Title
Utility Sector Impacts of Reduced Electricity Demand

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Abstract

This report presents a new approach to estimating the marginal utility sector impacts associated with electricity demand reductions. The method uses publicly available data and provides results in the form of time series of impact factors. The input data are taken from the Energy Information Agency's Annual Energy Outlook (AEO) projections of how the electric system might evolve in the reference case, and in a number of side cases that incorporate different efficiency and other policy assumptions. The data published with the AEO are used to define quantitative relationships between demand-side electricity reductions by end use and supply-side changes to capacity by plant type, generation by fuel type and emissions of CO_2, Hg, NO_x and SO_2. The impact factors define the change in each of these quantities per unit reduction in site electricity demand. We find that the relative variation in these impacts by end use is small, but the time variation can be significant.

1 Introduction

Energy conservation and efficiency policies are designed to reduce the demand for energy without reducing the availabililty of products or services supplied through the use of that energy. Reduced energy use has associated environmental impacts–for example reductions to emissions of CO_2 and other greenhouse gases (GHGs)–that contribute to the societal costs and benefits of the policy. To evaluate these potential impacts both the energy required to achieve a given level of economic activity, and the associated environmental impacts, must be specified under a baseline scenario and under a scenario that incorporates the policy change. Evaluating the differences between the two provides a way to estimate the marginal policy impacts, which become a factor in the decision of whether to implement the policy.

The analysis methods used to evaluate these marginal social and environmental impacts often require that the enactment of a given legal rule be studied in isolation. The magnitude of the impact of a single rule on total national energy use is likely to be small and difficult to estimate, so this creates a somewhat artifical technical problem. In reality many state and federal rulemakings are enacted as part of more general ongoing programs. The impacts associated with a series of rules over an extended period of time are much larger and can be captured with a much greater degree of accuracy. The problem then becomes to find a way to allocate the total impacts to each of the individual rules or activities that make up the program.

In this paper we apply this concept to the analysis of the utility sector impacts of the U. S. Department of Energy (DOE) Appliance and Equipment Standards Program [3]. This program has published energy conservation standards for dozens of equipment types over the last two decades, with aggregate program impacts estimated at several quads of primary energy per year [10]. This corresponds to roughly 10% of U.S. electricity and natural gas consumption by the residential, commercial and industrial sectors combined. The regulatory process requires national-level estimates of utility sector impacts for each rule individually, which have until now been provided using a modified version of the National Energy Modeling System (NEMS) [1]. NEMS is a mid-range energy forecast model developed and maintained by the Energy Information Administration (EIA) within DOE. It is used to generate the Annual Energy Outlook (AEO), which provides projections of U.S. energy supply and demand and related economic and demographic variables [5]. Here we define, implement and validate an alternative approach that starts with the aggregate impacts of different policy packages specified as EIA side cases, and allocates their impacts to the individual end-use demand reductions within each side case. The method is used to provide estimates of changes to total installed power plant capacity, generation, and related emissions as a function of sector (commercial, industrial and residential) and end-use.

The dataset for this analysis is derived from the 2014 Annual Energy Outlook. Each edition of the AEO presents a reference case projection of U.S. supply of and demand for electricity, natural gas, petroleum fuels *etc.*The reference case incorporates all federal and state policies or programs that are active at the time of the AEO publication. To analyze the potential impacts of policies that are under consideration but not yet implemented, the EIA also publishes a series of side cases. We use the reference case as the baseline scenario, and a selection of side cases as examples of policy packages that incorporate different conservation and efficiency measures focused on equipment efficiencies and building measures. The data published with the AEO are used to define quantitative relationships between the demand-side reductions and changes to capacity, generation and emissions.

2 Overview

2.1 Approach

The flow chart in Figure 1 provides a schematic of the calculation approach. For a selection of side cases, we develop data sets of *deltas*, defined as the difference between a given quantity in the side case and the reference case. For any quantity X, the delta ΔX is defined as

$$\Delta X_K(y) = X_R(y) - X_K(y), \tag{1}$$

where

- y is the forecast year,
- X is any of the quantities used in the analysis,
- K is the scenario label,
- R is the label for the reference case.

The deltas are positive if the value in the reference case is larger than the value in the side case. The data series used are end-use electricity demand in the residential, commercial and industrial sectors (the demand side data), electricity generation and installed capacity by fuel type, and power sector emissions of carbon dioxide (CO_2), mercury (Hg), nitrogen oxides (NO_x) and sulfur dioxide (SO_2) (the supply side data).

Load shape information, *i.e.*the specification of the time-varying profile of electricity consumption associated with a particular end-use, provides an important link between the supply and demand sides. The NEMS code includes hourly load shapes for a number of residential and commercial end-uses (see Table 4). The correlation between end-use load shapes and generation is mediated by the system load duration curve [7]. The relative proportion of electricity demand by end use determines the shape of the hourly electric system load. The hourly system load is converted to a load duration curve which defines the number of hours per year that the system load is at or above a given level. The load duration curve is used to determine the expected annual hours of operation for different types of generation, which is an input to the algorithms that determine investment in new capacity. Changes to electricity demand can therefore influence the fuel mix of generation as well as its absolute level. This analysis incorporates the load shape information by assigning each hour to one of three time periods: on-peak, shoulder and off-peak. Electricity savings by end-use are then converted to electricity savings by time period. Generation is also classified into base, intermediate and peak-serving types based on the capacity factor (see Section 4). We use a set of allocation rules to connect changes in base, intermediate and peak loads to changes in the level of generation in each of these categories. We develop direct correlations between the supply-side changes in generation by fuel type and changes in emissions and installed capacity. The end result is a set of coefficients that can be used to relate a unit reduction of demand for a given sector and end-use to to the induced reductions in the supply side variables. At each step the model is tested by comparing the predicted deltas to the actual deltas.

2.2 Selection of Side Cases

EIA side cases are selected for use in this analysis based on two criteria. The first is that the package of policies being modeled must primarily affect the demand side through enhanced equipment efficiencies or building shell measures, with minimal direct intervention on the supply side. This ensures that any observed changes on the supply side are driven by the demand side, *i.e.*that the side case represents the type of cause and effect relationship we want to model. Based on this criterion seven candidate side cases were identified as listed in Table 1. [1]

The second criterion is that the magnitude of the change to the supply of and demand for electricity must be large enough to allow reasonably accurate estimation of the related utility sector impacts. As a rule of thumb a difference on the order of a few percent is minimal. These changes are quantified in Table 2 using total generation by fuel type and sales of electricity to customers, both measured in TWh. The table shows the totals for the period 2015-2040 for the reference case and for each of the seven side cases listed in Table 1. In the lower half of the table the percentage difference between the side case and the reference case is provided (the 2013 technology case has higher electricity use than the reference case, so the differences are positive). By the second criterion, the supply and demand changes in the ESICA, Extended Policy and No GHG Concern cases are too small to provide reliable impacts estimates. Hence, the analysis presented here relies on the data published for the reference case and the side cases 2013 Technology, Best Available Technology, High Demand Technology, and Low Electricity Demand (2013-tech, best-tech, high-tech, and low-elec). As an

[1]The EIA description of the side cases can be found in Appendix E to the AEO2014.

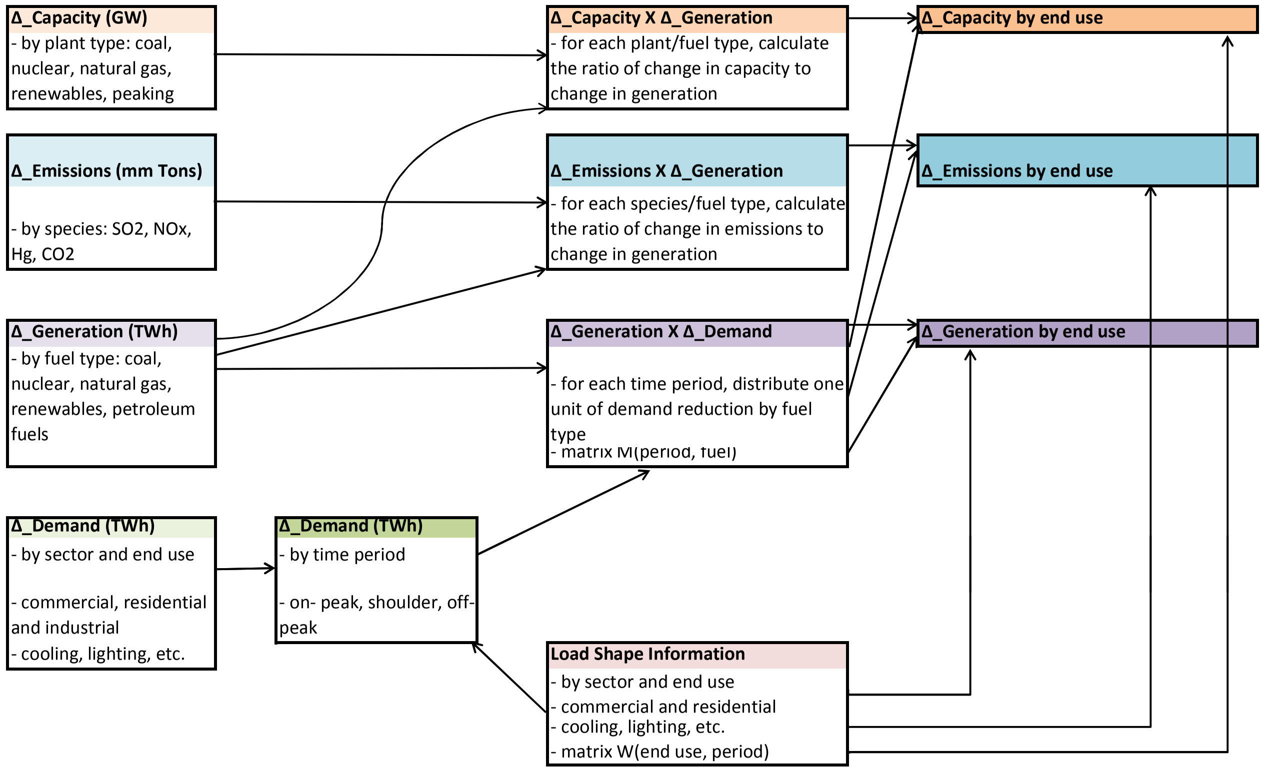


Figure 1: Flow chart illustrating the calculation steps.

