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Modeling the Capacity and Emissions Impacts of Reduced Electricity Demand.

Part 1. Methodology and Preliminary Results.

Katie Coughlin, Hongxia Shen, Peter Chan, Brian McDevitt, and Andrew Sturges

Energy Analysis Department
Environmental Energy Technologies Division
Lawrence Berkeley National Laboratory
Berkeley, CA 94720

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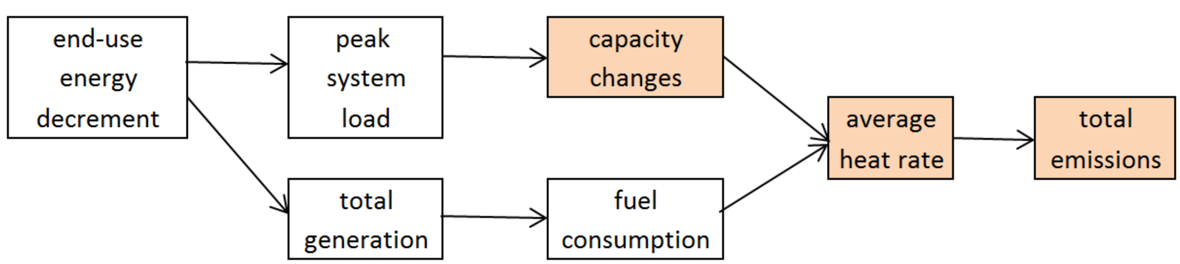
1 Introduction

Policies aimed at energy conservation and efficiency have broad environmental and economic impacts. Even if these impacts are relatively small, they may be significant compared to the cost of implementing the policy. Methodologies that quantify the marginal impacts of reduced demand for energy have an important role to play in developing accurate measures of both the benefits and costs of a given policy choice. This report presents a methodology for estimating the impacts of reduced demand for electricity on the electric power sector as a whole. The approach uses the National Energy Modeling System (NEMS), a mid-range energy forecast model developed and maintained by the U.S. Department of Energy, Energy Information Administration (EIA)(DOE EIA 2013). The methods and assumptions implemented in NEMS receive extensive exposure and scrutiny with each publication of EIA's annual forecast, the Annual Energy Outlook (AEO) (DOE EIA 2012a). Lawrence Berkeley National Lab (LBNL) has used NEMS to estimate the utility sector impact of the Department of Energy's (DOE) Appliance and Equipment Standards Program for nearly a decade (DOE EERE 2013).[1] The goal of the present study is to simplify the methods that have been developed for DOE, without any loss of accuracy, and to make the results available to a broader community.

Each edition of the AEO presents a reference case projection of U.S. energy supply, demand, prices and other quantities. 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, EIA also publishes a series of special case studies. For example, AEO2012 includes several scenarios that explore higher penetrations of building and equipment technolgies that reduce energy demand (the Extended Policy, High Demand Technology, and Best Available Building Technology scenarios (DOE EIA 2012a)). In a similar spirit, we wish to model the potential impacts of improved efficiency for products that are covered by DOE rules, with a focus on electricity. Within NEMS this translates to modeling the impact of a reduction, relative to the reference case, in electricity demand for a particular end-use. Figure 1 illustrates how a change in demand flows through to the larger system (the shaded boxes in the figure define the quantities that are reported as the output of our analysis). Demand reductions lead in a straightforward way to a reduction in the required amount of generation (TWh). If the end-use is peak-coincident, there will also be a reduction in the required total installed capacity (GW). Additional complications arise because the end-use also has a specific pattern in space and time, captured by its *load shape,* which may vary regionally. The particular time during which electricity is saved affects the dispatch of installed generation units, and may alter the economically optimal mix of generation types (fuel and/or technology) that are constructed over the analysis period. The total reduction in power sector primary energy use and emissions depends on both the magnitude and the composition of the generation reduction, and will therefore be end-use dependent.

Figure 1: Flow chart illustrating how demand changes impact the electric power sector.



We refer to the modified version of NEMS run at LBNL to implement the demand reductions as NEMS-BT. The official EIA version that is used to produce the AEO is simply called NEMS. To simplify the NEMS-based methodology, we define a set of test scenarios to be run with NEMS-BT, and use these to develop a set of algebraic *response coefficients* that estimate the reductions in

[1] These analyses are documented in the Technical Support Documents published for each standards rulemaking, available through the DOE website.

primary energy, emissions and installed capacity per unit of generation reduction. The test scenarios cover a range of end-uses that capture the full spectrum of load shape types, from flat (represented by refrigeration) to highly peak-coincident (represented by space cooling). This report presents the methodology and preliminary estimates of the coefficients based on the AEO2012 versions of NEMS and NEMS-BT. A second report will investigate alternative NEMS-based approaches, and provide a more thourough discussion of the computational issues that arise in modifying a complex model such as NEMS.

The report is organized as follows: In the rest of this section the traditional NEMS-BT approach is reviewed and an outline of the new *reduced form* NEMS methodology is presented. Section 2 provides an overview of how the NEMS model works, and describes the set of NEMS-BT runs that are used as input to the reduced form approach. Section 3 presents our NEMS-BT simulation results and post-processing methods. In Section 4 we show how the NEMS-BT output can be generalized to apply to a broader set of end-uses. In Section 5 we disuss the application of this approach to policy analysis, and summarize some of the issues that will be further investigated in Part 2 of this study.

1.1 Background

Previous work at LBNL investigated in some detail the way that NEMS-BT responds to demand reductions for end-uses that are strongly coincident with the system peak, specifically residential and commercial air conditioning (Hamachi LaCommare et al. 2002; LaCommare et al. 2004). NEMS-BT runs have also been used to estimate the broader economic impacts of reduced natural gas demand (Carnall, Dale, and Lekov 2011). However, for the majority of DOE equipment standards rulemakings, utility sector impacts are estimated using what we call the *simple decrement approach*. A time series of annual energy savings for a specific sector (commercial, industrial or residential) and end-use (water-heating, lighting *etc.*) is assumed to be available from an exogenous analysis.[2] NEMS-BT includes code modifications that apply this decrement to the annual electricity end-use demand calculated internally by NEMS. The code changes are documented in Appendix D to this report.

For any single product the electricity savings resulting from a proposed standard are too small, relative to toal U.S. electricity use, to induce changes to the AEO reference case that are above the noise level. The traditional approach used at LBNL works around this problem as follows:

1. The annual demand for the appropriate end-use and sector in the AEO Reference case is decremented by an amount equal to the exogenously calculated value times an integer factor (multiplier) m>1.
2. NEMS-BT is run with the decremented end-use demand to produce a modified projection.
3. The difference between the reference case and the modified case is used to estimate time series for

[2] Methods to estimate the annual energy savings from a proposed rule are described in the National Impacts Analysis chapter of the Technical Support Document for each product.

(a) The change in generation and electric power sector primary fuel consmption,

(b) The change in installed capacity by fuel/technology type, especially at the end of the forecast period,

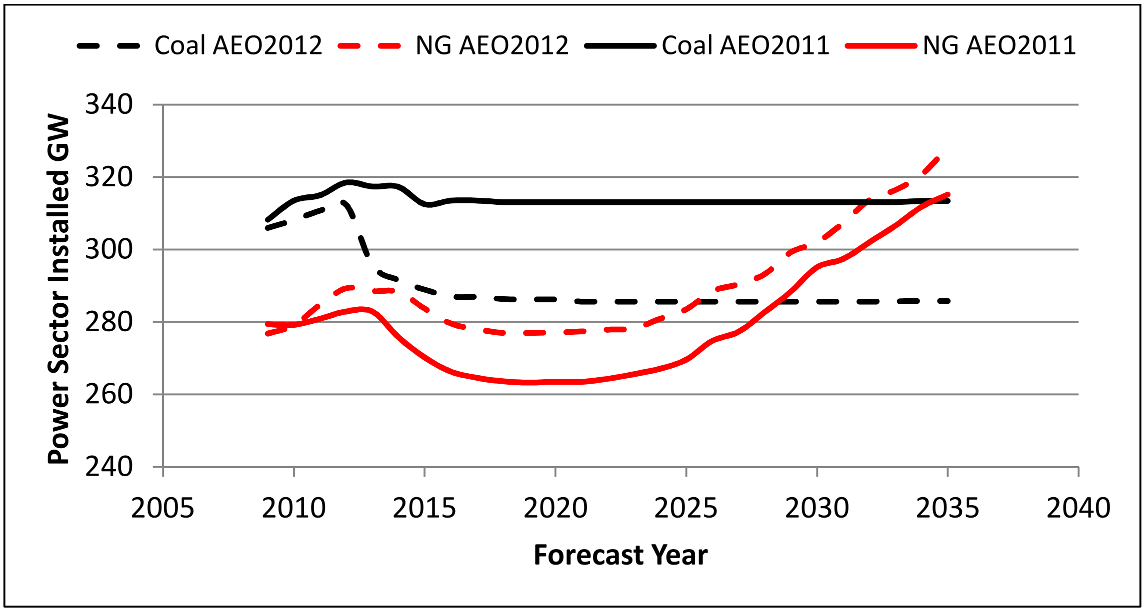
(c) The change in power sector emissions of SO_2, Hg, NO_x and CO_2.

4. Steps 2 through 4 are repeated for several values of *m*, *e.g.* *m*=2, 4 and 6,
5. The results obtained for different values of *m* are extrapolated to *m*=1.

The extrapolateed *m*=1 results are used to define the utility sector impacts of the proposed policy. As DOE generally considers several different trial standard levels for each rule, a large number of NEMS-BT runs are required to complete this analysis. Strictly speaking, extrapolation of the results as a function of *m* is only valid if the variable under consideration is a continuous function of electricity demand. This is not the case for generation capacity which is always installed in discrete lumps. Generation dispatch also depends in a complex and sensitive manner on the relative proportions of installed capacity by fuel type. Hence, it is difficult to assess the precision of the estimates obtained by extrapolating from larger to smaller decrements.

With respect to precision, it may be useful to note that there is an inherent uncertainty in the use of AEO for policy analyses that arises from the simple fact that the future is unknown. Programs such as efficiency standards operate over a medium- to long-term time horizon, and typically use the full AEO forecast period in the analysis of potential program impacts. From one year to the next, there can be fairly significant changes to the projections published in AEO. These do not represent errors *per se*, but reflect the changing economic, social and environmental context within which any hypothesis about the future must be made. This is illustrated in Figure 2, which shows the magnitude of installed capacity as a function of time as projected by AEO2011 and AEO2012 for coal and natural gas combined cycle. Relative to AEO2011 (solid lines), the AEO2012 projections (dashed lines) show a significant and persistent drop in coal GW, which is partially balanced by an increase in natural gas capacity. The magnitude of these edition-dependent changes is about 7-10%. This represents an intrinsic level of uncertainty for any quantity projected by AEO and provides a useful bound on the level of precision that is really meaningful.

Figure 2: Comparison of capacity projections from AEO2011 and AEO2012.



1.2 Overview of Reduced Form Approach

Although the demand reductions for any individual standard may be too small to rise above the noise level in NEMS, the cumulative impact of the program is significant. Rather than develop impact estimates product-by-product, the idea with the reduced-form approach is is to understand the effects of the program as a whole, and define a way to allocate these to each standard individually. This is done here by defining a set of algebraic factors (*response coefficients*) that relate changes in fuel consumption (quads), installed capacity (GW) and pollutant emissions (tons) to a given change in generation (TWh). As with the simple decrement approach, the site electricity demand reduction is assumed to be given. The change in generation is equal to the site reduction times a factor representing transmission and distribution losses.

For this analysis the demand reduction is introduced in year y_b and held constant over the rest of the forecast period. The decrement is applied to a single sector and end-use proportionally across census divisions, and is chosen to be large enough to produce measurable changes to the AEO reference case. Several runs are conducted with varying y_b to examine the effect of the change in start date. To capture load shape effects, we perform and analyze NEMS-BT runs for a set of canonical end-uses which cover the range of load-shape types: cooling (peak-coincident), refrigeration (baseload) and lighting (intermediate). Runs have also been conducted for electric space-heating. For other end-uses, we assume that the impacts can be calculated using a weighted sum of the response coefficients for the end-uses cooling (cl), lighting (lt), refrigeration (re) and heating (ht). The weight coefficients are constructed based on load shape data included with the NEMS code. The motivation for this approach is that, as noted above, changes to the mix of generation types are mostly due to the load shape associated with the demand reductions. Logically, all demand reduction scenarios that produce the same decrement load shape should have the same effect on the power sector. It follows that, if a load shape can be constructed as a weighted sum of the load shapes for (cl, ht, lt, re), the corresponding power sector impacts should be well-approximated using the same weighted sum of response coefficients.

The simulation results are presented as differences (or *deltas*) between the test scenario and the reference case. For comparison, we also construct deltas for some of the EIA high effiency scenarios. As we will show, the output from the NEMS-BT test runs tends to be noisy compared to the EIA published cases. We introduce two averaging methods to help smooth the test scenario results. The first is to construct an ensemble average over runs for a fixed sector and end-use but having different decrement start dates y_b. The second is to develop time-averaged response coefficients for five-year sub-periods within the AEO forecast period.

2 Simulation Methodology

2.1 NEMS overview

NEMS consists of a number of independent modules that represent different components of the energy sector such as coal production, liquid fuels production *etc.* We are primarily interested in electricity demand and the electric power sector, which are handled in the Electricity Market Module (EMM) and the Commercial and Residential Demand Modules (DOE EIA 2011a; DOE EIA 2011c; DOE EIA 2011b). NEMS also has an Integrating Module that manages the interaction between the different sectoral modules, and a Macroeconomic Module that handles supply-demand feedbacks between the energy sector and the rest of the economy. Broadly speaking, the model builds up the supply-side and demand-side separately, and adjusts prices to achieve equilibrium between the two. A single-cycle NEMS run produces a projection of supply and demand variables for the entire forecast period, which for AEO2012 is 2010-2035. Decisions about whether to build new capacity in year y are based on the expected return on investment, which requires an *a priori* forecast of electricity demand and prices for years beyond y. NEMS uses a multi-cycle algorithm to align these *a priori* forecasts with the prices that are calculated from the supply-demand equilibrium. This is referred to as *perfect foresight* (DOE EIA 2012b).

Generally the variables projected in the AEO may show complicated behavior during the first ten years or so of the forecast period, then settle down to a relatively smooth trend. This can be seen in Figure 2, which shows that the ups and downs are mostly confined to the first few years. Not suprisingly, the NEMS-BT runs show some sensitivity to the year in which the decrement begins. This may be partly due to the pronouncd drop in coal capacity that occurs in the AEO2012 projection between 2012 and 2015. Any alteration to electricity demand that affects the timing of this drop will result in a substantial difference from the reference case. In reality, although the magnitude of the change illustrated in Figure 2 is credible given current trends away from coal-fired generation, there is considerable uncertainty about the timing. Our approach of averaging over an ensemble of runs with differing start years is intended to smooth over some of the volatility due to the timing of generation additions, and hopefully produce results that are more robust given this uncertainty.

For the electric power sector, supply-side variables are disaggregated onto 22 EMM regions, which are subdivisions of NERC reliability regions (DOE EIA 2011a). On the demand-side, variables are disaggregated by census division. Supply-side projections include annual generation and installed capacity by fuel and technology type, primary energy consumed by the power sector by fuel type, and total emissions of NO_x, SO_2, CO_2 and Hg. Emissions are not regionally disaggregated. A list of the fields used in this analysis and the NEMS Tables from which they were extracted is given in Appendix C. On the demand side, NEMS produces projections of residential and commercial building energy use for an extensive list of end-uses. NEMS also contains load shape information for a more limited set of end-uses. These load shapes, multiplied by the appropriate annual end-use energy consumption, are used to build up an estimate of the hourly system load in each EMM region. The system load is converted to a load duration curve, which is then used to determine whether new generation is required. NEMS also uses the load duration curves to model dispatch of existing generation units, which in turn affects the revenues to generation owners.

2.2 Test Run Scenarios

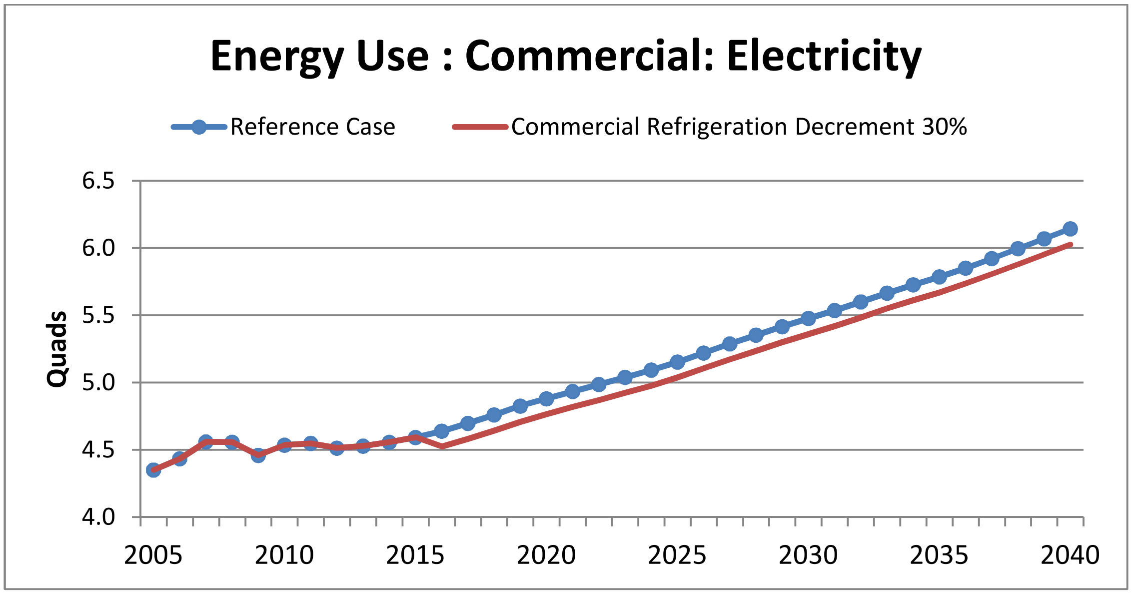
The results presented in this report are based on a set of 40 test runs incorporating fixed decrements to four commercial and residential end-uses as listed in Table 1. The Table lists both the magnitude of the decrement in absolute terms, and relative to the end-use under investigation. Figure 3 shows the decrement pattern for start year 2016. The figure compares total commercial electricity demand in the reference case and for a commercial refrigeration decrement; relative to total electricity demand these decrements are on the order of 2-3%. The eight sector/end-use combinations are each run five times, with varying start years y_b = (2015, 2016, 2017, 2019, 2021).

