Demand response: A carbon-neutral resource?

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ABSTRACT

Recent literature on demand response raises questions about the long-term capacity and carbon emissions impacts of expanding its deployment. To provide economy-wide insights into how demand response, capacity planning, and carbon emissions might interact in the future, we perform economic forecasts using a computational general equilibrium model based on the Energy Information Administration's National Energy Modeling System. We develop multiple scenarios of assumptions about the load-shifting and load reduction potential of demand response based on prior literature. The results of these scenarios suggest that demand response can defer large amounts of peak capacity construction. Contrary to expectations of increased carbon intensity, the results of our scenarios also suggest that demand response will have little impact on overall carbon emissions from electric power generation. This suggests that demand response can serve as a long-term, low-cost alternative for peak-hour load balancing without increasing carbon emissions.

Keywords:

- 1. Demand Response**
- 2. Electric Power**
- 3. Carbon Dioxide Emissions**
- 4. Load Management**

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1. Introduction

Demand response (DR) refers to programs that incentivize electric power customers to change their patterns of consumption (Kathan et al., 2012). DR has been used extensively in industrial and commercial sectors since the 1970s, but today's DR is being transformed by technology and market innovations. Wholesale markets are incentivizing DR to participate in markets, smart grid technologies and dynamic pricing are enabling faster and better control of DR resources, and increasingly system aggregators are enabling smaller entities to participate. Many agree that DR can, on the one hand, reduce daily peak loads and contribute to system reliability, and on the other hand, reduce the cost of electricity supply. DR's impact on carbon emissions, by contrast, is less well understood.

The limited understanding of the emissions impacts of DR is especially noteworthy considering the attention given to the long-term impacts of DR and related energy policies. Recent work focuses on the potential for DR to enable renewable electricity resources (see Aghaei and Alizadeh 2013 for a review). But the broader issue of the role of DR in a carbon-constrained future has received little attention.

This paper's goal is to illuminate the role of DR in a carbon-constrained future. To achieve this goal, we use a scenario modeling approach that covers the entire US energy economy and multiple possibilities for DR program implementation. We also use regression analysis to elucidate further insights from the scenario analysis. Specifically, this paper characterizes the capacity and emissions consequences of DR at highly aggregated levels, at large scales of DR deployment, and over an extended planning horizon. Given trends of increasing DR utilization in the U.S. (and globally), what should we expect the capacity and emissions impacts of DR programs to be? Based on the findings from the literature reviewed below, we anticipate that in the short run, increasing DR deployment will increase carbon

dioxide emissions by shifting demand from relatively less-carbon-intensive peak capacity to relatively more-carbon-intensive non-peak capacity. The likely effects on CO₂ emissions in the long term are more difficult to forecast.

The paper is organized as follows. Section 2 provides a review of literature surrounding the environmental impacts of DR. Section 3 outlines our research design and the scenario modeling approach used. The results of the scenario modeling approach are presented in Section 4. In turn, Section 5 presents the methodology and results from our regression analysis, applied to the results of the scenario modeling approach. Section 6 provides conclusions.

2. The Environmental Attributes of DR: A Review of the Literature

While DR has been demonstrated to induce energy savings through load shaving (Gottwalt et al. 2011, Gilbraith and Powers 2013) and enable low-carbon renewable capacity (Algahei and Alizadeh 2013; Kiliccote et al. 2012; Ma et al. 2013), shifting load from peak to off-peak periods could increase carbon emissions from baseload (Goldman et al. 2010) and distributed backup generation. In contrast, the ability of DR to defer construction of peak capacity (Heffner 2010; De Castro and Dutra 2011; NYISO 2007) may constitute a strategic option for reducing emissions. If near-term peak capacity options are more carbon-intensive, utility planners may reduce emissions by using DR to defer construction of peak capacity until less carbon-intensive peak capacity options are available.

The review by Aghaei and Alizadeh (2013) underscores the potential for DR to fundamentally change grid fuel mix by enabling intermittent forms of renewable capacity, particularly wind and solar. Noteworthy examples from this stream of research include Falsafi, Zakariazadeh, and Jadid (2014), Sioshansi and Short (2009), Roscoe and Ault (2010), Klobasa (2010). The US Department of Energy has given serious attention to this possibility by re-conceptualizing DR as “Flexible Response” - load that can be manipulated to serve a variety of purposes, including balancing renewable generation (Ma, et al. 2013). Response-automation technologies such as AutoDR show great promise for enabling renewable capacity in work by Lawrence Berkeley National Laboratory’s Demand Response Research Center (Kiliccote et al. 2012; Kiliccote et al. 2010; Watson, et al. 2012). Impacts on capacity types other than renewable

resources have also been mentioned in more general DR papers. The DR valuation framework proposed by Grayson Heffner proposes that, in the long-term, DR could defer peak capacity builds used to meet reserve requirements (Heffner, 2010: Appendix A). This long-term capacity avoidance could translate to a benefit for customers in the form of reductions in rates. De Castro and Dutra (2011) argue that DR-induced capacity avoidance could be significant enough to inspire political opposition from industries providing peak capacity and its related fuels.

Beyond impacts to capacity, researchers have begun to examine the emissions impacts of DR. Goldman et al. (2010) argue that the effects of DR on emissions remain ambiguous, and that there is a serious possibility that DR will increase emissions from the electric power sector. This provides motivation for merging EE and DR programs in order to pair reliability benefits of DR with emissions benefits of EE (Goldman et al. 2010). Conversely, Gilbraith and Powers (2013) use the GE-MAPS simulation model to suggest favorable environmental outcomes from expanded DR, arguing that a real-time pricing (RTP) program would likely reduce greenhouse gas emissions in New York City. This study explores the uncertainty of the long-term CO₂ emissions impacts of DR in the US. We expand on these research themes and extend the work of Baek and Hadley (2012), who modeled the effects of DR on power plant dispatch, but ignored the uncertainties of load shifting and the deferral of peak capacity investment over a multi-year period. We create sensitivities in order to test the influence of certain characteristics of DR on CO₂ emissions, and we draw attention to DR's impacts on various forms of capacity.