Name	**Short Name**	**Description**
Extended Policies	ext-policy	Assumes extension of all existing tax credits and policies that contain sunset provisions except ethanol and biofuels, and additional rounds of efficiency standards and building codes.
2013 Demand Technology	2013-tech	Assumes that future equipment purchases in the residential and commercial sectors are based only on the range of equipment available in 2013.
Best Available Demand Technology	best-tech	Assumes that all future equipment purchases in the residential and commercial sectors are made from a menu of technologies that includes only the most efficient models available in a particular year, regardless of cost.
High Demand Technology	high-tech	Assumes earlier availability, lower costs, and higher efficiencies for more advanced residential and commercial equipment.
Low Electricity Demand	low-elec	Begins with the Best Available Demand Technology case and also assumes greater improvement in industrial motor efficiency.
ESICA	esica	Assumes passage of the energy efficiency provisions in the Energy Savings and Industrial Competitiveness Act, S. 1392.
No GHG Concern	no ghg	No GHG emissions reduction policy is enacted, and market investment decisions are not altered in anticipation of such a policy.

Table 1: AEO2014 side cases considered for this analysis.

Scenario	Coal	Dist Gen	Gen for Own Use	Natural Gas	Nuclear	Oil	Pumped Storage	Renewables	Sales to Customers
2013-tech	47,054	53	387	39,946	22,325	472	76	19397	128,936
best-tech	41,098	2	387	30,907	21,823	412	75	16231	110,161
esica	46,208	53	387	36,377	21,988	456	76	17920	122,691
ext-policy	45,687	39	387	33,647	21,823	450	76	18931	120,264
high-tech	44,139	23	387	30,731	21,858	430	76	16606	113,476
low-elec	37,936	3	387	30,228	21,823	394	75	15801	105,874
no ghg	46,926	60	387	36,062	21,865	459	76	17888	122,948
reference	46,253	57	387	36,611	21,959	456	76	17936	122,961
Percent Change Relative to Reference									
2013-tech	2%	-6%	0%	9%	2%	3%	0%	8%	5%
best-tech	-11%	-96%	0%	-16%	-1%	-10%	-1%	-10%	-10%
esica	0%	-7%	0%	-1%	0%	0%	0%	0%	0%
ext-policy	-1%	-32%	0%	-8%	-1%	-1%	0%	6%	-2%
high-tech	-5%	-60%	0%	-16%	0%	-6%	0%	-7%	-8%
low-elec	-18%	-95%	0%	-17%	-1%	-14%	-1%	-12%	-14%
no ghg	1%	5%	0%	-2%	0%	1%	0%	0%	0%

Table 2: Total electricity generation and sales summed over 2013-2040 (upper table, all quantities in TWh), and percent change relative to the reference case (lower table).

additional validation test, we use the coefficients defined by this approach to estimate the supply-side deltas for the Extended Policy case.

Table 2 shows very large changes in distributed generation (DG) for the best-tech and low-elec scenarios. In the reference case DG increases from near zero in 2015 to 9 GW in 2040 but does not increase at all in the best-tech and low-elec scenarios. As DG is a very small portion of total generation, this capacity type are neglected in our analysis in favor of a focus on the principal categories of coal, natural gas, renewables, nuclear and petroleum-based fuels. The change in DG is however part of a broader issue with these two scenarios: a reduction in the installed capacity of peak-load serving technologies (steam and combustion turbines) relative to the reference case which is large compared to the reduction in generation. In the AEO2014 reference case, the electric power sector installed capacity for combustion turbines increases from about 140GW in 2012 to 220 GW in 2040, while for steam turbines it decreases somewhat from 100 GW to 70 GW. In the best-tech and low-elec scenarios, by 2040 total GW combustion turbines decrease slightly below 100 GW, while steam turbines drop dramatically to about 30 GW.[2] These are absolute decreases which are not off-set by increases in other forms of generation either inside or outside of the electric power sector. The AEO documentation provides little detail on how these scenarios are specified so it is unclear why these capacity reductions occur. It seems reasonable to assume that somehow the adoption of peak-shifting or peak-reducing measures leads to a greatly reduced need for peak-load serving capacity. Our modeling framework assumes that energy savings drive electricity generation reductions, and these in turn drive the emissions and installed capacity reductions. Consistent with they way the NEMS code functions, we also assume that the load shapes associated with each end-use are constant in time, so the flattening of peaky loads cannot be accounted for. This leads to relatively larger errors in our model estimates of peak-serving capacity reductions.

2.3 AEO Data Tables

Table 3 identifies the specific tables published with the AEO, and the data fields that were collected for use in this analysis. The data were downloaded using the on-line *AEO Table Browser* [4]. The

[2]The other scenarios are somewhere in between these two extremes.

Table Name	Quantity	Units	Sub-categories
Electric Power Projections by EMM Region	net summer generating capacity	GW	plant type
Electric Power Projections by EMM Region	generation by fuel type	TWh	fuel type
Electric Power Projections by EMM Region	power sector emissions	mm Tons	species (CO_2, Hg, NO_x, SO_2)
Energy Consumption by Sector and Source	electricity generation	quad	fuel type
Energy Consumption by Sector and Source	electricity consumption	quad	sector
Residential Sector Key Indicators and Consumption	electricity consumption	quad	end-use
Commercial Sector Key Indicators and Consumption	electricity consumption	quad	end-use

Table 3: AEO data table names and variables used.

tables provide annual values for each field for the years 2012-2040. For this analysis, to avoid numerical problems due to very small deltas, we use the data starting in the year 2019.

3 Demand-side Data

This analysis makes use of two NEMS datasets related to building end-use energy consumption: time series of annual energy consumption and load shape information.[3] Time series of annual energy consumption include demand for electricity for the residential, commercial and industrial sectors. As noted above, the demand side deltas are defined as the difference between electricity demand in the reference case and in the side case. These deltas are defined as

$$\Delta D_K(u, y) = D_R(u, y) - D_K(u, y), \tag{2}$$

where

- y is the forecast year,
- u is a label for the combined sector/end-use,
- D_R is the electricity demand in the reference case,
- D_K is the electricity demand in scenario K.

The commercial and residential sector and end-uses are listed in Table 4; this table includes the list of end-use codes that are used in the figures below. The industrial sector electricity demand is not broken down by end-use. The NEMS output files actually provide annual energy consumption numbers for a longer list of end-uses than shown in Table 4 [6, 8], but only those end-uses listed in the table have independent load shapes. The annual energy consumption for end-uses without an associated load shape are assigned to the *other* category.

The distribution of the energy decrements by end-use is illustrated for the residential and commercial sectors in Figure 2. The figures show only the end-uses for which the annual energy use is

[3]Detailed time series of annual energy demand by fuel type are output in the RESDBOUT and KDBOUT files available with the NEMS code package.

Residential	Commercial	Code
space cooling	space cooling	cl
cooking	cooking	co
electric clothes dryers	–	ed
freezers	–	fr
space heating	space heating	ht
lighting	lighting	lt
–	office equipment non-pc	on
–	office equipment pc	op
other	other	ot
refrigeration	refrigeration	re
–	ventilation	vt
water heating	water heating	wh

Table 4: List of end-uses and end-use codes.

significant. Both the temporal pattern and the relative percentage allocated to each end-use differ to some degree between the various scenarios. These differences in the pattern of demand reductions are presumably what drive the differences in the supply-side deltas, and correlating the two is the basis of our analysis approach.

In the NEMS model, the correlation between end-use load shapes and generation dispatch and new construction is mediated by the load duration curve [7]. On the demand side, the total hourly system load within a given region is defined as the hourly demand for each end-use multiplied by the hourly load load shape for that end-use. The sum across end-uses provides an estimate of total system load, which is then converted to a load duration curve which defines the number of hours per year that the system load is at or above a given level. The load duration curve is input to the supply-side calculations, which use this information to determine the economically optimal mix of generation for that region. NEMS constructs the load duration curves in blocks related to time-of-day (weekday afternoon, weekend evening *etc.*) [7]. The definition of these periods is similar to the common usage of peak, off-peak and shoulder hours in utility time-of-use rates [2]. To make the correspondence with the supply-side data, we assign the hourly load profiles to peak, off-peak and shoulder periods as described in the next section.

3.1 End-use to time-period assignment

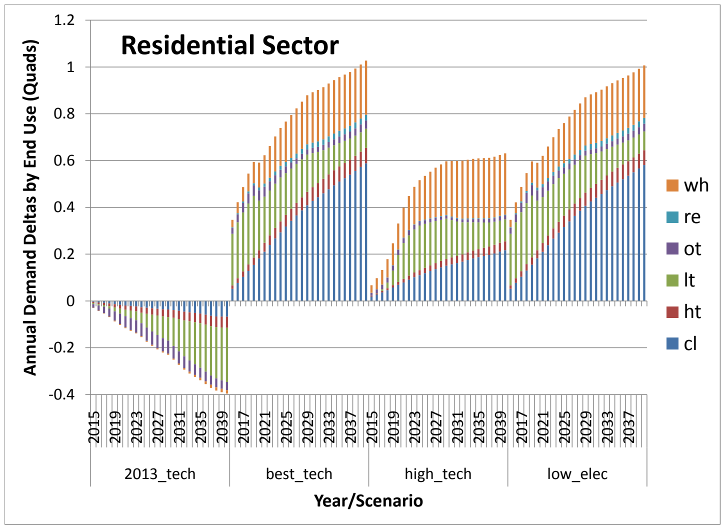
NEMS load shape data are provided as normalized profiles that satisfy the equation

$$\Sigma_m \Sigma_d \Sigma_h N(m,d) ls(u,m,d,h) = 10,000 \tag{3}$$

where

- u is the label for the combined sector/end-use,
- m is the month,
- d is an index defining the day type (weekend, weekday, peak day),
- h is the hour of day,
- $ls(u,m,d,h)$ is the load shape profile,
- $N(m,d)$ is the number of days of type d in month m.

