geothermal Heat Pump	15%
	NG Heat Pump	15%
Space Cooling	Room AC	42%
	Central AC	25%
	Electric Heat Pump	25%
	NG Heat Pump	15%
Water Heating	NG Water heater	30%
	Electric Water heater	50%
	Distillate Water heater	15%
	LPG Water heater	30%
	Solar Water heater	30%
Cooking	NG Cooking	83%
	LPG Cooking	83%
	Electric Cooking	83%
Clothes Drying	NG Clothes Dryer	47%
	Electric Clothes Dryer	90%
Dish Washing	Dish Washer	15%
Freezing	Freezer	37%
Refrigeration	Refrigerators	10%
Cloth Washing	Cloth washer	30%

Commercial

End-use	Hurdle rate
Typical and mid range technologies	0.18
High efficiency technologies	0.24

Elasticity

Energy Service Demand	UP	LO
Commercial-Space Cooling	-0.15	-0.05
Commercial-Cooking	-0.05	0
Commercial-Space Heating	-0.1	0
Commercial-Hot Water Heating	-0.1	0
Commercial-Lighting	-0.15	0
Commercial-Electric Equipment	-0.05	0
Commercial-Refrigeration	0	0
Residential-Space Cooling	-0.15	-0.05
Residential-Clothes Dryers	-0.05	0
Residential-Clothes Washers	-0.05	0
Residential-Dish Washers	-0.05	-0.03
Residential-Electric Appliances	-0.2	-0.05
Residential-Space Heating	-0.05	0
Residential-Hot Water Heating	-0.05	0
Residential-Cooking	0	0
Residential-Lighting	-0.1	0
Residential-Refrigeration	-0.05	-0.03

Growth constraints

Residential end-use	Technology	Growth rate constraint
Space heating	Electric radiator, natural gas furnace, natural gas radiator, LPG furnace, wood heater	5%
	Distillate furnace, distillate radiator	20%
Heat pump	Electric heat pump, natural gas heat pump	5%
	Geothermal heat pump	20%
Space cooling	Room AC, Central AC	5%
Water heating	Natural gas water heater, electric water heater, LPG water heater	5%
	Distillate oil water heater	20%
Cooking	Natural gas stove, LPG stove, electric stove	5%
Clothes washing	Electric clothes washing	5%
Clothes drying	Natural gas clothes drying, electric cloth drying	5%
Dish washing	Electric dish washer	5%
Freezing	Electric freezer	5%
	Electric up freezer	20%
Refrigeration	TFA, SFA, BFA refrigerator	5%
Lighting	Incandescent, compact fluorescent, torchieres, solid state lighting	5%
Pool pump	Electric pool pump, solar pool pump	5%

Commercial end-use	Technology	Growth rate constraint
Space heating	Electric boiler, natural gas furnace, natural gas boiler, oil furnace, oil boiler	5%
Heat pump	Air source heat pump, natural gas heat pump, geothermal source heat pump	5%
Space cooling	Wall window AC, central AC, electric rooftop, natural gas rooftop, reciprocating chiller, centrifugal chiller, gas fired chiller (typical)	5%
	Scroll chiller, screw chiller, gas fired chiller (engine driven)	20%
Water heating	Electric water heater, natural gas water heater, solar water heater, heat pump water heater	5%
	Electric booster water heater, gas booster water heater, gas instantaneous water heater, oil water heater	20%
Cooking	Electric induction range, electric range, gas range	5%
Ventilation	Constant air volume ventilation (CAV), variable air volume ventilation (VAV)	5%
Lighting	Incandescent (100W), compact fluorescent (23W), metal halide, PAR38 halogen (90W), Fluorescent lamps, high pressure sodium lamps 150 (HPS 150), LED 100 HPS	5%
	Incandescent (72W), incandescent halogen, HIR PAR, LED Edison, LED HPS	20%
Refrigeration	Supermarket rack, walk-in refrigerator, reach-in refrigerator, ice machine, beverage merchandiser refrigerator, vending machine, walk-in freezer, reach-in freezer	5%

Share constraints

Residential

End-use	Technology	Share Constraint Type	Year	Share Constraint
Residential space cooling*	Room AC	Up	2010-2050	20%
	Central AC	Up	2010-2050	75%
Residential lighting	Torchieres	Up	2010-2050	35%
Residential cooking**	Electric stove cooking	Lo	2010-2050	49%

* We assume the share of room AC and central AC remains the same in all years.

** Share of electric cooking will be at least the same as in 2010.

Commercial

End-use	Technology	Share Constraint Type	Year	Share constraint
Commercial space cooling*	Wall window AC	Up	2010-2050	12%
	Central AC	Up	2010-2050	85%
Commercial miscellaneous	Natural gas	Up	2010	65%
			2012-2050	50%
Commercial cooking**	Electric cooking	Up	2010-2050	24%
Commercial lighting***	Incandescent	Lo	2012	17%
		Lo	2015	10%
		Lo	2017	7%
		Lo	2020	4%

* We assume the share of room AC and central AC remains the same in all years.

** Share of electric cooking will be at least the same as in 2010.

*** Incandescent light bulbs will gradually phase out.

APPENDIX D. POLICY DESCRIPTIONS FOR CA-TIMES SCENARIOS

Policies	Descriptions
Biofuel Subsidies	- Corn ethanol: Federal Volumetric Ethanol Excise Tax Credit (i.e., "blender's credit") of \$0.45/gal. Assumed to expire in 2015. - Sugar cane ethanol: Same as corn ethanol. - Cellulosic ethanol: Federal tax credit of \$1.01/gal. Based on the Food, Conservation and Energy Act of 2008 (i.e., the "farm bill"). Assumed to expire in 2020. - Biodiesel: Federal tax credit of \$1.00/gal for biodiesel from soy and animal tallow, \$0.50/gal for biodiesel from yellow grease. Based on American Jobs Creation Act of 2004. Assumed to expire in 2015.
Biofuel Import Tariffs	- Sugar cane and other types of imported ethanol: Import duty of \$0.54/gal.
Transportation Fuel Taxes[1]	- Gasoline: California state tax of \$0.49/gal (includes excise tax and state, county, and local sales taxes). Federal excise tax of \$0.184/gal. Assumed to always be the same. - Diesel: California state tax of \$0.49/gal (includes excise tax and state, county, and local sales taxes). Federal excise tax of \$0.244/gal. Assumed to always be the same. - Ethanol and E-85: No additional taxes other than those for gasoline. - Jet Fuel (kerosene-type): Federal excise tax of \$0.044/gal for commercial aviation. - Aviation gasoline: Federal excise tax of \$0.194/gal. Assumed to always be the same. - Liquid Petroleum Gases (LPG): Federal excise tax of \$0.183/gal. Assumed to always be the same. - Compressed Natural Gas (CNG): Federal excise tax of \$0.044/gal. Assumed to be the same as jet fuel. Assumed to always be the same. - Liquefied Natural Gas (LNG): Federal excise tax of \$0.243/gal. Assumed to always be the same. - Liquefied H_2: Federal excise tax of \$0.184/gal. Assumed to be the same as conventional gasoline. Assumed to always be the same. - FT liquid fuels from coal: Federal excise tax of \$0.244/gal. Assumed to be the same as conventional diesel. Assumed to always be the same. - FT liquid fuels from biomass: Federal excise tax of \$0.244/gal. Assumed to be the same as conventional diesel. Assumed to always be the same.
CA Pavley I and Corporate Average Fuel Economy (CAFE) Standards	- Light-duty passenger cars: New model-year vehicle fleet must achieve 263 gCO_2/mile (33.8 mpg) in 2012, strengthening to 225 gCO_2/mile (39.5 mpg) in 2016, assumed to remain constant thereafter. - Light-duty passenger trucks: New model-year vehicle fleet must achieve 346 gCO_2/mile (25.7 mpg) in 2012, strengthening to 298 gCO_2/mile (29.8 mpg) in 2016, assumed to remain constant thereafter.
LEV III Light-Duty Vehicle GHG Emission Standards and CAFE for 2017-2025	- GHG emissions rate of new model-year light-duty cars and trucks declines 4.5% per annum (on a gCO_2-eq per mile basis) between 2017 and 2025. Based on notices of intent and an interim technical assessment by DOT-NHTSA, EPA-OTAQ, and CARB, which analyzes the feasibility of an annual rate of improvement of 3 to 6% (EPA-DOT-CARB 2010). - Light-duty passenger cars: New model-year vehicle fleet must achieve 215 gCO_2/mile (41.4 mpg) in 2017, strengthening to 149 gCO_2/mile (59.8 mpg) in 2025, assumed to remain constant thereafter. - Light-duty passenger trucks: New model-year vehicle fleet must achieve 285 gCO_2/mile (31.2 mpg) in 2017, strengthening to 197 gCO_2/mile (45.1 mpg) in 2025, assumed to remain constant thereafter.
Electric Vehicle Subsidies	- Light-duty plug-in hybrid electric vehicles (PHEVs) and BEVs: Tax credit for new plug-in electric vehicles is worth \$2,500 plus \$417 for each kWh of battery capacity over 5 kWh. The portion of the credit determined by battery capacity cannot exceed \$5,000; therefore, the total amount of the credit allowed for a new plug-in electric vehicle is \$7,500. Based on the Energy Improvement and Extension Act of 2008, and later the American Clean Energy and Security Act of 2009. Credit is supposed to expire for each manufacturer soon after it has sold 200,000 cumulative PHEV/BEVs for use in the U.S, but in the model it is assumed to expire in 2018. - Additionally, California's Clean Vehicle Rebate Program (CVRP) is assumed to provide \$2500 per BEV and \$1500 per PHEV until 2023.