3. Research Design

GT-NEMS is the tool used to generate the scenarios analyzed in this study. GT-NEMS is a computational general equilibrium (CGE) model based on the 2013 distribution of the Energy Information Administration (EIA)'s National Energy Modeling System, which generated EIA's 2013 Annual Energy Outlook (EIA 2013a). The Annual Energy Outlook forecasts energy supply and demand for the U.S. through 2040. Other than modifications necessary to operate the National Energy Modeling System model on networked servers at the Georgia Institute of Technology, GT-NEMS is equivalent to the National Energy Modeling System. GT-NEMS is

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thus documented by way of reference to the documentation for the National Energy Modeling System.

GT-NEMS is a computational model based on microeconomic general equilibrium theory. Linear programming algorithms and other optimization techniques provide the foundation with which GT-NEMS develops forecasts of the US energy future. GT-NEMS uses twelve modules, plus a thirteenth integrating module, to simulate various sectors of the energy economy. These twelve sectors are each modeled by a respective module, and the corresponding twelve modules are: Macroeconomic Activity, Residential Demand, Commercial Demand, Industrial Demand, Transportation Demand, Oil and Natural Gas Supply, Natural Gas Transmission and Distribution, Coal Market, Renewable Fuels, Liquid Fuels (formerly the Petroleum Market Module), International Energy, and Electricity Market. Figure 1 below provides a graphical layout of the modular structure of GT-NEMS. GT-NEMS performs an iterative optimization process that results in the price and quantity that balance the demand and supply of numerous energy products[§]. These results are intended as forecasts of general trends rather than specific predictions of future outcomes, making GT-NEMS well-suited for offering insights about alternative policy and technology scenarios.

GT-NEMS models electric power systems through a regional planning approach that makes use of one module, the Electricity Market Module, and its four constituent sub-modules (EIA 2013b). The Electricity Market Module divides the US into 22 regions based on North American Electricity Reliability Corporation regional boundaries^{**}. The Electricity Market Module performs separate projections of power demand and the cost-minimizing supply

[§] Recent discussions of the financialization of energy commodities bear relevance to the way GT-NEMS computes energy prices. GT-NEMS does not simulate financial markets, but does account for financial markets through its macroeconomic module. Some scholars and analysts have argued that growing participation of speculative traders in oil futures markets has caused all energy prices to become correlated with oil prices. However, other scholars have shown that this correlation is due to exogenous demand shocks and does not indicate a true relationship between oil prices and other energy prices, let alone one caused by speculation and its effect on inventories (see <http://www.oxfordenergy.org/wpcms/wp-content/uploads/2012/04/The-Financialization-of-Oil-Markets-Potential-Impacts-and-Evidence.pdf>). Strict correlation between the price of oil and the prices of other energy commodities would also imply negative elasticities of substitution between oil and other fuels for generating electricity, and EIA finds many of these elasticities of substitution to be positive (see <http://www.eia.gov/analysis/studies/fuelelasticities/pdf/eia-fuelelasticities.pdf>). Finally, it is known that wholesale electricity prices are largely driven by daily demand cycles; retail electricity prices in most parts of the US are set by regulatory authorities, moreover, causing them to respond very weakly to changes in the price of any fuel.

^{**} A map of these regions can be viewed at http://www.epa.gov/cleanenergy/images/eGRID_subregions.gif

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necessary to meet that demand for each region. In computing estimates of cost-minimizing supply choices, the Electricity Market Module uses survey data from EIA’s Form 860, 861, and 923 surveys, as well as North American Electricity Reliability Corporation projections and data from the Federal Energy Regulatory Commission’s Form 1 survey. More information about these data sources can be found in Appendix A. These inputs are used to characterize end-use load shapes, costs and performance of capacity types, and other key variables within the Electricity Market Module. GT-NEMS does not represent power system engineering elements such as reactive power and voltage management in detail, which may present further opportunities for demand response grid services.^{††}

3.1 Modeling DR in GT-NEMS

The modeling of DR in GT-NEMS shows what may be possible if system-wide load reductions over the top 1% of hours were to be expanded through increasing customer enrollment in load reduction programs. The representation of DR in GT-NEMS resembles a pumped storage capacity option. DR is modeled as reducing peak load but requiring that some portion of the load reduction be made up through off-peak generation. Direct load control programs closely resemble dispatchable pumped storage resources from the utility’s perspective, for example. GT-NEMS represents customer choice by constraining the total amount of DR that can be built in electric power systems; this constraint is conceptualized as the “limit” on the number of customers willing to enroll in DR programs. GT-NEMS does not alter prices to either wholesale or retail customers when dispatching its DR resources. Given that DR is constrained to operating in the top 1% of hours ranked by system load as described below, however, the revenue impacts to utilities would be dwarfed by the impact of the other 99% of yearly hours’ prices and operating costs. GT-NEMS also assumes a flat variable cost of operating DR for all regions and all years of the forecast – about \$0.21/MWh. Because DR is constrained to being dispatched during peak periods, DR would continue to be the most economic option until the variable operating costs began approaching the peak period system lambda calculated in GT-

^{††} For example, management of loads requiring reactive power could be used to provide volt/VAR optimization at lesser cost than use of power plants or synchronous generators. This opportunity appears not to have been explored in the literature.

