Using Utility Load Data to Estimate Demand for Space Cooling and Potential for Shiftable Loads

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1 Introduction

Space cooling is a significant use of energy in the United States, consuming about 10% of total electricity sales (EIA 2009). Cooling also drives the peak electricity demand and the associated need for peaking generation capacity. Peaking generators used to meet much of this demand are often less efficient than baseload generators. High demand on hot days also creates additional stress on electricity transmission and distribution (T&D) infrastructure. These concerns have prompted greater interest in the control of space cooling loads to improve efficiency of the electric power sector. Options for control of cooling loads include the ability to temporarily reduce demand for cooling through demand response (DR) programs or the use of thermal energy storage (TES) to shift demand.

Both DR and TES are already used in some regions of the United States[1] but can potentially be used at a greater scale to provide additional system benefits by enabling the integration of variable renewable generators (VG) such as solar and wind. DR can rapidly reduce electricity demand and provide operating reserves such as frequency regulation, contingency spinning reserves, and load-following reserves (Kueck et al. 2008).[2] Greater amounts of some of these ancillary services will be required with increased penetration of VG, and DR can potentially provide a relatively low-cost source of reserves. TES can also aid in renewable integration by changing load patterns over longer time scales. In the United States, the summertime demand for electricity peaks in the late afternoon, while wind energy often peaks in the evening (Denholm and Hand 2011). Correlation of solar energy production and load is greater but still limited—solar production peaks at noon while electricity demand peaks several hours later.[3]

TES has several advantages over electricity storage devices such as pumped hydro or batteries. Most importantly, it effectively stores energy at higher round-trip efficiencies. Most electricity storage devices typically store energy with a total round-trip efficiency of less than 80% (Denholm et al. 2010). Thermal storage efficiency can be closer to 100%.[4] It can also be deployed at the point of use, decreasing need for transmission and lowering transmission losses (Gansler et al. 2001). The primary disadvantage of thermal storage is that it is tied to an end use, and the demand for cooling varies over multiple time scales.

Knowledge of the amount of energy that is shiftable over various time scales is a prerequisite to evaluating the potential large-scale benefits of cooling-related DR and TES. Understanding this hourly and daily variation in demand is particularly important to

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[1] Air conditioning load control is widely used by utilities to temporarily reduce demand. The role of controlled cooling for DR and load control applications has been widely studied. An example study with a brief literature review is provided by Yin et al. (2010).
[2] DR can provide electricity services over multiple time scales. This includes ancillary services during any time it is available as well as reducing peak demand and associated capacity requirements.
[3] Solar insolation peaks at noon; production from a photovoltaic system depends on system orientation.
[4] The concept of "round-trip efficiency" is not easily defined in TES systems in part because it must be compared to the conventional alternative. However, by many measures the efficiency of TES is commonly cited as well above 90%, and sometimes higher than 100%, because a cold-storage-based cooling system can use less electricity than its conventional alternative (Willis and Parsonnet 2010; MacCracken 2003).

understand the potential role of DR and TES as an enabling technology for grid integration of VG.

While modeled and actual data for individual buildings exist, there is less data on the aggregated system demand for cooling and the total system-level potential for TES. In this paper, we utilize a simple "top-down" methodology to isolate hourly cooling demand using historical utility loads. By comparing demand on representative "mild" (low cooling demand) days to other days during the cooling season, we extract an estimate of the hourly cooling demand. We estimate the hourly and total cooling demand across various regions in the United States and compare estimates using our methodology to previous estimates of total cooling demand.

2 Methods

The primary motivation of this work is to apply a simple, transparent, and reproducible method that would enable an understanding of the potential role of cooling-related DR and TES in the large-scale deployment and integration of VG. Studies of wind and solar integration have found that penetrations of 20%–30% (on an energy basis) can be accommodated by "low-cost" flexibility options such as changing operational practices and effectively utilizing markets (GE Energy 2010). Beyond this level, it becomes increasingly difficult to use VG due to the limited correlation of VG supply with normal loads (Denholm and Hand 2011). Energy storage of various types has been suggested to further enable VG integration. Thermal storage provides one option; in Demark, hot storage has been suggested due to the large amount of heating demand during cold, windy months (Blarke and Lund 2008). In the United States, the warmer climate may make cold storage economically viable. A large fraction of the U.S. population lives in regions where cooling is required during many months of the year.

Understanding the benefits and limits of VG in the grid requires time-series simulations, which include hourly (or sub-hourly) profiles of demand and VG sources such as wind and solar. These datasets are used in increasingly complex models that simulate the operation of the grid, including the present and future mix of conventional and VG and may include impacts of forecast error, transmission power flows, and the need for operating reserves (Milligan et al. 2010). As a result, incorporating DR or TES into these simulations requires an estimate of the hourly (or sub-hourly) demand for cooling energy. This is very different than conventional electricity storage technologies such as pumped hydro or batteries, which are completely controllable and largely independent of weather and human behavior.

2.1 Traditional Methods for Estimating Hourly Cooling Demands

We have found limited analyses or datasets that can provide the total, hourly demand for cooling over large areas and for recent years. We have found a number of studies that perform "bottom-up" simulations of individual buildings (Deru et al. 2011). These studies typically have the ability to isolate cooling load and even examine the benefits of storage to individual buildings. A review of methods to simulate building energy demand is provided by Swan and Ugursal (2009) and Kavgic et al. (2010). Bottom-up analyses use building simulation tools that include the hourly heating and cooling requirements for individual buildings using historical weather data (Hopkins et al 2011; Polly et al. 2011; Hendron and Engebrecht 2010). These studies often aggregate a large number of buildings and have the ability to provide estimates of cooling demand over large regions. Examples include estimates for California (Brown and Koomey 2002) and Texas (Heiple and Sailor 2008). We also identified one study that estimates the cooling demand for the entire United States (Huang and Broderick 2000). A limitation of bottom-up models is their data and computational intensity, which require detailed estimates of building stock characteristics and complete meteorological data for the simulation years. Use of actual year data (as opposed to typical meteorological year data) is important if the data is to be used for grid integration analysis. Grid simulations typically use the load and real or simulated wind and solar data for one or more of the corresponding years.[5]

An alternative to bottom-up approaches are top-down methods that attempt to determine the load patterns of large groups of consumers. There are a number of statistical approaches that can be used to correlate historical temperature data with total load (FERC 2009; Valor 2001). Utilities commonly use commercial software packages that project total load based on weather forecasts and historical demand patterns combined with heuristics and experience to produce accurate day-ahead forecasts of total load (Kueck et al. 2008).