[1] For current federal fuel tax information, see the following U.S. Internal Revenue Service (IRS) webpage: http://www.irs.gov/publications/p510/ch01.html#d0e2009. For current state gasoline and diesel tax information, see the following API webpage: http://www.api.org/statistics/fueltaxes/.

GHG Emission Performance Standard for New Power Plants	- Establishes a greenhouse gases emission performance standard for all baseload generation of local publicly owned electric utilities at a rate of emissions of greenhouse gases that is no higher than the rate of emissions of greenhouse gases for combined-cycle natural gas baseload generation [California Senate Bill (SB) 1368]. This essentially equates to "no new coal plants in California". In CA-TIMES, the law is applied to coal steam, coal IGCC, and coal-to-H_2 plants.
Low Carbon Fuel Standard (LCFS) biofuels scenario	- This is a scenario based upon one particular mix of fuel production that could meet the LCFS out to 2020. It is one means of satisfying the LCFS policy but other fuel mixes could as well. In California, the LCFS is a more stringent requirement than the RFS2, and the different incentives will likely result in a different fuel mix and CI values compared to the volume mandates in the federal RFS2 requirement (Yeh and Sperling 2013). We combined the latest ICF scenarios projecting the necessary biofuel volumes to meet California's LCFS by 2020 across three possible scenarios, and use our expert judgment to derive at minimum energy requirement of different types of biofuels (See Figure D.1). We keep the volume constant 2020-2022 to reflect the minimum constraint of the RFS2 requirement till 2022. Work is ongoing to incorporate a more flexible policy representation of the LCFS.
Renewable Portfolio Standard (RPS)	- By 2020 and each year subsequent, 33% of California electricity generation must come from renewable sources (excluding hydro). Assumed to remain constant thereafter. Based on Executive Order S-14-08 and Executive Order S-21-09.
Renewable Electricity Incentives	- <u>Renewable electricity production tax credit (PTC)</u>: Credit of 2.2 cents/kWh for Wind, Geothermal, and Closed-loop biomass; and 1.1 cents/kWh for all other renewables (Open-loop biomass, Landfill gas, Hydroelectric, Municipal Solid Waste, Hydrokinetic "Flowing Water" Power, Small Hydroelectric, Tidal Energy, Wave Energy, and Ocean Thermal). Duration of credit is 10 years for facilities placed in service by the end of 2012 (wind) or 2013 (all others). Thus, all credits assumed to expire by 2022/2023. Note that Solar is excluded from the production tax credit because it receives the investment tax credit. - <u>Business energy investment tax credit (ITC) for renewables</u>: Credit equal to 30% of capital expenditures for Solar and Fuel cells. No maximum credit for solar; a maximum of $3,000/kW for fuel cells. In general, credits are available for eligible systems placed in service before the end of 2016. In CA-TIMES, credits are assumed to expire in 2016. Note that as of 2009, other types of renewable generation are allowed to take the ITC; however, they would then have to forfeit the PTC. In CA-TIMES, it is assumed that only solar and fuel cells can take the ITC.
Zero Emissions Vehicle (ZEV) Mandate vehicle scenario	- See description below
80% GHG Reduction Goal by 2050	- Reduce GHG emissions to 1990 levels by 2020, and 80% below 1990 levels by 2050. Based on a California Executive Order S-3-05. Only applies to fuel combustion emissions in CA-TIMES. Interim emission targets between 2020 and 2050 are linearly interpolated.
Energy Efficiency Standards for Industrial and Agricultural Sectors	- Average annual efficiency improvement of generic end-use sector technologies in the Industrial, and Agricultural sectors. Efficiency gains are over and above those assumed in the Reference Case, and are technically feasible with today's technologies. Industrial (0.41% per year); Agricultural (0% per year). Based on the *Baseline – high efficiency* scenario of McCarthy et al. (McCarthy, Yang et al. 2008) compared to the *Baseline demand* scenario.

Zero Emissions Vehicle (ZEV) Mandate vehicle Policy constraint

The ZEV constraint is a linear constraint where a certain percentage of the total car and light truck mix must qualify as ZEVs or TZEVs. Each type of vehicle is given a weighting factor (depending on the year), which enhances or reduces its ability to contribute to the ZEV percentage.

The overall constraint can be written as:

$$\sum a_{i,t} X_{i,t} \geq ZEV\%_t$$

where $a_{i,t}$ is the weighting factor for a given vehicle type i in year t
and $X_{i,t}$ is the percentage of all cars and trucks sold that is of type i in year t
and ZEV% is the target ZEV percentage in year t

There are 7 types of cars/trucks that can contribute to meeting the ZEV requirement:

1. BEV100 (Battery Electric Vehicle with 100 mile range),
2. BEV200 (200 mile range),

3. FCV (Hydrogen Fuel Cell Vehicle),
4. PHEV10 (Plug-in Hybrid Vehicles with 10 mile all electric range),
5. PHEV30 (Plug-in Hybrid Vehicles with 30 mile all electric range),
6. PHEV40 (Plug-in Hybrid Vehicles with 40 mile all electric range), and
7. PHEV60 (Plug-in Hybrid Vehicles with 60 mile all electric range)

In CA-TIMES, we have multiple technologies that for each PHEV type since the PHEV's alternative power source could run on gasoline, diesel or biofuel, and each vehicle also comes in a car or light-truck version.

In the equation above, the coefficients will differ by year and for each vehicle type.

	BEV100	BEV200	FCV	PHEV10	PHEV30	PHEV40	PHEV60
2012-2017	3	4	9	1.1	2*	2.5	2.75*
2018-2025	1.5	2.5	4	0.4	0.6	0.7	0.9

* these values are estimated from other values

The ZEV percentage target changes each year.

year	ZEV Credit %
2012	3%
2013	3%
2014	3%
2015	6%
2016	6%
2017	6%
2018	5%
2019	7%
2020	10%
2021	12%
2022	15%
2023	17%
2024	20%
2025	22%

The equation is rewritten to get rid of sales percentages and use actual numbers of cars and light trucks sold instead. Since $X_{i,t}$ and $ZEV\%_t$ are percentages of total cars sold, one can multiple by the total number of cars and light trucks sold in year t to get the numbers of cars sold of type i ($Y_{i,t}$).
$X_{i,t} = Y_{i,t}$ / Total LDVs sold_t

$$\sum a_{i,t} X_{i,t} (TotalLDVSold_t) \geq ZEV\%_t (TotalLDVSold_t)$$
$$\sum a_{i,t} Y_{i,t} \geq ZEV\%_t (TotalLDVSold_t)$$
$$\sum a_{i,t} Y_{i,t} - ZEV\%_t (TotalLDVSold_t) \ \geq 0$$

where $a_{i,t}$ is the weighting factor for a given vehicle type i in year t
$Y_{i,t}$ is the number of cars sold of type i in year t
and $ZEV\%_t$ is the target ZEV percentage in year t

This formulation gives the CA-TIMES model full flexibility as to how to meet the ZEV mandate. However, there is an additional constraint where full ZEVs (i.e. BEV100, BEV200 and FCVs) must comprise a given fraction of total ZEV mandate compliance. This is set up in the exact same way:

$$\sum a_{i,t}Z_{i,t} \geq MinZEV\%_t$$

except now the set of $Z_{i,t}$ only comprises BEVs and FCVs and the $MinZEV\%_t$ target is another set of targets for each year.

References

California Air Resources Board. 2012 Proposed Amendments To The California Zero Emission Vehicle Program Regulations.

Low Carbon Fuel Standard Policy scenario

The LCFS sets a performance standard on the average fuel carbon intensity of on-road transportation fuel mix in California before 2020. LCFS can be met with a wide range of low-carbon transportation fuels, such as electricity, natural gas, biogas, and hydrogen; though the main source of compliance is biofuels. The California LCFS is more stringent than the RFS2, and the different incentives will likely result in a different fuel mix and CI values compared to the volume mandates in the federal RFS2 requirement (Yeh and Sperling 2013). We combined the latest ICF scenarios projecting the necessary biofuel volumes to meet California's LCFS by 2020 across three possible scenarios, and use our expert judgment to derive at minimum energy requirement of different types of biofuels (See Figure D.1). Work is ongoing to incorporate a more flexible policy representation of the LCFS.