The profiles for heating and cooling are regionally varying, and are converted to national-average profiles using the methods described in [1]. The load shape data allocate the annual electricity use for u to a particular month, day type and hour. The actual electricity demand in year y is equal to the load shape times the annual time series divided by 10,000.



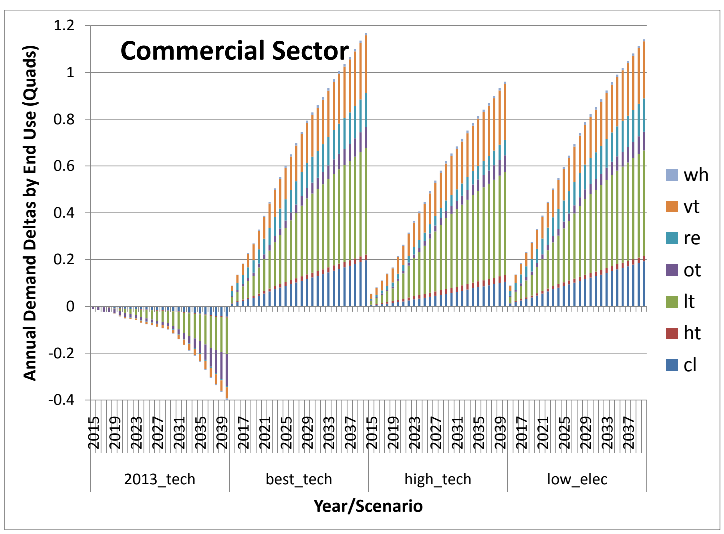


Figure 2: Annual demand deltas by end-use for the residential (upper) and commercial (lower) sectors. The end-use codes are defined in Table 4.

Period	**Hour Ending**																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Summer																								
On-peak	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0
Shoulder	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0
Off-peak	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
Winter																								
On-peak	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Shoulder	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
Off-peak	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1

Table 5: Assignment of hours to time-of-day periods.

For this analysis, we assign hours to the three time-of-day periods using the definitions listed in Table 5. The column headers represent the 24 hours ending at 1am, 2am *etc.*, and the rows represent the time periods. For each hour/period, the table entry is equal to 1 if that hour has been assigned to the given period and 0 otherwise. These assignments are used only for weekdays and the peak day; following conventional practice, all weekend hours are assigned to off-peak. The assignments shown in the table are based on a review of the period definitions used for utility time-of-use tariffs [2]. The assignment is also seasonal, with summer defined as the months of May through September, and winter as all other months. The data in the table define a filter $\phi(m, d, h, n)$ that is equal to one if the hour h of day-type d and month m is in period n, and equal to zero otherwise. This filter is used to define the load shape to end-use mapping with

$$w(u, n) = (\Sigma_{m,d,h}\, ls(u, m, d, h)N(m, d)\phi(m, d, h, n))/10,000. \tag{4}$$

As every hour is allocated to one period, the sum $\Sigma_p\, \phi(m, d, h, n) = 1$ and therefore

$$\Sigma_n\, w(u, n) = 1. \tag{5}$$

The values $w(u, n)$ provide a distribution of the electricity consumption associated with end-use u over the three periods indexed by n; these distributions are shown in Figure 3; The figure shows, as expected, that the cooling end-use has the largest proportion of electricity use during the on-peak period (red in the figure), and heating has the largest electricity use in the winter, off-peak period.

The weights w are used to convert the annual demand deltas by end-use to demand deltas by period:

$$\Delta D_K(n, y) = \Sigma_u\, w(u, n)\Delta D_K(u, y). \tag{6}$$

The commercial *other* load shape is used for the industrial sector deltas. The resulting pattern of demand deltas by period, for each scenario, is shown in Figure 4.

4 Supply-side Data

In this section we discuss the preparation of the supply-side data, and the modeling steps that relate different supply-side quantities to one another. The method used to link supply to demand is discussed in the next section.

Supply-side data include electricity generation and fuel consumption by fuel type, installed capacity by plant type, and emissions of different pollutants. The principal fuel and plant types are listed in Table 6. There are additional plant and fuel types included in NEMS, but they are minimally affected by the policy scenarios considered here, so are not used.

The fuel consumption data are provided in energy units (quadrillion BTu or quads), and the generation data in terawatt hours (TWh). These data are related through a generalization of the notion of a *heat rate*. For a single power plant, the heat rate is equal to the energy content[4] of the amount of fuel consumed per unit of generation output. The heat rate thus incorporates the energy losses associated with generation. More generally, we define fuel-specific heat rates as the ratio of fuel

[4]Typically measured as the low heating value.

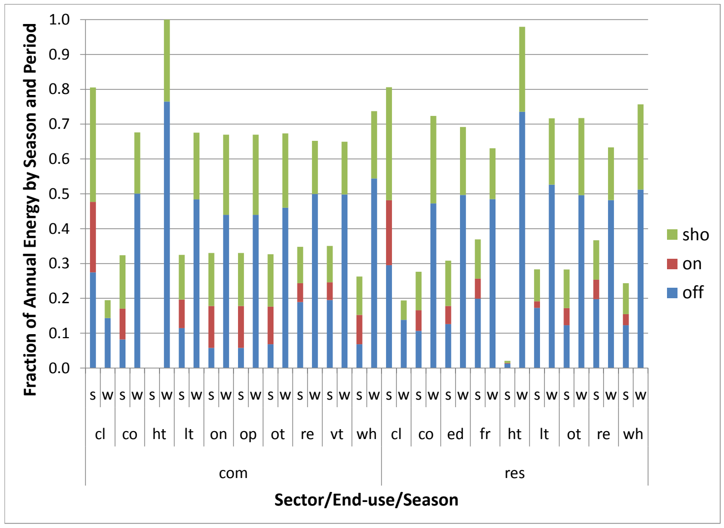


Figure 3: Distribution of demand deltas over time periods for each sector/end-use. The end-use codes are defined in Table 4.

Figure 4: Demand deltas by period (on-peak, off-peak and shoulder).

Fuel Type	Plant Type	Code	Capacity Factor
coal	coal	cl	0.75
natural gas	combined cycle	ng	0.52
petroleum	–	pf	–
oil and gas	combustion turbine	pk	0.032
oil and gas	steam turbine	pk	0.049
renewables	renewables	rn	0.39
uranium	nuclear	ur	0.91

Table 6: List of fuel types, associated plant types and capacity factors for the reference case. The table also shows the fuel or technology codes used in the figures.

consumption in quads to generation in TWh for each fuel type. The heat rate can be defined as an average, using data for the entire grid, or on the margin, using the deltas.

Coal, nuclear and renewables appear in both the set of fuel types and the set of plant types. The other two fuel types, natural gas and petroleum-based fuels (oil), do not map directly onto plant types. There are three NEMS plant type categories that use either gas or oil: natural gas combined-cycle (ngcc), oil and gas steam (ogs), and combustion turbine/diesel (ctd). Combined-cycle plants use only natural gas. The steam and combustion turbines use both gas and oil but the AEO tables don't provide a breakdown of generation by fuel type for these capacity types. The various fuel and plant categories are listed in Table 6. The table also includes a capacity factor (based on reference case data), defined as the average hourly generation divided by the total installed capacity for the plant type.[5] The value for renewables represents an average over all renewable generation types (hydro, solar, wind and biomass combustion). The capacity factor is equivalent to the fraction of hours per year that each plant type operates, and can be used to distinguish those plants that are used to serve base, intermediate or peak loads. Here we assign coal and nuclear to base load, natural gas and renewables to the intermediate category, and oil and gas steam and combustion turbine/diesel to peak plants.

4.1 Notation

Our notation for the primary data is:

- y is the forecast year,
- K is the scenario label,
- R is the label for the reference case,
- p is the label for plant type,
- $C_K(p, y)$ is the installed capacity in GW,
- f is a label for fuel type,
- $G_K(f, y)$ is the generation in TWh,
- $Q_K(f, y)$ is the fuel primary energy consumption in quads,
- s is a label for the pollutant species,
- $M_K(s, y)$ is the power sector emissions in short tons.
- $h_K(f, y)$ is the fuel-specific marginal heat rate.

As with the demand data, the deltas are defined for each quantity as the difference between the reference case value and the scenario value; for example

$$\Delta Q_K(g, y) = Q_R(g, y) - Q_K(g, y). \qquad (7)$$

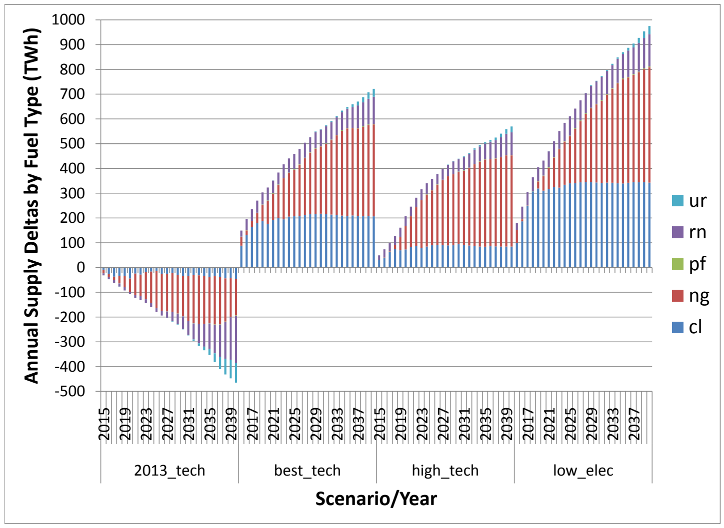


Figure 5: Generation deltas by fuel type.

The supply-side deltas for generation are illustrated in Figure 5.