2.2 A Simplified Top-Down Approach

The method we apply here provides a very simple top-down approach of estimating total cooling load. The method uses historical hourly utility loads and relies on the differences in demand between cool and warmer days. Figure 1 shows the hourly electricity demand for a utility in Colorado for three weeks in 2005 and the framework for our methodology. Several patterns are visible, including a relatively low demand in the spring and somewhat increased demand in the winter characterized by two daily peaks. Each week starts on a Monday; somewhat reduced demand can be observed on the weekend (the last two days). The greatest demand is during the summer, dominated by a cooling demand that peaks in the late afternoon and into the early evening.

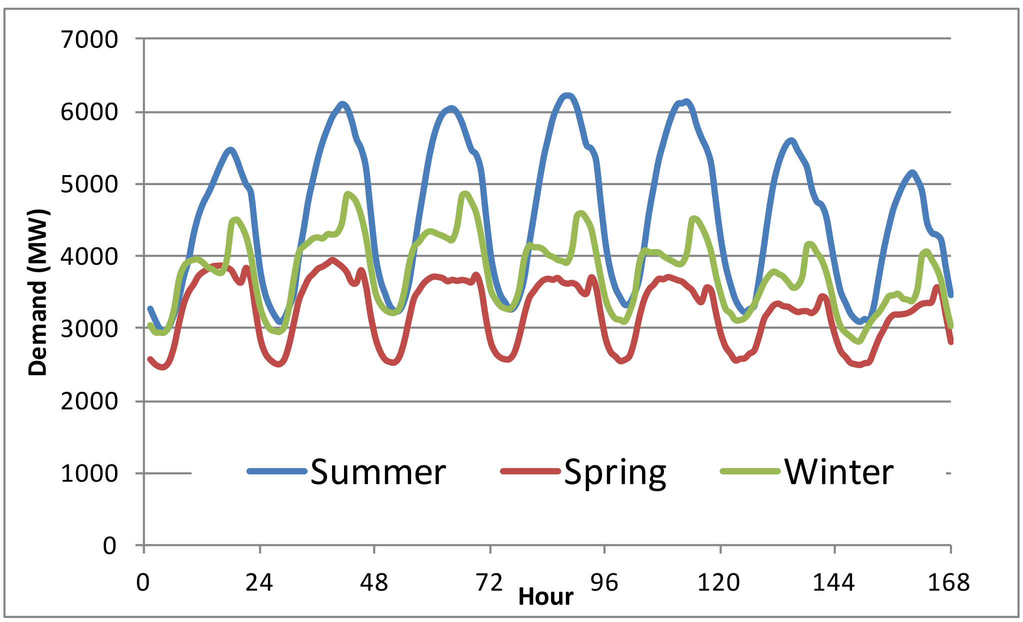

Figure 1. Seasonal demand patterns in Colorado (Public Service Company of Colorado–East)

While the most dramatic difference between load patterns is seasonal, there are still variations in the total and peak demand within a season, driven by differences in weather.

[5] For example, the Western Wind and Solar Integration Study (GE Energy 2010) performed simulations based on wind, solar, and load patterns in the years 2004–2006. Simulations incorporating cooling demand and thermal storage would require corresponding data for these three years.

Figure 2 demonstrates this difference and provides the basis for our methodology. The figure superimposes the hourly load reported by the Los Angeles Department of Water and Power (LADWP) from May 4, 2005, and June 17, 2005. If these two days are equivalent in all other factors, the only difference in demand between them should be space cooling driven by temperature. As a result, subtracting the difference is the incremental hourly and total cooling load.

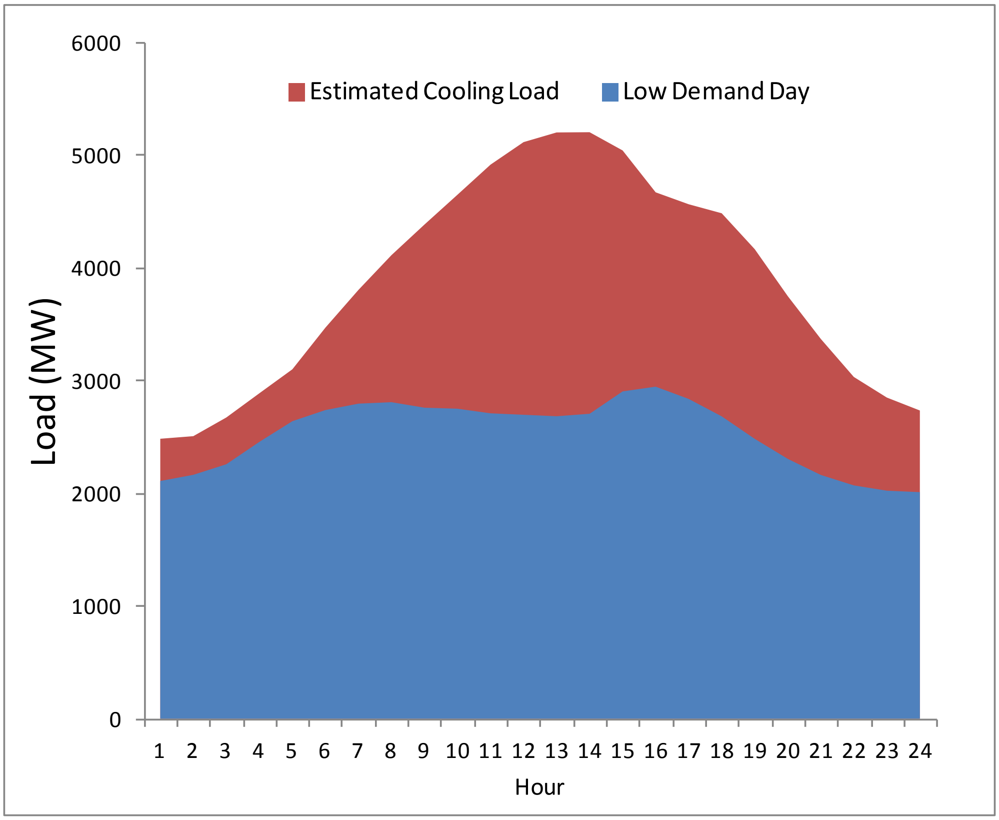

Figure 2. Demand difference within the cooling season (data from LADWP)

Theoretically, this approach can be repeated by subtracting the total hourly demand from a base or reference day in which there is little or no cooling demand from all other days within the cooling season. This should produce an hourly cooling demand, which can be summed to estimate the annual demand.