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7 NEMS. For shoulder season peak periods, which have the lowest system lambda values, the
8 average system lambda across all regions begins at \$19.61/MWh in 2013 and rises to
9 \$50.26/MWh in 2040. Peak period system lambda values are much higher. DR would thus
10 remain the most economic option over a wide range of variable costs. Therefore, were capacity
11 payments to DR resources included in the costs of DR deployment, the capacity investments and
12 dispatch decisions of GT-NEMS would change very little.
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19 **3.2 Key parameters in DR modeling**
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21 GT-NEMS users can construct DR scenarios using two key parameters, in addition to
22 parameters common to other supply-side options. These two key parameters unique to the DR
23 option in GT-NEMS are called “STFAC” and “STLIM.” STFAC is a ratio of the off-peak
24 generation that must be delivered to compensate for each unit of on-peak load reduction via DR.
25 Because of this definition, STFAC captures the extent to which load that is reduced on peak via
26 DR is shifted to non-peak periods, which in GT-NEMS include both intermediate and base loads.
27 The reference case value for STFAC used by EIA’s 2014 Annual Energy Outlook is 96%,
28 meaning that of every MWh reduced, 96% of that MWh is “recovered” in off-peak energy
29 consumption. The STFAC percentage represents the percent of peak energy reduction that is not
30 reduced, i.e. the fraction of DR that does not prompt efficiency. A STFAC value of 96% means
31 that DR prompts a reduction response for only 4% of the on-peak energy reduced. The other key
32 parameter, STLIM is defined as the percent of peak load in a region that is allowed to be met by
33 DR resources. In practical terms, STLIM is an upper limit on the capacity of DR resources that
34 can be constructed in a region. Users are allowed to determine STLIM values for each region and
35 for each year of the GT-NEMS forecast; a limitation of this approach is that the user may not
36 differentiate season-specific STLIM values, which would be appropriate for modeling the DR
37 potentials found by Gils (2014). By contrast, users are only allowed to specify one STFAC value
38 for all forecast years and all GT-NEMS regions. The reference case values for STLIM used by
39 EIA’s 2014 Annual Energy Outlook show the average regional STLIM value steadily increasing
40 from less than 1% in 2012 to about 3% in 2030. Figure 2 illustrates how these two key
41 parameters are used in GT-NEMS.
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DR is dispatched in GT-NEMS by transferring load from peak periods to non-peak periods when it is cost-minimizing to do so. To facilitate the complexity and scale of its computations, GT-NEMS uses a simplified load duration curve. The GT-NEMS load duration curve is broken down by season-type – Summer, Winter, and “Shoulder,” the last of which represents demand patterns likely to be seen in Spring and Fall. These seasons are in turn separated into three time slices: peak, intermediate, and off-peak. Figure 3 depicts the GT-NEMS load duration curve in the year 2014 for Region 20, which represents most of the state of California. As shown in the figure, GT-NEMS defines three season-types. The peak period of each season is defined as the season’s top 29.28 hours of system load. The duration of each load slice is roughly constant across all three seasons. GT-NEMS generates one such curve for each of its 22 electricity market module regions.

GT-NEMS allows DR to decrease load only during the peak demand periods – the top 87.84 hours of the year – and energy saved during those periods is shifted to intermediate or base load periods. The peak demand period represents the top 23 hours in each season, and annual peak demand represents roughly the top 70 hours of the year. A fraction of the energy saved via an on-peak load reduction spread over the 23 hours of the seasonal peak is transferred to either the intermediate or the off-peak load slices and spread over the 1000+ hours in that slice.

Figure 3 illustrates using the peak load reduction forecast in the reference case for Region 20 in year 2030. The peak load reduction achieved through DR is 670 MW, which when spreads across the 29.28 hours of the summer peak translates to 19,618 MWh of peak energy avoided. 96% of these avoided MWhs - approximately 18,833 MWh - are then spread over the 1,464 hours of summer base load. This energy shift results in an increase to the summer base load slice of approximately 13.4 MW, which is not visible given the scale of Figure 3. Region 20’s STLIM value in 2030 is 2%, which means that GT-NEMS allows Region 20 to meet about 1.13 GW of its peak demand with DR. In the reference case, Region 20 only uses about 60% of the DR it is allowed to use. This is because Region 20 does not build sufficient DR capacity to be able to meet 2% of peak demand through DR.

3.3 Modeling the upper limit on DR capacity

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For developing an alternative STLIM input parameter, we turned the most recent comprehensive estimate of DR potential for the US performed by Baek et al (2012). To explore the effects of a significant increase in DR deployment over business-as-usual assumptions, we chose to build a sensitivity based upon the most aggressive “Full Deployment” scenario. Potential peak load reduction values are provided in Baek et al. for each of the 17 Electricity Market Module regions within the Eastern Interconnection, as shown in Table 1 below. We use these results in GT-NEMS by first setting the 2030 value of STLIM for each Electricity Market Module region to the 2030 potential peak load reduction values in Baek et al. for the Full Deployment scenario. We then developed a linear growth rate to interpolate between the default 2013 STLIM values in GT-NEMS and the 2030 STLIM values taken from Baek et al.

This linear growth rate was used to assign STLIM values to the years between 2013 and 2030 for each region^{**}. Because STLIM is only a limit on how much DR may be used in a region and not an expression of that region’s actual potential peak load reduction, our scenario remains more conservative than Baek et al.’s Full Deployment scenario. Also, worth emphasizing is that these are the potential peak load reductions for each region and not for each customer within a region.

^{**} Non-linear rates of advanced metering infrastructure and other DR-enabling technologies are assumed in Baek et al. to occur within each state. However, these values are not provided for the EMM regions, nor are annual values of potential peak load reduction (i.e. DR capacity) for the EMM regions. We determined that the fidelity loss in using linear growth rates for the EMM region STLIM values was not significant and that linear growth from 2013 to 2030 was appropriate as a sensitivity rather than a prediction. Further work may include exploring the impacts of DR if non-linear growth rates are used, particularly rapid ramp-up rates in early years. It is expected that this sensitivity would compel the results from the current DR scenarios seen in later years to occur in earlier years.

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7 The five Electricity Market Module regions that lie outside of the Eastern Interconnection
8 received special treatment during the development of STLIM values. Those areas are the
9 ERCOT interconnection, which covers most of Texas, and the Western Interconnection. These
10 regions' STLIM values for 2030 were calculated by multiplying the 2030 value for potential
11 peak load reduction under Baek et al.'s Business-as-Usual scenario by a "scenario growth"
12 factor. The "scenario growth" factor is the regional average percent difference between Baek et
13 al.'s 2030 potential peak load reduction under the Business-as-Usual scenario and the 2030
14 potential peak load reduction under the Full Deployment scenario. The resulting STLIM values
15 were 36% for the ERCOT interconnection and approximately 27% for regions constituting the
16 Western Interconnection^{§§}.
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57 ^{§§} The four Western Interconnection regions share identical 2030 potential peak load reduction values in Baek et al.'s
58 Business-as-Usual case, so applying the average difference between 2030 Business-as-Usual results and 2030 Full
59 Deployment results produces identical values 2030 values for these regions.
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3.4 Defining the load-shift parameter

We chose the alternative value for DR load-shifting, also known as “energy payback,” with guidance from prior studies of DR program impacts, focusing on studies of real-time and critical peak pricing programs rather than studies of time-of-use programs. This selective focus in our review was employed on grounds offered by the Federal Energy Regulatory Commission’s National Assessment of Demand Response potential. In this study, FERC does not classify time-of-use programs as demand response. Federal Energy Regulatory Commission’s excluded time-of-use programs on the grounds that time-of-use rates do not respond in the near-term to grid conditions, such as unexpected surges in demand or sudden forced shutdowns of power plants. Similarly, Baek et al. (2012) do not include time-of-use rates in their definition of demand response, and including time-of-use rates in their study would likely alter their estimation of demand response potential significantly. Since GT-NEMS models DR as a resource that responds to grid conditions – through the dispatch decision making of the model’s virtual utility firms – it would be inconsistent to use information on time-of-use programs to form assumptions guiding the modeling of DR in GT-NEMS.