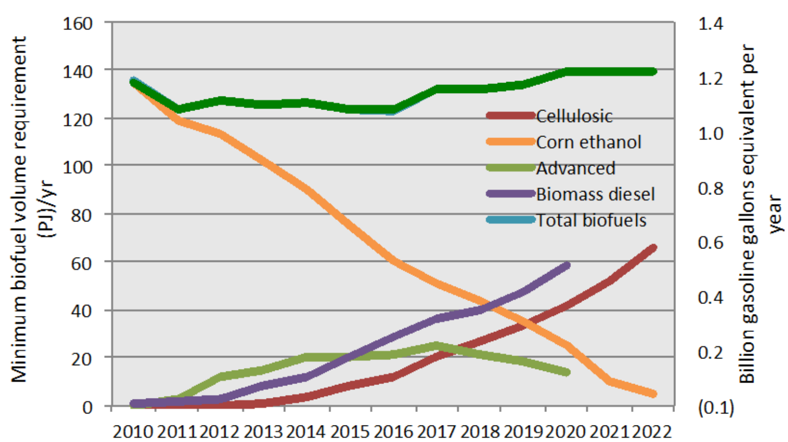


Figure D.1. Minimum energy requirements for biofuels to meet the California's LCFS (and the RFS2) before 2022.

APPENDIX E. MORE DETAILED SCENARIO RESULTS

Table E.1. Annualized Total Costs by Category (Million 2010$), BAU scenario

	Energy Supply			End Use Sectors				
Year	Electricity	Fuels & Energy Supply	Total	Transportation	Residential	Commercial	Total	Total
2010	1,611	1,896	3,507	14,194	20,130	6,607	40,931	44,438
2015	2,736	2,451	5,188	62,379	17,301	6,831	86,511	91,699
2020	5,436	4,696	10,132	111,549	16,847	8,686	137,083	147,215
2025	7,513	8,038	15,551	159,058	17,593	10,096	186,747	202,298
2030	8,391	8,753	17,144	192,076	19,097	10,729	221,903	239,047
2035	8,908	11,863	20,771	209,273	19,741	11,071	240,085	260,856
2040	8,120	13,765	21,885	226,904	21,458	11,890	260,252	282,137
2045	8,574	15,029	23,603	235,536	22,728	12,657	270,920	294,523
2050	8,274	15,442	23,716	246,170	23,853	13,385	283,408	307,124
Total (undiscounted)	279,458	374,823	654,281	6,755,689	805,037	418,234	7,978,959	8,633,240
Total (discounted)	116,704	141,103	257,807	2,652,108	377,881	184,570	3,214,559	3,472,365

Table E.2. Annualized Total Costs by Category (Million 2010$, undiscounted), GHG-Step scenario

	Energy Supply			End Use Sectors				
Year	Electricity	Fuels & Energy Supply	Total	Transportation	Residential	Commercial	Total	Total
2010	1,611	1,901	3,512	14,194	20,130	6,607	40,931	44,443
2015	3,180	2,528	5,709	56,777	17,724	5,966	80,467	86,175
2020	7,171	5,048	12,219	101,447	17,845	7,166	126,458	138,677
2025	11,027	7,477	18,503	145,648	19,211	8,053	172,912	191,415
2030	14,644	9,389	24,033	175,973	21,438	9,811	207,222	231,255
2035	19,877	12,096	31,973	192,099	23,542	11,929	227,570	259,543
2040	24,404	14,839	39,243	207,646	27,819	14,887	250,352	289,595
2045	30,579	16,449	47,028	218,414	34,233	18,923	271,570	318,599
2050	35,899	24,103	60,003	278,225	54,751	24,283	357,259	417,261
Total (undiscounted)	664,362	417,038	1,081,401	6,358,076	1,033,100	474,768	7,865,944	8,947,345
Total (discounted)	232,837	151,720	384,556	2,465,335	442,416	189,328	3,097,079	3,481,635

APPENDIX F. NON-CORE EXPERIMENTAL TIMES MODELS/SCENARIOS

This appendix describes several innovative stand-alone models that use TIMES algorithm (cost-minimization) but are currently too computational intensive to be included in CA-TIMES v1.5. These new modeling techniques demonstrate areas that we consider critical to improve upon the existing model. We demonstrated how these improvements can be made and the expected results. We expect to incorporate these new methodologies, or will develop simpler approaches to incorporate these new modeling techniques into the main model in the future.

F.1 Hydrogen Infrastructure Model

This section describes a stand-alone model (H2TIMES) that has been developed to simulate the development of hydrogen infrastructure in California using the TIMES modeling framework. It attempts to build the least cost H_2 infrastructure needed to meet an exogenously specified demand for hydrogen in 8 regions of the state. More information can be found in the detailed paper (Yang and Ogden 2013).

The goal of the H2TIMES modeling is to develop a policy relevant, spatially-representative detailed hydrogen infrastructure transition optimization model for California. The purpose of the analysis is to understand the context and influence of different policies on the development, cost and emissions associated with hydrogen deployment in California. H2TIMES has a special focus on low-carbon and renewable hydrogen futures by 2050.

Spatial details of H2TIMES

The hydrogen demand in H2TIMES is distributed among eight regional clusters in order to account for differences in hydrogen demand density and total demand in different regions of the state, which will influence the cost of hydrogen production and delivery. Data from the US Census (US_Census_Bureau 2000) identifies 55 urbanized areas in California, which have a population of greater than 50,000 people. These urbanized areas are distributed into eight regional clusters, and the assumption is made that a separate fuel infrastructure is developed in each of these regional clusters (i.e. hydrogen produced in and for one regional cluster is not available to meet the demand for hydrogen in another cluster). The level of spatial disaggregation was chosen for this study in order to understand the development of distinct regional hydrogen infrastructures that have different demand levels and densities. Figure F.1 shows a map of the seven clusters in California.

For each cluster, pipeline and hydrogen truck delivery distances are calculated to deliver hydrogen to a network of refueling stations in each cluster. These distances are then translated into the capital and operating cost inputs for pipeline and liquid truck delivery infrastructure in each regional cluster. Intracity (local distribution) pipeline distances for a given urbanized area are calculated using an idealized city model developed by Yang and Ogden (Yang and Ogden 2007).

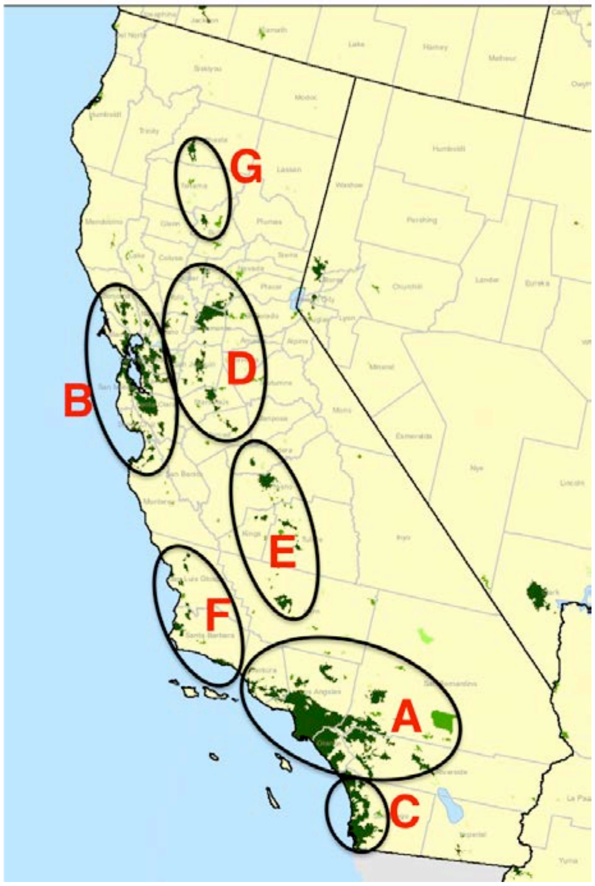


Figure F.1.Map of regional clusters within the H2TIMES model. Dark green areas show the spatial extent of each individual urbanized area.