There are a number of limitations to this simplistic approach. Most obviously there are significant variations in demand patterns based on factors other than weather. There is inherently reduced demand for electricity during weekends and holidays. So the increased demand between a Saturday and a weekday may reflect factors other than temperature. This effect can potentially be captured by establishing an appropriate "base" day (e.g., comparing a hot weekend day to a cooler weekend day).

Figure 3 illustrates this approach conceptually, showing the hourly load for central Maryland between June 1 and June 21, 2005. At the bottom is the assumed base demand profile (no cooling) with the same shape on weekdays but a different (lower) base demand on weekends. Demand greater than the base demand pattern is assumed to be cooling demand.

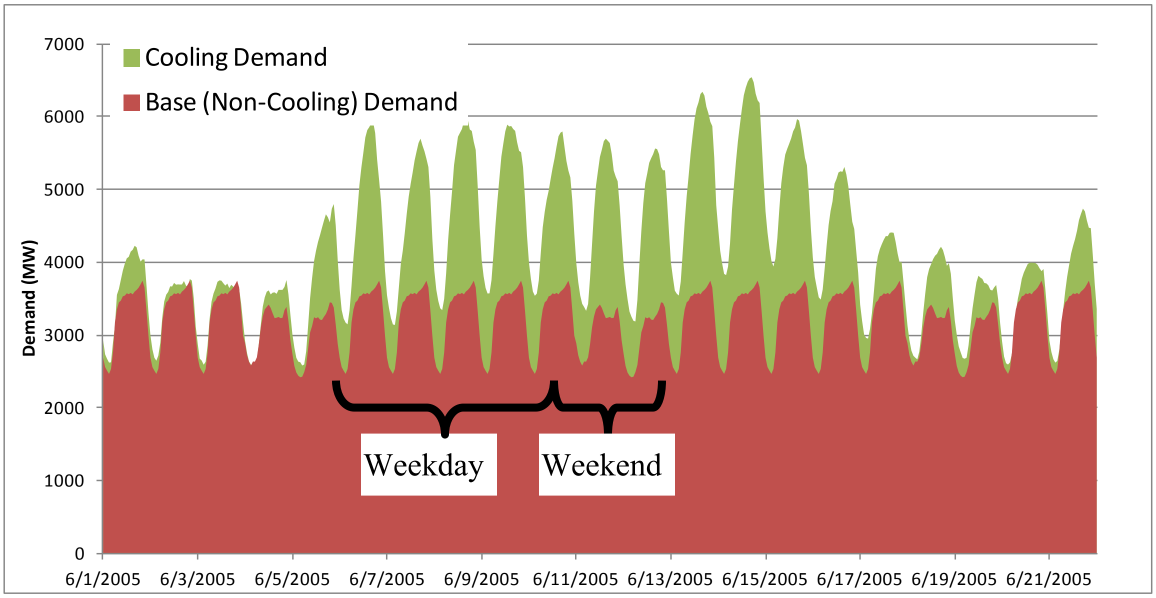

Figure 3. Demand difference within the cooling season (data from Baltimore Gas & Electric)

To generate a reference (non-cooling) day, our base-case approach was to pick separate reference days for weekdays, Sundays, and Saturdays. For weekdays, we picked the five non-holiday[6] days with the lowest demand and excluded the absolute lowest two of these five. These exclusions should help reduce the effect of poor data, power outages, or other anomalies for the reference day. We then generated an hourly profile for a "non-cooling day" by averaging the hourly profiles of the remaining three days. This generated a composite 24-hour base demand for each utility. We repeated the process for weekends, separately picking the lowest three Sundays and Saturdays, dropping the absolute lowest, and generating a composite hourly demand for each day. Each of these three-day profiles (weekday, Saturday, and Sunday) was then subtracted from all the other days during the cooling season.

The other critical assumption in our method is choosing the cooling season; simply subtracting the lowest load day from all days would mischaracterize heating, lighting, and other loads during the non-cooling season.

The cooling season for each utility was based on historical temperature and cooling degree data. Temperature data was obtained and assigned to each utility, and the cooling season in the base case is defined as any day with an average temperature of 65°F or higher. This is a conservative approximation that captures the majority of the cooling season. This includes the majority of the commercial cooling load; although, for

[6] Days excluded from being considered as "reference" days were: New Year's Day, Martin Luther King, Presidents', Memorial, Independence, Labor, Columbus, Veteran's, Thanksgiving, Christmas, and New Year's Eve.

simplicity, it deliberately ignores parts of the commercial cooling season, which in some cases can be year-round. Figure 4 illustrates the cooling season, base demand, and cooling demand for an entire year, along with the daily average temperature. It should be noted that this method actually produces a series of cooling days as opposed to a continuous season. The figure also shows the daily average temperature.