Given the limitations of using time-of-use program data to characterize the DR inputs in GT-NEMS, we use price elasticity values from Taylor, Schwartz, and Cochell (2005) analysis of real-time pricing programs to calculate alternative values of load-shift inputs. We then take the average result – a 17% load shift - and used it as our alternative input for the STFAC parameter in GT-NEMS.

We begin with the formulae for own-price elasticity of demand and cross-price elasticity of demand. The own-price elasticity of demand is defined as

$$\epsilon_{own:p} = \frac{\Delta Q_p}{Q_p} \frac{P_p}{\Delta P_p}$$

Where

- $\epsilon_{own:p}$ = Own-price elasticity of electricity
- Q_p = Peak demand

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- P_p = Peak price
- ΔQ_p = Peak demand reduction due to DR
- ΔP_p = Implicit change in peak price necessary to elicit peak demand reduction

ΔP_p represents the change in peak price that would have been necessary to drive the reduction in demand observed in GT-NEMS through a price-based DR program, such as real-time pricing or critical-peak pricing. While GT-NEMS does not use price changes to drive changes in peak electricity demand, we can use own-price elasticity estimates to infer the change in peak price that would have been necessary to yield the demand reduction observed. As will be shown below, using a hypothetical change in peak price enables us to calculate the load shift parameter from price elasticity data.

The own-price elasticity formula can be re-written to express ΔP_p as

$$\Delta P_p = \frac{\Delta Q_p}{\epsilon_{own:p}} \frac{P_p}{Q_p}$$

The cross-price elasticity between peak demand and off-peak demand can similarly be re-written to express ΔQ_o , the change in off peak demand. The definition is

$$\epsilon_{cross:p,o} = \frac{\Delta Q_o}{\Delta P_p} \frac{P_p}{Q_o}$$

where

- Q_o = Off-peak demand
- $\epsilon_{cross:p,o}$ = Cross-price elasticity of electricity
- ΔQ_o = Change in off-peak demand due to DR program impact

Rewriting to obtain an expression of ΔQ_o we have

$$\Delta Q_o = \frac{\Delta P_p * Q_o}{P_p} \epsilon_{cross:p,o}$$

The load shift is simply the ratio of $\Delta Q_o / \Delta Q_p$, the change in off-peak load due to DR as a percentage of the change in peak load due to DR.

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For all variables except ΔQ_o and ΔP_p (the two unknowns), we use data from GT-NEMS on the shape of the load-duration curve used for each year in the NEMS forecast period, as well as data on the marginal cost of supply at each step in the load duration curve (the data depicted in Figure 2). For the purposes of calculating the load shift according to the elasticity equations above, we use the summer peak slice to represent Q_p , the quantity of peak demand.

We also use the summer off-peak slice to represent Q_o , the quantity of off-peak demand. We take the marginal cost at the peak slice in summer as P_p , the peak price^{***}. Lastly, GT-NEMS provides the load reductions that result from DR resources being dispatched at each slice for each season. We take the load reduction that occurs at the summer peak slice as ΔQ_p , the change in peak demand due to DR. The result is a 17% load shift. We find this value on par with assumptions of peak load shift from real-time pricing that appear in models used by Gilbraith and Powers (2013, Table 1)^{†††}, Gottwalt et al. (2011), and De Jonghe, Hobbs, and Belmans (2012).

3.5 DR Scenario Definitions

Table 2 defines the scenarios we create for exploring the long-term emissions impacts of DR. Aside from the parameter definitions appearing here, all other parameter definitions are the same as those used in EIA’s 2013 reference case assumptions. Moreover, the “Low DR Limit, High Load Shift” scenario parameters are identical to the EIA 2013 reference case.

Further evidence supports the idea that we can expect the deployments of DR found in Baek et al. (2012) to have the possibility of delivering a load shift 17%. Page 31 of Baek et al. breaks out the categories of DR that are driving the growth to an average 29% potential peak load reduction in the Full Deployment scenario. Moreover, appendix B in Baek et al. provides breakouts of same information by state. From these results, it is apparent that Full Deployment DR growth is driven by three factors: (1) residential pricing programs with enabling technologies, (2) interruptible tariffs for medium and large commercial and industrial customers, and (3) other types of DR programs for large commercial and industrial customers. For

^{***} This assumes that any price-driven DR in NEMS would be setting its price at, or in proportion to, the marginal cost of generation.

^{†††} Gilbraith and Powers (2013, pp.463) also mention having accessed EPRI data that show 80% of peak demand being unable to shift between peak and off-peak, which would imply a 20% load shift at most.

understanding the load-shifting properties of these types of programs, the Federal Energy Regulatory Commission’s Demand Response Impact and Value Estimation (DRIVE) model^{***} provides hourly impact profiles of DR programs showing how much load is reduced or increased at each hour during a DR event. Examination of the resource profiles for the high-growth DR categories in Baek et al.’s Full Deployment scenario reveals that these categories produce low load shifts and large energy savings compared to other DR categories. An average of the load shifting for each of Baek et al.’s high-growth DR categories, weighted by the amount of growth in that category, produces a load shift of only 12.1%. Thus it appears that a load shift as low as 17% would be compatible with the kind of growth in DR resources forecast in Baek et al. (2012).

4. Results of demand response analysis in GT-NEMS

Before examining the emissions and capacity impacts of DR, we first describe the effect of our scenarios on the forecasted deployments of DR itself. Figure 5 displays the trajectories of DR capacity and dispatch across the four scenarios. From these graphs, it is clear that raising the STLIM value – allowing DR to meet a larger share of peak demand – increases the amount of DR actually used by GT-NEMS. By contrast, reducing DR load-shifting diminishes DR deployment only slightly (by about 10% in the high STLIM case, in 2040). Table 3 illustrates that the deployment of DR capacity and dispatch in the year 2040 of the “High DR Limit, Low Load Shift” scenario. DR capacity is large and well-used in most regions, though the DR capacity levels do not approach the STLIM values set in Table 1.