H_2 infrastructure

The key central production technologies are coal gasification, natural gas reforming and biomass gasification, each of which have the option for carbon capture and sequestration (CCS). Once hydrogen is produced at these central plants, it can be delivered to refueling stations via two pathways: (1) transmission and distribution pipelines and (2) cryogenic hydrogen produced by a liquefier and then delivered by liquid hydrogen trucks. Compressed gas truck delivery is not considered as a long-term delivery solution because their low hydrogen capacity would necessitate too many deliveries. There are also onsite production options, where hydrogen is produced directly at the refueling station. Onsite stations produce hydrogen using steam reformers powered by natural gas (or biomethane) or electrolyzers powered by grid electricity (renewable electricity is also an option). These stations also store and dispense compressed hydrogen to vehicles.

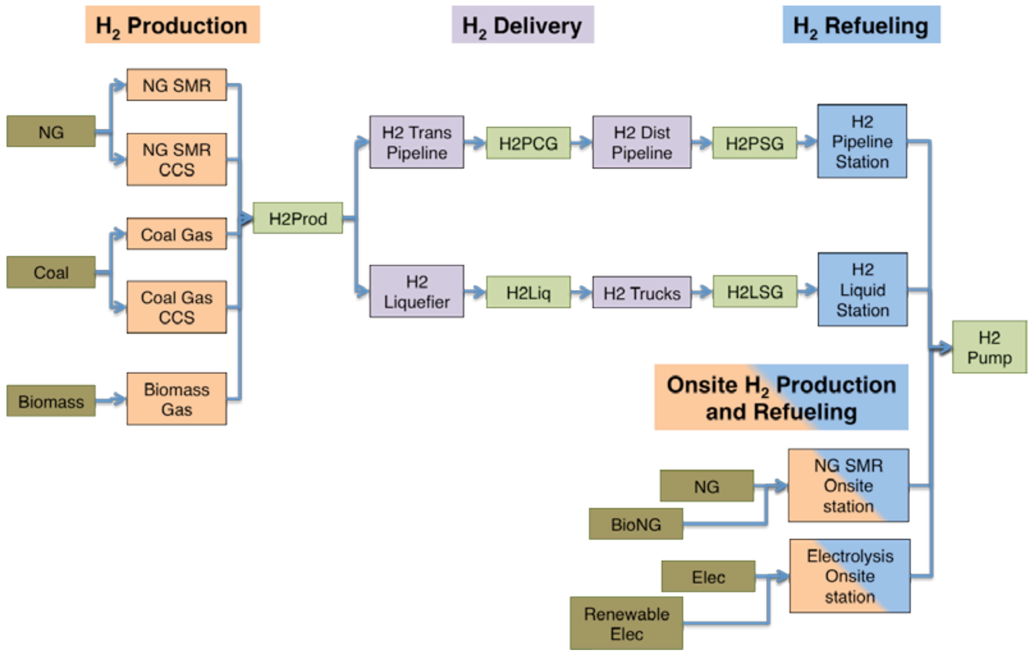


Figure F.2. Potential routes for hydrogen production and delivery available within the H2TIMES model to meet hydrogen demand at the refueling station.

Many of the key elements and components that make up hydrogen infrastructure have important economies of scale (e.g. central hydrogen production and liquefaction plants, pipeline networks and refueling stations. An exponential equation is typically used to model the cost of plants that exhibit economies of scale. However, the TIMES framework relies on linear programming, which does not allow costs to be expressed as exponential functions. There are two issues that arise with the typical TIMES approach to costs: (1) capital costs are proportional to capacity and (2) the model can invest in any amount of capacity, even unrealistically small sizes.

An innovative approach taken here, couples discrete investments with continuous capacity additions, to simulate declining costs with increasing scale (i.e. economies of scale). To do so, each technology that needs to simulate economies scale is split into two separate but necessary technologies - a fixed size component and a variable sized component. As a result, any technology represented with these two components will have a linear cost curve with a non-zero intercept (cost at zero capacity). Thus, at low capacity, the cost per unit of capacity is very large and declines until you reach the maximum plant size. This approach discourages investment at very small sizes and the linearization process leads to good agreement in costs between the exponential and linearized cost equations.

Renewable hydrogen and carbon intensity policy

A key element of the H2TIMES model is the inclusion of renewable and low-carbon policies to analyze their effects on the development of hydrogen infrastructure. Senate bill 1505 (SB1505) is a California state requirement that 33% of hydrogen supplied at refueling stations must be produced via renewable resources and have a 30% reduction in well to wheels emissions relative to gasoline. In H2TIMES, only hydrogen produced via biomass gasification, onsite electrolysis using renewable electricity and onsite steam reforming using biomethane can count towards the 33% renewable hydrogen mandate.

Base case modeling results

The *Base* case incorporates hydrogen regulations in effect in California. These include constraints imposed by SB1505, which requires that hydrogen achieve a 30% reduction in well-to-wheels (WTW) GHG emissions relative to gasoline (i.e. 30% reduction in EER-adjusted hydrogen (i.e. regulated) CI compared to gasoline) and also requires that 33% of hydrogen production come from renewable resources[2] (i.e. renewable mandate). The *Base* case also does not allow for the use of coal without CCS.

Figure F.3 shows that statewide by 2050, the majority of hydrogen production comes from coal gasification with CCS. Initially, hydrogen production comes exclusively from onsite natural gas reformers. Then in 2020, biomass gasification becomes the least-cost central production option and is generally built until the available resource is completely utilized by 2030. Since demand continues to grow, the next option is coal gasification with CCS (since coal gasification without CCS is prohibited in this scenario). It makes up the vast majority of additional generation after 2030. Central production makes up the vast majority of supply in the largest four regions, while onsite production is found in the smallest regions. In 2050, coal with CCS makes up 60% of total hydrogen production, while biomass makes up 15%.

There is significant growth in electrolysis in the 2040 to 2050 timeframe, due to the requirement for renewable hydrogen. The presence of the 33% renewable hydrogen mandate is satisfied in early years by biomass hydrogen, but the limited supply of biomass is constrained and additional renewable hydrogen production comes from renewable electrolysis and onsite reforming of biogas. In 2050, renewable electrolysis makes up 12% of total hydrogen production.

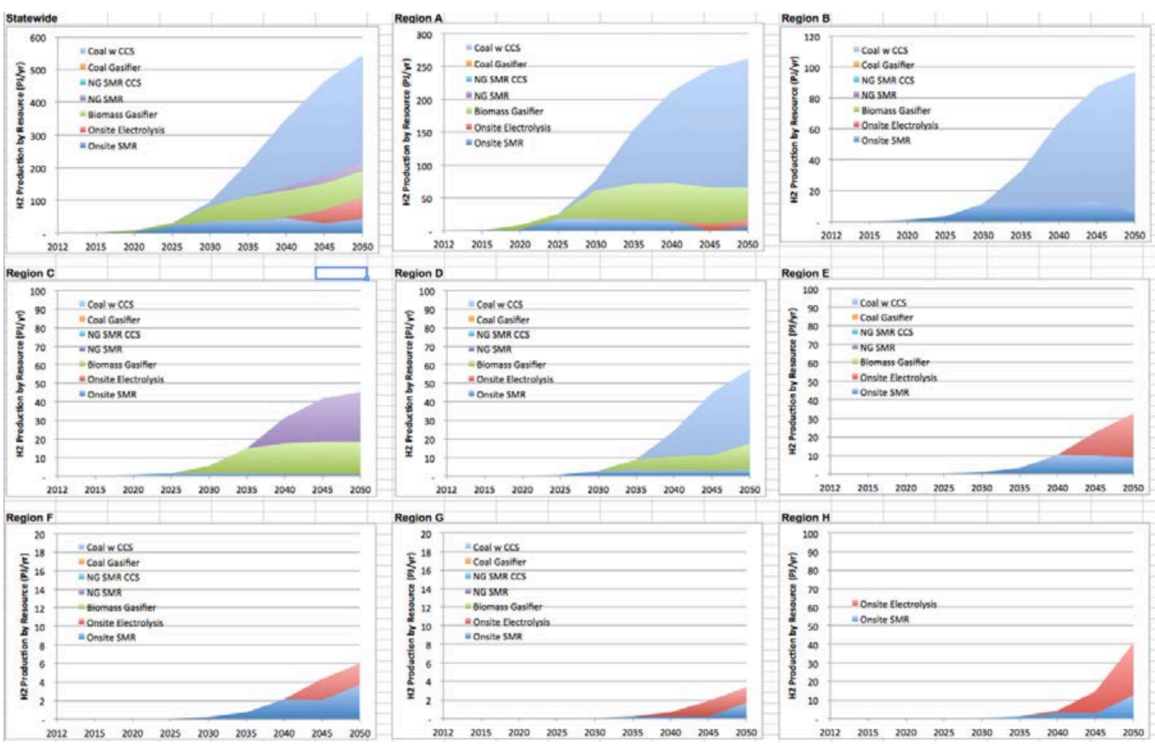


Figure F.3. Hydrogen production by production pathway for eight regional clusters and statewide for *Base* case scenario

The cost of hydrogen in the first two time periods (2012 and 2015) is set to match the results of an earlier study (Ogden and Nicholas 2011) and are quite high ($24/kg and $9/kg respectively) due to underutilization of small,

[2] Resources that are used to meet the renewable portfolio standard (RPS) for electricity supply are not eligible to meet this requirement (i.e. electrolysis from grid electricity that has some renewables due to RPS does not contribute to this renewable requirement).

high-cost early refueling stations. By 2020, the average cost of hydrogen has dropped to a little over $5/kg and then declines further to around $4/kg. In some of the small regional clusters where significant electrolysis occurs (i.e. clusters E-H), costs tend to spike after 2040 as a result of the high cost of electrolysis and renewable electricity, raising statewide average price from $3.80/kg in 2040 to $4.20/kg in 2050.