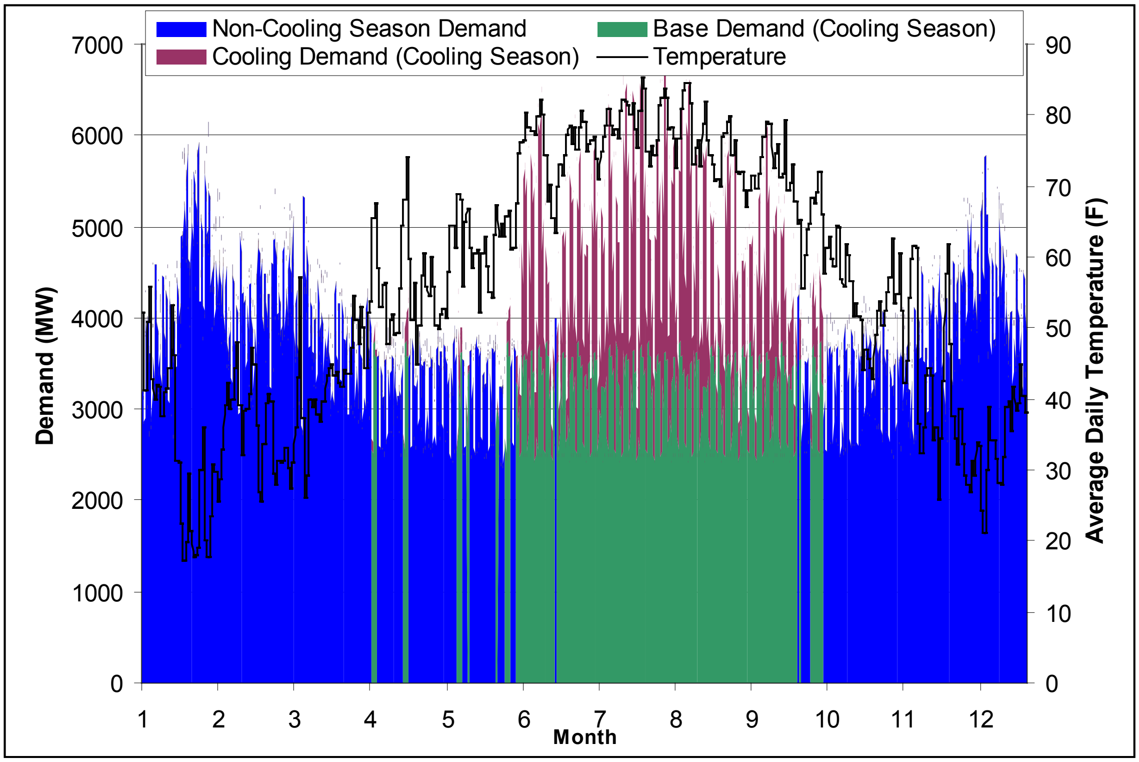

Figure 4. Demand difference for the entire year in central Maryland (data from Baltimore Gas & Electric)

Figure 4 shows that isolating the cooling season is important to avoid characterizing heating loads as cooling. In some locations in the southern United States, cooling may be required during much of the year. This introduces a potential source of error in those locations, especially due to seasonal variations in load due to lighting. The most extreme case is southern Florida, as shown in Figure 5, where cooling is required nearly year-round. (The sharp drop in demand in October is due to a hurricane that produced power failures.)

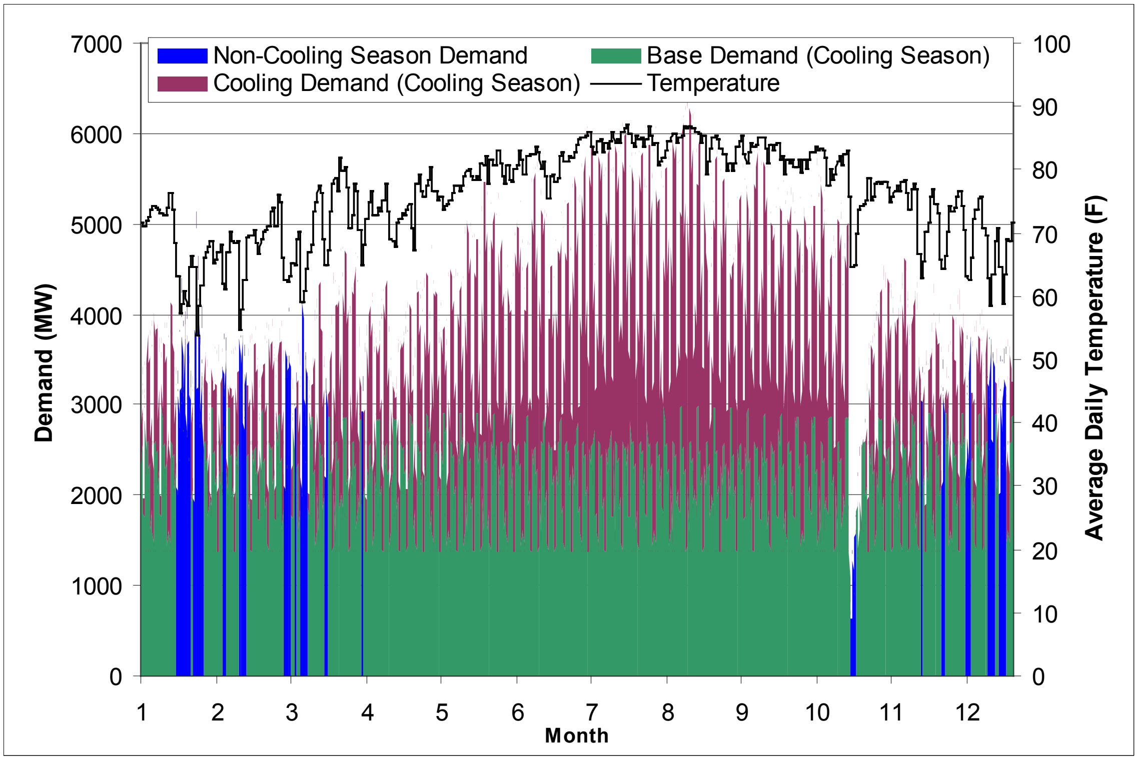

Figure 5. Demand difference for the entire year in southern Florida (data from Progress Energy Florida-South)

We applied this methodology to 300 utilities, market sub-regions, or balancing areas in the United States for the years 2005 and 2006. Hourly load data was obtained from Platts, although this data is publically available from the Federal Energy Regulatory Commissions (FERC) Form 714 filings. The total annual load in this dataset is 3,928 TWh for 2005 and 3,936 TWh for 2006. This compares well with U.S. Energy Information Administration (EIA) estimates of electric sector total generation (excluding industrial and commercial self-generation) for the lower 48 states of 3,929 TWh and 3,941 TWh in 2005 and 2006, respectively, or a difference of less than 1%.[7] Processing of the data was performed in a Microsoft Excel/VBA environment. It should be noted that this load data is measured at the "busbar," which is essentially at the point of generation, and includes losses in the T&D system, which will impact a comparison of our results to end-use estimates, as discussed in the next section.

[7] This is calculated by taking the total electric sector generation (including utilities, independent power producers, and electric sector co-generation) plus imports, excluding commercial and industrial generators, whose load is not "seen" by utilities, and subtracting Hawaii and Alaska. This means that industrial and commercial cooling loads met by self generation are not included in this analysis but represent a very small fraction of total cooling demand (EIA 2007).

3 Results and Discussion

3.1 Cooling Profiles

The methods produce an hourly cooling load for each of the 300 load regions in the United States. This data could be aggregated to various geographical regions such as states or census regions.[8] Figure 6 provides an example of an hourly cooling profile for an entire year for both single utility service territory (Arizona Public Service) and all utilities in Arizona aggregated to the state level.