^{***} The DRIVE model is available online at <http://www.ferc.gov/industries/electric/indus-act/demand-response/drive-model-v36.zip>. Hourly DR impact profiles are contained in the hidden sheets of the DRIVE Excel workbook.

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The high levels of DR deployment forecast in the “High DR Limit” scenarios cause large impacts on capacity forecast by GT-NEMS. Figure 5 shows the changes in total capacity among the four scenarios simulated. Under the “High DR Limit” scenarios, nearly 150 fewer gigawatts of capacity are built by the year 2040 than under “Low DR Limit” scenarios. The conclusion that follows is straightforward; when utility-dispatchable DR is allowed to meet large portions of peak demand, it is likely that proportionately-large amount of capacity will be avoided. Worth noting is that the DR dispatch levels in 2040 nearly equal the amount of avoided capacity, suggesting that DR is a close substitute for this deferred capacity.

Further data confirms our expectation that capacity builds avoided through DR would have been built to meet peak demand. Figure 6 displays the differences in capacity of conventional steam and combustion turbines powered by petroleum (diesel, residual fuel oil, and distillate fuel oil) and natural gas. These fuels, especially the petroleum-based fuels, represent the most expensive fuels modeled in GT-NEMS, and their usage is concentrated in plants with low capacity factors – i.e. plants that serve peak demand. Figure 6 shows that the 150 GW of total capacity avoided in the year 2040 under the High DR Limit scenarios can be accounted for almost entirely by these forms of peak capacity¹². While the capacity avoided under the DR scenarios amounts to just over 10% of total capacity by 2040, the capacity avoided amounts to about 50% of the conventional steam and combustion turbine capacity in 2040. Thus, if DR is allowed to meet large amounts of peak demand, it is likely that system planners will retire expensive existing units and avoid building new peaking units with low capacity factors.

Despite predictions that DR will significantly reduce end-use prices in the long run, such a phenomenon is not observed in the results of the DR scenarios. The three major electricity demand sectors in GT-NEMS are the Residential Sector, the Commercial Sector, and the Industrial Sector. The prices forecast for each of these sectors over the 2013-2040 indicate that the impact of the DR scenarios upon electricity prices is quite modest, but consistently negative in scenarios with a high DR limit (Figure 7). When we examine these in comparison to the

¹² The downward trend reflects on the one hand, a flattening in growth of steam turbines powered by diesel and natural gas, and on the other hand, an exacerbation of the already-negative growth rate (i.e. retirement rate) for combustion turbines powered by residual fuel oil and distillate fuel oil.

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7 reference case – Low DR Limit, High Load Shift – we find that electricity prices are lower in
8 scenarios with a High DR Limit than in scenarios with a Low DR Limit.
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10 These modest electricity price reductions are due to the system cost savings. The demand
11 response scenarios result in reduced annual expenses by utilities in multiple areas of capacity and
12 infrastructure cost. Three specific areas that exhibit strong annual expense reductions are
13 Transmission Infrastructure, Fixed O&M Costs, and Capital Additions. The projections of annual
14 expense in each of these three categories are graphed in Figure 8. The impact of DR on these
15 categories is linear in the “aggressiveness” of the scenario – that is, the scenarios in order from
16 least impact to greatest impact are Low DR Limit, High Load Shift (the reference case); Low DR
17 Limit, Low Load Shift; High DR Limit, High Load Shift; and High DR Limit, Low Load Shift.
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25 Indeed, the High DR Limit, Low Load Shift scenario produces considerable savings over
26 time. In the Transmission Infrastructure category, this scenario yields a cumulative savings of \$7
27 billion; in the Fixed O&M Costs category, the scenario yields a cumulative savings of \$13
28 billion; and in the Capital Additions category, the scenario yields a cumulative savings of \$8
29 billion.
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34 What of the emissions impacts of DR? Despite having large impacts on capacity, our
35 modifications do little to change the impact of DR on emissions. The CO₂ emissions forecast by
36 GT-NEMS are largely unaffected by either the DR limit or the DR load shifting (i.e. the “energy
37 payback”). Figure 9 illustrates this absence of impact, showing at most a difference of 5 million
38 metric tons of CO₂ in 2040. This change is less than 1% to the total US emissions value at 2040,
39 which is above 685 million metric tons in all scenarios. Purely minor differences between cases
40 persist across the entire forecast period. The conclusion is that high levels of DR deployment,
41 which result in any degree of load-shifting, will likely have little effect on emissions.
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49 Moreover, while distributed generation is likely to drive CO₂ emissions from DR, the
50 estimated increase is slight in comparison to the overall magnitude of CO₂ emissions from the
51 electric power sector. We estimate the increase in CO₂ emissions by analyzing the fuel
52 composition of customer-owned distributed generation forecast by GT-NEMS (Figure 10).
53 Natural gas increasingly dominates the fuel portfolio of US customer-owned distributed
54 generation throughout the GT-NEMS forecast. We combine this fuel portfolio forecast with EIA
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web information on marginal CO₂ emissions from power generation from each fuel¹³, using it to calculate the fuel-weighted average CO₂ emissions per kWh from distributed generation. We then assume that distributed generation is used to make up the DR-reduced energy that is not shifted from peak to off peak. That is, we assume that the grid energy consumption that is reduced on-peak and not made up off-peak is made up by distributed generation on-peak¹⁴. While the emissions from distributed generation used as DR backup are understandably greatest under a scenario of low load shifting and high DR penetration (Figure 10), the greatest emissions still amount to less than 0.1% of the CO₂ emissions from electric power. Thus it seems that emissions from distributed generation used to back up DR in our scenarios will not make a major contribution to US CO₂ emissions.

5. Results of Regression Analysis of DR Scenarios

While the basic outputs of GT-NEMS forecast aggregate-level outcomes, the relationship between outcome variables requires greater clarification. For example, we see that combustion turbine capacity builds are far less in some of the DR scenarios than in the reference case, but what's driving this difference cannot be established by looking at these results alone. Moreover, while the GT-NEMS documentation explains how variables are related in the model's optimization formulae, it remains unclear which causal variables change dramatically over the course of a forecast and truly "drive" the outcome variables observed.