4.2 Marginal Heat Rates

The marginal heat rate is the ratio of energy consumption in quads to generation in TWh, calculated using the deltas:

$$h_K(f, y) = \frac{\Delta Q_K(g, y)}{\Delta G_K(g, y)}. \tag{8}$$

Figure 6 shows the marginal heat rates for coal and natural gas, for each scenario, over the period 2019-2040 (the units in the figure are BTu/Wh; 1 quad/TWh = 1000 BTu/Wh). The data for coal are shown in red and gas are shown in black. In both cases the average heat rate calculated for the reference case (solid line) is shown for comparison. The average heat rate is defined as the ratio of total quads to total generation for each fuel. Recall that the plant level heat rate is the ratio of fuel quads in to TWh out, which is effectively a measure of the plant's generation efficiency. The average heat rate represents the generation-weighted average of plant efficiencies over all the installed capacity in the system, with higher heat rates indicating lower efficiency. The marginal heat rate defines the same average over only those plants that are affected by the policy change. It is therefore sensitive to the types of technology that sit at either the dispatch margin, the construction margin, or both. The marginal heat rates are larger than the average for coal, and less than the average for natural gas. Generally, it is expected that less efficient plants are dispatched last, which is consistent with the coal data but not the natural gas. It may be that reduced demand is delaying the new construction of higher efficiency gas plants. For this analysis we use a simple average over scenarios to define a single marginal heat rate $h(f, y)$ for each fuel type. The scenario-averaged marginal heat rates are shown in Figure 7; once again the figure includes the reference case average heat rates for comparison. NEMS uses a convention in which nuclear and renewable power plants are assigned nominal heat rates and included in the fuel consumption measures. Here we adopt the same convention, using a value of 10.5 BTu/Wh for nuclear, and 10.0 BTu/Wh for renewables.

[5] The capacity factors are calculated from Table 59 of a NEMS output Excel file that was obtained directly from EIA. These

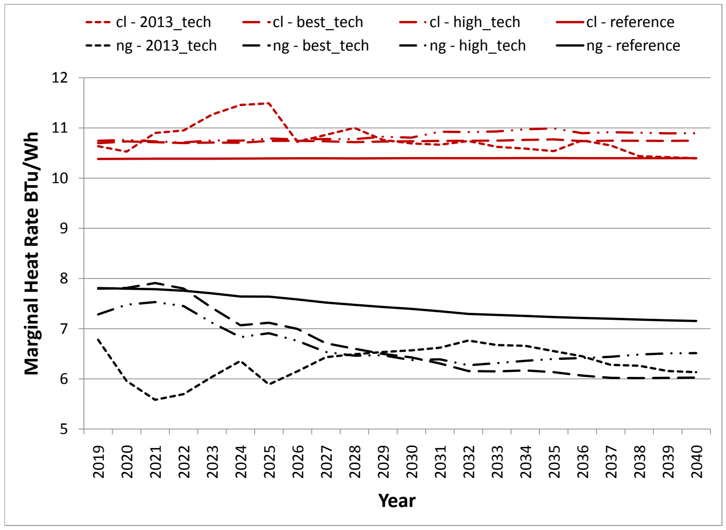


Figure 6: Marginal heat rates for coal (red) and natural gas (black). For both fuels the reference case average heat rate is shown as a solid line.

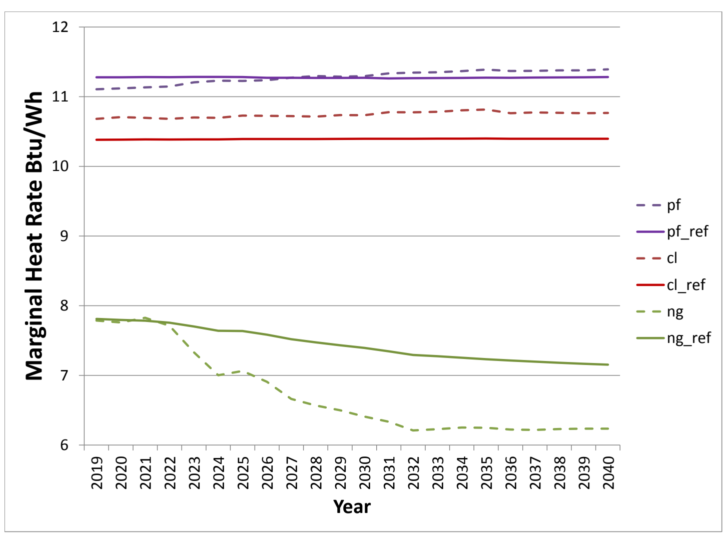


Figure 7: Scenario-averaged marginal heat rates by fuel type (dashed lines) and reference case average heat rates (solid).

Species	Fuel	Coefficient	R-squared
CO_2	cl, pf	1.05E+02	1.000
CO_2	ng	5.76E+01	1.000
NO_x	cl, pf	9.14E-02	0.981
NO_x	ng	2.33E-02	0.981
Hg	cl, pf	3.86E-01	0.995
Hg	ng	0.00E+00	0.995
SO_2	cl, pf	1.25E-01	0.942
SO_2	ng	0.00E+00	0.942

Table 7: Coefficients and R-squared values for the emissions model.

4.3 Marginal Emission Intensities

Emissions result from fuel combustion, so we expect the emissions to be most closely correlated with the amount of fuel consumed to generate a unit of electricity. Hence, our modeling approach estimates an emissions intensity in units of mass of pollutant per quad of fuel consumed. These will be related back to generation using the marginal heat rate. We assume that the two sets of deltas are related as:

$$\Delta M_K(s,y) = \Sigma_f\, \beta(s,f)\Delta Q_K(f,y) \tag{9}$$

Linear regression, based on the data for all scenarios and the years 2019-2040, was used to estimate the coefficients $\beta(s,f)$. As these coefficients depend primarily on the chemistry of combustion, for simplicity we assume that they are time-independent.

We use a number of assumptions to simplify the analysis. There are no combustion emissions associated with nuclear and renewable electricity production, so $\beta = 0$ for these fuels. Emissions of SO_2 and Hg are assumed to be zero for natural gas. The emissions factors for petroleum and coal are very similar, so we assume that $\beta(s,cl) = \beta(s,pf)$ for all species s. The model output is illustrated in Figure 8 which shows the actual change in emissions of NO_x for each scenario (blue lines) compared to the estimated change (red lines). Plots of the estimated mercury and sulfur emissions are qualitatively similar. The estimated CO_2 emissions are almost identical to the actual CO_2 data, presumably because these emissions are not affected by power plant technologies. The regression coefficients, and R-squared values for the emissions model are summarized in Table 7 (the table shows only non-zero coefficients).

4.4 Marginal Capacity Reductions

Most generally, the relationship between capacity and generation is written as

$$\Delta C_K(p,y) = \Sigma_f\, \delta(p,f,y)\Delta G_K(f,y). \tag{10}$$

NEMS uses an econometric approach to define the dispatch of existing capacity and make decisions regarding the construction of new capacity [7]. While this can in principle lead to quite complicated dependencies between the variables, for this work we adopt a simplified approach in which the off-diagonal terms of the array $\delta(p,f,y)$ are set equal to zero, with combined cycle capacity related to total generation from natural gas, and peaking capacity to generation from petroleum. There are two reasons for this. The first is just practicality; our primary interest here is in physical quantities (fuel use, emissions) and how they are affected by energy policy. Installed capacity does not directly influence these quantities, as the relationship between capacity and generation is mediated by the economic aspects of electricity production. Given the large uncertainty in economic projections, any apparent gain in precision may be meaningless in real terms. The second reason is that, as noted above, the AEO data do not provide separate accounting of natural gas *vs.*petroleum use for

data are not published on the AEO table browser.

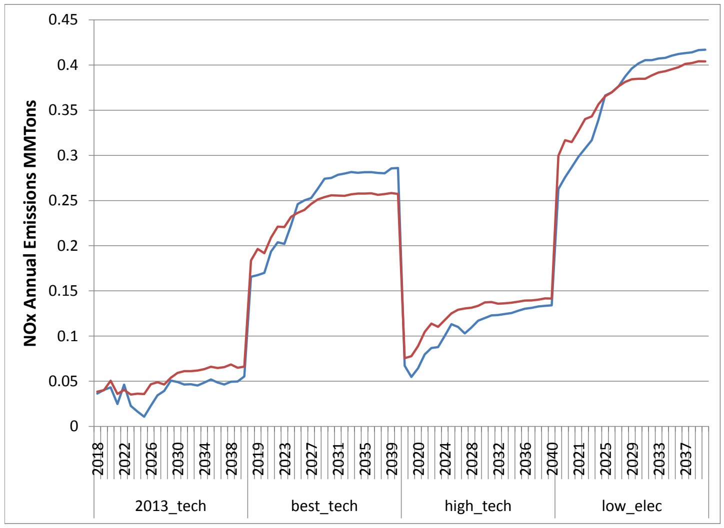


Figure 8: Actual (blue) and estimated (red) NO_x emissions reductions for each scenario.

Fuel	Slope	R-squared
cl	1.00	1.00
ng	0.97	0.92
pk	0.95	0.78
rn	0.97	0.90

Table 8: Slope and R-squared values for linear fits to the estimated *vs.*actual GW-deltas shown in Figure 9.

peak-serving generation, so estimation of the separate use of these fuels requires another model. This breakdown would introduce non-diagonal terms into the matrix δ. Our preliminary attempts to develop such a model did not provide a substantial improvement relative to the simpler approach.

The approach works well for the coal, renewables and nuclear, and is less precise in predicting the installed capacity for natural gas and peak plants. The model output is illustrated in Figure 9, which shows a scatter plot of the predicted capacity delta *vs.*the actual capacity delta by plant type. Each point on the plot represents one year and scenario. A simple test for bias is to fit these data to a straight line with zero intercept. If the slope of the line is not equal to one, it means that the model over- (slope > 1) or under- (slope < 1) predicts the data. The slopes and R-squared values for these linear fits are presented in Table 8. The model shows a slight tendency to under-predict installed capacity for all plant types except nuclear. As noted in the introduction, the model fit for peak-serving capacity is significantly worse than for the other plant types, but the bias remains small.