We have also examined the results of NEMS runs with varying decrement sizes. The response coefficient approach effectively imposes a linear relationship between the change in primary energy use, emissions and capacity and the change in generation. The first three variables scale directly with generation, so this is reasonable. Capacity is more complicated, and it is important to find a decrement magnitude that is in an approximately linear response regime. Too small and the capacity response is pure noise, too large and the effect on prices and other variables will start to push the solution away from the reference case in ways that might not be appropriate. The decrement sizes listed in Table 1 are all in a regime where they are large enough to produce results above the noise, and where a doubling of the decrement roughly doubles the capacity and other impacts.

Table 1: List of runs by sector and end-use.

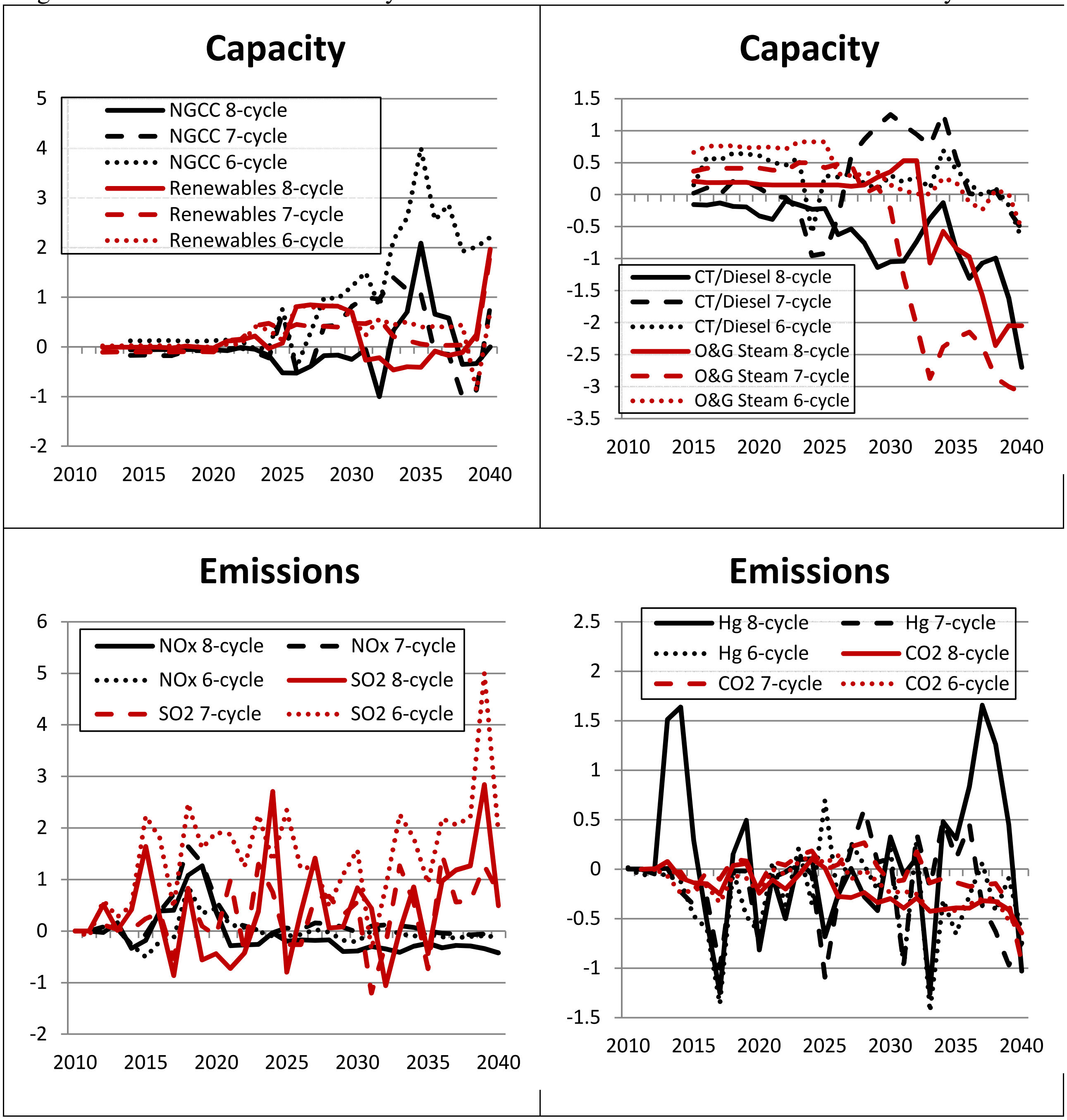
Run Name	Sector	End-use	Decrement %	Decrement TWh
maccommcl20	commercial	cooling	20	33
maccommht30	commercial	heating	30	16
maccommlt10	commercial	lighting	10	30
maccommre30	commercial	refrigeration	30	34
macresdcl10	residential	cooling	10	32
macresdht20	residential	heating	20	16
macresdlt15	residential	lighting	15	30
macresdre30	residential	refrigeration	30	33

Figure 3: Commercial electricity demand with and without the decrement



All the data presented here are taken from from runs conducted at LBNL with the macro-economic module on.All scenarios are run for seven cycles, unless the internal convergence criteria is met and the run terminates earlier. In some cases, runs are not sufficiently converged after seven cycles to provide reliable results; these are excluded from the downstream processing. NEMS uses an internal metric called GPA to track intra-cycle convergence. The convergence criteria are based on prices and quantities demanded; there are many other variables computed in a NEMS run and not all of these will necessarily show the same level of convergence. The noise level in the simulations can be estimated, at least qualitatively, by looking at how the numerical values for a particular set of variables change in cycle n+1 compared to cycle n. By definition, perfect convergence is achieved when solution values remain constant for all n. Realistically, perfect convergence may not be achievable with a complex optimization model like NEMS.

Figure 4: Difference between a 9-cycle reference case solution and solutions with few cycles.



* The vertical axis is the percent change relative to the 9-cycle output.

The behavior of the power sector quantities of interest as a function of the cycle index *n* is illustrated in Figure 4. The figure compares the output of solutions for cycle *n*= 6, 7, and 8 relative to a solution with *n*=9. The vertical axis is the percent difference between the *n* cycle solution and the 9-cycle solution. Although the official end of the forecast period is 2035, NEMS internal tables output data through 2040. The extra five years are part of the internal *a priori* forecast used for investment decisions as discussed above. There is significant volitility in the solution behavior for years beyond 2025, with no clear pattern indicating improved convergence for increasing *n*. This is particularly clear in the plots for Hg and the peaking capacity types Oil & Gas Steam and Combustion Turbine/Diesel. In this report, the 7-cycle solution is used as the reference case. Based on these plots, the uncertainty due to non-convergence in years up to 2035 is about 3-5%. Data beyond 2035 is not used due to the much larger amplitude of fluctuations.

3 Analysis of Test Runs

3.1 Simulation Output

The simulation results are presented as differences (or *deltas*) between the test scenario and the reference case. For comparison, we also construct deltas for some of the EIA high effiency scenarios. This section, and Appendix A present summary output for the years 2016-2035 for these scenarios. The capacity and generation data are plotted by generation type as stacked bar charts. All data are summed over the NEMS sub-categories conventional and advanced, with and without CCS. To simplify the plots, some of the NEMS reporting cateogries have been summed into a single type: *peaking* generation is equal to the sum of Oil & Gas Steam plus Combustion Turbine/Diesel, and the *other* generation type include Pumped Storage, Fuel Cells and Distributed Generation. The rest of the generation types are as reported by NEMS. The NEMS reported imports to and exports from the U. S. of electricity are not included in these totals. Figure 5 shows the capacity deltas from a single NEMS-BT run, the commercial refrigeration decrement run with start year 2016 (maccommref2016), and for comparison the same deltas for the EIA High Demand Technology (Hightech) case. For illustrative purposes the data are plotted through 2040. In the NEMS-BT run there are differences from the reference case even before the start year of the decrement; this is due to NEMS internal forecast procedure. Qualitatively, the two runs show similar behavior but the NEMS-BT run is much noisier. The scale of the reduction in the Hightech case is almost ten times larger, and the technologies implemented for this case include many different end-uses. This is presumably what leads to the more regular behavior.

Figure 5 Capacity reductions by technology type. Hightech (left) and maccommref30_2016.

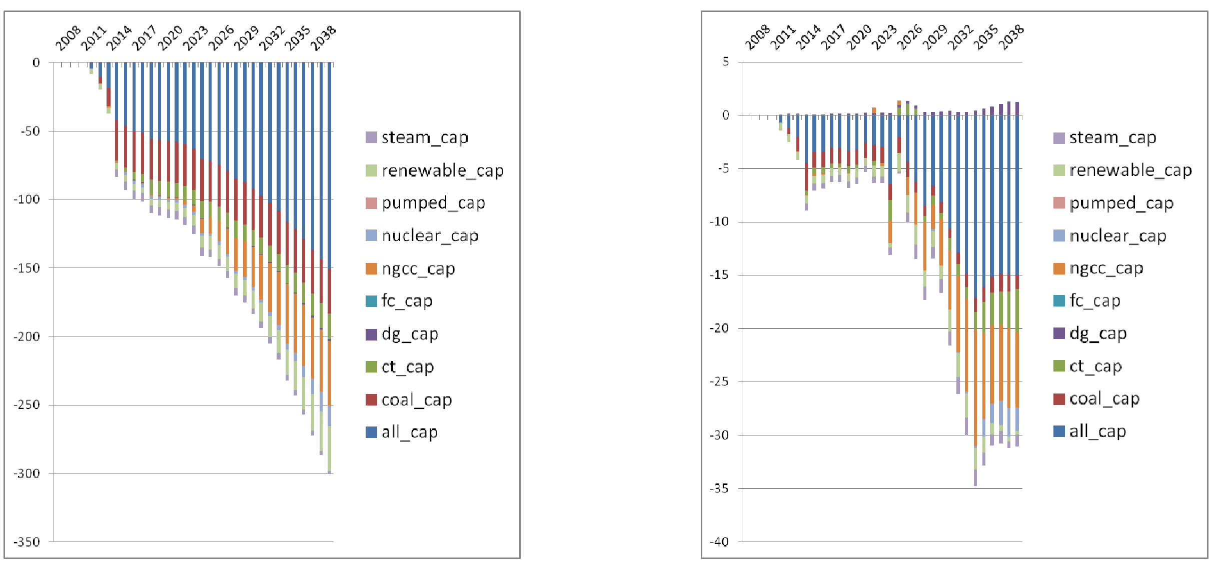
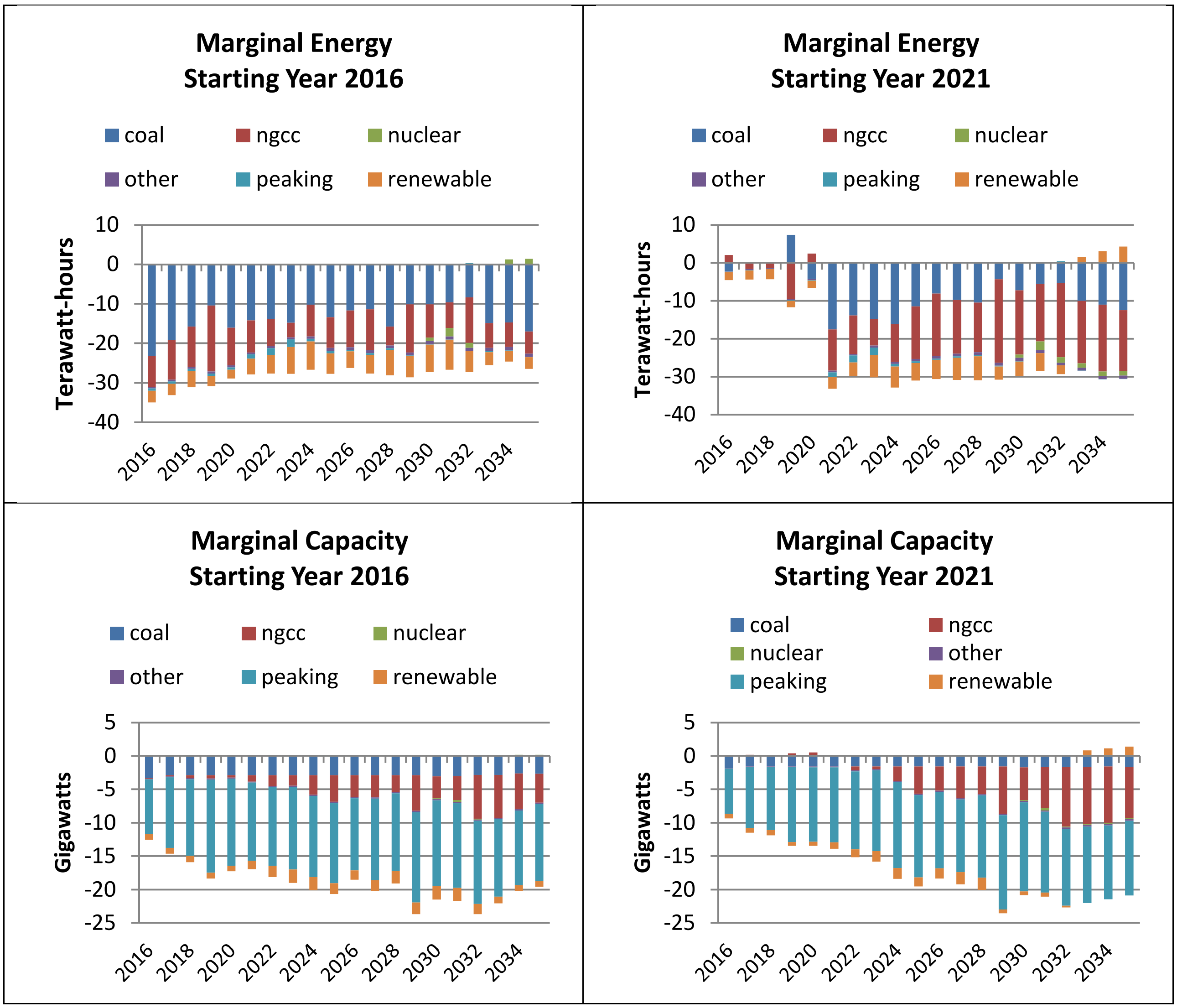


Figure 6 illustrates the effect of differing start years on the generation (*i.e.* energy, upper plots) and capacity variables. The plots on the right show a run with start year 2016, while on the left the start year is 2021. The difference in the timing of the decrement is clear on the generation plot. There is a small deviation from the reference case before the start year in the TWh plot for 2021. This is due to the perfect foresight method, which will move the entire forecast period away from the reference case in response to any change. The capacity plots show the much more pronounced effect of the *a priori* forecast that is used in capacity investment decisions, which leads to a substantial change in capacity five years before the start of the decrement.

Figure 6 Comparison of results for different start years (commercial refrigeration).



To smooth over some of the volatility associated with varying the start year of the decrement, for each sector and end-use we use a simple average of the simulation output over all the start years. Appendix A shows figures illustrating these average runs for all 8 sector/end-use combinations.