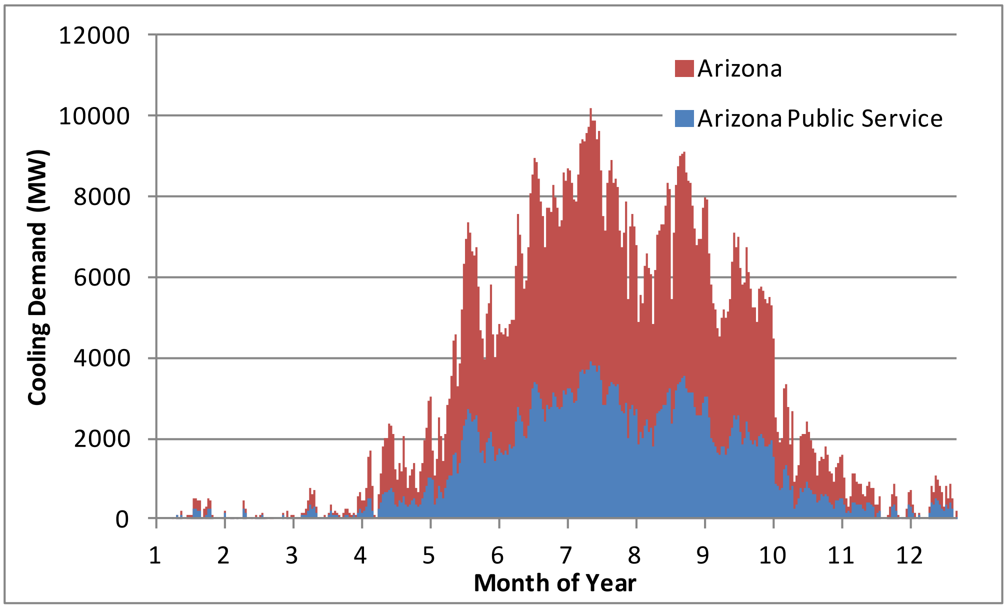

Figure 6. Example of estimated cooling load patterns for Arizona Public Service and the state of Arizona in 2005

These profiles show expected trends, such as the greater relative need for cooling in warmer locations, but also reveal a variety of phenomenon that can be "spot-checked" for some basic validation. For example, Figure 7 shows the cooling demand in Florida, Illinois, and New York in 2005. Of note is the dramatic decrease in cooling demand in Florida beginning at about hour 7,100 (October 25). This is due to dramatically reduced temperatures and local power outages associated with Hurricane Wilma. While this demonstrates a general indication of the well-established correlation between temperature and cooling demand, it does not explicitly validate the accuracy of our methods. For some basic indication of the usefulness of this approach, we also compared total annual cooling demand with other estimates, as discussed in the following section.

[8] Many of the transmission areas cross state boundaries. To aggregate to the state level, GIS techniques were used to assign the population (and corresponding loads) between the various states.

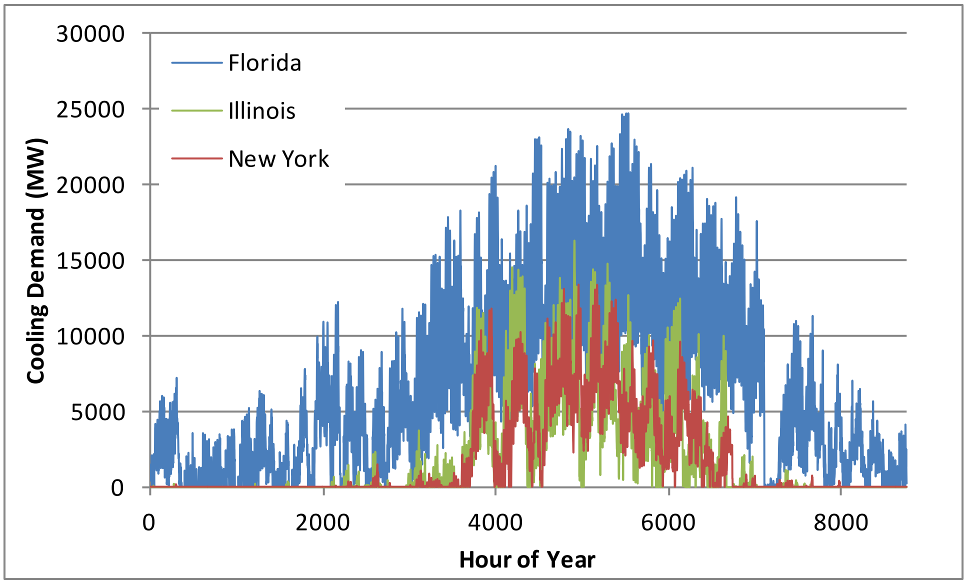

Figure 7. Example of estimated cooling load patterns for Florida, Illinois, and New York in 2005

3.2 Comparisons to Bottom-Up Estimates

We found a limited set of data to compare to our approach—primarily datasets generated by the EIA, including the Residential Energy Consumption Survey (RECS), Commercial Building Energy Consumption Survey (CBECS), and Annual Energy Outlook (AEO).[9] Appendix B describes these sources and estimation methods in more detail. Table 1 summarizes the annual cooling demand estimates using our methods aggregated to the national level, with comparisons to previous estimates using bottom-up methods.

Table 1. Summary of National Cooling Demand Estimates and Comparison to Previous Estimates

Source	Space Cooling Demand (GWh)		% Difference from Base Case (at load)		Notes
	2005	2006	2005	2006	
Base Case Results (busbar)	**444**	**423**	NA	NA	
Base Case Results (at load)	**413**	**393**	**NA**	**NA**	This value is the busbar case multiplied by 0.93
AEO 2007	378	NA	-8.5%	NA	Annual Energy Outlook
AEO 2008	393	369	-4.8%	-6.1%	
AEO 2009	NA	401	NA	2.0%	
RECS/ CBECS	399	NA	-3.4%		Sum of residential cooling from 2005 and commercial cooling from 2003

Two sets of base case results are provided. The first row provides the estimates using the base dataset, measured at the point of generation. These values include both electricity

[9] These sources are all available from the EIA via www.eia.gov.

consumed by the end user, as well as losses in T&D. The second row provides an estimate of the actual end-use cooling demand by removing T&D losses. This distinction is based on where electricity is measured. When measured at the point of generation (using our method using reported load data), these estimates include electricity effectively consumed by space cooling due to T&D losses, which average about 7% nationally (EIA 2012). However, bottom-up space cooling estimates are generated at the point of load, or what a customer would see at the meter. For a better comparison, we removed a T&D loss factor of 7% and base comparisons of previous estimates to the values in the second row. It should be noted that losses are largely a function of the load (since resistive losses are proportional to the square of the current). Since space cooling is associated with periods of peak demand, we would expect the losses associated with cooling to be higher than average, which would potentially result in our adjusted estimates being slightly higher than estimates that do not account for T&D losses.[10]

Overall, our top-down estimates are similar to but somewhat higher than estimates in the literature. We can hypothesize at least one reason for our method producing higher net cooling loads (in addition to the effect of marginal T&D losses at a rate greater than average). Previous estimates of space cooling generally include only residential and commercial buildings. While this should capture the large majority of cooling, it likely does not capture cooling demands in industrial facilities. Our estimates of space cooling include all buildings, including industrial buildings and any other space cooling systems that are not captured in reported estimates. We would expect industrial buildings to be a relatively small fraction of total cooling demand, but we could find no estimates in the literature.