5 Linking Supply to Demand

In Section 3.1 we calculated a set of weights $w(u, n)$ that distribute the energy savings associated with sector/end-use u over the three periods indexed by n. In this section, we define the correspondence between marginal changes to energy demand in period n and changes to generation of different fuel types f. The end result is a set of time-dependent weights $v(n, f, y)$ that allocate a unit of demand

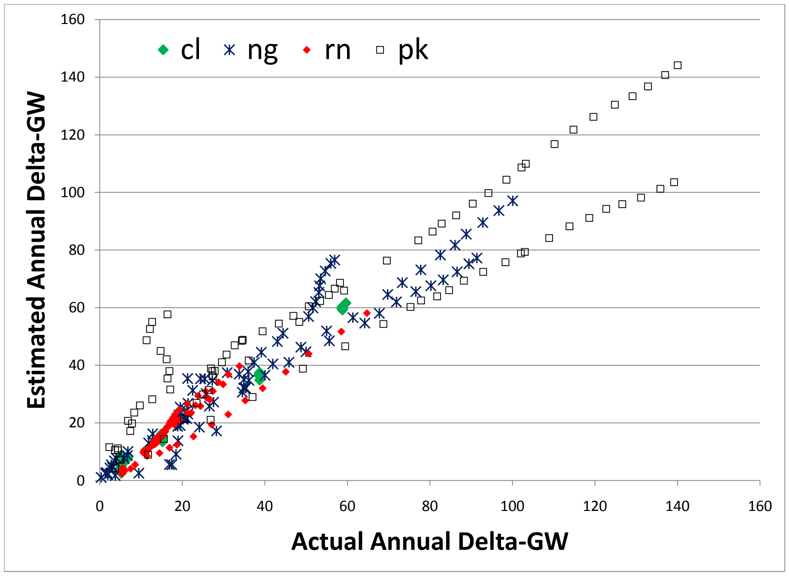


Figure 9: Scatter plot of the estimated *vs.*actual capacity changes by plant type. Each point corresponds to one year and scenario.

reduction in period n to each of the fuel types. The weights v are calculated assuming the correspondence between base, intermediate and peaking plants identified through the capacity factors in Table 6.

The notation used is:

- y is the forecast year,
- u is the label for the combined sector/end-use,
- n is the label for the period (on-peak, off-peak, shoulder),
- $w(u, n)$ is the weight defining the distribution of one unit of end-use demand across periods,
- $v(n, f, y)$ is the weight defining the distribution of one unit of period-n demand across generation fuel types,

To begin with, the electricity demand reductions are rescaled to account for transmission and distribution losses, and any small differences between generation and demand that result from imports, exports and other factors neglected here. The rescaling step ensures that

$$\Sigma_n \, \Delta D_K(n, y) = \Sigma_n \, \Delta G_K(f, y) \tag{11}$$

for each K and y.

We then apply a set of allocation rules that are defined to be consistent with the definition of base, intermediate and peak plants. The calculation proceeds by taking the generation changes ΔG and allocating the fuel types to the periods assuming:

1. petroleum generation occurs only during on-peak periods,
2. coal and nuclear generation occur during all periods and are allocated proportionally,
3. the on-peak demand not served by petroleum, coal or nuclear is served by natural gas,

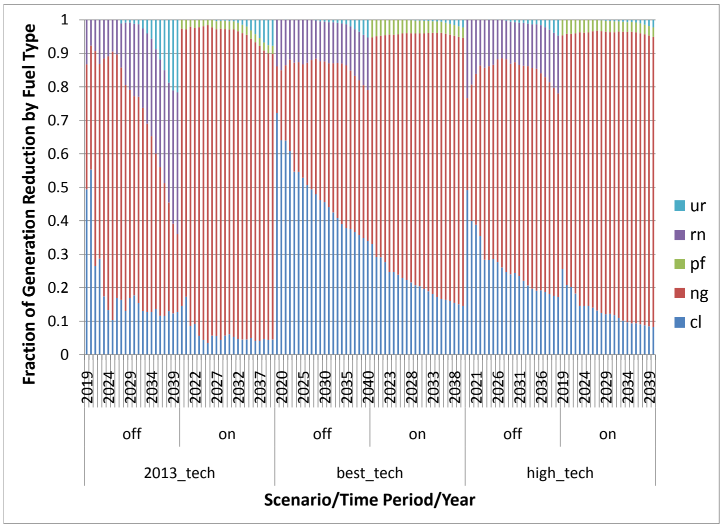


Figure 10: Distribution of a unit of on- or off-peak generation by fuel type.

4. remaining natural gas and renewable generation are allocated to the shoulder and off-peak periods proportionally.

This approach dis-aggregates the generation deltas into periods such that

$$\Delta G_K(f, y) = \Sigma_n \, \Delta G'_K(n, f, y). \tag{12}$$

These are converted to weight factors for each scenario, v_K;

$$v_K(n, f, y) = \frac{G'_K(n, f, y)}{\Delta G_K(f, y)}. \tag{13}$$

A simple average across scenarios converts the intermediate factors to the weights $v(n, f, y)$.

$$v(n, f, y) = 0.25 \Sigma_K \, v_K(n, f, y) \tag{14}$$

The results of this calculation are illustrated in Figure 10, which shows the time series of v for the of on- and off-peak periods and three scenarios (the shoulder period is similar to the off-peak, and the low-elec scenario is very similar to the best-tech).

6 Results and Validation

6.1 Definition of impact factors

In this section we define the impact factors, which determine the response of the electric system to unit changes in electricity demand for a given sector and end-use (u). These impact factors are calculated by multiplying the various quantities defined above. The notation is summarized below.

- u is the label for the combined sector/end-use,
- f is the label for generation fuel type,
- p is the label for capacity plant type,

- s is the label for pollutant species,
- $L(y)$ is the transmission and distribution loss factor,
- $g(u, f, y)$ is the generation fuel-share weight,
- $q(u, y)$ is the marginal heat rate (quads of primary energy per TWh site electricity),
- $m(u, s, y)$ is the emissions impact factor,
- $c(u, p, y)$ is the capacity impact factor.

6.1.1 Fuel-share weights

We define $g(u, f, y)$ as the fraction of the unit reduction in demand for u that is allocated to generation fuel type f:

$$g(u, f, y) = \Sigma_n \, w(u, n)v(n, f, y) \tag{15}$$

where $w(u, n)$ is defined in equation 4 and $v(n, f, y)$ is defined in equation 14. The generation fuel-shares g satisfy

$$\Sigma_f \, g(u, f, y) = 1. \tag{16}$$

6.1.2 Marginal heat rates by end-use

The marginal heat rates convert a unit of demand reduction (measured in site TWh) to a decrease in total fuel consumption, or primary energy, for the grid as a whole. At this step in the calculation we incorporate the transmission and distribution (T&D) loss rate $L(y)$. The fuel-specific heat rates $h(f, y)$ of equation 8 do not include the T&D losses because h is defined using only supply-side data. For sector/end-use u the marginal heat rate $q(u, y)$ is defined as the weighted sum over fuel types:

$$q(u, y) = L(y)\Sigma_f \, g(u, f, y)h(f, y). \tag{17}$$

As noted above this definition includes quads associated with nuclear and renewable electricity. Figure 11 shows the marginal heat rates for different end-uses in the residential and commercial sectors. The spread in heat rates across end-uses is less than 5% and the variation in time is approximately 20%. Heat rates are lowest for cooling and highest for heating. The high heat rate for heating is due to the large off-peak component, which uses a lot of coal. The low heat rate for cooling is due to the dominance of natural gas use in peak periods as evident in Figure 10. Our method will under-estimate somewhat the heat rate for cooling, as we are not fully accounting for the lower efficiency of natural gas when used in single-cycle steam or combustion turbines.

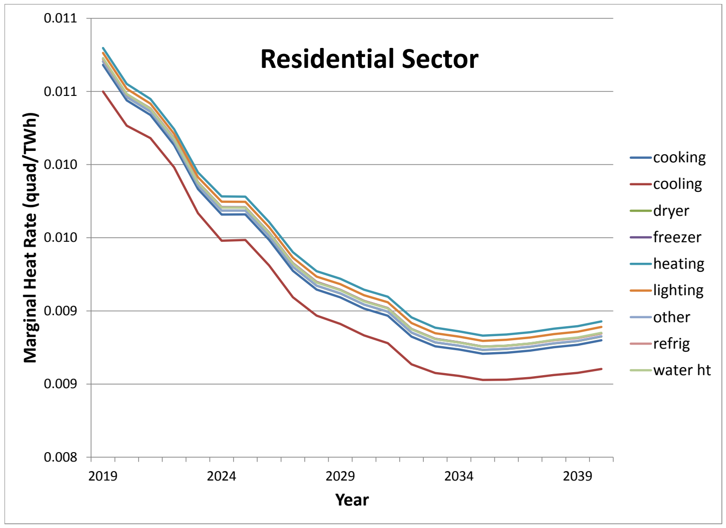
6.1.3 Marginal emissions intensities

The emissions are related to fuel consumption in quads which is related to generation through the fuel-specific marginal heat rate. Defining $m(u, s, y)$ as the emissions impact factor for species s and sector/end-use u, the equation is

$$m(u, s, y) = L(y)\Sigma_f \, g(u, f, y)h(f, y)\beta(s, f, y). \tag{18}$$

The AEO does not publish estimates of the CH_4 and N_2O emissions associated with combustion of fossil fuels. For these pollutants, the power sector emissions are estimated using fuel-specific emissions intensity factors published by the EPA [9]. These data provide constant values of $\beta(s, f)$ as shown in Table 9. Tables 10 to 12 provide the emissions impact factors for select years.

The emissions intensities, especially for CO_2, are strongly correlated with the marginal heat rates. The low emissions intensity for cooling may be surprising as summer peak loads are generally associated with high emissions. However, on an annual basis, the fraction of cooling load that is served by peak generation is relatively small, and total petroleum fuel use is a small fraction of natural gas use. Hence, the relatively high proportion of peak load served by natural gas leads to somewhat lower emissions for cooling than other end uses. While cooling emissions of CO_2 would increase somewhat if the lower generation efficiencies of single-cycle turbines were included in the marginal heat rates, the low spread in these coefficients as a function of end use suggest that the change would be on the order a few percent at most.