Overall, the regulated carbon intensity is relatively low, 4346 gCO_2e/kg[3] in 2012 (60% below gasoline) and declines to 1626 g/kg in 2050 (85% below gasoline). Each of the pathways chosen by the model has relatively low carbon emissions. The highest carbon sources in this scenario are production hydrogen from natural gas (both onsite and central) (~50-61% reduction from gasoline). All other options are lower carbon including onsite electrolysis with renewable electricity (100% reduction from gasoline), biomass gasification (~95% below gasoline), and coal with CCS (~92% below gasoline). After 2025, the broad investment in coal with CCS lowers average carbon intensity significantly and in 2040, the addition of renewable electrolysis further reduces carbon intensity.

The H2TIMES model allows the user to alter input assumptions about resource and technology costs, technology characteristics and policy and societal constraints. Changes in these inputs will lead to differences in the model choices and the evolution of H_2 infrastructure pathways, their cost and emissions. Understanding these choices and how they are influenced by technical and policy options is a key element to this analysis and modeling tool.

For additional details and sensitivity analysis on these results, the reader is directed to (Yang and Ogden 2013).

Future work

H2TIMES is built on the TIMES modeling framework and has the benefits as well as some of the limitations of that platform. H2TIMES is a standalone TIMES model that focuses exclusively on hydrogen infrastructure in California. It has been developed with an eye towards incorporating these elements into the full CA-TIMES model. This will allow for several improvements.

- Better integration with economy-wide policies, such as the renewable portfolio standard, statewide carbon reduction goals and cap and trade policies
- Better representation of resource availability and competition, especially for resources with limited availability such as biomass and renewable energy
- Endogenously calculated demand for hydrogen vehicles and fuels
- Improved understanding of the role of hydrogen in the larger energy economy

F.2 Consumer Vehicle Choice Model

Motivation

As described in the above sections, 4E (energy, economy, environment, engineering) models like TIMES, have been used as reliable tools for developing transition scenarios for climate change policies, as they can incorporate interdisciplinary subjects in a well-coordinated fashion. Though they can work well with economic and technological parameters, their function has been quite limited when representing behavioral parameters or consumer choices. Due to this deficiency, the investments in new technologies have been typically optimized for a homogenous market in the 4E models, which many times do not result in the decisions in line with real-life scenarios as it involves heterogeneity in consumer preferences. This factor becomes especially important when it

[3] Raw CI values can be obtained by multiplying the regulated CI values by the EER (2.3 in 2012, 2.0 in 2020, 1.8 in 2025 and 1.75 in 2035).

comes to representing transportation sector, as consumer choice is one of the most important aspects of decision-making for light-duty vehicles.

An illustrative model, COCHIN-TIMES (COnsumer CHoice INtegration in TIMES) is developed involving only the light-duty vehicle sector for California. A vehicle choice model (MA^3T: Market Allocation of Advanced Automotive Technologies) developed by Oak Ridge National Laboratory is used as a primary data source for consumer preference and utility data in the COCHIN-TIMES model (Zhenhong Liu 2010). The exogenously-defined end-use demand in the TIMES model (i.e. light-duty VMT) is disaggregated into 27 separate consumer groups and each consumer group is further divided into fixed number of slightly varying instances in order to capture heterogeneity and variation among car buyers.

Methodology

In order to include qualitative parameters into the cost-minimization framework, an appropriate variable should be introduced such that it captures the 'perceived value' of the technology, based on its attributes and the preferences of the consumer. This measure is defined as 'utility' in economic theory. The usage of utility as a preference scale has been extremely valuable in behavioral economics to understand the choice decisions of consumers (Simon 1959).

The proposed approach would be implemented by including the "market demand response" of consumer vehicle choice preferences extracted in the form of utility cost, from an existing vehicle choice model and brought into the TIMES model. In this case, for the vehicle choice model, MA^3T (Market Allocation of Advanced Automotive Technologies) model developed by Oak Ridge National Laboratories (Liu & Greene, 2010) is considered.

MA^3T model is a nested multinomial-logit model developed by Oak Ridge National Laboratory for predicting the penetration rates of advanced vehicle technologies in the US, based on several input parameters such as vehicle attributes, regional market segmentation, energy prices and policies. The model has 1458 consumer segments throughout the country divided based on region, driving behavior, risk attitudes, home-charging availability, work-recharging availability, and parking availability.

The model uses these vehicle technology attributes to calculate utility cost, also termed as total generalized cost, (which is the weighted sum of utility cost attributes) for each technology in each market segment, given by the equation:

$$\mathrm{C}_{ijkl} = \sum_z \mathrm{w}_{zjkl}\ \mathrm{f}_z\ (x_{zijkl}) \qquad \text{(Equation 1)}$$

Where,

C_{ijkl} the total generalized cost of the vehicle technology 'i' in market segment 'jkl' (expressed in \$/vehicle), which is the weighted cost of functions of various input attributes.
'w' the weightage of input attribute 'z'
x_{zijkl} denotes the parameter values related to the input attribute 'z'
f_z the function computed from the parameter values of input attribute 'z'
'i' the vehicle technology
'jkl' represents the nested market segment (region 'j', driving behavior 'k', and attitude 'l')

The generalized cost is divided into two major components: tangible and intangible costs. Tangible costs are direct costs from the vehicle that can be quantified easily, such as vehicle purchase price, and fuel costs. These costs are already incorporated into the existing structure of TIMES model. Intangible (i.e. non-monetary) costs are indirect costs that are not normally quantified for vehicles (shown in Figure F.4).

Figure F.4. Intangible Cost Components of MA^3T consumer vehicle choice model

Intangible Cost Component	Description
Limited EV range	Cost of the consumer willing to spend on rental cars in a year based on their value of perceived anxiety due to range limitations of the owned vehicle. It is calculated based on the charge sustaining capability of the vehicle, how much or how long the consumer drives every day, and the attitude of consumer towards technology risk. This attribute monetizes the anxiety of the consumer when it comes to using limited range EVs.
Refueling station availability	Cost associated with the ease of access to recharging and refueling infrastructure. This cost captures the fuel availability and the ease at which the consumer can have access to refuel his vehicle. It depends on the fuel infrastructure itself, as well as the driving behavior of the consumer; if the consumer is prone to drive more, he or she has the need to refuel often. For example, in the year 2010, gasoline cars have an easier access to fueling stations than hydrogen cars, hence the gasoline cars have a lower cost associated with this compared to hydrogen cars.
Model Availability Cost	Cost associated with the number of vehicle models available for a given vehicle technology. It is assumed that, when the vehicle technology is new to the market and has limited sales, the models available to sell are also limited. So, if the user prefers to have a different model car in the given new vehicle technology, it may not be readily available until there is a sizeable market demand for it. This disutility is captured in this cost attribute..
New Technology Risk Premium	Cost calculated based on the willingness to accept the technology risk and the perceived riskiness of new vehicle technologies. The consumers in this model are divided into early adopters, early majority and late majority, based on their attitude towards technology risk. For example, when a certain vehicle technology is new to the market, early adopters are more willing explore them rather than the other two groups. They have a lesser “risk premium” cost compared to the other consumer groups.
Towing Capability	Cost calculated based on the towing capacity of the vehicle technology. This cost is technology specific, and not consumer group specific. A few vehicle technologies, such as gasoline cars or diesel cars have a better towing capability than electric vehicles, for example. If a consumer prefers to have a better towing capacity for his vehicle, this cost attribute captures it.

These generalized cost terms in each consumer group nested segment are used to calculate the purchase probabilities for the particular vehicle technology for each consumer group. These indirect or intangible costs are included as an additional cost to the TIMES model. The schematic of the model is show in Figure F.5.