Alternatively, we can think of at least one source of underestimation in our methods. In some buildings, particularly those with high internal gains, we would anticipate space cooling to have some constant level of demand, even during relatively cool temperatures. While this would affect our estimates of total demand, it would probably have less impact on the desired goal (estimating shiftable thermal load) especially if this demand were constant.

There are likely additional sources of error, particularly in regions with longer cooling seasons as noted earlier. Seasonal changes in lighting demand patterns could have a significant impact when comparing a cool winter day when days are shorter (but still in the cooling season) to a hot summer day. This impact will be relatively small in places where we compare days that are only a few weeks or months apart but could be larger in locations like Florida.

The estimates can be compared to RECS/CBECS data at the regional as well as national level. Figure 8 compares the results from our approach to these previous estimates. The first column represents the summed estimates from RECS 2003 and CBECS 2005, while the other two columns use our base case assumptions measured at the load site. These results cannot be directly compared since they represent different years. This is especially

[10] For example, a 1999 estimate of T&D losses for California was 8.1% on average and 8.6% on peak (Brown and Koomey 2002).

important given the year-to-year variability of weather, which can be observed in Table 1 by the 5%–6% decrease in cooling demand from 2005 to 2006 shown both in the AEO 2008 estimates and using our approach. This comparison does illustrate that this top-down method for estimating cooling energy works reasonably well across all regions of the country.

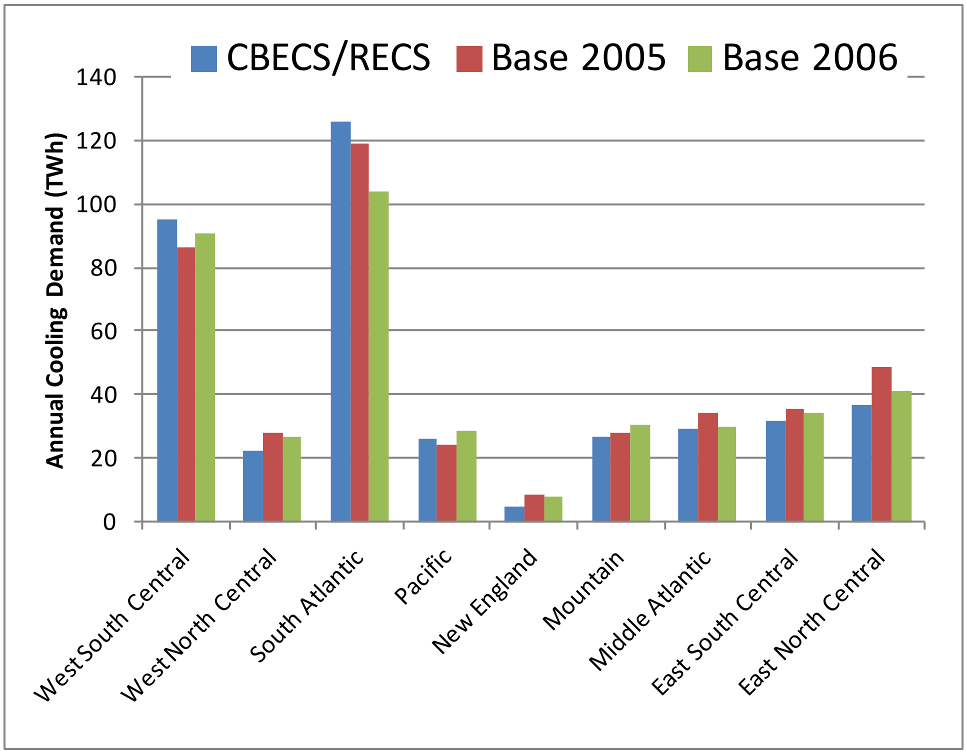

Figure 8. Regional estimates of annual cooling demand

3.3 Sensitivities

Overall, as indicated by Table 1, our estimates are typically within 10% of previous estimates, with limitations described previously. As noted earlier, our methods are driven in part by the choice of reference days and cooling season. To determine the sensitivity of our results to the cooling season assumption, we evaluated the impact of changing the temperature threshold assumption. This allows an estimate of the amount of cooling load that is not captured in the base case 65°F threshold for the cooling season. Specifically, we set the threshold for the cooling season to any day with an average temperature of 60°F and 70°F, compared to the base case of 65°F. This is essentially equivalent to capturing a larger or smaller percentage of the commercial cooling season. At the 60°F threshold, more commercial cooling is included while the residential cooling load will change very little since residential electric heating loads will be minor and almost the entire cooling season will have already been captured at the 65°F threshold. At the 70°F threshold, some amount of both residential and commercial cooling load will not be included in the estimate. The lower temperature threshold increased the total annual cooling demand by about 5% for both 2005 and 2006. The higher temperature decreased the total annual cooling demand by about 8% and 11% for 2005 and 2006, respectively.

4 Discussion and Conclusions

Given the amount of space cooling and its coincidence with peak demand, it is an important source of both responsive demand and shiftable load via TES. Understanding the potential large-scale deployment of these technologies, as well as their role in integrating renewable energy, requires knowledge of the demand for cooling over multiple time scales. We applied a simple method to estimate hourly space cooling demand using historical utility load data. Subtracting hourly demand for a cool "reference" day led to demand estimates that are within 10% of previous estimates.

Application of these profiles to DR and TES requires a number of assumptions and caveats. First, there are obvious market adoption issues associated with these technologies. Our method generates a profile for cooling across customer classes as opposed to bottom-up methods that isolate loads to individual buildings or building types. Adoption of DR or TES might be more common among large industrial or commercial customers whose demand profiles are different from residential profiles. A more accurate approach may be to combine top-down and bottom-up models to provide a starting point for estimations of cooling profiles that could be used for regional studies of responsive or shiftable cooling demand.

