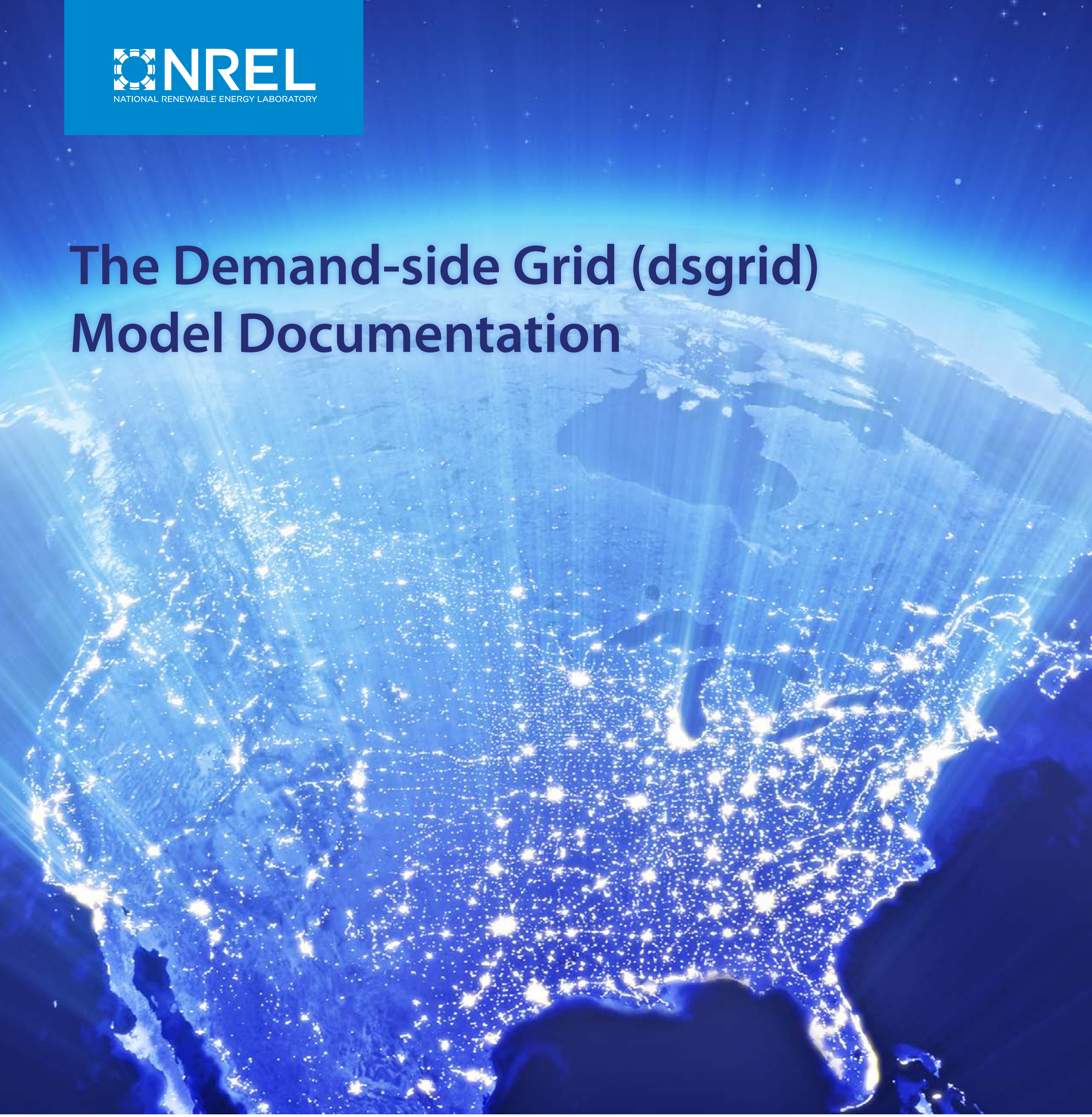

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The Demand-side Grid (dsgrid) Model Documentation

Electrification Futures Study

The Demand-Side Grid (dsgrid) Model Documentation

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NOTICE

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Preface

This report is one in a series of Electrification Futures Study (EFS) publications. The EFS is a multi-year research project to explore widespread electrification in the future energy system of the United States.

This report documents a new model, the demand-side grid (dsgrid) model, which was developed for the EFS and in recognition of a general need for a more detailed understanding of electricity load. dsgrid utilizes a suite of bottom-up engineering models across all major economic sectors—transportation, residential and commercial buildings, and industry—to develop hourly electricity consumption profiles for every county in the contiguous United States (CONUS). The consumption profiles are available by subsector and end use as well as in aggregate. This report documents a bottom-up modeling assessment of historical (2012) consumption and explains the key inputs, methodology, assumptions, and limitations of dsgrid.

The EFS is specifically designed to examine electric technology cost advancement and adoption for end uses across all major economic sectors as well as electricity consumption growth and load profiles, future power system infrastructure development and operations, and the economic and environmental implications of electrification. Because of the expansive scope and the multi-year duration of the study, research findings and supporting data will be published as a series of reports, with each report released on its own timeframe. Future research to be presented in future planned EFS publications will rely on dsgrid to analyze the hourly electricity consumption under scenarios with various levels of electrification. In addition to providing electricity consumption data for the planned EFS analysis, dsgrid can be used for other analysis outside the EFS research umbrella.

More information and the supporting data associated with this report, links to other reports in the EFS study, and information about the broader study are available at www.nrel.gov/efs.

Acknowledgments

The Electrification Futures Study (EFS) is led by researchers at the National Renewable Energy Laboratory (NREL) but relies on significant contributions from a large collaboration of researchers from the following research organizations: U.S. Department of Energy (DOE), Evolved Energy Research, Electric Power Research Institute, Lawrence Berkeley National Laboratory, Northern Arizona University, and Oak Ridge National Laboratory. We would like to thank all contributors for useful analysis, data, and input throughout the project.

A technical review committee of senior-level experts provided invaluable input to the overall study, with some committee members sharing thoughtful comments on this specific report as noted below. Although the committee members offered input throughout the study, the results and findings from this analysis and the broader EFS do not necessarily reflect their opinions or the opinions of their institutions. The technical review committee is comprised of the following individuals:

Doug Arent, Joint Institute for Strategic Energy Analysis (committee chair)	Jonathan Hughes, University of Colorado Boulder
Sam Baldwin, DOE	Michael Kintner-Meyer, Pacific Northwest National Laboratory
Steve Brick, Clean Air Task Force	John Larsen, Rhodium Group
Steve Clemmer, Union of Concerned Scientists	Bryan Mignone, ExxonMobil Research and Engineering Company
Laura Cozzi, International Energy Agency	Granger Morgan, Carnegie Mellon University
Francisco de la Chesnaye, Electric Power Research Institute	Patrick Riley, GE Global Research
Keith Dennis, National Rural Electric Cooperative Association	Laurie ten Hope, California Energy Commission
Carla Frisch, DOE	Joan Ogden, University of California Davis
Arnulf Grubler, International Institute for Applied Systems Analysis	Susan F. Tierney, Analysis Group, Inc.
Howard Gruenspecht, Massachusetts Institute of Technology	

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List of Acronyms

ACS	American Community Survey
ADOPT	Automotive Deployment Options Projection Tool
AEO	Annual Energy Outlook (U.S. EIA)
AMY	actual meteorological year
ANSI	American National Standards Institute
AWWARF	American Water Works Association Research Foundation
BCAP	Building Codes Assistance Project
BFG	blast furnace gas
BIT	bituminous coal
BLQ	black liquor
CBECS	Commercial Buildings Energy Consumption Survey
CBP	County Business Patterns (U.S. Census Bureau)
CEE	Center for Energy and Environment
CEMS	continuous emission monitoring systems
CHP	combined heat and power
CONUS	contiguous United States
DFO	distillate fuel oil
DG	distributed generation
dGen	Distributed Generation Market Demand (model)
DHI	diffuse horizontal irradiance
DHR	diffuse horizontal radiation
DHW	domestic hot water
DNI	direct normal irradiance
DNR	direct normal radiation
DOE	U.S. Department of Energy
DOE CHP DB	U.S. DOE Combined Heat and Power Installation Database
DPV	distributed photovoltaics
EFS	Electrification Futures Study
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EPW	EnergyPATHWAYS weather (file type)
ERCOT	Electric Reliability Council of Texas
EST	Eastern Standard Time
EVI-Pro	Electric Vehicle Infrastructure Projection Tool
eVMT	electric vehicle miles traveled
FAA	Federal Aviation Administration

FERC	Federal Energy Regulatory Commission
GCAM	Global Change Assessment Model
GHI	global horizontal irradiance
GHR	global horizontal radiation
GTM	Greentech Media
GW	gigawatt
HDV	heavy-duty vehicle
HVAC	heating, ventilation, and air conditioning
IAC	industrial assessment center
IAM	integrated assessment model
IEA	International Energy Agency
IGATE-E	Industrial Geospatial Tool for Energy Evaluation
IPCC	Intergovernmental Panel on Climate Change
ISO	independent system operator
LBNL	Lawrence Berkeley National Laboratory
LDV	light-duty vehicle
LFG	landfill gas
LIG	lignite coal
MDV	medium-duty vehicle
MECS	Manufacturing Energy Consumption Survey
MG	million gallons
MISO	Midcontinent Independent System Operator
MRAE	mean relative absolute error
MSB	biogenic municipal solid waste
NAHB	National Association of Home Builders
NAICS	North American Industry Classification System
NEEA	Northwest Energy Efficiency Alliance
NEMS	National Energy Modeling System
NESSIE	National Electric System Simulation Integrated Evaluator
NGA	National Governors Association
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
NTD	National Transit Database
NYISO	New York Independent System Operator
ORNL	Oak Ridge National Laboratory
OTR	Other
PAT	Parametric Analysis Tool
PBA	principle building activity

PEV	plug-in electric vehicle
PNNL	Pacific Northwest National Laboratory
PV	photovoltaics
RBSA	Residential Building Stock Assessment
RBSAM	Residential Building Stock Assessment Metering
RECS	Residential Energy Consumption Survey
RFO	residual fuel oil
RTO	regional transmission organization
SAE	statistically adjusted end-use
SEDS	State Energy Data System
SERA	Scenario Evaluation, Regionalization and Analysis (model)
SIC	Standard Industrial Classification
SUB	subbituminous coal
T&D	transmission and distribution
TMY	typical meteorological year
ULRD	Utility Load Research Data
UZA	urbanized area
WDS	wood/wood waste solids
WECC	Western Electricity Coordinating Council

Executive Summary

Electrical load is the backdrop for all power systems analysis. As a coequal partner in the supply-demand balance that must be maintained on electrical grids at all times and for all timescales, load is a major source of variability and uncertainty in grid operations. In the context of our evolving energy systems, with increasing shares of variable renewable energy, potential electrification of transport and other end uses, and the emerging ability to control energy use at the kilowatt-scale using grid-level information, obtaining a deeper understanding of electrical load is more important now than it has ever been before. Despite this, many studies of future grid systems understandably continue to place more emphasis on supply-side resources such as generation and transmission, given that they are fewer in number and are better understood in terms of cost and performance.

Load forecasting has been at the heart of utility planning for decades, but it is typically done in a top-down manner that lacks the granularity in time, geography, end use, and technology that is needed to explore the potential impact of technological shifts. Purely econometric methods that rely on historical load data combined with projections of economic and demographic parameters are common. More sophisticated methods include combining econometric techniques with simple engineering models of a limited number of key end uses. Nonetheless, there is evidence that these methods may be falling short. For example, Carvallo et al. (2017) find systemic overestimates of load growth in utility integrated resource plans. These overestimates are certainly partially explained by the recession that followed the 2008 financial crisis but are persistent enough to suggest other factors (e.g., energy efficiency adoption and performance) may have been systematically misestimated. This suggests that more complementary, bottom-up engineering- or physics-based modeling that incorporates technology and behavioral detail may be a valuable addition to the load forecasting process.

Analyses exploring future scenarios of the power sector also typically employ relatively simple scaling of historical loads. To some extent, this is a matter of necessity; renewable integration studies have demonstrated the importance of modeling systems with significant quantities of wind or solar generation using time-synchronized load, wind, and solar data. Because it is net-load that is most important for system operations, these timeseries must all reflect the same weather as it was experienced simultaneously across the region of interest. Thus, historical hourly load data are taken from the same year from which the wind and solar data sets are derived, and a basic scaling factor is applied. For example, MacDonald et al. (2016) project hourly load in 2030 using a single growth rate assumption of 0.7% applied to all hours. Although expedient, this methodology is insufficient to capture the impact of significant demand-side technological change, such as widespread electrification, which could drastically impact load shapes and demand-side flexibility.

The primary purpose of the demand-side grid model (dsgrid) is to fill these gaps by creating comprehensive load data sets at a sufficient temporal, geographic, sectoral, and end-use resolution to enable detailed analyses of current patterns and future projections of end-use load. Furthermore, the dsgrid platform uses a bottom-up methodology that allows highly resolved analysis of “what-if” scenarios. dsgrid leverages detailed sectoral energy models to provide hourly time series of load by subsector, end use, and county covering a full year (see Figure ES-1). Although dsgrid currently emphasizes electricity load data, its component sector models for residential buildings, commercial buildings, and industry provide information on other fuel use, including natural gas. The data sets can thus be leveraged to support analysis of numerous demand-side technology-driven changes, such as energy efficiency, electrification, and operational flexibility (i.e., demand response). The electricity use data are time-synchronized with solar and wind data sets so as to be suitable for use in power systems analysis.

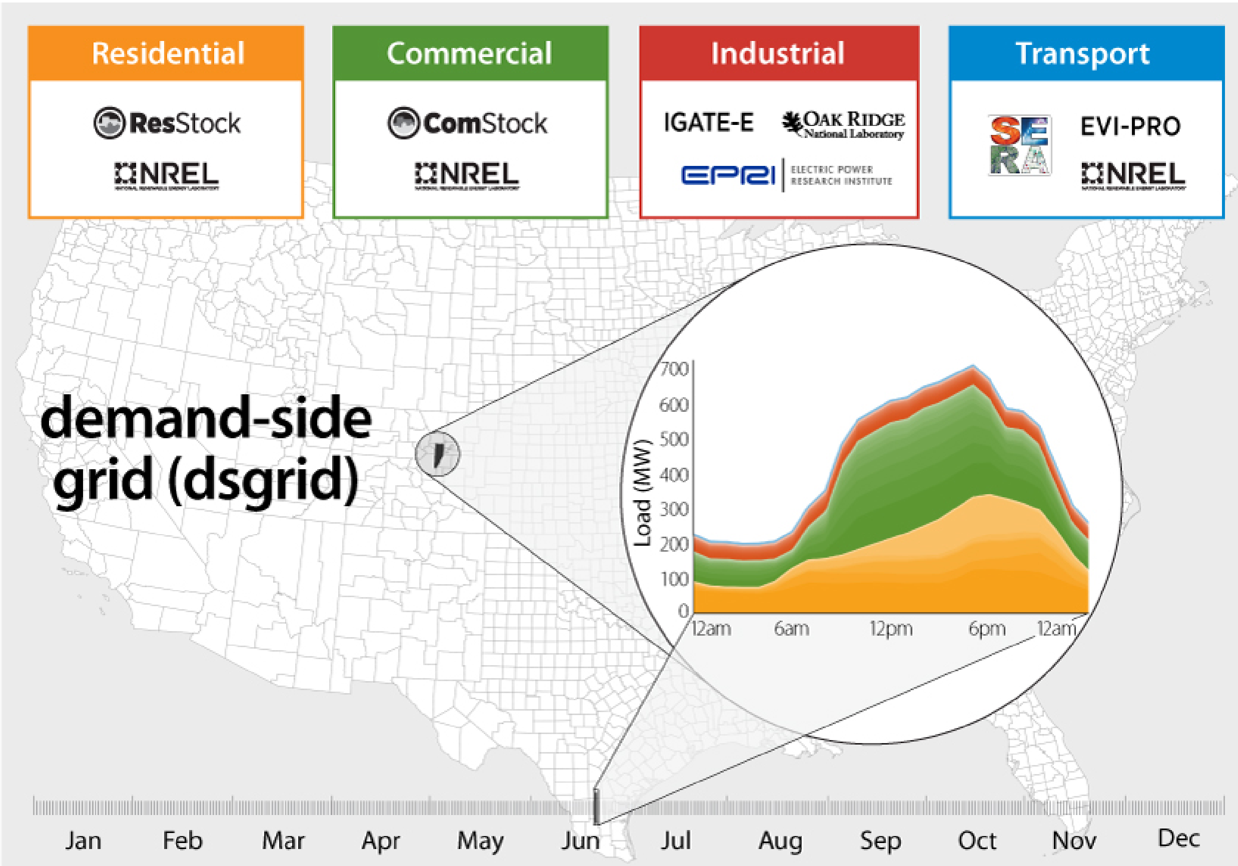

Figure ES-1. dsgrid provides load data for the contiguous United States at high geographic, temporal, and sectoral resolution.

This report documents dsgrid and its initial data set, which covers electricity demand in the contiguous United States (CONUS) for the historical year of 2012. We start with a historical year to enable model calibration and validation, as well as the development of a mathematical description of our model residuals that can be applied to future-year "what-if" scenarios to remove known errors between our bottom-up modeling and historical load shapes. This work is part of the Electrification Futures Study (EFS),[1] for which the dsgrid team will be developing future load snapshots that describe projected year 2050 under baseline and a range of electrification assumptions.

[1] www.nrel.gov/efs

Within dsgrid's architecture, each sector's energy use is modeled with separate methodologies. The core sector models, which provide the most detailed level of modeling available in dsgrid, cover about 80% of 2012 annual electricity demand (Figure ES-2).[2] An additional 17% is then represented with sector-level gap models, which are coarser in both inputs and outputs than the fully detailed sector models, but nonetheless leverage some of the core data (e.g., load shapes) and provide hourly demand timeseries resolved at least to the subsector and state level. The remaining 3% is electricity used for unmodeled commercial subsectors.

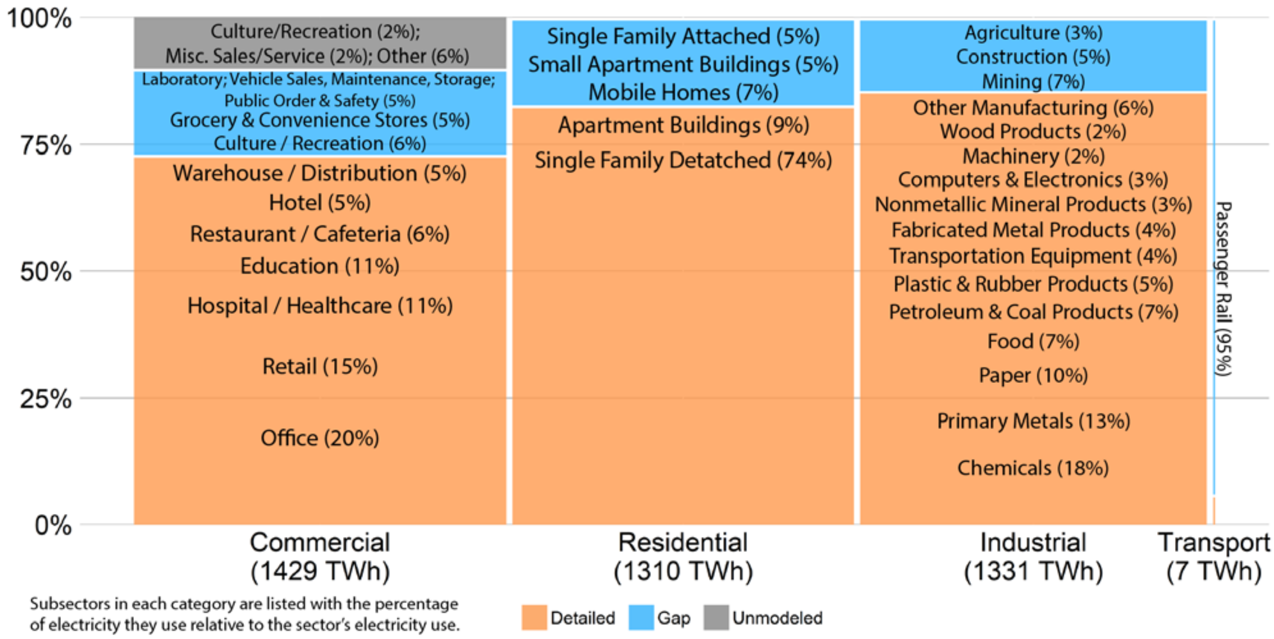

Figure ES-2. dsgrid models about 80% of 2012 U.S. electricity use in detail.

Brief descriptions of the detailed sector methodologies follow:

- **Residential and Commercial Buildings:** Building loads are estimated using ResStock and ComStock, which use similar statistical methodologies and OpenStudio modeling infrastructure to simulate the U.S. single-family detached and commercial building stock electricity consumption by end-use. These models sample from thousands of probability distributions to produce hundreds of thousands of EnergyPlus simulations, which are then weighted to represent subsector building stocks at the county level. This detailed modeling covers single family homes and commercial buildings mappable to the 16 DOE commercial "prototype buildings" (Goel et al. 2014).
- **Industrial Manufacturing:** Industrial manufacturing loads are modeled with the Industrial Geospatial Analysis Tool for Energy Evaluation (IGATE-E), which uses plant-level databases, the Manufacturing Energy Consumption Survey, and the Electric Power Research Institute's Load Shape Library to construct hourly time series of electricity use by manufacturing subsector and end use. Because manufacturing processes vary greatly, IGATE-E does not attempt direct simulation of loads but rather compiles data from

[2] That is, 80% of the site demand is from residential buildings, commercial buildings, industry, and transport. This measure excludes such subsectors as public water supply, municipal wastewater treatment, and exterior roadway lighting.

multiple sources and applies statistical techniques to estimate energy consumption down to the end-use level. Because IGATE-E only models manufacturing, the additional industrial sectors of agriculture, mining, and construction comprise our industrial gap model.

- **Transportation**: Given the focus in this report on constructing a model of historical electricity use for the year 2012, and the very low deployment of plug-in electric vehicles in that year, we describe the detailed transportation modeling methods that will be used in future work to capture EV location and charging; but no detailed sector-level results for transportation are presented.[3] When this capability is developed for the EFS future model year snapshots, on-road plug-in electric vehicle operation will be described using the Scenario Evaluation and Regional Analysis (SERA) model and the Electric Vehicle Infrastructure Projection Tool (EVI-Pro). SERA describes vehicle infrastructure requirements and will be used to disaggregate vehicle adoption to the county level. EVI-Pro simulates hourly charging profiles based on travel data and charging preference assumptions (e.g., residential charging as opposed to reliance on public charging). The historical 2012 data set includes a transportation gap model that describes electricity use in passenger trains.

While the sector models cover approximately 80% of annual electricity demand, they do not provide full coverage of all electricity use in the United States, nor do they account for such load modifiers as distributed generation or transmission and distribution (T&D) losses. The model therefore incorporates additional data sources and uses them to create gap models, distributed generation models, and a model of losses (Figure ES-3). The sectoral gap models describe building types not modeled in detail; electricity used for agriculture, mining and construction; and electricity used for passenger rail transport. dsgrid additionally contains supplemental gap models that represent electricity used for municipal water services and outdoor lighting. Distributed generation from solar photovoltaics, combined heat and power, and other distributed thermal generators is estimated on hourly, state, and sectoral bases using a variety of data sources. The distributed generation data combined with historical electricity sector data are key to enabling the calculation of model residuals and related visualizations used to calibrate and validate the model. In total, the dsgrid model structure is a confederation of data sets and programmatic methods that are available to aggregate, disaggregate, visualize, and perform statistical analysis on an overall description of U.S. electricity demand for one model year.

[3] The data visualized in Figure 2 for Transport consists of a small orange sliver topped with a longer blue sliver; the blue sliver is labeled "Passenger Rail (95%)." The orange sliver represents 381 GWh of electricity used in the U.S. for light-duty vehicles in 2012 that is not modeled in this version of dsgrid.

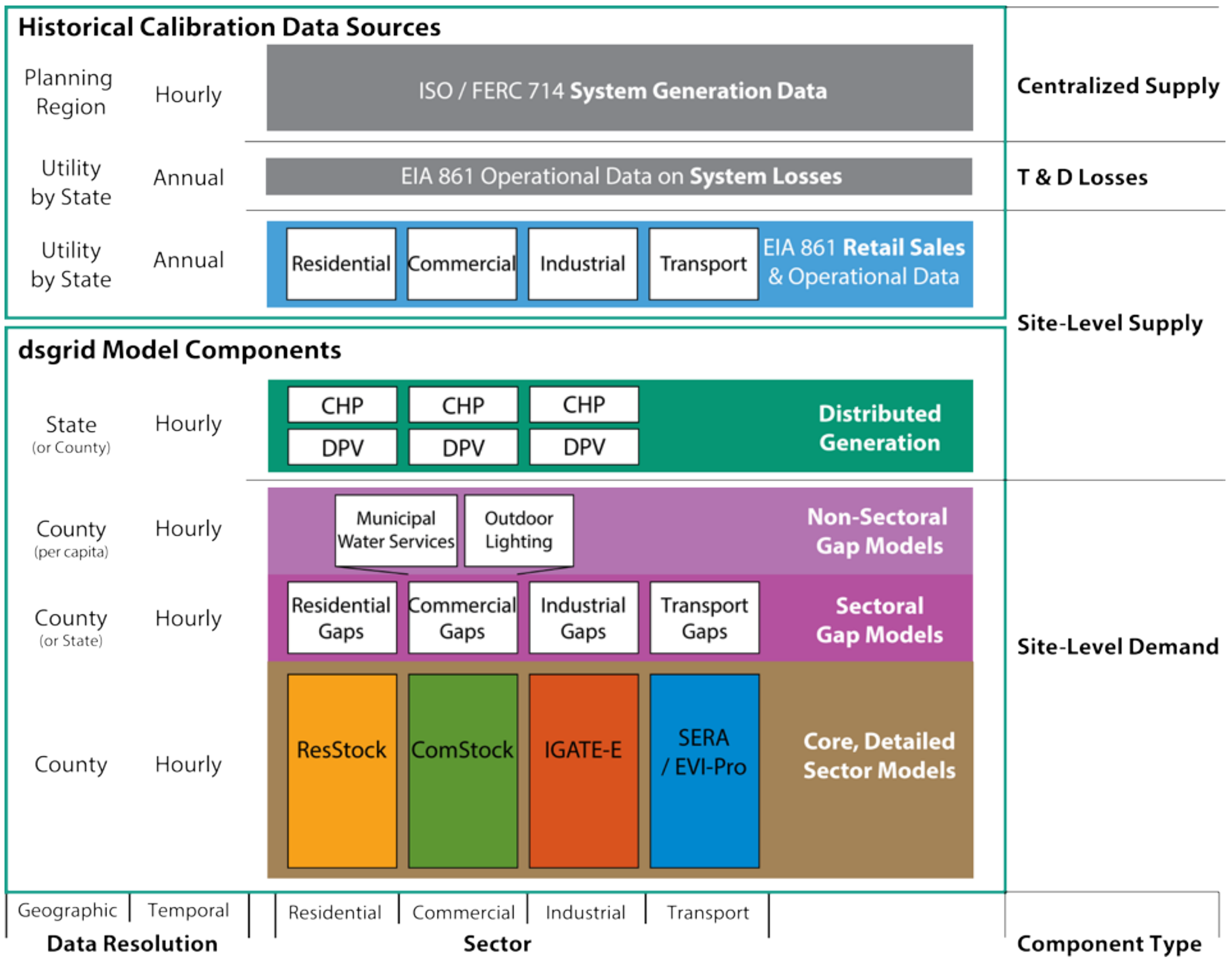

Figure ES-3. dsgrid input data architecture

All acronyms are defined in the acronyms list on page vi.

Data Set Summary

The dsgrid historical snapshot for 2012 is a more highly resolved starting point for power sector studies than has heretofore been available. Except for the transportation gap model, which is at the state level, the detailed sectoral models and the sectoral gap models are available at the county level by subsector and end use. End use breakdowns are provided for the detailed sector models (residential and commercial buildings, and industrial manufacturing) as well as for the residential gap model. The detailed building models include hourly data on natural gas and district heating and cooling use, in addition to electricity. For all fuels, building energy use is reported across nine end uses: fans, pumps, space heating, space cooling, heat rejection (commercial only), interior lights, exterior lights, water systems, and interior equipment. Industrial manufacturing electricity use is reported for the 12 U.S. Energy Information Administration (EIA) Manufacturing Energy Consumption Survey end uses: conventional boiler use; process heating; process cooling and refrigeration; machine drive; electrochemical processes; other process use; facility heating, ventilation, and air conditioning (HVAC); facility lighting; other facility support; onsite transportation; other nonprocess use; and end use not reported.

The data set is summarized at the annual level for the contiguous United States in Table ES-1. The detailed and gap models described above, plus gap models for roadway and parking outdoor lighting and for public water supply and wastewater treatment (county-level, based on per-capita energy use estimates) form the dsgrid-core components. Together with the hourly residuals,[4] these components, which are shaded green in Table ES-1, provide an hourly estimate of site electricity use at the state level. To obtain load profiles that need to be met at the bulk power level, one can subtract the contribution from distributed generation and then add in the estimate of T&D losses as appropriate depending on model context. These components are shaded blue.

Table ES-1. Summary of Contiguous U.S. Electricity Use in Terawatt-Hours, Top-Down and Represented in dsgrid

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load[a]					3,910
Derived	T&D losses					199
Top-down	Annual energy[b]	1,370	1,350	981	7	3,708
dsgrid	Distributed generation	3	31	204	–	237
dsgrid-core	Gap models	218	454	184	6	862
dsgrid-core	Detailed sector models	1,169	1,107	893	–	3,170
Derived	Total site energy[c]	1,372	1,381	1,184	7	3,945
Derived	Annual sector residuals[d]	-15	-180	107	1	-87
Derived	Hourly residuals[e]					-126

[a] FERC Form 714 and independent system operator (ISO) reporting

[b] U.S. Energy Information Administration (EIA) Form 861

[c] Total site energy is the top-down annual energy plus distributed generation. This is all the load we are expecting to model with the bottom-up detailed sector and gap models.

[d] The sector level residuals are equal to the total site energy minus the gap and detailed sector model components.

[e] The hourly residuals reported in the Total column are the sum of the state-level hourly residuals, which factor in top-down hourly load, T&D losses, distributed generation, and the dsgrid-core model components.

dsgrid model components necessary to represent site-energy use at the hourly level are shaded green. Components that may be factored in to estimate bulk power system load are shaded blue-grey.

Although the top-down data do not exist to compute hourly residuals resolved by sector, the top-down annual energy data available from U.S. Energy Information Administration (EIA) Form 861, along with our sectoral estimate of distributed generation, do provide the means to compute sectoral residuals on an annual basis. Based on this total site energy estimate, we see from Table ES-1 that for the contiguous United States, about 35%, 35%, 30%, and 0.2% of site electricity use is attributable to residential, commercial, industrial, and transportation subsectors respectively; dsgrid bottom-up estimates capture this energy use within ±1% for the residential sector. For commercial, industrial, and transport, dsgrid estimates fall within ± 15%.

Examining the data at this most aggregated level is helpful, but it belies model discrepancies that are apparent when the data are examined at a finer level of temporal or geographic resolution.

[4] The hourly residuals are computed by comparing the bottom-up load data to top-down bulk power system hourly load data and factoring in T&D losses and distributed generation.

For example, Figure ES-4 depicts the dsgrid bottom-up load data (detailed sector models and gap models) and T&D losses alongside the historical hourly load data, and the historical hourly load data plus our distributed generation estimates. From this, we can see that our bottom-up modeling is able to capture seasonal load shape changes (e.g., the double-peak common in winter, and the single afternoon peak common in summer), but it regularly exaggerates the differences between weekday and weekend energy use, as well as between daytime and nighttime energy use, the latter especially during cooling season (e.g., summer and spring). Such discrepancies between the modeled results and the historical data occur because we do not artificially constrain our bottom-up models with top-down data. The model residuals that result therefore point to aspects of our bottom-up understanding of demand-side energy systems that need improvement.

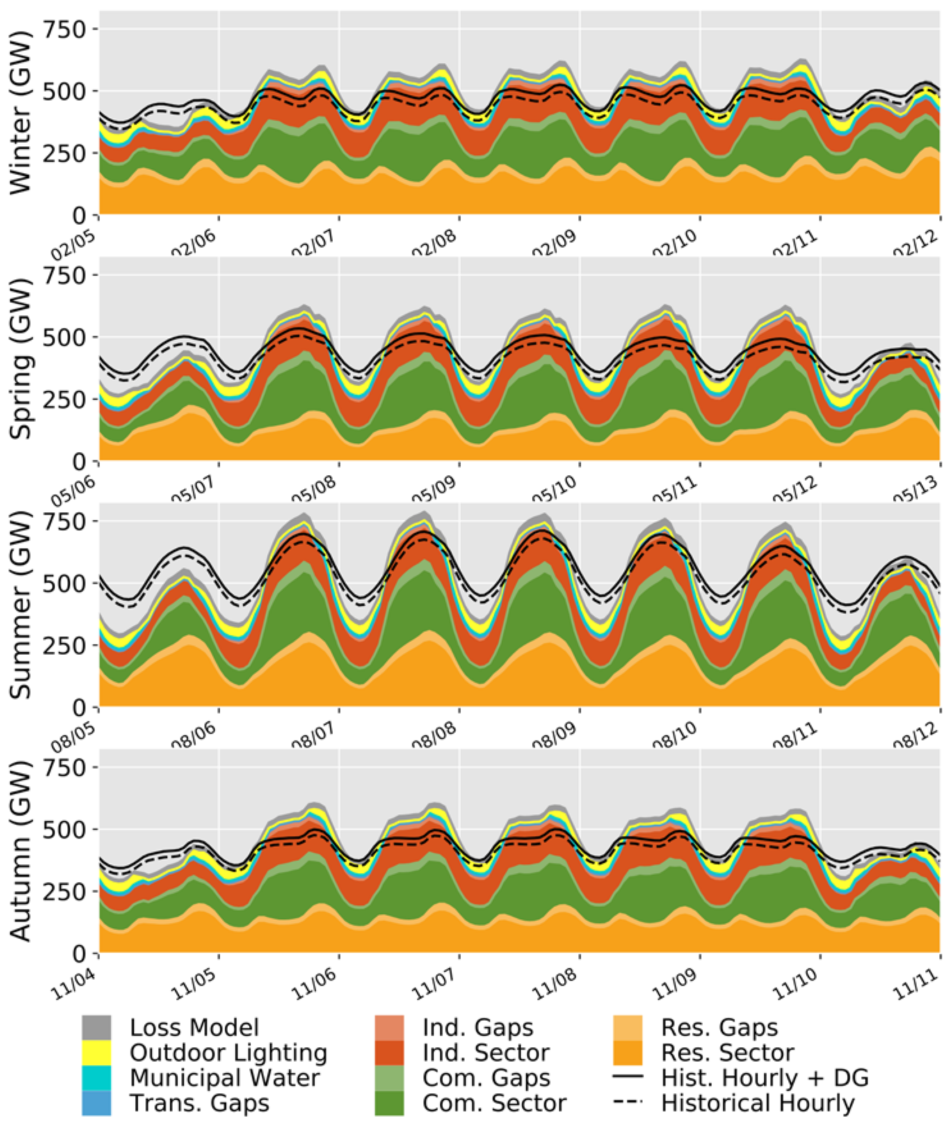

Figure ES-4. Bottom-up sector model and gap model load in gigawatts (GW) compared to bulk-level historical hourly load for the entire contiguous United States (CONUS), for four representative weeks

Each week starts on a Sunday, and all data are plotted time-synchronized in Eastern Standard Time.

An initial effort to understand the information contained in our hourly and sectoral residuals is shown in Figure ES-5, which depicts energy-weighted average fit statistics at different levels of geographic, temporal, and sectoral aggregation. The calculation details are provided in the body of the report, but in all cases, what is shown is 1 minus a measure of relative error (i.e., 1.00 indicates zero error) averaged over geographic units using the total annual site energy estimate in total or by sector as the weight.

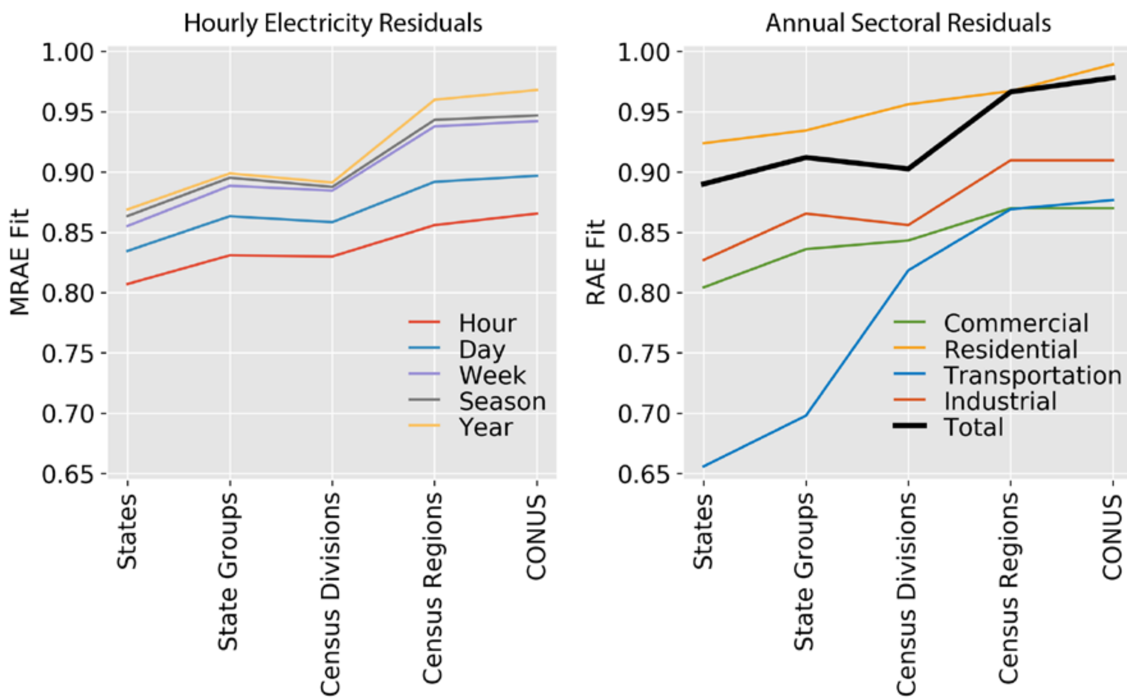

Figure ES-5. dsgrid fit statistics for total site energy as a function of geographic, temporal, and sectoral resolution

At the most aggregated level, dsgrid bottom-up sectoral and gap models capture the expected site load within a relative error of 4%. At the least aggregated levels for which we calculate residuals, the energy-weighted mean relative absolute error is about 20% for hourly electricity, and the energy-weighted relative absolute error ranges from 35% (transportation) to less than 10% (residential) for annual energy use by sector.

The levels of geographic resolution are states (48 plus Washington, D.C.), state groups (24 described in the body of the report), census divisions (9), census regions (4), and the CONUS (1).

First, examining the hourly electricity residuals, we see confirmation of what we saw in Table ES-1, namely that at the annual level aggregated to all of CONUS, the dsgrid bottom-up models captures the site energy represented in the historical hourly load data combined with the dsgrid distributed generation models to within a relative error of 4%. However, if we examine the model at the most resolved level for which hourly residuals are available (state-level and hourly), the level of fit drops almost to 80%. Where is most of the fit lost? Temporally, the first large gap occurs when we go from weeks to days; this likely speaks to the weekday-weekend discrepancy apparent in Figure ES-4. The daytime-to-nighttime shifts similarly show up in the difference between the hour and day curves. Geographically, there is a large difference between census divisions and census regions, and a more modest but significant difference between states and state groups. For these hourly residuals, which rely on a disaggregation of system load data reported by independent system operator (ISO) region or FERC Form 714 planning region, a significant portion of the error introduced by disaggregating from the state group to the state level may be attributable to that process (and not to the bottom-up modeling alone).

Examining the sectoral residuals, the relative maturity of the residential modeling is immediately apparent, as its level of agreement with the total annual energy use reported by state on EIA Form 861 plus our distributed generation estimates is above 92% at all levels of disaggregation (down to states). The level of fit for all other sectors is below 85% at the state level, but it is greater than 80% for the other two main electricity-consuming sectors: commercial and industrial.

Overall, these results show that we can model U.S. electricity load at high resolution, especially if we leverage the model residuals computed here to patch the now-revealed discrepancies between our modeling and historical data. We also know the likely sources of some of these discrepancies. For commercial buildings, we are aware of inaccuracies and uncertainties related to count and size of commercial buildings by type, especially for those building types not well represented in CoStar. In contrast, industrial manufacturing plant locations are fairly well known,[5] but because IGATE-E does not directly model the energy use of industrial processes, it relies on the DOE industrial assessment centers (IAC) database to create estimates of energy intensity. Relying solely on the IAC Database is problematic because it underrepresents industries dominated by very large plants and it may be subject to selection bias. Low data availability further necessitates using energy intensity metrics based on number of employees rather than other normalization factors that may be better correlated to energy use such as annual sales. The temporal discrepancies apparent in the hourly residuals are not all that surprising given this was the sector modeling teams' first time providing hourly modeling results as an end product. Demand-side energy research has historically had a much stronger focus on pure energy efficiency measured on an annual basis than on the temporal specificity required to understand interactions with the grid. Moving forward, we expect to conduct more hourly and subhourly calibration at the sectoral, subsectoral, and end-use levels using utility- and facility-scale metered data to develop stochastic modeling of operational schedules, control set-points, and occupant behavior.

Looking Forward

dsgrid is a new model designed to provide a solid basis for exploring questions related to future electricity load and its relationship to grid operations. Because it is a new model, this documentation represents the beginning of an investigation more so than the end of an analysis. The model validation documented in this report makes plain the fact that the commercial and industrial models in particular need more sectoral-level calibration, and that all the models would benefit from additional temporal calibration. To that end, additional calibration of the building models to metered data is both ongoing and in various stages of planning as future work. To make the model usable in the meantime, we are also developing methods to mathematically summarize the model residuals in a manner that can be applied to dsgrid scenarios built by modifying the baseline model documented in this report (e.g., to represent load in future years).

[5] IGATE-E relies on the MNI database for this information.

Subsequent stages of the EFS will include developing dsgrid future-year snapshots of 2050 electrical load based on the PATHWAYS outputs for the EFS electrification scenarios (Mai et al. 2018) and evaluating the potential flexibility of those future loads. Under most scenarios, we expect significant growth in on-road electric vehicle deployment by 2050. For this reason, transportation, while not a significant part of the dsgrid historical load snapshot documented here, is anticipatorily included in the methodological documentation.

In addition to the work planned for EFS, the dsgrid data set and modeling framework now exist as a resource for investigating questions about U.S. electricity load, from regional differences in coincidence with wind and solar generation, to the potential impact of particular energy efficiency measures or demand response programs. Some of the underlying data sources are actually more granular than the county level, so we also anticipate interest in more-localized, distribution-level modeling. The data on fuel use other than electricity, especially for the residential and commercial building sectors, could also enable more detailed analysis of interactions between natural gas, electricity, and water networks.

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1 The Need for a Detailed Model of Electrical Load

Electrical load is the backdrop for all power systems analysis. As a coequal partner in the supply-demand balance that must be maintained on electrical grids at all times and for all timescales, load is a major source of variability and uncertainty in grid operations. Load forecasting has been at the heart of utility planning for decades, but it is typically done in a top-down manner that lacks the granularity in time, geography, end use, and technology that is needed to explore the potential impact of technological shifts. Purely econometric methods that rely on historical load data combined with projections of economic and demographic parameters are common. More sophisticated methods include combining econometric techniques with simple engineering models of a limited number of key end uses. Nonetheless, there is evidence that these methods may be falling short. For example, Carvallo et al. (2017) find systemic overestimates of load growth in utility integrated resource plans. These overestimates are certainly partially explained by the recession that followed the 2008 financial crisis but are persistent enough to suggest other factors (e.g., energy efficiency adoption and performance) may have been systematically misestimated. Forecasting future load is only going to become more difficult and more important as new demand-side appliances, control technologies, and other distributed energy resources are adopted, and as wind and solar generation compose a larger portion of our power supply. This suggests that more complementary, bottom-up engineering- or physics-based modeling that incorporates technology and behavioral detail may be a valuable addition to the load forecasting process.

In the past, U.S. electricity consumption experienced rapid unexpected change coincident with important electricity sector developments. For instance, the first wave of air conditioning adoption in the 1960s and 1970s coincided with the construction of many new petroleum-fueled generators and was swiftly followed by an oil embargo that made the operation of those new generators significantly more expensive than expected (U.S. EIA 2016; Bhatnagar and Rahman 1986; U.S. EIA 2012). Overall, conditions such as these resulted in the traditional growth-based treatment of electrical load being insufficient. We thus turned to new approaches, including energy efficiency and demand response (Hurley, Peterson, and Whited 2013; Alliance to Save Energy 2013).

The pressures on the power system are arguably greater today. Like air conditioning before it, electric vehicles are poised to become a new large load for many households and businesses (McNerney et al. 2016; Banister et al. 2012; Egbue and Long 2012). Heat pumps are also gaining market share, primarily in the southern United States, but with a growing potential to compete in cold climates as well (Baxter and Groll 2017; Lapsa and Khowailed 2014). At the same time, new generation resources such as wind and solar, and complementary resources such as battery and other forms of energy storage, are coming online and complicating grid planning and operations. In the meantime, aggressive energy efficiency efforts in the form of utility programs, state-level goals, and federal appliance standards have proceeded apace. The International Energy Agency (IEA) estimates that U.S. energy efficiency investments since 1990 have reduced the total final energy consumption required to provide the same services by up to 7.44

quadrillion British thermal units (Quads) per year [2,181 terawatt-hours (TWh) per year][6] (IEA 2015). Utility planners have sometimes underestimated the future impacts of such energy efficiency efforts and other causes of low load growth, which has made it more difficult to create cost-effective plans for satisfying future load while also integrating wind and solar (Kavalec et al. 2016; Carvallo et al. 2017).

Given the impacts of continued adoption of air conditioning and distributed solar photovoltaics, the nascent adoption of electric vehicles, and the shift of some economic activity away from industry and toward more commercial service work, there is some reason to expect that future load profiles may become peakier (NGA 2016). On the other hand, energy efficiency, energy storage, and demand response (load scheduling and shifting) technologies, as well as the emergence of some forms of computing and other miscellaneous electrical loads as a base load may mitigate this trend such that peak load becomes less of a concern (Schwartz et al. 2017; Zarakas et al. 2017). Recent data give credence to perhaps both these things happening, with very different balances being achieved at a regional level. That is, peak and annual load growth have decoupled in many places but not necessarily in the same direction. For instance, the northeastern United States has seen peak load growth higher than annual load growth (NGA 2016), while California has been revising its forecasts in the opposite direction (Kavalec et al. 2016). In the South, peak and annual growth rates have been similar in recent years (EIA 2014a). Because transmission and distribution (T&D) infrastructure are sized to handle peak load (i.e., the largest coincident power draw anticipated by system planners or experienced in a given year), these distinctions are important to capture with regard to both planning and operations.

Though accurately capturing the split between overall and peak load growth remains important, increasing levels of wind and solar deployment are also moving us beyond this paradigm where annual demand, peak demand, and coincidence factor[7] are sufficient metrics for describing the state of current and future electricity loads. Recent renewable integration studies clarify that future power system operations will focus on balancing net load, that is, load minus all variable generation contributions from wind and solar. For systems with large contributions from solar photovoltaics (PV), it emerges that the daily minimum net-load point is just as important as the daily peak (net-)load point, and that many days will have a peak in the morning in addition to one in the afternoon or evening.[8] For systems with large contributions from wind, the most challenging times for system operations are even harder to locate, given the seasonal, weekly, and diurnal variability of the wind resource.

[6] This statistic includes all energy use, not just use in the electricity sector. For 2014, the IEA estimates the U.S. "total final consumption" equaled 17,458 TWh and that there would have been an additional 2,181 TWh in the absence of all energy efficiency investments since 1990. This compares to EIA's reporting of 2014 primary energy use and electricity sales to the residential, commercial, industry and transportation sectors of 22,138 TWh in total, with just 3,764 TWh attributed to electricity sales (which like the total final consumption metric, excludes system losses) (U.S. EIA 2017).

[7] Coincidence factor is calculated over some set of system sub-components, for instance, substations, feeders, or customers, and is the system peak load divided by the sum of the individual component peaks. The coincidence factor is 1.0 if all sub-components peak at the same time and otherwise is less than 1.0.

[8] Though this is a fairly common pattern in the winter, in areas with high PV penetrations we also see this pattern emerge in the summer, when traditionally there has been a single clear peak sometime in the afternoon that is approximately coincident with peak air conditioning loads.