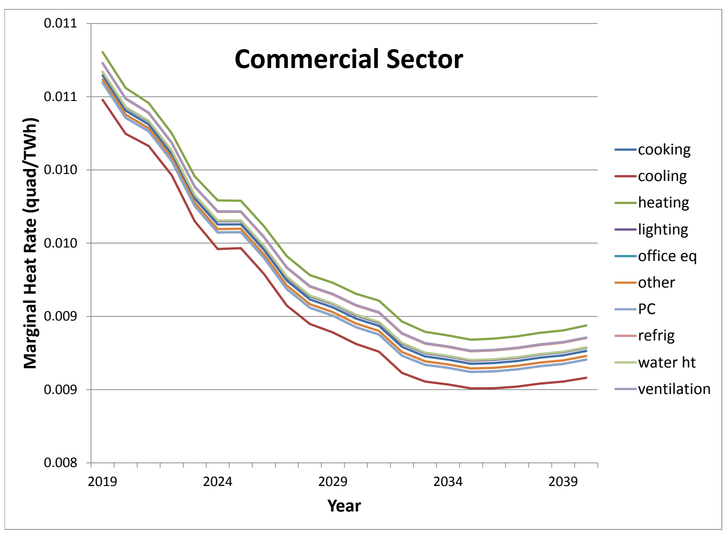


Figure 11: Marginal heat rate by end-use for the residential and commercial sectors.

Fuel	CH_4	N_2O
cl	11	1.6
ng	1.0	0.1
pf	3.0	0.6

Table 9: Emissions intensities for CH_4 and N_2O in grams/mmbtu.

CH_4					
Commercial	2020	2025	2030	2035	2040
cooking	7.75E-05	6.21E-05	5.30E-05	4.54E-05	4.07E-05
lighting	7.80E-05	6.25E-05	5.34E-05	4.57E-05	4.10E-05
office equipment (non-pc)	7.49E-05	6.01E-05	5.13E-05	4.39E-05	3.94E-05
office equipment (pc)	7.49E-05	6.01E-05	5.13E-05	4.39E-05	3.94E-05
other uses	7.58E-05	6.08E-05	5.19E-05	4.44E-05	3.99E-05
refrigeration	8.08E-05	6.46E-05	5.52E-05	4.72E-05	4.24E-05
space cooling	7.15E-05	5.74E-05	4.90E-05	4.20E-05	3.77E-05
space heating	8.35E-05	6.68E-05	5.70E-05	4.88E-05	4.38E-05
ventilation	8.09E-05	6.48E-05	5.53E-05	4.73E-05	4.25E-05
water heating	7.83E-05	6.28E-05	5.36E-05	4.59E-05	4.12E-05
Residential	2020	2025	2030	2035	2040
clothes dryers	7.91E-05	6.34E-05	5.41E-05	4.63E-05	4.16E-05
cooking	7.79E-05	6.24E-05	5.33E-05	4.56E-05	4.10E-05
freezers	8.06E-05	6.45E-05	5.51E-05	4.71E-05	4.23E-05
lighting	8.15E-05	6.53E-05	5.57E-05	4.77E-05	4.28E-05
other uses	7.91E-05	6.33E-05	5.41E-05	4.63E-05	4.16E-05
refrigeration	8.05E-05	6.44E-05	5.50E-05	4.71E-05	4.23E-05
space cooling	7.22E-05	5.79E-05	4.95E-05	4.23E-05	3.81E-05
space heating	8.31E-05	6.64E-05	5.67E-05	4.85E-05	4.36E-05
water heating	7.97E-05	6.38E-05	5.45E-05	4.67E-05	4.19E-05
CO_2					
Commercial	2020	2025	2030	2035	2040
cooking	7.91E-01	7.03E-01	6.34E-01	5.80E-01	5.30E-01
lighting	7.95E-01	7.05E-01	6.37E-01	5.82E-01	5.32E-01
office equipment (non-pc)	7.78E-01	6.93E-01	6.26E-01	5.73E-01	5.25E-01
office equipment (pc)	7.78E-01	6.93E-01	6.26E-01	5.73E-01	5.25E-01
other uses	7.83E-01	6.97E-01	6.29E-01	5.76E-01	5.27E-01
refrigeration	8.10E-01	7.17E-01	6.46E-01	5.90E-01	5.39E-01
space cooling	7.67E-01	6.83E-01	6.17E-01	5.66E-01	5.21E-01
space heating	8.21E-01	7.26E-01	6.54E-01	5.97E-01	5.43E-01
ventilation	8.10E-01	7.17E-01	6.47E-01	5.91E-01	5.39E-01
water heating	7.97E-01	7.07E-01	6.38E-01	5.83E-01	5.33E-01
Residential	2020	2025	2030	2035	2040
clothes dryers	7.97E-01	7.08E-01	6.39E-01	5.84E-01	5.33E-01
cooking	7.90E-01	7.02E-01	6.34E-01	5.80E-01	5.29E-01
freezers	8.09E-01	7.16E-01	6.46E-01	5.90E-01	5.38E-01
lighting	8.10E-01	7.17E-01	6.47E-01	5.91E-01	5.38E-01
other uses	7.97E-01	7.07E-01	6.38E-01	5.84E-01	5.32E-01
refrigeration	8.08E-01	7.16E-01	6.45E-01	5.89E-01	5.38E-01
space cooling	7.69E-01	6.85E-01	6.19E-01	5.68E-01	5.21E-01
space heating	8.18E-01	7.24E-01	6.52E-01	5.95E-01	5.42E-01
water heating	7.99E-01	7.09E-01	6.40E-01	5.85E-01	5.33E-01

Table 10: Emissions impact factors for CH_4 and CO_2 in million tons per site TWh.

Hg					
Commercial	2020	2025	2030	2035	2040
cooking	2.39E-03	1.87E-03	1.57E-03	1.32E-03	1.18E-03
lighting	2.41E-03	1.88E-03	1.58E-03	1.33E-03	1.19E-03
office equipment (non-pc)	2.31E-03	1.80E-03	1.52E-03	1.27E-03	1.14E-03
office equipment (pc)	2.31E-03	1.80E-03	1.52E-03	1.27E-03	1.14E-03
other uses	2.34E-03	1.83E-03	1.54E-03	1.29E-03	1.15E-03
refrigeration	2.50E-03	1.95E-03	1.64E-03	1.38E-03	1.23E-03
space cooling	2.21E-03	1.73E-03	1.45E-03	1.21E-03	1.08E-03
space heating	2.59E-03	2.02E-03	1.70E-03	1.43E-03	1.28E-03
ventilation	2.50E-03	1.95E-03	1.64E-03	1.38E-03	1.23E-03
water heating	2.42E-03	1.89E-03	1.59E-03	1.33E-03	1.19E-03
Residential	2020	2025	2030	2035	2040
clothes dryers	2.44E-03	1.91E-03	1.60E-03	1.35E-03	1.20E-03
cooking	2.40E-03	1.88E-03	1.58E-03	1.32E-03	1.18E-03
freezers	2.49E-03	1.95E-03	1.64E-03	1.37E-03	1.23E-03
lighting	2.52E-03	1.97E-03	1.66E-03	1.39E-03	1.24E-03
other uses	2.44E-03	1.91E-03	1.60E-03	1.34E-03	1.20E-03
refrigeration	2.49E-03	1.94E-03	1.64E-03	1.37E-03	1.23E-03
space cooling	2.23E-03	1.74E-03	1.46E-03	1.22E-03	1.09E-03
space heating	2.57E-03	2.01E-03	1.69E-03	1.42E-03	1.27E-03
water heating	2.46E-03	1.92E-03	1.62E-03	1.36E-03	1.21E-03
N_2O					
Commercial	2020	2025	2030	2035	2040
cooking	1.12E-05	8.86E-06	7.54E-06	6.41E-06	5.75E-06
lighting	1.12E-05	8.93E-06	7.59E-06	6.46E-06	5.79E-06
office equipment (non-pc)	1.08E-05	8.57E-06	7.28E-06	6.20E-06	5.56E-06
office equipment (pc)	1.08E-05	8.57E-06	7.28E-06	6.20E-06	5.56E-06
other uses	1.09E-05	8.68E-06	7.38E-06	6.28E-06	5.63E-06
refrigeration	1.16E-05	9.24E-06	7.86E-06	6.69E-06	6.00E-06
space cooling	1.03E-05	8.18E-06	6.96E-06	5.92E-06	5.31E-06
space heating	1.20E-05	9.56E-06	8.13E-06	6.92E-06	6.20E-06
ventilation	1.17E-05	9.26E-06	7.87E-06	6.70E-06	6.01E-06
water heating	1.13E-05	8.97E-06	7.62E-06	6.48E-06	5.82E-06
Residential	2020	2025	2030	2035	2040
clothes dryers	1.14E-05	9.06E-06	7.70E-06	6.55E-06	5.87E-06
cooking	1.12E-05	8.91E-06	7.58E-06	6.45E-06	5.78E-06
freezers	1.16E-05	9.23E-06	7.84E-06	6.67E-06	5.99E-06
lighting	1.18E-05	9.34E-06	7.94E-06	6.75E-06	6.06E-06
other uses	1.14E-05	9.05E-06	7.69E-06	6.54E-06	5.87E-06
refrigeration	1.16E-05	9.22E-06	7.83E-06	6.66E-06	5.98E-06
space cooling	1.04E-05	8.26E-06	7.02E-06	5.97E-06	5.35E-06
space heating	1.20E-05	9.51E-06	8.08E-06	6.88E-06	6.17E-06
water heating	1.15E-05	9.13E-06	7.76E-06	6.60E-06	5.92E-06

Table 11: Emissions impact factors for Hg (tons) and N_2O (million tons) per site TWh.