3.2 Response Coefficients

The response coefficients are parameters that measure how a reduction in generation induces a corresponding change in emissions, fuel consumption and capacity build-out. A first approximation is easily obtained simply by taking the appropriate ratios of the deltas. These ratios are defined as follows:

- K is used to label different scenarios; $K=R$ is the label for the reference case.
- y is used to label the year.
- For any quantity X_K, the *delta* ΔX in year y is defined as:

$$\Delta X(y) = X_K(y) - X_R(y)$$

- $IC_K(y,g)$ is the installed capacity for generation type g (GW).
- $G_K(y,g)$ is the total generation for generation type g (TWh)
- $Q_K(y,f)$ is the total power sector primary fuel consumption for fuel type f in (quads).
- $EM_K(y,s)$ is the total power sector emissions of pollutant species s (million short tons).
- $h_K(y)$ is the marginal heat rate averaged over all technology and fuel types:

$$h_K(y) = \frac{\sum_f \Delta Q_x\,(y,f)}{\sum_g \Delta G_K\,(y,g)}$$

- $\varepsilon_K(y,s)$ is the marginal emissions intensity averaged over all technology and fuel types:

$$\varepsilon_K(y,s) = \frac{\Delta \mathrm{EM_K(y,s)}}{\sum_g \Delta \mathrm{G_K(y,g)}}$$

- $\delta_K(y,g)$ is the capacity reduction per unit generation reduction for generation type g:

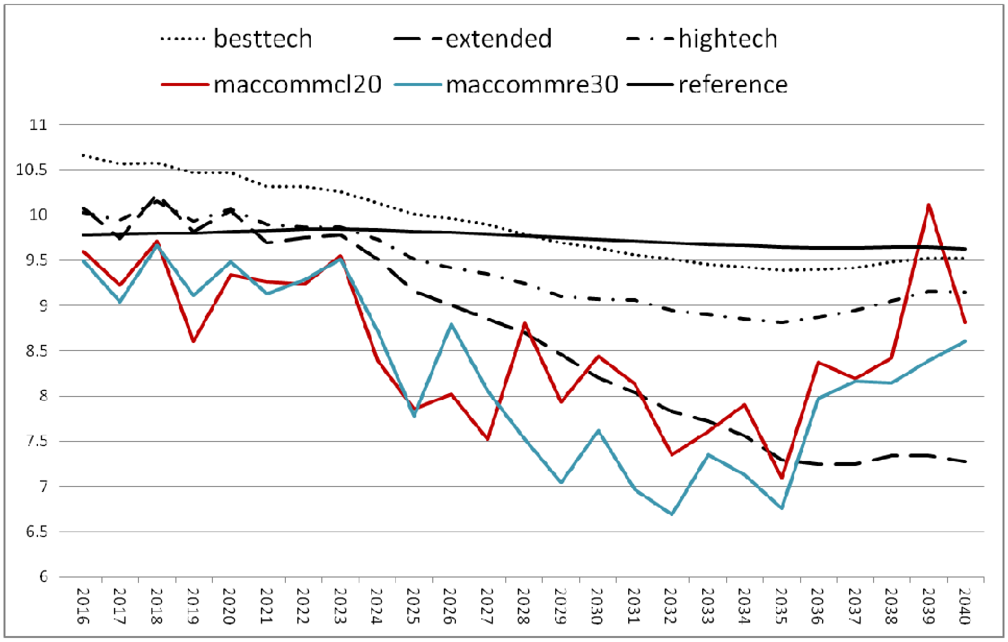
$$\delta_K(y,g) = \frac{\Delta IC_K(y,g)}{\sum_g \Delta G_K(y,g)}$$

- $\alpha_K(y,g)$ is the fraction of generation reduction contributed by generation type g:

$$\alpha_K(y,g) = \frac{\Delta G_K(y,g)}{\sum_g \Delta G_K\,(y,g)}$$

Figure 7 shows the marginal heat rate $h_K(y)$ for a number of scenarios: the NEMS-BT runs for commercial cooling and refrigeration for individual runs with start year 2016, the reference case, and the three EIA high efficiency cases. The figure shows the simulation output through 2040; the increased noise in the last five years is evident. The Extended Policy case is closest to the equipment efficiency NEMS-BT cases in terms of the magnitude of energy savings and the technology focus, and in the heat rates as well. In general all the time series show a similar pattern. The heat rate tends to decrease over time because the demand reduction is off-setting more efficient generation. The decrease levels off and starts to reverse near the end of the period. The plot again illustrates the relative noisiness of the NEMS-BT runs. Other simulations with different start years may show heat rates above the reference case average in the early years, similar to the Extended case. Appendix A provides plots of the marginal heat rates and pollutant intensities for all the ensemble-averaged sector and end-use runs.

Figure 7 Marginal heat rates (Mbtu per kWh) for a variety of scenarios



3.2.1 Time Averaging Methods

To smooth out the noise in the time series, we define four five-year block averages over the period 2016-2035. For any variable *X*, the five-year average over period *p*, *X'(p)*, is defined as

$$X'(p) = \frac{1}{5}\sum\nolimits_{j=0,4} X\left(y_p + j\right), \quad y_p = 2011 + 5p$$

The average of h_K, is then

$$h'_K(p) = \frac{\sum_f \Delta Q'_K(p,f)}{\sum_g \Delta\, G'_K(p,g)}$$

The time-averaged ratios are defined by first averaging the numerator and denominator separately, then taking the ratio. This method gives more stable results than the alternative of taking the ratio first and then averaging. The time-averaged coefficients for emissions, and for the fraction of generation by fuel type (α) are all defined in the same way as the heat rate. For the capacity to energy time averaged ratio (δ) we use a slightly different definition. Because the capacity investment decision is sensitive to demand growth as well as demand, we define the response coefficient as the ratio of *ΔIC* in period *p* to the average of *ΔG* in periods *p* and *p-1*. We use the years 2011-2015 to define a period *p=0* average of *ΔG*.

3.2.2 Results

The results of this analysis are presented in Figure 8 and Figure 9; the full set of coefficients is provided in Appendix B. Figure 8 plots the response coefficient values for the percentage generation reduction (α) and the capacity reductions (δ) by fuel type, for the commercial sector all end-uses. The figure also includes the coefficients calculated for the Extended Policy scenario. The coefficients for the residential sector are similar, except that the impact of residential cooling on peaking capacity is less pronounced. Note that some of the capacity coefficients are negative; this means that the scenario shows a net increase in GW relative to the reference case. This happens primarily for the intermediate loads, where the demand reduction may induce a shift of generation from one category to another and result in an increase for some categories. The net effect on capacity is always negative. As expected, the cooling end use is the only one that leads to a signficant overall decrease in total installed capacity. The other capacity reductions are due not to a decrease in system peak load, but to a lower requirement for generation over-all. Although the Extended Policy case incorporates a variety of end-use efficiency improvements, the capacity response coefficients are quite similar to the NEMS-BT cooling run, suggesting that cooling dominates the capacity impacts for this case as well.

Figure 8 Response coefficients for capacity and fraction of generation by fuel type.

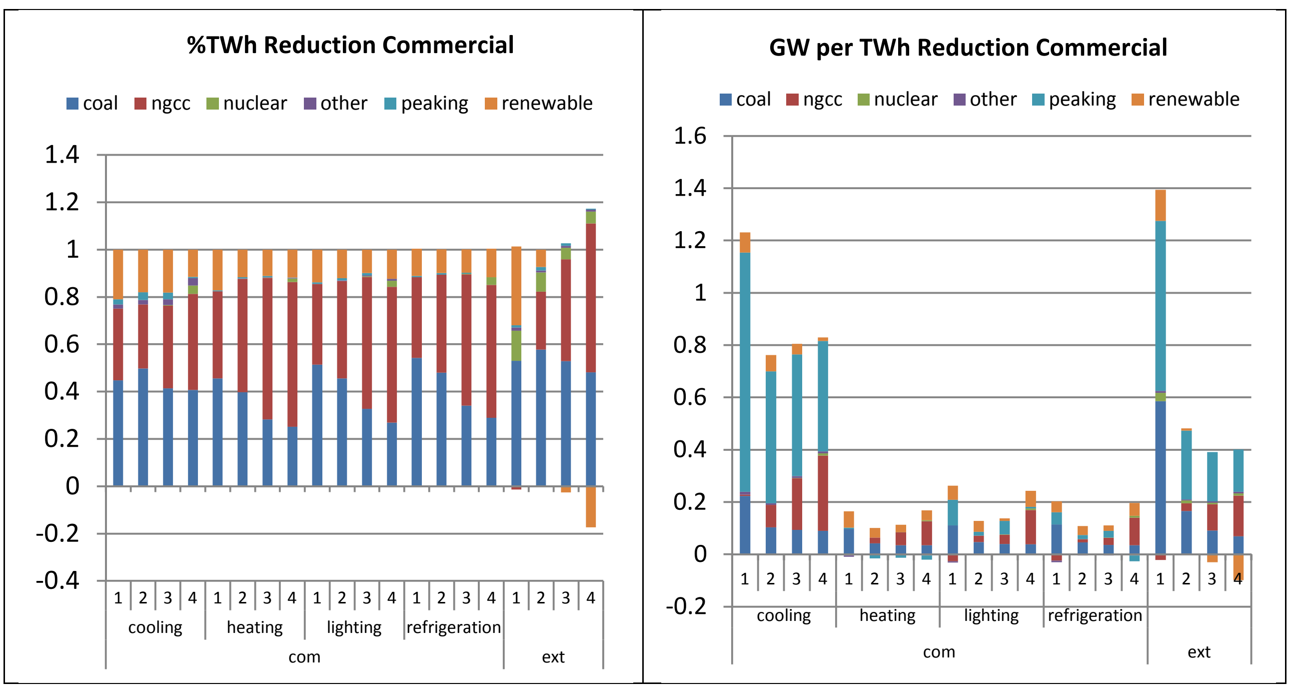
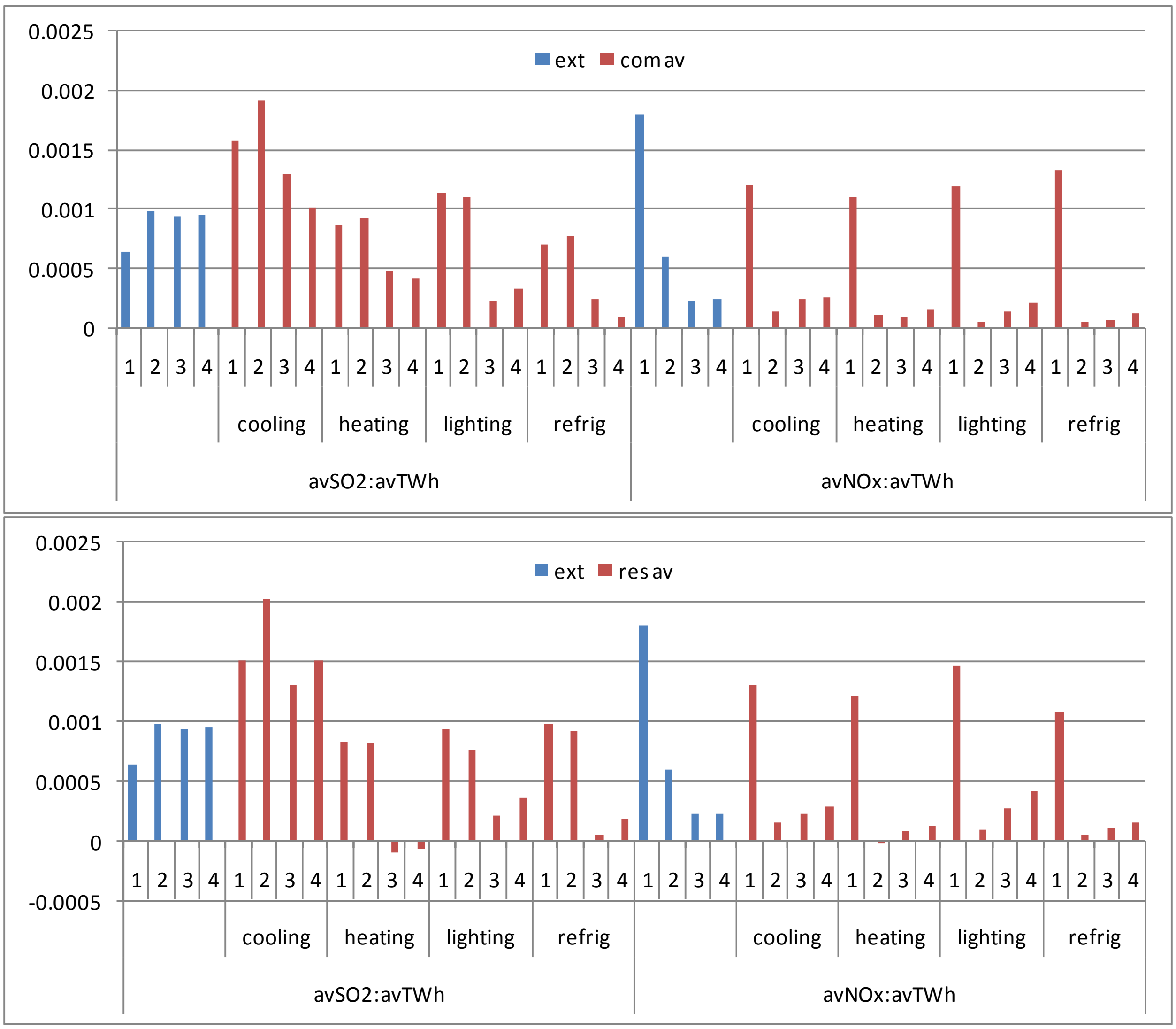


Figure 9 shows the emissions coefficients; in this figure both the commercial (top) and residential (bottom) data are plotted, as well as the coefficients for the Extended Policy case (blue bars). NO_x is plotted on the left, and SO_2 on the right. For NO_x emissions, all cases show a very large reduction in the marginal emissions rate in the later periods. The pattern is relatively insensitive to end-use. The SO_2 emissions intensity decreases somewhat over time for the NEMS-BT runs; the values are similar for heating, lighting and refrigeration, and larger for cooling. This is consistent with the fact that the composition of the cooling energy decrement includes more single cycle, oil or diesel generation, which would lead to larger sulfur emissions. The Extended policy case does not show a reduction over time in SO_2 intensity, but the coefficients are of similar magnitude.

Figure 9 Response Coefficients for SO2 and NOx Emissions



4 Generalization to All End Uses

In this section we develop the weight coefficients that will be used to relate the simulation results for cooling, heating, lighting and refrigeration to other end-uses. The analysis focuses on end-use load shapes that are explicitly modeled in NEMS. The implicit assumption is that if load shape A is a weighted linear sum of load shapes B and C, then the shape-dependent downstream impacts can also be estimated as a linear sum with the same weights. This is an appoximation, but is consistent with the way load duration curves are constructed within NEMS.

The discussion begins with a review of NEMS load shape data and energy consumption projections. We then describe the regression model used to develop the weight coefficients, and present the results.

4.1 Methodology

4.1.1 NEMS load shape data

This analysis makes use of two NEMS datasets related to building end-use energy consumption: load shape information, and time series of annual energy consumption (*i.e.* the commercial and residential electricity demand projections output by NEMS). The weight coefficients that we will derive are based on the reference case demand projections. These are broken down by sector, end-use, and census division. The residential and commercial data are analyzed separately. For a given sector the notation is:

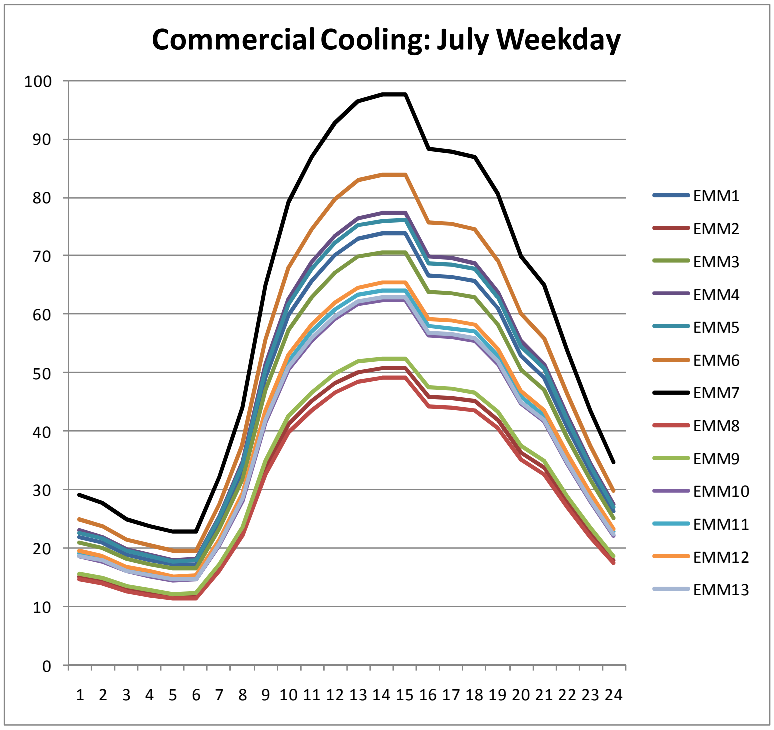
- u is an index used to label the end-use,
- cd is an index defining the census division,
- y is the year of the forecast period,
- $e(u,cd,y)$ is the annual electricity demand in TWh.

NEMS provides annual demand values for an extensive list of end-uses (DOE EIA 2011c; DOE EIA 2011b). Load shapes are explicitly represented for a smaller subset of all end-uses. For the residential sector, these are space heating, cooling, water heating, cooking, refrigeration, freezers, electric clothes dryers, lighting and other. The commercial sector load shapes are space heating, cooling, ventilation, water heating, cooking, lighting, refrigeration, office equipment-personal computer (PC), office equipment non-PC, and other. End-uses without a specific load shape are assigned to the "other" category. For both sectors space heating and cooling load shapes vary by region. Because the load shape information is used to construct load duration curves, which in turn are input to the generation dispatch and new construction decisions, the regional disaggregation is a function of the supply-side EMM regions rather than by census division. Load shapes do not vary with the analysis year y.

The load shape data allocates the annual electricity use for u to a particular month, day type and hour. For space-conditioning loads, regional variation is captured by varying the proportion of energy use assigned to each month. This is illustrated in Figure 10, which shows the load shape for commercial cooling for a July weekday. The plot shows the 13 EMM regions that were used in AEO2010 (beginning with AEO2011, the EMM module uses 22 EMM regions, however the independent load shape data still maps to the 13 regions used previously). Our notation for the load shape data is:

- r is an index defining the EMM region,
- d is an index defining the day type (weekend, weekday, peak day),
- m is an index defining the month,
- h is an index defining the hour.
- $ls(u,r,m,d,h)$ is the load shape profile.

Figure 10 Commercial cooling hourly load shapes by EMM region.