Renewable integration studies have also demonstrated the importance of modeling systems with significant quantities of wind or solar generation using time-synchronized load, wind, and solar data (Holttinen et al. 2017). Because it is net-load that is most important for system operations, these timeseries must all reflect the same weather as it was experienced simultaneously across the region of interest. For this reason, renewable integration studies have generally relied on historical hourly load data taken from the same year from which the wind and solar data sets are derived. For example, the following description from MacDonald et al. (2016, Supplementary Information Section 1.3) is typical:

> The electric load data was expanded from 2006–2008 to 2030 estimated levels. To estimate the 2030 load, quarterly gross domestic product figures from the Bureau of Economic Analysis (72) were applied to the expansion (and contraction) of the load to 2011, and then a 0.7% per year growth rate (73) was applied to 2030. The result is a 14% increase in the demand for each hour.

However, we know that this methodology is insufficient to capture the impact of significant demand-side technological change.

The primary purpose of dsgrid is to create comprehensive electricity load data sets at a sufficient temporal, geographic, sectoral, and end-use resolution to enable detailed analyses of current and future projections of end-use load. The data sets can be leveraged to support analysis of demand-side energy efficiency, electrification, and operational flexibility (i.e., demand response); and are time-synchronized with solar and wind data sets so as to be suitable for renewable integration studies.

The initial effort described here is part of the Electrification Futures Study (EFS);[9] thus, our initial focus is on developing time-synchronous electricity data suitable for studying the impact of electrified loads on future power systems. This work is proceeding in two stages. What is documented here is a mesoscale model of current electrical loads built using a variety of national-level data sets, bottom-up building energy simulations driven by historical-year weather files, and a detailed accounting of electricity use in industrial manufacturing and transportation. We focus initially on modeling a historical year of electricity use to enable model validation, calibration, and development of an error model that can be carried forward into our future-year data sets.

In the next stage of the EFS, using dsgrid, we will develop future-year snapshots of electrical load and evaluate the potential flexibility of those future loads. These snapshots will be based on the EFS electrification scenarios for 2050 as represented in the outputs of the EnergyPATHWAYS model (Williams et al. 2014). Under most scenarios, we expect significant growth in electric vehicle deployment by 2050. For this reason, transportation, while not a significant part of the dsgrid historical load snapshot documented here, is anticipatorily included in the methodological documentation.

[9] For more information, see https://www.nrel.gov/analysis/electrification-futures.html.

1.1 Overview of Load Models Described in the Literature

Previous investigations of these kinds of long-term questions about electricity demand,[10] including how electricity demand impacts power system planning and operations in relation to various societal factors and goals,[11] have used models intended to capture an entire energy system or economy, of which energy demand is a part; load forecasting models used for electricity system planning[12]; models of electricity load flexibility; and sector-specific energy models. In this section, the authors describe some of the more prominent efforts in each of these categories. In Section 1.2, we summarize them in relation to the aims of dsgrid.

1.1.1 Energy System and Economy Models

The National Energy Modeling System (NEMS)

NEMS[13] is a modular energy-economy modeling system used to construct the U.S. Energy Information Administration (EIA) Annual Energy Outlook (AEO) and to conduct other U.S. energy systems analysis. Four NEMS modules are of primary interest here: Commercial Demand, Industrial Demand, Residential Demand, and Transportation Sector Demand. Together, they comprise all the NEMS end-use demand modules. The demand modules all accept as inputs energy prices and macroeconomic indicators, and they then compute changes in sector demand based on assumptions about technology cost, equipment standards, tax and other relevant policies. Energy consumption by fuel type is output at the U.S. census division level. NEMS then iterates to converge on equilibrium energy prices and quantities (EIA 2009).

The Residential Demand Module and the Commercial Demand Module use the most recent Residential Energy Consumption Survey (RECS) or Commercial Building Energy Consumption Survey (CBECS) respectively as their base year and then project residential and commercial energy use forward several decades. The current end year is 2050. NEMS refers to these as structural models, that is, they provide an accounting of energy use by tracking building and appliance stock, including both quantity and performance characteristics, which are influenced by macroeconomic parameters, energy prices, and technology learning effects. The modules output energy use by fuel type and end use. For commercial buildings, there is a distinction between major and minor fuels and end uses. The minor fuels and end uses are modeled in less detail. Energy efficiency standards, building energy standards, and customer adoption of energy efficiency and distributed generation technologies (e.g., PV and combined heat and power or CHP) are some of the main factors captured beyond basic macroeconomic trends (EIA 2017d, 2017e). Residential demand is modeled by tracking housing and appliance stocks (EIA 2017d). Commercial building energy use is primarily tracked by floor area per building type, overall energy use intensity (in British thermal units per square feet [kBtu/ft^2]), and changes to energy

[10] Greening, Boyd, and Roop (2007); FERC (2009); Boßmann and Staffell (2015); Alstone et al. (2016b); Shoreh et al. (2016); Klingler, Elsland, and Boßmann (2017); Wilson et al. (2017)
[11] EIA (2017c); Williams et al. (2014); Mai et al. (2014); Melaina et al. (2016); California Energy Commission Staff (2017); Alstone et al. (2017); DOE (2017b)
[12] Here, we leave aside purely statistical or econometric models (e.g.., regressions on historical load, population and economic indicator data coupled with population and economic forecasts), as they are less able to account for the major technological changes we expect to see over the long term.
[13] NEMS: National Energy Modeling System, https://www.eia.gov/outlooks/aeo/info_nems_archive.php

use intensity, based on equipment efficiency and building shell upgrades. Distributed generation adoption then reduces the net load seen by the wider energy system (EIA 2017e).

The Industrial Demand Module receives employment data and the value of industrial shipments, beyond energy price, as additional inputs from the NEMS Integrating Module. These data are used to adjust the demand from 15 manufacturing and 6 non-manufacturing subsectors. Five of the manufacturing industries are modeled with detailed process flows (i.e., engineering representations of individual process steps); two are modeled with detailed end-use accounting; the energy demand of the remaining eight is based on a simpler end-use accounting and a motor stock model for machine drive electricity use. Manufacturing industries classified as energy-intensive are more likely to have a process flow model. All industry, manufacturing and non-manufacturing is modeled using three end-use components: boilers/steam/cogeneration, buildings, and process/assembly. We have so far been characterizing the process/assembly portion, which accounts for about 55% of industrial energy use. Building energy use is a small (about 4%) component of industrial energy use, and so is not modeled in detail, but it is a simple function of employment and industrial output per subsector. Process and building heating is supplied from the boilers/steam/cogeneration module, which consumes fuels to produce steam and electricity. Existing CHP plants are represented directly, and new ones are built to meet new thermal energy requirements, and to consume biomass waste products (e.g., in the pulp and paper industry). The non-manufacturing industrial sectors are modeled with unit energy consumption parameters per ton of throughput or dollar of shipments, as well as interactions with the Commercial and Transportation Sector Demand modules. Unit energy consumption is derived from a variety of data sources specific to agriculture, mining, and construction. The commercial and transportation demand modules supply parameters concerning construction demand, commercial building energy intensity, and vehicle fuel efficiencies. Benchmarking for the start year is done with a combination of EIA Manufacturing Energy Consumption Survey (MECS) and State Energy Data System (SEDS) data (EIA 2014b).

The Transportation Sector Demand module estimates passenger travel demand across several transportation modes, and it then uses those estimates along with stock models representing several vehicle types and their efficiencies by vintage to output energy demand by fuel type and mode. Transportation modes are quite various; they include private and fleet light-duty vehicles; aircraft; marine, rail, and truck freight; mass transit; military transportation; and recreational boating. Light-duty cars and trucks are captured in a stock model, and vehicle miles are estimated at the household and fleet levels. Fifteen alternate fuel vehicle types are modeled relative to the baseline of conventional gasoline light-duty vehicles. Aircraft energy use is primarily modeled based on global macroeconomic indicators and fleet efficiency. The freight transportation modes are modeled together, and they are responsive to the growth in industrial output. All other transportation modes are lumped into miscellaneous energy demand submodule (EIA 2016c).

Energy-Economic and Integrated Assessment Models (IAMs)

This class of models represents all the physical, economic, and technological systems related to the global energy system and its greenhouse gas emissions. The level of modeling detail varies by model, but at their core, these are simulations models used to design and compare "what-if" scenarios regarding human energy systems and their interactions with physical and climate systems (e.g., water and land use, and climate change impacts). These models have been used extensively to inform national energy strategies and assess long-term options in the context of international efforts to mitigate climate change impacts (e.g., scenarios used by Edenhofer et al. [2015]). Given its central role in transformation pathways for global energy systems, the electric power sector is a major focus of many IAMs. IAMs cover electricity generation to various levels of detail (Kriegler et al. 2014), projecting long-term energy demand (in TWh consumed) and capacity requirements (in gigawatts [GW] deployed) based on socioeconomic projections, technology evolution (e.g., cost and efficiency of supply and demand technologies), and supply-demand balancing factors (e.g., power plants capacity factors). One IAM many U.S. researchers are familiar with is the Global Change Assessment Model (GCAM).[14]

EnergyPATHWAYS

EnergyPATHWAYS is a stock rollover, multi-decadal energy accounting tool designed for analysis of energy system transformation.[15] It is not a forecasting tool, but it instead simulates the whole energy economy at high fidelity given user specified decisions and produces energy demand, service demand, system costs, emissions, and the resulting infrastructure build. The tool is structured to be reusable for different geographic extents and resolutions, and it has been used outside the United States in Europe and Mexico.

Our primary interest for dsgrid is the U.S. model, early versions of which were developed by Williams et al. (2014). In the U.S. model, most demand-side data come from NEMS while supply side data comes from a variety of sources, including the National Renewable Energy Laboratory (NREL). For the EFS, more detailed input data than what is available from NEMS are being used in some cases, which has required extending some model structures. For instance, electrifiable industrial end uses are being modeled as stocks instead of as exogenously specified energy requirements, state-level population projections from the University of Virginia Demographics Research Group are being used instead of census population projections, and county-level heating and cooling electricity shapes from NREL for the 2010–2012 weather years replace a single month-hour average heating and cooling shape for the entire United States.

EnergyPATHWAYS models the electricity system with an annual-hourly dispatch, and it includes storage, flexible load, and electric fuel production, which informs costs, emissions, and the need for new infrastructure. In addition, the 8,760 hourly load values are assembled bottom-up from energy demand projections and subsectoral or technology-specific normalized electricity profiles for different geographies. In this way, it captures the changing load-shape patterns from electrification, energy efficiency, or growth in service demand.

1.1.2 Load Models and Projections for Electricity System Planning

Renewable Electricity Futures

The Renewable Electricity Futures study (NREL 2012; Hostick et al. 2014) examined a range of possibilities for the United States power system in 2050. To understand the impact of electricity load, the project team bracketed future load with low- and high-demand cases and adjusted sectoral load shapes to account for changes in some building end uses. The High-Demand Baseline was based on the 2009 AEO, which required extrapolations for 2030–2050. This was

[14] "Global Change Assessment Model," Joint Global Change Research Institute, http://www.globalchange.umd.edu/gcam/
[15] "EnergyPATHWAYS," Evolved Energy Research, http://energypathways.readthedocs.io/en/latest/

done by continuing electricity intensity trends by households for the residential sector, by unit floor space for the commercial sector, and per real dollar of shipments for industry. In this case, only industrial sector electricity intensity was projected to decline—by 35% from 2010 to 2050. The AEO also provided regional load shape information.

The Low-Demand Baseline modeled more significant changes—primarily energy efficiency gains in all sectors—and significant vehicle electrification. To estimate load shapes for buildings, overall efficiency projections (in energy use intensity units; e.g., kilowatt-hour [kWh]/ft^2-yr) were applied to a stock model accounting of new, existing, and retrofitted buildings; the resulting overall energy use was then allocated to end uses based on regionalized projections of end-use shares per year that accounted for such expectations as there being less efficiency gains for miscellaneous electrical loads than for other end uses. These steps were executed in the Lawrence Berkeley National Laboratory Building End-Use Loads Forecaster spreadsheet model, whose inputs and outputs are NEMS-formatted end-use load shapes, which are hourly and for three representative days. Industrial load shapes were primarily adjusted by choosing load factors that simultaneously fit Electric Power Research Institute (EPRI) load factor data, overall load duration curve data, and electricity sales by sector. Electric vehicle load curves were adopted from previous work (Parks, Denholm, and Markel 2007; Markel et al. 2009).

Itron's Statistically Adjusted End-Use (SAE) Model

The SAE load forecasting approach combines appliance stock models for individual end uses with an econometric model that maps end-use energy estimates to overall expectations for utility loads (Enterline and Fox 2010). This model is used to construct long-term estimates of energy efficiency across 30 end uses, and it has been used in several long-term electricity planning studies (WECC 2013; Enterline and Fox 2010; Carvallo et al. 2017). Temporally, it provides seasonal and peak adjustments. Sectorally, it provides technical potential energy efficiency estimates for existing technologies. Residential and commercial building end uses are modeled with an equipment stock approach and square footage trends. Data sources include NEMS output, census data on heating shares by state, the Federal Energy Regulatory Commission (FERC) demand response potential study (FERC 2009), and additional data on appliance saturation and efficiency compiled from state and utility-level studies (Wagner and Barbose 2012).

Power System Planners

The California Energy Commission has been regularly compiling load forecasts covering one decade since the mid-1990s. The projections are a combination of econometric regressions and some bottom-up analysis by sector. Kavalec et al. (2016) give low-, mid-, and high-demand forecasts for annual electricity use and non-coincident peak demand over 20 forecast zones, with detailed analysis of energy efficiency, distributed PV, and energy use by industrial subsector. Demand response contributions are also tallied. BC Hydro applies a similar method to conduct their long-term load forecasting (BC Hydro 2012). Of course, all electric utilities must perform some type of load forecasting; Carvallo et al. (2017) describes the methods used by 11 utilities and analyzes their performance in terms of historical forecast errors for annual energy and peak demand. Three of the utilities studied used the SAE approach already reviewed, one used a bottom-up engineering model, and the rest applied either timeseries or cross-sectional regression.

Load Shape Models

Boßmann and Staffell (2015) describe two country-level models of future load shapes for Europe, focusing on results for Germany and Britain. eLOAD[16] works by decomposing current load shapes into portions associated with "relevant applications" and the remainder. Thus, end uses of interest can be modeled differently than the remaining load, to which a basic scaling factor may be applied. The end uses of interest are modeled in turn using the FORECAST model,[17] which combines a stock accounting approach with stochastic simulation of technology adoption decisions. DESSTinEE[18] is a spreadsheet simulation model grounded more in macroeconomics; it models the demand for energy services as a function of population and income. Load shapes are produced from a basic breakdown of current load by end use by imposing the projected energy demands and weather (in the form of heating degree days) and forming a model of the residuals between historical load data and simulation results for the same year.

1.1.3 Models of Electricity Load Flexibility

FERC Demand Response Potential Study

In a study related to load modeling, FERC (2009) estimated the potential percentage drop in peak load by customer class and state for three beyond-business-as-usual scenarios, which required estimating the breakdown of peak load by sector and end use. Normalized load shapes by customer segment in the form of regression models over weather, air conditioning saturation, and periodicity over multiple frequencies (season, month, day-of-week, hourly) were estimated from utility hourly load data from 21 states. Temperature-dependent and non-temperature-dependent loads were distinguished. The only end use modeled in some detail was air conditioning; even so, there was no explicit data on the hourly load shape difference between customers with and without air conditioning. That difference was inferred by regressing over the utility load data and appliance saturation estimates that were available. These data and the methodology were adjusted and applied to the Western Interconnection in Satchwell et al. (2013). Overall, this type of demand response modeling can be characterized as relying heavily on utility reporting and surveys concerning current demand response programs and load shapes overlaid with minimal additional information on technology saturation levels.

Demand Response Estimates by Lawrence Berkeley National Laboratory

Work done by Lawrence Berkeley National Laboratory (Olsen et al. 2013) to estimate demand response resource by sector and end use is in many ways the predecessor to dsgrid. Their methodology for constructing demand response resource curves starts with estimates of hourly load by end use, constructed by merging many data sources. Geographically, these estimates originally covered only the western United States, but they have since been extended to the whole United States at the resolution of utility-state intersection (Hale, Stoll, and Novacheck 2018). Commercial building loads are estimated using a model of the California commercial building stock developed from California Commercial End-use Survey data. The load shapes are derived from building energy simulations across California, which obviously do not cover the

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[16] eLOAD: electricity LOad curve ADjustment, http://reflex-project.eu/model-coupling/model-eload/
[17] FORECAST: FORecasting Energy Consumption Analysis and Simulation Tool, "Methodology," http://www.forecast-model.eu/forecast-en/content/methodology.php
[18] DESSTinEE: Demand for Energy Services, Supply and Transmission in Europe, https://wiki.openmod-initiative.org/wiki/DESSTinEE.

full range of U.S. climates. Therefore, they are further adjusted using a linear regression relating temperature variability to load variability, in addition to being scaled and offset to match predicted monthly energy consumption, when applied to other locations. Residential load by end use is treated similarly. The underlying data set in that case is a residential end-use forecast from the California Energy Commission for 2020. Several other data sources are used to model agricultural pumping, data center, municipal lighting, water pumping, refrigerated warehouse, and manufacturing loads.

In a series of reports, Lawrence Berkeley National Laboratory extends and applies their demand response estimation methodologies to California (Alstone et al. 2016a, 2017). For that work, they had access to extensive advanced metering infrastructure and demographic data at the customer level from the three major investor-owned utilities in California.[19] The data were clustered, the load data were disaggregated by end use using first-order engineering models, and projections were then made to the study years.

1.1.4 Sectoral Models

Many sector-specific models have been proposed to project electricity consumption at various levels of spatial and temporal resolution. This includes is a vast body of literature on modeling building electricity use, both for commercial and residential buildings. Transportation has been studied quite thoroughly, with different researchers tending to focus on the different subsectors, led by light-duty vehicles, road shipment of freight, air travel, and public transportation. Publicly available energy analysis of industrial subsectors and end uses has tended to be less comprehensive due to the incredibly diverse and business-sensitive nature of industrial activity.

In this section, we summarize notable efforts in each of these areas. In relation to dsgrid, we are interested in (1) whether these models accurately capture energy use over large geographic regions, provide sufficient spatial and temporal resolution to be useful in regional or national, hourly or finer temporal resolution power system models, and (2) whether they can model future energy use based on capturing descriptions of technological change either exogenously or endogenously. We generally find many efforts to be lacking in one or more of these areas, each of which is necessary to couple sector-level energy models with power system models suitable for renewable energy integration studies; but, one can imagine sector-level models being extended to serve such a purpose.

1.1.4.1 Buildings Sector

(Swan and Ugursal 2009) review building end-use energy consumption modeling techniques and categorize the techniques as “top-down,” “bottom-up statistical,” or “bottom-up engineering” models. These categories, along with positive and negative attributes of each, are described in Table 1, which was adapted from Swan and Ugursal (2009). In what follows, we focus on the two types of bottom-up models: bottom-up statistical and bottom-up engineering, because these better align with dsgrid’s needs for temporal resolution, sectoral resolution, and ability to describe technological change. Bottom-up *statistical* models focus on describing the stochastic, occupant-driven temporal variation in energy used for individual end uses, and they have mostly been restricted to residential buildings based on the availability of, for example, time use surveys

[19] Demographic data were available for all 11 million utility customers. The hourly load data set covers 300,000 customers.

and metered data. In contrast, bottom-up *engineering* models focus on accurately capturing building thermodynamics over typical weather conditions, which is accomplished by simulating single-building energy use as an outcome of physical interactions between building equipment, building envelope, and weather that are driven by deterministic occupant schedules (Crawley et al. 2001).

Table 1. Positive and Negative Attributes of the Three Major Building Energy Modeling Approaches[a]

	Top-Down	Bottom-Up Statistical	Bottom-Up Engineering
Focus	Sector-wide annual energy use and trends	Stochastic occupant-driven temporal variations in energy use	Energy use driven by weather, building physics, and occupant schedules
Positive Attributes	Conducts long-term forecasting in the absence of any discontinuity	Encompasses occupant behavior	Models new technologies and policy implications
	Includes macroeconomic and socioeconomic effects	Imputes typical end-use energy contribution	Determines each end-use energy consumption by type, rating, etc.
	Requires simple input information	Includes macroeconomic and socioeconomic effects	Determines end-use qualities based on simulation
	Encompasses trends implicitly	Uses billing data and simple survey information	
Negative Attributes	Relies on historical consumption information	Is subject to multicollinearity	Assumes occupant behavior and unspecified end uses
	Provides no explicit representation of end uses	Relies on historical consumption information	Requires detailed input information
	Provides coarse analysis	Requires large survey sample to exploit variety	Is computationally intensive
			Does not incorporate macroeconomic factors

[a] Adapted from Swan and Ugursal (2009)

Residential Buildings

Several proposed residential bottom-up models identify the contribution of each end use to the aggregate energy consumption profile of the residential sector. Capasso et al. (1994) developed a bottom-up statistical model for evaluating the impact of demand side management on residential customers, although this analysis did not include weather parameters. A bottom-up statistical model of Finnish residential appliances by end use, with application to estimating potential demand-side management effects is given by Paatero and Lund (2006). A similar effort for the United Kingdom, which was validated using a year's worth of metered data from 22 homes, is described by Richardson et al. (2010).

Richardson, Thomson, and Infield (2008) introduce a Markov-chain technique to generate synthetic occupancy patterns, based on survey data of people's time-use in the United Kingdom. The stochastic model maps occupant activity to appliance use, creating highly resolved synthetic demand data. Widén and Wäckelgård (2010) follow a similar approach to relate residential power demand to occupancy profiles in Sweden. Muratori et al. (2013) propose a model, validated against metered data, to simulate hourly electricity demand of U.S. households, based on a Markovian behavioral model calibrated using the American Time Use Survey. The resulting profiles have been used to simulate residential demand response programs (Muratori and Rizzoni 2016) and the impact of PEV charging (Muratori 2018). Johnson et al. (2014b) predict residential power demand based on occupant behavior using a similar Markovian model also driven by the American Time Use Survey data. Fischer, Härtl, and Wille-Haussmann (2015) describe detailed modeling of residential electricity use for Germany, focusing on non-weather-dependent end uses. The resulting hourly power profiles by end use were validated against metered data for 430 households. Wills, Beausoleil-Morrison, and Ugursal (2017) adapt and validate the Richardson model to simulate Canadian residential appliance and lighting demands using 22 high-resolution, measured demand profiles from dwellings in Ottawa, Canada. Overall, these models demonstrate the ability to capture the time-dependent nature of residential loads by end use using a combination of metered data, occupant survey data, and a variety of statistical simulation techniques. However, because they do not incorporate engineering models of multiple building subsystems interacting with environmental conditions, they can only be used to model limited shifts in technology or policy (e.g., changes that are limited to a single end use or are primarily driven by a change in occupant schedules).

Early bottom-up engineering modeling efforts involved using 16 multifamily residential building prototype models (Ritschard and Huang 1989) and 8 single-family residential prototypes (Ritschard, Hanford, and Sezgen 1992) in 16 climates to develop a database of hourly residential building loads. Huang, Hanford, and Yang (1999) updated and expanded the Ritschard et al. (1992) prototypes to 112 single-family and 63 multifamily residential building prototypes, and they used them to determine the contributions of various enclosure components and internal gains to residential heating and cooling demand. Building on the earlier work by Ritschard et al. (1992) and Huang et al. (1999), Hopkins et al. (2011) increased the number of prototypes by an order of magnitude by simulating all 4,382 homes sampled for the 2005 RECS. Many important energy-related parameters, such as insulation levels, air tightness, and heating/cooling equipment efficiency are not collected by RECS and thus had to be sampled from probability distributions. ResStock, the latest research effort to model the U.S. single-family housing stock, uses 350,000 statistically sampled building models, drawing on building characteristics data from the 2009 RECS, the U.S. Census Bureau's American Community Survey (ACS) and 10 other data sources (Wilson et al. 2016, 2017).

Commercial Buildings

Significant effort has been made to examine energy use in commercial buildings from a bottom-up engineering perspective. Some models, such as those developed by Fonseca and Schlueter (2015) use simplified, algebraic hourly models to describe end uses in buildings. Others, such as Yang, Li, and Augenbroe (2018); Heeren et al. (2013) use quasi steady-state approaches (*ISO 13790:2008: Energy Performance of Buildings – Calculation of Energy Use for Space Heating and Cooling* 2008, 137), which also avoid differential equation-based physical modeling. These simplified models generally require few inputs and run quickly, making them attractive in high-level studies of the commercial building stock over long time scales (Yang, Li, and Augenbroe 2018). Other studies use whole-building energy modeling software that directly simulates zonal or finer-scale thermodynamics and is resolved at the hourly or subhourly level (Heiple and Sailor 2008); B. Griffith et al. 2007; Griffith et al. 2008; Sezgen et al. 1995; Coffey et al. 2015; Dirks et al. 2015). These models promise greater accuracy at a cost of longer computational times and higher input data requirements.

Another issue in commercial building stock modeling is the development of archetypes that represent a larger segment in aggregate after weighting factors are applied to the simulation results for each model. Reinhart and Davila (2016) use as few as 13 archetypical building models to model commercial building energy use in Ireland, whereas 3,168 archetypical models have been used in the case of Italy to represent 877,144 commercial buildings. Similarly, U.S. analysis is often done using a subset of the 17 DOE "reference building" (Deru et al. 2011) or "prototype building" models (Goel et al. 2014), which, depending on the scope of the study in terms of building types and climate regions, can result in a few up to 272 archetype buildings (e.g., Hart et al. (2015) uses 30, covering six building types and five climate zones). Dirks et al. (2015) use approximately 2,000 archetypes to model the eastern half of the United States. As pointed out by Brogger and Wittchen (2017), a challenge of the archetype approach is ensuring the archetype models are actually representative of the stock. To overcome this limitation with archetype modeling, a different approach has been taken by Coffey et al. (2015) in which each building within the defined stock is modeled using a combination of 3-D building geometry and high-level information (e.g., floor area and use type). The approach required an expert system that was used to create individual whole building energy models, which results in a requirement for significant input data that may not be available on a national scale while simultaneous greatly expanding the size of the required simulation set.

When evaluating the magnitude of errors in multi-sector commercial analyses, Reinhart and Davila (2016) demonstrate that large-scale studies only match the energy consumption of the aggregate building stock within 1%–19% of site energy use on an annual basis. while not addressing issues of time of use. Akbari et al. (1993); Sezgen et al. (1995) both attempt to address this by applying load shapes developed from additional data sources. Though this approach may be adequate for predicting future scenarios where the load shape is not expected to change significantly, it is inadequate for predicting future scenarios where new technologies are expected to change the load shape, which is the case when considering electrification of the building stock. The Heiple and Sailor (2008) model is one of the few building stock models that has been validated for both annual energy consumption and load shape. In this case, the load shape for a tractable geographic extent was validated against top-down models of the city, allowing for derivation of measured data for a larger entire region containing that city.

Most of the bottom-up, physics-based models for buildings represent occupant behavior by applying schedules that dictate both the presence of occupants (e.g., occupant component of thermal loads, and hot water use) and their impact on equipment controls (e.g., lighting system status; heating, ventilation, and air conditioning [HVAC] control mode; and HVAC set points). Many of these schedules are based on previous research into this topic. Heiple and Sailor (2008) note that these schedules can noticeably impact the overall results, and they suggest creating additional archetype divisions with different operating schedules. Kim and Srebric (2017); Chen, Hong, and Luo (2018) examine data sources and methodologies to develop diverse and stochastic schedule sets for university buildings and offices respectively. This research is very promising, and it will be an excellent candidate for inclusion in stock-wide modeling, particularly as additional classifications of commercial buildings are considered in the literature.

Summary

Ideally, there would be building stock models covering large geographic extents informed by both detailed stochastic modeling of occupant behavior (bottom-up statistical models) and detailed modeling of building physics interacting with weather, occupant behavior, and equipment controls (bottom-up engineering models). However, the current state of the art is that these two types of modeling approaches are practiced separately. The occupant-focused statistical models (which are mostly restricted to the residential sector) typically have good temporal and end-use resolution but a limited ability to model technological change because they are stochastic simulations based on historical time-of-use-surveys and metered data. The physics-focused engineering models (for both residential and commercial buildings) are well suited to model the energy impacts of technological change by end use, but they struggle with achieving accurate temporal resolution. This shortcoming is primarily driven by the historical emphasis on whole-building, annual energy efficiency metrics; a lack of hourly data by end use for calibration; and the naturally wide variance in occupant behaviors and control settings that in some sense should be averaged out when the primary concern is creating energy efficient designs for buildings that may be used by multiple occupants over the course of their designed lifetimes. This report documents efforts to begin to calibrate bottom-up engineering building stock models (particularly ResStock and the newly minted ComStock) on an hourly or subhourly basis. We expect to see more such efforts given the increasingly urgent need to describe both time-dependence of energy use and the potential impacts of technological change.

1.1.4.2 Transportation Sector

Electricity load modeling for the transportation sector, especially as it focuses on the adoption and charging profiles of passenger PEVs, has been proposed by many researchers in response to the potential for these vehicles to capture significant market share. Though some studies, especially those with a focus on climate change mitigation, also examine demand trends in other transportation subsectors (Garrido and Mahmassani 2000; Kamakate and Schipper 2009; Eom, Schipper, and Thompson 2012; Muratori et al. 2017; Winchester et al. 2013; Boeing 2015; Paulley et al. 2006), significant electricity consumption is not typically projected for those subsectors due to a lack of mature technological options (e.g., electric air or marine transport).

Several vehicle-to-grid studies leverage travel information surveys to predict PEV charging demand (Clement-Nyns, Haesen, and Driesen 2010; Denholm and Short 2006; Duvall et al. 2007; Green, Wang, and Alam 2011). Bashash and Fathy (2012), for example, propose a control-oriented model representing the collective charging dynamics of PEVs that uses the U.S. National Household Travel Survey to predict the number of PEVs connected to the grid at any given time. Other studies use behavioral models to predict vehicle use and charging patterns (Muratori, Moran, et al. 2013) or queuing theory to estimate the overall charging demand of a population of PEVs (Li and Zhang 2012). Ashtari et al. (2012) instrumented 76 PEVs in Winnipeg, Canada, to record vehicle driving and parking patterns. One-second charging profiles were used to calibrate a stochastic method to predict PEV charging loads and capture the relationship of vehicle departure, arrival, and travel time for different charging scenarios (e.g., residential versus workplace and different charging power levels).

In this context, NREL, in partnership with the California Energy Commission, developed the Electric Vehicle Infrastructure Projection (EVI-Pro) model[20] to simulate spatially and temporally resolved demand for PEV charging at residential, workplace, and public destinations based on real-world travel data (Wood et al. 2017). EVI-Pro anticipates consumer charging behavior while capturing variations with respect to housing type (single-unit versus multiunit dwellings), travel period (weekdays versus weekends), and regional differences in travel behavior and vehicle adoption.

1.1.4.3 Industrial Sector

Given the highly complex, heterogeneous, and proprietary nature of the industrial sector, and a corresponding lack of comprehensive data sources, detailed models of its energy consumption have lagged models of other sectors. In past studies, top-down estimates based on projections from the EIA AEO, which is produced annually using NEMS, have been common (Hostick et al. 2012; Holmes et al. 2014). Though these studies provide a good baseline of aggregate energy consumption within the industrial sector, their granularity is typically limited to the census division level.

In addition to using AEO data, many studies incorporate data from EIA's MECS. This national survey is conducted every four years and collects information on U.S. manufacturing establishments, their energy-related building characteristics, and their energy consumption and expenditures (EIA 2017a). Within the MECS, detailed estimates of energy consumption by industry type and census region are available at the end-use level. Additionally, the DOE Advanced Manufacturing Office has used these data in numerous studies of specific manufacturing industries.[21]

Though these studies provide useful information for the individual industries covered, they demonstrate the primary issue in modeling industrial sector energy use, which is that there is no "one size fits all" bottom-up modeling approach. Although various industries may share similar processes and end uses, their energy consumption may vary greatly depending on what type of product is being produced, and no one data source describes process units consistently across all industrial manufacturing subsectors. As a result, detailed technology level models are rare, limiting the granularity that can be achieved by an industrial sector model.

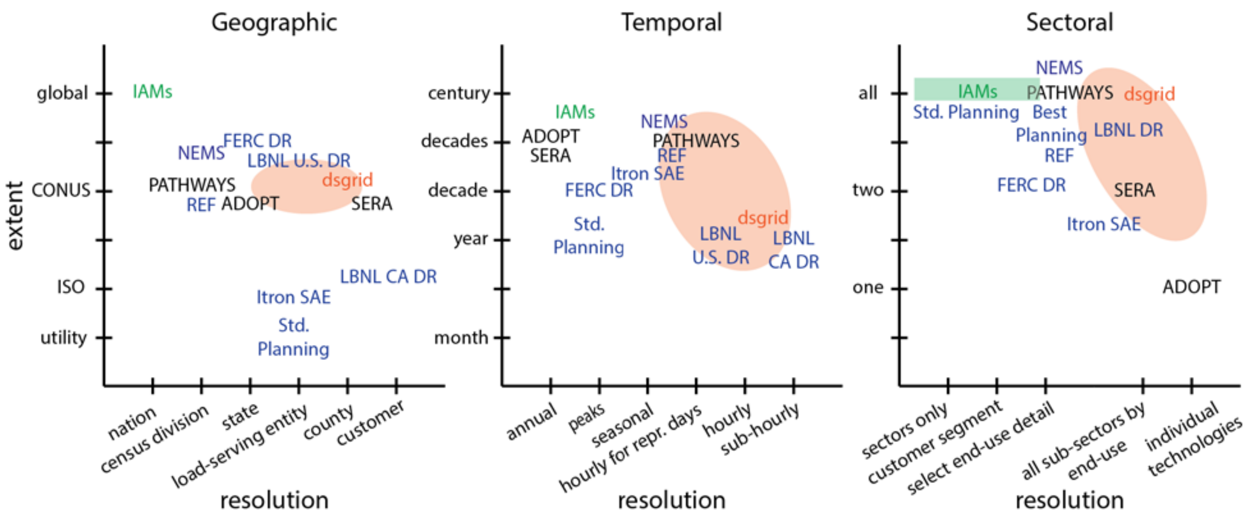
1.2 Scope of dsgrid

dsgrid is a model of U.S. electricity use with an unprecedented combination of temporal, geographic, and sectoral detail and coverage (Figure 1). Previous load models focused on similar questions have reasonably focused on (1) seasonal and peak load effects and (2) building end uses that are widespread and either (a) large as a proportion of peak load with the potential to be controlled (for demand response studies) or (b) with significant energy efficiency potential.

[20] EVI-Pro: Electric Vehicle Infrastructure Projection Tool, https://www.afdc.energy.gov/evi-pro-lite
[21] The so-called Bandwidth Studies are listed at "Energy Analysis by Sector," DOE, https://energy.gov/eere/amo/energy-analysis-sector.

A recent effort to develop more end-use and geographic specificity (Olsen et al. 2013) is leveraged here, but what the report describes is fundamentally different in scope.

dsgrid uses large-scale building energy modeling and gridded meteorological data to accurately reflect regional differences in equipment types as well as weather to enable realistic multidimensional “what-if” analyses. It also provides hourly subsectoral detail on industrial manufacturing loads and captures other important non-building loads. Projections of future load will include detailed modeling of PEVs, both passenger and commercial vehicles, coupled with multiple charging strategy and scheduling flexibility assumptions.



DR	Demand Response (Potential Studies)	**NEMS**	National Energy Modeling System
FERC	Federal Energy Regulatory Commission	**Planning**	Refers to utility/ISO/PUC planning efforts
IAM	Integrated Assessment Model	**REF**	Renewable Electricity Futures (Study)
LBNL	Lawrence Berkeley National Laboratory	**SAE**	Statistically Adjusted End-Use (Model)

This graphic only shows load model resolution. The modeling resolution for other energy system components (e.g., electricity supply) modeled by the referenced tools (e.g., IAMs or NEMS) may differ.

Figure 1. Load models summarized by their geographic, temporal, and sectoral extents and resolution

dsgrid provides an unprecedentedly detailed picture of current and, when coupled with EnergyPATHWAYS, future continental United States (CONUS) electricity load

In the remainder of this report, the authors describe dsgrid: its modeling approach and initial baseline results for one historical year. Future work will use outputs from the EnergyPATHWAYS model to develop detailed descriptions of future load scenarios.

The dsgrid data sets and model are a timely effort to understand the time-varying nature of electrical demand and flexibility at an unprecedented level of detail that will be used to explore future scenarios of the U.S. electric sector.

2 Model Architecture: A Composite Picture Built Up from Sector Models

So that it can provide the necessary sector level details and compute residuals against historical electricity-sector data, dsgrid was not developed as a single model but rather as a confederation of models and data sets bound by processes for comparing and harmonizing data across several levels of geographic, temporal, and sectoral resolution.

In this section, the authors summarize the model as a whole and its constituent parts. We first provide an overall architectural view (Section 2.1). This is followed by brief descriptions of the sector models, which are provided in two “flavors”: (1) detailed, bottom-up models whose data are available at hourly resolution by subsector, end use, and county, and (2) gap models that rely on a mixture of top-down and bottom-up data sources and are typically coarser than the detailed models in at least one dimension (Section 2.2). After summarizing the sector-level modeling as a whole (Section 2.2.5), we describe two additional gap models, models of distributed generation, and derived data sets describing system losses and model residuals (Section 2.3).

2.1 Architectural Overview

The heart of the dsgrid model is the bottom-up detailed sector modeling described briefly here and in more detail in Section 2.2 and Appendices A, B, and C. However, to create a comprehensive picture of U.S. electrical load, the model must also account for other aspects of system load, such as loads not captured in detail by the sector models, distributed generation, and T&D losses; and should also be calibrated and validated against historical data. To accomplish these goals the detailed bottom-up sector models are complemented by coarser gap models, distributed generation models, and several historical electric-sector data sets within an analytic framework that allows comparison and computation across different levels of geographic, temporal, and sectoral resolution (Figure 2, next page).

The detailed bottom-up energy modeling for each sector is conducted with separate methodologies, following the overall philosophy of leveraging and supporting the energy modeling work conducted by research groups focused on particular end-use sectors, rather than attempting to recreate or repurpose such work from a pure power systems point of view. The scope and methods used for each sector model are thus products of prior work done by each sector modeling team combined with modifications necessary to meet the temporal and geographic resolution required by dsgrid. Brief descriptions of the methodologies follow:

- **Residential and Commercial Buildings (NREL)**: Building loads are estimated using ResStock and ComStock, which use similar statistical methodologies and OpenStudio modeling infrastructure to simulate U.S. single-family detached and commercial building stock electricity consumption by end-use. These models sample from thousands of probability distributions to produce hundreds of thousands of EnergyPlus simulations, which are then weighted to represent subsector building stocks at the county level. This detailed modeling covers single family homes and commercial buildings mappable to the 16 DOE commercial “prototype buildings” (Goel et al. 2014).
- **Industrial Manufacturing (EPRI/ORNL)**: Industrial manufacturing loads are modeled with the Industrial Geospatial Analysis Tool for Energy Evaluation (IGATE-E), which

uses plant-level databases, the Manufacturing Energy Consumption Survey, and the Electric Power Research Institute's Load Shape Library to construct hourly time series of electricity use by manufacturing subsector and end use. Because manufacturing processes vary greatly, IGATE-E does not attempt direct simulation of loads but rather compiles data from multiple sources and applies statistical techniques to estimate energy consumption down to the end-use level. Because IGATE-E only models manufacturing, the additional industrial sectors of agriculture, mining, and construction comprise the industrial gap model.

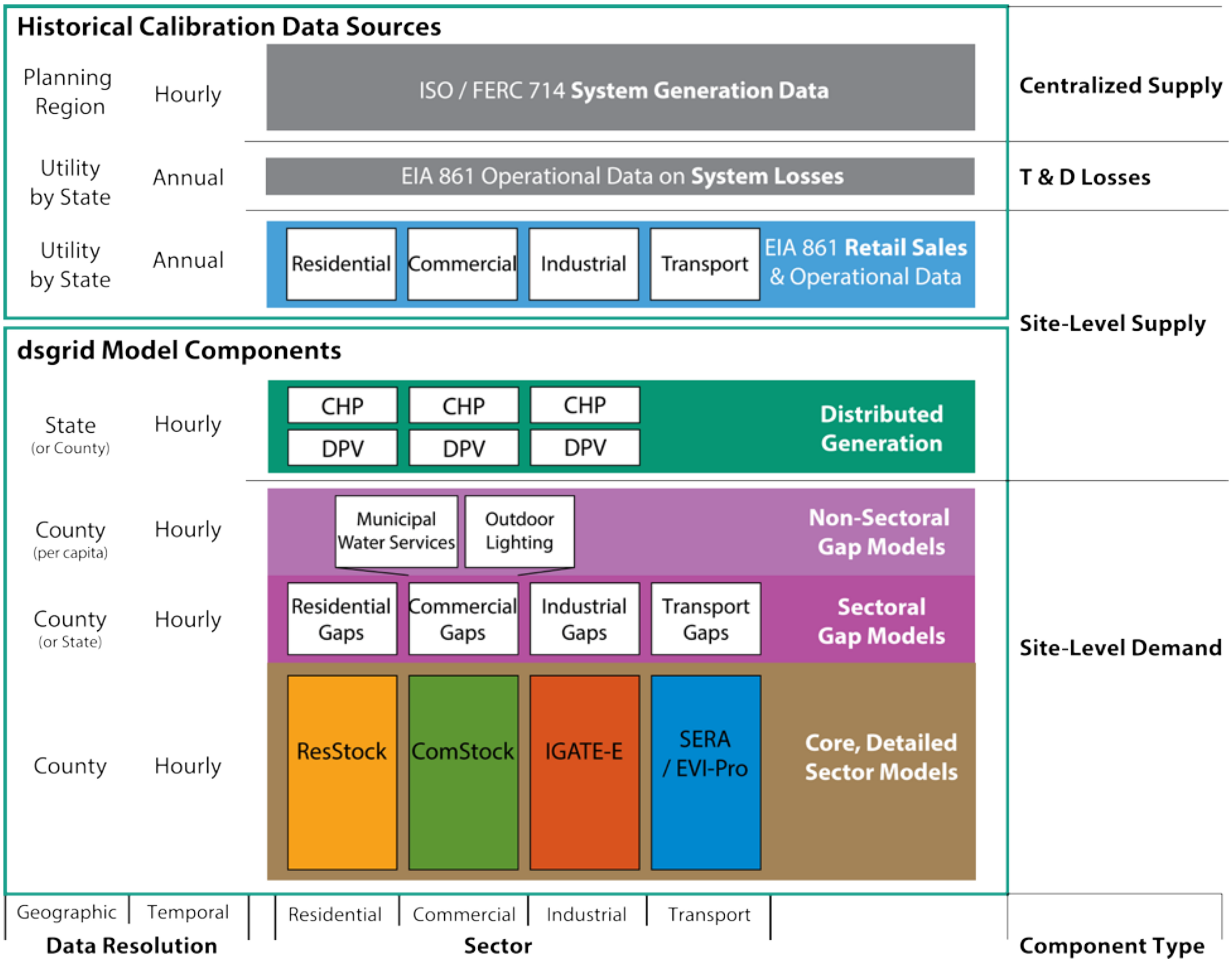


Figure 2. dsgrid input data architecture

CHP = combined head and power

DPV = distributed solar photovoltaics

EIA = U.S. Energy Information Administration

EVI-Pro = Electric Vehicle Infrastructure Projection Tool

FERC = Federal Energy Regulatory Commission

IGATE-E = Industrial Geospatial Tool for Energy Evaluation

ISO= Independent System Operator

SERA = Scenario Evaluation, Regionalization and Analysis model

- **Transportation (NREL)**: Given the focus in this report on constructing a model of historical electricity use we describe the detailed transportation modeling methods that will be used in future work to capture EV location and charging; but no detailed sector-level results for transportation are presented. When this capability is developed for the EFS future model year snapshots, on-road plug-in electric vehicle operation will be described using the Scenario Evaluation and Regional Analysis (SERA) model and the Electric Vehicle Infrastructure Projection Tool (EVI-Pro). SERA describes vehicle infrastructure requirements and will be used to disaggregate vehicle adoption to the county level. EVI-Pro simulates hourly charging profiles based on travel data and charging preference assumptions (e.g., residential charging as opposed to reliance on public charging). The historical data set includes a transportation gap model that describes electricity use in passenger trains.

For the initial historical snapshot described here, the year being modeled by dsgrid is 2012. This choice is based on data availability, including meteorological data that impacts some of the sector models and ultimately needs to be time synchronized with the renewable generation data to be used in the electricity supply modeling portion of EFS. The current baseline years for the sector models are

- **Residential Buildings:** 2009 RECS and 2010–2014 ACS
- **Commercial Buildings:** 2012 CBECS
- **Industry:** 2014 MECS
- **Transportation**: 2012 National Transit Database

The sector models that are not primarily calibrated to 2012-specific data sets are scaled to represent the historical 2012 model year. For example, for the residential sector, the 2010–2014 ACS provides dwelling unit counts by census tract, but when calibrating against 2009 RECS energy consumption data, the 2009 RECS dwelling unit counts are scaled up to match the occupied dwelling unit counts from the 2010–2014 ACS for each building type and census division. Industry scaling from 2014 back to 2012 is done using the EIA SEDS data, which show about a 1% increase in industrial retail electricity use over that time (EIA 2017b).

Moving up from the bottom of Figure 2, the dsgrid gap models capture (1) residential, commercial, industrial, and transport subsectors that are not handled in our detailed sectoral modeling and (2) municipal/utility end uses such as municipal lighting, and water pumping and treatment. The magnitude of most of these gaps is first estimated using data products from the EIA and other federal agencies, namely, the EIA Residential Energy Consumption Survey (RECS), the Commercial Building Energy Consumption Survey (CBECS), the AEO, the National Transit Database (NTD), and the County Business Patterns data (EIA 2013d, 2016a, 2015a; FTA 2017; U.S. Census Bureau 2018). We then form our gap model by assigning a proxy timeseries to each of the gap magnitudes identified in those data sets. For some subsectors we also geographically downscale our estimates using additional data sources available from the bottom-up models. The processes and specific assumptions made for each gap are described in Section 2.2 (sectoral gap models) and in Section 2.3.1 (municipal end uses). The temporal resolutions of the gap energy magnitude data are uniformly annual. The geographic and sectoral resolutions vary. Some of the key data are only available at the census division level or for the nation as a whole, but in all cases, we can geographically downscale at least to the state, and sometimes to the county.

To approximate total site-level grid-delivered electricity use by sector and state, the authors estimate hourly distributed generation from customer-sited PV, combined heat-and-power (CHP), and distributed thermal plants, and subtract this from the sum of the detailed and gap bottom-up load models. The distributed generation models are distinguished by sector (residential, commercial, or industrial) to facilitate annual by-sector, by-state comparisons to historical by-sector electricity demand. The hourly profiles, in addition to facilitating the creation of grid-delivered electricity profiles, allow for hourly by-state comparisons to historical total electricity demand. The main data sources for our distributed PV (DPV) model are Perea et al. (2017) and Sigrin et al. (2016). CHP and distributed thermal capacity, generation, and behind-the-meter fractions are estimated using EIA Forms 860 and 923 (EIA 2013a, 2018), and the DOE CHP Database (ICF Inc. and DOE 2016). CHP and distributed thermal hourly profiles are generated from continuous emission monitoring systems (CEMS) data (US EPA 2016; EPA 2013).

To calibrate and validate the initial dsgrid data set for historical year 2012, we leverage two historical electricity-sector data sets. Shown at the top of Figure 2, with no sectoral resolution and coarse geographic resolution, we have a historical data set of hourly electrical load that is comprised of independent system operator (ISO) data, and FERC Form 714 filings (FERC 2016; SPP 2016; pjm 2016; MISO 2016; ISO New England 2016; NYISO 2016). The native resolution of that data is at the utility, balancing authority, or ISO region level. For this version of dsgrid we use a version of the data set that has first been disaggregated down to individual transmission nodes, and then re-aggregated up to the state level. In future versions we plan to enable analysis at the county or utility level by fully leveraging the nodal disaggregations, but it was not tractable to achieve a reliable geographic matching at that level of detail within the scope of this initial project. This load data represents the system operator perspective, that is, it is equal to generation plus imports minus exports, and is thus the total amount of generation plus net imports that the system had to obtain to meet its load and cover all T&D losses.

Annual retail sales data are available from EIA Form 861 (EIA 2013b), where they are reported by sector (i.e., residential, commercial, industrial, and transport[22]) for every utility by state. EIA Form 861 also reports the amount of electricity furnished or consumed by respondent without charge, which we add to the commercial retail sales. These data—electricity consumption by sector and state—represent the total amount of electricity sold or furnished to utility customers, and thus excludes system losses. These data are more resolved sectorally and geographically than are the top-down hourly load data, but they are temporally coarser. EIA Form 861 also reports losses by utility and state, and this is the main data source for our loss model.