NO_x					
Commercial	2020	2025	2030	2035	2040
cooking	6.24E-04	5.22E-04	4.56E-04	4.02E-04	3.64E-04
lighting	6.28E-04	5.25E-04	4.59E-04	4.04E-04	3.66E-04
office equipment (non-pc)	6.08E-04	5.10E-04	4.46E-04	3.93E-04	3.57E-04
office equipment (pc)	6.08E-04	5.10E-04	4.46E-04	3.93E-04	3.57E-04
other uses	6.14E-04	5.14E-04	4.50E-04	3.97E-04	3.59E-04
refrigeration	6.45E-04	5.38E-04	4.70E-04	4.14E-04	3.74E-04
space cooling	5.91E-04	4.96E-04	4.34E-04	3.83E-04	3.48E-04
space heating	6.61E-04	5.50E-04	4.80E-04	4.22E-04	3.82E-04
ventilation	6.46E-04	5.39E-04	4.71E-04	4.14E-04	3.75E-04
water heating	6.30E-04	5.26E-04	4.60E-04	4.06E-04	3.67E-04
Residential	2020	2025	2030	2035	2040
clothes dryers	6.33E-04	5.29E-04	4.62E-04	4.07E-04	3.68E-04
cooking	6.25E-04	5.23E-04	4.57E-04	4.03E-04	3.64E-04
freezers	6.44E-04	5.37E-04	4.69E-04	4.13E-04	3.74E-04
lighting	6.48E-04	5.40E-04	4.72E-04	4.16E-04	3.76E-04
other uses	6.33E-04	5.28E-04	4.62E-04	4.07E-04	3.68E-04
refrigeration	6.43E-04	5.37E-04	4.69E-04	4.13E-04	3.74E-04
space cooling	5.94E-04	4.98E-04	4.36E-04	3.85E-04	3.50E-04
space heating	6.58E-04	5.48E-04	4.78E-04	4.21E-04	3.80E-04
water heating	6.36E-04	5.31E-04	4.64E-04	4.09E-04	3.70E-04
SO_2					
Commercial	2020	2025	2030	2035	2040
cooking	7.75E-04	6.06E-04	5.09E-04	4.27E-04	3.82E-04
lighting	7.81E-04	6.10E-04	5.13E-04	4.30E-04	3.85E-04
office equipment (non-pc)	7.49E-04	5.85E-04	4.92E-04	4.12E-04	3.68E-04
office equipment (pc)	7.49E-04	5.85E-04	4.92E-04	4.12E-04	3.68E-04
other uses	7.59E-04	5.92E-04	4.98E-04	4.18E-04	3.73E-04
refrigeration	8.10E-04	6.32E-04	5.32E-04	4.46E-04	3.99E-04
space cooling	7.15E-04	5.59E-04	4.70E-04	3.94E-04	3.51E-04
space heating	8.38E-04	6.54E-04	5.50E-04	4.62E-04	4.13E-04
ventilation	8.11E-04	6.33E-04	5.33E-04	4.47E-04	4.00E-04
water heating	7.85E-04	6.13E-04	5.15E-04	4.32E-04	3.86E-04
Residential	2020	2025	2030	2035	2040
clothes dryers	7.92E-04	6.18E-04	5.20E-04	4.36E-04	3.90E-04
cooking	7.79E-04	6.08E-04	5.11E-04	4.29E-04	3.83E-04
freezers	8.08E-04	6.31E-04	5.31E-04	4.45E-04	3.98E-04
lighting	8.17E-04	6.38E-04	5.37E-04	4.50E-04	4.03E-04
other uses	7.91E-04	6.18E-04	5.20E-04	4.36E-04	3.90E-04
refrigeration	8.07E-04	6.30E-04	5.30E-04	4.45E-04	3.98E-04
space cooling	7.21E-04	5.64E-04	4.74E-04	3.97E-04	3.54E-04
space heating	8.33E-04	6.50E-04	5.47E-04	4.59E-04	4.11E-04
water heating	7.98E-04	6.23E-04	5.24E-04	4.40E-04	3.93E-04

Table 12: Emissions impact factors for NO_x and SO_2 in million tons per site TWh.

6.1.4 Marginal capacity factors

The capacity changes induced by a unit reduction in demand for sector/end-use u are defined as $c(u, p, y)$ with:

$$c(u, p, y) = L(y)\Sigma_f \, g(u, f, y)\delta(p, f, y). \tag{19}$$

Figure 12 shows the capacity factors for different end-uses in the residential and commercial sectors. As expected the capacity impact factor for cooling is significantly larger than for other end uses, with a larger proportion of peak. With this approach, all end uses contribute somewhat to net capacity changes.

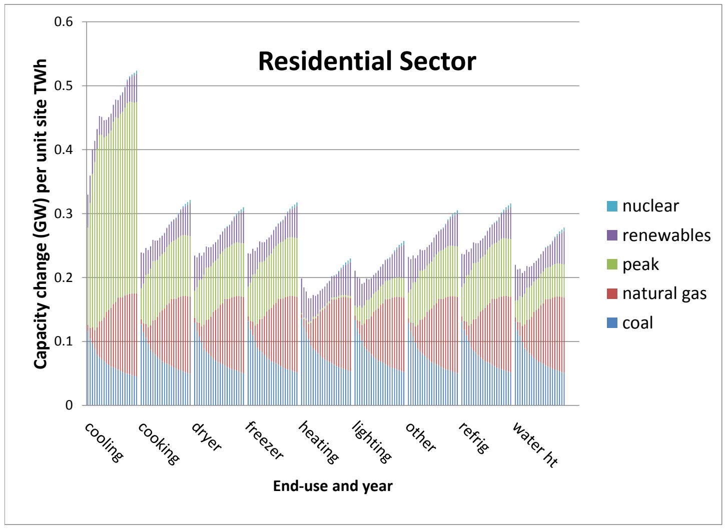
6.1.5 Validation

To validate the model, we reconstruct the supply deltas based on the computed impact factors and the demand deltas. Table 13 shows a summary of results for the four scenarios used in the analysis, as well as for the extended policy scenario. The data in the table are averages over the period 2019-2040 of the deltas for emissions and installed capacity. The model results are not very precise but provide correct order-of-magnitude estimates. The loss of precision in emissions estimates relative to the results shown in Table 7 is due to the variability in the marginal heat rates. Another source of error is that the measures in the AEO scenarios are not exclusively related to electricity demand reduction; for example, the The extended policy scenario includes incentives for renewables that are not captured by our methodology. Hence, the relatively low precision in the model estimates does not necessarily mean that the impact factors do not correctly represent the effect of demand reductions alone.

6.2 Comparison with Other Methods

The impact factor estimates depend on both the methodology used, and the AEO edition. This section presents a comparison of impact factors calculated using the same methodology but with AEO2013 data, and using a different methodology. The comparisons are presented in figures13 to 16. Any difference between the results labelled AEO2013 *vs.*AEO2014 are due entirely to changes in the AEO projections. The AEO2013 data were also used to calculate impact factors using the *NEMS-BT* approach described in [1]. NEMS-BT refers to a version of the NEMS code that includes code modifications that allow the demand-side data to be decremented directly. With this approach, a fixed demand reduction for a single sector and end use is introduced in the year 2015, and held constant over the rest of the forecast period. As the decrement must be large enough to produce measurable changes relative to the AEO reference case, it represents a significant decrease to the end use electricity consumption. The end-uses tested were cooling, lighting and refrigeration. Several NEMS runs were conducted with varying decrement magnitude to test for convergence. This approach was used in the Department of Energy Appliance Standards Program to estimate utility sector impacts for rules published in 2013 and earlier years. While in principle the decrement approach could provide a more direct measure of the impact of changing demand for one end use, in practice the results tend to be quite volatile and sensitive to the magnitude of the decrement. It is not possible to use this direct approach with realistic levels of demand reduction for a single end use, because the decrement magnitudes are so small that they are the same order as convergence error in NEMS.

Figure 13 shows the marginal heat rate computed using the methods described here for AEO2013, AEO2014 and the value computed with the NEMS-BT method based on AEO2013 (labelled NEMS-BT2013). The plot shows the average value of the marginal heat rate over the period 2020-2040 for cooling, lighting and refrigeration. Differences between AEO2013 and AEO2014 are systematic, with higher heat rates on the margin for AEO2013. This reflects differences in the projected fuel mix and generation technologies between the two forecasts. The NEMS-BT method tends to predict a somewhat lower heat rate for all end-uses. Lower heat rates mean that more efficient generation is being affected at the margin. This is evident in Figure 14 which shows the distribution of a unit of generation reduction across fuel types. AEO2013 projected a relatively large increase in natural gas generation, and that larger proportion is reflected in the composition of the decrement. For lighting and refrigeration the NEMS-BT approach under-estimates the coal share of generation relative to the



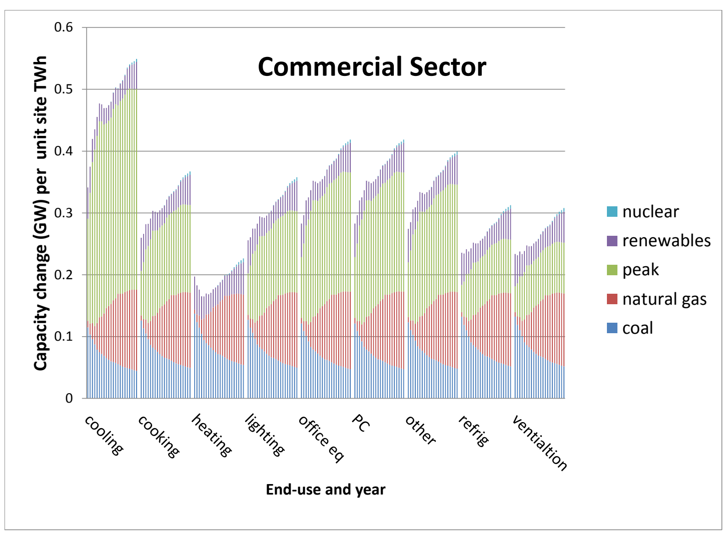


Figure 12: Capacity impact factors by end-use for the residential and commercial sectors.

Emissions	Data	Estimate	Data	Estimate
	CO_2	CO_2	Hg	Hg
2013-tech	-81	-114	-0.15	-0.28
best-tech	304	255	0.85	0.64
ext-pol	66	46	0.1	0.11
high-tech	178	203	0.37	0.51
low-elec	448	349	1.37	0.87
	NO_x	NO_x	SO_2	SO_2
2013-tech	-0.04	-0.08	-0.03	-0.09
best-tech	0.23	0.18	0.29	0.21
ext-pol	0.04	0.03	0.06	0.03
high-tech	0.1	0.15	0.13	0.16
low-elec	0.35	0.25	0.43	0.28
Capacity	Data	Estimate	Data	Estimate
	coal	coal	natural gas	natural gas
2013-tech	-5	-12	-20	-18
best-tech	37	27	40	36
ext-pol	6	4	22	8
high-tech	14	22	30	29
low-elec	56	37	42	49
	renewables	renewables	nuclear	nuclear
2013-tech	-20	-7	-1.9	-0.3
best-tech	16	14	0.7	0.6
ext-pol	-16	3	0.7	0.1
high-tech	14	12	0.5	0.5
low-elec	19	20	0.7	0.8

Table 13: Estimated and actual average deltas for capacity and emissions, for five scenarios.