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Appendix A: Base Case Regional Cooling Demand

	Total A/C Load (GWh)		Peak A/C Load (MW)	
	2005	2006	2005	2006
Alabama	9,179	9,922	6,297	6,618
Arizona	15,157	16,200	10,031	11,016
Arkansas	5,403	5,911	3,915	4,567
California	24,047	27,350	24,282	32,389
Colorado	2,692	2,803	4,015	3,914
Connecticut	2,630	2,337	3,087	3,600
Delaware	2,188	2,003	2,060	2,251
Florida	59,730	45,235	24,386	22,249
Georgia	19,242	21,628	14,686	15,610
Idaho	1,771	2,318	1,924	2,204
Illinois	16,055	13,582	16,101	17,387
Indiana	8,035	6,621	7,193	7,624
Iowa	3,676	3,239	4,131	4,271
Kansas	4,883	4,849	3,962	4,302
Kentucky	5,661	5,162	4,837	5,466
Louisiana	12,325	11,603	7,214	6,429
Maine	426	438	705	826
Maryland	3,743	3,426	3,524	3,850
Massachusetts	4,240	3,909	5,412	6,615
Michigan	13,104	10,168	14,809	16,694
Minnesota	5,092	5,068	5,808	6,195
Mississippi	8,477	5,719	4,302	3,467
Missouri	11,856	10,195	10,046	10,375
Montana	316	452	592	700
Nebraska	3,419	3,100	3,341	3,439
Nevada	5,527	6,304	4,625	4,600
New Hampshire	667	533	835	959
New Jersey	10,637	9,636	11,185	12,632
New Mexico	2,201	2,075	1,711	1,565
New York	14,992	12,633	13,277	16,054
North Carolina	7,345	7,251	6,276	6,907
North Dakota	710	830	1,010	1,263
Ohio	12,786	11,232	13,736	15,402
Oklahoma	9,859	9,782	6,750	6,986
Oregon	959	1,192	2,495	3,585
Pennsylvania	11,462	10,252	10,969	13,215
Rhode Island	815	781	1,109	1,400
South Carolina	17,007	16,349	15,331	14,058

South Dakota	548	567	699	610
Tennessee	15,290	16,375	13,315	14,611
Texas	65,074	70,171	35,565	38,668
Utah	1,909	2,213	2,038	2,263
Vermont	381	306	464	543
Virginia	17,450	15,968	15,141	16,806
Washington	1,469	1,440	2,660	3,571
West Virginia	736	650	828	946
Wisconsin	2,732	2,439	3,081	3,460
Wyoming	393	390	573	614

Appendix B: National Energy Use Estimates

The most common methods of estimating national end uses of energy stem from surveys and analyses conducted by the EIA. There are two surveys relevant in this context: RECS and CBECS. The process by which this information is analyzed and used is given in Figure B-1. The surveys are independent and each has two components: the user component and the supplier component. The user component is meant to gather information about the buildings and how they are used. The supplier component is directed to the utilities that service the particular building and are for gathering total energy use data.

The data analysis is different for RECS and CBECS. RECS uses an approach that incorporates less building physics (such as estimating building heat loss coefficients) than the CBECS analysis. However, both use non-linear regression analysis (in the case of CBECS this is only for certain fuels) to determine the effects of various parameters on building energy use and to estimate end-use consumption.

This information forms the basis for the National Energy Modeling System (NEMS), which projects future energy use for the U.S. economy as a whole. This is then compiled and released in the AEO.

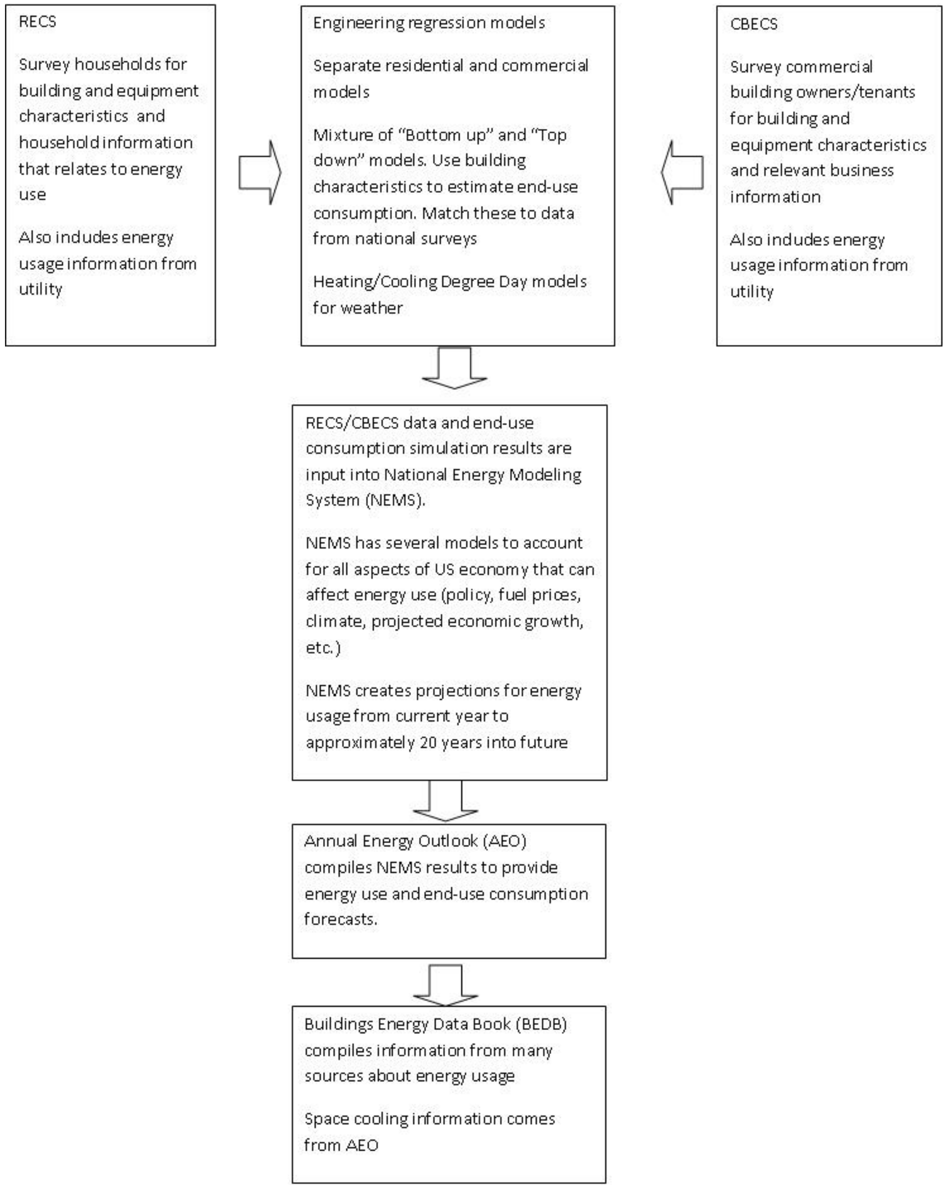

Figure B-1. Energy use survey information analysis and flow

Residential Energy Consumption Survey (RECS)