In Section 2.3, in addition to further describing the gap and distributed generation models, the authors describe how we estimate system losses and compute model residuals. Hourly system losses are estimated by combining the historical hourly load, historical annual sales, and historical system losses data. Model residuals are estimated by combining the historical data sets,

[22] In the coming decades, we expect significant amounts of electricity used to charge EVs to show up in EIA filings as residential, commercial or industrial, rather than as transportation, electricity use based on behind-the-meter charging at residences and commercial or industrial sites.

the hourly system losses model, and the dsgrid components—detailed bottom-up sector models, gap models, and distributed generation models.

2.2 Sector Models

The core of dsgrid leverages previous work by four energy modeling teams, each of which brings multiple large-scale data sets together to form a holistic picture of an individual sector: residential buildings, commercial buildings, industrial manufacturing, and transportation. The four modeling teams have deep institutional experience estimating the energy use of their various sectors, although usually on an annual or seasonal, rather than hourly basis. By expanding the temporal, and in some cases, geographic resolution of these energy-use estimates, harmonizing assumptions, and undertaking a collaborative calibration effort, dsgrid creates a highly resolved picture of United States electricity use.

2.2.1 Residential Sector

ResStock is a bottom-up simulation methodology for modeling residential building stocks with a high degree of granularity. In development by NREL since 2013 (Wilson et al. 2016, 2017), ResStock characterizes the energy use of U.S. single-family detached housing[23] using a hierarchical structure of conditional probability tables and detailed energy simulations of hundreds of thousands of representative buildings.

2.2.1.1 Input Data Sets

The conditional probability distributions are synthesized from data queried, translated, aggregated, and extrapolated from 11 sources, including U.S. census data, RECS, builder surveys, and other data from field studies. These data are supplemented by engineering estimates where data are lacking. Details of the housing stock characterization data model can be found in Wilson et al. (2017). A summary of the input data sources is shown in Table 2. The data sources are described in detail in Appendix A.

[23] ResStock is currently limited to single-family detached housing. Capabilities for low-rise multifamily and mobile homes are under development.

Table 2. Building Characteristics, Dependencies, and Data Sources

		Dependencies								Data Sources												
	Characteristics	**Location**	**Vintage**	**Heating Fuel**	**Usage Level**	**Daytime Use**	**Floor Area**	**Number of Stories**	**Found. Type**	**2009 RECS (EIA 2012)**	**NAHB**	**IECC 2009**	**RBSA (NEEA 2012)**	**Ritschard et al. 1992**	**ACS**	**Labs et al. 1988**	**Chan et al. 2012**	**Wenzel et al. 1997**	**Lucas and Cole 2009**	**Eng. Exp. & Calibration**	**Geographic Resolution**	**Number of Options**
Meta	*Location*																				TMY3	216
	Vintage	✓													•						C	7
	Heating fuel	✓	✓							•											C	6
	Usage level																			•	U.S.	3
	Daytime use																				U.S.	2
Geometry	*Floor area*	✓	✓							•											R	6
	Number of stories	×	✓				✓		✓	•											R	3
	Foundation type	✓									•					•					48	5
	Attached garage	×	✓				✓			•											R	2
	Orientation																				U.S.	4
Envelope	Window type	✓	✓							•		•								•	R	5
	Wall insulation	✓	✓								•			•							R	8
	Attic insulation	✓	✓								•		•								R	7
	Foundation insulation	✓	✓								•									•	R	5
	Air leakage	✓	✓				✓	✓	×								•			•	R	12
Equipment	Heating system type	✓	✓	✓						•	•										R	6
	Heating system efficiency	✓	✓								•							•		•	R	10
	Cooling system type	✓	✓							•											R	7
	Cooling system efficiency	✓	✓								•							•		•	R	7
	Duct insulation, tightness	✓	✓						✓			•							•	•	U.S.	5
	DHW system type	✓	×	✓						•											R	5
	DHW system efficiency																	•		•	U.S.	3
	Cooking type	✓	×	✓						•											R	10
	Clothes dryer type	✓	×	✓						•											R	10

	Characteristics	Dependencies: Location	Vintage	Heating Fuel	Usage Level	Daytime Use	Floor Area	Number of Stories	Found. Type	Data Sources: 2009 RECS (EIA 2012)	NAHB	IECC 2009	RBSA (NEEA 2012)	Ritschard et al. 1992	ACS	Labs et al. 1988	Chan et al. 2012	Wenzel et al. 1997	Lucas and Cole 2009	Eng. Exp. & Calibration	Geographic Resolution	Number of Options
Occupancy	Heating, cooling set points	✓				✓				•											TMY3	3
	Cooking usage				✓	✓														•	U.S.	3
	Clothes dryer usage				✓	✓														•	U.S.	3
	Lighting, appliances, MELs				✓	✓				•										•	U.S.	3

✓ = direct dependency   × = indirect dependency   *italics* = archetype parameters   MELs = miscellaneous electric loads

C = Census Tract   R = Regional (custom)   TMY3 = 216 typical meteorological year subregions   NAHB = National Association of Home Builders

ResStock statistically represents housing stock characteristics with 6,000 conditional probability distributions derived from 11 data sources. This table provides information on how each parameter's probability distributions depend on other *archetype parameters*, as well as each parameter's data sources, geographic resolution, and number of options (bins).

ResStock also depends on geospatial weather data. It uses 216 climate subregions as the core geographic resolution for its building energy simulations (see Figure 3). The 216 subregions are clusters of approximately 84,000 National Solar Radiation Data Base 10-km^2 grid cells that are grouped based on proximity, elevation, and data similarity, using a method described in Lopez (2011). For this work, 216 EnergyPlus weather (EPW) files, one for each climate subregion's representative location, was assembled using National Solar Radiation Database (NSRDB) data from 2012 as described in Appendix H.

To achieve consistency with the commercial, industrial, and transportation sector components of dsgrid, ResStock results are mapped from the 216 TMY3 locations to the 3,107 counties in the CONUS. This mapping is done using census-tract-level household data from the 2012 ACS combined with a geospatial filter that excludes non-residential land. The filter is derived from a 200-m residential land mask computed from LandScan Nighttime and Daytime Gridded Population data (ORNL 2011) and Homeland Security Infrastructure Program facility location data (HSIP 2012). This mapping uses iterative proportional fitting to mesh data from the ACS Public Use Microdata and the American Housing Survey to ultimately account for the distribution of building types, vintage, heating fuel, cooling type, floor area, and household income within census tracts. Aggregated timeseries results for each county are standardized to Eastern Standard Time (EST) to synchronize electrical load profiles across all U.S. time zones.

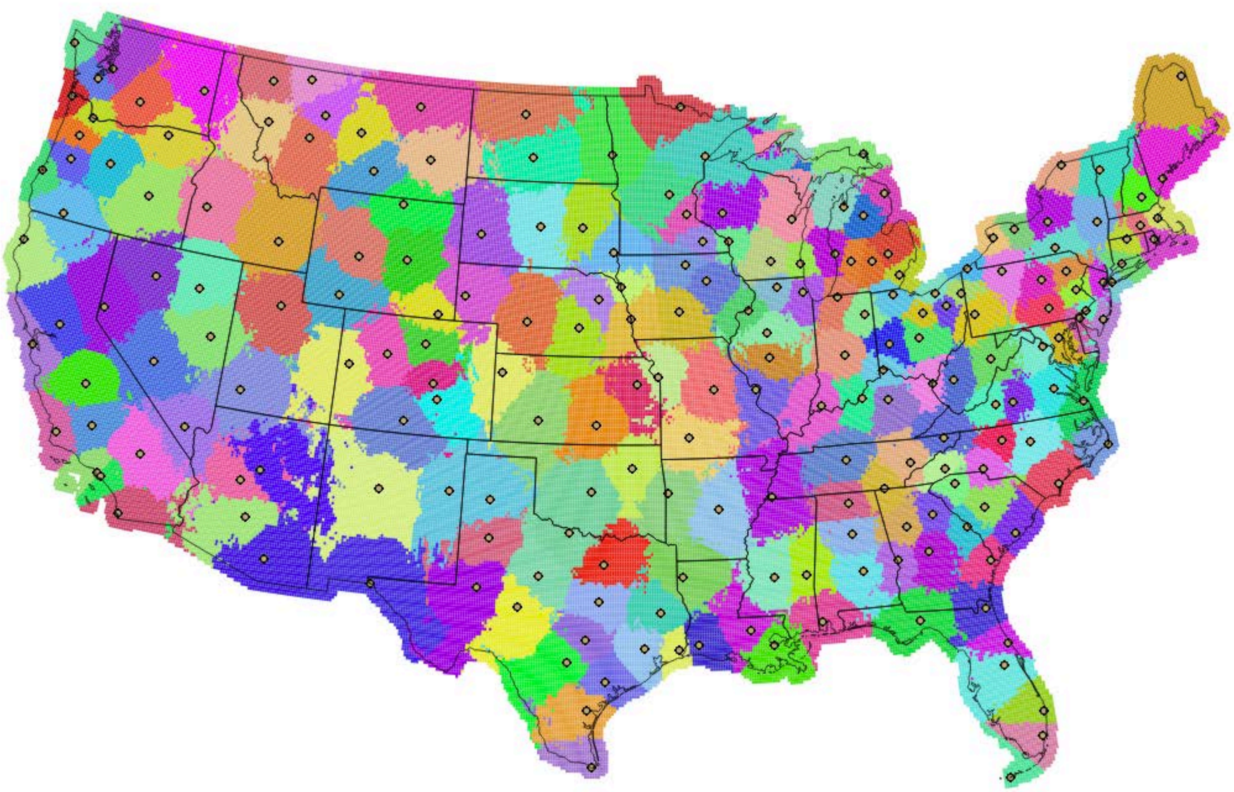


Figure 3. ResStock simulations use 216 climate subregions, each represented by a single weather station.

2.2.1.2 Methodology

The data sets described above are used to create a hierarchy of thousands of conditional probability tables that collectively define more than 100 building components. Statistical sampling based on a modified Latin hypercube sampling approach is used to select representative homes from the parameter space defined by the housing stock data model (Wilson et al. 2016). Detailed subhourly building energy simulations modeling a year's worth of operations are assembled using OpenStudio and run in EnergyPlus (Roth, Goldwasser, and Parker 2016; Crawley et al. 2000). For this project, the energy consumption of the single-family housing stock of the CONUS is represented by 350,000 building/location models run on Peregrine, NREL's high-performance computer, or distributed cloud computing.

Convergence testing of simulation results sliced various ways led us to select 350,000 as the number of building/location models (combinations of building characteristics and climate locations) to represent the current U.S. housing stock. Weighting factors are used to scale results up from 350,000 to the 73.2 million regularly occupied single-family detached homes included in the analysis, based on the 2010–2014 ACS (Manson et al. 2017; U.S. Census Bureau 2017).

2.2.1.3 Output Data

Each EnergyPlus simulation produces timeseries results of whole-building electricity and fuel use, as well as electricity and fuel use by end use. ResStock simulations typically use ten-minute timesteps for zone calculations with smaller timesteps used for HVAC system calculation on an as-needed basis. Timeseries results can be reported with ten-minute resolution but are aggregated to hourly resolution for dsgrid. The end uses reported for dsgrid ResStock analysis are based on standard EnergyPlus reportable meters, and the dsgrid bottom-up residential data set reports hourly timeseries of:

- Fans: electricity (kWh)
- Pumps: electricity (kWh)
- Heating: electricity (kWh)
- Cooling: electricity (kWh)
- Interior lights: electricity (kWh)
- Exterior lights: electricity (kWh)
- Water systems: electricity (kWh)
- Interior equipment: electricity (kWh)
- Heating: gas (kBtu)
- Water systems: gas (kBtu)
- Interior equipment: gas (kBtu)
- Water systems: water (gal)

Customizable OpenStudio scripts can be applied to report consumption for more detailed end uses, such as plug loads, cooking, and clothes drying. Additional reports related to building performance (e.g., relative humidity and zone temperatures) can also be generated.

The output timeseries are provided at the county level and are time-synchronous with 2012 meteorological data, based on the geospatial disaggregations and weather data transformations described above.

2.2.1.4 Calibration

ResStock, and building energy modeling in general, have previously focused on predicted annual energy savings results for applications related to energy efficiency in buildings. ResStock is currently calibrated by comparing modeled energy use by fuel type to the corresponding energy use metrics given in the 2009 RECS (EIA 2013d) for slices of the housing stock, such as region, vintage, and space heating fuel type. Iterative changes to model inputs were made to bring modeled consumption into better agreement with the reference consumption. The use of ResStock for producing electric load profiles under various scenarios is being validated as part of this effort. Models for bottom-up load modeling can generally be categorized as models that generate either (1) aggregated load profiles or (2) agent load profiles for individual buildings or appliances. Individual building agent load profiles reflect the stochastic behavior of event-based load spikes (e.g., toaster on for five minutes), which when summed over hundreds or thousands of buildings, approach the smoothness of aggregated load profiles needed for bulk power system analysis. Initially, dsgrid and ResStock focus on the former category of aggregated load profiles, though the latter category of agent load profiles is of interest for other applications.[24]

In 2016, NREL completed initial validation of the non-weather dependent end use load profiles (e.g., appliances, plug loads) generated by ResStock. In 2017, the validation effort focused on the weather-dependent end uses (e.g., space heating, space cooling, and domestic water heating). Sources of measured electric load profiles being used for validating ResStock include:

- **Utility Load Research Data (ULRD):** Electric utility companies collect load profile data from a sample of their customers for various internal and external uses. NREL has obtained a collection of ULRD for one or more years from about 30 U.S. electric utilities. The hourly load profiles are typically aggregated by customer class; residential customers that use electricity for space heating are sometimes split into a separate “space heat” class. Commonwealth Edison (ComEd) is one utility that splits ULRD into single-family and multifamily classes as well. Thus, the ComEd ULRD is particularly useful for validating ResStock single-family load profiles. Figure 4 summarizes some of the residential data in this data set, which is clearly summer peaking.

[24] Though ResStock models individual buildings, it cannot yet model event-based load spikes for most end uses.

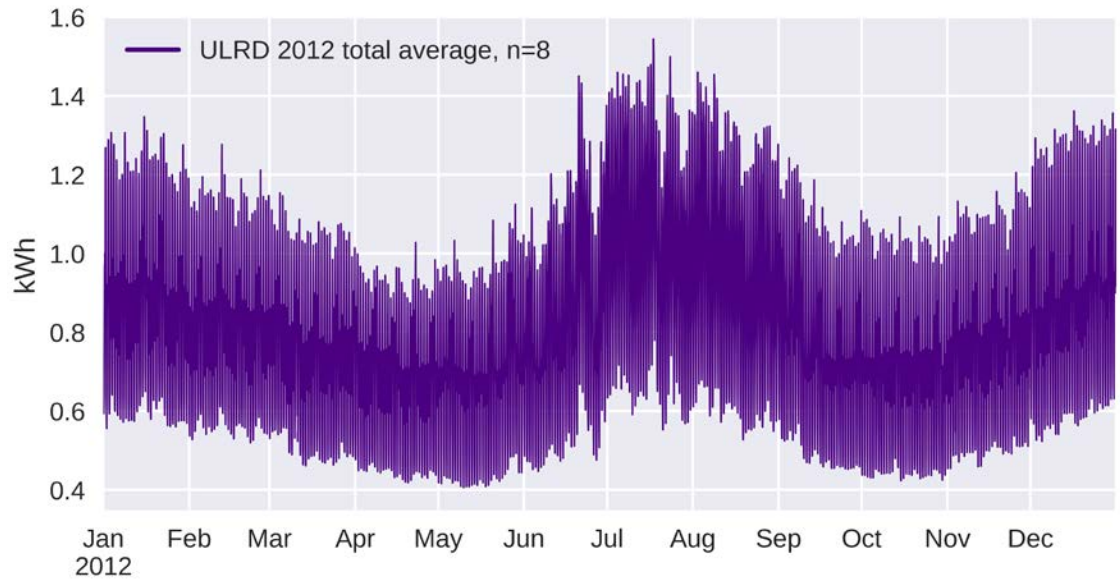


Figure 4. Average of residential load profiles from eight electric utilities available in the Utility Load Research Data (ULRD)

- **End Use Submetering Studies:** These studies measure the load profiles of individual end uses (e.g., heating, cooling, water heating, appliances, and miscellaneous plug loads) within individual buildings. The data collection is usually expensive and intrusive to building occupants, so submetering studies are uncommon and typically limited in terms of number of homes, geographic scope, and representativeness. The Residential Building Stock Assessment Metering (RBSAM) study, which recorded data at 15-minute intervals for over 150 end uses in about 100 single-family homes in the Pacific Northwest (Larson et al. 2014), is the primary submetering study used for ResStock validation. Notable changes made to ResStock inputs based on comparing ResStock outputs to the RBSAM data set are shown in Figure 5, Figure 6, and Figure 7. Additional plots showing preliminary calibration of weather-dependent end uses are included in Appendix A.

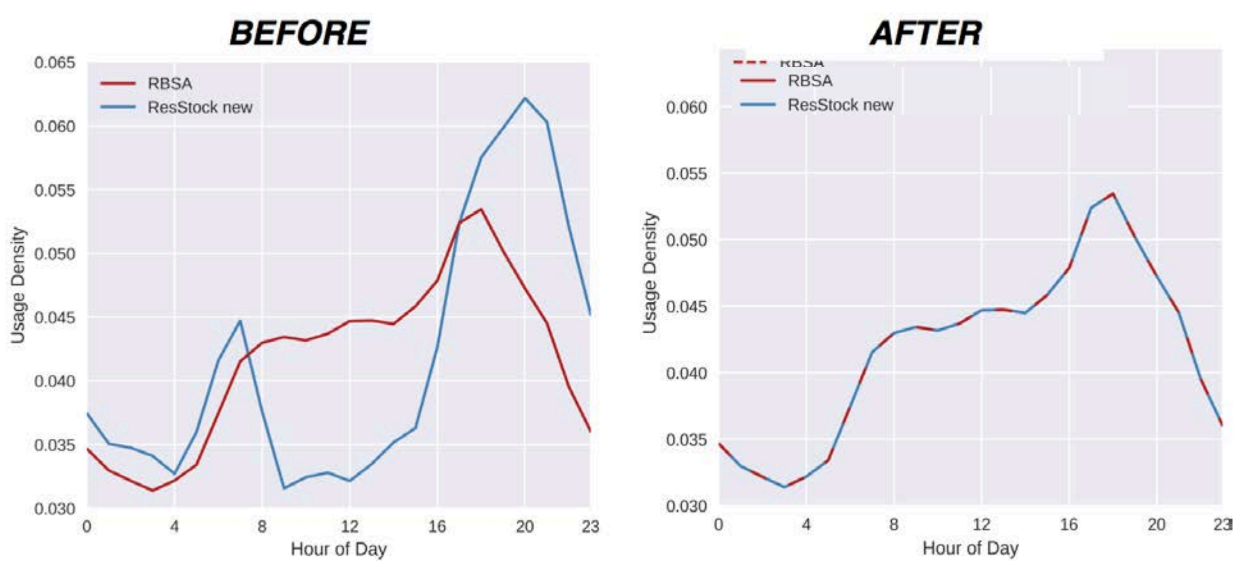


Figure 5. The ResStock plug load schedule was updated to use the measured plug load profile from RBSAM (mid-day valley eliminated).

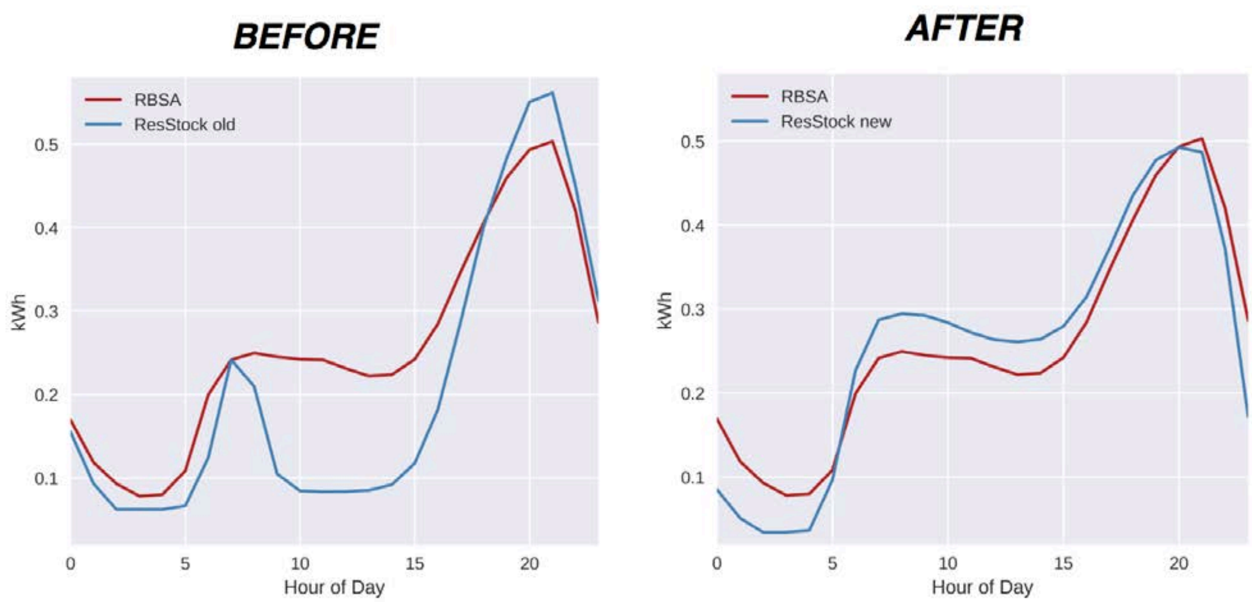


Figure 6. The ResStock lighting schedule algorithm was updated to eliminate the deep mid-day valley and more closely match measured lighting use from RBSAM.

The algorithm is a piecewise function with six components that are functions of building latitude, season, and sunrise/sunset times.

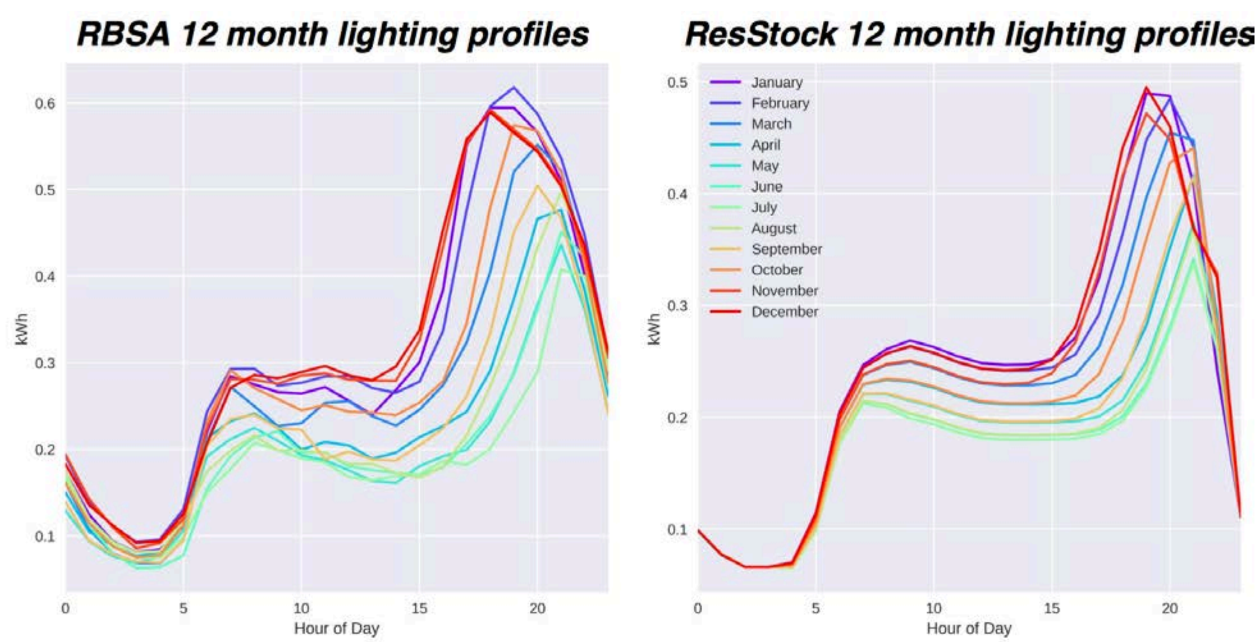


Figure 7. After modification, the ResStock lighting schedule algorithm results in an improved match to the RBSAM data for all months of the year.

Other model improvements include addressing unrealistic coincidence in occupant behavior regarding exhaust ventilation and hot water use events. For exhaust ventilation (e.g., bathroom, kitchen, and clothes dryer exhaust), the model was changed from simulating every home having exhaust ventilation events at the same time to using a probability distribution to assign timing of the exhaust events. This had the effect of spreading spot ventilation out over the day realistically for the sample of homes modeled in ResStock. For hot water use, a change was made to use 1,615 repeating weeks for the draw profile instead of a set of 50 annual draw profiles. This led to significantly more diversity in hot water draw patterns across homes, and it reduced the occurrence of unrealistically coincident water heater electricity demand.

2.2.1.5 Subsector Gap Model

When ResStock was initially developed, NREL's residential modeling algorithms were focused on single-family detached housing, based on a history of developing energy modeling and optimization tools for research involving large, production homebuilders in the U.S. Department of Energy (DOE) Building America Program (Christensen et al. 2006; Wilson et al. 2014). Consequently, ResStock currently does not represent multifamily housing, including duplexes, and low-, mid-, and high-rise residential buildings.[25] Mobile homes are also not currently represented. Larger multifamily buildings, in particular, mid- and high-rise residential buildings, are represented as part of the commercial building stock (Deru et al. 2011). To facilitate comparison to EIA Form 861 residential data (EIA 2013c), the dsgrid detailed residential sector model is ultimately comprised of the ComStock mid- and high-rise apartment building subsectors sitting alongside the ResStock results in a single data file.

The remaining residential subsectors form the residential gap model (Table 3). The energy use for these gap subsectors is approximated by scaling the RECS 2009 energy use by the number of dwelling units reported in the 2010–2014 ACS divided by the number of dwelling units in RECS 2009. These factors are computed by subsector for the 27 reportable domains in RECS 2009 (large states and groups of states) (Table 4). The energy use is then distributed to counties based on the 2010–2014 ACS occupied-only housing unit counts, again, on a residence-type basis.

Table 3. Residential Subsectoral Gaps: Size and Proxy Timeseries Description

Subsector	Est. Portion of CONUS Residential Electricity Use (%)	Proxy Timeseries: Description	Proxy Timeseries: Geographic Resolution	Proxy Timeseries: End-Use Resolution
Mobile homes	7.2	Single-family detached (1,000 ft^2 size bin)	State	Same as ResStock
Low-rise apartments	5.0	Mid-rise apartments (ComStock)	State	Same as ComStock
Single-family attached (duplexes and townhomes)	4.7	Single-family detached (1,000 ft^2 size bin)	State	Same as ResStock

[25] ResStock multifamily capabilities are under development as of 2018.

The proxy timeseries for the residential gap model are also summarized in Table 3. As can be seen in the table, low-rise apartments use the mid-rise apartment load timeseries, broken down by end use, from ComStock; and the other two gap subsectors, single-family attached and mobile homes, use timeseries from ResStock, not the full county-level data, but the portion describing homes smaller than 1,500 ft^2. In all cases, for each building type and county, if a county-level proxy timeseries is available, it is used. If no proxy timeseries is available at the county level, the state-level aggregate is used. In all cases, the proxy timeseries are scaled to match the electricity use (megawatt hours [MWh]) per building type and county estimated based on RECS 2009 (energy use) and the 2010–2014 ACS (energy use scaled to 2012 using Table 4, and downscaled to counties based on relative building counts).

Table 4. Residential Scaling Factors: 2010–2014 ACS Occupied Dwelling Units Divided by RECS 2009 Dwelling Units, by Building Type and Census Division

Census Division	Single Family Detached	Single Family Attached	Apartments in 2 to 4 Unit Buildings	Apartments in Five5 or More Unit Buildings	Mobile Homes
East North Central	100%	109%	98%	100%	108%
East South Central	96%	84%	135%	106%	116%
Middle Atlantic	99%	105%	103%	106%	93%
Mountain	100%	85%	160%	138%	89%
New England	105%	92%	100%	97%	134%
Pacific	106%	112%	96%	99%	94%
South Atlantic	102%	133%	103%	110%	83%
West North Central	102%	101%	116%	113%	72%
West South Central	107%	58%	89%	103%	121%

2.2.2 Commercial Sector

ComStock is a bottom-up, physics-based model developed for this project by NREL to capture energy-related characteristics and model energy use of the U.S. commercial building stock. The ComStock methodology builds on the framework established by ResStock (Wilson et al. 2017) but differs in several ways guided by the unique physical and operational characteristics of, as well as the data available for, commercial buildings. Primary differences include how the geospatial distribution of buildings is calculated and how empirical data are translated into building energy model inputs. ComStock is described here in brief. Detailed information on the data, process, and assumptions used to develop ComStock are available in Appendix B.

The ComStock model is comprised of five parts:

- A database of commercial building characteristics
- Conditional probability tables synthesized from these data

- A sampling methodology implemented in the Parametric Analysis Tool[26]
- Model articulation using the OpenStudio software development kit[27] to create statistically representative models; the programmatic re-creation and customization of DOE prototype buildings[28] within this framework[29] is a key building block.
- The EnergyPlus building energy simulation engine.[30]

ComStock results consist of scaled, statistically representative building load profiles for the CONUS commercial building stock with county-level granularity. The modeling process is modular and highly flexible, such that alternate input data sets can easily be substituted and various OpenStudio scripts (termed "measures") can be inserted into the workflow. Thus, ComStock can be used to explore alternate geographies or years, as well as energy efficiency or demand response measures that model alternate design or operational decisions.

2.2.2.1 Input Data Sets

We initiate the ComStock workflow with a hierarchical structure of conditional probability tables for nine major determinants of commercial building energy use: building location (i.e., county), building type, floor-to-ceiling height, building energy code, primary HVAC system, number of floors, total floor area, and vintage. We synthesize conditional probability tables with binned values for each of these building characteristics (with the exception of energy code) from national data sets, namely CBECS (EIA 2016a) and CoStar, which is a building-level commercial real estate inventory from which we derive aggregates at the census block level (CoStar 2017). The resulting probability tables distill critical building characteristics at appropriate geo-spatial extents, for instance indicating that about 74% of primary schools in the United States are one story and 15% have two stories.

[26] For information about the OpenStudio Parametric Analysis Tool, see www.openstudio.net and the Parametric Analysis Tool 2.1.0 (PAT) Interface Guide at http://nrel.github.io/OpenStudio-user-documentation/reference/parametric_analysis_tool_2/.
[27] For information about the software development kit, see https://www.openstudio.net/developers.
[28] For information about DOE prototype models, see the U.S. Department of Energy Building Energy Codes Program, "Commercial Prototype Building Models," https://www.energycodes.gov/development/commercial/prototype_models, last updated April 14, 2016.
[29] For information about the OpenStudio-Standards Gem framework, see https://github.com/NREL/openstudio-standards.
[30] For information about EnergyPlus, see energyplus.net.

Each building is assumed to meet the minimum energy efficiency requirements of either ASHRAE Standard 90.1 (ASHRAE 2016) or the DOE "reference buildings" pre-2004 assumptions (Deru et al. 2011). We assume building codes are commensurate with building vintage (e.g., if a building was constructed in 1994, we assume it adheres to the 1980–2004 ASHRAE 90.1 standards). In future work, we will derive state- and county-specific code compliance from the Building Codes Assistance Project database and more-granular code adoption data derived from municipality and county data-sources (BCAP 2017). We may also use the last retrofit year field in the CoStar data to capture the proportion of older buildings that should now be considered compliant with newer building codes based on having been deeply renovated. Additional building characteristics are derived primarily from building type and code set using defaults specified in the DOE prototype buildings (Goel et al. 2014) and the NREL Sector Model (B. Griffith et al. 2007), and are subsequently maintained by NREL in the OpenStudio suite of modeling tools.[31] The major building characteristics captured by ComStock, their interdependencies, and data sources are summarized in Table 5.

[31] See Footnote 29.

Table 5. Building Characteristics, Dependencies, Data Sources, and Number of Variable Values Used in the ComStock Modeling Process

		Dependencies							Data Sources						
	Characteristics	**Division**	**Location (county)**	**CoStar Building Type**	**DOE Prototype Building**	**Vintage**	**Number of Floors**	**Building Shape**	**CBECS (EIA 2012)**	**RECS (EIA 2009)**	**CoStar (2017)**	**DOE Prototype Buildings**	**NREL Sector Model**	**NREL NSRDB**	**# of Options (bins) if table exists**
Meta	*Division*														9
	Location (county)	X									X				N/A[b]
	CoStar building type		X								X				102
	DOE prototype building			X								X			17
	Vintage	X			X				X	X					10
	Energy code		X			X									6
	Space type breakdown[a]											X			
	Weather data		X											X	
Geometry	Rotation[c]												X		8
	Number of floors				X				X	X					16
	Area				X				X	X					10
	Floor-to-ceiling height				X				X						46
	Building shape				X										12
	Aspect ratio[d]							X					X		6
	Window-to-wall ratio[a]				X							X			
Envelope	Construction type[a]				X							X			
	Wall properties[a]				X							X			
	Windows properties[a]				X							X			
Internal Loads	People[a]				X	X						X			
	Lights[a]				X							X			
	Plug loads[a]				X	X						X			

		Dependencies							Data Sources						
	Characteristics	Division	Location (county)	CoStar Building Type	DOE Prototype Building	Vintage	Number of Floors	Building Shape	CBECS (EIA 2012)	RECS (EIA 2009)	CoStar (2017)	DOE Prototype Buildings	NREL Sector Model	NREL NSRDB	# of Options (bins) if table exists
	Elevators[a]				X	X						X			
	Kitchen equipment[a]				X	X						X			
Service Water Heating	Showers, sinks, etc.[a]				X							X			
	Laundry[a]				X							X			
Schedules	Operation schedules[a]				X	X									
HVAC	HVAC system type[e]				X				X						52
	HVAC controls[a]		X		X							X			
	HVAC efficiencies[a]		X		X							X			

italics = archetype parameters, which are building characteristics whose values influence the conditional probability tables of other building characteristics

[a] For energy simulations, values of these parameters are determined using EnergyPlus/OpenStudio defaults based on the dependencies shown
(i.e., no probability tables are associated with these characteristics).

[b] The number of counties is dependent on the analysis area.

[c] Rotation is defined as 8 orientation bins offset by 45 degrees, with a uniform probability distribution.

[d] Aspect is defined as 6 bins between about 0.5 and 6.5. Each shape uses only some of the bins.

[e] We infer HVAC system type based on the main heating and cooling types recorded in (EIA 2016a), using lookup logic from (Griffith et al. 2008).

ComStock, along with ResStock, utilizes actual meteorological year (AMY) weather files derived from the NSRDB as an input into the EnergyPlus simulation engine (Appendix H). However, ComStock uses individual weather files for each county in the CONUS. Each weather file location was chosen to be the closest NSRDB grid cell to the LandScan grid cell with the highest daytime population in the county (ORNL 2011).

2.2.2.2 Methodology

The conditional probability tables created from ground-truth data sets are stored in tab-separated-values file format, and the Parametric Analysis Tool is used to sample these tables hierarchically.

We apply the same Latin hypercube stratified sampling methodology as ResStock (Wilson et al. 2016), selecting values for building characteristics based on the relative probabilities (i.e., frequencies) of those values, as described in CBECS 2012 and CoStar data. The resulting sets of building characteristics are translated into inputs for energy models in OpenStudio and EnergyPlus format using the Parametric Analysis Tool and OpenStudio measures (Roth, Goldwasser, and Parker 2016). This process is completed for 350,000 building simulations on internal server systems and cloud-computing infrastructure. Weighting factors are applied to scale results from the simulated 350,000 buildings to the total number of commercial buildings in the CONUS as estimated by CBECS 2012 (EIA 2016a).

2.2.2.3 Output Data

ComStock output data are similar to those of ResStock. The reported end uses are based on standard EnergyPlus reportable meters:

- Fans: electricity (kWh)
- Pumps: electricity (kWh)
- Space heating: electricity (kWh)
- Space heating: gas (kBtu)
- Space cooling: electricity (kWh)
- Interior lights: electricity (kWh)
- Exterior lights: electricity (kWh)
- Water systems: electricity (kWh)
- Water systems: gas (kBtu)
- Interior equipment: electricity (kWh)
- Interior equipment: gas (kBtu)
- Space cooling: district cooling (kBtu)
- Space heating: district heating (kBtu)
- Heat rejection: electricity (kWh)

When space heating or cooling is provided by district systems, the quantity of energy reported is the amount of thermal heating or cooling energy delivered to the building. To capture the load this represents in terms of electricity and natural gas, we assume conversion factors of 0.58 kWh electricity/ton cooling-hour for district cooling and 1.25 kBtu natural gas/kBtu heating for district heating (Xcel Energy 2016).

Based on the reported metadata of each simulation, the results are categorized on a county-by-county basis. The data are reported by commercial subsector and end use by summing across all applicable data points within each county to achieve aggregated load timeseries. These values, along with a scaling factor of 9.034, which is a result of simulating approximately one seventh of all commercial buildings in each county and a simulation failure rate of approximately 15%, is persisted and transferred to dsgrid.[32]

2.2.2.4 Calibration

The modeling techniques used in the creation of the ComStock building energy models are based on a significant body of peer-reviewed work completed by NREL, the Pacific Northwest National Laboratory, and Lawrence Berkeley National Laboratory over the last decade (Deru et al. 2011). The inputs have been reviewed by numerous experts, including ASHRAE committee members who design these buildings professionally. These models are under a constant state of update and review through the OpenStudio Standards Gem, an open-source project whose continual testing and development is supported by several ongoing projects.

As ComStock is still in early stages of development, additional calibration steps are in progress. Two primary categories of error are currently being examined in the ComStock model. The first class of error stems from the uncertainty regarding the number of commercial buildings in the United States, the square footage of said buildings, and their primary use. The second class is due to uncertainty in the modeling assumptions being applied and potential bugs in their implementation. All work in the immediate future is focused on finding and addressing these error sources to (1) improve our estimate of the total stock being modeled in terms of number and size of buildings by type and (2) improve our estimates of the energy use of these buildings at different timescales (e.g., annual, hourly, and subhourly).

Data sources (e.g., CBECS and CoStar) disagree on such basic data as the number, size and type of commercial buildings. Some of these differences arise from different definitions of what constitutes a commercial building. Determining the validity of these data sets relative to one another, however, requires a set of ground-truth observations. The ComStock team is proceeding by obtaining such observations from various public and private utility data sets. Doing so allows for verification of the number of buildings of various rate classes, albeit for limited sets of geographies. Additional data sets for building types that are not bought and sold frequently (e.g., federal buildings and schools) are also being incorporated to further supplement CBECS and CoStar.

The modeling assumptions built into the OpenStudio Standards Gem reflect the best information available from existing sources. Many of the inputs are taken from building energy performance codes such as ANSI-ASHRAE 90.1, which governs what properties buildings must have based on their age, type, and location to minimally comply with energy efficiency codes. Other inputs are taken from the ASHRAE Advanced Energy Design Guides, which are a series of publications written by experts on designing particular building types. The approach to modeling many of the complex building controls and equipment was taken from the DOE prototype buildings, which have been developed by NREL, the Pacific Northwest National Laboratory, and Lawrence Berkeley National Laboratory over the last decade (Deru et al. 2011; Goel et al. 2014). Additionally, because of the sheer number of inputs required for each building energy model,

[32] Factoring the simulation failure rate into the overall scaling factor represents an implicit assumption that simulation failures are evenly distributed across geographies, building types, etc. The authors do not expect that assumption to be fully correct, but did also not find any clear, easily correctable trends in the specific simulations that failed. This is an area we will look at closely and correct in future work.

some inputs and modeling assumptions were developed using professional engineering expertise developed by the ComStock team over many years of modeling buildings for a diverse array of research projects and field studies.

2.2.2.5 Subsector Gap Model

The DOE "reference buildings" and "prototype buildings" represent 17 commercial building types that are then replicated across climate zones and vintage to create hundreds to thousands of archetypes (Deru et al. 2011; Goel et al. 2014).[33] These models[34] serve as a baseline standard from which each simulated building is articulated in EnergyPlus. The building types documented in the CBECS 2012 and CoStar data sets must therefore be mapped to these DOE prototype buildings for modeling purposes. To avoid producing inaccurate energy models, building types that did not have a reasonable prototype equivalent were excluded from ComStock, and they are instead included in the gap model. See Appendix B for the full mapping from CBECS and CoStar building types to DOE prototype buildings, along with associated building counts used for this analysis.

The CBECS building types included in the commercial building gap model are listed along with their annual energy use in Table 6. These building types are those that are not mappable to the DOE prototype buildings but are mappable to CoStar building types (Table C-3 and surrounding text). This latter mapping is then used to downscale the electricity use reported in CBECS to counties based on the CoStar building counts. The proxy timeseries for these gaps are the aggregated ComStock timeseries, summed over subsectors and end use. If a county-level profile is available, it is used; if not, a state-level profile is applied. Unlike with the residential gap model, we do not expect the end-use breakdowns to hold when applied to these various building types[35] and so do not supply them.

[33] The DOE "reference buildings" span 16 building types: Large Office, Medium Office, and Small Office; Warehouse; Stand-alone Retail and Strip Mall; Primary School and Secondary School; Supermarket; Quick Service Restaurant and Full Service Restaurant; Hospital and Outpatient Health Care; Small Hotel, Large Hotel; and Midrise Apartment. The DOE "prototype buildings" do not include a Supermarket model, but they add a High-Rise Apartment. Thus, the two sets of archetypical building models together represent 17 commercial building types.
[34] ComStock builds off of the OpenStudio Standards gem, which is a programmatic implementation of the DOE prototype buildings. At the time of this writing, 16 building types: all of those listed above except for Supermarket; are available. Because of deficiencies in the CoStar data, we are also not able to distinguish between Mid-Rise and High-Rise Apartments, nor between Primary and Secondary Schools (school buildings are generally under-represented in CoStar) at this time. As such, this version of dsgrid provides results for 14 commercial building sub-sectors: Large Office, Medium Office, Small Office, Warehouse, Stand-alone Retail, Strip Mall, Primary School, Quick Service Restaurant, Full Service Restaurant, Hospital, Outpatient Health Care, Small Hotel, Large Hotel, and Midrise Apartment. Future planned work to add Supermarkets to the prototype buildings, and to supplement CoStar with data sources that better represent public-sector building counts, should remedy these shortcomings.
[35] Commercial buildings are much more heterogenous than residential buildings, both in design and use. For example, the end use breakdowns between grocery stores, vehicle repair shops, and libraries look very different; and, the temporal distribution of load will be very different between offices, libraries, and religious buildings. The inability to match a CBECS or CoStar building type to a prototype building essentially signals that we do not yet have an energy model that properly captures one or both of these aspects.

Table 6. Commercial Sector Subsectoral Gaps: Size and Proxy Timeseries Description

Subsector	Est. Portion of CONUS Commercial Electricity Use (%)	Proxy Timeseries		
		Description	Geographic Resolution	End-Use Resolution
Grocery store/food market	2.7	ComStock aggregation	County	None
Recreation	2.0	ComStock aggregation	County	None
Religious worship	1.9	ComStock aggregation	County	None
Entertainment/culture	1.6	ComStock aggregation	County	None
Laboratory	1.5	ComStock aggregation	County	None
Convenience store	1.2	ComStock aggregation	County	None
Vehicle service/ repair shop	1.2	ComStock aggregation	County	None
Convenience store with gas station	1.0	ComStock aggregation	County	None
Library	0.9	ComStock aggregation	County	None
Vehicle storage/ maintenance	0.7	ComStock aggregation	County	None
Other public order and safety	0.6	ComStock aggregation	County	None
Vehicle dealership/ showroom	0.6	ComStock aggregation	County	None
Fire station/police station	0.5	ComStock aggregation	County	None

2.2.3 *Industrial Sector*

The Industrial Geospatial Analysis Tool for Energy Evaluation (IGATE-E) is a model that utilizes multiple data sources and statistical approaches to estimate the energy consumption of manufacturing plants across the United States. Originally developed by Oak Ridge National Laboratory in 2012, the tool has been used to investigate the potential for demand response and CHP at the plant levels (Alkadi et al. 2013; Bhandari et al. 2018).

IGATE-E can be differentiated from the other sector models used by dsgrid in that it does not attempt direct simulation of loads, because of the highly complex and specialized nature of manufacturing processes. For example, process heating, which represents one of the largest opportunities for electrification within the manufacturing subsector, is comprised of more than 10 types of heating operations[36] and 20 distinct system types[37] used to carry out these operations (LBNL et al. 2015). Furthermore, the applicability of each of these operational categories and

[36] LBNL et al. (2015) provides basic descriptions of agglomeration and sintering, calcining, curing, drying, fluid heating, forming, high-temperature heating and melting, low-temperature heating and melting, heat treating, incineration/thermal oxidation, metals reheating, smelting, and other heating processes.
[37] LBNL et al. (2015) categorizes process heating systems as fuel-based, electric-based, steam-based, or other; where other is comprised of systems such as heat recovery, heat exchange, and fluid heating. That report lists 14 kinds of fuel-based furnaces and 11 electricity-based process heating technologies.

systems varies greatly from one manufacturing industry to another. Because of the impracticality of modeling so many different use cases, IGATE-E instead compiles data from multiple sources and applies statistical techniques to estimate energy consumption down to the plant and end-use levels. Because IGATE-E only models manufacturing, the additional industrial subsectors of agriculture, mining, and construction comprise the industrial gap model.

2.2.3.1 Input Data Sets

Within IGATE-E, several data sets are used to estimate energy consumption for the manufacturing subsector. The primary data sets are the DOE Industrial Assessment Centers (IAC) Database and the Manufacturers' News, Inc. (MNI) EZ Select database. The IAC Database is a public data source that contains information on more than 18,000 plant-level assessments (DOE 2017a). The assessments date to 1981 and primarily focus on small- and medium-sized plants.[38] Although the IAC Database contains a large amount of data, its relevancy may be limited in industries where fewer recent assessments have been completed and where large manufacturing plants play a major role. Furthermore, because plants must choose to undergo an assessment, a self-selection bias may be present, with a recent analysis of IAC participants indicating participants were less energy efficient than their peers (Dalzell, Boyd, and Reiter 2017). Though a detailed evaluation of the statistical validity of the IAC Database was not conducted, Figure 8 summarizes how many assessments are available by both industry and assessment year. For its use in this analysis, IGATE-E ignores assessments that do not provide information on a plant's NAICS code. As a result of this requirement, IGATE-E only uses assessment data from 2002 onward, limiting problems that could have arisen from using older data.

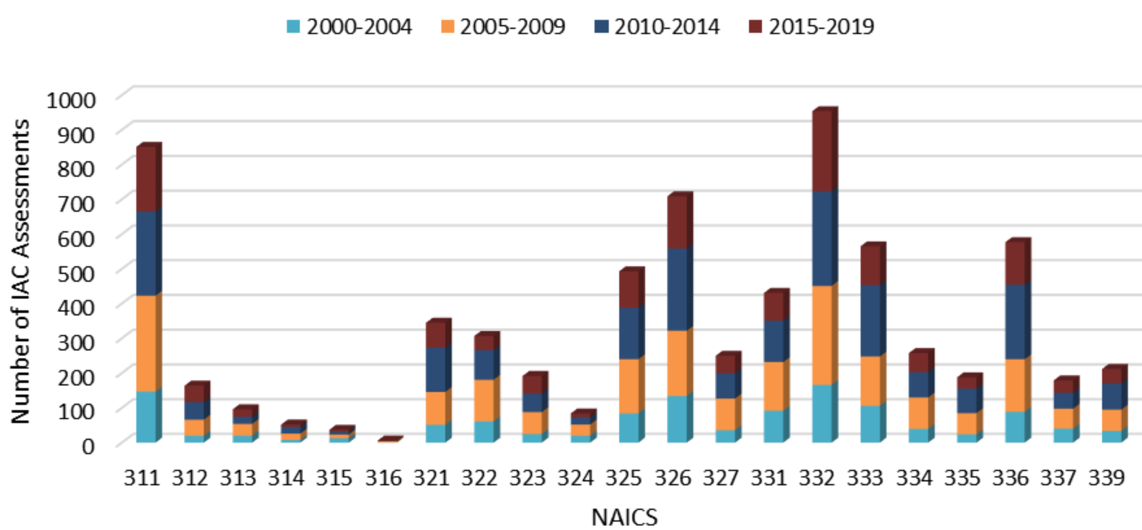


Figure 8. Number of IAC assessments by industry and year (as of March 2018)

For assessments occurring before 2002, results are available by SIC code only.

NAICS = North American Industry Classification System

[38] Eligibility requirements to qualify for an IAC Assessment include energy bills between $100,000-/yr and 2,500,000/yr.

Additional data sources have been explored to supplement this database; however, the proprietary/competitive nature of plant-level information has made it difficult to find additional data beyond what is currently available from the IAC Database.