5.1 Regression Model Specification

We use regression analysis to develop further insights about the impacts of DR in GT-NEMS forecasts. To analyze the differences across scenarios, we created panel data structure that represented each scenario as a different set of regions. Essentially, we construct the scenario parameters as "treatments" that are administered to different samples of EMM regions. With our four DR scenarios and 22 Electricity Market Module regions, we create a total of 88 cross-sectional observations in our panel dataset. We then use dummy variables to assign these cross-

¹³ <http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11>

¹⁴ In other words, (1-STFAC) is the load that is met by distributed generation during peak load reductions.

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sectional observations to their corresponding DR scenario. Because we have the entire population of 22 regions in our samples, our inference is to the hypothetical “average Electricity Market Module region.” While a very abstract concept, this remains useful for demonstrating the strength of relationships between the predictive variables in forecasts by GT-NEMS.

Our generalized model specifications were as follows. For carbon emissions,

$$MMtons_Carbon_{t,r} = b_0 + \beta\Psi_{i,t,r} + \varepsilon$$

Where:

- $MMtons_Carbon$ represents million tons of carbon dioxide emitted
- t indexes years
- r indexes regions
- i indexes the following fuel types: coal, natural gas, petroleum, nuclear, renewable, fuels used for distributed generators, and energy reductions through demand response resources
- Ψ is a vector of terawatt-hours of electrical energy from each of the fuel-types indexed by i
- ε represents the error term

For analyzing electric energy generated from various fuel types, we use the following model:

$$TWh_{k,t,r} = b_0 + \beta\Psi_{j,t,r} + \gamma_{j,t,r} + p_{k,t,r} + z\delta_{t,r} + \varepsilon$$

Where:

- k identifies the fuel-type whose electrical energy output is the dependent variable
- j indexes all fuel types that are not of fuel-type k . The total set of fuel-types are, again: coal, natural gas, petroleum, nuclear, renewable, fuels used for distributed generators, and energy reductions through demand response resources
- TWh_k represents terawatt-hours of electrical energy produced from fuel-type k
- $p_{k,t,r}$ represents the price of a fuel-type
- δ represents regional electrical energy sales, in terawatt-hours

$\mu_{c,t,r}$ indexes the prices of the following plant-types: steam coal, combustion turbine, combined-cycle combustion turbine, oil/gas-fired steam, renewables, off-peak distributed generation, and peak distributed generation. We gather data for these inputs from table forms of

GT-NEMS’ basic outputs, as well as from the basic GT-NEMS outputs on construction of DR capacity, dispatch of DR capacity, and peak loads.

In examining the data, we conducted several tests to further specify the model. We first observed heteroskedasticity in the errors, requiring robust standard error estimation. We then conducted the Breusch-Pagan test for a panel effect, finding the test to be significant at the 0.0001 confidence level. We also use the Breusch-Pagan test for cross-panel correlation in the error terms, and this test also shows a significant result at the 0.0001 level. We thus use a feasible generalized least-squares model with assumed heteroskedastic errors and cross-panel error correlation in all of our analyses¹⁵.

5.2 Regression Analysis of Emissions, Generation, and Capacity

Table 4 shows the results of a regression of CO₂ (in MMT) on TWh of electricity generation from the primary energy sources that impact carbon emissions for all four scenarios across all regions. In each scenario, DR is found to have a negative, statistically significant impact on carbon emissions, suggesting that DR will displace the expensive, more-polluting peak resources. However, DR also appears to reduce carbon emissions to a greater extent when load shifting is high, suggesting that DR may be shifting load to renewable capacity or combined-cycle natural gas capacity serving intermediate loads in some regions.

We then carried out regressions on the use of two important fuel types, coal and natural gas, to understand the effects of DR dispatch on these two major fuels that are widely used and contribute to CO₂ emissions. The regression results for use of coal-fired power (Table 5) affirm the suspicion among certain practitioners that DR would increase emissions by shifting peak load to off-peak load. Coal use increases significantly when load-shifting is high, regardless of the level of constraint on DR deployment.

The regression results for the use of natural gas further affirm suspicions regarding the impact of DR on emissions. Regions deploying more DR will use less natural gas, no matter whether load-shifting and DR deployment is high or low (Table 6). The range of effect of natural

¹⁵ We perform these tests on the data for all regions together and on the data for each region individually, finding the same results from both Breusch-Pagan tests; we thus use the same model specification for all modeling.

gas is much smaller, and lower on average, when load shifting is low, and the range of effect is bigger when load shifting is high. As expected, these results suggest that DR with high load-shifting may induce regions to substitute coal for natural gas in the base load and intermediate portions of the power supply curve.

5.3 Regional Analysis of DR's impact on CO₂ Emissions

Since the national regression may mask effects occurring at the regional level, we carried out further regression analyses, focusing on specific NEMS regions. Figures 10 and 11 graphically illustrate the regression analysis of DR dispatch for four individual regions, across all four scenarios. We selected two pairs of regions (i.e. four regions total), such that each pair has comparable peak loads, but different patterns of DR resource deployment. The regions in the first pairing, SPNO and SRGW, have medium-level peak loads in comparison to the other 20 regions. SPNO is forecast to have a summer peak demand of about 14 GW by 2015, while SRGW is forecast to have a peak of about 19 GW by 2015. SPNO represents the northern half of a US power exchange market known as the “Southwest Power Pool.” As such, SPNO covers most of Kansas and the western half of Missouri. SRGW covers most of the state of Illinois and the eastern half of Missouri.

Figure 11 illustrates the varying effects on CO₂ emissions made by various levels of DR dispatch across the four regions. SPNO exhibits a pattern of CO₂ emission responses that appears correlated with the amount of load-shifting delivered by DR; the coefficients are significantly below zero at the 95% confidence level when load shifting is high. This suggests that low-carbon off-peak resources in the SPNO region are used to meet shifted loads, and that the shifted loads may even encourage use of these low-carbon resources. SRGW's CO₂ emissions exhibit no clear response to DR dispatch in three scenarios, their coefficients being statistically insignificant at the 95% confidence level; High DR Limit, Low Load Shift is the exception, exhibiting a significant negative response of CO₂ emissions to DR dispatch. This could be due to the low levels of DR dispatch being dwarfed by the much greater dispatch of other resources in the first two scenarios, and the load-shifting of the High DR Limit, High Load Shift scenario being met by high-carbon resources.