Defining $n(m,d)$ as the number of days of type d in month m, the load shapes are normalized so that

$$\sum_m \sum_d \sum_h n\,(m,d) ls(u,r,m,d,h) n(m,d) = 10{,}000$$

The actual electricity demand for end-use and sector u in year y is proportional to the product of $e(u,cd,y)$ and the load shape. To construct this product, the two sets of variables need to use the same spatial disaggregation. NEMS uses a constant matrix to transform variables from the demand-side (cd) to the supply-side (r). There is a matrix for the residential sector and one for the commercial sector ($MR(r,cd)$ and $MC(r,cd)$ respectively).[3]. The matrix elements are equal to total sectoral electricity use disaggregated onto both EMM regions and census divisions for a particular year (not specified in the documentation). As we are ultimately interested in the supply-side impacts, so we transform the demand variables to representation by EMM region, and define the annual electricity use as

$$E1(u,r,m,d,h,y) = \left[\sum_{cd} w(r,cd) e(u,cd,y)\right] ls(u,r,m,d,h) \equiv \epsilon(u,r,y) ls(u,r,m,d,h)$$

where $w(r,cd)$ is calculated from either MR or MC appropriately normalized. With this definition,

$$\sum_r \epsilon(u,r,y) = \sum_{cd} e(u,cd,y) \equiv E(u,y)$$

[3] These matrices are specified in the NEMS data files KDBOUT and RESDBOUT

The AEO2012 reference case projections of $E(u,y)$ show that there is little change in the relative proportions of electricity demand by end-use over the forecast period; equivalently the ratio $E(u,y)/\sum_u E(u,y)$ is approximately independent of y. Hence, the model can be simplified by replacing $E(u,y)$ by the its value averaged over the N years of the forecast period:

$$\bar{E}(u) = \frac{\sum_y E(u,y)}{N}$$

Another simplification is to work with national average data for the space-conditioning end-uses. Combining the time-averaging over years y and a demand-weighted average over regions r we arrive at a load shape

$$ls1(u,m,d,h) = \frac{\sum_r \left(\sum_y \epsilon(u,r,y)\right) ls(u,r,m,d,h)}{\bar{E}(u)}$$

(For non-space-conditioning end uses, *ls1* identical to *ls*). With these approximations, the combination of the magnitude of demand and the load shape for each end-use is given by the product $\bar{E}(u)\ ls1(u,m,d,h)$.

4.1.2 Regression Model

In this section we use the index u to represent all end-use load shapes *except* cooling, lighting and refrigeration. These three load shapes are indexed by v. The goal of the regression model is to estimate coefficients $\beta(u,v)$ such that

$$ls1(u,m,d,h) = \sum_v \beta(u,v) ls1(v,m,d,h)$$

The coefficients $\beta(u,v)$ are defined independently for each sector, and most generally may depend on the variables m, d and h. Further simplification can be made by reducing the 72 values indexed by hour and day type to a few periods indexed by $i=1,\ldots,ni$. This approximation is reasonable, given that NEMS constructs the load duration curves in blocks related to time-of-day (weekday afternoon, weekend evening *etc*.) (DOE EIA 2011a). The definition of these periods is similar to the common usage of peak, off-peak and shoulder hours in utility time-of-use rates (Coughlin et al. 2008).

Table 2 Assignment of weekday/peak day hours to time-of-day periods.

	Hour Ending																							
period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1 (on)	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
2 (sho)	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
3 (off)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1

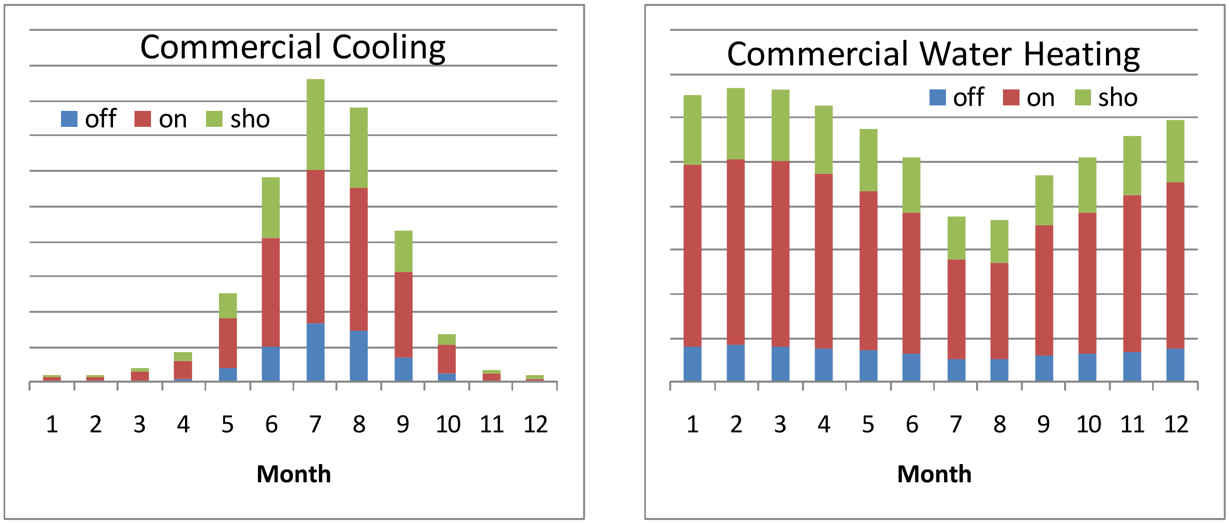
The assignment of hours to periods is given in

Table 2. The filter in the table is applied to weekdays and the peak day, and all hours on the week end day are assigned to off-peak. This process produces a *periodized* load shape variable

$$ls2(u,m,i) = \sum_{(h,d)\in i} ls1(u,m,d,h)$$

An example of this periodized shape information is given in Figure 11, which shows the data for commercial cooling and water-heating. The month index is plotted on the horizontal axis; the vertical axis is arbitrary as only the relative fractions are important.

Figure 11 Commercial cooling and water-heating energy use by period.



The model equation then becomes

$$ls2(u,m,i) = \sum_{v} \beta(u,v)\, ls2(v,m,i)$$

4.2 Results

For each of the end uses *u* which do have load shapes but do not have NEMS-BT decrement runs, we use the equation above to determine the coefficients to determine the coefficients $\beta(u,v)$. The equation is solved using a standard least-squares regression method. In a preliminary analysis the independent variables *v* consisted of cooling (cl), lighting (lt) and refrigeration (re) only. This produced reasonable results for all end-uses except heating, so NEMS-BT decrement runs were performed for heating. Hence, heating (ht) may be included as a fourth independent variable in the regression model.

Four variants of the model have been tested:

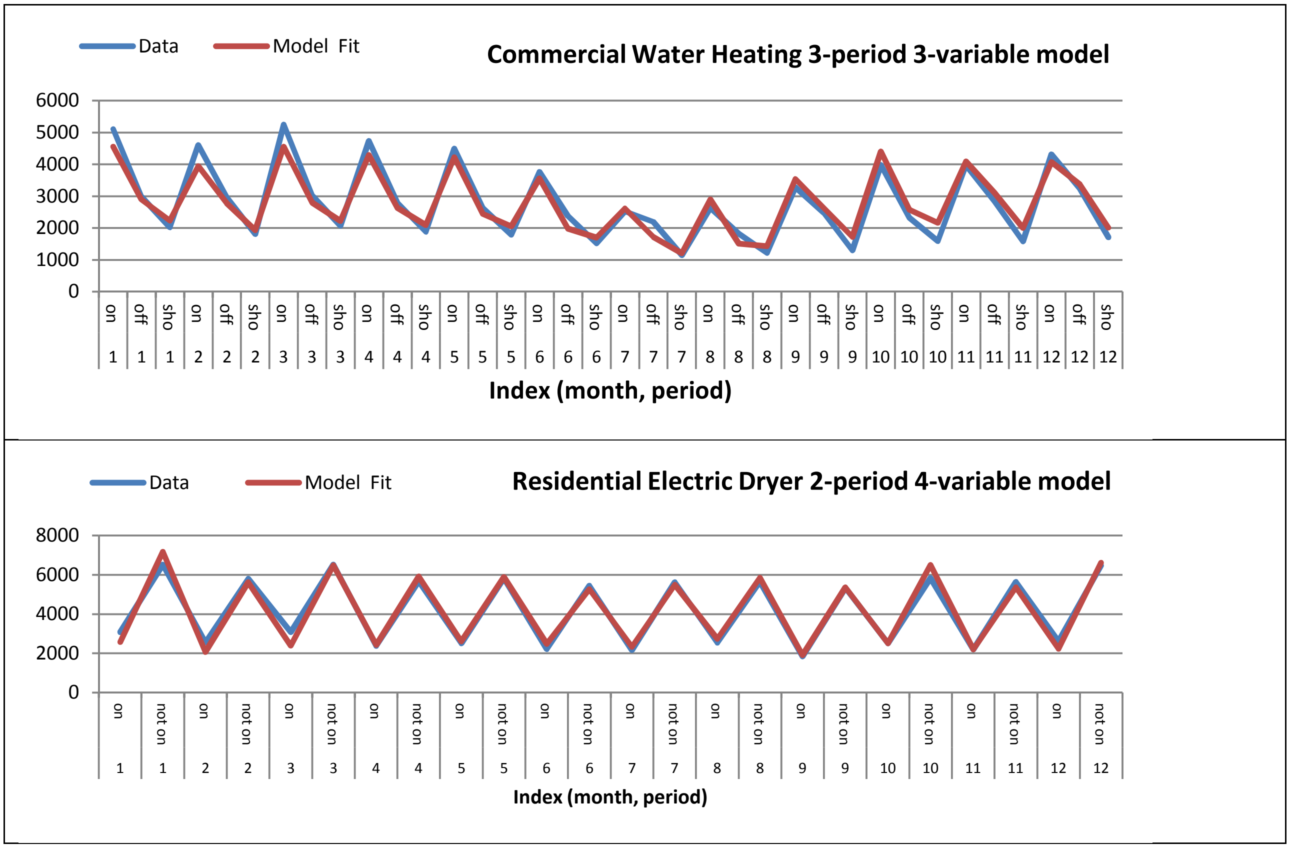
1. Three independent variables (cl, lt, re) and three period-averaged load shapes,
2. Four independent variables (cl, ht, lt, re) and three period-averaged load shapes,
3. Three independent variables (cl, lt, re) and two period-averaged load shapes,
4. Four independent variables (cl, ht, lt, re) and two period-averaged load shapes.

The two period-averaged data was constructed from *ls*2 by summing the off-peak and shoulder periods into a single *not-on-peak* value. The regression coefficients for all four variants are presented in Table 3. The R-squared measure of goodness of fit is generally excellent. Commercial load shapes appear to be more regular and therefore easier to fit than residential shapes. Adding the heating end-use as an independent variable has little effect on the solution. Commercial water heating (wh) is the least well-fit, with the 3-period model providing significantly better results than the 2-period variant. For the residential load shapes, the 2-period, 4-variable model provides the best results as measured by the R-squared. The somewhat poorer results for residential are presumably due to larger variation in the load shapes, particularly between weekend and weekday. Figure 12 illustrates the deviation between the original end-use load shape and the regression fit for the least well-fit end-uses, commercial water-heating (wh) and residential electric clothes dryers (ed). Even for these cases the fits are quite good.

Table 3 Weight coefficients for all four variants of the regression model.

		Commercial 3 periods					**Commercial 2 periods**				
end-use	**code**	**a_cl**	**a_lt**	**a_re**		**R_sq**	**a_cl**	**a_lt**	**a_re**		**R_sq**
cooking	co	0.009	1.265	-0.277		0.992	0.014	1.243	-0.257		0.983
office non-PC	on	0.067	1.972	-1.027		0.982	0.070	2.058	-1.128		0.957
office PC	op	0.067	1.972	-1.027		0.982	0.070	2.058	-1.128		0.957
other	ot	0.041	1.673	-0.704		0.985	0.045	1.741	-0.786		0.923
ventilation	vt	0.002	-0.048	1.045		0.995	0.003	-0.060	1.058		0.996
water heating	wh	-0.103	1.534	-0.415		0.920	-0.087	1.624	-0.537		0.775
		a_cl	**a_lt**	**a_re**	**a_ht**	**R_sq**	**a_cl**	**a_lt**	**a_re**	**a_ht**	**R_sq**
cooking	co	0.004	1.264	-0.263	-0.008	0.992	0.008	1.242	-0.243	-0.007	0.985
office non-PC	on	0.063	1.971	-1.017	-0.005	0.982	0.066	2.057	-1.119	-0.005	0.957
office PC	op	0.063	1.971	-1.017	-0.005	0.982	0.066	2.057	-1.119	-0.005	0.957
other	ot	0.036	1.672	-0.689	-0.008	0.985	0.039	1.740	-0.774	-0.006	0.928
ventilation	vt	-0.023	-0.052	1.106	-0.033	0.999	-0.027	-0.065	1.128	-0.036	0.999
water heating	wh	-0.117	1.532	-0.383	-0.017	0.921	-0.087	1.624	-0.538	0.000	0.775
		Residential 3 periods					**Residential 2 periods**				
end-use	**code**	**a_cl**	**a_lt**	**a_re**		**R_sq**	**a_cl**	**a_lt**	**a_re**		**R_sq**
cooking	co	-0.104	0.199	0.795		-0.121	-0.180	0.011	1.108		0.769
electric dryer	ed	-0.085	-0.039	1.039		0.329	-0.140	-0.165	1.253		0.835
freezer	fr	-0.005	-0.036	1.043		0.993	0.003	-0.011	1.004		0.994
other	ot	-0.081	0.362	0.631		0.429	-0.131	0.259	0.817		0.867
water heating	wh	-0.147	0.337	0.728		0.608	-0.246	0.052	1.178		0.956
	code	**a_cl**	**a_lt**	**a_re**	**a_ht**	**R_sq**	**a_cl**	**a_lt**	**a_re**	**a_ht**	**R_sq**
cooking	co	0.027	-0.222	0.823	0.278	0.317	-0.070	-0.660	1.406	0.319	0.979
electric dryer	ed	-0.007	-0.290	1.055	0.166	0.504	-0.064	-0.625	1.458	0.219	0.966
freezer	fr	0.001	-0.054	1.045	0.012	0.993	0.005	-0.025	1.011	0.007	0.994
other	ot	0.009	0.074	0.650	0.190	0.607	-0.047	-0.255	1.046	0.244	0.973
water heating	wh	-0.102	0.191	0.738	0.096	0.647	-0.200	-0.227	1.302	0.133	0.977

Figure 12 Comparison of original load shape data and model fits.



5 Discussion

The application of the reduced form NEMS-based model presented here proceeds in several steps:

1. Given a time series of site electricity savings, the corresponding generation reductions are estimated as the site savings times a transmission and distribution loss factor. (The national average T&D loss factor from AEO2012 is 1.0737 and is constant over time.)
2. For end-uses (cl, ht, lt, re) the coefficients presented here can be used to estimate the capacity, primary energy and emissions impacts directly for each year within the forecast period 2016-2035.
3. For other end-uses, first construct the appropriate weighted sum of response coefficients. For example, to estimate the marginal heat rate for end use *u*:

$$h'_u(p) = \sum_u \beta(u,v) h'_v(p)$$

   In this equation we have replaced the scenario index *K* with the end-use label *u*, with the understanding that the response coefficient is based on the ensemble average scenario for a given sector and end-use. These coefficients are presented in Appendix B. We recommend the use of the 3-period 3-variable model for commercial, and the 2-period 4-variable model for residential.

4. To produce a time-series estimate of the reductions in primary energy, the fraction of generation by fuel type, or emissions, multiply the generation savings in year *y* by the coefficient for the period that contains that year. These projected values can be summed over the analysis period to produce a cumulative total. To extrapolate these variables beyond 2035, we recommend using the response coefficients defined for the period 2031-2035.
5. Time series for capacity changes by fuel type can be obtained using the method outlined in Step 4. However, because capacity changes are cumulative, the interpretation of the response is somewhat different. The capacity to energy ratios in a given period represent the changes that would occur during that period if a program had *started* in period 1. For a program which starts in period p, the capacity changes can be estimated as the difference between period $p+j$ and period p for $j \leq 1$. Similarly, extrapolation beyond period 4 should be based on difference between the period 4 and period 3 coefficients. While this approach is approximate it should proivide a reasonable order of magnitude for the impacts outside the AEO forecast period. It is effectively a linearization of the capacity impacts; the roughly linear growth in capacity evident in the Hightech case (Figure 5) indicates that it is consistent with the way NEMS extrapolates trends in the later years of the forecast period.

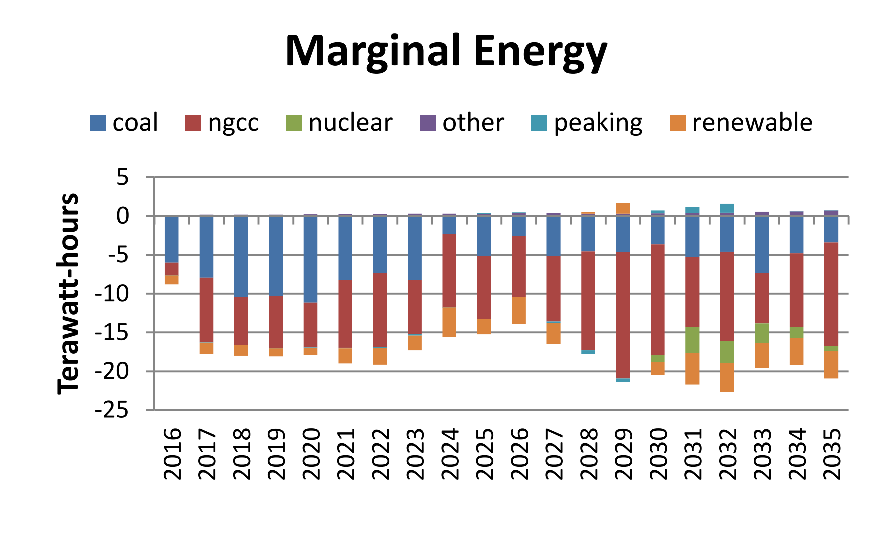
To reiterate, the response coefficients define annualized values for the changes in emissions, primary energy, capacity and composition of the generation reduction by fuel type, relative to a unit reduction in generation. For all quantities except capacity, these can be summed to define cumulative impacts over a given period. Capacity is already a cumulative measure. To use this approach for program start dates between 2012-2016, the period 1 coefficients for all variables except capacity can be used. We expect, based on NEMS internal logic, that period 1 capacity changes from programs which begin between 2012-2016 would be negligible, however for subsequent periods such changes may be estimated from the coefficients. This approach does *not* provide a method to back-cast impacts before 2012.