The MNI database is a commercial data set that provides industry, location, and employment information for approximately 294,000 manufacturing sites across the United States, which provides approximately complete coverage of manufacturing establishments, see Footnote 44. Other sources were considered for this purpose, such as the Dun & Bradstreet Hoovers database, but the MNI was found to be the most cost-effective based on the needs of the project. Together, the MNI and IAC data sets are used to develop plant-level energy and demand estimates.

To refine IGATE-E's initial energy consumption estimates, data from the 2014 MECS are used. Finally, end-use level consumption information by industry (i.e., three-digit NAICS) from the MECS, along with data from EPRI's Load Shape Library,[39] is used to construct disaggregated 8,760 load shapes. Table 7 summarizes the manufacturing plant characteristics, modeling methods, and data sources used by IGATE-E.

Table 7. Manufacturing Plant Characteristics, Modeling Methods, and Data Sources used by IGATE-E

		Methods					Data Sources			
Resolution	**Characteristics**	**Regression Analysis**	**Energy Analysis**	**Energy Analysis**	**Load Factor**	**Load Shape Analysis**	**IAC Database**	**MNI EZ Select**	**2014 EIA MECS**	**EPRI Load Shape**
Plant Level	Location (State/County/Zip Code)		X					X		
	Industry Code (NAICS/SIC)	X	X		X		X	X		
	Energy Consumption (kWh or MMBtu/yr)	X			X		X			
	Electricity Demand (kW/month)				X		X			
	Number of Employees	X	X				X	X		
Industry Level	Industry Code (NAICS/SIC)			X		X			X	
	Energy Consumption (kWh or MMBtu/yr)			X					X	
	End-Use Energy Consumption (kWh/yr)					X			X	
Sectoral Level	Load Shapes by End-Use					X				X

[39] The EPRI Load Shape Library provides representative industrial load shapes by end-use and region. Daily load shapes are provided for various scenarios (i.e., weekday versus weekend and peak season vs. off-peak season). Load shapes are derived from simulations using the EPRI NESSIE (National Electric System Simulation Integrated Evaluator) model platform. The inputs to NESSIE are derived from data estimated by the EIA's National Energy Modeling System (NEMS) as well as from data collected by EPRI through its laboratory testing and research.

2.2.3.2 Methodology

To estimate electricity consumption within the manufacturing subsector, IGATE-E performs regression analyses of energy consumption versus number of employees using data from the IAC Database. Regression results are developed for individual industries based on their North American Industry Classification System (NAICS)[40] code; this system is used to classify business establishments according to their primary economic activity, specifically the type of product being produced. Within the model, a linear regression analysis is conducted by industry for every three- and four-digit NAICS code.[41]

Working within this framework, the basic premise of IGATE-E is that manufacturing facilities producing similar products (as categorized by their NAICS code) will utilize similar processes that ultimately have similar energy intensities (i.e., energy usage per product produced). Currently, number of employees is used as a proxy for the product being produced.[42] Using these industry-specific regression results, aggregate energy usage is estimated for each plant using employment information from the MNI database. Finally, usage estimates are adjusted by industry (three-digit NAICS) and census region to better align with the MECS.

Hourly annual load shapes are created by combining industry-level load factor estimates with diurnal load shapes provided by sector and end use from the EPRI Load Shape Library. Load factors are estimated from the IAC Database data by conducting a regression analysis of peak electricity demand versus annual electricity use and then estimating an average load factor for each industry based on the slope of these regressions. Plant-level peak electricity demand falls out by combining load factor with annual energy consumption estimates. The EPRI Load Shape Library provides daily load shapes by sector and end use for various scenarios (e.g., weekday versus weekend). To disaggregate energy consumption at the end-use level, data from the 2014 MECS (by three-digit NAICS) is applied. Next, categories included in the EPRI Load Shape Library are matched to the most appropriate MECS end-use category (Table 8). Finally, disaggregated load shapes are constructed for each industry based on end-use consumption estimates from the 2014 MECS and load shapes from the EPRI Load Shape Library. The resulting load shapes are either "stretched" or "flattened" on an industry-by-industry basis to match the load factor estimates derived previously. Within IGATE-E, load shapes are applied at the individual plant-level based on a plant's peak electricity demand.

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[40] For more information, see https://www.census.gov/eos/www/naics/.
[41] Within IGATE-E, a minimum of five IAC assessments per regression is enforced. While most four-digit industries have enough data to meet this requirement, those that do not utilize three-digit regressions.
[42] IGATE-E originally utilized annual sales data for this purpose; however, inconsistencies in quality and the sporadic availability of this data limited its value. Although nominally annual sales should correlate better to energy usage than number of employees, the latter data field is more consistently provided in IGATE-E's data sets, and it has thus proven to be a better proxy in practice.

Table 8. End-Use and Load Shape Category Mapping

2014 MECS End-Use Category	EPRI Load Shape Library Category
Conventional Boiler Use	Other
Process Heating	Process Heating
Process Cooling and Refrigeration	Other
Machine Drive	Machine Drives
Electro-Chemical Processes	Other
Other Process Use	Other
Facility HVAC	HVAC
Facility Lighting	Lighting
Other Facility Support	Other
Onsite Transportation	Other
Other Nonprocess Use	Other
End Use Not Reported	Other

2.2.3.3 Output Data

For use in dsgrid, plant-level peak demand estimates are compiled by county and NAICS code. These peak demand values are then mapped to the corresponding normalized load shape. Load shapes are available on a per-four-digit NAICS code and time zone basis (conforming to the dsgrid convention of 2012 as experienced in EST, with end-of-hour data points, and accounting both for time zones and for varying daylight saving time policies). Within the load shapes, electricity consumption detail is provided for the following end-use categories: conventional boiler use, process heating, process cooling and refrigeration, machine drives, electrochemical processes, other process use, facility HVAC, facility lighting, other facility support, onsite transportation, and other nonprocess use. These categories match those reported in the MECS.[43]

2.2.3.4 Calibration

Several differences emerge when IGATE-E's estimates are compared to the 2014 MECS. Industries where consumption is significantly underestimated include:

- 322: Paper
- 324: Petroleum and Coal Products
- 325: Chemicals
- 331: Primary Metals.

In reviewing the MECS, these industries were found to have the highest energy intensities, suggesting the lack of regression data for large manufacturing plants may be limiting IGATE-E's

[43] In addition to electricity consumption, IGATE-E also estimates annual natural gas consumption at the individual plant-level. Currently, however, no effort has been made to disaggregate natural gas usage by end-use category.

accuracy in these cases. For industries where consumption is significantly overestimated, discrepancies in the number of establishments and employees considered by MECS compared to IGATE-E may be the primary issue.[44]

While additional research is being conducted to understand these differences, IGATE-E's initial estimates are adjusted by industry and census region to match the MECS. This is accomplished by scaling individual plant estimates so that aggregate consumption estimates match those from the 2014 MECS. The primary drawback to this is that errors in the MECS are ultimately reproduced by IGATE-E. Future efforts will focus on further developing IGATE-E's optimization approach to avoid "overadjusting" initial estimates to match the MECS.

2.2.3.5 Subsector Gap Model

Within the industrial sector, IGATE-E's methodology has specifically been developed for the manufacturing subsector. Subsectors not covered by IGATE-E include agriculture, forestry, fishing and hunting; mining, quarrying, and oil and gas extraction; and construction. In dsgrid, these non-manufacturing subsectors are represented in the industrial gap model using annual electricity estimates from the AEO and generalized load shapes from the EPRI Load Shape Library. To develop county level results for these subsectors, AEO national estimates are first disaggregated to the state level based on employment data from the U.S. Census Bureau's Statistics of U.S. Businesses and then at the county level based on number of establishments data from the U.S. Census Bureau's County Business Patterns (CBP).

Table 9. Industrial Sector Subsectoral Gaps: Size and Proxy Timeseries Description

		Proxy Timeseries		
Subsector	Est. Portion of CONUS Industrial Electricity Use (%)	Description	Geographic Resolution	End-Use Resolution
Mining, quarrying, and oil and gas extraction	8.8	IGATE-E generic industrial load shape	County	None
Construction	6.4	IGATE-E generic industrial load shape	County	None
Agriculture, forestry, fishing and hunting	3.7	IGATE-E generic industrial load shape	County	None

2.2.4 Transportation Sector

For dsgrid, we are primarily interested in electrification of road transportation, namely electricity use for passenger and commercial plug-in hybrid electric vehicles and battery electric vehicles. To model this electricity use, we rely on three NREL models, as summarized in Figure 9:

[44] For example, while the MNI database and the U.S. Census 2015 Statistics of U.S. Businesses (https://www.census.gov/programs-surveys/susb.html) largely agree on the number of manufacturing establishments, reporting 294,427 and 292,825 respectively; the 2014 MECS estimates 175,107 establishments.

- **Automotive Deployment Options Projection Tool (ADOPT):** used to inform vehicle adoption and vehicle attributes (e.g., range and fuel economy)
- **Scenario Evaluation and Regional Analysis (SERA):** used to provide spatially distribute regional vehicle adoption
- **Electric Vehicle Infrastructure Projection Tool (EVI-Pro):** used to generate hourly charging profiles based on travel data and charging preference assumptions (e.g., residential charging as opposed to reliance on public charging).

Core bottom-up transportation modeling in dsgrid focuses on electrification of on-road transportation via PEVs (including plug-in hybrids), for both light-duty and medium- and heavy-duty vehicles. All other forms of transportation (e.g., rail, air, marine, and off-road vehicles) are considered in the gap model. Moreover, we do not consider alternative electrification strategies such as battery swapping or dynamic charging technologies (e.g., embedded roadway or catenary charging) that may be especially appropriate for heavy-duty on-road vehicles (Navidi, Cao, and Krein 2016; Cordoba Ledesma 2015). Note that although off-road vehicles are generally considered a transportation gap in dsgrid, energy consumed by off-road vehicles used in construction, agriculture, or mining would be categorized as an industrial, rather than a transportation gap, in line with energy consumption statistics (EIA 2017c).

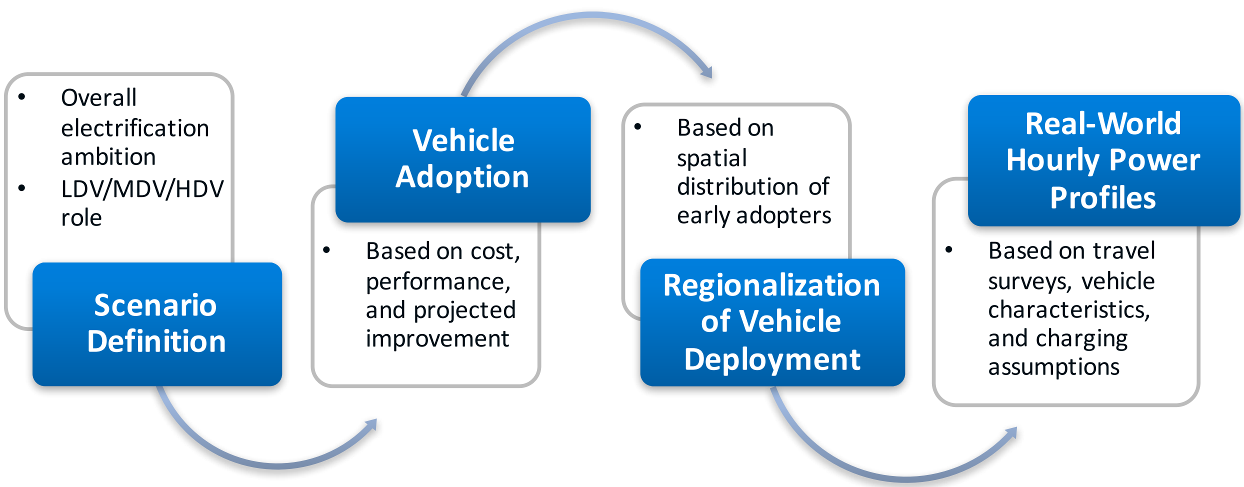

Figure 9. Transportation modeling scheme for the road subsector

LDV = light-duty vehicle, MDV = medium-duty vehicle, HDV = heavy-duty vehicle

The electricity consumption in road transportation in 2012, however, was very limited, with roughly 70,000 plug-in electric passenger vehicles on the road concentrated in a few urban areas (IHS Markit 2017). This number represents about 0.4 TWh of electricity, or less than 0.05% of U.S. electricity use (EIA 2015a). Therefore, it is not included in the 2012 historical dsgrid snapshot that is the focus of this documentation, but we do here document the methodology that will be used to model PEV charging load profiles and flexibility for future scenario snapshots that include higher PEV market shares. We also describe our transportation gap model, which consists of a first-order spatial and temporal disaggregation of transit rail electricity use, which accounted for approximately 6.6 TWh in 2012 (EIA 2015a).

In the remainder of this section, we document how PEV electricity use will be estimated in the EFS future load snapshots using SERA and EVI-Pro, given (1) an exogenously specified fleet of electric vehicles (informed by ADOPT runs for passenger PEVs) and (2) how rail transit electricity use has been disaggregated in the gap model. Given electrification scenarios designed as part of the EFS project, which define overall (national) adoption of electrified technologies in the transportation sector (Mai et al. 2018), SERA will be used to disaggregate to the county level and EVI-Pro will be used to develop hourly charging profiles. Charging flexibility and willingness to delay charging will be assessed in a scenario framework based on bounding conditions and expert judgement. The potential to use that flexibility to provide grid services and participate in demand response will not be considered here, but it will be assessed using operational grid models in future work.

2.2.4.1 Input Data Sets

To describe electricity use in the on-road transportation sector, we rely on vehicle registration data from IHS Automotive, vehicle attributes from the ADOPT model, consumer attitude and preference for alternative fuel vehicles included in the SERA model, and numerous travel surveys and charging behavior assumptions included in the EVI-Pro model. Table 10 summarizes the dependencies and data sources used to model plug-in vehicle electricity use in dsgrid.

Table 10. Vehicle Characteristics, Dependencies, and Data Sources Used in the dsgrid Transportation Modeling Process

		Dependencies						Data Sources					
Category	**Characteristics**	**Overall electrification**	**EFS scope**	**Consumer preference**	**Technology development**	**Infrastructure availability**	**Charging behavior**	**EIA AEO**	**EFS assumptions**	**IHS Automotive**	**ADOPT (sources therein)**	**SERA (sources therein)**	**EVI-Pro (sources therein)**
Subsectors	Transportation electricity use	x						x					
	Passenger PEVs		x	x	x	x			x		x	x	x
	Commercial PEVs		x		x	x						x	
	Others		x		x	x		x					
Passenger Vehicles	Overall PEV adoption	x	x	x	x	x			x	x	x		
	Spatial disaggregation	x		x		x						x	
	PEV characteristics		x		x						x		
	PEV use patterns			x		x	x						x
	Charging profiles (hourly)						x						x

		Dependencies						Data Sources					
Commercial Vehicles	Overall PEV adoption		x		x	x			x	x			
	Spatial disaggregation						x					x	
	Electrification strategy			x		x			x				
	Vehicle attributes				x							x	
	Vehicle use patterns					x	x					x	
	Charging profiles (hourly)						x					x	x

2.2.4.2 Methodology

Electricity use for passenger light-duty vehicles is modeled using a suite of mature tools developed by an NREL transportation team. These tools project vehicle adoption in the light-duty sector and alternative fuel infrastructure build-outs, and they model the energy use of individual passenger and commercial vehicles, including charging profiles for PEVs. The version of dsgrid documented here focuses on electrification of road transport, including passenger vehicles as well as medium- and heavy-duty commercial vehicles. Three different models are combined to arrive at hourly, county-level electric vehicle charging profiles. Detailed transportation models are used to project electrification of road transportation (which makes up approximately 79% of the approximately 26 quads of 2012 transportation energy consumption and is the most likely sector to be impacted by electrification). Other subsectors (rail, marine shipping, and aviation) are not be considered in detail.

The ADOPT tool will be used to inform passenger vehicle adoption scenarios over time based on characteristics of the existing vehicle fleet, technical and cost targets, and policy assumptions (Brooker et al. 2015). ADOPT will also project attributes and characteristics of future vehicles (e.g., battery capacity and vehicle range, and fuel economy) ADOPT provides yearly estimates of sales and vehicle stock at the county level that are further geospatially resolved using the SERA model (Bush et al. 2017). SERA has a highly geographically resolved understanding of transportation demands— down to the 0.5-km scale—and it will properly regionalize the ADOPT projections as needed and provide regional estimates of the resulting annual electricity demand. SERA will also be used to estimate potential for electrification for medium and heavy-duty commercial vehicles based on scenarios informed by relevant literature and current truck traffic volumes resolved in time and space. Medium-duty battery electric vehicles and buses will be modeled based on relevant literature in a scenario approach (i.e., educated assumptions about electrification of the existing fleet). In the heavy-duty road sector—although battery-powered trucks are technically conceivable—the range and the fuel energy density (both in terms of weight and volume) requirements make the deployment of PEVs harder (even though some private companies have been working to develop such products). Therefore, truck electrification will be modeled based on instantaneous charging, either wireless charging or charging via electrified road corridors (catenary charging). These charging profiles will be estimated for key corridors using heavy-duty traffic information and spatially disaggregated using the SERA model.

Finally, given a projected adoption of passenger and medium-duty PEVs for a given year, EVI-Pro will be used to estimate hourly charging profiles (Wood et al. 2017). EVI-Pro considers different recharging infrastructure scenarios, informed by the SERA model, including preferential use of residential, workplace, and public charging stations. EVI-Pro uses real-world travel data to simulate spatially and temporally resolved demand for PEV charging at homes, workplaces, and public destinations. It anticipates consumer charging behavior while capturing variations with respect to housing type (single versus multiunit dwellings), travel period (weekdays versus weekends), and regional differences in travel behavior and vehicle adoption. Figure 10 illustrates the main modeling steps in EVI-Pro.

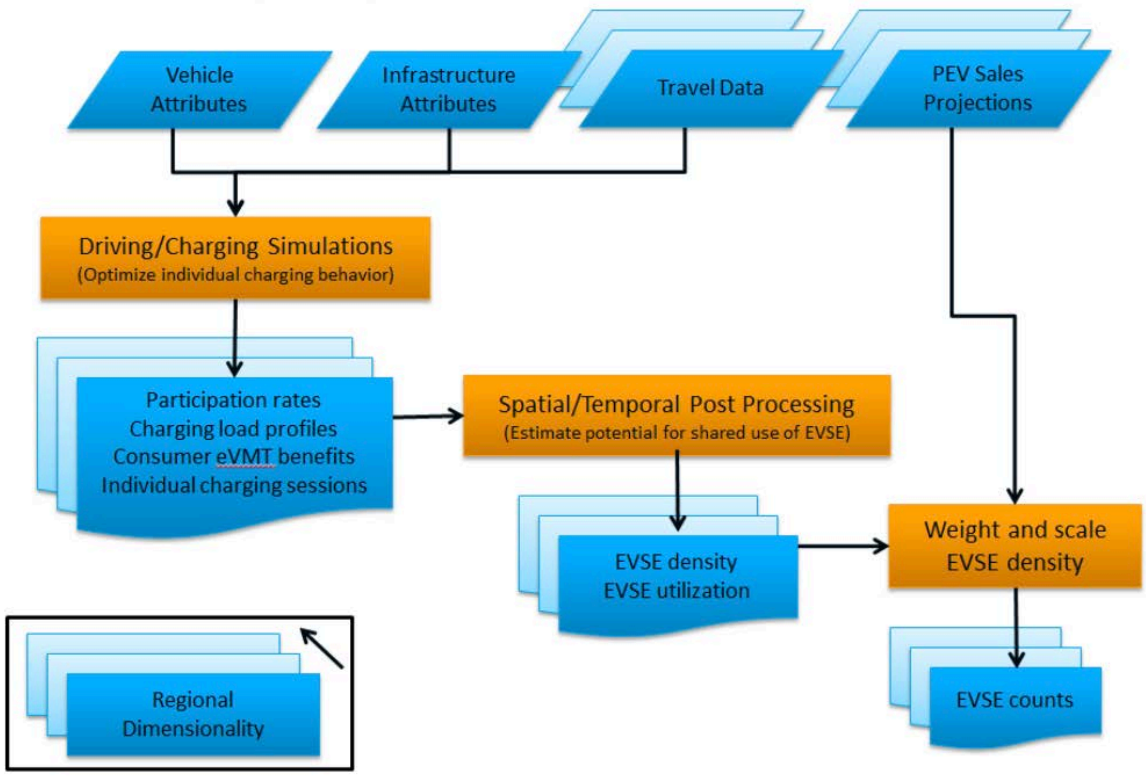

Figure 10. EVI-Pro model structure

Source: Wood et al. (2017)
eVMT = electric vehicle miles traveled

A fundamental assumption in EVI-Pro is that consumers prefer charging scenarios that enable them to complete all their current travels (which are driven in gasoline vehicles) and to maximize the miles driven on electricity (for plug-in hybrid electric vehicles). To define which charging scenarios consumers will elect, individual travel days from available travel surveys are simulated in the model. Each travel day is simulated multiple times for each potential combination of charging behavior (e.g., L1-Home, L2-Home, and L1-Home plus L1-Work) and the lowest-cost option if then selected, considering different levels of consumer preference for alternative charging solutions.

Past works using ADOPT, SERA, and EVI-Pro focused primarily on light-duty vehicles. For the future load snapshots, the team plans to construct a fairly detailed model of medium- and heavy-duty electric vehicles, based on the EFS focus on on-road transport electrification. To estimate the adoption of such vehicles the team will leverage internal expertise and coordinate with the scenario development group to produce realistic projections.

2.2.4.3 Output Data

ADOPT, SERA, and EVI-Pro are mature models that have been used extensively to answer a variety of questions related to transportation sector transformation and potential implications in terms of refueling infrastructure deployment and impact on the electric grid. The EFS, however, will push the boundaries of the three models by integrating them to generate spatially and temporally highly-resolved profiles for a set of different electrification scenarios. For the future scenario load snapshots, the models will be combined to produce hourly baseline charging and charging flexibility metrics (e.g., charging “schedulability” profiles) by subsector and scenario (specified by a set of charging preferences) for each county in the CONUS.

2.2.4.4 Calibration

SERA and EVI-Pro, which will be used to project future electricity demand for road transportation, have been calibrated using current vehicle use and statistics based on available regional and National travel surveys (Bush et al. 2017; Wood et al. 2017).

2.2.4.5 Subsector Gap Model

dsgrid models on-road transportation at a high level of detail. For the purposes of describing dsgrid, all other transportation subsectors are “gaps.” For this version of dsgrid, we focus on the amount of electricity used for transportation in 2012, a total of about 7.0 TWh. Most of the electricity used in transportation in 2012 was used by trains: 6.6 TWh partitioned among intercity rail, transit rail, and commuter rail, per EIA (2015a). This energy use is disaggregated in the transportation gap model to produce hourly profiles using a first-order disaggregation method based on NTD data (FTA 2017). In particular, total electricity consumption for rail is disaggregated spatially based on annual electric energy expenditure for propulsion (in kWh), as reported by NTD for 67 companies covering 45 U.S. urban areas (FTA 2017). To resolve this demand hourly, because no detailed modeling is available, we leverage data on hours of operation for different days of the week and number of rail cars operating in each day, which are also available in the NTD. Table 11 summarizes this gap model. Additional details are provided in Appendix D.

Table 11. Transportation Sector Subsectoral Gaps: Size and Proxy Timeseries Description

		Proxy Timeseries		
Subsector	**Est. National Electricity Use (TWh)**	**Description**	**Geographic Resolution**	**End-Use Resolution**
Passenger rail	6.6	Constructed based on hours of operation and number of rail cars operating by day type	State	None

2.2.5 Summary

The purpose of dsgrid is to estimate potential future load shapes, especially as they might be impacted by energy efficiency, electrification, and demand response (i.e., set-point and operational modifications made in support of grid operations). Given this, an initial gap analysis of our planned model was completed up front to assess how much electricity use—and how much of all potentially electrifiable site energy use—is covered by the bottom-up sector models, as these proportions give a first indication of how well we should expect to be able to model major shifts in future electricity load. We have also revisited the gap analysis to accurately reflect what in the end is covered in our detailed and gap sector models, as well as what energy use remains unmodeled by dsgrid.

The analysis uses subsectoral data available in 2009 RECS, 2012 CBECS, 2014 MECS and the 2012 historical data available in the AEO 2015 (EIA 2013d, 2016a, 2017a, 2015a).[45] We surveyed the sector modeling teams to determine which subsectors are fully described, which are included in our sectoral gap models, and which are not included in either of these categories. The proportion of U.S. electricity use and total site energy use modeled in detail, coarsely, or not at all was then estimated by tagging subsectors in the national-level data sets. Details about the model coverage analysis methods and results are available in Appendix E.

For the baseline dsgrid snapshot described here, perhaps the most important metrics are those associated with 2012 electricity use. As shown in Figure 11, dsgrid models about 80% of current U.S. electricity use at full subsector and end-use resolution. Looking across all electricity use, one can see the largest gaps are in commercial and residential buildings. Industrial energy use that is not covered by IGATE-E includes mining, construction, and agriculture. Transportation electricity use is currently very small and consists mostly of passenger rail, which is not modeled in detail by dsgrid but is assigned an hourly timeseries of electricity use by state. The actual sectoral gaps are listed in detail above, in Table 3, Table 6, Table 9, and Table 11, and in the surrounding text.

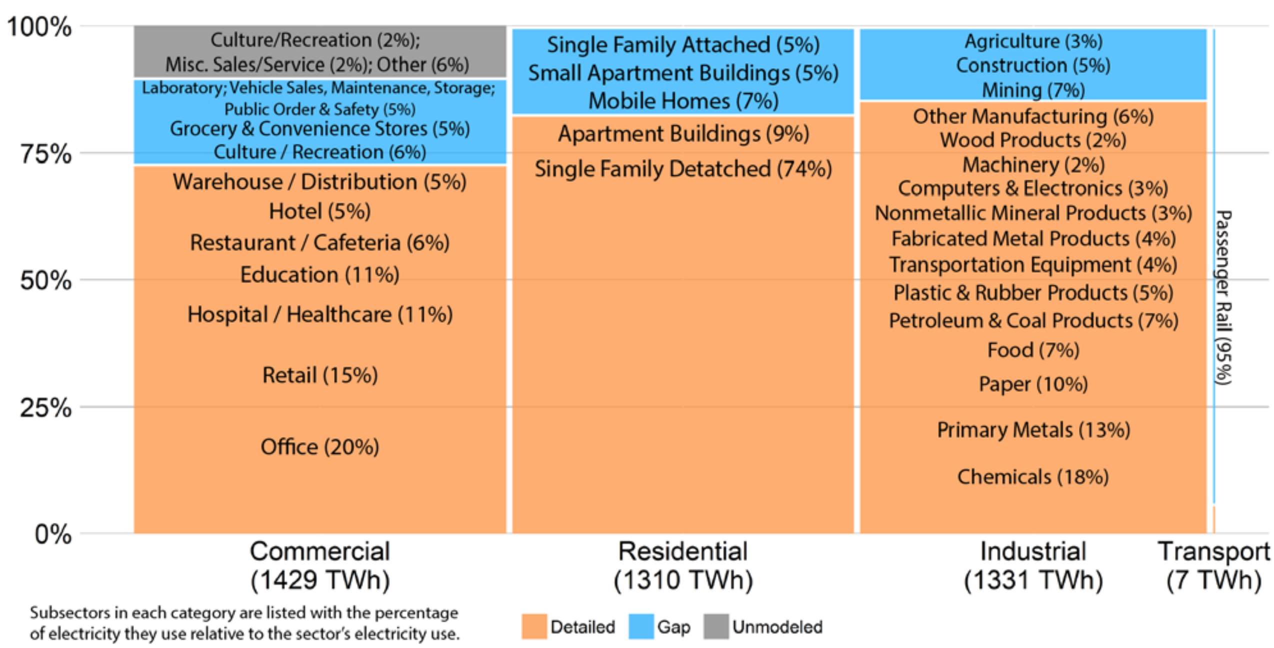

Figure 11. dsgrid models about 80% of 2012 U.S. electricity use in detail.

[45] It is generally the case that coverage in our sector models is mostly determined by sub-sector rather than by geography or end use.

Looking forward to questions of end-use electrification and operational flexibility—and recognizing that our sector models model all energy use, not just electricity—we extend our analysis of model coverage to compare total energy use by each fully modeled subsector against the total energy use of the sector. This comparison is done on a site energy basis, based on dsgrid's focus on loads as they are experienced from the utility customer perspective. The results of that breakdown are shown in Figure 12.

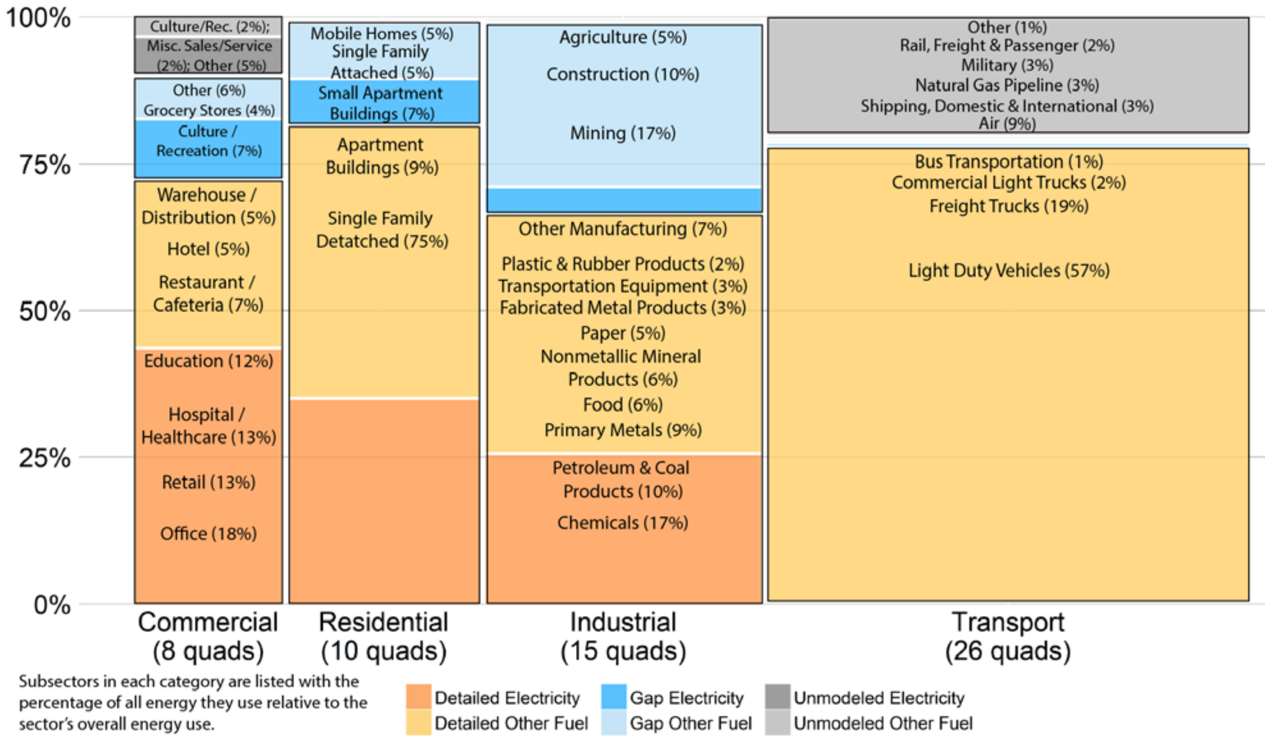

Figure 12. dsgrid models about 76% of 2012 U.S. site energy use in detail.

When examining site energy use, the large roles of transportation and industry in our energy economy quickly become clear, as does the large potential for electrification. With a coverage by this metric of 76%, dsgrid appears to be well-positioned to tackle questions about what potential roles end-use electrification could play in our energy future. While electricity made up only 23% of site energy use in 2012, 76% of the non-electric remainder was used for nominally electrifiable end uses, including electrifiable transport (comprising 46% of non-electric energy consumption) and space and water heating (17%) (Appendix E).

The significant gaps in coverage from a site energy perspective are approximately the same as those from the electricity-only perspective for commercial and residential buildings, as well as industry. For transport, fuel use other than electricity opens additional subsectors, such that the most significant gap in our transportation modeling when all fuels are considered is no longer rail, as it was when we just looked at electricity. Considering all fuels, the biggest transportation subsectors we do not model in detail are air, shipping and freight, natural gas pipelines, and military transport.

The electricity and energy coverages provided by the core sector models, plus a description of their geographic, temporal, and sectoral extents and resolution, are summarized in Table 12. Each sector model was further developed for this project, compared to where they were at the start in order to support the needs of power system modelers in general, and the EFS specifically. Of the four sectors, residential and transportation started at fairly mature levels of model development. The residential team thus focused on validating the ResStock hourly profiles by end use, and geographically downscaling the results to counties by leveraging the ACS and other geographic information system data layers. The transportation team focused on developing supplemental models of rail electricity use, and electrification of medium- and heavy-duty vehicles, the latter in anticipation of later stages of the EFS. Before this project, IGATE-E had been used to estimate demand response and CHP potential for the industrial manufacturing sector. Work for the EFS included further validation of annual energy use estimates, and improved methods for constructing hourly timeseries of electricity load. ComStock did not exist before this work, but it was possible to build the model up in a timely manner by leveraging the DOE prototype buildings and the methodology pioneered by the ResStock team.

Table 12. Geographic, Temporal, and Sectoral Extents, Resolutions, and Biggest Gaps for dsgrid's Constituent Models

		Buildings		Industry	Transport	
		ResStock	**ComStock**	**IGATE-E**	**SERA**	**EVI-PRO**
Geographic	**Extent**	Contiguous United States	Contiguous United States	United States	Contiguous United States	Contiguous United States
	Resolution	County	County	ZIP Code	0.5-km grid	County (flexible)
Temporal	**Extent**	Annual	Annual	Annual	Decadal	Daily
	Resolution	Subhourly	Subhourly	Hourly	Annual	Subhourly
Sectoral	**Extent**	Single-family detached	Sixteen DOE commercial prototype buildings	Manufacturing	Passenger and commercial vehicle stocks	PEVs
	Resolution	6,000 conditional probability distributions adjust 80 model inputs.	3,400 conditional probability distributions adjust nine model inputs.	86 four-digit NAICS codes	Flexible based on inputs	Residential, workplace, and public recharging
	Subsectoral Gaps	Single family attached, 2–4 unit apartments, mobile homes	Grocery store, recreation, religious worship, entertainment/culture, laboratory, convenience store, vehicle service/repair; Other building types are not modeled.	Agriculture and forestry, mining and other extractive industries, construction	Electricity for transport by rail; other fuel used for air, natural gas pipelines, military transport, shipping, rail is not modeled.	
End-Use	**Resolution**	Fans, pumps, heating, cooling, interior lights, exterior lights, water systems, interior equipment	Fans, pumps, heating, cooling, interior lights, exterior lights, water systems, interior equipment, district heating, district cooling, heat rejection	Boilers, process heating, process cooling, machine drives, electrochemical processes, facility HVAC, facility lighting, facility other, non-process uses		EV charging
2012 Electricity Coverage		1,310 TWh 83% detailed model, 17% gap model	1,429 TWh 73% detailed model, 16% gap model, 10% unmodeled	1,331 TWh 86% detailed model, 14% gap model	7 TWh 5% detailed model, 95% gap model	
2012 Site Energy Coverage		10 Quads 83% detailed model, 17% gap model	8 Quads 74% detailed model, 17% gap model, 9% unmodeled	15 Quads 67% detailed model, 33% gap model	26 Quads 79.4% detailed model, 0.1% gap model, 20.5% unmodeled	

2.3 Gap and Derived Models

To develop a complete picture of U.S. electricity use, dsgrid includes gap models for subsectors that are nominally classified as commercial but are unrelated to commercial buildings, and distributed generation models. Derived components describing power system losses and model residuals are constructed by leveraging top-down data sources that describe load from the electricity sector point-of-view and by comparing them to the other components of dsgrid.

2.3.1 Non-Sectoral Gap Models

Several types of energy use fall outside easy categorization. There are municipal uses of energy, such as water distribution and treatment, wastewater treatment, and outdoor lighting. There are also commercial enterprises such as amusement parks and ski resorts that in a sense could be categorized as "commercial buildings" but defy traditional building energy modeling. The EIA, at least on Form 861, designates all these subsectors as commercial (EIA 2013c). Here we limit our attention to the three municipal subsectors mentioned above: water supply, wastewater treatment, and outdoor lighting.

2.3.1.1 Municipal Water Services

Municipalities and other water utilities provide two main services: public water supply and wastewater treatment. Public water supply involves providing, treating, and distributing water to buildings and other locations such as parks and campgrounds. Energy is required to move the water, typically through pipelines, and to treat it to bring its quality up to drinking water level. After use, some water is in turn collected by wastewater utilities, which treat it to make it suitable for returning to the environment. This is also an energy-intensive process.

Pabi et al. (2013) provide a detailed description of the public water supply and wastewater treatment processes used in the United States and develop a national-level estimate of electricity used for those purposes in 2011; they find that these processes were responsible for about 1.8% of all U.S. electricity use. Our gap model uses the Pabi et al. (2013) numbers, first broken down on a per capita basis and then built back up for our geographic scope in 2012.[46]

For public water supply, the decomposition was accomplished by computing an average energy intensity in kilowatt-hours per million gallons supplied (kWh/MG) as shown in Table 13, and combining this with the estimate that each public water system user uses 171 gallons per day[47] (Pabi et al. 2013). Because the total U.S. population in 2011 was about 313 million,[48] the per capita use of public water is about 166 gallons per day and thus the annual energy use for public water supply is estimated to be 125 kWh per year per person for most locations in the CONUS. For eight counties in Southern California, we apply an additional 7,610 kWh/MG of pumping energy (Navigant Consulting, Inc. 2006), bringing the annual energy use for those counties up to 586 kWh per year per person. The counties this estimate applies to are Ventura, Los Angeles,

[46] The estimates in Pabi et al. (2013) are for the entire U.S. The scope of this report is the continental U.S. (excludes territories, Alaska, and Hawaii).
[47] This number was originally derived from USGS data on public water withdrawals and EPA data on population served by public water systems, both reporting for the year 2005.
[48] This is the number cited in Pabi et al. (2013). Updated estimates are higher—315.3 million for the states and Puerto Rico in 2011. We use the number cited in the source paper since it is likely more in line with the information that was used to estimate the population served data in Table 14.

Orange, Riverside, San Diego, San Bernardino, Imperial, and Inyo, which were selected based on an examination of the description of California's hydrologic regions found in California Department of Water Resources (2009).

Table 13. Public Water Supply Energy Intensity and Population Served

Source	Energy Intensity (kWh/MG)	Population Served
Surface	1,600	205,181,000
Groundwater	2,100	89,225,000
Desalination	12,000	9,416,000
	Population-weighted average: 2,069	**Total: 303,822,000**

Summary of data from Pabi et al. (2013)

The estimate of annual electricity used per capita for wastewater is computed similarly, except that the unit of service in this case is millions of gallons of water treated per day, rather than population served. Average energy intensity is computed as in Table 14, from which we also find that 35,845 MG were treated in 2011. After combining that estimate of amount of water treated per day with the U.S. population in 2011, we estimate that 114 gallons of water are treated per capita per day, which translates to an average energy use of 96 kWh per year per person.

Table 14. Municipal Wastewater Treatment Energy Intensity and Quantity Treated

Treatment Type	Energy Intensity (kWh/MG)	Water Treated (MG/day)
Less than secondary	750	422
Secondary	2,080	13,142
Greater than secondary	2,690	16,776
No discharge	2,960	1,815
Pumping reuse water	1,280	3,500
Partial	830	190
	Population-weighted average: 2,310	**Total: 35,845**

Summary of data from Pabi et al. (2013)

To create hourly profiles by county, we multiply the energy per person per year by the U.S. Census Bureau population-by-county estimates for 2012 (Ruggles et al. 2017); we then use daily residential water use profiles from AWWARF (1999) (Figure 13a) as a proxy for when energy is needed for conveyance and treatment. We assume that the energy needed for the public water supply roughly follows the "total" profile and that the energy needed for wastewater treatment roughly follows the "indoor" profile, because all the water being used must be supplied, but water used outdoors does not generally flow back to the wastewater treatment plant. To create the daily profiles actually used in dsgrid (Figure 13b), we additionally layer on information pulled from wastewater treatment load profiles reported by Thompson et al. (2008). In Figure 1 in that report, we first see that even though the water use profiles in AWWARF (1999) are for residences only and the wastewater treatment plant presumably serves establishments other than households, the residential water use pattern of one peak in the morning and another in the evening are still apparent in the load profiles for an entire wastewater treatment plant. This does not cause us to make any adjustments to the profiles, but it does give us some confidence that the residential water use shapes are a reasonable, if far from ideal, starting point. Second, we notice that the wastewater treatment plant has a large baseload; that is, its load is typically between 1,500 kW and 2,200 kW. By pulling the minimum and maximum load for each day shown, we further estimate an average ratio of daily minimum to daily maximum load of 0.75, and we impose this on our public water supply and the wastewater treatment load shapes in going from Figure 13a to Figure 13b. Finally, based on comparing the timing of the two peaks in Figure 13a, to the timing of the two peaks in the Thompson et al. (2008) Figure 1 curves, we also impose a time shift of two hours on the wastewater treatment load curve. That is, we assume it takes two hours from when water is used for the wastewater treatment plant to see that water use as an increase in its electricity usage.

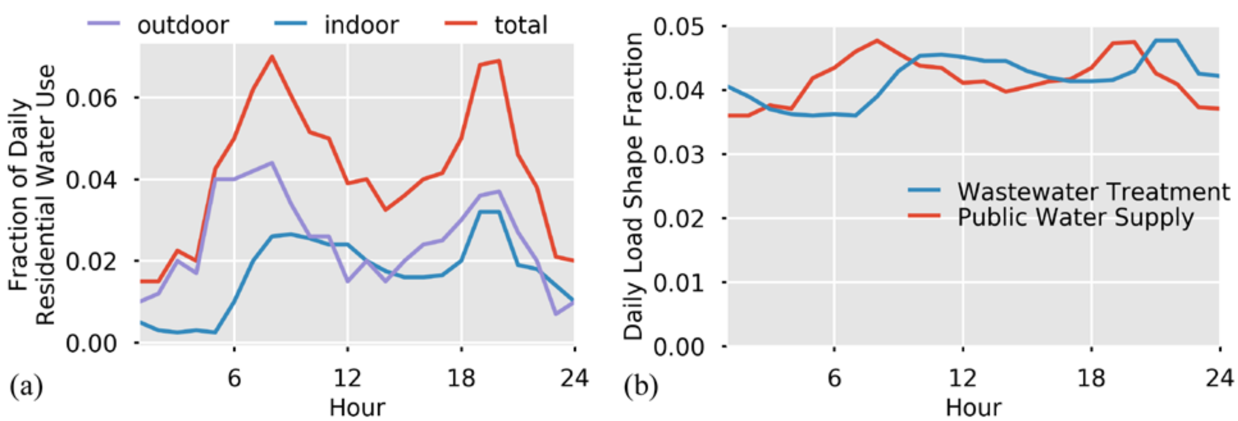

Figure 13. Diurnal profiles for (a) residential water use (AWWARF 1999) and (b) dsgrid municipal water services gap model

2.3.1.2 Outdoor Lighting

Buccitelli et al. (2017) provide national-level estimates of all lighting energy use in the United States, first broken down into the gross categories of residential, commercial, industrial, and outdoor, and then providing significant granularity for types of fixtures and bulb technologies used per subsector and room-type (residential), per sub-subsector (commercial and industrial) and per application type (outdoor). Because the dsgrid sectoral models already estimate their own lighting use, the interest here is in the estimates for outdoor lighting energy use. Buccitelli et al. (2017) provide descriptions and energy use estimates for nine outdoor lighting applications: airfields, billboards, commercial and industrial building exteriors, communication towers, parking, railways, roadways, sports fields, and traffic signals. The total energy use Buccitelli et al. (2017) attribute to these outdoor lighting applications in 2015 is 202 TWh; they estimate that only three contribute more than 1 TWh to the total, namely parking (103 TWh), roadways (63 TWh), and commercial and industrial exterior lighting (33 TWh). Commercial and industrial exterior lighting is represented in ComStock and IGATE-E. Our outdoor lighting gap model represents the parking and roadway lighting components based on these and additional data in Buccitelli et al. (2017) combined with per-capita normalization and solar data that indicate when these types of outdoor lights would be expected to turn on and off.

In addition to presenting 2015 estimates, Buccitelli et al. (2017) update earlier (Ashe et al. 2012) estimates of 2010 lighting energy use based on revised methodology. We therefore normalize these estimates for 2010 and 2015 by the national population in those years and then interpolate to obtain 2012 per-capita estimates of electricity use for outdoor lighting for parking and roadways (Table 15). Ultimately, electricity consumed for these applications is specified by county using the same population by county estimates used in the municipal water services gap model (Ruggles et al. 2017).

Table 15. Estimates of Absolute and Per-Capita Energy Used for Outdoor Lighting

Energy Estimate Year	Units[a]	Parking	Roadway
2010	TWh/yr	113	66
	kWh/person-year	365	213
2015	TWh/yr	103	63
	kWh/person-year	321	196
2012	kWh/person-year	349	207

[a] Values in TWh/yr are from Buccitelli et al. (2017). Those estimates are normalized to kWh/person-year with U.S. population estimates of 309,348,193 for 2010, and 320,896,618 for 2015. We interpolate by year and scale by the fact that 2012 is a leap year to obtain the normalized value for 2012.

Hourly load shapes are determined by inverting county-level, per-unit solar radiation profiles constructed from NSRDB data initially accessed for the distributed PV model (Section 2.3.3). To smooth out the hourly profiles, and recognizing that the on and off times of outdoor lighting are not fully synchronous, we first compute a moving-window average of solar radiation for each hour in the day (using standard time convention throughout the year), and we then invert the profile using the function:

$$f = \begin{cases} 0 & x > t \\ \frac{1}{2}\left(\cos\left(\frac{\pi}{t} \cdot x\right) + 1\right) & 0 \leq x \leq t \end{cases}$$

where f is the outdoor lighting fraction, x is the solar radiation fraction, and t is a threshold value representing that a certain fraction of solar radiation (compared to the annual maximum) implies that all outdoor lighting (at least for parking lots and roadways) should be off. For this version of dsgrid, profiles are generated using a moving window average that for every data point takes the mean of the solar radiation for that day and time along with the solar radiation at the same hour of the day for the previous 30 days and the coming 30 days; and we take the threshold on fractional solar radiation to be 0.05 in the above equation. The resulting transformation is illustrated in Figure 14.

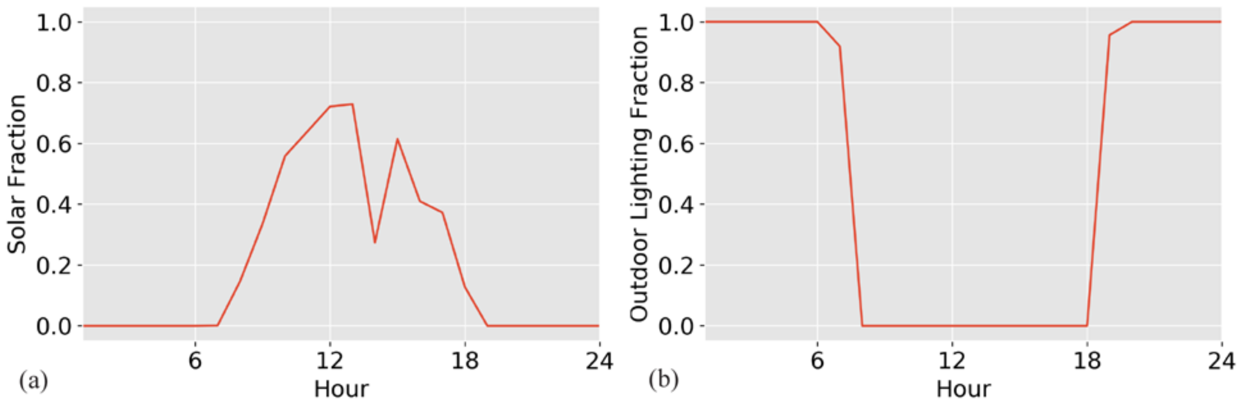

Figure 14. Sample single-day (a) solar radiation profile and (b) the outdoor lighting profile that results for the same day from applying the transformation described above

The sample is Washington, D.C. on March 15, 2012.

2.3.2 Distributed Generation Models

Because dsgrid is primarily a bottom-up model of site energy use, distributed generation estimates must be layered on to estimate the net load that is ultimately served by load-serving entities/distribution utilities. In the CONUS in 2012, approximately 78,319 MW of CHP and other fuel-based distributed generation capacity and 1,475 MW of DPV generation were operating and serving a variety of residential, commercial, and industrial loads. Together, these two technologies comprise our distributed generation model.