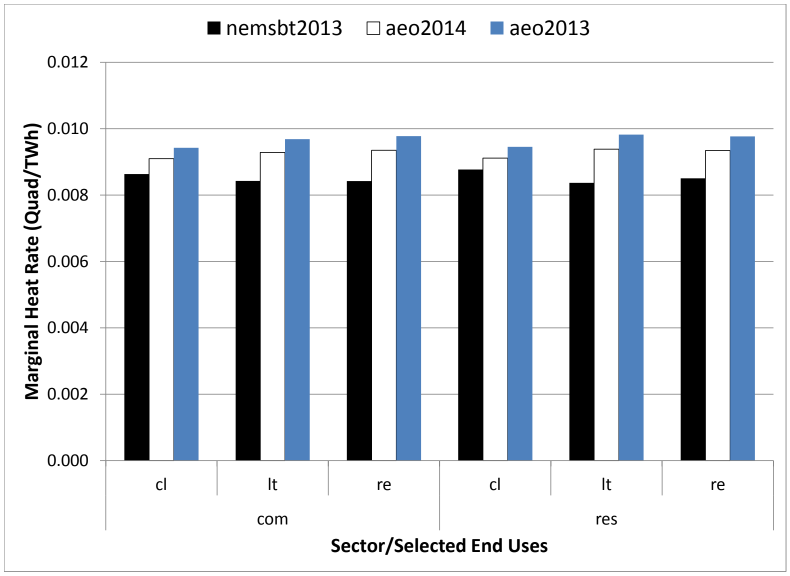


Figure 13: Comparison of the average marginal heat rate for AEO2013, AEO2014 and the NEMS-BT2013 method.

new allocation method described here, and over-estimates the reduction in petroleum fuel generation for cooling.

Figure 16 shows the marginal capacity impact factors by plant type for all three analyses. Relative to the new allocation approach, NEMS-BT tends to under-estimate capacity changes for lighting and refrigeration and over-estimate for cooling, particularly in the residential sector. This is most likely due to the way that the weather-driven cooling peak is handled in the NEMS code. NEMS defines the space cooling peak day load-shape as 150% of the weekday, while the peak day load-shapes for other end-uses are either unchanged, or changed by a small amount. Hence, the NEMS peak capacity requirement is driven almost exclusively by cooling. Figure 15 compares the marginal emissions impact factors for the four power sector pollutants tabulated in NEMS. Again it is clear that the allocation method described in this report greatly smooths out the differences between end-uses that are evident in the NEMS-BT approach.

7 Conclusions

We have presented a new approach to estimating the marginal utility sector impacts associated with demand reductions that uses publicly available data and provides results in the form of time series of impact factors. The approach takes as input a set of projections of how the electric system might evolve under different scenarios; in this report we use the EIA's Annual Energy Outlook reference case, and a number of side cases that incorporate different efficiency and other policy packages. The data published with the AEO are used to define quantitative relationships between demand-side electricity reductions by end use and supply-side changes to capacity, generation and emissions as a function of fuel and plant type. The approach provides useful estimates of fuel consumption, emissions and capacity reductions associated with reduced demand for electricity. We find that the relative variation in impacts by end use is small, but the time variation can be significant. Using the model to try to predict the supply-side changes given some demand-side changes in different AEO scenarios shows that

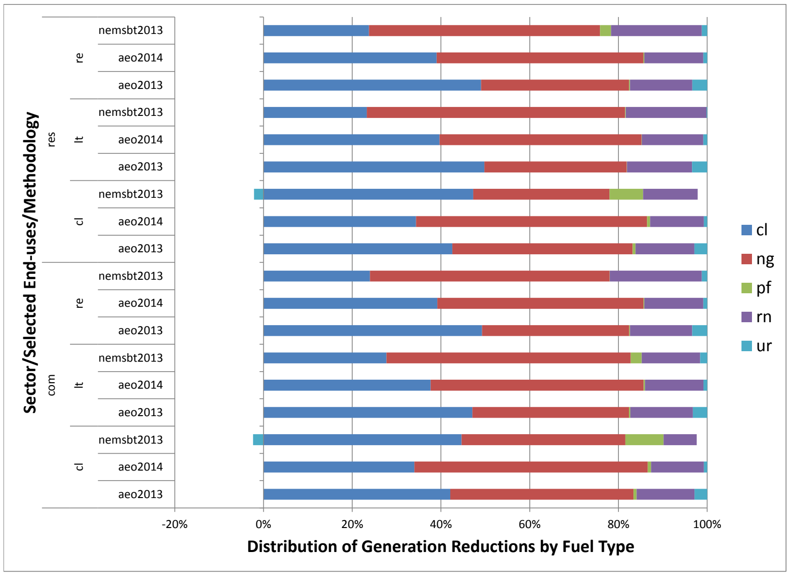


Figure 14: Comparison of the distribution of generation reductions by fuel type for AEO2013, AEO2014 and the NEMS-BT2013 method.

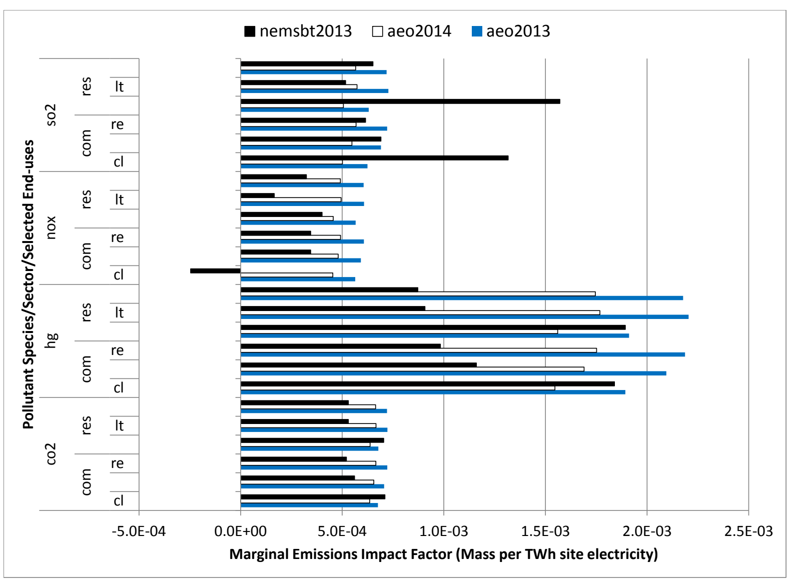


Figure 15: Comparison of the average emissions impact factors for AEO2013, AEO2014 and the NEMS-BT2013 method.

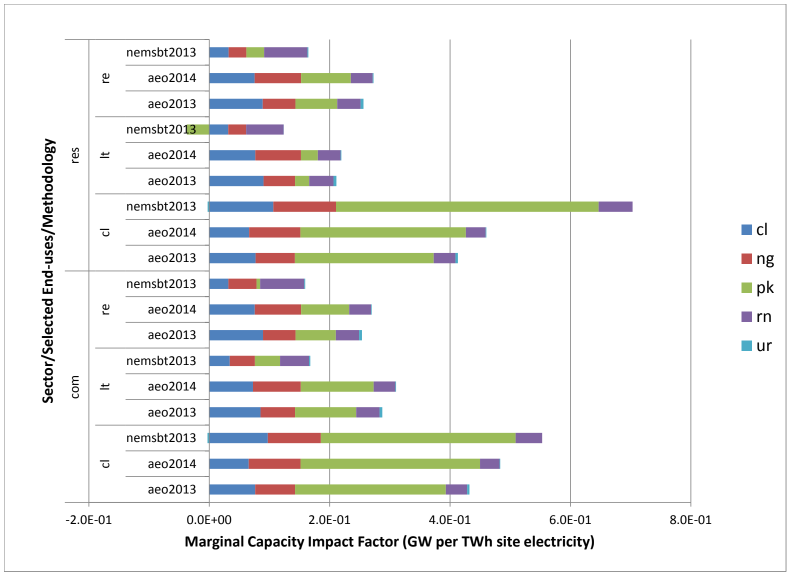


Figure 16: Comparison of the average capacity impact factors for AEO2013, AEO2014 and the NEMS-BT2013 method.

it provides the correct order-of-magnitude, but the actual precision is difficult to estimate since the AEO scenarios generally include measures that affect the supply-side directly.

This approach essentially takes the output of a complex, somewhat inaccessible model (NEMS) and converts it to a form that is easily used in policy analysis: impact factors that allocate utility-sector impacts to specific end uses. The precision of the impact factors, in the sense of their usefulness in predicting NEMS outputs, could probably be improved by making some changes to the methodology. In particular, separating the portion of natural gas that is used in less efficient, peak-serving generation would affect the marginal heat rates associated with peak loads, as well as the associated emissions. The model might also be improved by adjusting the definition of peak, shoulder and off-peak periods. However, there is always a large uncertainty inherent to any projection of the future, so it is not clear whether these improvements would really translate to more meaningful numbers.

What is perhaps more interesting about this approach is that it clarifies the principal cause-and-effect relationships that operate within complex input-output models like NEMS. In particular, physical relationships such as the correlation of emissions with fuel consumption are well predicted using a simple model. Marginal heat rates, which depend on both physical and economic criteria (since the relative cost of different fuels affects what plants are dispatched) are more variable across scenarios and hence more difficult to predict using a simple approach.

This approach takes end use on the demand side as the independent variable, but any set of variables that influence electricity demand can be analyzed in the same way. For example, it could be interesting to use this approach to look at how the utility sector is impacted by changes in fuel prices, or or changes to demand-side expenditures.

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