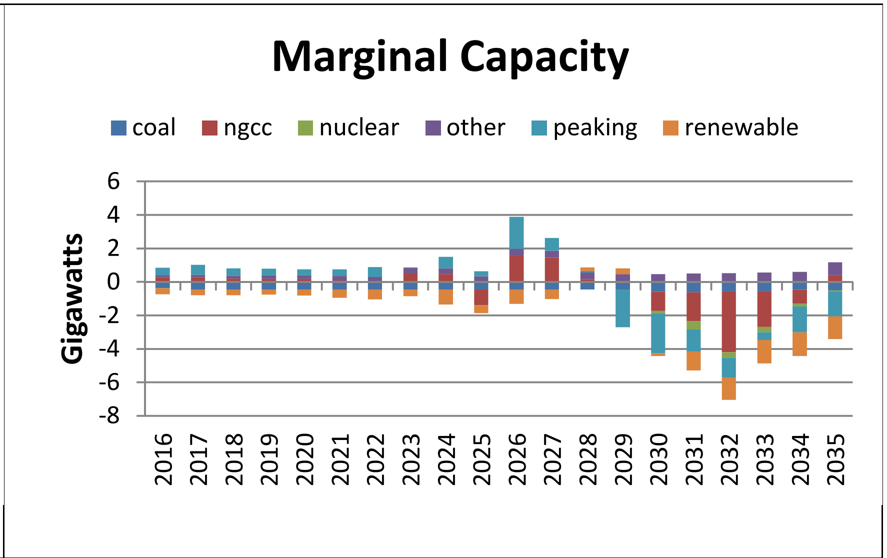
The reduced form NEMS-based methodology can be used to estimate electric power sector impacts of electricity demand reductions for any program or policy for which a projection of the demand reduction is known. This provides a relatively simple and transparent way to capture these potentially important impacts that is consistent with the EIA projections of the energy system published in the AEO. It is also straightforward to update the coefficients with each AEO edition.

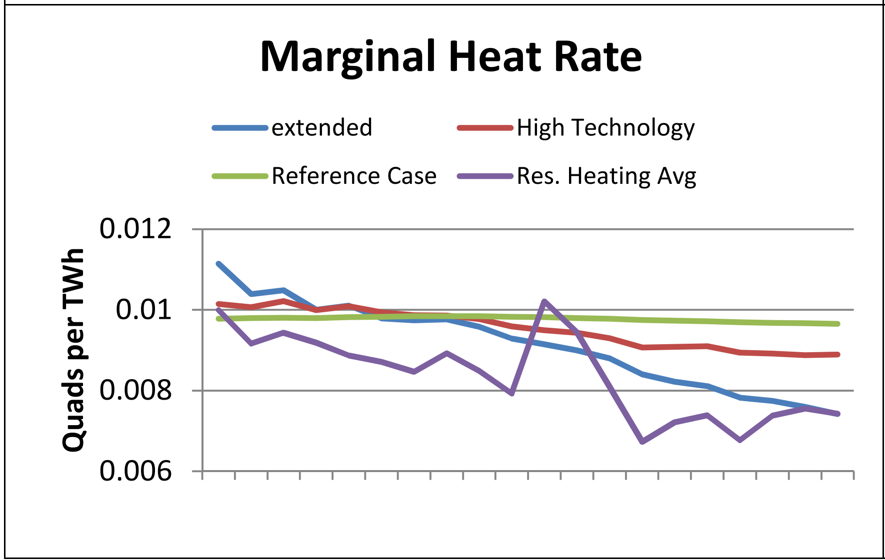
We have provided a brief discussion of some issues related to convergence and numerical noise in the results. Part 2 of this study will explore an alternative NEMS-based approach that may improve the convergence of the test scenarios. Continuing work will also attempt to estimate the magnitude of non-linear economic feed-backs as modeled by NEMS *vs*. the direct linear response. Finally, the impact of variation in the spatial pattern of electricity demand reductions will be investigated.

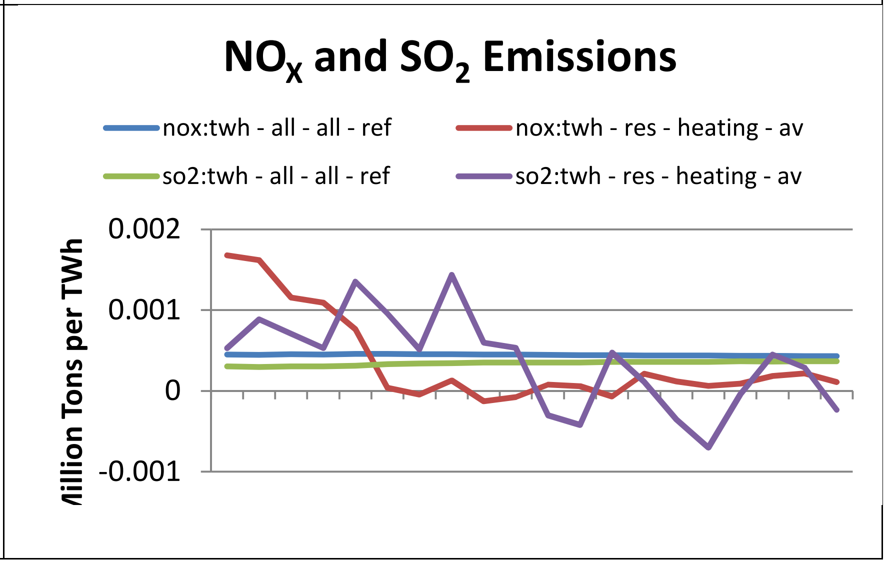
Appendix A: Summary output for 2016–2035