2.3.2.1 Combined Heat and Power

The DOE Combined Heat and Power (CHP) Installation Database provides information on CHP plants that are large and small (1 kW to 1,633,000 kW); are of different types (e.g., steam turbine, fuel cell, reciprocating engine fueled by coal, oil, natural gas, wood, and waste heat); provide different services (e.g., for manufacturing, universities, hospitals, agriculture, and utilities); and operate all over the United States. However, though this data source provides capacity and location information in addition to the characteristics already described, it does not provide any indication of typical operation schedules or annual generation quantities (ICF Inc. and DOE 2016).

In contrast, using both EIA Form 860 and EIA Form 923, it is possible to obtain estimates of capacity, generation, and direct use (portion of generated electricity used behind the meter) by plant, but only for those that provide reports (generally plants 1 MW and larger). That is, these EIA data do not comprehensively account for all CHP plants, but for those that are represented, a good deal of operational data is provided (EIA 2013a, 2018).

Hourly profiles of plant operation are even harder to come by. Operational profiles by operating unit are available from the U.S. Environmental Protection Agency (EPA) for a subset of the plants that report on EIA Form 860. These data comes from continuous emission monitoring systems (CEMS) (U.S. EPA 2016; EPA 2013), which are generally required for thermal plants with nameplate capacity greater than 25 MW (EPA 2009). To assemble an hourly model of how CHP and other behind-the-meter thermal generation operated in 2012, all these data sources were brought together to estimate capacity, capacity factor (annual generation expressed as a fraction of nameplate capacity running for an entire year), and behind-the-meter fraction for all relevant, known plants by sector and by state. Hourly profiles were assigned based on selecting a profile from the CEMS data, adjusting it to match the capacity factor, and then shifting it to fit the modeled plant's time zone.

As explained in detail in Appendix I, our CHP model accepts the DOE CHP Installation Database as the ground-truth regarding CHP capacity, adds to it some behind-the-meter thermal (but not CHP) capacity from the EIA data sources, and then proceeds to fill in operational details via a matching process that accounts for such characteristics as sector, NAICS code, plant prime mover, plant size, and plant location. A similar (but necessarily abbreviated) matching process is applied to select a starting-point CEMS profile, which is then adjusted to match the required capacity factor. The profile is scaled by the behind-the-meter fraction identified from the EIA data. In the end, these profiles are aggregated up to the sector level by state, differentiated by CHP and not-CHP. A capacity and generation summary for select states and all of the CONUS is provided in Table 16. The starting-point CEMS profiles are shown for select weeks in Figure 15.

Table 16. Combined Heat and Power and Distributed Thermal Model: Capacity and Behind-the-Meter Generation Summary

	Capacity (GW)				Behind-the-Meter Generation (TWh)			
State	**Ind.**	**Com.**	**Res.**	**Total**	**Ind.**	**Com.**	**Res.**	**Total**
TX	17.3	0.4	0.000	17.6	38.1	1.5	0.000	39.6
CA	6.8	1.9	0.002	8.7	23.3	5.3	0.005	28.6
LA	7.2	0.0	—	7.2	15.5	0.2	—	15.7
NY	3.4	2.1	0.106	5.6	14.6	6.4	0.316	21.3
MI	3.0	0.3	—	3.3	6.6	0.6	—	7.2
AL	3.2	0.0	—	3.2	8.9	0.0	—	8.9
FL	2.8	0.4	—	3.2	9.5	1.5	—	11.1
NJ	2.8	0.3	0.006	3.2	12.3	1.1	0.019	13.4
PA	2.3	0.5	0.005	2.8	6.3	1.5	0.014	7.8
IN	2.4	0.1	—	2.5	4.1	0.3	—	4.3
All others	20.1	4.0	0.007	24.1	62.7	10.5	0.020	73.2
Total	**71.2**	**10.2**	**0.125**	**81.5**	**201.8**	**29.0**	**0.375**	**231.2**

Res. = residential, Com. = commercial, and Ind. = industrial

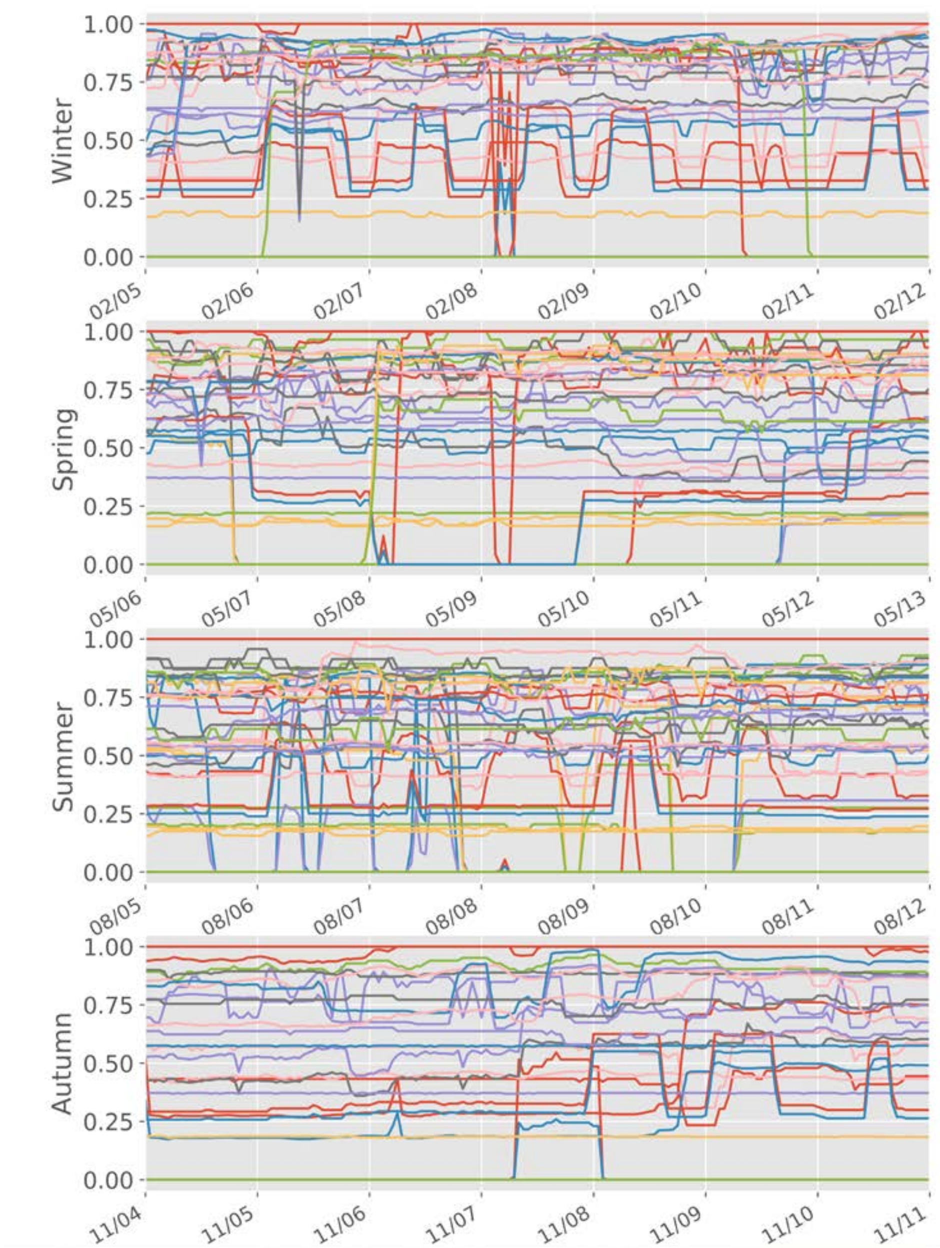

Figure 15. CEMS CHP plant capacity factor profiles

2.3.2.2 Distributed Photovoltaics (DPV)

County-level distributed PV capacity was determined by using the dGen model (Sigrin et al. 2016) to geographically disaggregate and then segment by panel tilt and orientation, state-level historical estimates of distributed PV capacity compiled by GTM Research and the Solar Energy Industries Association (Perea et al. 2017). The county-level capacity totals were then allocated proportionally by population density across NSRDB geographic grid cells (Wilcox 2012), and the System Advisor Model (NREL 2014) was used to generate profiles based on solar panel tilt and orientation, along with the solar radiation timeseries available for each NSRDB site. Table 17 summarizes the capacity and annual generation captured by this model of 2012 DPV in the CONUS.

Table 17. Distributed Photovoltaics Capacity and Generation Summary

State	Capacity (MW)				Generation (GWh)			
	Res.	Com.	Ind.	Total	Res.	Com.	Ind.	Total
CA	875	425	425	1,724	1,347	663	664	2,674
NJ	153	334	334	821	190	421	421	1,032
AZ	173	79	79	331	289	133	132	553
MA	34	75	75	184	41	92	92	225
PA	41	67	67	175	49	83	82	214
CO	78	45	45	169	120	68	69	257
NY	62	33	33	127	78	40	39	157
MD	31	26	26	84	40	35	34	109
All others	178	203	203	585	232	276	281	789
Total	**1,624**	**1,287**	**1,287**	**4,199**	**2,386**	**1,810**	**1,814**	**6,010**

2.3.3 Electricity Sector Load Data

To calibrate and validate the 2012 dsgrid data set, we leverage two categories of load data that cover the entire electricity sector from the supply side: historical hourly load data such as those available from the FERC Form 714 reports (FERC 2016) and the utility data reported on EIA Form 861 (EIA 2013a). The data used are summarized in Table 18.

Table 18. Top-Down Data on U.S. Power System Demand Used in dsgrid to Define System Losses and Model Residuals

Source	Fields	Temporal Resolution	Geographic Extent	Geographic Resolution
FERC 714 and ISO Reporting[a]	Planning area electricity demand	Hourly	CONUS	FERC Planning Region/ISO Subregion
EIA Form 861[b] Retail Sales	Retail sales by sector	Annual	U.S.	Utility-state intersection
EIA Form 861[b] Operational Data	Energy furnished or consumed without charge, energy losses	Annual	U.S.	Utility-state intersection

[a] FERC (2016); SPP (2016); pjm (2016); MISO (2016); ISO New England (2016); NYISO (2016)

[b] EIA (2013a)

Hourly load data for 2012 were derived from FERC Form 714 and from the ISOs cited in Table 18. For consistency, the source data were converted to hour-ending (if not already reported as such) and shifted to EST where necessary. To determine the load at the state level, the source data were first disaggregated to the transmission nodes represented in the Multiregional Modeling Working Group 2015–2026 Summer Peak load flow case in the Eastern Interconnection[49] and the Western Electricity Coordinating Council (WECC) Transmission Expansion Planning Policy Committee 2024 Common Case in the Western Interconnection (Brinkman et al. 2016). Next, the load was aggregated to the state level based on the location of each node derived above. Load for Texas was determined by aggregating all the nodes mentioned above that are located in Texas along with the historical hourly load provided by the Electric Reliability Council of Texas (ERCOT 2017).

Data from two EIA Form 861 tables are used. The total amount of electricity provided by load-serving entities in 2012 is estimated by taking the retail sales by sector (residential, commercial, industrial, and transportation) from the Retail Sales table, and adding to it the energy listed in the Operational Data table as "furnished without charge" or "consumed by respondent without charge." Per EIA (2013b), the residential sector is defined as any customers whose energy is primarily consumed for residential end uses (i.e., "space heating, water heating, air conditioning, lighting, refrigeration, cooking, and clothes drying"); "manufacturing, construction, mining, agriculture (irrigation), fishing, and forestry establishments" are considered to comprise the industrial sector; and transportation is described as "railroads and railways." Everything else is defined as falling in the commercial sector, which therefore includes commercial buildings but also "public street and highway lighting, municipalities, divisions or agencies of State and Federal Governments under special contracts or agreements, and other utility departments, as defined by the pertinent regulatory agency and/or electric utility." Because of this latter description, the energy listed as "furnished without charge" or "consumed by respondent without charge" is ultimately added to the commercial retail sales. As shown in Table 19, more than half this energy is furnished by just six of the 2,190 reporting utilities, and at least 8.8 TWh appears to be associated with California water projects.

Table 19. Largest Providers of Energy Furnished or Consumed without Charge in 2012 as Reported on EIA Form 861

Furnished without Charge				Consumed by Respondent without Charge			
Utility Name	**State**	**Quantity (TWh)**	**Proportion of Total (%)**	**Utility Name**	**State**	**Quantity (TWh)**	**Proportion of Total (%)**
New York State Electric and Gas Corporation	NY	3.7	32%	California Dept. of Water Resources	CA	7.4	42%
Western Area Power Administration	CO	2.9	25%	Metropolitan Water District of Southern California	CA	1.4	8%
PUD No 2 of Grant County	WA	1.5	13%	Bonneville Power Administration	OR	1.2	7%
Remaining 2,187 reporters		3.6	30%	Remaining 2,187 reporters		7.5	43%
	Total	**11.7**	**100%**		**Total**	**17.5**	**100%**

[49] Data provided by Energy Visuals, Inc., http://www.energyvisuals.com/

We also use the EIA Form 861 Operational Data on Total Energy Losses to inform our model of system losses.

All these historical data are used at the state level. Although the EIA Form 861 data are natively provided at a finer resolution (the utility-state intersection level), that level of resolution does not map cleanly to counties. Furthermore, some of the historical hourly load data are provided at a resolution coarser than single states. For these reasons, we find it most straightforward to use these historical data at the state level or coarser and leave it as future work to refine our mappings between political and electrical geography.

2.3.4 Derived Models

The historical electricity sector data are used to construct two derived components of dsgrid. There is an hourly, state-level model of power system losses (T&D), and we compute two sets of residuals: annual by sector by state and all electricity load hourly by state.

2.3.4.1 System Losses

T&D power system losses are the difference between the amount of electricity generated by utilities and independent generators and the amount of electricity consumed by end users as measured by on-site electricity meters. Estimates of these losses are created and included in the dsgrid historical load data set (1) to provide a way to estimate system-level load based on the dsgrid site-level demand data, and (2) to facilitate the calculation of hourly model residuals.

The historical electricity sector data provides two estimates of system losses. There is direct reporting of losses in the EIA Form 861 Operational data. We can also estimate system losses by subtracting the sum of the EIA Form 861 annual energy by sector (sales plus energy furnished or consumed without charge) from the hourly historical load data. The latter estimate falls out because the FERC Form 714 and ISO reporting represents generation plus imports minus exports for each reporting power system, and therefore includes all the system losses; whereas the sales and electricity furnished statistics represent site (i.e., metered) electricity load, which does not include losses.

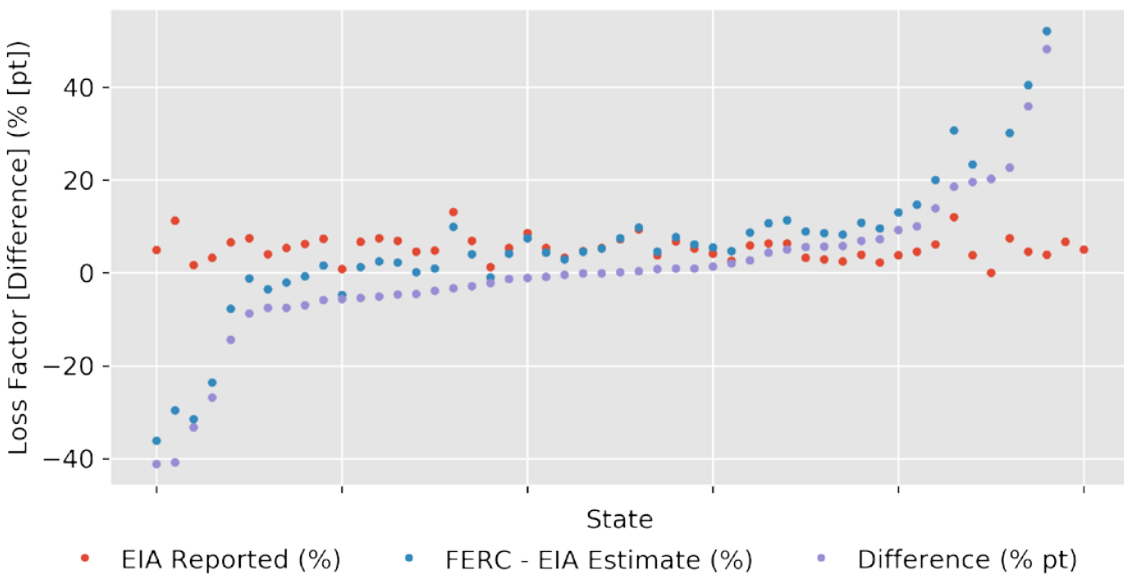

Figure 16. Raw state-level loss factors (a) derived from utility reported losses (EIA Reported) and (b) estimated by comparing historical hourly supply and annual metered load data (FERC-EIA estimate), ordered by (c) their difference (estimate - reported)

To develop our model of system losses, we compare these two loss estimates, both expressed as a loss factor (%) relative to the EIA annual energy reported by state.[50] This exercise reveals large discrepancies for several states, some for which the reported EIA annual energy is greater than the aggregated hourly load data (resulting in negative load factor estimates) and others for which the reported EIA annual energy is much smaller than the aggregated hourly load data (resulting in loss factors greater than 15% or even 20%) (Figure 17). Based on the provenance of the hourly load data, it is not too surprising that the disaggregation to states is inaccurate. Perhaps more surprising are the very low loss estimates we obtain for some states using EIA data alone (e.g., West Virginia and Utah's estimates are less than 1%, see Table J-1 in Appendix J.)

[50] Per Section 2.3.3, this consists of annual sales reported by sector plus electricity furnished or consumed without charge.

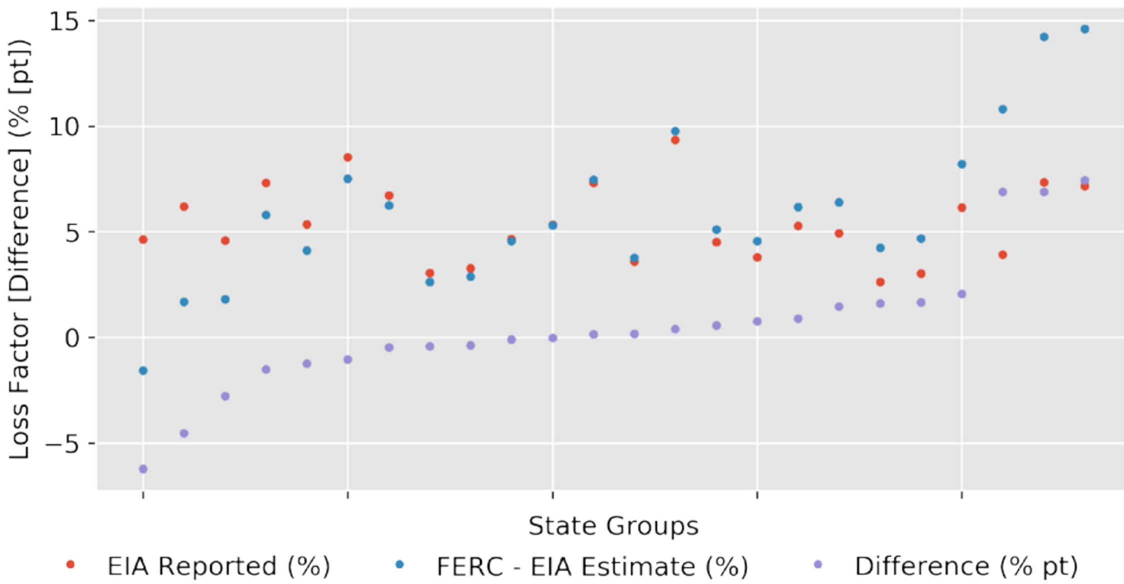

Figure 17. Loss factors for state groupings

The state groupings were developed to mitigate the greatest discrepancies seen in the raw state-level data. The loss factors used in the dsgrid system losses model are the values shown in this figure for EIA Reported.

Given this finding, and our general knowledge of electrical system topology (e.g., the extents of the Eastern, Western, and ERCOT interconnections, and the footprints of ISOs/RTOs[51]), we developed groupings of states that mitigate the worst of these discrepancies. The resulting reported and estimated loss factors are shown in Figure 17 and reported in Table 20.The dsgrid system losses model applies the loss factors estimated using only EIA data (losses, annual sales, and energy furnished or consumed without charge) for the state groupings; that is, each state in a particular group is assigned the corresponding loss factor highlighted in Table 20. These loss factors generally fall into a reasonable range (2.5%–9.5%), and 12 of 24 are within one percentage point of the estimate obtained by comparing historical hourly system load and historical annual metered load data. The discrepancies that remain between the two loss factor estimates point to two areas of future work: the development of better mappings between electrical and political geography, and the development of a better/more resolved understanding of system losses.[52]

[51] RTO = regional transmission organization

[52] Some jurisdictions, e.g., ERCOT (http://www.ercot.com/mktinfo/metering/dlfmethodology, http://www.ercot.com/content/wcm/key_documents_lists/143946/2018_Transmission_Loss_Factors_Final.xlsx) collect detailed information on T&D losses. From these data we see that there are real regional differences in loss factors, and differences depending on line loadings and weather. The dsgrid system losses model relies on national level data sets, which are subject to reporting and geographical mapping error, for expediency. Untangling the reporting and mapping errors from true regional differences, and disaggregating transmission from distribution losses would be appropriate areas of future work.

Table 20. Loss Factors Applied at the State Level to Create the System Losses Derived Model

State Groups	EIA Annual Site Energy (TWh)	EIA Annual Losses (TWh)	Reported Loss Factor (%)	FERC Hourly Load (TWh)	FERC – EIA Loss Estimate (TWh)	Estimated Loss Factor (%)	Estimated - Reported (% pt)
CO, MT, UT, WY	118.1	5.5	4.6	116.2	-1.9	-1.6	-6.2
AL, FL, GA, MS	487.8	30.3	6.2	496.0	8.2	1.7	-4.5
CA, NV	304.3	13.9	4.6	309.7	5.5	1.8	-2.8
ID, OR, WA	166.1	12.2	7.3	175.7	9.6	5.8	-1.5
MI	105.0	5.6	5.4	109.4	4.3	4.1	-1.2
OH	153.0	13.1	8.5	164.5	11.5	7.5	-1.0
KS, NE, SD	83.3	5.6	6.7	88.5	5.2	6.2	-0.5
KY, WV	120.0	3.7	3.0	123.1	3.2	2.6	-0.4
VA	108.0	3.5	3.3	111.1	3.1	2.9	-0.4
LA	84.9	4.0	4.7	88.8	3.9	4.6	-0.1
PA	144.9	7.7	5.3	152.6	7.7	5.3	0.0
NC	128.4	9.4	7.3	138.0	9.6	7.5	0.1
ME, NH, VT	28.1	1.0	3.6	29.1	1.1	3.8	0.2
OK	59.9	5.6	9.4	65.8	5.8	9.8	0.4
DE_NJ	86.7	3.9	4.5	91.1	4.4	5.1	0.6
SC	78.1	3.0	3.8	81.6	3.6	4.6	0.8
TX	366.2	19.4	5.3	388.8	22.6	6.2	0.9
DC, MD	73.2	3.6	4.9	77.9	4.7	6.4	1.5
CT, MA, RI	93.0	2.4	2.6	96.9	3.9	4.2	1.6
IA, IL, IN, WI	364.2	11.0	3.0	381.2	17.0	4.7	1.7
AZ, NM	98.4	6.1	6.2	106.4	8.1	8.2	2.1
NY	147.2	5.8	3.9	163.1	15.9	10.8	6.9
MN, ND	83.0	6.1	7.3	94.8	11.8	14.2	6.9
AR, MO, TN	226.1	16.2	7.2	259.2	33.0	14.6	7.4

Data used in the derived model are highlighted.

Finally, the hourly system losses are estimated based on a rearrangement of the expression

$$\text{System Load}(t) = \text{Metered Electricity} \cdot (1 + \text{Loss Factor}),$$

into

$$\text{Metered Electricity}(t) = \frac{\text{System Load}(t)}{1 + \text{Loss Factor}}.$$

This yields an estimate of hourly losses equal to:

$$\text{Losses}(t) = \text{System Load}(t) - \text{Metered Electricity}(t)$$

$$= \text{System Load}(t) \cdot \frac{\text{Loss Factor}}{(1 + \text{Loss Factor})},$$

which we compute by state using the historical hourly system load and the loss factors highlighted in Table 20.

2.3.4.2 Residuals

The distributed generation models described in Section 2.3.2, the historical electricity-sector data described in Section 2.3.3, and the system losses model just described enable us to calculate model residuals for the initial dsgrid data set for historical year 2012. As depicted in Figure 18, two sets of residuals are calculated—one for each historical electric-sector data set. The left side of Figure 18 shows the process of comparing the sum of the EIA Form 861 annual load data and the distributed generation models to the dsgrid bottom-up models (detailed and gap) to compute annual residuals by state and sector. Similarly, the right side of Figure 18 outlines the process for computing hourly, all-electricity residuals.

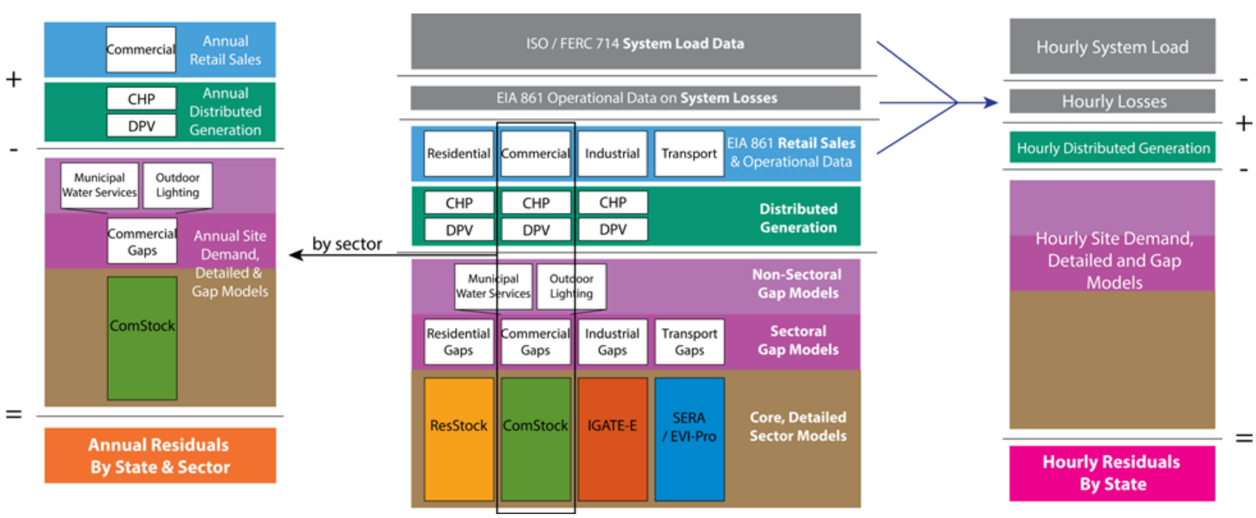

Figure 18. Model residuals are calculated using electricity sector data and distributed generation models.

Mathematically, computing hourly residuals for each state starts with the following relationship for all electricity demand at a given time *t*:

$$\text{System Load}(t) - \text{Losses}(t) = \text{Detailed Load}(t) + \text{Gap Load}(t) - \text{Distributed Generation}(t) + \varepsilon_t,$$

where system load is the total amount of generation plus net imports that must be provided by the system, the losses model is as defined in the above section, the other time varying terms are dsgrid model components, and ε_t accounts for all site-load residuals currently missed by our model. We therefore calculate hourly residuals as:

$$\varepsilon_t = \text{System Load}(t) - \text{Losses}(t) - \text{Detailed Load}(t) - \text{Gap Load}(t) + \text{Distributed Generation}(t).$$

The mathematical expression for the annual sectoral residuals is similar. For those we start from the expression:

$$\text{Annual Retail Sales}(s) = \text{Detailed Load}(s) + \text{Gap Load}(s) - \text{Distributed Generation}(s) + \varepsilon_s,$$

where *s* represents the sector: residential, commercial, industrial, or transportation. The sector residuals are thus:

$$\varepsilon_s = \text{Annual Retail Sales}(s) - \text{Detailed Load}(s) - \text{Gap Load}(s) + \text{Distributed Generation}(s).$$

Both types of residuals are calculated at the state level and analyzed in what follows.

3 Historical Year Model Overview

The data included in this version of dsgrid are summarized in Table 21. All the components described in Figure 18 are included; namely, the historical hourly load derived from ISO and FERC Form 714 reporting is in the first row. Together with the third row, which is EIA Form 861 data on retail sales (plus energy furnished without charge, which has been added to the commercial column), this is the ground truth to which we compare the core dsgrid data. The core dsgrid data consist of the bottom-up sector models plus the gap models, which, when they are summed together, represent an estimate of site electricity use. These data are supplemented with models of distributed generation, and with T&D losses, to enable the calculation of residuals and the creation of modeling-relevant aggregated load profiles.

Table 21. Summary of Contiguous U.S. Electricity Use in Terawatt-Hours, Top-Down and Represented in dsgrid

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load[a]					3,910
Derived	T&D losses					199
Top-down	Annual energy[b]	1,370	1,350	981	7	3,708
dsgrid	Distributed generation	3	31	204	–	237
dsgrid-core	Gap models	218	454	184	6	862
dsgrid-core	Detailed sector models	1,169	1,107	893	–	3,170
Derived	Total site energy[c]	1,372	1,381	1,184	7	3,945
Derived	Annual sector residuals[d]	-15	-180	107	1	-87
Derived	Hourly residuals[e]					-126

[a] FERC Form 714 and independent system operator (ISO) reporting

[b] U.S. Energy Information Administration (EIA) Form 861

[c] Total site energy is the top-down annual energy plus distributed generation. This is all the load we are expecting to model with the bottom-up detailed sector and gap models.

[d] The sector level residuals are equal to the total site energy minus the gap and detailed sector model components.

[e] The hourly residuals reported in the Total column are the sum of the state-level hourly residuals, which factor in top-down hourly load, T&D losses, distributed generation, and the dsgrid-core model components.

dsgrid model components necessary to represent site-energy use at the hourly level are shaded green. Components that may be factored in to estimate bulk power system load are shaded blue-grey.

From this summary, we see that the order of magnitude of electricity use is similar for the residential, commercial, and industrial sectors, at around 1,000 TWh each. Electricity used for transportation in 2012 was about two orders of magnitude less, rounding up to 10 TWh. The relative maturity of the dsgrid sector models is also apparent: at this highest level of aggregation, our residential modeling is within about 1% of site energy use, whereas commercial and industrial estimates are within 15%. Examining the hourly—rather than the sectoral—residuals, when all the hourly residuals are summed up directly, allowing positive and negative errors to cancel out, dsgrid is overall overestimating site electricity use by about 3%.

The calculation of sectoral and hourly residuals depends on our assumptions about distributed generation, for which there is no definitive source of ground truth. However, modeling distributed CHP, other distributed thermal generators, and distributed PV (see Section 2.3.2 and Appendix I) yields estimates of 0.2%, 2%, and 17% of sectoral electricity coming from behind-the-meter generation for the residential, commercial, and industrial sectors respectively.

We gain further insight into the model, including temporally correlated errors, by exploring the hourly timeseries data. For example, the modeled load per sector (detailed sectoral and gap) and T&D losses are plotted alongside the historical hourly load and the historical hourly load plus the modeled distributed generation in Figure 19 (next page) for four weeks, one selected from each season, for all of the contiguous United States. Overall, this shows that dsgrid is capturing seasonal load shapes—winter and autumn days display the double-peak pattern, whereas load in spring and summer demonstrates only one peak per day—but regularly exaggerates the differences between weekday and weekend energy use, as well as between daytime and nighttime energy use, the latter especially during cooling season (e.g., summer and spring).

The differences between dsgrid data and the historical load data are more clearly visible in Figure 20, which is structured similarly to Figure 19, but with the data grouped to explicitly plot the portion of load met by distributed generation and the hourly residuals. When the hourly residuals are positive they represent missing load, we refer to them as "underage," and they are plotted between the modeled load and system loss components. Negative residuals represent overestimates of load; these are referred to as "overage" and are plotted above the historical hourly load plus DG line. In addition to explicitly showing the residuals that are implicit in Figure 19, these plots verify the correctness of our residuals calculations and demonstrate how the component categories of the dsgrid model fit together. Regional versions of Figure 19 and Figure 20 are available in Appendix G.

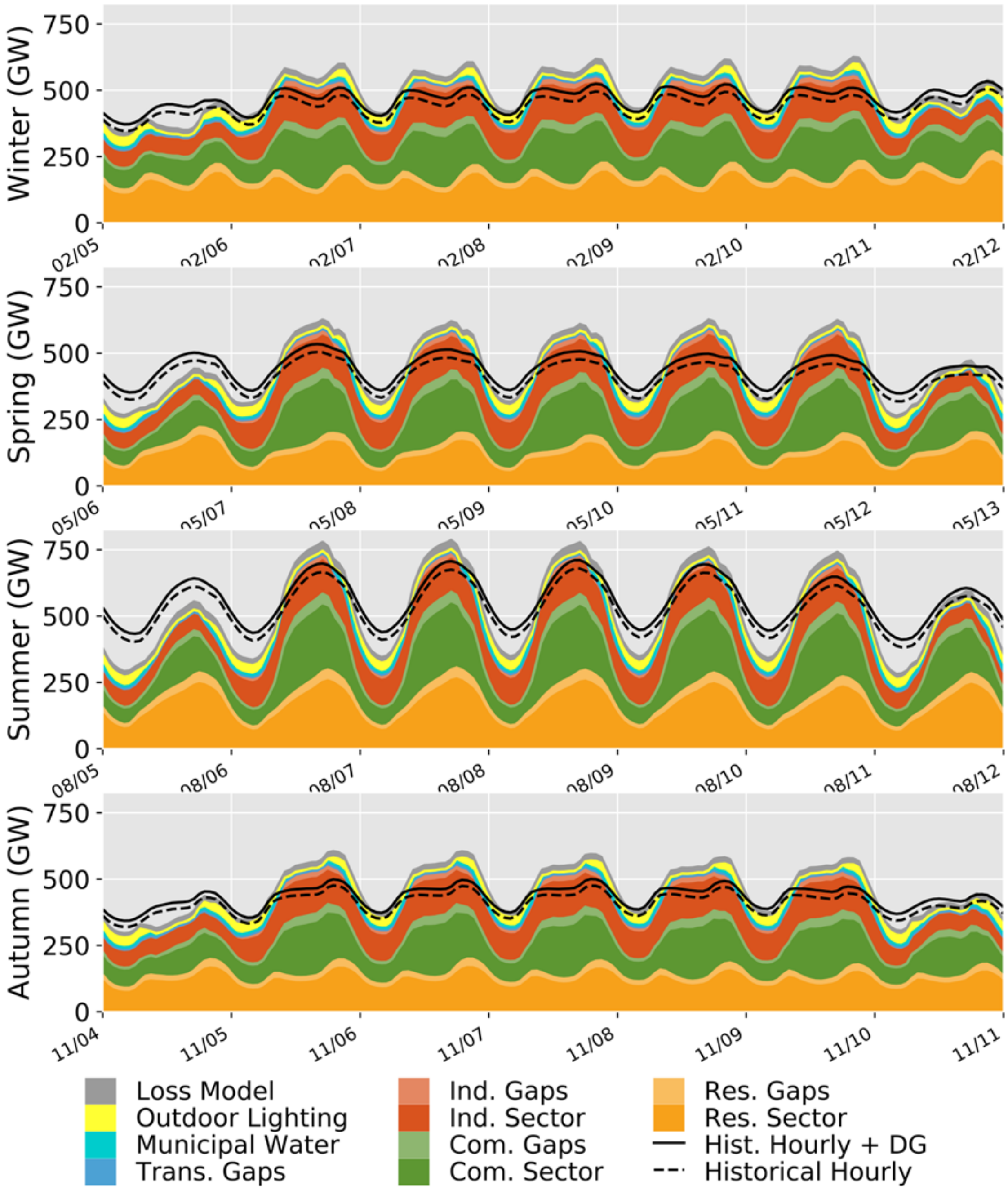

Figure 19. Bottom-up detailed sectoral model and gap model load compared to bulk-level historical hourly load for all of the CONUS in 2012, for four representative weeks

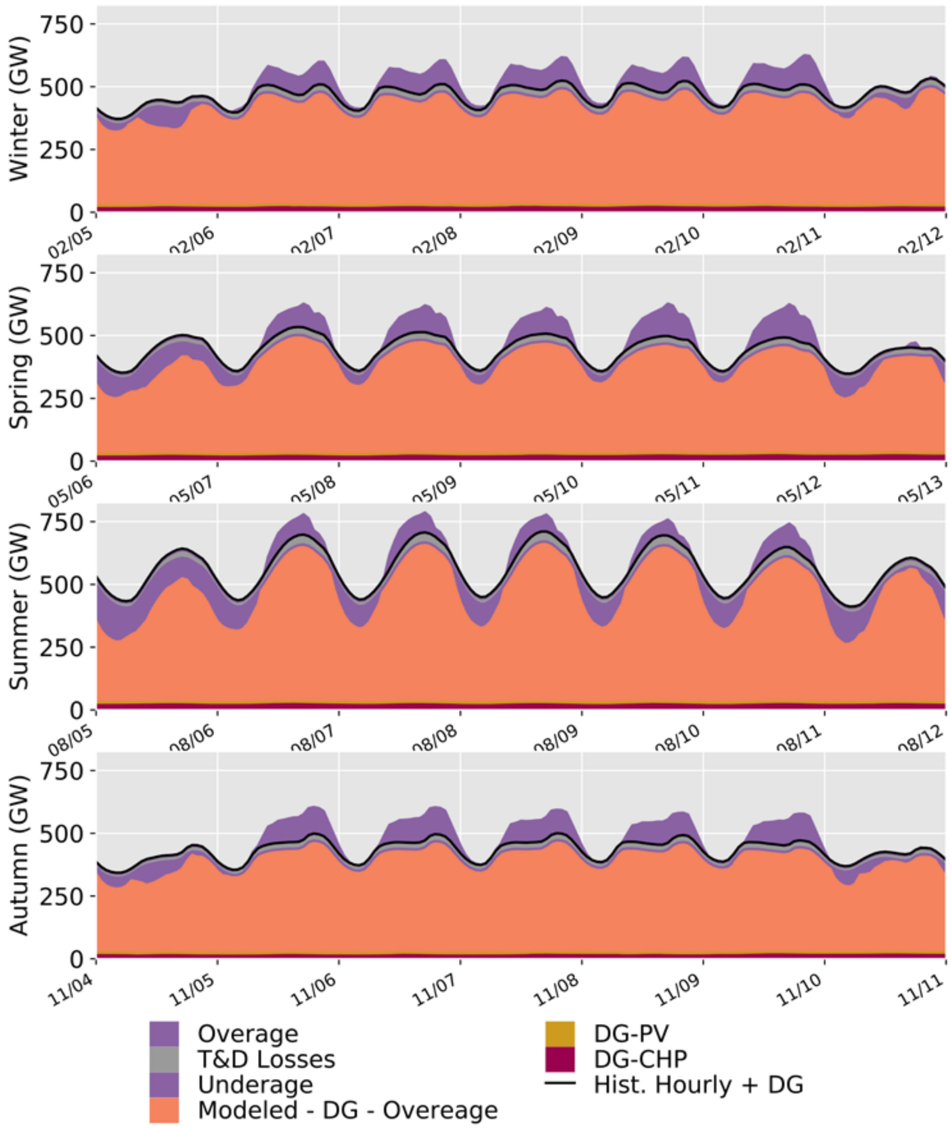

Figure 20. dsgrid hourly residuals plotted along with the bottom-up model data, T&D loss estimates, and historical bulk power load data, for the contiguous United States

To get a clearer understanding of model fit, we analyze the hourly and sectoral residuals computed at different geographic, temporal, and sectoral resolutions. To do this, the dsgrid model is first aggregated to different temporal and geographic resolutions. Temporally, we summarize the size of the all-electricity hourly residuals at the following levels of aggregation, with all aggregations based on EST:

- Hour
- Day
- Week
- Season (based on solar solstices and equinoxes)
- Year.

Geographically, we summarize both types of residuals at these levels of aggregation:

- State (48 in the contiguous United States)
- State groups (24 from the loss model component, Table 20)
- Census division (9 in total, see Appendix G)
- Census region (4 in total, see Appendix G)
- CONUS.

To create summary fit statistics, we rely on relative absolute error metrics, suitably averaged over the relevant dimensions. For the hourly residuals, there is no sectoral dimension and we begin by calculating mean relative absolute error (MRAE) over the temporal dimension, calculating one MRAE for each geographical unit *g*:

$$\mathrm{MRAE}_g = \frac{\sum_t \frac{|\varepsilon_{t,g}|}{E_{t,g}}}{\sum_t 1}, \;\; E_{t,g} = \text{System Load}(t,g) - \text{Losses}(t,g) + \text{Distributed Generation}(t,g)$$

This statistic is then inverted into a measure of fit:

$$(\text{MRAE Fit})_g = 1 - \mathrm{MRAE}_g,$$

and averaged over the geographical units using the annual site energy as the weighting factor:

$$\text{MRAE Fit} = \frac{\sum_g (\text{MRAE Fit})_g \cdot \sum_t E_{t,g}}{\sum_{g,t} E_{t,g}}.$$

For the sectoral residuals, there is no temporal dimension. For the individual sectors, we therefore have a basic relative absolute error (RAE) statistic for each geographical unit *g*:

$$\mathrm{RAE}_{s,g} = \frac{|\varepsilon_{s,g}|}{E_{s,g}}, \quad E_{s,g} = \text{Annual Electricity}(s,g) + \text{Distributed Generation}(s,g).$$

and if we convert to a fit metric and perform an energy-weighted average we get:

$$(\text{RAE Fit})_{s,g} = 1 - \mathrm{RAE}_{s,g},$$

$$(\text{RAE Fit})_s = \frac{\sum_g (\text{RAE Fit})_{s,g} \cdot E_{s,g}}{\sum_g E_{s,g}} = \frac{\sum_g \left(E_{s,g} - |\varepsilon_{s,g}|\right)}{\sum_g E_{s,g}}.$$

To calculate overall fit across all sectors, the final formula is leveraged to compute:

$$(\text{RAE Fit})_{total} = \frac{\sum_g \left(\sum_s E_{s,g} - \left|\sum_s \varepsilon_{s,g}\right|\right)}{\sum_{g,s} E_{s,g}}.$$

The resulting fit statistics are plotted in Figure 21.

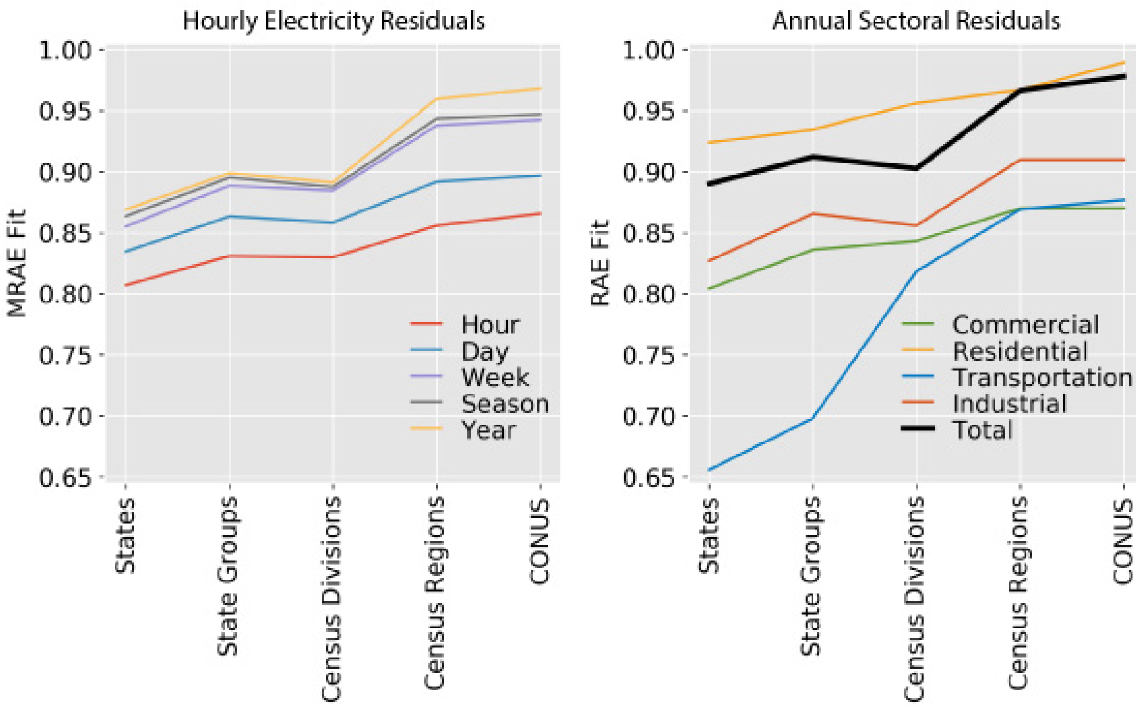

Figure 21. dsgrid fit statistics for total site energy as a function of geographic, temporal, and sectoral resolution

First examining the hourly electricity residuals, we see visual confirmation of what we saw in Table 21, namely that in total (annual values for the contiguous United States), the dsgrid bottom-up models capture the site energy represented in the historical hourly load data combined with the dsgrid distributed generation models to within a relative error of 4%. However, if we examine the model at the most resolved level for which hourly residuals are available (state-level and hourly), the level of fit drops almost to 80%. Where is most of the fit lost? Temporally, the first large gap occurs when we go from weeks to days; this likely speaks to the weekday-weekend discrepancy apparent in Figure 19 and Figure 20. The daytime-to-nighttime shifts similarly show up in the difference between the hour and day curves. The load duration curves[53] in Figure 22, which represent the hourly CONUS data, are another confirmation of these trends. Specifically, consistent with its provenance as a confederation of sectoral energy models historically focused on annual energy use metrics, dsgrid is capturing the total amount of load reasonably well, but it contains significantly more load variability than the historical data.

Geographically, there is a large difference between census divisions and census regions, and a more modest, but significant difference between states and state groups. For these hourly residuals, which rely on a disaggregation of system load data reported by ISO region or FERC Form 714 planning region, a significant portion of the error introduced by disaggregating from the State Group to State level may be attributable to that process (and not to the bottom-up modeling alone).

[53] Load duration curves are constructed by sorting timeseries load data in descending order and plotting the result.

Examining the sectoral residuals, the relative maturity of the residential modeling is immediately apparent, as its level of agreement with the total annual energy use reported by state on EIA Form 861 plus our distributed generation estimates is above 92% at all levels of disaggregation (down to states). The level of fit for all other sectors is below 85% at the state level, but it is greater than 80% for the other two main electricity-consuming sectors: commercial and industrial.

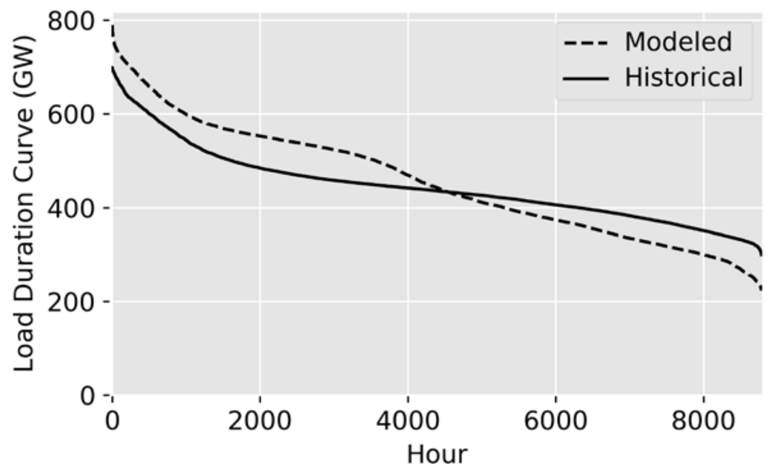

Figure 22. Historical and dsgrid load duration curves for the CONUS in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

The detailed sector models provide information on both subsector and end-use breakdowns down to the county, hourly level. The annual CONUS summary for the residential detailed (i.e., ResStock and midrise apartments from ComStock) and gap models is in Table 22 in absolute terms (GWh). Table 23 reports the relative proportions of electricity by end use per subsector, and of electricity use by subsector for the entire residential sector. The diurnal load shapes for the sector, broken down by end use, and averaged over each season and weekday/weekend combination are shown in Figure 23.

Table 22. Residential Subsectors, Summary of Electricity by End Use for the CONUS in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Interior Lights (GWh)	Space Heating (GWh)	Fans (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	430,941	223,229	138,204	131,556	101,198	95,846	28,036	1,342	—	1,150,352
Mobile Home	36,646	18,185	7,707	7,690	7,229	9,211	1,254	47	—	87,970
Apartment in Building 2 to 4 Units	22,346	8,805	9,275	4,324	9,158	—	11,158	780	279	66,125
Single Family Attached	28,485	11,454	6,075	5,306	5,065	6,326	990	97	—	63,797
Midrise Apartment Building [a]	6,174	2,503	2,720	1,236	2,641	—	3,247	250	87	18,858
Total	**524,593**	**264,176**	**163,980**	**150,113**	**125,290**	**111,383**	**44,685**	**2,516**	**366**	**1,387,102**

[a] The current version of ComStock does not model water heating. See Footnote 54 for more information.