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Further interesting patterns emerge when examining the results for MROE and NYLI regions – two regions with the lowest peak demand levels. MROE represents the northeastern portions of Wisconsin and Michigan, while NYLI represents the Long Island portion of New York. MROE’s CO₂ emissions exhibit no clear response to DR dispatch under any scenario. Similar to SRGW, this may be due to low levels of DR deployment, but could also be due to a mix of low-carbon and high-carbon off-peak resources used to meet shifted load. Meanwhile, NYLI exhibits CO₂ emissions reductions in the Low DR Limit, High Load Shift case, as well as in the High DR Limit, Low Load Shift case. This could be due to load-shifting encouraging the use of low-carbon or carbon-free off-peak resources, such as intermediate solar and wind power.

Examining the projected generation by fuel source for each of these four regions adds further insight into why the regions’ CO₂ emissions respond differently to DR dispatch. Figure 12 displays the projected generation by fuel type for SPNO, SRGW, MROE, and NYLI, and illustrates the forecast of DR capacity and DR dispatch across these four regions under the most aggressive scenario – High DR Limit, Low Load Shift. SPNO deploys DR resources earlier and to a much greater level than SRGW, despite having similar peak demand levels. A similar pattern emerges in the comparison of the NYLI region and the MROE region; NYLI deploys a much greater level of DR resources, and begins deploying them earlier, than does MROE. Thus the extent that DR reduces CO₂ emissions appears to depend on the proportion of no-carbon, low-priced renewable fuel in a region’s generation portfolio. Three principles support this interpretation of the figures. First, three of the four regions – all but NYLI – rely primarily upon coal and nuclear power for base-load generation. Second, while nuclear is a no-carbon resource, nuclear is not dispatchable. Because nuclear plants retain high capacity factors and many operate under “must-run” conditions, they cannot be ramped-up to meet loads shifted to off-peak periods by DR dispatching. Third, wind and solar have zero fuel costs, making them the most attractive options for dispatch. Due to the peak and intermediate-load availability of solar, and the intermediate and base-load availability of wind, these options would be both economically and environmentally attractive for meeting loads shifted off-peak by DR dispatching. The regions with the most observations of statistically-significant low-carbon responses to DR dispatch, SPNO and NYLI, also exhibit the greatest renewable generation in their portfolios – mostly wind

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in SPNO, and other renewables in NYLI. Overall, it appears that load-shifting due to DR dispatch provides a greater opportunity for low-carbon renewable fuels to meet demand, thus helping regions reduce their carbon emissions on the margin.

5. Conclusions

Overall, we find that DR is likely to have little impact on CO₂ emissions from the U.S. electricity sector under a variety of scenarios and ways that DR might operate. Neither large nor small levels of load-shifting between peak and off-peak periods appear to significantly change CO₂ emissions. Further, large increases in peak load that can be reduced by DR also do not produce much change in electric power CO₂ emissions. Finally, we find that even the CO₂ emissions from distributed generation used to back up DR load reductions are unlikely to contribute significantly to overall electric power sector CO₂ emissions.

Regions do appear to differ in the impact that DR would have on CO₂ emissions. In particular, regions with a large portion of off-peak, low-carbon, ramping renewable generation in their energy portfolio can reduce carbon emissions on the margin by dispatching DR. Wind turbines and solar PV fit this description, by delivering post-peak output. Wind generation's off-peak output has even been displacing off-peak generation in recent years¹⁶. By contrast, regions with a large portion of nuclear power in their baseline appear less able to reduce their carbon emissions through DR dispatch due to difficulties with ramping nuclear power.

These conclusions turn primarily on the assumption that DR is allowed only to operate during the top 1% of load hours. GT-NEMS restricts DR resources to operation within this time period, and as DR programs expand in scale they are likely to expand in scope as well, operating at intermediate portions of system load duration curves. The use of DR for ancillary services and regulation will expand the number of hours over which DR resources operate, thus increasing the opportunities for DR resources to impact CO₂ emissions – positively or negatively. In either event, allowing DR to meet large portions of peak demand produces significant peak capacity

¹⁶ See <http://www.eia.gov/todayinenergy/detail.cfm?id=12831>

deferrals. Future modeling should consider allowing DR to reduce load in more segments of the load duration curve, such as the summer intermediate segment, reflecting a common use of DR. In addition, future DR modeling in GT-NEMS should be refined to reflect the differences in seasonal DR potential found by Gils (2014).

Overall, GT-NEMS shows that DR can defer substantial investments in additional capacity, thereby delivering significant cost savings to electric power systems. Specifically, the combination of high DR potential with minimal load shifting produces considerable energy savings over time, as well as cumulative savings of \$28 billion in transmission infrastructure, fixed O&M costs, and capital additions. This scenario also avoids the need for 150 GW of capacity in comparison to the Reference case, and this avoided capacity is primarily oil-fired steam and single-cycle combustion turbine units. Thus it appears that across the US, DR could deliver peak capacity deferrals and power system cost savings while remaining carbon neutral.

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Figure Captions

Figure 1: Graph of the modular structure of GT-NEMS (from EIA:

http://www.eia.gov/oiaf/aeo/overview/figure_2.html)

Figure 2: Illustration of key DR parameters in GT-NEMS

Figure 3: Load duration curve in GT-NEMS for Region 20 in 2014. Region 20 represents most of the CAISO territory in California.

Figure 4: Peak load reduction for summer of 2030 for Region 20 in the Reference case

Table 1: Regional STLIM values in 2030, across 22 NERC regions

(Source: adopted from Baek et al., 2012, Table 21)

Table 2: DR scenario definitions

Figure 5: National DR dispatch and DR capacity values for the forecast period in four scenarios

Table 3: Regional impacts in 2040 of high DR limit and low load shift scenario (in % of generation)

Figure 6: Total capacity and peak capacity (i.e. steam and conventional combustion turbine capacity) for 2013-2040 under DR scenarios.

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Figure 7: Electricity prices for the three major demand sectors over 2013-2040 under DR scenarios

Figure 8: Investment and operating expenses over 2013-2040 under DR scenarios.

Figure 9: National carbon emissions from the power sector under the DR scenarios

Figure 10: Percent of customer-owned distributed generation fired by each of four fuels in the reference case, left; CO₂ emissions from DG used to back up DR load reductions, right

Table 4: Regression results describing the marginal impact of DR dispatch on CO₂ emissions across 22 EMM regions

Table 5: Regressions results for explaining electric power generation from coal, measured in terawatt-hours

Table 6: Regression results for explaining electric power generation from natural gas, measured in terawatt-hours

Figure 11: regression coefficients for the impact of demand response on carbon dioxide emissions in four regions. The left axis in each graph represents the value of the coefficient upon DR dispatch in a regression of the model for explaining carbon emissions; the units of this axis are million tonnes of annual CO₂ emissions increased per 1 GW of DR dispatch.