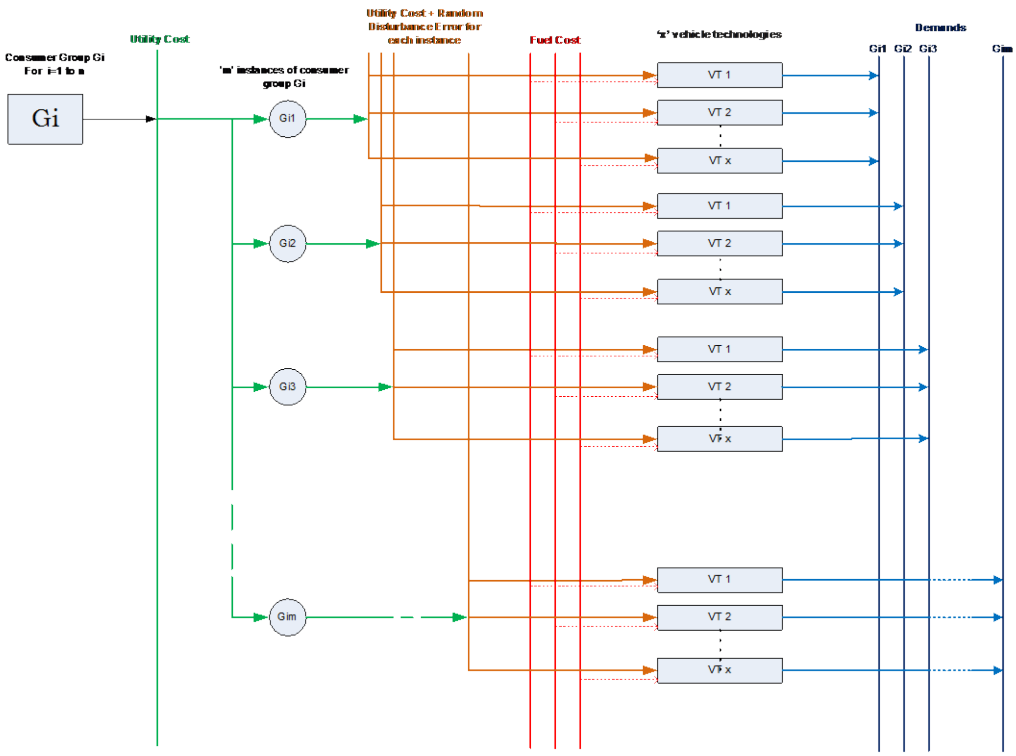


Figure F.5. Reference Energy System of COCHIN-TIMES model

The vehicle cost and efficiency projections, and fuel price projections are obtained from AEO 2012 data (U.S. EIA 2012). Total light-duty vehicle demand for California in terms of MVMT is extracted from VISION model (VISION 2011). In order to capture heterogeneity in consumer behavior, the demand is divided into different consumer groups. Twenty-seven different market segments are considered from the MA^{3}T model as shown in Figure F.6. The state of California is divided into rural (outside MSA), suburban (Inside MSA-Suburb) and urban (Inside MSA-Central City) sub-regions, based on Census population data (US Census Bureau, 2010). The rural population constitutes about 5% of the total, suburban population constitutes about 80%, and the urban population constitutes about 15% of the total (Bureau 2010). These regions are further divided into people based on their attitude towards technology risk in terms of fixed percentage, namely, early adopters (16%), early majority (34%) and late majority (50%). The driving behavior is also captured in each group—they are divided based on their average annual miles driven, namely, modest driver or low annual VMT (8656 miles), average driver or medium annual VMT (16068 miles) and frequent driver or high annual VMT (28288 miles) (Zhenhong Liu 2010). In addition to these consumer group divisions, each group is divided into 'clones' or 'instances' that have the same utility cost, but have an additional random disturbance term that follows cumulative extreme value distribution function. This is done to capture difference of choices within the same group.

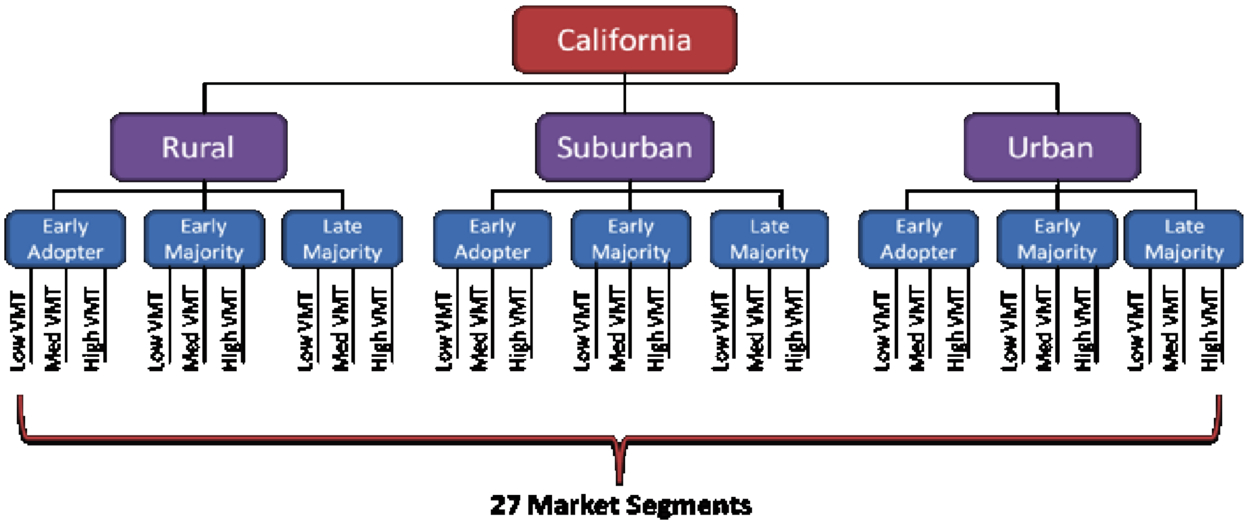


Figure F.6. Market Segments represented in the COCHIN-TIMES model

Preliminary Results

The model uses the least cost linear-programming approach to solve for the optimal vehicle technology for the society for a given year, so that the overall system cost is minimized. The standard TIMES model without consumer choice integration will minimize the net present value of owning a vehicle, including vehicle purchase cost, fuel cost and non-fuel expenses, throughout the model period with a discount rate of 5%.

In the COCHIN-TIMES model, where consumer choices are integrated, the utility costs are extracted from MA^3T model for the respective consumer groups and vehicle technologies. In order to match the cost term to mimic the market demand response of the MA^3T model, the utility costs are scaled to match the purchase probabilities of MA^3T model.

A comparative analysis was performed between the reference case scenarios of the models, with and without vehicle consumer choice element in them. Except for the demand disaggregation and an additional utility cost term, the rest of the technological, economic, and environmental parameters are the same for both the models. Figures E.7 and E.8 show the percentage distribution of new technology sales in both the models without any additional constraints. It is observed that in the TIMES model (without the consumer choice integration), the investments tend to follow the 'winner takes all phenomenon', where in the model invests in only ONE technology in any given year, here the model chooses diesel cars for the initial years followed by gasoline plug-in hybrids with 10 mile charge depleting range, and in the year 2035, hydrogen internal combustion engine (ICE) car is chosen (Figure F.7). This can be attributed to the model assumption that the hydrogen fuel price is expected to meet the future DOE goal of $ 2/Kg in the year 2035 (Joseck 2010). Also, in the TIMES model, 'penny switching' occurs, where when one technology gets slightly cheaper, the entire model flips to that solution.

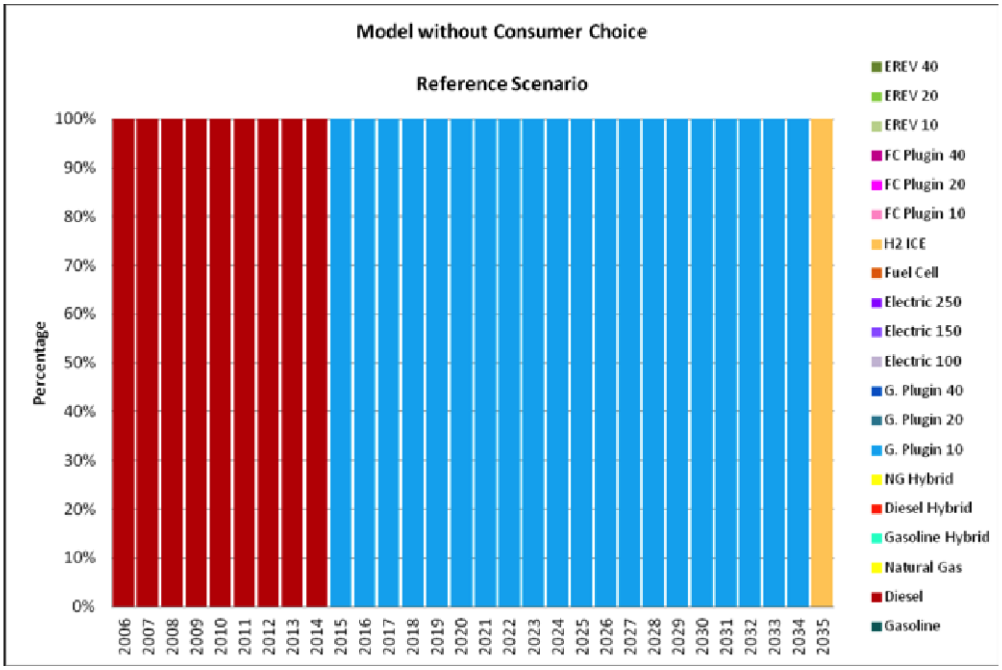


Figure F.7. Percentage distribution of new vehicle technology sales in TIMES: reference case scenario