Table 23. Residential Electricity Proportions by Subsector and End Use for the CONUS in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Interior Lights (%)	Space Heating (%)	Fans (%)	Water Systems (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	37.5	19.4	12.0	11.4	8.8	8.3	2.4	0.1	—	82.9
Mobile Home	41.7	20.7	8.8	8.7	8.2	10.5	1.4	0.1	—	6.3
Apartment in Building 2 to 4 Units	33.8	13.3	14.0	6.5	13.8	—	16.9	1.2	0.4	4.8
Single Family Attached	44.6	18.0	9.5	8.3	7.9	9.9	1.6	0.2	—	4.6
Midrise Apartment Building [a]	32.7	13.3	14.4	6.6	14.0	—	17.2	1.3	0.5	1.4
Total	**37.8**	**19.0**	**11.8**	**10.8**	**9.0**	**8.0**	**3.2**	**0.2**	**0.0**	**100.0**

[a] The current version of ComStock does not model water heating. See Footnote 54 for more information.

These results show that on the continental scale, ResStock and ComStock (for midrise apartment buildings) find interior equipment to be the largest group of loads in residences, with a relatively flat profile. The next largest end uses (space cooling, interior lighting, and space heating) show stronger seasonal and diurnal patterns. Fan, exterior lighting and pumping energy is more prominent in multifamily than single-family buildings. As shown in Appendix G, the relative importance of these end uses varies considerably across regions; however, interior equipment is the largest end use across all the census divisions, comprising 33% (West South Central) to 48% (New England) of residential energy use.

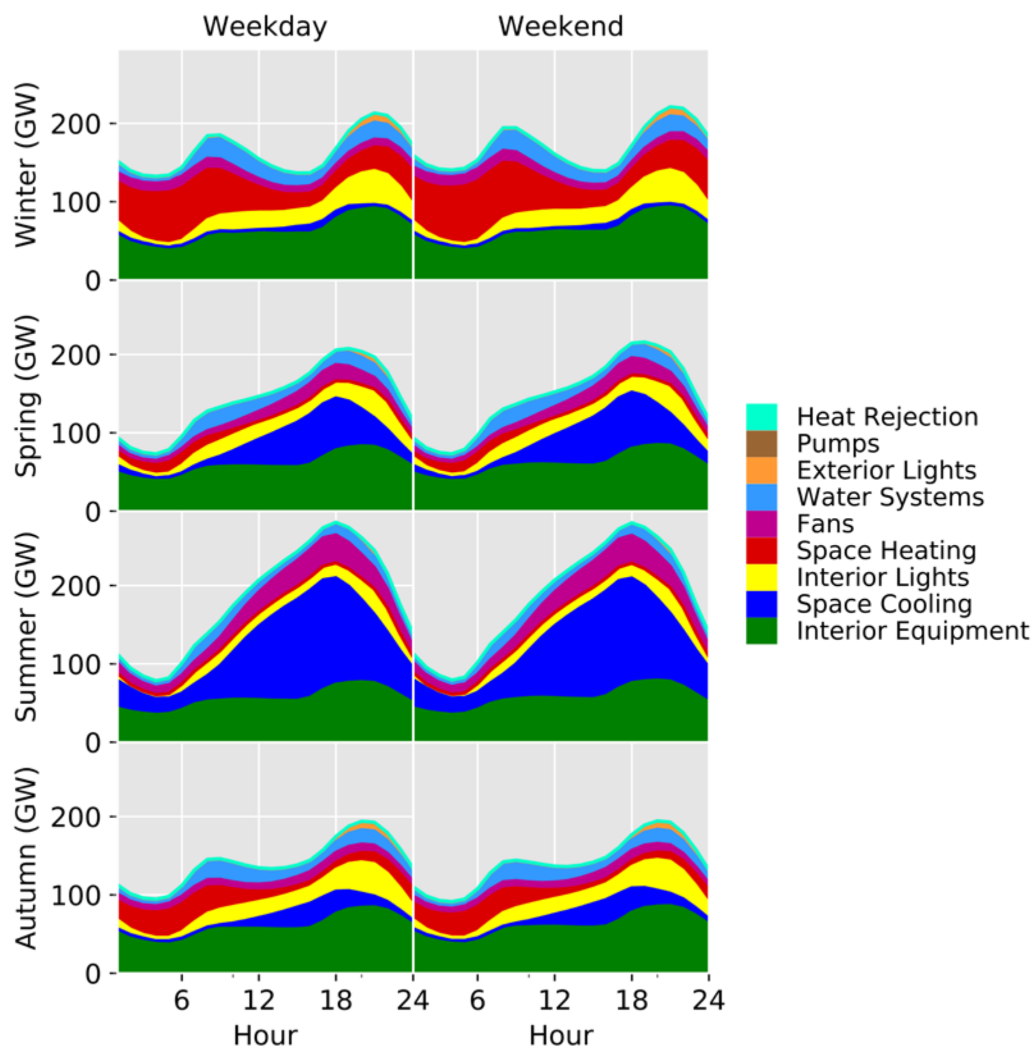

Figure 23. Residential electricity use diurnal patterns by season, modeled for the CONUS in 2012

End-use information is only provided for the commercial building subsectors that are modeled in detail.[54] The annual summaries for the CONUS are provided in Table 24 and Table 25 on an absolute basis and a proportional basis respectively. These data demonstrate considerable differences in the relative importance of end uses depending on the commercial building type that is being modeled. For example, although interior equipment is the largest end use for large offices, the largest subsector in the stock model, it is not the largest end use for the sector as a whole. That distinction instead falls to interior lighting, largely based on its importance in retail buildings, both standalone buildings and strip malls. Also, while significant work is still to be done to calibrate ComStock, especially regarding capturing building types that appear underrepresented in the CoStar data (e.g., schools, government offices, and other public buildings), the stock model does demonstrate the relative importance of office and retail buildings, as compared to building types such as hotels and restaurants, when accounting for U.S. electricity use.

Table 24. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the CONUS in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Large Office	79,566	92,373	61,201	53,542	16,165	1,342	7,537	2,822	314,548
Strip Mall	170,722	24,812	38,248	22,080	34,871	7,583	131	54	298,501
Standalone Retail Store	72,456	22,961	22,286	14,389	11,016	7,126	57	23	150,314
Medium Office	19,490	22,237	14,368	11,388	6,934	741	789	275	76,222
Small Office	15,961	21,861	10,893	8,286	6,235	1,424	80	50	64,791
Warehouse	20,906	8,321	7,058	1,984	10,120	6,280	49	26	54,742
Full Service Restaurant	9,906	22,215	5,592	4,634	2,767	914	56	20	46,105
Large Hotel	9,188	14,671	8,412	7,994	2,309	499	463	164	43,700
Hospital	6,702	8,875	4,455	4,686	513	8	775	359	26,373
Primary School	4,759	3,796	2,241	1,871	612	421	77	37	13,813
Outpatient Treatment Facility	3,726	5,503	1,504	987	1,334	—	170	76	13,299
Small Hotel	1,075	1,508	147	112	716	87	14	5	3,664
Quick Service Restaurant	88	521	174	126	52	4	1	1	966
Total	**414,544**	**249,654**	**176,579**	**132,077**	**93,644**	**26,430**	**10,198**	**3,912**	**1,107,037**

[54] In addition, information on electricity used for water heating is not provided in the current version of ComStock. According to the 2012 CBECS, only 4% of energy used for water heating in commercial buildings comes from electricity, that is, about 6 TWh of the total 148 TWh (507 trillion BTU) for the entire United States. This end use will be modeled in future versions of ComStock.

Table 25. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the CONUS in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Large Office	25.3	29.4	19.5	17.0	5.1	0.4	2.4	0.9	28.4
Strip Mall	57.2	8.3	12.8	7.4	11.7	2.5	0.0	0.0	27.0
Standalone Retail Store	48.2	15.3	14.8	9.6	7.3	4.7	0.0	0.0	13.6
Medium Office	25.6	29.2	18.9	14.9	9.1	1.0	1.0	0.4	6.9
Small Office	24.6	33.7	16.8	12.8	9.6	2.2	0.1	0.1	5.9
Warehouse	38.2	15.2	12.9	3.6	18.5	11.5	0.1	0.0	4.9
Full Service Restaurant	21.5	48.2	12.1	10.1	6.0	2.0	0.1	0.0	4.2
Large Hotel	21.0	33.6	19.2	18.3	5.3	1.1	1.1	0.4	3.9
Hospital	25.4	33.7	16.9	17.8	1.9	0.0	2.9	1.4	2.4
Primary School	34.5	27.5	16.2	13.5	4.4	3.0	0.6	0.3	1.2
Outpatient Treatment Facility	28.0	41.4	11.3	7.4	10.0	—	1.3	0.6	1.2
Small Hotel	29.3	41.2	4.0	3.1	19.5	2.4	0.4	0.2	0.3
Quick Service Restaurant	9.1	53.9	18.0	13.0	5.3	0.4	0.1	0.1	0.1
Total	**37.4**	**22.6**	**16.0**	**11.9**	**8.5**	**2.4**	**0.9**	**0.4**	**100.0**

The seasonal and diurnal patterns of the detailed commercial building models' electricity use are shown in Figure 24. Large commercial buildings are generally more isolated from environmental conditions, and they use less daylight than residential buildings, such that we see a more prominent role for interior lighting and fans, and relatively less heating and cooling as compared to Figure 23. As modeled, some commercial building types also use significant quantities of electricity for exterior lighting. After further model calibration, we may find this result to be an overstatement given the Buccitelli et al. (2017) estimate of 33 TWh for the exterior lighting of commercial and industrial buildings altogether as compared to our estimate of 93 TWh for commercial buildings alone. Based on the overall dsgrid validation results and the end-use shapes shown here, commercial building lighting, space cooling, and interior equipment schedules are strong candidates for additional sectoral calibration, both diurnally and by weekday/weekend.

Industrial manufacturing electricity use, as modeled by IGATE-E, is summarized in Table 26 and Table 27 (following pages). This sector is even more diffuse than the commercial sector. One subsector alone (Iron and Steel Mills and Ferroalloy Manufacturing) accounts for more than 10% of electricity use. Four additional industries (Petroleum and Coal Products Manufacturing; Basic Chemical Manufacturing; Pulp, Paper, and Paperboard Mills; Plastics Product Manufacturing) use more than 5% of sectoral electricity. Together, these five industries comprise about 37% of total electricity use; the remaining 63% is spread out over an additional 81 categories.

The largest electrical end use, according to our model, is machine drive, which accounts for 449 TWh of the total of 893 TWh. However, some manufacturing industries' electricity use is dominated by process heating, for example, Iron and Steel Mills and Ferroalloy Manufacturing, Foundries, and Nonferrous Metal (except Aluminum) Production and Processing. Semiconductor and Other Electronic Component Manufacturing stands out for facility HVAC being as important an electrical end use as machine drive. The diurnal patterns modeled by IGATE-E, by end use and taken in total across all of manufacturing, are shown in Figure 25. Based on dsgrid's underprediction of weekend energy use, the weekday/weekend scheduling shown here is another potential source of error that the dsgrid team will investigate moving forward, in tandem with similar calibrations for residential and commercial buildings.

dsgrid also provides load shapes and limited sectoral and end-use information for its gap models (commercial, industrial, transportation, municipal water, and outdoor lighting) and distributed generation models. CONUS-level summary data for these components are presented in Appendix F. Some analogous information is also presented for these components at the census division level in Appendix G.

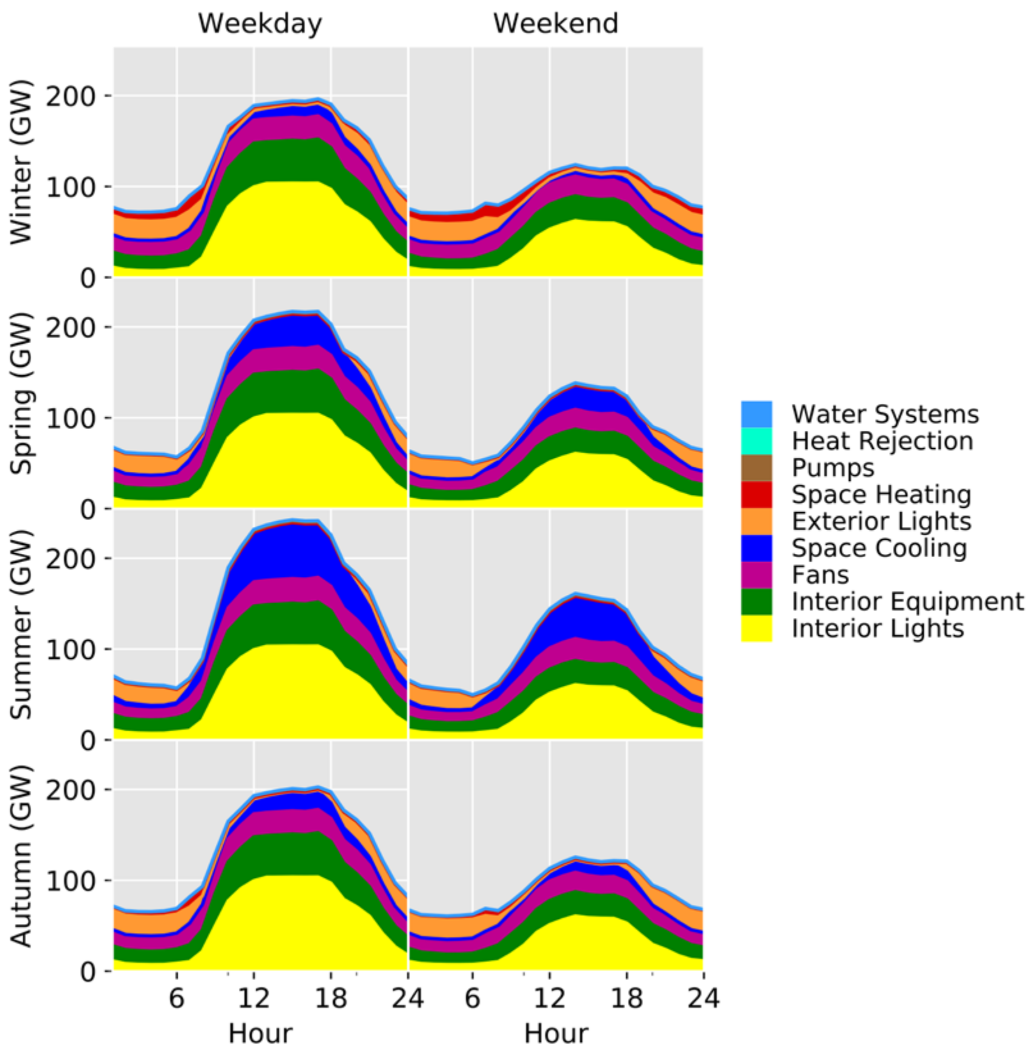

Figure 24. Commercial electricity use diurnal patterns by season, as modeled by ComStock for the CONUS in 2012

Table 26. Industrial Manufacturing Subsectors, Summary of IGATE-E Electricity Results by End Use for the CONUS in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Iron and Steel Mills and Ferroalloy Manufacturing	25,740	33,045	5,981	21,982	1,422	4,199	1,489	1,148	450	1,883	157	264	97,760
Petroleum and Coal Products Manufacturing	54,092	2,264	2,538	971	2,824	1,690	476	656	498	750	7	69	66,835
Basic Chemical Manufacturing	33,489	2,156	3,733	9,943	5,639	2,406	900	705	1,245	803	149	148	61,316
Pulp, Paper, and Paperboard Mills	45,452	2,361	2,639	493	1,005	2,306	2,028	645	2,770	301	122		60,122
Plastics Product Manufacturing	25,843	7,733	4,880	—	3,862	4,562	—	1,099	241	—	207	—	48,426
Pharmaceutical and Medicine Manufacturing	21,874	1,412	2,463	6,586	3,735	1,585	596	467	824	532	99	98	40,272
Converted Paper Product Manufacturing	29,841	1,553	1,745	327	667	1,524	1,345	428	1,837	199	81	—	39,546
Animal Slaughtering and Processing	9,820	973	1,909	51	5,963	1,680	412	456	699	504	211	95	22,773
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	11,556	749	1,320	3,549	2,013	848	321	252	444	287	53	53	21,445
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	11,503	741	1,284	3,420	1,940	827	310	243	428	276	51	51	21,073
Other Chemical Product and Preparation Manufacturing	9,734	627	1,089	2,904	1,647	701	263	206	364	235	44	43	17,856
Motor Vehicle Parts Manufacturing	6,810	1,935	3,307	114	889	2,214	867	697	147	276	248	211	17,716
Other Nonmetallic Mineral Product Manufacturing	8,279	3,929	1,003	274	601	767	334	237	138	—	59	25	15,645
Other Wood Product Manufacturing	11,436	971	1,154	45	110	922	166	244	274	167	38	52	15,580
Semiconductor and other Electronic Component Manufacturing	3,472	1,806	3,648	342	1,736	1,390	1,107	738	132	327	39	290	15,027
Printing and Related Support Activities	7,800	601	2,454	164	1,078	1,224	207	406	122	—	158	—	14,213
Foundries	3,574	4,577	823	3,012	195	578	204	157	62	258	21	36	13,497
Nonferrous Metal (except Aluminum) Production and Processing	3,496	4,447	785	2,846	184	553	193	149	58	244	20	34	13,010
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	6,995	453	797	2,140	1,214	512	194	152	268	173	32	32	12,961
Other Fabricated Metal Product Manufacturing	5,707	1,954	2,029	505	422	1,278	470	437	—	—	89	26	12,917
Architectural and Structural Metals Manufacturing	5,263	1,806	1,888	471	394	1,188	439	408	—	—	83	25	11,965
Dairy Product Manufacturing	5,081	502	973	26	3,020	857	209	231	354	255	107	48	11,663
Aerospace Product and Parts Manufacturing	4,147	1,178	2,011	69	540	1,347	527	424	89	168	151	128	10,779

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Fruit and Vegetable Preserving and Specialty Food Manufacturing	4,150	411	807	21	2,522	710	174	193	296	213	89	40	9,628
Beverage Manufacturing	3,322	393	1,088	19	1,815	860	229	305	148	705	188	40	9,113
Glass and Glass Product Manufacturing	4,633	2,192	555	151	332	425	184	131	76	—	32	14	8,725
Cement and Concrete Product Manufacturing	4,593	2,183	560	153	337	428	187	133	77	—	33	14	8,698
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	1,965	1,026	2,097	198	1,004	797	641	427	76	189	23	168	8,610
Paint, Coating, and Adhesive Manufacturing	4,518	292	514	1,379	782	330	125	98	173	111	21	20	8,363
Motor Vehicle Manufacturing	3,130	893	1,545	54	418	1,032	407	328	69	130	117	99	8,221
Bakeries and Tortilla Manufacturing	3,532	350	682	18	2,127	601	147	163	249	180	75	34	8,158
Other Food Manufacturing	3,424	339	659	17	2,050	581	142	157	240	173	72	33	7,888
Rubber Product Manufacturing	4,021	1,204	762	—	604	712	—	172	38	—	32	—	7,544
Alumina and Aluminum Production and Processing	1,998	2,545	451	1,638	106	318	111	86	34	140	12	20	7,457
Coating, Engraving, Heat Treating, and Allied Activities	3,229	1,111	1,171	294	245	736	274	254	—	—	52	15	7,381
Steel Product Manufacturing from Purchased Steel	1,848	2,353	416	1,510	98	293	102	79	31	129	11	18	6,888
Other Electrical Equipment and Component Manufacturing	1,775	1,456	1,048	492	406	621	231	143	29	—	44	—	6,245
Fiber, Yarn, and Thread Mills	3,698	530	920	0	228	452	112	92	127	—	54	—	6,214
Grain and Oilseed Milling	2,643	261	509	13	1,586	449	110	121	186	134	56	25	6,094
Veneer, Plywood, and Engineered Wood Product Manufacturing	4,461	377	442	17	42	354	63	93	104	63	14	20	6,051
Animal Food Manufacturing	2,555	254	501	13	1,570	440	108	120	184	133	55	25	5,960
Other General Purpose Machinery Manufacturing	2,480	575	1,215	60	241	829	138	219	57	—	60	—	5,873
Other Miscellaneous Manufacturing	1,932	681	1,421	41	420	819	111	286	94	—	34	14	5,854
Forging and Stamping	2,408	825	860	214	179	541	200	186	—	—	38	11	5,462
Communications Equipment Manufacturing	967	506	1,039	98	499	395	318	212	38	94	11	83	4,260
Fabric Mills	2,387	343	602	0	150	295	73	61	84	—	35	—	4,030
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	1,962	146	806	15	66	667	—	134	48	—	44	19	3,905
Engine, Turbine, and Power Transmission Equipment Manufacturing	1,500	346	725	36	143	495	82	130	34	—	35	—	3,527

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Industrial Machinery Manufacturing	1,471	339	710	35	140	485	80	128	33	—	35	—	3,457
Agriculture, Construction, and Mining Machinery Manufacturing	1,454	335	699	35	138	478	79	125	33	—	34	—	3,411
Motor Vehicle Body and Trailer Manufacturing	1,279	364	625	22	168	418	164	132	28	52	47	40	3,339
Electrical Equipment Manufacturing	922	760	556	263	217	328	123	77	16	—	23	—	3,286
Metalworking Machinery Manufacturing	1,347	312	657	33	130	448	75	118	31	—	32	—	3,183
Medical Equipment and Supplies Manufacturing	992	349	722	21	212	417	56	145	48	—	17	7	2,986
Commercial and Service Industry Machinery Manufacturing	1,225	283	592	29	117	405	67	106	28	—	29	—	2,880
Sugar and Confectionery Product Manufacturing	1,238	123	241	6	755	212	52	58	89	64	27	12	2,877
Computer and Peripheral Equipment Manufacturing	640	337	703	67	340	266	217	145	26	64	8	57	2,869
Lime and Gypsum Product Manufacturing	1,375	653	167	46	100	128	56	40	23	—	10	4	2,601
Textile and Fabric Finishing and Fabric Coating Mills	1,461	211	370	0	93	182	45	37	52	—	22	—	2,473
Ship and Boat Building	899	258	453	16	123	302	120	97	20	38	35	29	2,392
Other Textile Product Mills	1,214	161	299	7	152	244	10	56	113	—	57	—	2,313
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	968	333	350	88	73	220	82	76	—	—	15	5	2,209
Clay Product and Refractory Manufacturing	1,113	530	137	38	82	104	46	32	19	—	8	3	2,112
Spring and Wire Product Manufacturing	913	314	331	83	69	208	77	72	—	—	15	4	2,088
Other Transportation Equipment Manufacturing	781	222	382	13	103	255	100	81	17	32	29	24	2,039
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	622	144	305	15	61	208	35	55	14	—	15	—	1,475
Household Appliance Manufacturing	410	336	241	113	93	143	53	33	7	—	10	—	1,437
Manufacturing and Reproducing Magnetic and Optical Media	294	153	310	29	148	118	94	63	11	28	3	25	1,275
Railroad Rolling Stock Manufacturing	453	130	225	8	61	150	60	48	10	19	17	14	1,196
Seafood Product Preparation and Packaging	511	51	100	3	315	88	22	24	37	27	11	5	1,194
Boiler, Tank, and Shipping Container Manufacturing	478	163	166	41	34	105	38	35	—	—	7	2	1,069
Office Furniture (including Fixtures) Manufacturing	501	37	208	4	17	172	—	35	12	—	11	5	1,003
Audio and Video Equipment Manufacturing	205	107	216	20	103	82	66	44	8	19	2	17	888

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Tobacco Manufacturing	320	38	103	2	171	82	22	29	14	66	18	4	867
Electric Lighting Equipment Manufacturing	233	191	137	64	53	81	30	19	4	—	6	—	817
Cut and Sew Apparel Manufacturing	319	39	229	—	14	135	—	27	17	—	6	—	786
Sawmills and Wood Preservation	488	42	49	2	5	39	7	10	12	7	2	2	666
Cutlery and Handtool Manufacturing	237	81	85	21	18	54	20	18	—	—	4	1	540
Textile Furnishings Mills	225	30	56	1	29	46	2	11	21	—	11	—	431
Other Furniture Related Product Manufacturing	136	10	55	1	4	45	—	9	3	—	3	1	268
Other Leather and Allied Product Manufacturing	132	17	21	1	8	23	1	5	1	—	1	—	209
Footwear Manufacturing	48	6	8	0	3	8	1	2	1	—	0	—	76
Leather and Hide Tanning and Finishing	27	3	4	0	2	5	0	1	0	—	0	—	43
Hardware Manufacturing	14	5	5	1	1	3	1	1	—	—	0	0	31
Apparel Accessories and Other Apparel Manufacturing	6	1	4	—	0	2	—	0	0	—	0	—	14
Apparel Knitting Mills	1	0	1	—	0	0	—	0	0	—	0	—	2
Total	**449,086**	**106,835**	**82,372**	**67,815**	**63,218**	**56,031**	**19,226**	**16,901**	**14,683**	**10,449**	**4,030**	**2,702**	**893,346**

Table 27. Industrial Manufacturing Electricity Proportions for Subsectors and End Uses as Modeled for the CONUS in 2012 by IGATE-E

Subsector	Machine Drive (%)	Process Heating (%)	Facility HVAC (%)	Electro Chemical Processes (%)	Process Cooling And Refrigeration …	Facility Lighting (%)	Other Process Use (%)	Other Facility Support (%)	Conventional Boiler Use (%)	End Use Not Reported (%)	Onsite Transportation (%)	Other Nonprocess Use (%)	Total (%)
Iron and Steel Mills and Ferroalloy Manufacturing	26.3	33.8	6.1	22.5	1.5	4.3	1.5	1.2	0.5	1.9	0.2	0.3	10.9
Petroleum and Coal Products Manufacturing	80.9	3.4	3.8	1.5	4.2	2.5	0.7	1.0	0.7	1.1	0.0	0.1	7.5
Basic Chemical Manufacturing	54.6	3.5	6.1	16.2	9.2	3.9	1.5	1.2	2.0	1.3	0.2	0.2	6.9
Pulp, Paper, and Paperboard Mills	75.6	3.9	4.4	0.8	1.7	3.8	3.4	1.1	4.6	0.5	0.2	—	6.7
Plastics Product Manufacturing	53.4	16.0	10.1	—	8.0	9.4	—	2.3	0.5	—	0.4	—	5.4
Pharmaceutical and Medicine Manufacturing	54.3	3.5	6.1	16.4	9.3	3.9	1.5	1.2	2.0	1.3	0.2	0.2	4.5
Converted Paper Product Manufacturing	75.5	3.9	4.4	0.8	1.7	3.9	3.4	1.1	4.6	0.5	0.2	—	4.4
Animal Slaughtering and Processing	43.1	4.3	8.4	0.2	26.2	7.4	1.8	2.0	3.1	2.2	0.9	0.4	2.5
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	53.9	3.5	6.2	16.6	9.4	4.0	1.5	1.2	2.1	1.3	0.2	0.2	2.4
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	54.6	3.5	6.1	16.2	9.2	3.9	1.5	1.2	2.0	1.3	0.2	0.2	2.4
Other Chemical Product and Preparation Manufacturing	54.5	3.5	6.1	16.3	9.2	3.9	1.5	1.2	2.0	1.3	0.2	0.2	2.0
Motor Vehicle Parts Manufacturing	38.4	10.9	18.7	0.6	5.0	12.5	4.9	3.9	0.8	1.6	1.4	1.2	2.0
Other Nonmetallic Mineral Product Manufacturing	52.9	25.1	6.4	1.8	3.8	4.9	2.1	1.5	0.9	—	0.4	0.2	1.8
Other Wood Product Manufacturing	73.4	6.2	7.4	0.3	0.7	5.9	1.1	1.6	1.8	1.1	0.2	0.3	1.7
Semiconductor and Other Electronic Component Manufacturing	23.1	12.0	24.3	2.3	11.6	9.2	7.4	4.9	0.9	2.2	0.3	1.9	1.7
Printing and Related Support Activities	54.9	4.2	17.3	1.2	7.6	8.6	1.5	2.9	0.9	—	1.1	—	1.6
Foundries	26.5	33.9	6.1	22.3	1.4	4.3	1.5	1.2	0.5	1.9	0.2	0.3	1.5
Nonferrous Metal (except Aluminum) Production and Processing	26.9	34.2	6.0	21.9	1.4	4.3	1.5	1.1	0.4	1.9	0.2	0.3	1.5
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	54.0	3.5	6.1	16.5	9.4	4.0	1.5	1.2	2.1	1.3	0.2	0.2	1.5
Other Fabricated Metal Product Manufacturing	44.2	15.1	15.7	3.9	3.3	9.9	3.6	3.4	—	—	0.7	0.2	1.4
Architectural and Structural Metals Manufacturing	44.0	15.1	15.8	3.9	3.3	9.9	3.7	3.4	—	—	0.7	0.2	1.3
Dairy Product Manufacturing	43.6	4.3	8.3	0.2	25.9	7.4	1.8	2.0	3.0	2.2	0.9	0.4	1.3
Aerospace Product and Parts Manufacturing	38.5	10.9	18.7	0.6	5.0	12.5	4.9	3.9	0.8	1.6	1.4	1.2	1.2
Fruit and Vegetable Preserving and Specialty Food Manufacturing	43.1	4.3	8.4	0.2	26.2	7.4	1.8	2.0	3.1	2.2	0.9	0.4	1.1
Beverage Manufacturing	36.5	4.3	11.9	0.2	19.9	9.4	2.5	3.3	1.6	7.7	2.1	0.4	1.0

Subsector	Machine Drive (%)	Process Heating (%)	Facility HVAC (%)	Electro Chemical Processes (%)	Process Cooling And Refrigeration ...	Facility Lighting (%)	Other Process Use (%)	Other Facility Support (%)	Conventional Boiler Use (%)	End Use Not Reported (%)	Onsite Transportation (%)	Other Nonprocess Use (%)	Total (%)
Glass and Glass Product Manufacturing	53.1	25.1	6.4	1.7	3.8	4.9	2.1	1.5	0.9	—	0.4	0.2	1.0
Cement and Concrete Product Manufacturing	52.8	25.1	6.4	1.8	3.9	4.9	2.1	1.5	0.9	—	0.4	0.2	1.0
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	22.8	11.9	24.4	2.3	11.7	9.3	7.4	5.0	0.9	2.2	0.3	1.9	1.0
Paint, Coating, and Adhesive Manufacturing	54.0	3.5	6.1	16.5	9.4	3.9	1.5	1.2	2.1	1.3	0.2	0.2	0.9
Motor Vehicle Manufacturing	38.1	10.9	18.8	0.7	5.1	12.6	5.0	4.0	0.8	1.6	1.4	1.2	0.9
Bakeries and Tortilla Manufacturing	43.3	4.3	8.4	0.2	26.1	7.4	1.8	2.0	3.1	2.2	0.9	0.4	0.9
Other Food Manufacturing	43.4	4.3	8.4	0.2	26.0	7.4	1.8	2.0	3.0	2.2	0.9	0.4	0.9
Rubber Product Manufacturing	53.3	16.0	10.1	—	8.0	9.4	—	2.3	0.5	—	0.4	—	0.8
Alumina and Aluminum Production and Processing	26.8	34.1	6.0	22.0	1.4	4.3	1.5	1.1	0.4	1.9	0.2	0.3	0.8
Coating, Engraving, Heat Treating, and Allied Activities	43.7	15.1	15.9	4.0	3.3	10.0	3.7	3.4	—	—	0.7	0.2	0.8
Steel Product Manufacturing from Purchased Steel	26.8	34.2	6.0	21.9	1.4	4.3	1.5	1.1	0.4	1.9	0.2	0.3	0.8
Other Electrical Equipment and Component Manufacturing	28.4	23.3	16.8	7.9	6.5	9.9	3.7	2.3	0.5	—	0.7	—	0.7
Fiber, Yarn, and Thread Mills	59.5	8.5	14.8	0.0	3.7	7.3	1.8	1.5	2.0	—	0.9	—	0.7
Grain and Oilseed Milling	43.4	4.3	8.4	0.2	26.0	7.4	1.8	2.0	3.1	2.2	0.9	0.4	0.7
Veneer, Plywood, and Engineered Wood Product Manufacturing	73.7	6.2	7.3	0.3	0.7	5.9	1.0	1.5	1.7	1.0	0.2	0.3	0.7
Animal Food Manufacturing	42.9	4.3	8.4	0.2	26.3	7.4	1.8	2.0	3.1	2.2	0.9	0.4	0.7
Other General Purpose Machinery Manufacturing	42.2	9.8	20.7	1.0	4.1	14.1	2.4	3.7	1.0	—	1.0	—	0.7
Other Miscellaneous Manufacturing	33.0	11.6	24.3	0.7	7.2	14.0	1.9	4.9	1.6	—	0.6	0.2	0.7
Forging and Stamping	44.1	15.1	15.7	3.9	3.3	9.9	3.7	3.4	—	—	0.7	0.2	0.6
Communications Equipment Manufacturing	22.7	11.9	24.4	2.3	11.7	9.3	7.5	5.0	0.9	2.2	0.3	2.0	0.5
Fabric Mills	59.2	8.5	14.9	0.0	3.7	7.3	1.8	1.5	2.1	—	0.9	—	0.5
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	50.2	3.7	20.6	0.4	1.7	17.1	—	3.4	1.2	—	1.1	0.5	0.4
Engine, Turbine, and Power Transmission Equipment Manufacturing	42.5	9.8	20.6	1.0	4.1	14.0	2.3	3.7	1.0	—	1.0	—	0.4
Industrial Machinery Manufacturing	42.5	9.8	20.5	1.0	4.1	14.0	2.3	3.7	1.0	—	1.0	—	0.4
Agriculture, Construction, and Mining Machinery Manufacturing	42.6	9.8	20.5	1.0	4.0	14.0	2.3	3.7	1.0	—	1.0	—	0.4
Motor Vehicle Body and Trailer Manufacturing	38.3	10.9	18.7	0.6	5.0	12.5	4.9	4.0	0.8	1.6	1.4	1.2	0.4
Electrical Equipment Manufacturing	28.1	23.1	16.9	8.0	6.6	10.0	3.8	2.3	0.5	—	0.7	—	0.4

Subsector	Machine Drive (%)	Process Heating (%)	Facility HVAC (%)	Electro Chemical Processes (%)	Process Cooling And Refrigeration …	Facility Lighting (%)	Other Process Use (%)	Other Facility Support (%)	Conventional Boiler Use (%)	End Use Not Reported (%)	Onsite Transportation (%)	Other Nonprocess Use (%)	Total (%)
Metalworking Machinery Manufacturing	42.3	9.8	20.6	1.0	4.1	14.1	2.3	3.7	1.0	—	1.0	—	0.4
Medical Equipment and Supplies Manufacturing	33.2	11.7	24.2	0.7	7.1	14.0	1.9	4.9	1.6	—	0.6	0.2	0.3
Commercial and Service Industry Machinery Manufacturing	42.5	9.8	20.6	1.0	4.1	14.0	2.3	3.7	1.0	—	1.0	—	0.3
Sugar and Confectionery Product Manufacturing	43.0	4.3	8.4	0.2	26.2	7.4	1.8	2.0	3.1	2.2	0.9	0.4	0.3
Computer and Peripheral Equipment Manufacturing	22.3	11.7	24.5	2.3	11.9	9.3	7.6	5.0	0.9	2.2	0.3	2.0	0.3
Lime and Gypsum Product Manufacturing	52.9	25.1	6.4	1.8	3.9	4.9	2.1	1.5	0.9	—	0.4	0.2	0.3
Textile and Fabric Finishing and Fabric Coating Mills	59.1	8.5	15.0	0.0	3.7	7.3	1.8	1.5	2.1	—	0.9	—	0.3
Ship and Boat Building	37.6	10.8	18.9	0.7	5.2	12.6	5.0	4.0	0.9	1.6	1.4	1.2	0.3
Other Textile Product Mills	52.5	7.0	12.9	0.3	6.6	10.5	0.4	2.4	4.9	—	2.5	—	0.3
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	43.8	15.1	15.8	4.0	3.3	10.0	3.7	3.4	—	—	0.7	0.2	0.2
Clay Product and Refractory Manufacturing	52.7	25.1	6.5	1.8	3.9	4.9	2.2	1.5	0.9	—	0.4	0.2	0.2
Spring and Wire Product Manufacturing	43.7	15.1	15.9	4.0	3.3	10.0	3.7	3.4	—	—	0.7	0.2	0.2
Other Transportation Equipment Manufacturing	38.3	10.9	18.7	0.6	5.0	12.5	4.9	4.0	0.8	1.6	1.4	1.2	0.2
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	42.2	9.8	20.7	1.0	4.1	14.1	2.4	3.7	1.0	—	1.0	—	0.2
Household Appliance Manufacturing	28.5	23.4	16.7	7.8	6.5	9.9	3.7	2.3	0.5	—	0.7	—	0.2
Manufacturing and Reproducing Magnetic and Optical Media	23.0	12.0	24.3	2.3	11.6	9.3	7.4	4.9	0.9	2.2	0.3	1.9	0.1
Railroad Rolling Stock Manufacturing	37.9	10.8	18.8	0.7	5.1	12.6	5.0	4.0	0.8	1.6	1.4	1.2	0.1
Seafood Product Preparation and Packaging	42.8	4.3	8.4	0.2	26.4	7.4	1.8	2.0	3.1	2.2	0.9	0.4	0.1
Boiler, Tank, and Shipping Container Manufacturing	44.7	15.2	15.5	3.8	3.2	9.8	3.6	3.3	—	—	0.7	0.2	0.1
Office Furniture (including Fixtures) Manufacturing	49.9	3.7	20.8	0.4	1.7	17.2	—	3.5	1.2	—	1.1	0.5	0.1
Audio and Video Equipment Manufacturing	23.0	12.0	24.3	2.3	11.6	9.3	7.4	4.9	0.9	2.2	0.3	1.9	0.1
Tobacco Manufacturing	37.0	4.4	11.9	0.2	19.7	9.4	2.5	3.3	1.6	7.6	2.0	0.4	0.1
Electric Lighting Equipment Manufacturing	28.6	23.4	16.7	7.8	6.5	9.9	3.7	2.3	0.5	—	0.7	—	0.1
Cut and Sew Apparel Manufacturing	40.6	5.0	29.1	—	1.8	17.1	—	3.4	2.2	—	0.8	—	0.1
Sawmills and Wood Preservation	73.4	6.2	7.4	0.3	0.7	5.9	1.1	1.6	1.8	1.1	0.2	0.3	0.1
Cutlery and Handtool Manufacturing	43.9	15.1	15.8	4.0	3.3	9.9	3.7	3.4	—	—	0.7	0.2	0.1
Textile Furnishings Mills	52.2	6.9	13.0	0.3	6.6	10.6	0.4	2.5	4.9	—	2.5	—	0.0
Other Furniture Related Product Manufacturing	50.8	3.8	20.4	0.4	1.7	16.9	—	3.3	1.2	—	1.1	0.5	0.0

Subsector	Machine Drive (%)	Process Heating (%)	Facility HVAC (%)	Electro Chemical Processes (%)	Process Cooling And Refrigeration ...	Facility Lighting (%)	Other Process Use (%)	Other Facility Support (%)	Conventional Boiler Use (%)	End Use Not Reported (%)	Onsite Transportation (%)	Other Nonprocess Use (%)	Total (%)
Other Leather and Allied Product Manufacturing	63.0	7.9	10.2	0.3	3.7	10.8	0.7	2.3	0.7	—	0.3	—	0.0
Footwear Manufacturing	63.0	7.9	10.2	0.3	3.7	10.8	0.7	2.3	0.7	—	0.3	—	0.0
Leather and Hide Tanning and Finishing	63.0	7.9	10.2	0.3	3.7	10.8	0.7	2.3	0.7	—	0.3	—	0.0
Hardware Manufacturing	43.6	15.0	15.9	4.0	3.3	10.0	3.7	3.5	—	—	0.7	0.2	0.0
Apparel Accessories and Other Apparel Manufacturing	39.9	5.0	29.5	—	1.8	17.3	—	3.5	2.2	—	0.8	—	0.0
Apparel Knitting Mills	39.8	5.0	29.5	—	1.8	17.3	—	3.5	2.2	—	0.8	—	0.0
Total	**50.3**	**12.0**	**9.2**	**7.6**	**7.1**	**6.3**	**2.2**	**1.9**	**1.6**	**1.2**	**0.5**	**0.3**	**100.0**

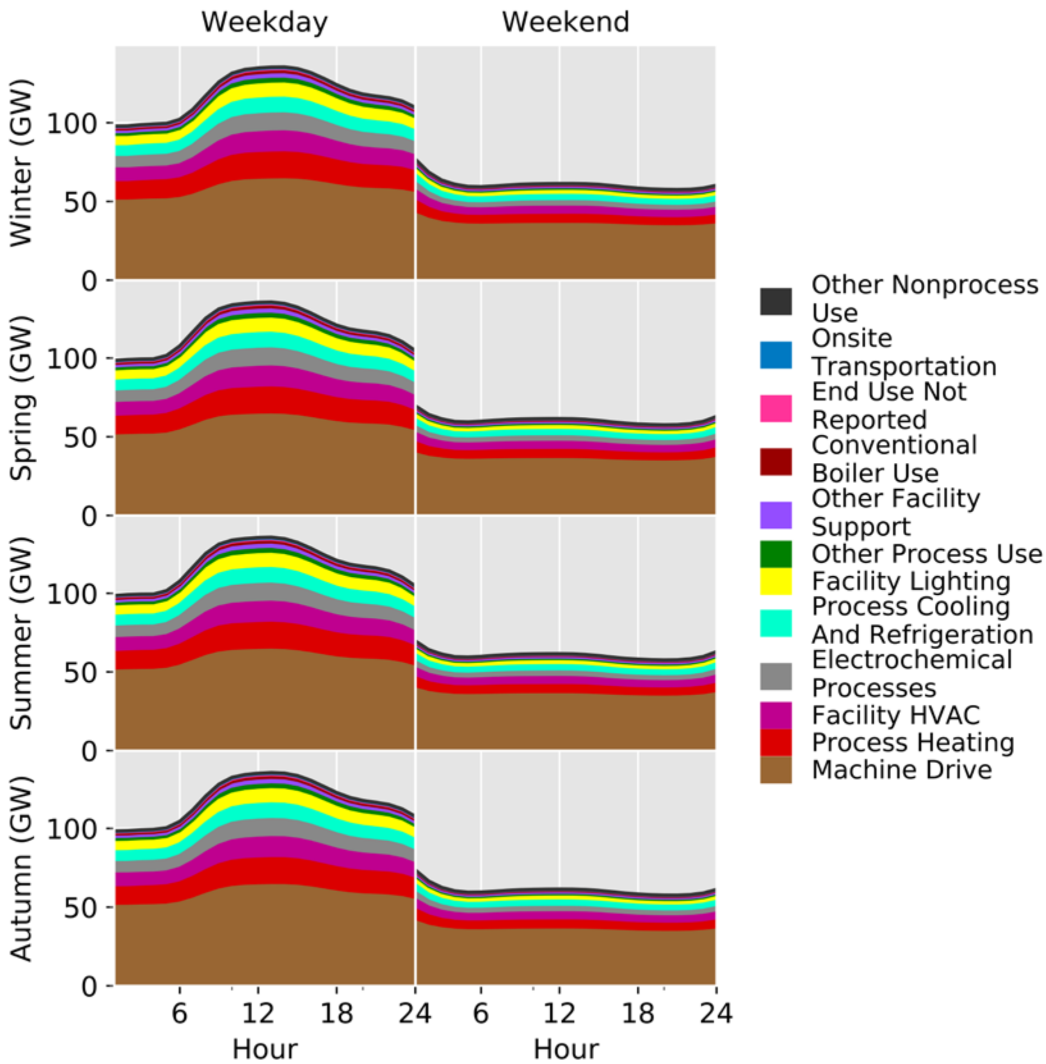

Figure 25. Industrial electricity use diurnal patterns by season, modeled for the CONUS in 2012

4 Future Work

dsgrid is a new model designed to provide a solid basis for exploring questions about future electricity load and its relationship to grid operations. Because dsgrid is a new model, this documentation represents the beginning of an investigation rather than the end of an analysis. Three areas of work are planned for the near future.

4.1 Additional ComStock Calibration

The ComStock model, although built from relatively mature prototype building energy models, is still under development and has not yet been fully calibrated against a sufficiently large body of hourly (or finer) commercial building metered data. In the near future, the team plans to conduct several rounds of comparing ComStock to metered data sets, making model adjustments accordingly, and again measuring level of agreement. Of most interest is comparing the ComStock load profile results to aggregated commercial sector utility consumption data. Consolidated Edison in New York, for example, releases historical 8,760 load data for portions of their service territory, and Commonwealth Edison releases significant customer data that has been anonymized but provides rate classification, which allows for the determination of commercial class customers. Calibration to these detailed energy data will provide valuable insights into ComStock's temporal accuracy, from which we expect to derive scheduling adjustments.

4.2 EFS Scenarios

In parallel with the dsgrid development efforts described here, the EFS team has been developing a set of electrification scenarios using the EnergyPATHWAYS model (Mai et al. 2018). As part of that process, some sector models described here provided inputs to EnergyPATHWAYS, so that the initial conditions of these two modeling efforts have been somewhat harmonized, as depicted on the left side of Figure 26. The next step of these efforts is shown on the right side of Figure 26, where EnergyPATHWAYS outputs in the form of descriptions of future building, industrial, and transportation stocks are translated and fed into the various components of dsgrid. Each component will then be run using these adjusted inputs to create annual snapshots of future electricity demand under multiple scenarios.

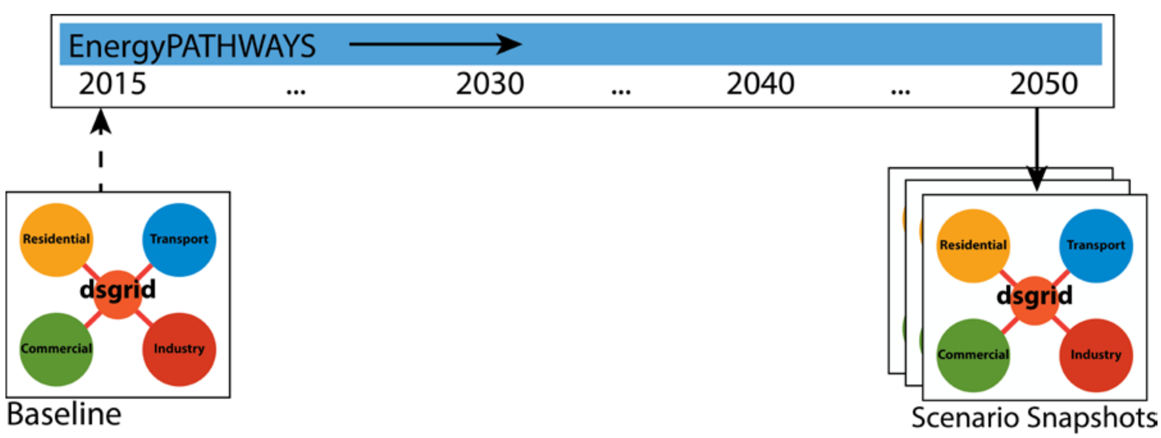

Figure 26. Relationship between dsgrid and decadal-scale adoption models

In anticipation of taking this step, the dsgrid and EnergyPATHWAYS teams have coordinated on (1) use of the LandScan population data sets for both current conditions and (2) a 2030 county-level projection. Population is a key determiner of the magnitude and geographic dispersion of energy use both now and as we might project it into the future. Thus, standardizing on finely resolved population data sets will help ensure between-model compatibility and realistic downscaling. Also, the dsgrid team has met with the EnergyPATHWAYS team to start evaluating what kinds of mappings will need to be performed to turn their outputs into dsgrid inputs.

In addition to translating EnergyPATHWAYS outputs into a form that is usable by the dsgrid sector models, we will also need to develop appropriate methods for projecting our gap models and residuals into the future, possibly adjusting them based on some EnergyPATHWAYS outputs as well. We look forward to implementing and executing this capability to construct the EFS electrification scenario snapshots in 2018–2019.

4.3 Power System Geography

Finally, the team will be mapping dsgrid data to the geography of U.S. power systems. Some state-level regulatory and reporting requirements notwithstanding, electric utilities and aggregations thereof are not generally aligned with political boundaries. Many electric utilities have service territories in more than one state; many geographic regions are served by multiple utilities; and the largest wholesale power markets (e.g., PJM and MISO) cover many states. The latter are typically broken down into regions, but even those are quite coarse and cross state boundaries. Relevant to dsgrid, they often cover areas with significantly different weather.