Figure 12: Projected generation by fuel type and DR deployment for the 2013-2040 period in four regions. The left axis represents the percent of the region's total generation from plants in the region, while the right axis represents the total GW of DR capacity and dispatch deployed in that region.

Tables and Figures

Figure 1

Figure 2

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Figure 3

Figure 4

FRCC	SRVC	SRSE	SPSO	MROW	RFCE	SRDA	SRGW	SPNO	ERCT	SRCE
0.47	0.38	0.36	0.31	0.29	0.29	0.29	0.29	0.29	0.271	0.27
RFCW	NYCW	NYLI	NYUP	MORE	RFCM	AZNM	CAMX	WECC	RMPA	NEWE
0.26	0.25	0.25	0.25	0.22	0.22	0.201	0.201	0.201	0.201	0.19

Table 1

Scenario Name	Low DR Limit		High DR Limit	
	High Load Shift (BAU)	Low Load Shift	High Load Shift	Low Load Shift
Average regional DR limit (STLIM) in 2040 (percent of peak that can be met by DR)	3%	3%	29%	29%
Load shift (STFAC) used for all Regions (percent of peak load reduction recovered in non-peak periods)	96%	17%	96%	17%

Table 2

Figure 5

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Table 3 (below)

	NERC egioms							
Scenarios:	ERCT	FRCC	MROE	MROW	NEWWE	NYCW	NYLI	
Low DR Limit, High Load Shift	2.92	3.17	1.62	5.1	3.36	2.47	2.98	
High DR Limit, Low Load Shift	23.01	17.1	1.05	20.89	11.59	20.68	19.34	
Low DR Limit, High Load Shift	2.55	2.66	0.46	2.33	1.64	3.09	0	
High DR Limit, Low Load Shift	15.53	14.69	0.95	17.9	8	17.72	16.25	
	NERC Regions							
Scenarios:	NYUP	RFCE	RFCM	RFCW	SRDA	SRGW	SRSE	
Low DR Limit, High Load Shift	5.08	3.18	3.55	3.45	0	2.79	2.99	
High DR Limit, Low Load Shift	29.72	30.71	7.24	11.47	14.41	2.41	11.56	
Low DR Limit, High Load Shift	4.17	3.01	0.89	3.01	0	0.84	2.54	
High DR Limit, Low Load Shift	23.39	24.71	4.89	9.49	12.14	2.17	8.15	
	NERC Regions							
Scenarios:	SRCE	SRVC	SPNO	SPSO	AZNM	CAMX	NWPP	RMPA
Low DR Limit, High Load Shift	2.77	3.02	5.45	5.22	2.44	1.6	1.96	1.44
High DR Limit, Low Load Shift	13.35	26.81	24.17	25.29	20.65	9.62	12.7	25.23
Low DR Limit, High Load Shift	2.48	2.53	3.42	4.13	1.82	1.89	1.85	1.75
High DR Limit, Low Load Shift	9.85	17.31	21.02	20.12	11.59	6.78	7.58	17.71

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Figure 6

Retail Electricity Prices

Figure 7

Figure 8

Figure 9

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Figure 10

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Dependent Variable: Million tons of CO ₂				
	Low DR Limit, High Load Shift	Low DR Limit, Low Load Shift	High DR Limit, High Load Shift	High DR Limit, Low Load Shift
GW DR Dispatched	-0.992***	-0.168***	-0.888***	-0.18***
TWh from Coal	1.072***	1.076***	1.072***	1.071***
TWh from Natural Gas	0.431***	0.432***	0.43***	0.429***
TWh from Petroleum	1.876***	1.434***	1.901***	2.152***
Constant	2.349***	2.254***	2.393***	2.349***
Adjusted Coefficient of Determination (R^2)	0.998	0.998	0.998	0.998
Wald chi-squared value (4 degrees of freedom)	783483	842166	776232	849976

*** indicates that all of the regression coefficients and the adjusted coefficient of determination are different from zero at the 0.001 level of significance.

Table 4

Dependent variable: MWh of electricity generation from coal	Low DR limit, High load shift	Low DR limit, Low load shift	High DR limit, High load shift	High DR limit, Low load shift
Independent variables:				
DR dispatch (GW)	4.401***	0.497***	4.884***	0.678***
Coal capacity (GW)	6.112***	6.143***	6.128***	6.188***
Coal price (\$/Btu)	-11.903***	-10.752***	-11.559***	-11.058***
Natural gas price (\$/Btu)	4.237***	4.601***	3.938***	4.378***
Biomass fuel price (\$/Btu)	3.908***	3.531***	3.807***	4.024***
Annual regional sales	-0.004***	0.005***	-0.008***	-0.004***
Constant	0.138***	-5.649***	1.475***	-3.194***
Adjusted Coefficient of Determination (R^2)	0.986	0.983	0.986	0.986
Wald chi-squared value (6 degrees of freedom)	7804837	7804837	7804837	7804837

*** indicates that all of the regression coefficients and the adjusted coefficient of determination are different from zero at the 0.001 level of significance

Table 5

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Dependent variable: MWh of electricity generation from natural gas	Low DR limit, High load shift	Low DR limit, Low load shift	High DR limit, High load shift	High DR limit, Low load shift
Independent variables:				
DR dispatch (GW)	-5.038***	-1.11***	-5.879***	-1.514***
Combined cycle natural gas capacity (GW)	4.952***	4.714***	4.919***	4.753***
Coal price (\$/Btu)	0.278***	0.308***	0.257***	0.26***
Natural gas price (\$/Btu)	-0.956***	-0.291***	-0.706***	0.11***
Biomass fuel price (\$/Btu)	3.046***	3.567***	4.573***	5.327***
Annual regional sales	0.008***	0.022***	0.017***	0.026***
Constant	-3.433***	-7.697***	-8.212***	-13.639***
Adjusted Coefficient of Determination (R^2)	0.904	0.8812	0.907	0.893
Wald chi-squared value (6 degrees of freedom)	2330247	2330247	2330247	2330247

Table 6

Figure 11

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Figure 12