In the COCHIN-TIMES model (Figure F.8), it is observed that the distribution of new technology investments are far diverse, mainly dominated by gasoline cars, followed by gasoline hybrids and gasoline plug-in cars in the later years. We can also see some level of market penetration of other advanced vehicle technologies, such as, extended range electric vehicles, fuel cell plugin hybrids, diesel hybrids, natural gas vehicles, and so on. This can be mainly attributed to the additional cost parameters in the utility cost that changes the dynamics of decision-making. The infrastructure cost, refueling cost and rental costs are very low for gasoline vehicles compared to diesel cars, and it is followed by hybrids for the initial years. When compared among the attitudes of consumer groups, early adopters seem to have more technology penetration, followed by early majority groups and late majority groups.

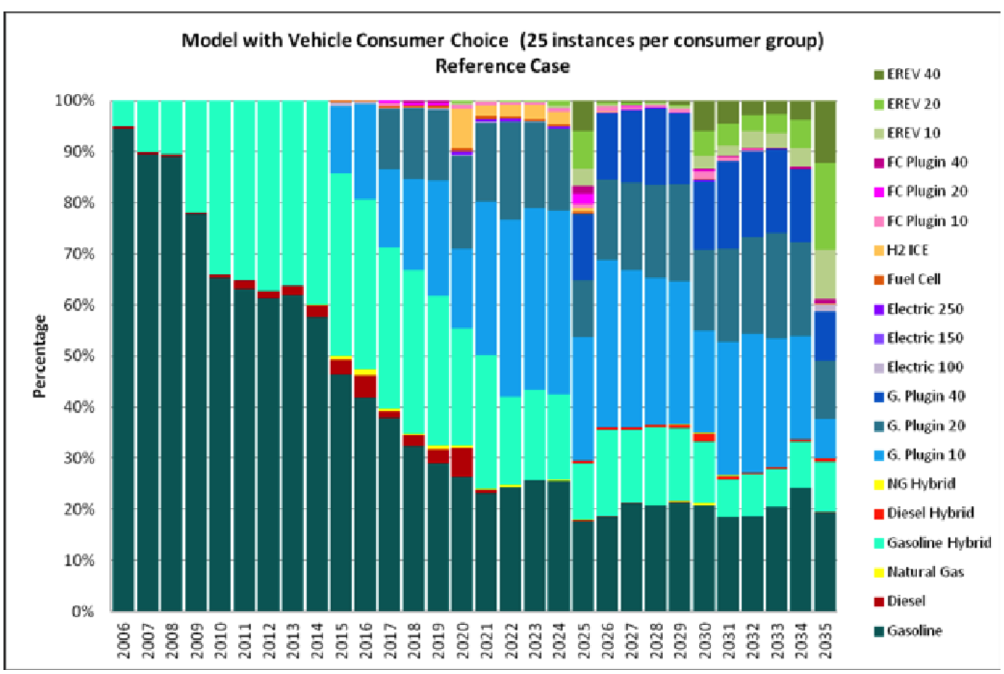


Figure F.8. Percentage distribution of new vehicle technology sales in COCHIN-TIMES: Reference Case Scenario

Future improvements needed

Based on the preliminary model results, we could conclude that segmenting the model into different consumer groups and including utility cost parameter has improved the diversity of the model results. There are a few limitations of the current COCHIN-TIMES model that we intend to improve in future work:

Currently there are no manufacturer limitations in the model, i.e. any limitations on the automobile production side. In real-life, automakers will not simply switch all vehicle production to advanced technologies in a very short timeframe, leaving behind the conventional cars. This explains the ease of market penetration in advanced vehicle technologies, especially in the plug-in hybrids and extended range vehicles in the later time periods. The future revisions in the model methodology can address this issue by representing a more realistic penetration pattern such as introducing learning or growth constraints. In reality, the automobile makers cannot make such a rapid switch to new technologies. It takes time for vehicle demand and manufacturing capacity to ramp up, and abandon old technologies such as gasoline cars. A realistic vehicle penetration rate can be modeled by calibrating with the historic projections of other vehicle choice models or by incorporating reasonable growth rate for those technologies.

At a given time, the utility costs extracted from MA^3T model are fixed for a vehicle technology for a given consumer group. The future version of the COCHIN-TIMES model will improve on a more endogenized representation of the components of utility cost in a more realistic manner. It will also be benchmarked with other vehicle choice models on the technology penetration rates and will be calibrated.

For example, the model currently has fixed refueling and infrastructure disutility cost for all time period. This barrier is particularly important for the penetration of hydrogen and natural gas cars. In reality, further penetration of technologies depend on the infrastructure built, which is in turn based on the previous time periods' vehicle sales. Similarly, the CHOCHIN-TIMES model does not have any learning curves for batteries and fuel cells, i.e. costs of vehicle technology is exogenously specified and independent of scenario. Finding ways to endogenize these exogenous assumptions can significantly improve the quality of future results.

F.3 Plug-in Electric Vehicle Charging Scenarios

The environmental impact of plug-in electric vehicles (PEVs) will depend upon the electricity generation sources that are used to charge these vehicles. And as discussed in the electricity generation section, the mix of electric power plants and therefore the cost and emissions from electric generation all change as a function of timeslice. In addition, PEVs are parked more than 90% of the time so there is significant potential for flexibility in the timing of recharging these vehicles.

The goal of the electricity grid is to match supply and demand for electricity, continuously and in real-time. Elements on the grid that can respond to real-time changes and can help to achieve that supply demand balance can be classified as active elements, whereas those that cannot can be called passive.

The traditional model has been to meet a continuously changing, but inflexible (i.e. passive) loads with an array of power plants, many of which are load-following (i.e. active). With the growth of passive intermittent renewables on the supply side, it is helpful to have active, flexible loads on the system to help maintain supply and demand balance.

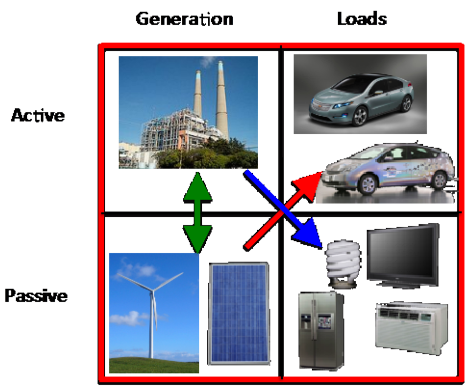


Figure F.9. Electricity system 2x2 matrix showing active and passive generation and loads.

One of the potential benefits of shifting vehicles from petroleum fuels to electricity is related to the improvements in grid operation that may result due to off-peak and flexible vehicle charging. Given the daily electricity demand profiles described in the last section (demand is higher in the afternoon and lowest at night), charging electric vehicles when other demands are lowest can improve overall capacity factors for power plants on the grid and lower the cost of electricity generation.

Flexibility in vehicle charging is also important. Electric vehicle owners have been shown to alter their charging patterns in response to time-of-use (TOU) prices. This responsiveness of PEV demand to utility incentives (in the figure below, off-peak pricing starts at midnight).

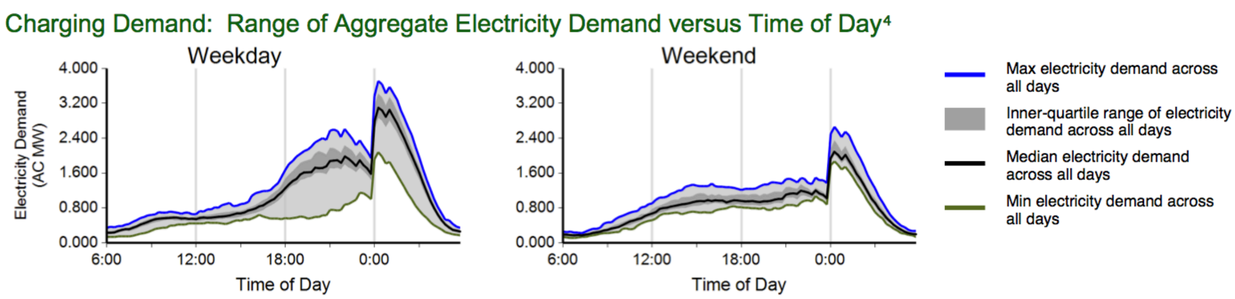


Figure F.10. Charging profiles for vehicles in California (ETEC 2012).