For the purposes of this report, we have focused on describing load at the state level or aggregates thereof, because this generally allows for high-level calibration and regional description; however, to apply this and future data sets to power system models, we will need to disaggregate and reaggregate the data based on the logic of electric utilities and transmission nodes. The FERC hourly load data used in this work was derived from disaggregations of regional load time series to transmission nodes that were created to support several ongoing renewable integration studies being conducted by NREL. We plan to retrace this logic and the geographic and electrical entities associated with it to assign dsgrid load timeseries to transmission nodes for the operational modeling portion of EFS.

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Appendix A. Residential Sector Model Details

A.1 Data Sources and Methodology Details

Detailed documentation of the ResStock methodology can be found in Wilson et al. (2017). For reference, a summary of the major input data sources is shown in Table A-1.

Table A-1. List of Data Sources Used to Derive Input Probability Distributions for ResStock

Full Reference	Number of Probability Distributions
"Residential Energy Consumption Survey (RECS), 2009 RECS Survey Data," U.S. Energy Information Administration, accessed in 2012, https://www.eia.gov/consumption/residential/data/2009/.	2,792
Used engineering experience or calibration because of a lack of data	1,235
Wanyu R. Chan, Jeffrey Joh, and Max H. Sherman, *Air Leakage of US Homes: Regression Analysis and Improvements from Retrofit* (Technical Report LBNL-5966E) (Berkeley, CA: Lawrence Berkeley National Laboratory, 2012, Eqn. 2 and Table 1).	1,050
Thomas P. Wenzel, Jonathan G. Koomey, Gregory J. Rosenquist, Maria C. Sanchez, and James W. Hanford, *Energy Data Sourcebook for the U.S. Residential Sector* (Technical Report LBNL-40297) (Berkeley, CA: Lawrence Berkeley National Laboratory, 1997).	760
American Community Survey: Five-Year Summary File," U.S. Census Bureau, 2012 (from *National Historical Geographic Information System, Minnesota Population Center, 2015).*	432
"New Construction Builder Practice Survey Data," National Association of Home Builders, 1982, 1987	152
Used default values from Eric Wilson, Cheryn Engebrecht Metzger, Scott Horowitz, and Robert Hendron, *2014 Building America House Simulation Protocols* (Technical Report NREL/TP-5500-60988) (Golden, CO: National Renewable Energy Laboratory, 2014), http://energy.gov/eere/buildings/downloads/building-america-2014-house-simulation-protocols.	96
"New Construction Overview," Home Innovation Research Labs 1999, 2007 (New Housing Characteristics; Insulation; Sheathing—Wall), http://www.homeinnovation.com/trends_and_reports/data/new_construction.	56
"Residential Building Stock Assessment: Single-Family Characteristics and Energy Use," Northwest Energy Efficiency Alliance, 2012.	52
Kenneth Labs, John Carmody, Raymond Sterling, Lester Shen, Yu Joe Huang, and Danny Parker, *Buildings Foundation Design Handbook* (Technical Report ORNL/Sub/86-72143/l) (Oak Ridge, TN: 1988).	48
International Code Council, *2009 International Energy Conservation Code* (Washington, D.C.: 2009).	40
Ronald L. Ritschard, James W. Hanford, and A. Osman Sezgen, *Single Family Heating and Cooling Requirements: Assumptions, Methods, and Summary Results* (Technical Report LBL-30377) (Berkeley, CA: Lawrence Berkeley National Laboratory, 1992).	36
R.G. Lucas and P.C. Cole, *Impacts of the 2009 IECC for Residential Buildings at State Level* (Technical Report PNNL-18545) (Richland, WA: Pacific Northwest National Laboratory, 2009)	35
"Building America Field Data Repository," National Renewable Energy Laboratory, 2015.	7

[a] The table lists the data sources used to develop the statistical model of housing stock characteristics used for this analysis.

A.2 Additional Calibration Details

Figure A-1 and Figure A-2 illustrate preliminary progress on calibrating weather-dependent end-use load profiles (space heating and air conditioning), using 2012 Utility Load Research Data (ULRD) from ComEd. This initial calibration used simple multipliers on the heating and cooling end uses; ongoing work involves determining the most appropriate parameter changes to achieve a similar result (e.g., thermostat setpoints, seasonal usage patterns, and number of homes using air conditioning).

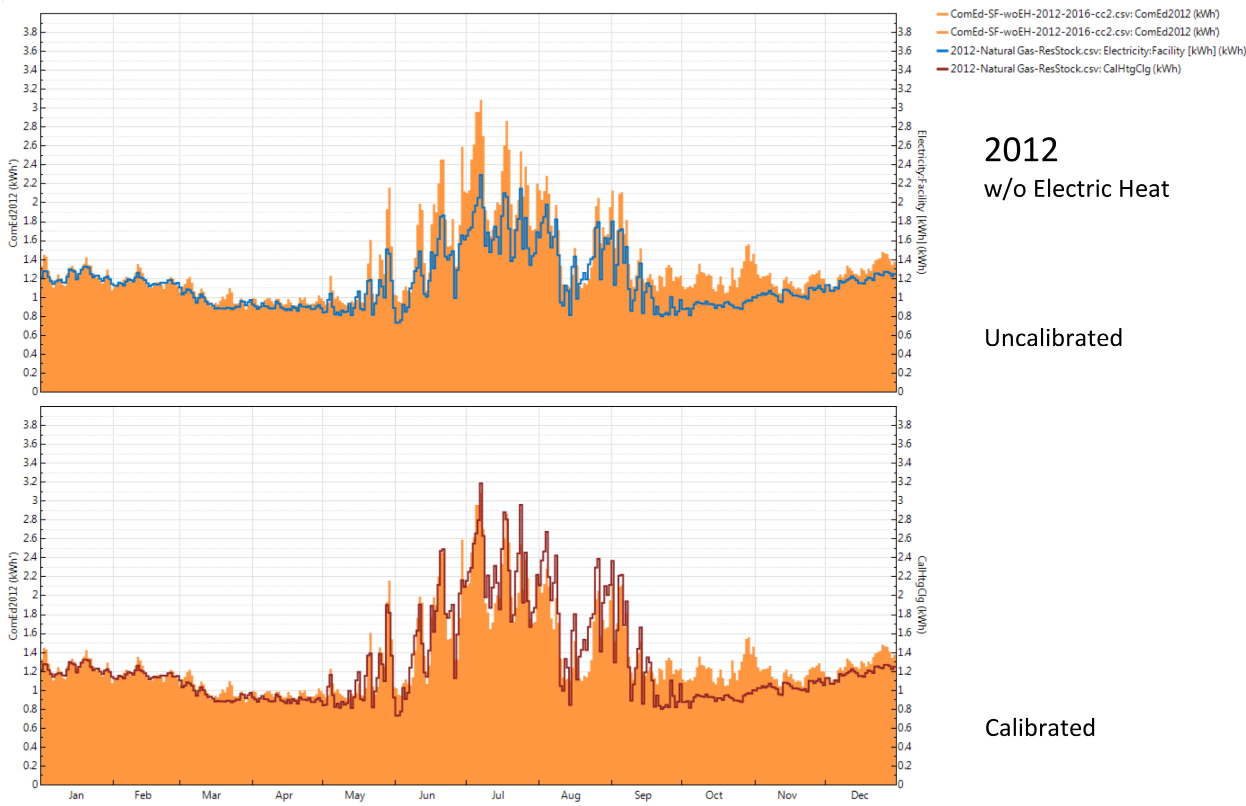

Figure A-1. Comparison of modeled and measured daily kWh load for average single-family homes in the ComEd service territory (2012 data; homes without electric space heating)

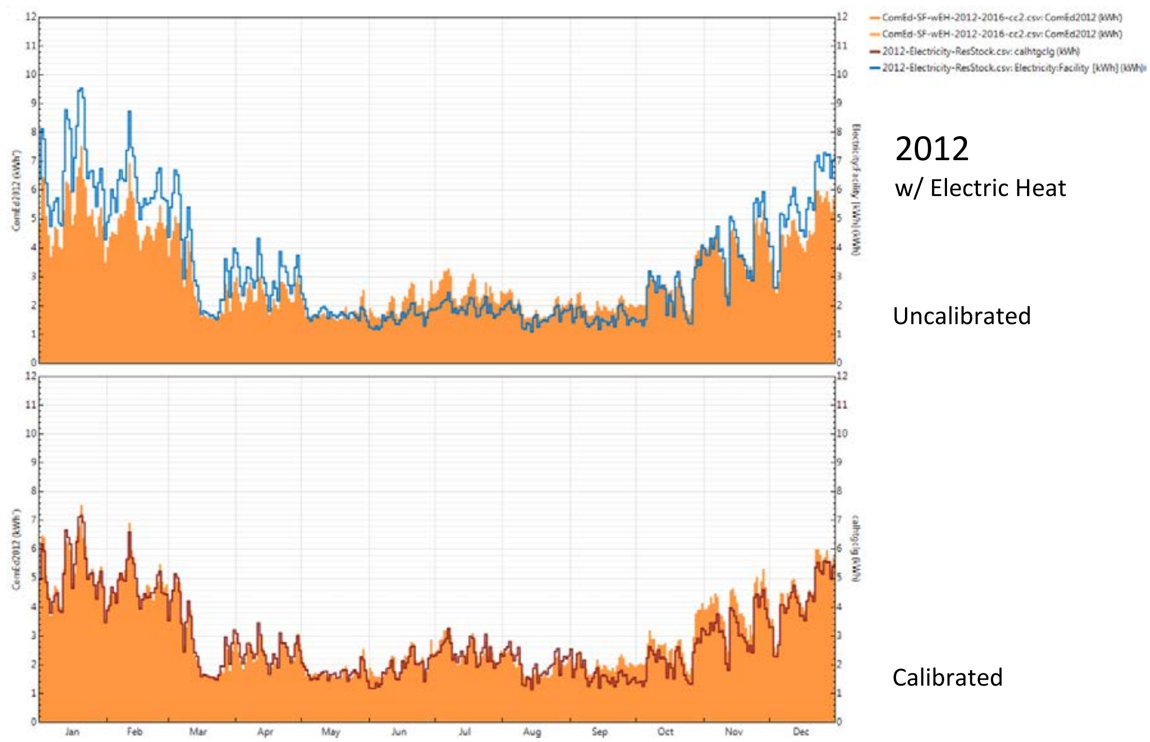

Figure A-2. Comparison of modeled and measured daily kWh load for average single-family homes in the ComEd service territory (2012 data; homes with electric space heating)

Appendix B. Commercial Sector Model Details

B.1 ComStock Overview

The commercial building sector stock model (ComStock) is a highly granular, bottom-up model that uses multiple data sources, statistical sampling methods, and advanced building energy simulations to estimate annual subhourly energy consumption of commercial buildings across the United States. The methodology used to develop ComStock closely mirrors that of the residential building stock model described by (Wilson et al. 2016).

The ComStock modeling process consists of four constituent parts: a database of real commercial building characteristics, conditional probability tables synthesized from these data, the Parametric Analysis Tool (PAT) used to translate probability tables to simulation inputs, and building energy simulations created using OpenStudio and simulated with EnergyPlus. The following sections build on the ComStock overview provided in Section 2.2.2, and describe in greater detail the data, modeling approaches, and assumptions used to develop ComStock. A flowchart of the ComStock modeling process is depicted in Figure B-1.

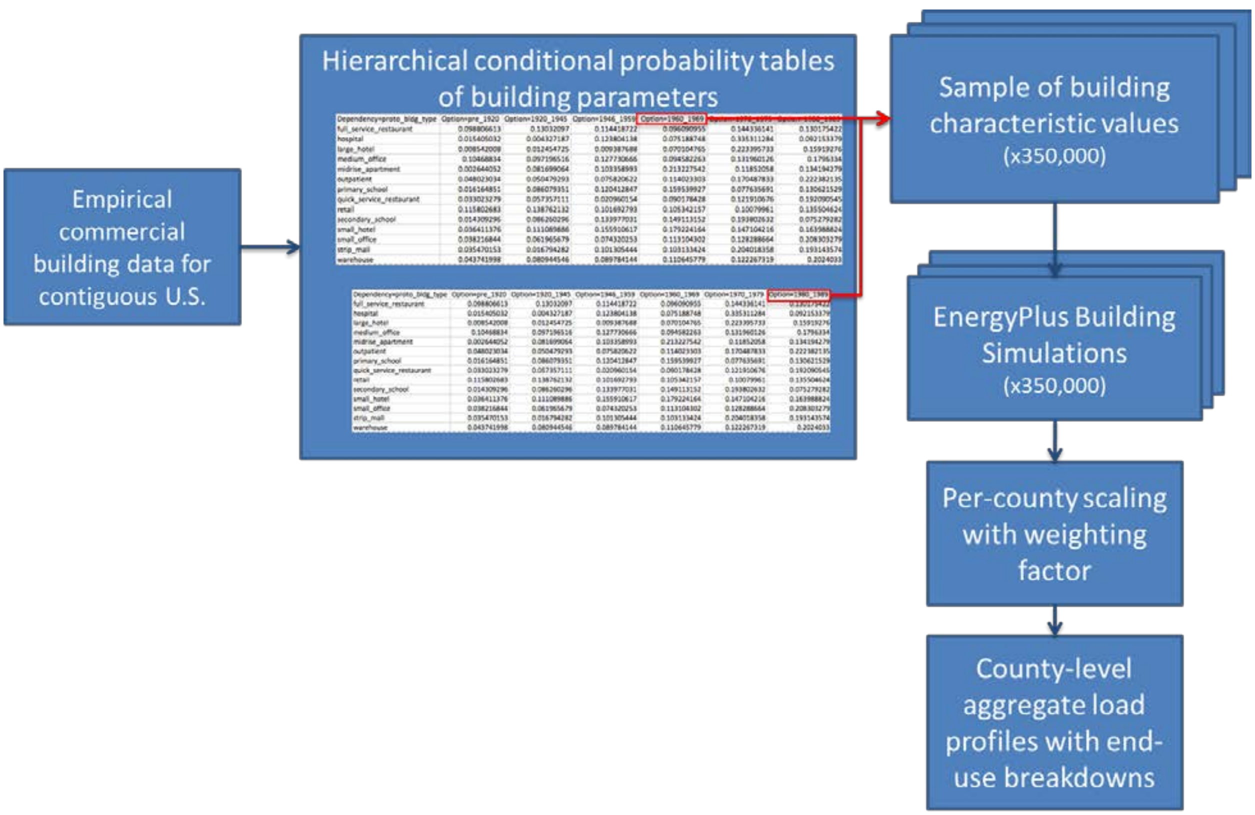

Figure B-1. Workflow used to characterize the U.S. commercial building stock and model energy use with county-level granularity

B.2 Commercial Building Characteristics

The scope of the ComStock model encompasses commercial buildings that can be mapped to the 16 DOE prototype buildings: full service restaurant, hospital, large hotel, midrise apartment, high-rise apartment, outpatient, primary school, quick service restaurant, retail, secondary school, small hotel, strip mall, warehouse, small office, medium office, and large office (Goel et al. 2014). In addition to Goel et al. (2014), Deru et al. (2011) provides additional background on the initial reference building models that were subsequently developed into the prototype buildings used for codes and standards analysis. Commercial buildings whose principle activities do not fall into one of the prototype building categories are currently not included in the core portion of ComStock.[55] They are instead captured by the dsgrid commercial gaps model.

Every aspect of a commercial building ultimately influences its energy consumption—often in complex and interrelated ways—thus necessitating robust modeling engines seeded with accurate building characteristics. The primary building characteristics needed to accurately model commercial building energy consumption were determined based on previous modeling experience, available data, and engineering judgement. Many building characteristics (e.g., number of floors, HVAC system type, and total area) depend on other influential variables (e.g., location, building type, and vintage). The building characteristics, dependencies, and data sources used to establish the ComStock database are shown in Table 5. The hierarchical dependency of the probability tables used to determine building simulation inputs are illustrated in Figure B-2. These dependencies are somewhat arbitrary (e.g., the number of floors in a building may be codependent on building location and building type). Further statistical analysis is needed to verify the optimal inheritance structure of these dependencies and the effects of these assumptions. For building characteristics listed in Table 5 that are not included in the Figure B-2 dependencies flowchart, parameters were assigned values based on established EnergyPlus and OpenStudio defaults.

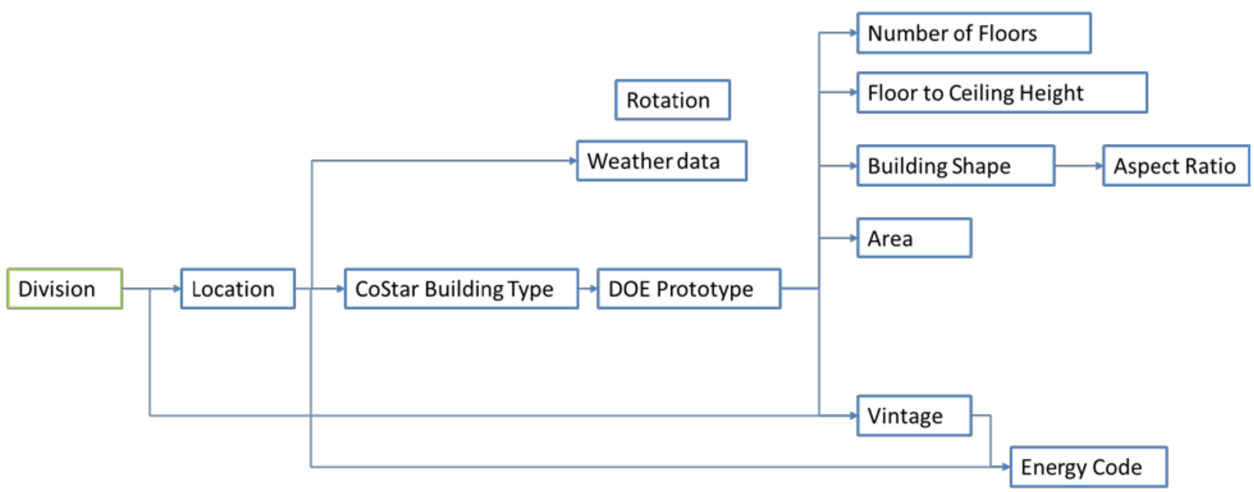

Figure B-2. Visualization of probability table heirarchy, sampled using a Latin hypercube sampling

[55] Supermarkets are a building type present in the original reference buildings, but they dropped from the prototype building set. They are currently in the process of being added back in as full-fledged prototype buildings, at which point they will also be incorporated into ComStock.

B.3 Commercial Building Stock Data Sources

Simulating end-use electrification in U.S. commercial buildings requires accurate high-resolution data on the type, size, location, and characteristics of existing commercial buildings. For these characteristics, we use a combination of the data contained within the U.S. Energy Information Administration (EIA 2016a) Commercial Buildings Energy Consumption Survey (CBECS) and CoStar (2017), a commercial real estate inventory with building point data.

2012 Commercial Buildings Energy Consumption Survey (CBECS)

The 2012 CBECS is a national building survey conducted by the EIA. The most recent CBECS began data collection in April 2013 for reference year 2012. The resulting data include surveyed information on energy-related building characteristics and energy usage details for buildings over 1,000 square feet in which at least 50% of the floorspace is used for commercial purposes. CBECS public-use microdata (EIA 2016a) consist of anonymized building details for 6,720 surveyed buildings. The smallest level of geographic resolution for these data is the census division—a relatively large geographic area covering multiple states and climate regions (Figure B-3). Each individual survey response also includes a sample weight, which represents the number of buildings in the general commercial building population that the observation represents.

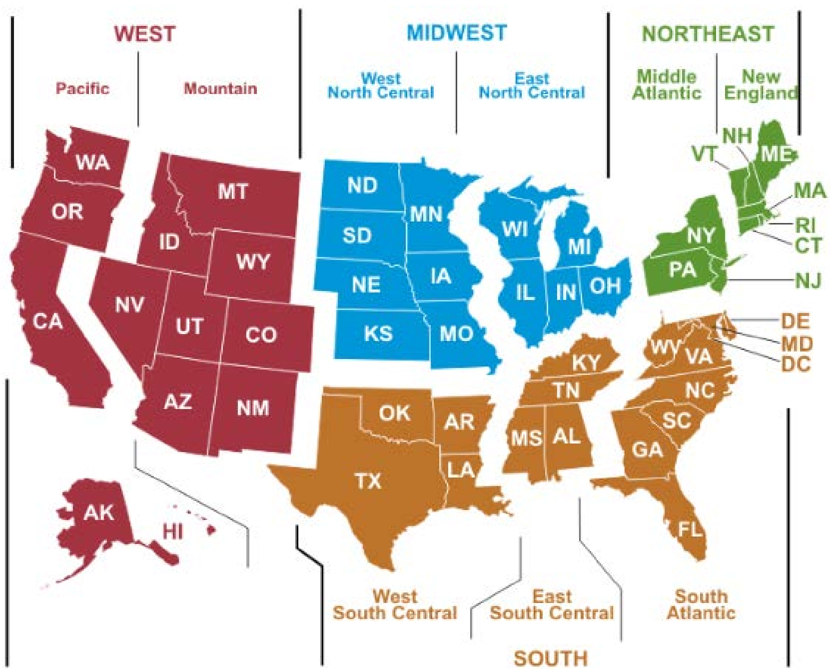

Figure B-3. The four U.S. census regions and nine census divisions, used by CBECS 2012

The buildings surveyed for CBECS were selected from a sampling frame of commercial buildings developed by EIA. This sampling frame consists of two parts: an area frame and a list frame. The area frame, which accounts for approximately 80% of the total frame, was first created in 2003 and was constructed using multi-stage area probability sampling. To create the frame, trained field staff walked or drove through selected areas (often the size of census tracts or groups of census tracts) and recorded information about every commercial building. The list frame, which accounts for about 20% of the total frame, consists of five administrative lists of government buildings, schools, hospitals, airports, and other large buildings, namely:

- U.S. federal buildings that are at least 200,000 square feet from Federal Real Property Council files obtained from the General Services Administration
- Four-year colleges and universities estimated to have at least 1,000,000 square feet of floorspace from the Integrated Postsecondary Education Data System
- Hospitals with at least 200,000 square feet of floorspace purchased from the IMS Healthcare Market Index
- Airports from the Federal Aviation Administration (FAA) Forms 5010, Airport Master Record file, and FAA enplanements data file
- Other large buildings over 200,000 square feet (e.g., hotels and offices) from the Common Premises Location file from Dun & Bradstreet.

Both the area and list frames were updated for the 2012 CBECS. The final sampling frame was stratified by building size and type; the number of sampled buildings within each subgroup was calculated to minimize the variance of the estimated energy consumption. Finally, the buildings to be sampled were chosen using a probability proportionate to size selection procedure.

For the selected buildings, the CBECS was administered in two phases. During the first stage, a trained interviewer administered a set questionnaire to the building respondent using a computer-assisted recorded interview tool, either in-person or by telephone. If the building respondent could not provide sufficient data, or the provided data were deemed erroneous using EIA regression models, a second phase of data collection was used. In this Follow-up Energy Suppliers Survey, EIA contacted the individual energy supplier for the building to obtain usage and expenditure data from the supplier's records.

During the subsequent data processing stage, items with nonresponses were treated with a hot-deck imputation technique, meaning the response for that missing item was randomly chosen from a completed response of another similar building. Additional steps were taken to adhere to confidentiality requirements by removing potentially identifying information from the public-use microdata file. This included masking specific square footage details and binning numeric responses for building characteristics such as floor-to-ceiling height and year of construction. For a full list of the confidentiality and masking procedures used by the EIA, refer to the *User's Guide to the 2012 CBECS Public Use Microdata File* (EIA 2016b). For more information on the methodology used to produce the CBECS data, visit the CBECS website.[56]

CoStar Realty Database

CoStar Group, Inc. is a commercial real estate information and marketing company. As one of its primary product offerings, CoStar maintains a full inventory of building point data (aggregated to the census block level for the purpose of this analysis) with information on building area and market subtype (CoStar 2017). In the CONUS, CoStar reports data for a total of 2,860,201 commercial buildings of 94 property subtypes, which is just over half the number of buildings estimated by CBECS.

[56] https://www.eia.gov/consumption/commercial/

According to CoStar, a team of research associates maintains the properties in CoStar's database through canvassing (500,000 properties nationwide annually); phone calls (10,000 calls daily to brokers, owners, developers, and real estate professionals); photographs (1 million taken annually); and data exchange (5.1 million changes per day) (CoStar Group, Inc. 2017).

Because the CoStar database is proprietary, additional documentation on CoStar sampling methodologies and data collection methods is difficult to ascertain. Public information on CoStar property data can be found on their website.[57]

Data Source Limitations

Due to the vast quantity and variation in U.S. commercial buildings, it is unsurprising that an accurate, high-resolution database of building counts, sizes, and types is difficult to create and maintain. The two nation-wide databases identified and described in this report—CBECS and CoStar—each entail limitations and uncertainties whose potential impacts were considered in the development of the ComStock database.

CBECS Limitations

With regard to building characteristics, the primary limitations of the available CBECS data are its coarse geographic resolution, limited number of sampled buildings, and inaccuracy of respondent reports. Because the highest available resolution of the CBECS data is the census division level, conducting analyses at the desired geospatial resolution for dsgrid (county) is infeasible without additional data manipulation.

The low number of surveyed buildings (6,720 total) in the 2012 CBECS provides only a limited measure of the expected variability and kurtosis in the commercial building stock. However, CBECS does provide relative standard error calculations for each estimate in the CBECS summary tables. CBECS uses the jackknife method for estimating these standard errors, whereby replicate weights are repeatedly used to estimate the statistic of interest and calculate the differences between these estimates and the full-sample estimate (EIA 2016a). Using the provided relative standard errors, calculations derived from CBECS data can be evaluated to determine the precision of the survey estimate relative to the true population value.

Another weakness of the CBECS method is the dependence on the knowledge and accuracy of the building respondents when questioned by EIA's trained surveyors. As analyzed in an EIA report that retrospectively evaluated the efficacy of the 2012 CBECS (EIA 2015b), square footage estimates and Principle Building Activity (PBA) designations collected during the building survey portion of CBECS were limited by the respondents' knowledge.

CoStar Limitations

Inadequate information regarding error metrics, survey forms, and geospatial coverage represents a fundamental limitation of CoStar data. Certain fields, such as square footage are more likely to be accurate, as they are critical to the commercial success of the data set and company, while other fields are not as obviously trustworthy. Additionally, the commercial nature of the data set leads to questions regarding coverage of real estate assets unlikely to be sold, such as publicly owned schools, hospital campuses, and federally owned properties. Although ascertaining the

[57] http://www.costar.com/

accuracy of these entries in individual municipalities is relatively easy, testing the accuracy of these measures across the United States is significantly more challenging.

B.4 Model Coverage and Gaps

Only DOE prototype buildings can be modeled in ComStock, so building types in CBECS and CoStar must be mapped to these 16 supported building types. The overall building count and floor area in ComStock is determined by the CoStar to DOE prototype mapping. Those buildings are then populated with additional characteristics based on the CBECS to DOE prototype mapping. This core model coverage is shown at the center of Figure B-4 as the circle labeled ComStock. The commercial building gap model consists of those CBECS building types that can be mapped to CoStar but not to the DOE prototype buildings. This is represented as the light green area surrounding ComStock. Energy represented in CBECS but not in ComStock and unmappable to CoStar is unmodeled but quantifiable; CoStar building types mapped to neither a DOE prototype nor CBECS are unrepresented and their energy use is completely unknown to this analysis. Those two slices of energy use are shown on the left and right sides of Figure B-4 respectively. Table B-1 and Table B-2 show the mapping between CoStar and DOE prototypes and 2012 CBECS and DOE prototypes respectively, along with the total number of buildings of those types reported in the CONUS. Table B-3 lists those 2012 CBECS building types that do not map to a DOE prototype building, along with their estimated electricity use and the CoStar building types they map to, if applicable.

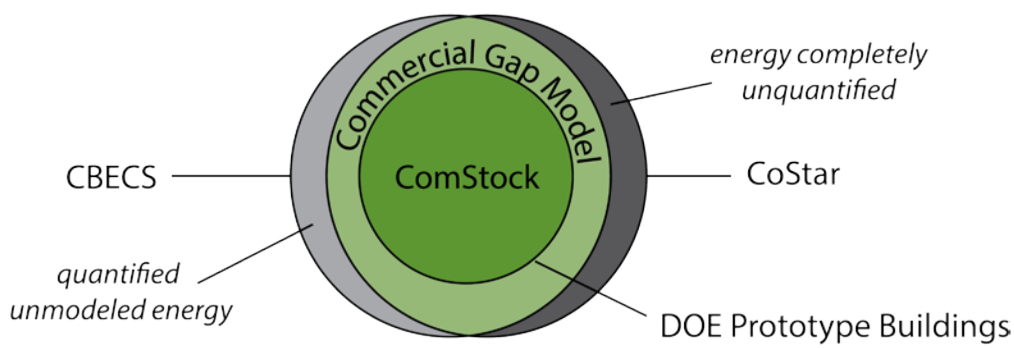

Figure B-4. Relationship between major data sources and commercial model coverage

Table B-1. Mapping of CoStar Building Combo Codes and DOE Prototype Buildings

CoStar Combo Code	DOE Prototype Building	CONUS CoStar Building Count
Flex_Light Distribution	warehouse	14,259
Flex_Light Manufacturing	warehouse	21,252
Flex_Showroom	strip_mall	6,205
Health Care_Assisted Living	midrise_apartment	11,013
Health Care_Congregate Senior Housing	midrise_apartment	1,055
Health Care_Continuing Care Retirement Community	midrise_apartment	1,140
Health Care_Hospital	hospital	4,700
Health Care_Rehabilitation Center	outpatient	2,872
Health Care_Skilled Nursing Facility	outpatient	6,009
Hospitality_Hotel	large_hotel	29,876
Hospitality_Hotel Casino	large_hotel	284
Hospitality_Motel	small_hotel	23,072
Hospitality_Single Room Occupancy Hotel	midrise_apartment	1,611
Industrial_Distribution	warehouse	32,783
Industrial_Service	warehouse	44,851
Industrial_Showroom	warehouse	7,038
Industrial_Truck Terminal	warehouse	6,605
Industrial_Warehouse	warehouse	410,878
Multi-Family_Apartments	midrise_apartment	528,468
Multi-Family_Dormitory	midrise_apartment	3,424
Office_Industrial Live/Work Unit	medium_office	2,101
Office_Loft/Creative Space	midrise_apartment	8,617
Office_Medical	outpatient	102,312
Office_Office Live/Work Unit	small_office	10,315
Office_Office/Residential	small_office	20,747
Retail_Bank	small_office	55,825
Retail_Bar	full_service_restaurant	15,715
Retail_Day Care Center	primary_school	17,046
Retail_Department Store	retail	2,937
Retail_Fast Food	quick_service_restaurant	77,699
Retail_Freestanding	retail	435,819
Retail_Garden Center	retail	5,412
Retail_Restaurant	full_service_restaurant	115,881
Retail_Storefront	strip_mall	134,575
Retail_Storefront Retail/Office	strip_mall	70,242
Retail_Storefront Retail/Residential	strip_mall	120,904
Specialty_Airplane Hangar	warehouse	2,899
Specialty_Post Office	strip_mall	19,897

CoStar Combo Code	DOE Prototype Building	CONUS CoStar Building Count
Specialty_Schools	primary_school	12,642
Specialty_Self-Storage	warehouse	29,984
Specialty_Sorority/Fraternity House	midrise_apartment	529
Matched count		*2,419,493*
Flex_R&D	no_match	9,699
Flex_Telecom Hotel/Data Hosting	no_match	1,057
Multi-Family_Manufactured Housing/Mobile Home Park	no_match	14,135
Office_Telecom Hotel/Data Hosting	no_match	976
Retail_Auto Dealership	no_match	43,599
Retail_Auto Repair	no_match	100,053
Retail_Bowling Alley	no_match	2,392
Retail_Convenience Store	no_match	46,419
Retail_Drug Store	no_match	15,895
Retail_Funeral Home	no_match	5,892
Retail_Health Club	no_match	4,350
Retail_Movie Theatre	no_match	2,811
Retail_Service Station	no_match	62,194
Retail_Supermarket	no_match	12,679
Retail_Truck Stop	no_match	760
Retail_Veterinarian/Kennel	no_match	7,076
Specialty_Airport	no_match	410
Specialty_Auto Salvage Facility	no_match	3,012
Specialty_Car Wash	no_match	16,241
Specialty_Cement/Gravel Plant	no_match	2,126
Specialty_Cemetery/Mausoleum	no_match	570
Specialty_Chemical/Oil Refinery	no_match	1,107
Specialty_Contractor Storage Yard	no_match	3,244
Specialty_Correctional Facility	no_match	412
Specialty_Drive-in Movie	no_match	46
Specialty_Landfill	no_match	144
Specialty_Lodge/Meeting Hall	no_match	12,922
Specialty_Lumberyard	no_match	698
Specialty_Marina	no_match	2,134
Specialty_Movie/Radio/TV Studio	no_match	959
Specialty_Parking Garage	no_match	3,753
Specialty_Parking Lot	no_match	3,422
Specialty_Police/Fire Station	no_match	2,626
Specialty_Public Library	no_match	1,498
Specialty_Radio/TV Transmission Facilities	no_match	611

CoStar Combo Code	DOE Prototype Building	CONUS CoStar Building Count
Specialty_Railroad Yard	no_match	250
Specialty_Recycling Center	no_match	414
Specialty_Religious Facility	no_match	37,475
Specialty_Shelter	no_match	1,134
Specialty_Shipyard	no_match	283
Specialty_Trailer/Camper Park	no_match	2,830
Specialty_Water Retention Facility	no_match	59
Specialty_Water Treatment Facility	no_match	496
Specialty_Winery/Vineyard	no_match	1,429
Sports & Entertainment_Amusement Park	no_match	659
Sports & Entertainment_Baseball Field	no_match	525
Sports & Entertainment_Casino	no_match	280
Sports & Entertainment_Golf Course/Driving Range	no_match	3,973
Sports & Entertainment_Horse Stables	no_match	948
Sports & Entertainment_Race Track	no_match	401
Sports & Entertainment_Skating Rink	no_match	978
Sports & Entertainment_Swimming Pool	no_match	569
Sports & Entertainment_Theater/Concert Hall	no_match	2,083
No match count		*440,708*
Industrial_Food Processing	not_commercial	3,870
Industrial_Manufacturing	not_commercial	105,632
Industrial_Refrigeration/Cold Storage	not_commercial	1,928
Industrial_Telecom Hotel/Data Hosting	not_commercial	1,216
Land_Commercial	not_commercial	379
Land_Industrial	not_commercial	59
Land_Residential	not_commercial	23
Specialty_Utility Sub-Station	not_commercial	1,524
Not commercial count		*114,631*
Total building count		**2,974,832**

[a] CoStar Combo Codes are derived from all possible combinations of Primary and Secondary property types within the CoStar data set.

Table B-2. Mapping of CBECS Detailed Principal Building Activity (PBAPLUS) and DOE Prototype Buildings, and Associated Building Counts

CBECS PBAPLUS Code	*PBAPLUS Description*	*DOE Prototype Building*	*CBECS* **Building** *Count (final weight for U.S.)a*
2	Admin Office	medium_office	558,062
3	Bank	small_office	91,071
4	Government Office	medium_office	113,270
5	Medical Office	small_office	50,438
6	Mixed-use Office	small_office	125,082
7	Other Office	small_office	74,451
9	Distribution	warehouse	151,361
10	Warehouse	warehouse	426,972
18	Diagnostic	outpatient	60,300
19	Clinic	outpatient	86,855
27	College	secondary_school	27,215
28	Primary School	primary_school	189,038
29	High School	secondary_school	42,708
30	Preschool	primary_school	67,726
31	Other School	primary_school	61,973
32	Fast Food	quick_service_restaurant	92,313
33	Restaurant	full_service_restaurant	178,595
35	Hospital	hospital	9,579
36	Nursing	midrise_apartment	29,535
37	Dorm	midrise_apartment	24,647
38	Hotel	large_hotel	29,982
39	Motel	small_hotel	60,913
40	Other Lodging	small_hotel	12,848
42	Retail	retail	336,273
43	Other Retail	strip_mall	58,821
50	Strip Mall	strip_mall	162,687
53	Bar/Lounge	full_service_restaurant	71,364
Matched count			*3,194,076*
8	Laboratory	no_match	15,505
11	Self-storage	no_match	208,836
12	Convenience Store	no_match	79,108
13	Convenience + Gas	no_match	51,652
14	Grocery Store	no_match	44,734
15	Other Food Sale	no_match	1,246
16	Fire/Police	no_match	68,908
17	Other Safety	no_match	8,655
20	Cold Storage	no_match	8,499

CBECS PBAPLUS Code	*PBAPLUS Description*	*DOE Prototype Building*	*CBECS* **Building** *Count (final weight for U.S.)a*
21	Religious Worship	no_match	411,799
22	Entertainment	no_match	51,180
23	Library	no_match	23,778
24	Recreation	no_match	100,363
25	Social	no_match	135,435
26	Other Assembly	no_match	41,258
34	Other Food Service	no_match	37,439
41	Vehicle Dealer	no_match	43,167
44	Postal	no_match	30,343
45	Repairs	no_match	84,492
46	Vehicle Service	no_match	214,001
47	Vehicle Storage	no_match	176,142
48	Other Service	no_match	113,568
49	Other	no_match	109,260
51	Enclosed Mall	no_match	1,379
52	Courthouse	no_match	6,278
No match count			*2,067,022*
1	Vacant	not_commercial	296,041
Not commercial count			*296,041*
Total building count			**5,557,138**

[a] Building counts are the total of the final weights associated with each instance of a CBECS PBAPLUS code. These values represent the entire U.S. (as opposed to the CONUS), as disaggregation by state is not feasible with CBECS data (whose highest level of granularity is division).

Table B-3. Mapping of CBECS Detailed Principal Building Activity (PBAPLUS) and CoStar Combo Codes for those PBAPLUS Categories without a DOE Prototype Match

CBECS PBAPLUS Code	*PBAPLUS Description*	*CoStar Combo Code*	*2012 CBECS Annual Electricity Use (TWh)*
8	Laboratory	Flex: R&D	19.0
12	Convenience Store	Retail: Convenience Store	14.5
13	Convenience + Gas	Retail: Service Station	12.1
		Retail: Truck Stop	
14	Grocery Store	Retail: Supermarket	33.7
16	Fire/Police	Specialty: Police/Fire Station	6.8
17	Other Safety	Specialty: Correctional Facility	8.0
21	Religious Worship	Specialty: Religious Facility	23.8
22	Entertainment	Sports & Entertainment: Theater/Concert Hall	20.2
23	Library	Specialty: Public Library	11.6
24	Recreation	Retail: Bowling Alley	24.8
		Retail: Health Club	
		Sports & Entertainment: Skating Rink	
		Sports & Entertainment: Swimming Pool	
41	Vehicle Dealer	Retail: Auto Dealership	7.9
46	Vehicle Service	Retail: Auto Repair	14.4
47	Vehicle Storage	Specialty: Auto Salvage Facility	8.6
		Specialty: Parking Garage	
		Gap Subtotal	*205.4*
1	Vacant	no_match	7.7
11	Self-storage	no_match	5.7
15	Other Food Sale	no_match	0.7
20	Cold Storage	no_match	12.7
25	Social	no_match	9.7
26	Other Assembly	no_match	14.0
34	Other Food Service	no_match	5.0
44	Postal	no_match	4.1
45	Repairs	no_match	3.7
48	Other Service	no_match	6.6
49	Other	no_match	36.7
51	Enclosed Mall	no_match	14.0
52	Courthouse	no_match	6.7
		Unmodeled Subtotal	**127.3**
		Total: Gap and Unmodeled	**332.7**

As shown in Table B-1, eight of the 102 combo codes defined by CoStar were determined not to be commercial building types. Fifty-three of the building combo codes cannot be adequately modeled using DOE prototype buildings. These unmatched building types account for 15% (440,708 buildings) of the total reported commercial buildings in the CONUS. Of the 53 CBECS PBAPLUS categories, 25 cannot be adequately modeled using DOE prototype buildings and one is not considered commercial. The unmatched building types account for 30% (1,596,473 buildings) of the statistically weighted CBECS commercial building estimate.

There is inherent uncertainty in the mappings defined in Table B-1 and Table B-2. For instance, one school building may be more closely aligned with a secondary school while another more closely aligns with a primary school. The implications of this mapping uncertainty on the ComStock modeling process differ for CoStar and CBECS data. Because CoStar data are used to define modeled building types, the unmatched CoStar building types are used to determine the unmodeled subsectors within ComStock. Therefore, the gap model heavily depends on this mapping, and uncertainty propagation is a significant concern. Potential unknown errors in CBECS building type mappings to prototype building types will lead to potential misrepresentation of building characteristic distributions dependent on prototype building type.

B.5 Modeling Details

The dependencies defined in Table 5 are mapped to discrete conditional probability distributions based on the sample-space segmentations shown in Figure B-2. The result is a flattened definition of a 12-dimensional probabilistic sample space maintained in a predefined spreadsheet interface. The calculation of the tabular values relies on several data sets stored and maintained by geospatial data science research staff at NREL. The calculations are performed using several Python libraries and PostGIS functionality contained in a PostgreSQL server also maintained by the NREL Geospatial Data Science team.

The discretized sample space so created is sampled based on a predetermined sample density. For the purpose of this analysis, a sample density of 350,000 simulations across the CONUS was used, based on previous analysis performed by the NREL Residential Buildings group (Wilson et al. 2016). The sample density will be examined in more detail in future work, particularly to determine key convergence criteria at different geo-temporal scales.

Appendix C. Industrial Sector Model Details

The Industrial Geospatial Analysis Tool for Energy Evaluation (IGATE-E) is a model that utilizes multiple data sources and statistical approaches to estimate the energy consumption of manufacturing plants across the United States. Originally developed by Oak Ridge National Laboratory in 2012, this tool has been used to investigate the potential for demand response and CHP at the plant level (Alkadi et al. 2013; Bhandari et al. 2018). Because industrial processes vary greatly, IGATE-E does not attempt direct simulation of loads, but rather compiles data from multiple sources and applies statistical techniques to estimate energy consumption down to the end-use level. Currently, IGATE-E is built in MATLAB with plans to release a web-based version in the future. IGATE-E's user interface is shown in Figure C-1.

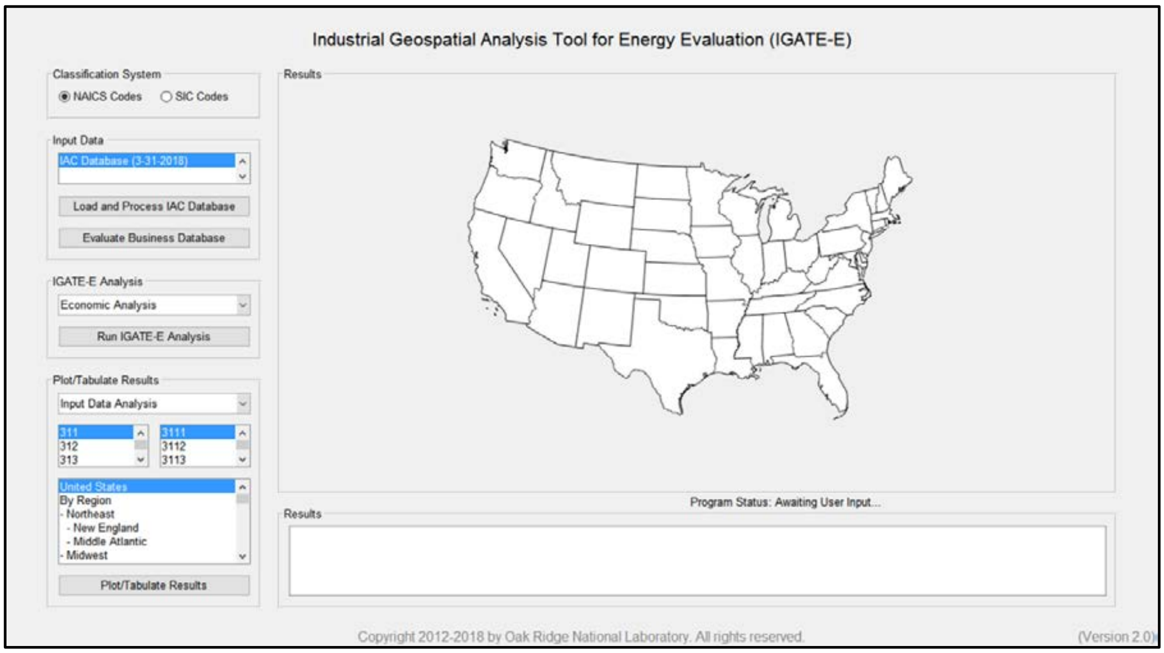

Figure C-1. IGATE-E Version 2.0

C.1 IGATE-E: Energy Consumption

The core functionality of IGATE-E involves estimating electricity and natural gas consumption for each manufacturing plant in the United States. To accomplish this, IGATE-E performs regression analyses of energy consumption versus number of employees using data from the Industrial Assessment Centers (IAC) database. Regression results are developed for individual industries based on their North American Industry Classification System (NAICS) or Standard Industrial Classification (SIC) system code. These systems are used to classify businesses according to their primary economic activity, specifically the type of product being produced.

Working within this framework, the basic premise of IGATE-E is that manufacturing facilities producing similar products (as categorized by their NAICS/SIC code) will utilize similar processes which ultimately have similar energy intensities (i.e., energy usage per product produced). In this case, number of employees are used as a proxy for the product being produced.[58] Within the model, a linear regression analysis is conducted by industry for every three- and four-digit NAICS/SIC code.[59] An example of these results is shown in Figure C-2 for the animal food manufacturing industry (NAICS 3111).

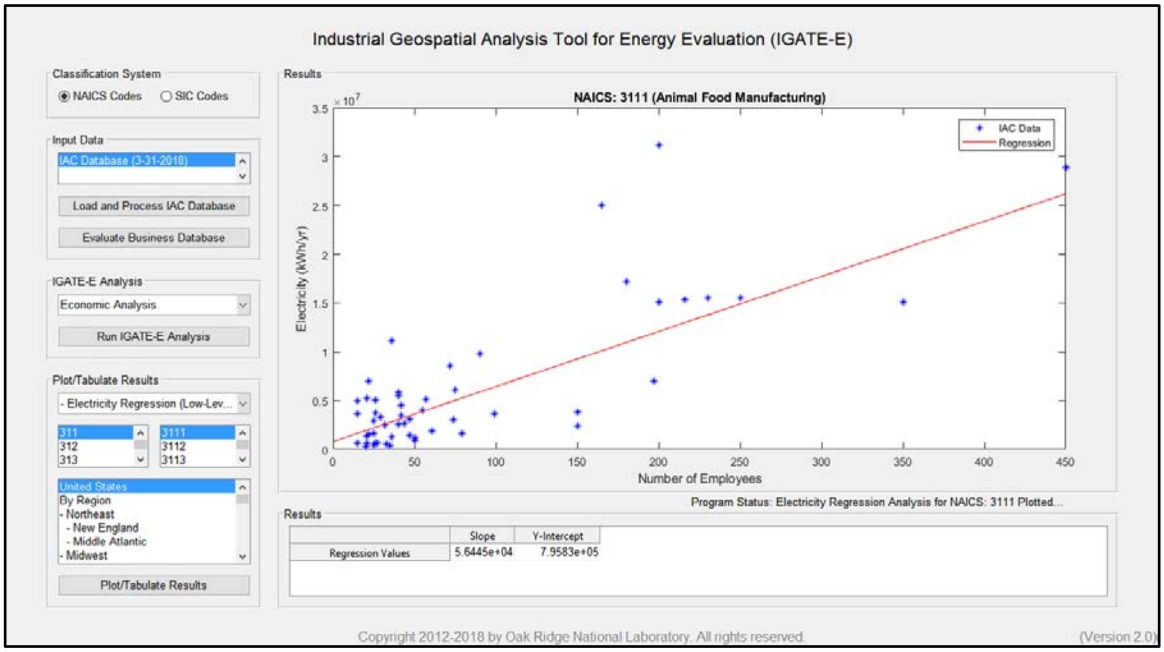

Figure C-2. NAICS: 3111 (Animal Food Manufacturing) regression results

Although this approach is comprehensive, some limitations exist. First, the IAC Database only contains data for small- and medium-sized plants,[60] limiting its relevance in industries where large manufacturing plants play a major role (DOE 2017a). Another limitation of the IAC Database is the age of its results, with assessment available back to 1981. Improvements in energy efficiency and labor productivity over the last 35 years may limit the accuracy of IGATE-E in industries where fewer recent assessments have been completed. For use in dsgrid, IGATE-E ignores assessments which do not provide information on a plant's NAICS code. As a result of this requirement, IGATE-E only uses assessment data from 2002 onward, limiting problems that could have arisen from using older data. Additional data sources have been explored to supplement this data; however, the proprietary/competitive nature of plant level information has made it difficult to find additional data beyond what is available from the IAC.

Using these regression results, energy consumption is estimated for individual plants based on employment information from the Manufacturers' News, Inc. (MNI) EZ Select database of approximately 294,000 manufacturing plants. These initial estimates are compared to the EIA's Manufacturing Energy Consumption Survey (MECS) at the three-digit NAICS code level (Table C-1).