Residential Heating

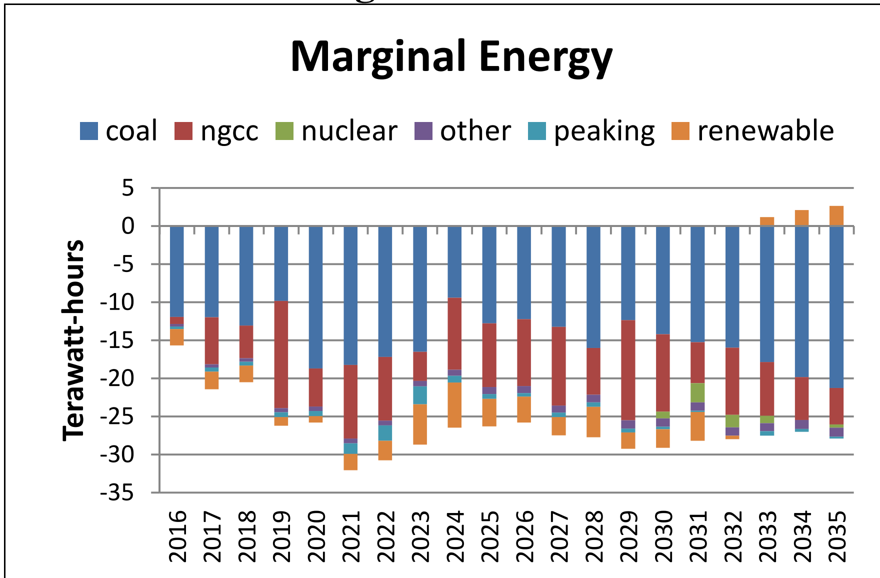


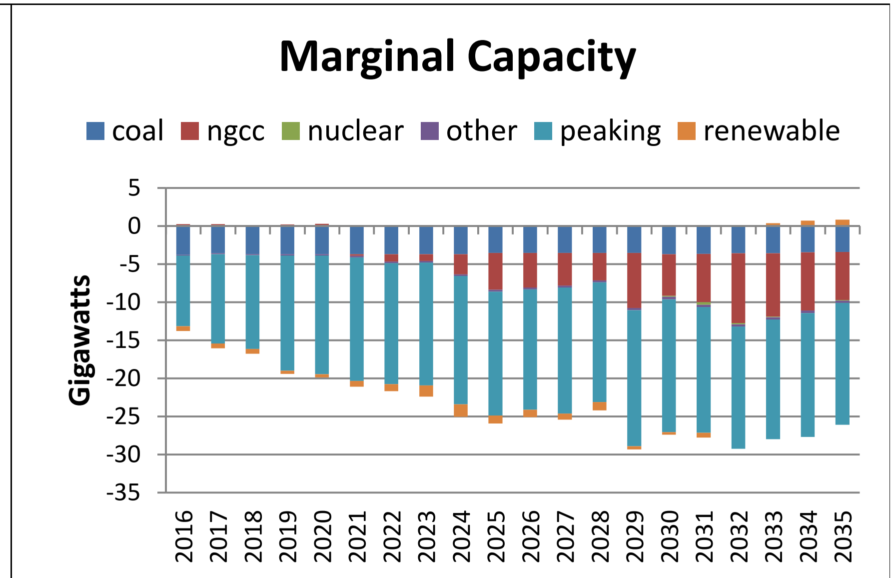


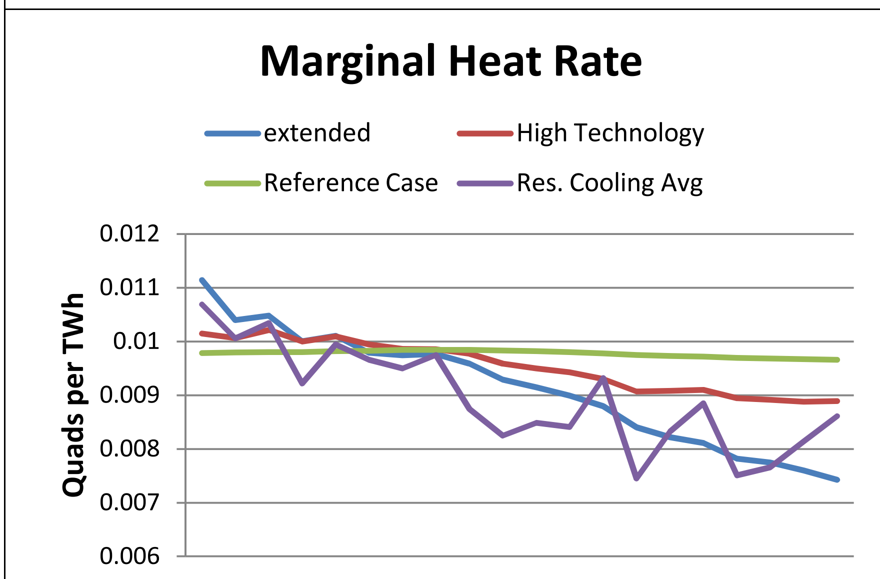


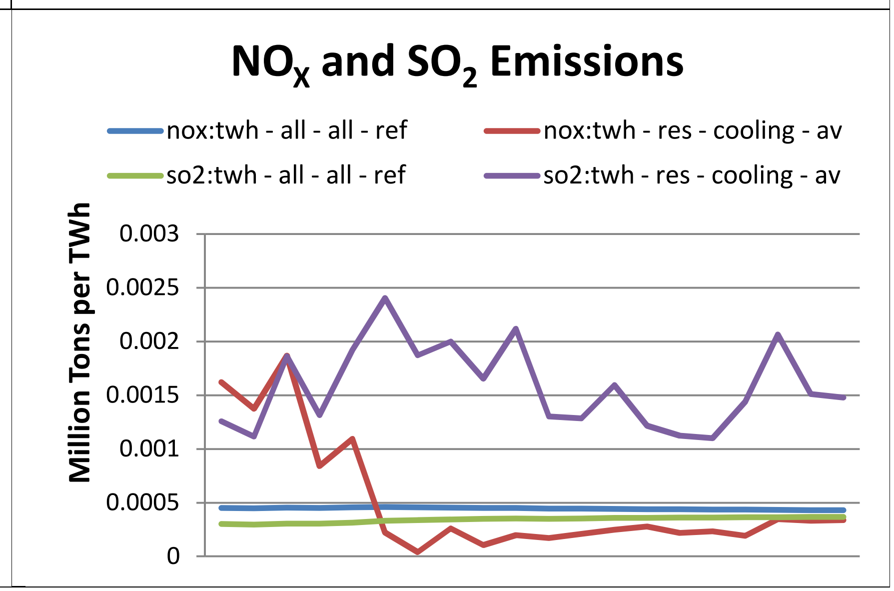


Residential Cooling

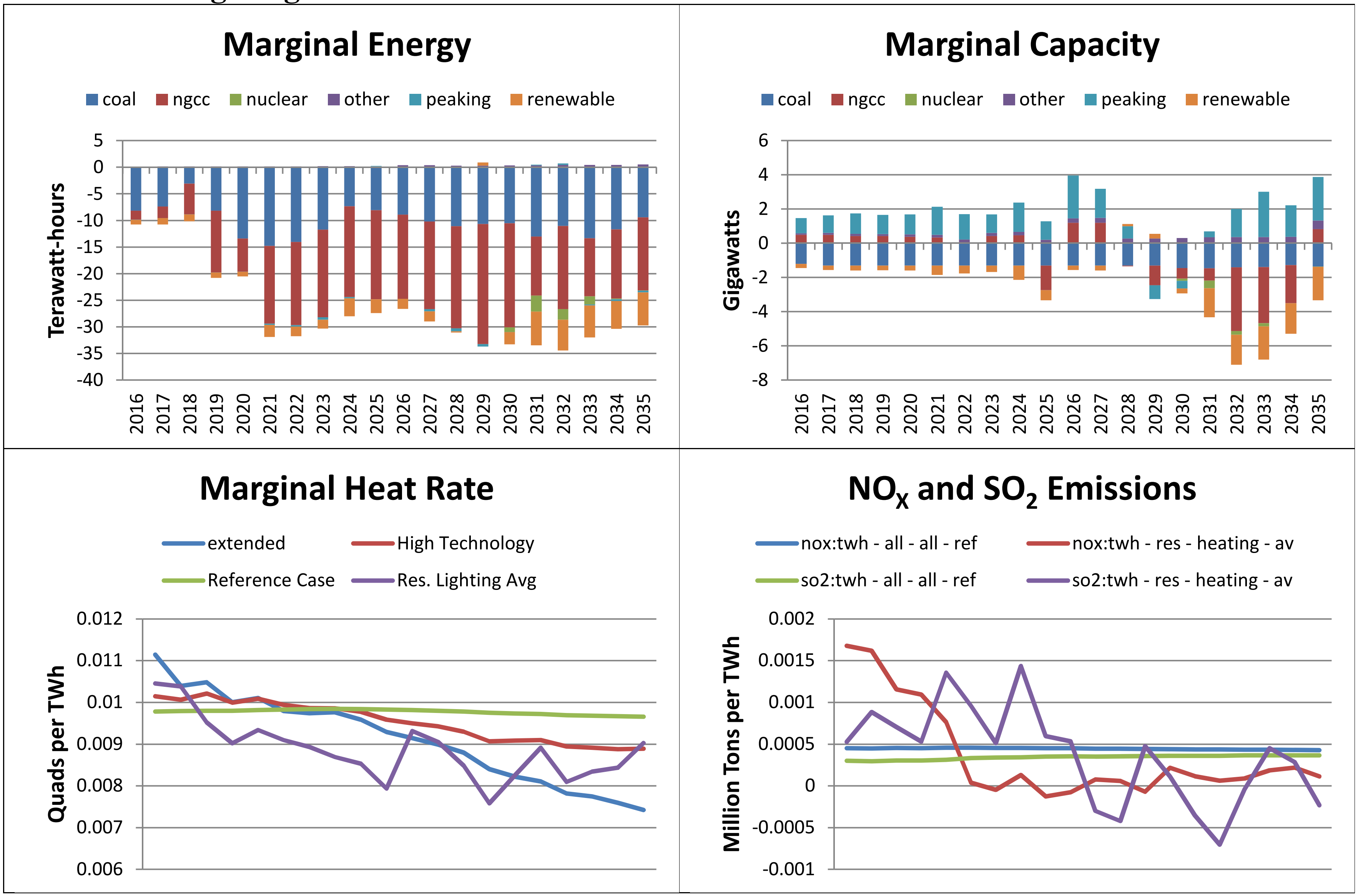




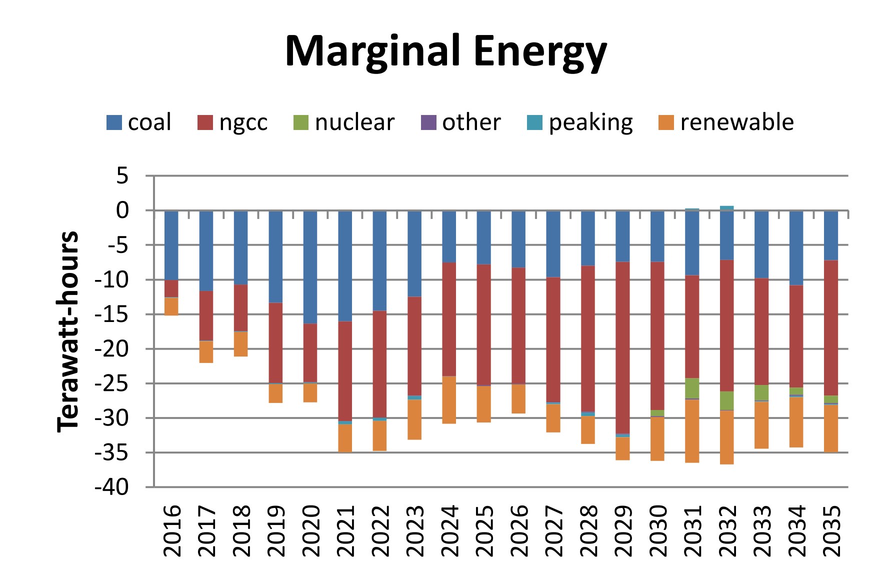


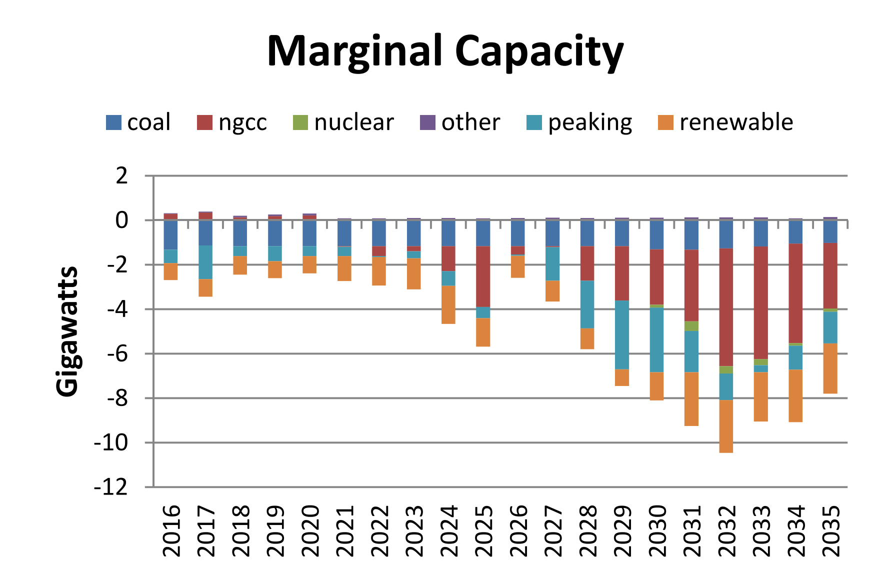


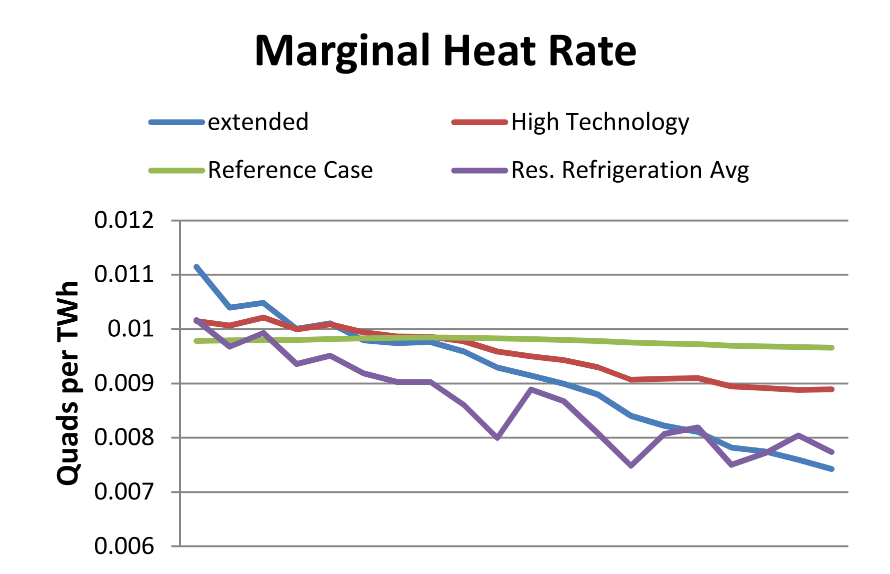
Residential Lighting

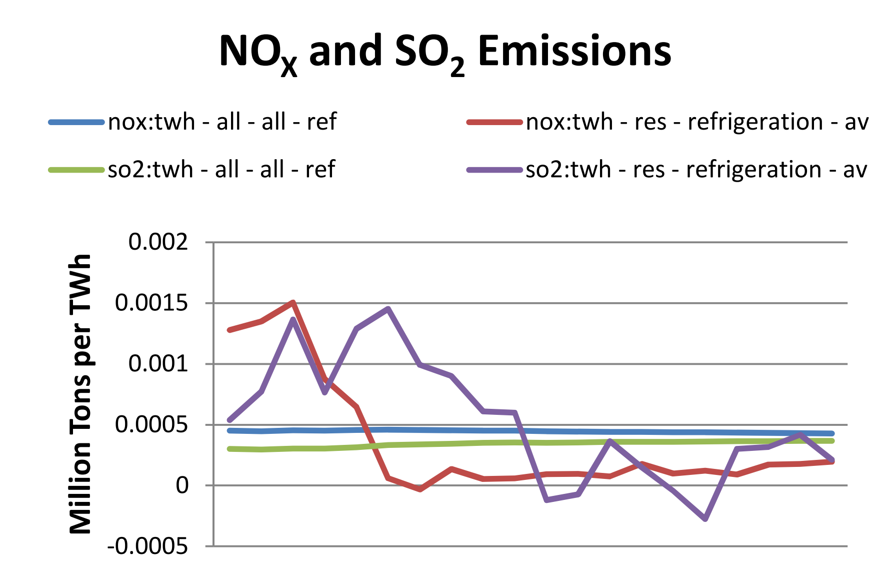


Residential Refrigeration

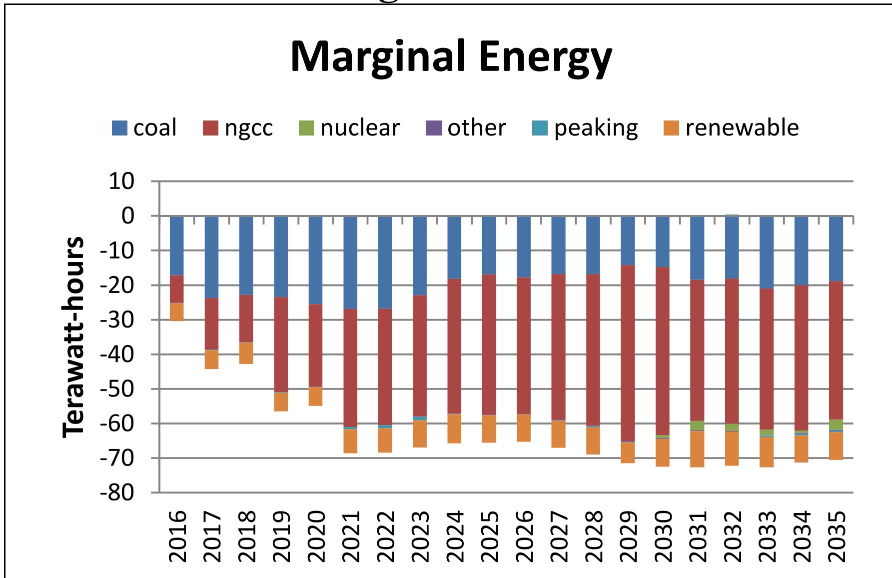


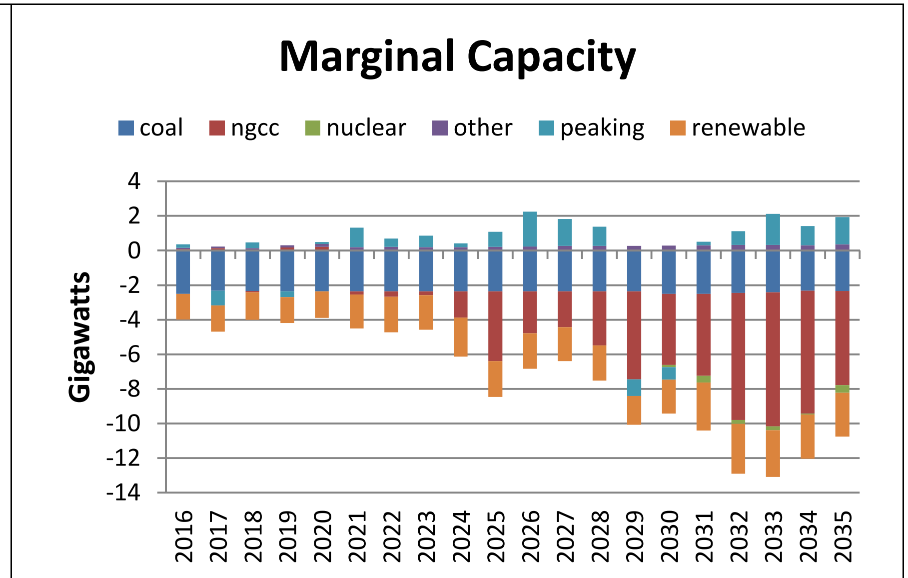


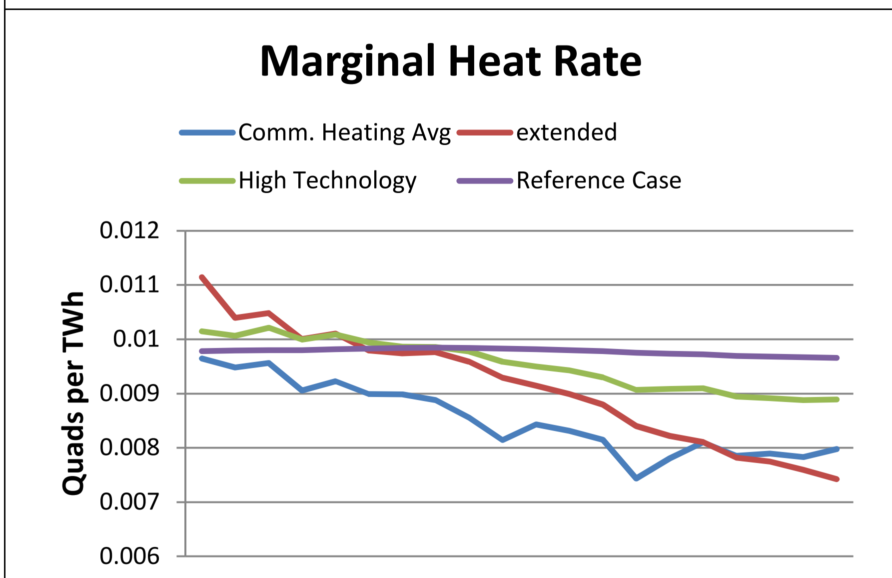


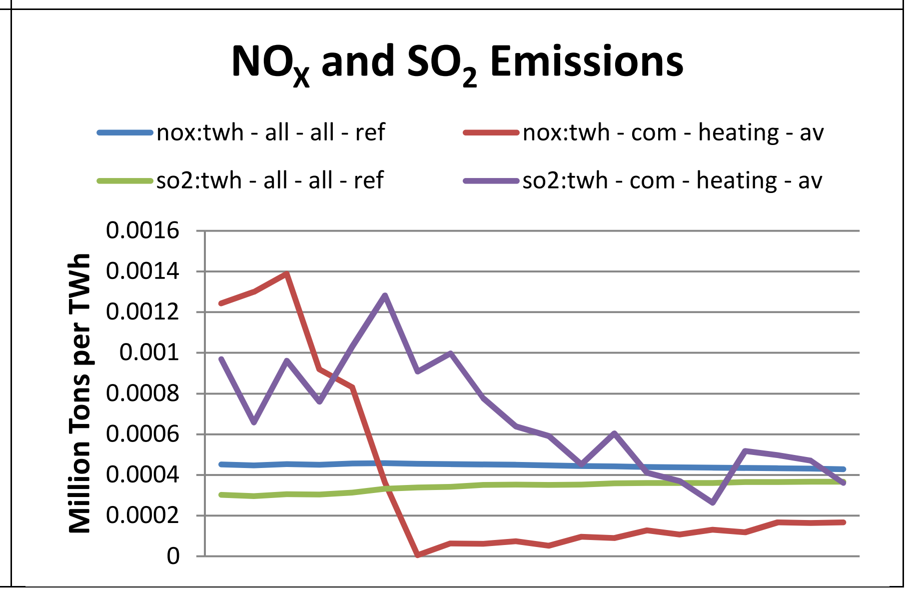


Commercial Heating

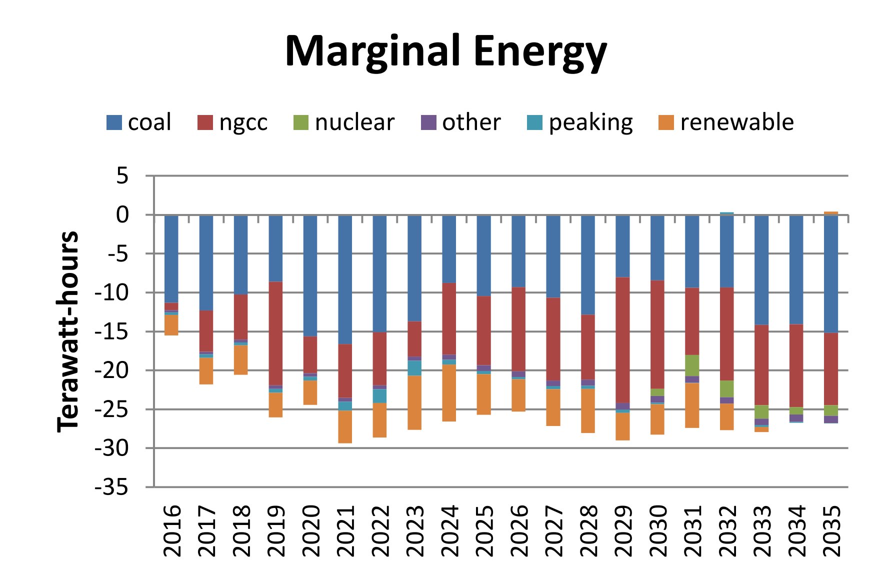


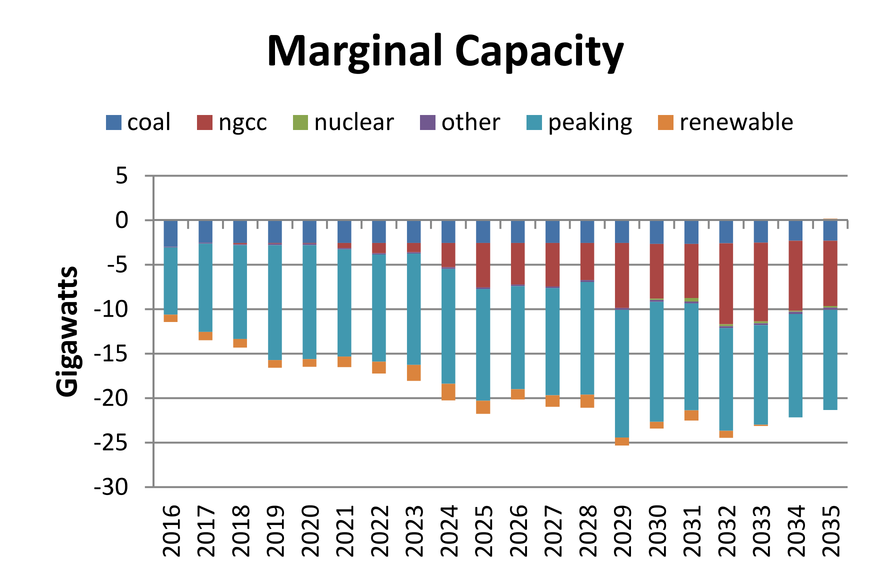