Modeling of electric vehicle charging should attempt to take the potential for these utility incentives to influence the pattern of vehicle charging. In TIMES, it is possible to set a fixed profile of charging by specifying the fraction of vehicle demand that occurs in each timeslice. The profile can come from real-world charging data (e.g. (Davies-Shawhyde 2011)) or from synthetic charging profiles. In this case, we choose to use a synthetic charging profile adapted from EPRI (EPRI and NRDC 2007) to fit our timeslice levels (3hr blocks). This profile (see Figure F.11) shows a symmetrical charging profile with highest levels at night (from 9pm until 3 am) and moderate levels of charging between 6pm and 9pm and also 3am to 6am. There is some charging also during work hours from 9am to 3pm due to workplace charging. Vehicle charging is lowest during commute hours (6-9am and 3-6pm), when presumably many vehicles are on the road.

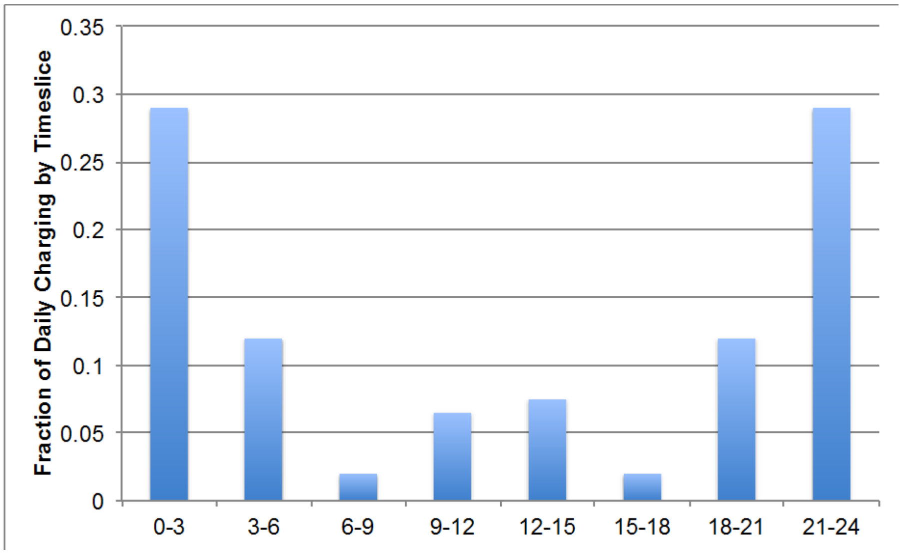


Figure F.11. Fixed vehicle charging profile based upon EPRI (2007).

It is also possible to allow the model to determine the best timeslices to charge vehicles with respect to overall system cost and operation. As previously discussed, allowing the model to shift charging can improve capacity factor of existing and future power plants and allow the model to build and operate lower cost baseload plants rather than more expensive peaking power plants. Another example is if there was an abundance of wind or solar generation during specific times of day, the model could choose to charge during these hours.

Since the TIMES model's objective function includes all of the capital and operating costs associated with operating electric power plants, the optimization will essentially minimize costs for the electric utility. While this approach ignores consumer behavior, preferences and convenience from the demand side, it is assumed that the utility can provide incentives (through time-of-use (TOU) or real-time (RTP) pricing. This can enable consumers' behavior to align with the cost-minimization approach exhibited by the model.

However, even with incentives, not all consumers will be able or willing to limit their charging to suite the best interests of the electric grid. Thus, the approach taken here is that some fraction of vehicle charging demands can be assumed to follow a fixed profile while the remaining charging demand can be optimized by the model to minimize costs and the fraction of fixed vs. variable charging can change over time.

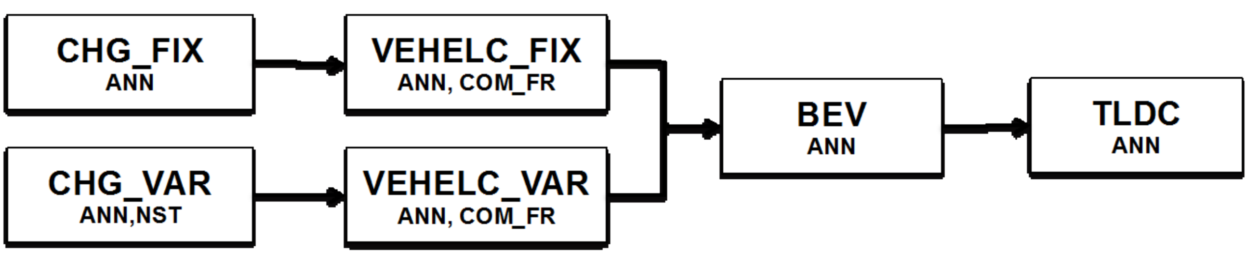


Figure F.12. Diagram of fixed and variable vehicle charging approach in TIMES

Figure F.12 shows the approach taken in the TIMES model to simulate both fixed and variable charging within the model. One constraint is that the total electricity over the course of the "day" is held constant, but charging can occur in any timeslice. The six seasonal "days" do not have the same quantity of electricity charging because they do not contain the same number of hours, and there are slight differences in driving patterns as a function of time of year (EIA).

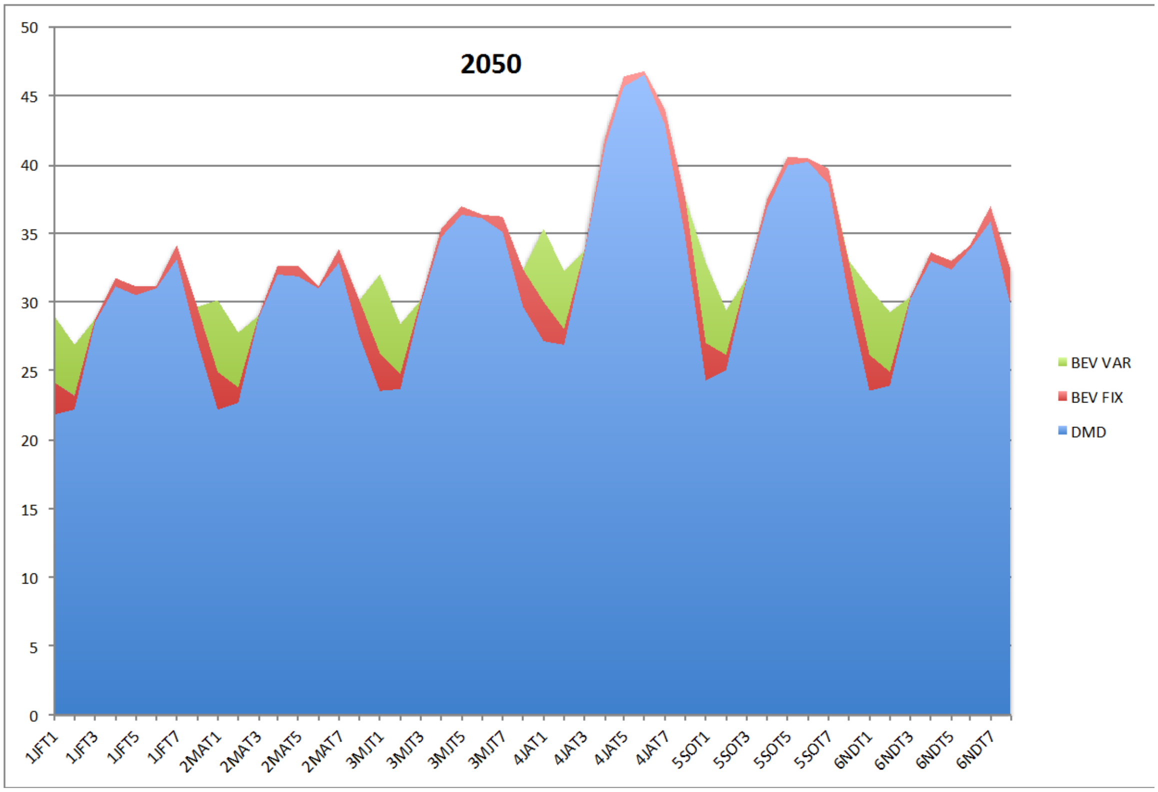


Figure F.13. Example of charging profiles of electric vehicles in 2050. DMD: other non-vehicle demand.

Figure F.13 shows some example results of this hybrid approach of fixed and variable vehicle charging. The figure shows non-vehicle electricity demand in blue, fixed profile charging in red and variable profile charging in green. While the majority of fixed charging occurs in off-peak (i.e. night time) timeslices (as per Figure F.11), all of the variable charging occurs in the off-peak timeslices.