RECS consists of information collected on thousands of homes across the United States; the 2009 survey included more than 12,000 homes in 16 states. The homes are randomly chosen to enable statistical analysis and extrapolation of the data to the entire nation. The household survey collects information via approximately 150 questions regarding the physical characteristics of the house, how it is used, what sort of equipment and appliances it has and household characteristics. The energy supplier survey is sent to all energy suppliers for homes that are part of the survey; it documents energy supplied to the household via different fuels.

The survey data is compiled and used to estimate national end-use consumption in two stages:

1. Use non-linear statistical techniques to estimate end-use consumption in survey households
2. Extrapolate using data from (1) to estimate regional and national end-use consumption.

End-Use Consumption in Survey Households

The process for estimating end-use consumption in survey households begins by splitting estimates according to fuel type: electricity, natural gas, fuel oil, liquefied petroleum gas, and kerosene (EIA 1999). The regression procedure is replicated for each fuel type independently. Each fuel has multiple end uses that consume it. The primary list of end uses is:

- Space heating
- Space cooling
- Water heating
- Refrigerators
- Appliances.

Electricity usage is affected by all of the uses above; other fuels are only affected by a subset. For example, fuel oil is only used for space heating, water heating, and appliances. For the specific case of electricity, further end uses are also defined:

- Lighting
- Cooking
- Dishwashers
- Clothes dryer
- Freezers.

When considering electricity, the magnitude of the baseline-estimated energy consumption of each of these 10 end uses is adjusted based on physical characteristics, such as age and type of equipment, as well as usage patterns that can be estimated from the survey data. The importance of these adjustments and the portion of the fuel that is consumed in each survey household by the 10 end uses are determined using a non-linear regression analysis. The process is iterative but is summarized below for electricity (Cureg 2012).

1. Assume that electricity consumption is affected by all possible relevant variables that are included in the consumer survey. The regression is performed using all end uses of a given fuel (and their adjustments) simultaneously.
2. Perform non-linear regression to determine the magnitude of these adjustments. An adjustment is essentially a multiplier for each variable. If the magnitude of an adjustment is not statistically different from zero, that variable does not affect consumption for that fuel. The variable is removed and the regression is repeated.

3. Step 2 is repeated until all remaining adjustments are significant. This minimizes the error between actual and estimated consumption of each fuel and provides the information needed to estimate each of the 10 end uses (or fewer if considering fuels other than electricity).
4. Actual consumption of each fuel is known for each survey household from the energy supplier survey; a scale factor is included to adjust the estimated consumption to match the actual consumption.

The building characteristics collected from the survey and the end uses that are estimated using this technique form the basis of the Residential Sector Demand Module of NEMS to project residential energy usage in the future.

Commercial Buildings Energy Consumption Survey (CBECS)

CBECS is similar to RECS except that it concerns non-industrial or manufacturing commercial buildings. Over 5,000 buildings are included in the survey and there is also a component to the survey for energy suppliers, similar to RECS. Four fuels are considered: electricity, natural gas, fuel oil, and district energy (supplying energy to multiple buildings from a single generation source). Similar to RECS, each fuel has multiple end uses that consume it. The primary list of end uses is:

- Space heating
- Cooling
- Ventilation
- Lighting
- Water heating
- Cooking
- Refrigeration
- Office equipment
    - Computers
    - Other electronic plug load
- Other uses.

The end-use consumption estimation is similar conceptually to the RECS methodology for natural gas and fuel oil. The steps for the regression analysis are reprinted below (EIA 2003):

1. Develop engineering algorithms that estimate end-use consumption for each building based on the survey parameters. Included in the engineering algorithm development is the specification of default parameters based on secondary sources.
2. Fit degree-day regression models to monthly consumption data for individual cases, as a basis for refining certain engineering parameters.

3. Fit a regression model to calibrate and adjust the engineering estimates.
4. Apply the fitted regression model to each CBECS case.
5. Re-scale the estimated end uses for each CBECS case to match the total consumption on the record for that case.

The regression analysis for electricity and district energy proved overly constraining and unreliable. Therefore, estimates were made for end uses from detailed engineering models. These models directly incorporate important building physics to estimate end-use consumption, unlike the RECS regressions or the CBECS regressions for natural gas and fuel oil. This includes estimating building shell heat transfer coefficients, building physical characteristics (e.g., conditioned floor area, number of floors, window characteristics, and floor height), equipment efficiency, outside surface temperature, ventilation rates, latent heat (relative humidity), and building usage (hours/day).

There is still a scaling factor applied to the estimates for individual buildings to match the estimated total fuel usage to energy supplier data for that building. A weighting factor is applied to each of the individual buildings that is used to extrapolate to national energy use and end-use consumption estimation. The results form the basis for the Commercial Building Module for NEMS.

National Energy Modeling System (NEMS)

Specific RECS and CBECS data inputs into NEMS are: housing stock characteristics, existing equipment stock characteristics, fuel type for end uses (e.g., gas or electric heat for space cooling), end-use consumption estimates, and market share of particular technologies (i.e., number of households with central air conditioning, room air conditioning, or none) (EIA 2011a; EIA 2011b). These data are combined with heating degree day and cooling degree day information to adjust for weather-related effects during the particular year the survey data were collected. Other factors, such as fuel costs, policy changes, equipment and housing replacement, expected consumer behavior, building envelope integrity, and distributed energy generation, are incorporated to obtain forecasts of 21 different end uses of energy in homes and 10 end uses for commercial buildings for up to 30 years in the future. This information is compiled to generate the AEO (EIA 2008).