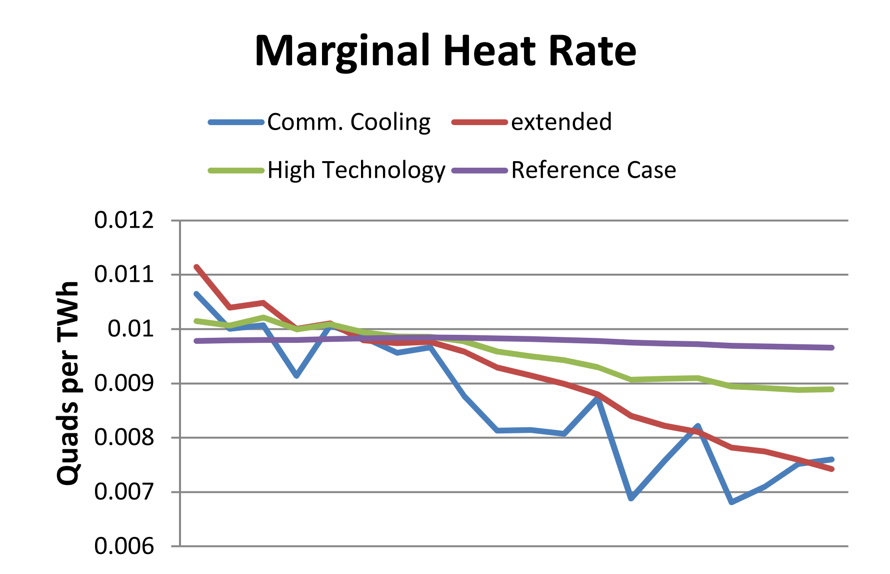


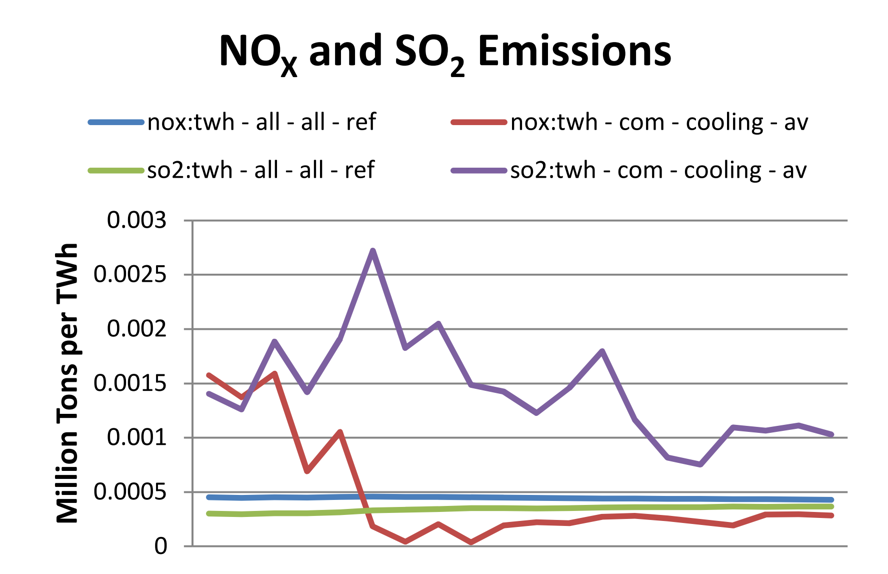


Commercial Cooling









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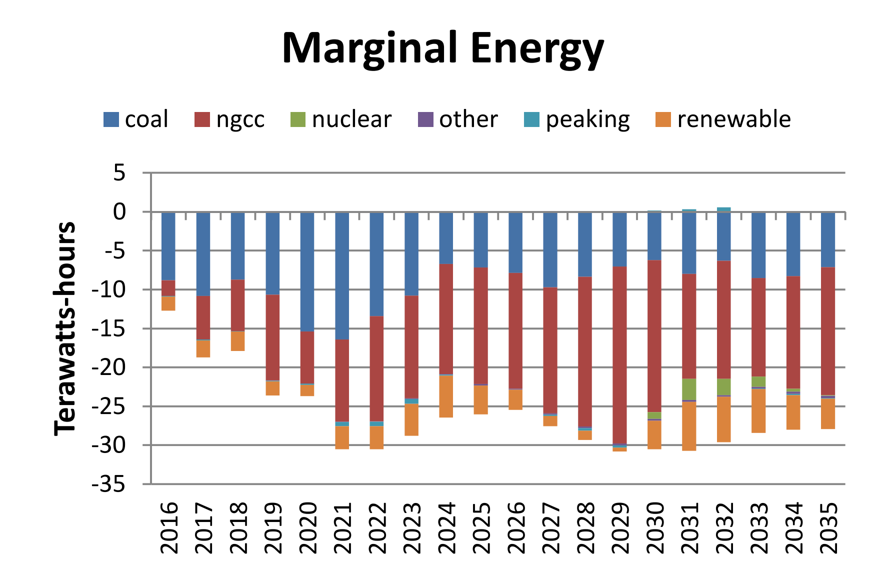
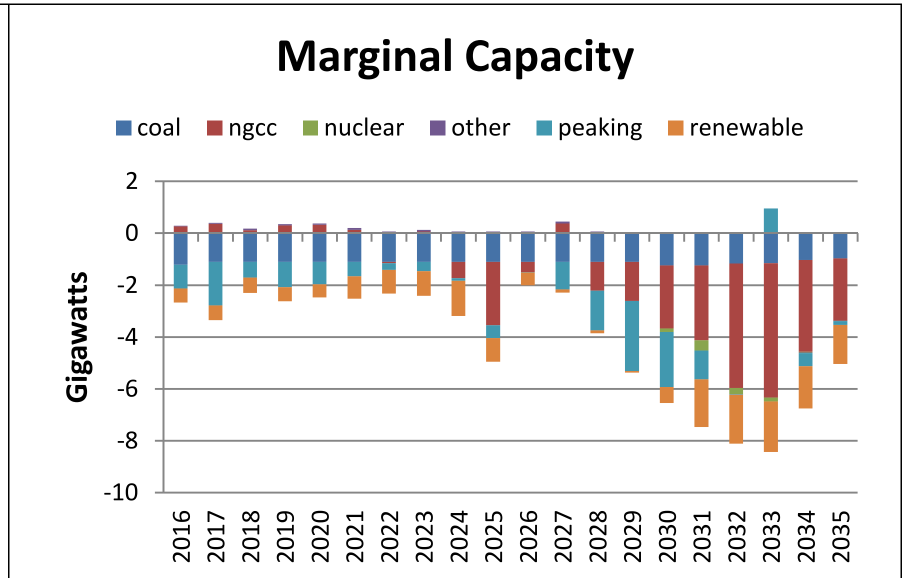
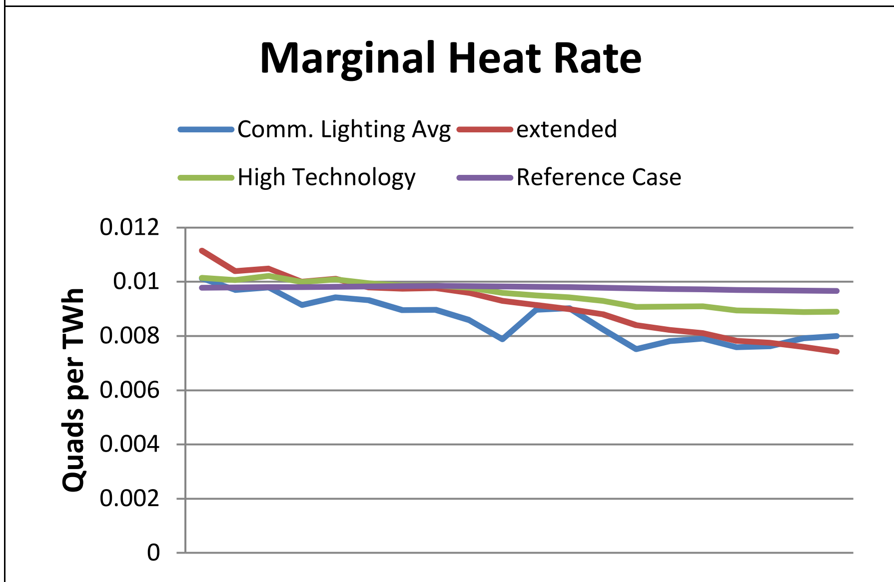
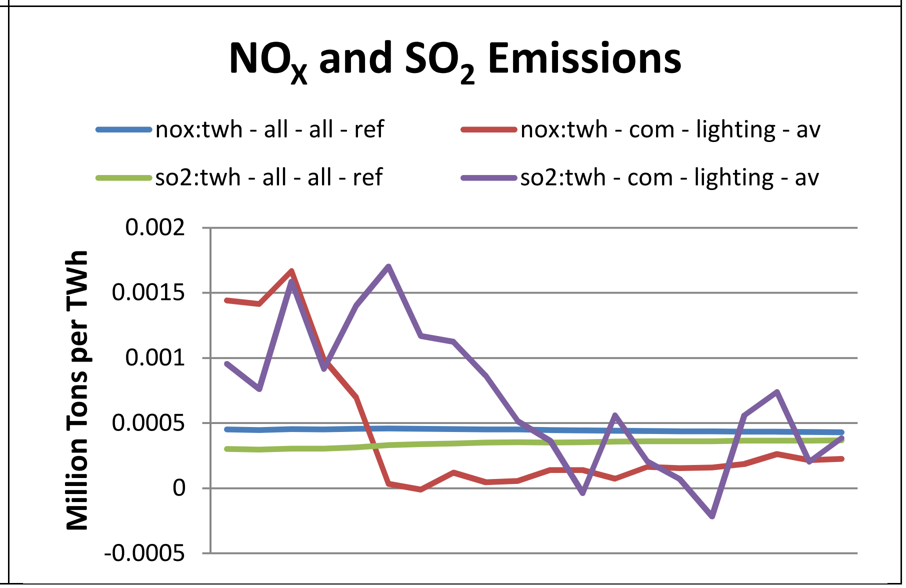
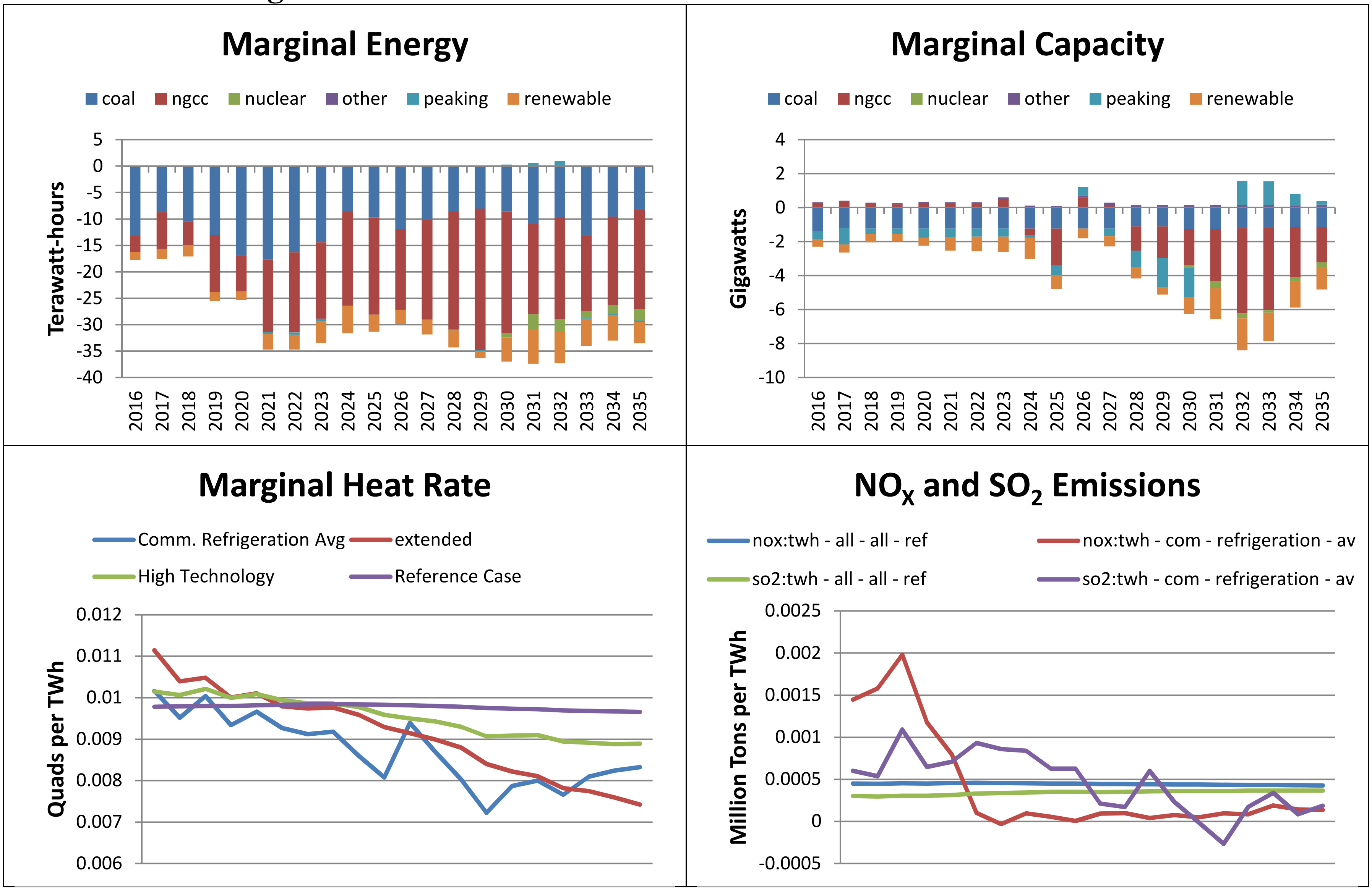




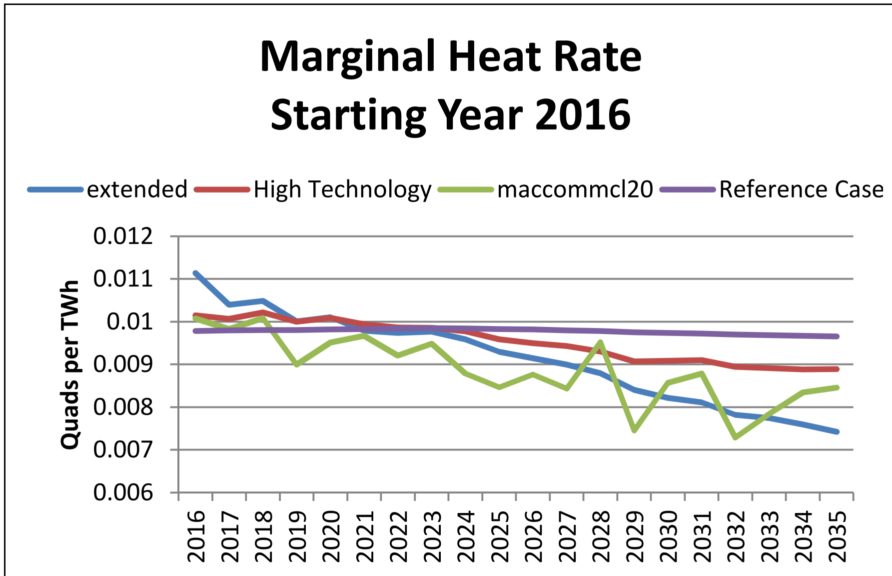


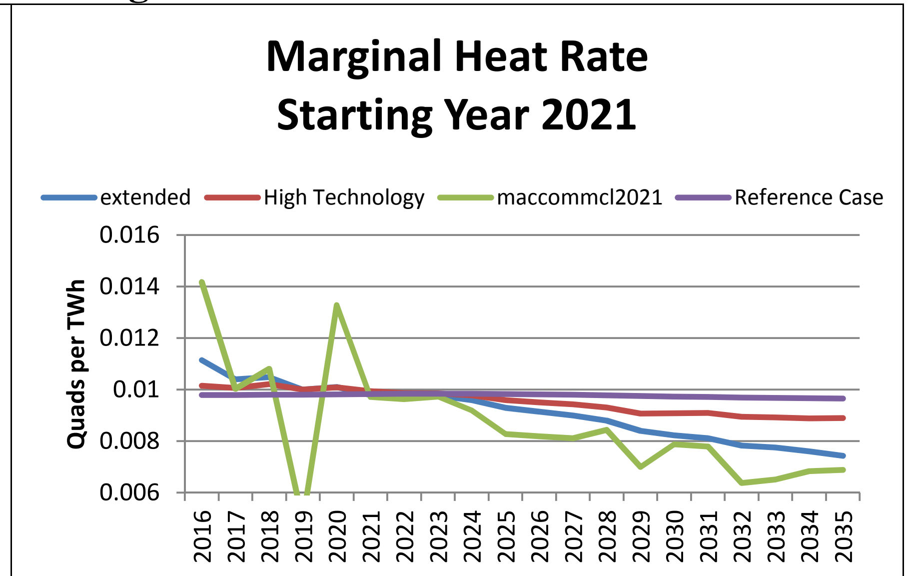


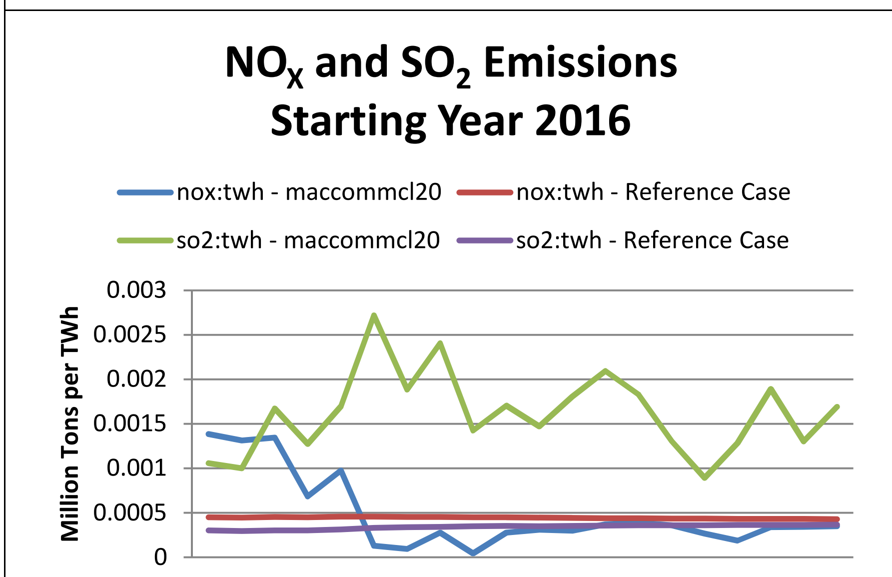
Commercial Refrigeration

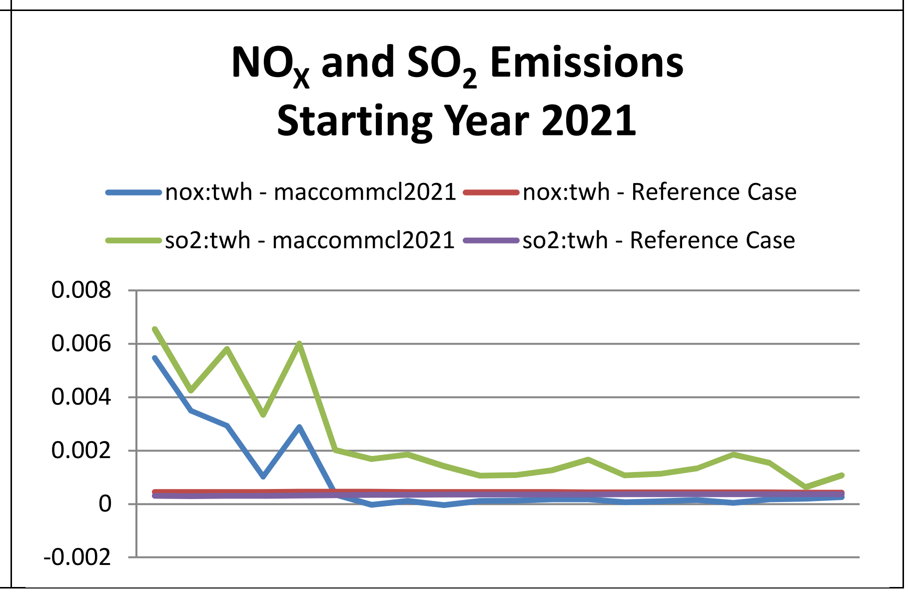


Start Year 2016 vs. 2021: Commercial Air Conditioning









Appendix B: Response Coefficients

Table 4 Capacity response coefficients by sector and end-use.

Capacity:Generation (GW/TWh)		Commercial				Residential			
end-use	**generation type**	**2016-2020**	**2021-2025**	**2026-2030**	**2031-2035**	**2016-2020**	**2021-2025**	**2026-2030**	**2031-2035**
cooling	coal	0.223	0.103	0.093	0.090	0.312	0.145	0.127	0.130
	nuclear	0.000	0.000	0.001	0.008	0.000	0.000	0.001	0.005
	ngcc	0.005	0.086	0.198	0.287	-0.018	0.075	0.177	0.278
	renewable	0.077	0.063	0.040	0.013	0.045	0.046	0.025	-0.010
	peaking	0.914	0.504	0.466	0.422	1.079	0.640	0.587	0.592
	other	0.011	0.007	0.007	0.008	0.012	0.009	0.010	0.011
	all	1.231	0.762	0.805	0.829	1.430	0.915	0.926	1.006
heating	coal	0.098	0.042	0.035	0.034	0.049	0.027	0.028	0.029
	nuclear	0.000	0.000	0.000	0.004	0.000	0.000	0.002	0.015
	ngcc	-0.004	0.022	0.049	0.092	-0.025	-0.001	-0.024	0.086
	renewable	0.062	0.037	0.028	0.038	0.040	0.035	0.013	0.072
	peaking	0.004	-0.012	-0.009	-0.016	-0.051	-0.025	0.022	0.065
	other	-0.005	-0.004	-0.004	-0.005	-0.020	-0.019	-0.025	-0.032
	all	0.155	0.085	0.101	0.148	-0.007	0.018	0.015	0.234
lighting	coal	0.110	0.046	0.040	0.039	0.183	0.059	0.045	0.045
	nuclear	0.000	0.000	0.001	0.006	0.000	0.000	0.001	0.005
	ngcc	-0.027	0.025	0.036	0.131	-0.063	0.002	-0.004	0.059
	renewable	0.054	0.042	0.010	0.061	0.038	0.025	0.003	0.059
	peaking	0.098	0.015	0.052	0.006	-0.154	-0.063	-0.025	-0.058
	other	-0.004	-0.003	-0.002	-0.001	-0.016	-0.008	-0.009	-0.012
	all	0.231	0.125	0.136	0.242	-0.012	0.015	0.011	0.098
refrigeration	coal	0.114	0.046	0.035	0.035	0.097	0.042	0.036	0.034
	nuclear	0.000	0.000	0.001	0.008	0.000	0.000	0.001	0.007
	ngcc	-0.024	0.012	0.028	0.105	-0.020	0.033	0.042	0.123
	renewable	0.042	0.034	0.020	0.048	0.065	0.049	0.029	0.068
	peaking	0.047	0.016	0.026	-0.022	0.061	0.014	0.059	0.034
	other	-0.006	-0.004	-0.004	-0.005	-0.005	-0.003	-0.003	-0.004
	all	0.173	0.104	0.106	0.170	0.198	0.134	0.163	0.262

Table 5 Heat rate and emissions response coefficients by sector and end-use.

Marginal Heat Rate/Emissions		Commercial				Residential			
end-use	**quantity**	**2016-2020**	**2021-2025**	**2026-2030**	**2031-2035**	**2016-2020**	**2021-2025**	**2026-2030**	**2031-2035**
cooling	heat rate (mbtu:kwh)	9.914	9.224	7.865	7.448	9.974	9.217	8.386	8.151
	SO2 (ton:GWh)	0.158	0.192	0.129	0.101	0.151	0.202	0.130	0.151
	Nox (ton:GWh)	0.121	0.013	0.025	0.026	0.131	0.017	0.023	0.029
	Hg (ton:PWh)	0.194	0.193	0.204	0.258	0.190	0.227	0.239	0.318
	CO2 (ton:GWh)	78.965	74.820	73.973	84.388	80.712	76.929	80.571	100.338
heating	heat rate (mbtu:kwh)	9.351	8.718	8.014	7.933	9.254	8.523	8.163	7.295
	SO2 (ton:GWh)	0.087	0.092	0.048	0.042	0.083	0.082	-0.009	-0.006
	Nox (ton:GWh)	0.110	0.011	0.010	0.015	0.121	-0.001	0.008	0.013
	Hg (ton:PWh)	0.179	0.133	0.121	0.144	0.093	0.167	0.122	0.107
	CO2 (ton:GWh)	76.496	66.858	59.329	60.985	75.154	65.142	73.814	74.003
lighting	heat rate (mbtu:kwh)	9.567	8.769	8.277	7.805	9.589	8.660	8.492	8.555
	SO2 (ton:GWh)	0.113	0.110	0.023	0.033	0.094	0.076	0.021	0.036
	Nox (ton:GWh)	0.119	0.005	0.013	0.021	0.147	0.009	0.027	0.042
	Hg (ton:PWh)	0.185	0.151	0.124	0.141	0.124	0.120	0.135	0.302
	CO2 (ton:GWh)	78.514	68.151	69.860	74.410	78.021	63.398	74.927	82.189
refrigeration	heat rate (mbtu:kwh)	9.708	8.867	8.187	8.056	9.669	8.789	8.204	7.835
	SO2 (ton:GWh)	0.071	0.078	0.024	0.010	0.097	0.093	0.006	0.019
	Nox (ton:GWh)	0.133	0.005	0.007	0.013	0.108	0.005	0.011	0.015
	Hg (ton:PWh)	0.199	0.152	0.132	0.160	0.187	0.161	0.137	0.128
	CO2 (ton:GWh)	82.552	68.631	65.065	67.757	80.699	69.503	67.363	67.303

Appendix C: List of Fields Extracted from AEO Tables

Table 6 List of fields extracted from AEO tables.

Table ID	Table Name	Quantity	Units
2	Energy Consumption by Sector and Source : Energy Use : Electric Power	Liquid Fuels	Quadrillion BTUs (quads)
		Natural Gas	
		Steam Coal	
		Nuclear	
		Renewable Energy	
		Electricity Imports	
59	Electricity Generating Capacity Electricity and Generation by Plant Type and Technology : Electricity : Electric Power	Coal	GW Billion kWh
		Oil and Natural Gas Steam	
		Combined Cycle	
		Combustion Turbine/Diesel	
		Nuclear Power	
		Pumped Storage	
		Fuel Cells	
		Renewable Sources	
		Distributed Generation	
62	Electric Power Projections for EMM Region : Electricity : Emissions	Mercury (Hg)	Tons
		Sulfur Dioxide	Million Tons
		Nitrogen Oxide	
		Carbon Dioxide	

Appendix D: AEO 2012 Code Changes

Commercial Module (comm.f) of NEMS

Definition of Variables

In the Consumption modeling subroutine (COMConsumption), insert the following codes at the end of the variable definition section.

```
!--- LBNL addition: common block definitions
      REAL*4 drC           !-- fractional decrement by Census Region and year
      REAL*4 SumDecrC(MNumCr-2,MNUMYR)    !-- decrement for commercial end-use by
Census Region and year
      REAL*4 ConsumpSum, DecrSum
      COMMON /LBLCAC1/ drC(MNumCr-2,MNUMYR)
!--- LBNL end addition
```

Decrement for End-Use Consumption

In the Consumption modeling subroutine (COMConsumption), find the following lines:

```
!  Aggregate national total across buildings for FTAB:
      DO s= 1, CMnumDHServ
       DO f= 1, CMnumMajFl
        CMUSDistServ (s,f,CURIYR)= 0.0
        DO b= 1, CMnumBldg
         CMUSDistServ (s,f,CURIYR)= CMUSDistServ (s,f,CURIYR) &
           + DistServConsump (MNUMCR,b,s,f,CURIYR) / 1000.0 ! Quads
        END DO ! b
       END DO  ! f
      END DO   ! s
```

Then insert the following codes immediately following the above lines:

```
!---  LBNL START
!     Decrement for Commerical Electricity Cooling
!     Fuel: Electricity=1
!     End-Use Service: 1 space heating, 2 space cooling, 3 water heating,
!     4 ventilation, 5 cooking, 6 lighting, 7 refrigeration,
!     8 office equipment - PCs, 9 office equipment - other than PCs, 10 other

!     --- Year (y) starts from 2016
!     --- drC(r,y) is fraction of total electricity consumption for commercial
end-use decremented in region r for year y
      IF (Y.GE.27) THEN
        ConsumpSum=0
        DO r = 1,MNumCr-2
          DO b = 1, CMnumBldg
            ConsumpSum = ConsumpSum + EndUseConsump(1,2,b,r,y) !calculate total
electricity consumption for the end-use in the current year
          END DO
        END DO
        DecrSum=33/293.071*1000 !33 twh annual decrement from 2016 to 2040 (the
unit for residential is MMBtu and for commercial is Trillion Btu)
        DO r = 1,MNumCr-2
          SumDecrC(r,y)=0
          drC(r,y)= DecrSum/ConsumpSum
!      --- Apportion decrement to consumption for all building types
          DO b=1, CMnumBldg
```

```
            SumDecrC(r,y)=SumDecrC(r,y) + EndUseConsump(1,2,b,r,y) * drC(r,y)
            EndUseConsump(1,2,b,r,y) = EndUseConsump(1,2,b,r,y) * (1-drC(r,y))
          END DO
          !--- Output file fort.91: current iteration, year, census region,
commercial decrement
          WRITE(91,*) CURITR, y+1989, r, SumDecrC(r,y)
        END DO
      END IF
!---  END LBNL
```

The above codes are for commercial electricity space cooling consumption with an annual decrement of 33 TWh for the years 2016-2040.

For other end uses , just replace EndUseConsump(1,2,b,r,y) with EndUseConsump(1,s,b,r,y), while s=1 for Space Heating, s=2 for Space Cooling, s=6 for Lighting, and s=7 for Refrigeration.

For other decrement start years, just replace (Y.GE.27) with (Y.GE.iyear), while iyear=26 for 2015, 28 for 2017, 30 for 2019, and 32 for 2021 (NEMS numbers the year 1990 as the first year).

The annual decrement 33 TWh can also be changed according to experiment settings.

Residential Module (resd.f) of NEMS

Definition of Variables

In the end-use consumption subroutine, insert the following codes at the end of the variable definition section. The Cooling Consumption Subroutine is RCLCON. The Heating Consumption Subroutine is RHTRCON. The Lighting Consumption Subroutine is LTCNS. The Refrigeration Consumption Subroutine is RREFCON.

```
!--- LBNL addition: common block definitions
      REAL*4 drR             !-- fractional decrement by Census Region and year
      REAL*4 SumDecrR(MNumCr-2,MNUMYR)   !-- decrement for residential cooling by
Census Region and year
      REAL*4 ConsumpSum, DecrSum
      COMMON /LBLCAC4/ drR(MNumCr-2,MNUMYR)
!--- LBNL end addition
```

Decrement for Cooling Consumption

At the end of the Cooling Consumption Subroutine (RCLCON), insert the following codes:

```
!---  LBNL START
!     Decrement for Residential Electricity Space Cooling
!     CONSUMPTION FUEL 1=Electricity 2=Geothermal 3=Gas

!     --- Year starts from 2016
!     --- drR(d,curiyr) is fraction of total electricity consumption for
residential space cooling decremented in region d for year curiyr
      IF (curiyr.GE.27) THEN
        ConsumpSum=0
        DO d = 1,MNumCr-2
          ConsumpSum=ConsumpSum+coolcn(curiyr,1,d) !calculate total electricity
consumption for this end-use in the current year
        END DO
        DecrSum=32/293.071*1000000000 !32 twh annual decrement from 2016 to 2040
(the unit for residential is MMBtu and for commercial is Trillion Btu)
```

```
        DO d = 1,MNumCr-2
          drR(d,curiyr)=DecrSum/ConsumpSum
          SumDecrR(d,curiyr)=coolcn(curiyr,1,d) * drR(d,curiyr)
          !--- Output file fort.92: current iteration, year, census region,
residential cooling decrement
          WRITE(92,*) CURITR, curiyr+1989, d, SumDecrR(d,curiyr)
          coolcn(curiyr,1,d)=coolcn(curiyr,1,d)*(1-drR(d,curiyr))
        END DO
      END IF
!---  END LBNL
```

The above codes are for residential electricity cooling consumption with an annual decrement of 32 TWh for the years 2016-2040.

For other decrement start years, just replace (curiyr.GE.27) with (curiyr.GE.iyear), while iyear=26 for 2015, 28 for 2017, 30 for 2019, and 32 for 2021 (NEMS numbers the year 1990 as the first year).

The annual decrement 32 TWh can also be changed according to experiment settings.

Decrement for Heating Consumption

At the end of the Heating Consumption Subroutine (RHTRCON), insert the following codes:

```
!---  LBNL START
!*******************************************************************
!  F    = FUEL NUMBER FROM RTEKCL FILE
!  FCON = FUEL NUMBER FOR CONSUMPTION AND DIAMONDS (AS FOLLOWS)
!          1=NG 2=El 3=DIS 4=LPG 5=Ker 6=Wood 7=GEOTHERMAL
!*******************************************************************
!     Decrement for Residential Heating Electricity
!     --- Year starts from 2016
!     --- drR(d,curiyr) is fraction of total electricity consumption for
residential heating decremented in region d for year curiyr
      IF (curiyr.GE.27) THEN
        ConsumpSum=0
        DO d = 1,MNumCr-2
          ConsumpSum=ConsumpSum+HTRCON(CURIYR,2,d) !calculate total electricity
consumption for this end-use in the current year
        END DO
        DecrSum=16/293.071*1000000000 !16twh annual decrement from 2016 to 2040
(the unit for residential is MMBtu and for commercial is Trillion Btu)
        DO d = 1,MNumCr-2
          drR(d,curiyr)=DecrSum/ConsumpSum
          SumDecrR(d,curiyr)=HTRCON(CURIYR,2,d) * drR(d,curiyr)
          !--- Output file fort.92: current iteration, year, census region,
residential cooling decrement
          WRITE(92,*) CURITR, curiyr+1989, d, SumDecrR(d,curiyr)
          HTRCON(CURIYR,2,d)=HTRCON(CURIYR,2,d)*(1-drR(d,curiyr))
        END DO
      END IF
!---  END LBNL
```

The above codes are for residential electricity heating consumption with an annual decrement of 16 TWh for the years 2016-2040.

For other decrement start years, just replace (curiyr.GE.27) with (curiyr.GE.iyear), while iyear=26 for 2015, 28 for 2017, 30 for 2019, and 32 for 2021 (NEMS numbers the year 1990 as the first year).

The annual decrement 16 TWh can also be changed according to experiment settings.

Decrement for Lighting Consumption

At the end of the Lighting Consumption Subroutine (LTCNS), insert the following codes:

```
!---  LBNL START
!     Decrement for Residential Lighting Electricity
!     --- Year starts from 2016
!     --- drR(d,curiyr) is fraction of total electricity consumption for
residential lighting decremented in region d for year curiyr
!     In this subroutine ltcns, y=curiyr
      IF (curiyr.GE.27) THEN
        ConsumpSum=0
        DO d = 1,MNumCr-2
          ConsumpSum=ConsumpSum+ltcon(CURIYR,d) !calculate total electricity
consumption for this end-use in the current year
        END DO
        DecrSum=30/293.071*1000000000 !30twh annual decrement from 2016 to 2040
(the unit for residential is MMBtu and for commercial is Trillion Btu)
        DO d = 1,MNumCr-2
          drR(d,curiyr)=DecrSum/ConsumpSum
          SumDecrR(d,curiyr)=ltcon(CURIYR,d) * drR(d,curiyr)
          !--- Output file fort.92: current iteration, year, census region,
residential cooling decrement
          WRITE(92,*) CURITR, curiyr+1989, d, SumDecrR(d,curiyr)
          ltcon(CURIYR,d)=ltcon(CURIYR,d)*(1-drR(d,curiyr))
        END DO
      END IF
!---  END LBNL
```

The above codes are for residential electricity lighting consumption with an annual decrement of 30 TWh for the years 2016-2040.

For other decrement start years, just replace (curiyr.GE.27) with (curiyr.GE.iyear), while iyear=26 for 2015, 28 for 2017, 30 for 2019, and 32 for 2021 (NEMS numbers the year 1990 as the first year).

The annual decrement 30 TWh can also be changed according to experiment settings.

Decrement for Refrigeration Consumption

At the end of the Refrigeration Consumption Subroutine (RREFCON), insert the following codes:

```
!---  LBNL START
!     Decrement for Residential Refrigeration Electricity
!     --- Year starts from 2016
!     --- drR(d,curiyr) is fraction of total electricity consumption for
residential refrigeration decremented in region d for year curiyr
      IF (curiyr.GE.27) THEN
        ConsumpSum=0
```

```
        DO d = 1,MNumCr-2
          ConsumpSum=ConsumpSum+REFCON(CURIYR,d) !calculate total electricity
consumption for this end-use in the current year
        END DO
        DecrSum=33/293.071*1000000000 !33twh annual decrement from 2016 to 2040
(the unit for residential is MMBtu and for commercial is Trillion Btu)
        DO d = 1,MNumCr-2
          drR(d,curiyr)=DecrSum/ConsumpSum
          SumDecrR(d,curiyr)=REFCON(CURIYR,d) * drR(d,curiyr)
          !--- Output file fort.92: current iteration, year, census region,
residential cooling decrement
          WRITE(92,*) CURITR, curiyr+1989, d, SumDecrR(d,curiyr)
          REFCON(CURIYR,d)=REFCON(CURIYR,d)*(1-drR(d,curiyr))
        END DO
      END IF
!---  END LBNL
```

The above codes are for residential electricity refrigeration consumption with an annual decrement of 33 TWh for the years 2016-2040.

For other decrement start years, just replace (curiyr.GE.27) with (curiyr.GE.iyear), while iyear=26 for 2015, 28 for 2017, 30 for 2019, and 32 for 2021 (NEMS numbers the year 1990 as the first year).

The annual decrement 33 TWh can also be changed according to experiment settings.

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