[58] IGATE-E originally utilized annual sales data for this purpose, however, inconsistencies in quality and the sporadic availability of this data limited its value.
[59] Within IGATE-E, a requirement of five IAC assessments is specified to perform an acceptable regression. While most 4-digit industries have enough data to meet this requirement, those that do not utilize three-digit regressions instead.
[60] Eligibility requirements to qualify for an IAC Assessment include energy bills between $100,000-/yr and 2,500,000/yr.

Table C-1. Comparison of IGATE-E estimates to 2014 MECS (Initial)

NAICS	Manufacturing Type	IGATE-E (GWh)	2014 MECS (GWh)	Difference (GWh)	Difference Relative to 2014 MECS (%)
311	Food manufacturing	77,186	76,701	485	0.6
312	Beverage and tobacco products	14,413	10,014	4,399	43.9
313	Textile mills	10,841	12,687	-1,846	-14.6
314	Textile product mills	19,013	2,748	16,265	591.9
315	Apparel manufacturing	2,118	803	1,315	163.8
316	Leather and allied products	2,000	316	1,684	532.9
321	Wood products	30,291	22,353	7,938	35.5
322	Paper manufacturing	36,490	99,474	-62,984	-63.3
323	Printing and related support	33,796	14,232	19,564	137.5
324	Petroleum and coal products	10,009	67,662	-57,653	-85.2
325	Chemical manufacturing	73,449	183,096	-109,647	-59.9
326	Plastics and rubber products	68,452	55,967	12,485	22.3
327	Nonmetallic mineral products	39,799	37,841	1,958	5.2
331	Primary metal manufacturing	85,595	138,437	-52,842	-38.2
332	Fabricated metal products	47,244	43,683	3,561	8.2
333	Machinery manufacturing	44,637	23,758	20,879	87.9
334	Computer and electronic products	24,385	32,864	-8,479	-25.8
335	Electrical equipment and components	14,229	11,764	2,465	21.0
336	Transportation equipment	42,729	45,584	-2,855	-6.3
337	Furniture and related products	9,155	5,169	3,986	77.1
339	Miscellaneous	39,298	8,863	30,435	343.4
	Total	**725,129**	**894,016**	**-168,887**	**-18.9**

By comparing IGATE-E's estimates to the 2014 MECS, multiple differences emerge. Industries where consumption is significantly underestimated include:

- 322: Paper
- 324: Petroleum and Coal Products
- 325: Chemicals
- 331: Primary Metals.

In reviewing the MECS, these industries were found to have the highest energy intensities, suggesting that the lack of regression data for large manufacturing plants may be limiting IGATE-E's accuracy in these cases. For industries where consumption is significantly overestimated, discrepancies in the number of establishments considered by MECS compared to IGATE-E may be the primary issue.[61]

While additional research is being conducted to understand these differences, IGATE-E's initial estimates are adjusted by industry and census region to match the MECS. This is accomplished by scaling individual plant estimates so that aggregate consumption estimates match those from the 2014 MECS (Figure C-3). The primary drawback to this is that errors in the MECS, are ultimately reproduced by IGATE-E. Future efforts will focus on the further development of IGATE-E's optimization approach to avoid "over adjusting" the initial estimates.

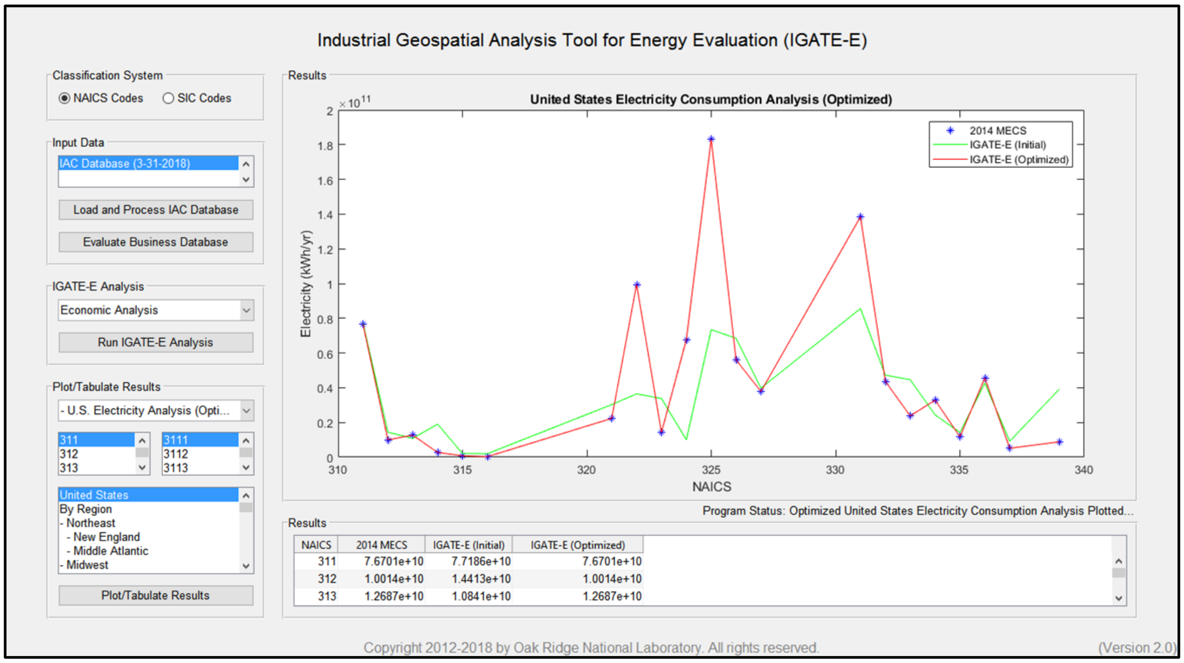

Figure C-3. Comparison of IGATE-E estimates to 2014 MECS (optimized)

C.2 IGATE-E: Load Shapes

To estimate hourly annual load shapes, a regression analysis of peak electricity versus electricity data from the IAC Database is conducted. Next, an average load factor is estimated for each individual industry based on the slope of these regressions.

$$Load\ Factor = \frac{1}{Slope * 8760}$$

These estimates are used along with energy consumption estimates to determine a plant's peak electricity demand. The resulting load factor estimates are shown in Figure C-4.

[61] For example, while the MNI database and the U.S. Census 2015 Statistics of U.S. Businesses (https://www.census.gov/programs-surveys/susb.html) largely agree on the number of manufacturing establishments, reporting 294,427 and 292,825 respectively; the 2014 MECS estimates 175,107 establishments.

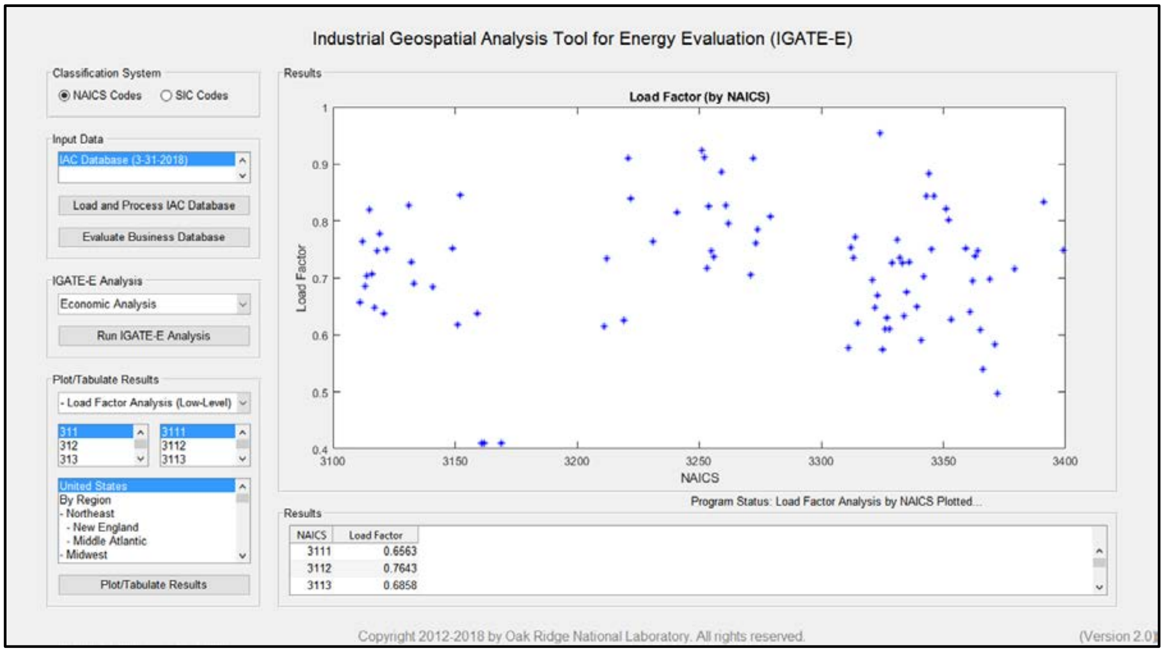

Figure C-4. IGATE-E load factor estimates by industry

To construct hourly annual load shapes, data from EPRI's Load Shape Library is utilized. This online repository provides daily load shapes by sector and end use for various scenarios (i.e., weekday versus weekend and peak season versus off-peak season). To estimate energy consumption at the end-use level, data from the 2014 MECS is applied. Next, categories included in the EPRI Load Shape Library are matched to the most appropriate MECS end-use category (Table C-2).

Table C-2. End-Use and Load Shape Category Mapping

2014 MECS End-Use Category	EPRI Load Shape Library Category
Conventional Boiler Use	Other
Process Heating	Process Heating
Process Cooling and Refrigeration	Other
Machine Drive	Machine Drives
Electro-Chemical Processes	Other
Other Process Use	Other
Facility HVAC	HVAC
Facility Lighting	Lighting
Other Facility Support	Other
Onsite Transportation	Other
Other Nonprocess Use	Other
End Use Not Reported	Other

Finally, disaggregated load shapes are constructed for each industry based on end-use consumption estimates from the 2014 MECS and load shapes from the EPRI Load Shape Library (Figure C-5). The resulting load shapes are either "stretched" or "flattened" on an industry-by-industry basis to match the load factor estimates derived previously. This approach is ultimately limited by the granularity and accuracy of the IAC Database, the MECS and the EPRI Load Shape Library.

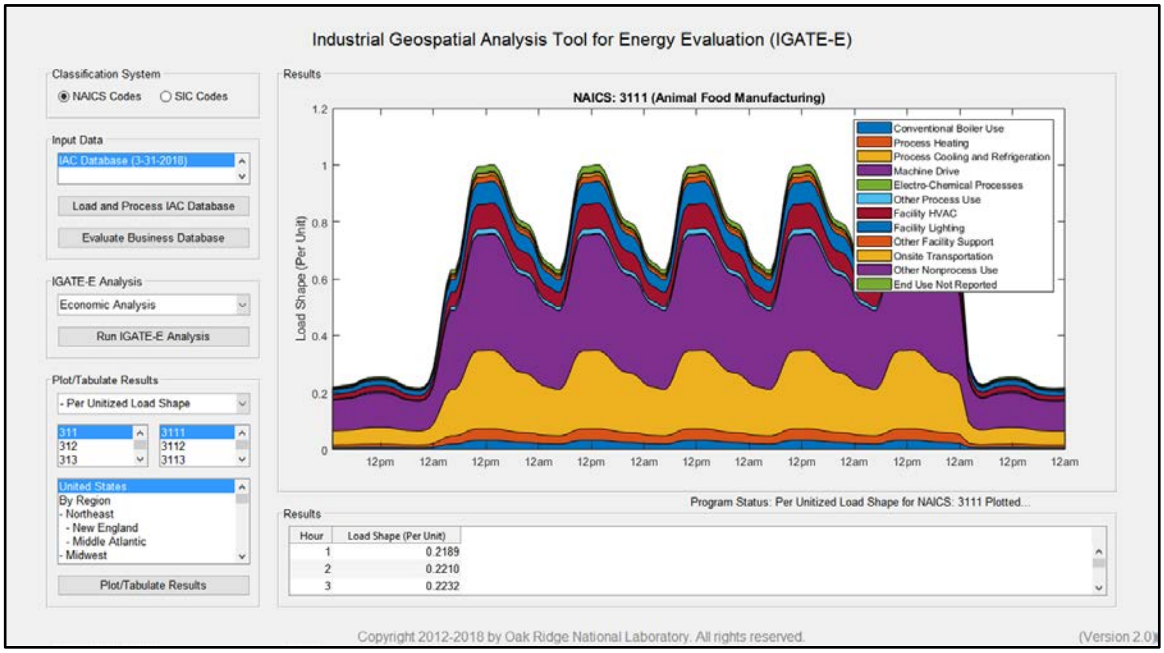

Figure C-5. NAICS: 3111 (Animal Food Manufacturing) normalized load shape

Within IGATE-E, load shapes are applied at the individual plant-level based on a plant's peak electricity demand. For use in dsgrid, plant-level peak demand estimates are compiled by county and NAICS code, with the resulting output being matched to the corresponding normalized load shape (with adjustments made to account for time zones and daylight-saving time policies).

C.3 Industrial Gap Model

Within the industrial sector, IGATE-E's methodology has specifically been developed for the manufacturing subsector. Subsectors not covered by IGATE-E include agriculture, forestry, fishing and hunting; mining, quarrying, and oil and gas extraction; and construction. In dsgrid, these non-manufacturing subsectors are represented in the industrial gap model using annual electricity estimates from the AEO, with generic load shapes taken from the EPRI Load Shape Library. To develop county level results for these subsectors, AEO national estimates are first disaggregated to the state level based on employment data from the U.S. Census Bureau's Statistics of U.S. Businesses, and then to the county level based on number of establishments data from the U.S. Census Bureau's County Business Patterns (CBP).

Appendix D. Transportation Sector Model Details

While dsgrid's general transportation focus is on electrification of on-road transportation, this report focuses on constructing a model of historical electricity demand for the year 2012. The transportation sector accounted for less than 0.2% of total electricity consumption in 2012 (7 TWh out of the total approximately 3,800 TWh consumed (see Figure 14) and vehicle electrification was still minimal (there were only approximately 75,000 PEV on the road in the country in 2012 [Cazzola et al. 2017]). Of the 7 TWh of electricity consumed for transportation in 2012, 6.6 TWh were used by intercity rail, transit rail, and commuter rail (EIA 2015a). Rail transportation is thus covered in dsgrid as a "gap"; this appendix describes the simple method used to estimate hourly electricity consumption profiles for electric transit in each state in 2012.

Methodologically, this appendix describes a process to disaggregate annual propulsion electric energy consumption estimates, obtained from the National Transit Database (NTD) (FTA 2017), spatially and temporally to generate a 50 x 8,784 matrix containing hourly energy consumption estimates for electric rail transit in every state in 2012.

D.1 The National Transit Database (NTD)

Formed in 1974, the National Transit Database (NTD) is a federal reporting program for transit agencies receiving federal funding under Federal Transit Administration (FTA) programs 5307 (Urbanized Area Formula) and 5311 (Rural Area Formula) (FTA 2017). NTD contains data related to the financial, operation, and condition of U.S. transit systems. It also requires monthly operating and safety statistics reports from agencies that file as a "Full Reporter" (those operating more than 30 vehicles). The FTA submits annual NTD reports summarizing all transit services and safety data to Congress for review and use.

NTD data products include transit provider profiles, national transit summaries and trends, transit data tables, monthly data tables, and historical timeseries. Transit data tables are the source for data from the Annual Module – a comprehensive report outlining the operations of all transit services in a given year. For 2012, the NTD contains an annual report from 67 electric transit services covering 45 U.S. urban areas that were leveraged to produce the dsgrid energy consumption estimates.

To generate hourly load profiles, three tables from the NTD 2012 Annual Module were used:

- **2012 Annual Databases Energy Consumption:** Reports annual energy consumption (in kWh propulsion) for transit services.
- **2012 Annual Database Service:** Reports annual operating hours and capacities (number of rail cars) for different scenarios, namely "Weekday," "Saturday," and "Sunday"
- **2012 Annual Database Agency UZAs:** Transit agency-to-urbanized area (UZA) crosswalk.

D.2 Methods

The total annual energy consumption (from the 2012 Annual Databases Energy Consumption) data by transit service reported by NTD was disaggregated temporally and spatially to produce hourly energy consumption estimates for electric transit in every state.

First, annual operating hours and capacities (from 2012 Annual Database Service) are used to compute an hourly utilization factor table, which is then used as a proxy to temporally disaggregate the annual energy consumption. An hourly utilization factor U_{ij} is defined for each transit service i and hour j based on the number of vehicles n_{ij}, operating for transit service i in hour j, and on the number of operating minutes t_{ij}, within that hour (e.g., if service starts at 7:30 a.m., the corresponding t_{ij} for the hour going from 7 a.m. to 8 a.m. would be 30 minutes):

$$U_{ij} = \frac{n_{ij}}{\max\ n_{i,j}\big|_{j=1}^{j=8764}} \cdot \frac{t_{ij}}{60}$$

The utilization factor varies between 0 and 1 and it represents the relative transit service load in each hour relative to the maximum service load conditions for that transit service (i.e., operating at max capacity for the full hour). Under the maximum load condition, $U = 1$. Under a half load condition (e.g., full capacity for half an hour and half capacity for full hour), $U = 0.5$. For no load $U = 0$. The resulting utilization matrix is a 67 x 8,784 matrix with each cell containing $U_{i,j}$ where i is a unique transit service and j is the hour of the year (Table D-1).

Table D-1. Sample Utilization Matrix

	1	**2**	**3**	…	**8,784**
$\boldsymbol{s_1}$	$U_{1\,1}$	$U_{1\,2}$	$U_{1\,3}$	$U_{1\,\ldots}$	$U_{1\,8784}$
$\boldsymbol{s_2}$	$U_{2\,1}$	$U_{2\,2}$	$U_{2\,3}$	$U_{2\,\ldots}$	$U_{2\,8784}$
$\vdots$	$U_{\vdots\,1}$	$U_{\vdots\,2}$	$U_{\vdots\,3}$	$U_{\vdots\,\ldots}$	$U_{\vdots\,8764}$
$\boldsymbol{s_{67}}$	$U_{67\,1}$	$U_{67\,2}$	$U_{67\,3}$	$U_{67\,\ldots}$	$U_{67\,8784}$

Hourly energy consumption estimates $e_{i\,j}$ for each transit service i and hour j are then derived from the annual energy consumption estimates E_i for each transit service i reported in the 2012 Annual Databases Energy Consumption as:

$$e_{i\,j} = \frac{U_{i\,j}}{\sum_{j=1}^{j=8,784} U_{i\,j}} \cdot E_i$$

Second, hourly energy consumption estimates are attributed to the appropriate urbanized area using the NTD's transit agency-to-UZA crosswalk (2012 Annual Database Agency UZAs) and then aggregated spatially by state for dsgrid reporting. The 67 transit services considered in the NTD data set are located in 45 urban areas that belong to 30 states. Some urban areas, however, span multiple states, as illustrated in Figure D-6 for the Portland urban area. For those urban areas that span multiple states, the energy consumption was allocated across states based on top-down annual electricity sales for the transportation sector (EIA 2013a).

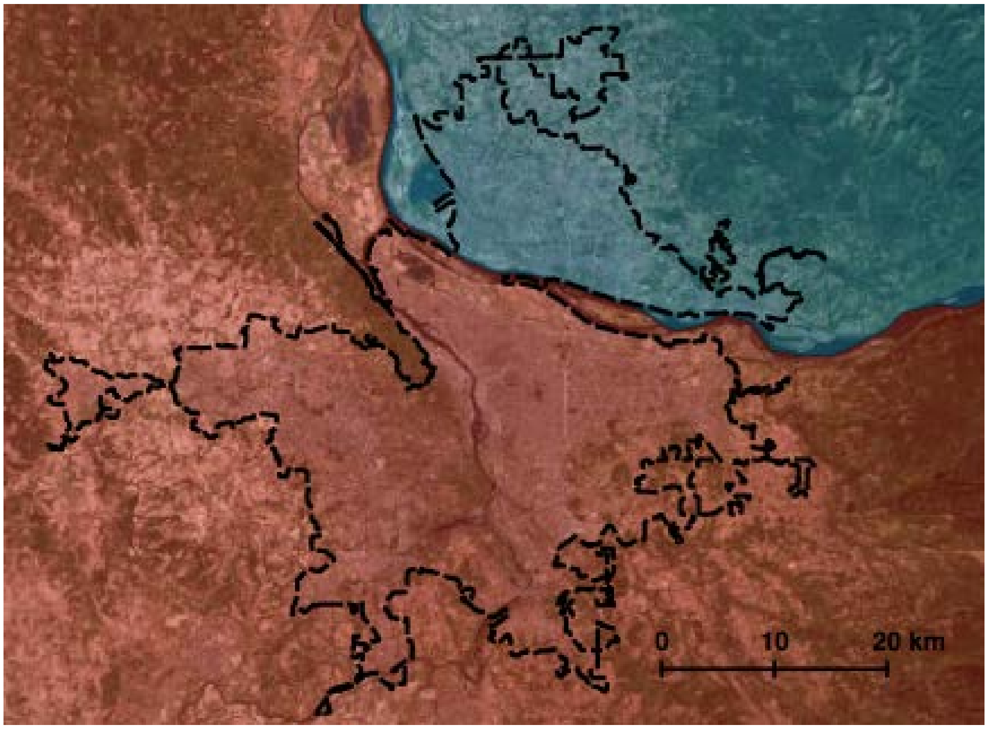

Figure D-6. The Portland, Oregon (red)-Washington (blue) urban area spans two states

Finally, all operating times were standardized to EST to sync electrical load profiles across all U.S. time zones.

D.3 Results

The methodology described above is used to generate a 50 x 8,784 matrix containing hourly timeseries of transit rail hourly electricity in kWh, one for each of the fifty states. Figure D-7 shows a map of the 2012 annual electricity demand for rail transport in each state. The magnitude of electric rail transit service varies a lot across the country: high energy demand is concentrated in large urban areas; many states have little to no electric rail transit.

To illustrate the hourly load profiles corresponding to rail transport, Figure D-8 shows the load profiles over one sample week for three states: California (CA), New York (NY), and Florida (FL). Results show the significant differences between week-end and weekdays as well as the impact of changes of service during each day (intra-hourly changes are not fully captured by the NTD data set used for this analysis).

Table D-1 shows the first 12 hours of the state-level energy estimates (in kWh) used in dsgrid.

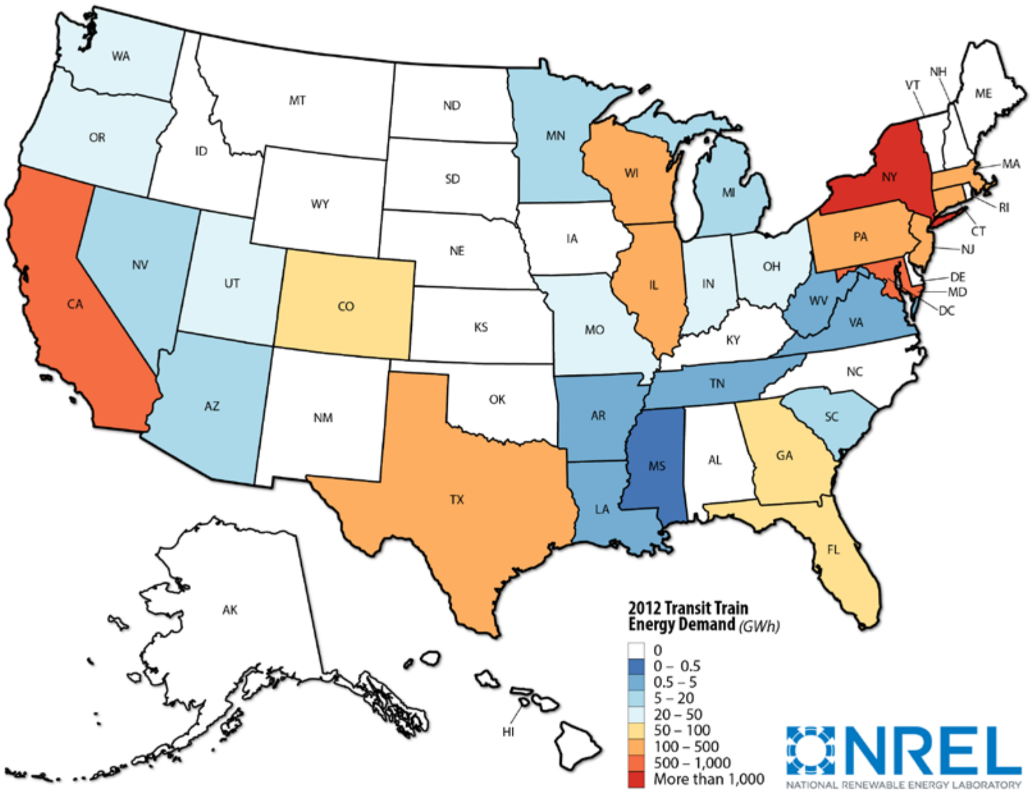

Figure D-7. 2012 annual electricity demand for rail transport by state

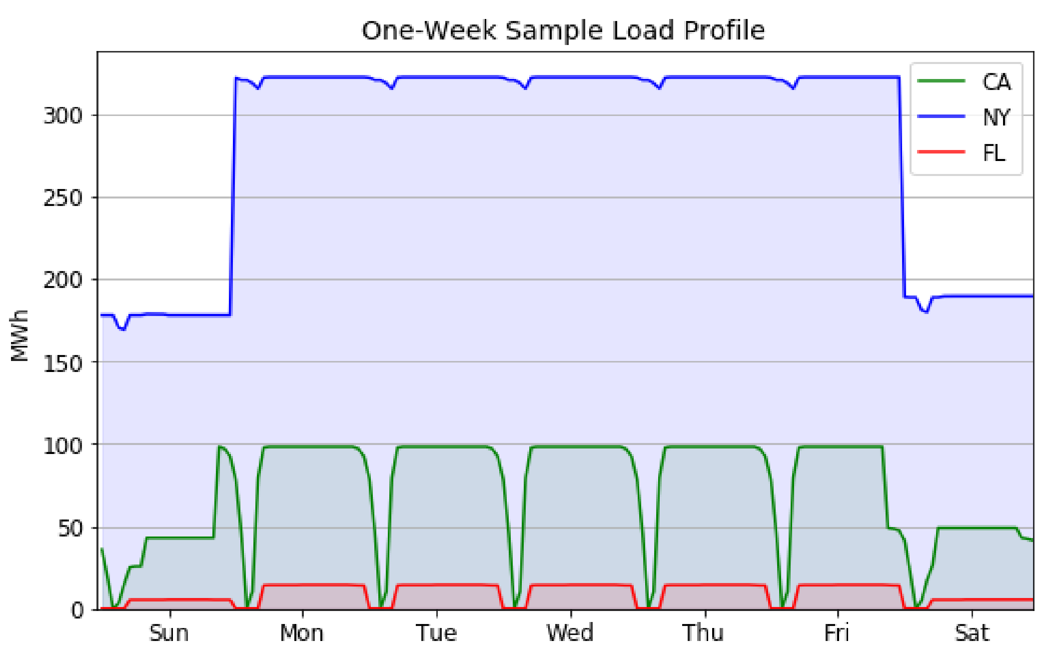

Figure D-8. Sample electrical transit load profiles for California, New York, and Florida

Profiles are shown in local time to better compare the operational profiles of different states.

Table D-1. Sample of Energy Estimation Matrix

State	1	2	3	4	5	6	7	8	9	10	11	12
AK	0	0	0	0	0	0	0	0	0	0	0	0
AL	0	0	0	0	0	0	0	0	0	0	0	0
AR	0	0	0	0	0	0	0	0	0	0	0	28
AZ	1,556	1,556	1,348	0	0	0	1,167	1,556	1,556	1,556	1,556	1,556
CA	43,027	42,460	41,480	35,874	19,017	0	3,569	14,936	25,193	25,744	25,744	43,027
CO	3,109	3,109	3,109	3,109	3,109	3,109	3,109	3,109	3,109	3,109	3,109	3,109
CT	26,709	26,709	26,709	19,142	17,806	26,709	26,709	26,709	26,709	26,709	26,709	26,709
DE	0	0	0	0	0	0	0	0	0	0	0	0
FL	0	0	0	0	0	5,431	5,431	5,431	5,431	5,431	5,431	5,431
GA	7,046	7,046	0	0	0	1,174	7,046	7,046	7,046	7,051	7,051	7,051
HI	0	0	0	0	0	0	0	0	0	0	0	0
IA	0	0	0	0	0	0	0	0	0	0	0	0
ID	0	0	0	0	0	0	0	0	0	0	0	0
IL	24,891	24,891	24,631	24,148	24,148	24,891	24,891	24,891	24,891	24,891	24,891	24,891
IN	1,389	1,389	555	0	0	926	1,389	1,389	1,389	1,389	1,389	1,389
KS	0	0	0	0	0	0	0	0	0	0	0	0
KY	0	0	0	0	0	0	0	0	0	0	0	0
LA	446	0	0	0	0	0	446	446	446	446	446	446
MA	19,594	4,089	0	0	0	3,607	19,594	19,594	19,594	19,594	19,594	19,594
MD	31,360	1,045	31,360	31,360	35,313	8,134	35,835	35,835	35,835	36,861	39,682	39,682
ME	0	0	0	0	0	0	0	0	0	0	0	0
MI	368	368	147	0	0	246	368	368	368	368	368	368
MN	1,697	1,697	1,697	1,697	1,697	1,697	1,697	1,697	1,697	1,697	1,697	1,697
MO	2,078	2,078	1,351	0	0	2,078	2,078	2,078	2,078	2,078	2,078	2,078
MS	0	0	0	0	0	0	0	0	0	0	0	39
MT	0	0	0	0	0	0	0	0	0	0	0	0

State	1	2	3	4	5	6	7	8	9	10	11	12
NC	0	0	0	0	0	0	0	0	0	0	0	0
ND	0	0	0	0	0	0	0	0	0	0	0	0
NE	0	0	0	0	0	0	0	0	0	0	0	0
NH	0	0	0	0	0	0	0	0	0	0	0	0
NJ	29,158	29,081	27,605	3,892	797	16,630	29,158	29,158	29,158	29,158	29,158	29,158
NM	0	0	0	0	0	0	0	0	0	0	0	0
NV	1,112	1,112	1,112	1,112	1,112	1,112	0	0	0	0	1,112	1,112
NY	177,970	177,970	177,970	170,402	169,067	177,970	177,970	177,970	178,586	178,586	178,586	178,473
OH	3,157	1,692	0	761	3,157	3,157	3,157	3,157	3,157	3,157	3,157	3,157
OK	0	0	0	0	0	0	0	0	0	0	0	0
OR	3,834	3,834	3,730	3,715	2,105	0	1,795	3,715	3,715	3,715	3,804	3,834
PA	17,850	6,498	2,230	2,230	8,955	19,122	19,285	22,506	24,103	24,103	24,130	24,130
RI	0	0	0	0	0	0	0	0	0	0	0	0
SC	0	0	0	0	0	0	163	336	336	336	336	336
SD	0	0	0	0	0	0	0	0	0	0	0	0
TN	0	0	0	0	0	0	0	0	0	17	17	171
TX	8,522	8,287	6,050	0	5,647	8,067	8,317	8,522	8,522	8,522	8,522	8,522
UT	1,797	0	0	0	0	0	0	0	0	0	0	3,594
VA	0	0	0	0	0	0	0	0	0	0	0	407
VT	0	0	0	0	0	0	0	0	0	0	0	0
WA	2,632	2,632	2,488	2,259	647	0	552	1,142	1,835	2,483	2,510	2,576
WI	3,391	3,391	3,391	1,130	0	0	3,391	3,391	3,391	3,391	3,391	3,456
WV	0	0	0	0	0	0	0	0	0	0	0	0
WY	0	0	0	0	0	0	0	0	0	0	0	0

Appendix E. Model Coverage Analysis Details

dsgrid requires the harmonization of multiple independent sectoral models *and* the representation of unmodeled sectors to completely depict present and potential future national electricity load. Accomplishing both requires both a calibration across sectoral models and a quantification of the contribution of unmodeled subsectors to total electricity and energy consumption.

To help meet these requirements, a top-down analysis of energy and electricity consumption was carried out across modeled and unmodeled subsectors. The results provide insights into the coverage of the dsgrid sectoral models, quantifying the relative contribution that each sectoral model can be expected to make to load totals while identifying gaps needing to be represented independently.

E.1 Method

Energy consumption estimates by subsector and end use were derived from the 2009 RECS (EIA 2013d), the 2012 CBECS (EIA 2016a), and 2014 Manufacturing Energy Consumption Survey (EIA 2017a). These sector-specific survey data were used to determine relative contributions of individual subsectors and end uses to total sectoral energy use, in terms of both electricity and overall energy.

The absolute contribution of individual subsectors and end uses to national electricity and energy consumption was subsequently determined by applying a calibration factor to each sector survey's energy use data, aligning each survey total with the AEO 2015 reported sectoral energy consumption for 2012. Because the ratio of electricity demand to total energy use differed between the sector surveys and their corresponding AEO sector values, a least-squares procedure was applied to co-optimize the calibration factors for best-fit alignment with both sectoral electrical demand and sectoral total energy consumption.

As the industrial survey data (MECS) only covered manufacturing subsectors, the calibration factor to match to the AEO sector total was calculated with respect to only the manufacturing subcomponent of the AEO industrial sector data. The AEO non-manufacturing subcomponent—which was further broken down into agriculture, construction, and mining subsectors—was added directly to the final data set (i.e., with a calibration factor of 1.0). A similar approach was applied to directly add AEO 2015's 2012 subsectoral transport data to the final data set, given the absence of a transport sector survey.

Each subsector in the reference data set could then be tagged as either modeled (either in detail or with a coarse gap model) or unmodeled, yielding an estimate of the size and location of gaps between the bottom-up model results and national totals. The list of modeled and unmodeled subsectors is provided in Table E-1.

Table E-1. Subsectors Categorized as Modeled in Detail, Sectoral Gap Model, or Unmodeled

Sector	Modeled Subsectors (Detailed)	Modeled Subsectors (Gap)	Unmodeled Subsectors
Residential Data source: RECS 2009	Single Family Detached Five+ Unit Apartment	Single Family Attached Two- to Four Unit Apartment Mobile Home	—
Commercial Data source: CBECS 2012	Administrative/Professional Office Bank/Other Financial Bar/Pub/Lounge Clinic/Other Outpatient Health College/University Distribution/Shipping Center Dormitory/Fraternity/Sorority Elementary/Middle School Fast Food Government Office Highschool Hospital/Inpatient Health Hotel Medical Office—Diagnostic Medical Office—NonDiagnostic Mixed Use Office Motel/Inn Non-Refrigerated Warehouse Nursing Home/Assisted Living Other Classroom Education Other Lodging Other Office Other Retail Preschool/Daycare Restaurant/Cafeteria Retail Store Strip Shopping Mall	Convenience Store Convenience Store with Gas Station Entertainment/Culture Fire Station/Police Station Grocery Store/Food Market Laboratory Library Other Public Order and Safety Recreation Religious/Worship Vehicle Dealership Showroom Vehicle Service Repair Shop Vehicle Storage/Maintenance	Courthouse/Probation Office Enclosed Mall Other Other Food Sales Other Food Service Other Public Assembly Other Service Post Office/Postal Center Refrigerated Warehouse Repair Shop Self-storage Social/Meeting Vacant

Sector	Modeled Subsectors (Detailed)	Modeled Subsectors (Gap)	Unmodeled Subsectors
Industrial Data Sources: MECS 2014 (manufacturing) + AEO 2015 (non-manufacturing)	Food Beverage and Tobacco Products Textile Mills Textile Product Mills Apparel Leather and Allied Products Wood Products Paper Printing and Related Support Petroleum and Coal Products Chemicals Plastics and Rubber Products Nonmetallic Mineral Products Primary Metals Fabricated Metal Products Machinery Computer and Electronic Products Electrical Equip., Appliances, and Components Transportation Equipment Furniture and Related Products Miscellaneous	Agriculture Construction Mining	-
Transportation Data source: AEO 2015	Bus Transportation Commercial Light Trucks Freight Trucks Light-Duty Vehicles	Rail—Passenger	Air Lubricants Military Use Natural Gas Pipeline Rail—Freight Recreational Boats Shipping—Domestic Shipping—International

E.2 Results

Electricity Gaps

Eighty percent of 2012 national electricity consumption is represented in one of dsgrid's four core sectoral models. An additional 16% is represented via coarser gap models. Detailed model gaps are split primarily between the commercial, residential, and industrial sectors, with only a small share of unmodeled electrical load in the transportation sector (due to transportation's small contribution to overall load in 2012). These breakdowns are shown in Figure E-1.

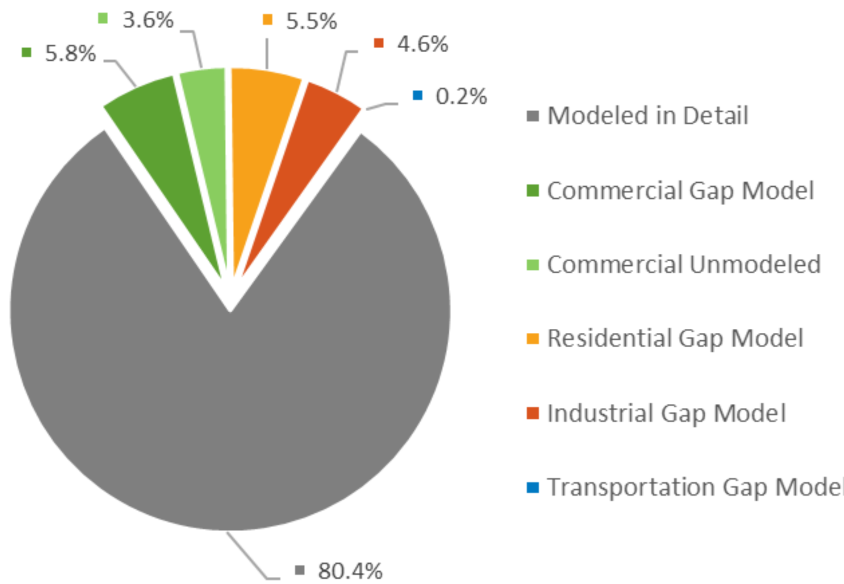

Figure E-1. Proportion of annual electricity use in each sectoral modeling category

The two single-largest subsectors in terms of annual electrical load not captured by a detailed core model are mobile homes (residential sector) and mining (industrial sector). Apartment buildings with 2–4 units (residential), single-family attached dwellings (residential) and construction (industry) were other non-core model subsectors each contributing more than 1% to total national load. Though the commercial buildings sector accounts the largest amount of non-core-model load by sector, its gaps are spread out over a larger number of unmodeled or coarsely-modeled subsectors. The largest non-core model subsectors by electrical load are summarized in Table E-2 and Table E-3.

Table E-2. Largest Subsectors Represented by Coarse Gap Models, by Total Electricity Use

Sector	Gap-Modeled Subsector	Proportion of Sector Electricity Use (%)	Proportion of National Electricity Use (%)
Commercial	Grocery Store / Food Market	2.7	1.0
	Recreation	2.0	0.7
	Religious Worship	1.9	0.7
Residential	Mobile Home	7.2	2.3
	2–4 Unit Apartment	5.0	1.6
	Single Family Attached	4.7	1.5
Industrial	Mining	6.5	2.1
	Construction	4.8	1.6
	Agriculture	2.7	0.9
Transportation	Rail-Passenger	94.6	0.2

Table E-3. Largest Unmodeled Subsectors, by Total Electricity Use

Sector	Unmodeled Subsector	Proportion of Sector Electricity Use (%)	Proportion of National Electricity Use (%)
Commercial	Other	3.0	1.0
	Other Public Assembly	1.1	0.4
	Enclosed Mall	1.1	0.4

Total Site Energy Gaps

Seventy-six percent of 2012 total national energy use is nominally captured by the four core sectoral models. Unlike with the electricity-only case, the largest modeling gaps are in transport and industry, which have more than twice as much unmodeled or coarsely-modeled energy as compared to the residential and commercial sectors. Figure E-2 provides a breakdown by sector and model type.

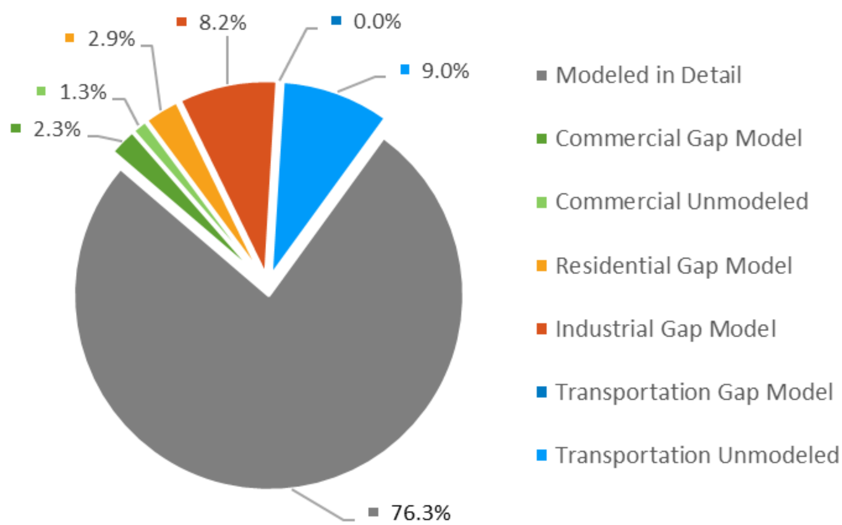

Figure E-2. Annual total site energy use gaps in sectoral models

The largest gap-model subsectors once again include mining, construction and 2–4 unit apartments, with various transport subsectors (most notably air transport) becoming significant gaps when consumption is analyzed in terms of all site energy. The largest non-core model subsectors by total site energy are summarized in Table E-4 and Table E-5.

Table E-4. Largest Subsectors Represented by Coarse Gap Models, by Total Site Energy Use

Sector	Unmodeled Subsector	Proportion of sector site energy use (%)	Proportion of national site energy use (%)
Commercial	Religious Worship	2.5	0.3
	Grocery Store/Food Market	2.3	0.3
	Recreation	2.1	0.3
Residential	2–4 Unit Apartment	6.7	1.2
	Single Family Attached	5.4	0.9
	Mobile Home	4.6	0.8
Industrial	Mining	17.2	4.3
	Construction	10.0	2.5
	Agriculture	5.4	1.3
Transportation	Passenger Rail	0.1	0.04

Table E-5. Largest Unmodeled Subsectors, by Total Site Energy Use

Sector	Unmodeled Subsector	Proportion of sector site energy use (%)	Proportion of national site energy use (%)
Commercial	Other	2.4	0.3
	Other Public Assembly	1.2	0.2
Transportation	Air	8.9	3.9
	NG Pipelines	2.9	1.3
	Military Transport	2.7	1.2
	International Shipping	2.5	1.1
	Freight Rail	1.7	0.7

Electric or Electrifiable Site Energy Coverage Analysis

The coverage analysis also categorized sector end uses by their viability for electrification to estimate overall electrification potential relative to model coverage. Because our categorization (Table E-6) is aligned with Table 1.1 in Mai et al. (2018), "electrifiable" in this instance does not carry its vernacular meaning but is more a statement about whether electrification of the end use or subsector is being considered by the wider Electrification Futures Study (EFS). Subsectors without detailed survey data (transportation and non-manufacturing industrial) were treated as a single end use.

Table E-6. Electrifiable and Non-Electrifiable End Uses by Sector

Sector	Electrifiable End Uses	End Uses Not Electrified in the EFS
Commercial	Space Heating Air Conditioning Ventilation Water Heating Lighting Cooking Refrigeration Office Equipment Computing	Other
Residential	Space Heating Air Conditioning Water Heating Refrigeration	Other
Industrial	Conventional Boiler Use Process Heating Process Cooling and Refrigeration Machine Drive Electro-Chemical Processes Facility HVAC Facility Lighting	End Use Not Reported Mining Agriculture Construction Other Facility Support Onsite Transportation Other Process Use Other Nonprocess Use
Transportation	Light-Duty Vehicles Commercial Light Trucks Freight Trucks Bus Transportation	Rail – Freight Rail – Passenger Shipping – Domestic Shipping – International Air Military Use Recreational Boats Lubricants Natural Gas Pipelines

We then summarize the proportion of site energy use that is either already electric, or is labeled as "electrifiable" above, and compare that to the remaining energy, that is, non-electric site-energy use in categories labeled as "end uses not electrified in the EFS." Based on these categorizations, 82% of national end-use energy use was considered electric or electrifiable, with 91% of that energy represented by a detailed sector model, and 8% covered by a gap model. Table E-7 provides a cross-tabulation across model fidelity and electrifiability.

Table E-7. End-Use Energy Share by Model Detail and Electrifiability

	Electric or Electrifiable Site Energy Use (%)	Non-Electric Energy whose Electrification is Not Considered in the EFS (%)
Detailed Model	74.2	2.1
Gap Model	6.1	7.3
Unmodeled	1.2	9.1

Appendix F. Historical Year Model Results, CONUS-Level Description of Gap Models and Distributed Generation

The residential gap model is summarized by subsector and end use in the body of the report alongside the detailed residential modeling. The other gap models are characterized by reduced resolution along at least one dimension. We summarize them here in the form of summary tables and diurnal load shape plots.

F.1 Commercial Gaps

The commercial building gap model does not include end-use information. The load shape for each subsector in the gap model follows the overall commercial building load shape at whatever finest level resolution is available. As a result, at the CONUS level of aggregation it is approximately equal to the top line load shape seen in Figure 24. Analogously, to the extent that the commercial gap model shape varies by region, the regional shapes are visible in the commercial diurnal plots available by census division in Appendix G.

We summarize the commercial building gap model here in Table F-1 and Table F-2.

Table F-1. Commercial Gap Model Annual Summary for the CONUS in 2012, by Subsector and Census Division

Census Division/ Subsector	South Atlantic	Pacific	East North Central	West South Central	Mid Atlantic	New England	West North Central	East South Central	Mountain	Total
Grocery Store/Food Market (GWh)	2,474	9,889	2,810	3,789	8,356	2,634	876	1,417	1,209	33,452
Recreation (GWh)	4,535	4,215	6,204	1,849	1,691	1,444	2,009	918	1,882	24,746
Religious Worship (GWh)	5,970	2,423	2,791	3,036	3,379	651	1,377	3,181	935	23,743
Entertainment Culture (GWh)	4,411	1,892	3,880	2,867	3,734	431	933	309	1,728	20,184
Laboratory (GWh)	5,460	3,052	3,135	807	2,626	2,123	-	135	1,630	18,968
Convenience Store (GWh)	3,695	804	2,111	2,089	1,503	1,370	1,162	661	1,074	14,468
Vehicle Service Repair Shop (GWh)	3,485	1,182	2,452	2,077	1,005	877	2,249	761	266	14,353
Convenience Store with Gas Station (GWh)	4,182	1,025	695	1,868	-	328	679	2,017	1,247	12,043
Library (GWh)	1,841	501	1,231	5,432	680	1,130	129	552	122	11,619
Vehicle Storage Maintenance (GWh)	1,399	2,486	1,736	318	492	526	688	598	263	8,507
Other Public Order and Safety (GWh)	2,252	474	1,013	2,973	554	88	245	283	121	8,003
Vehicle Dealership Showroom (GWh)	3,431	1,605	737	1,137	875	-	43	-	-	7,828
Fire Station/Police Station (GWh)	2,050	526	544	1,086	297	1,049	845	369	-	6,768
Total (GWh)	**45,186**	**30,074**	**29,340**	**29,328**	**25,191**	**12,650**	**11,235**	**11,202**	**10,476**	**204,682**

Table F-2. Commercial Gap Model Annual Summary for the CONUS in 2012, Proportions by Subsector and Census Division

Census Division/ Subsector	South Atlantic	Pacific	East North Central	West South Central	Mid Atlantic	New England	West North Central	East South Central	Mountain	Total
Grocery Store/Food Market (%)	5.5	32.9	9.6	12.9	33.2	20.8	7.8	12.6	11.5	16.3
Recreation (%)	10.0	14.0	21.1	6.3	6.7	11.4	17.9	8.2	18.0	12.1
Religious Worship (%)	13.2	8.1	9.5	10.4	13.4	5.1	12.3	28.4	8.9	11.6
Entertainment Culture (%)	9.8	6.3	13.2	9.8	14.8	3.4	8.3	2.8	16.5	9.9
Laboratory (%)	12.1	10.1	10.7	2.8	10.4	16.8	-	1.2	15.6	9.3
Convenience Store (%)	8.2	2.7	7.2	7.1	6.0	10.8	10.3	5.9	10.2	7.1
Vehicle Service Repair Shop (%)	7.7	3.9	8.4	7.1	4.0	6.9	20.0	6.8	2.5	7.0
Convenience Store with Gas Station (%)	9.3	3.4	2.4	6.4	-	2.6	6.0	18.0	11.9	5.9
Library (%)	4.1	1.7	4.2	18.5	2.7	8.9	1.1	4.9	1.2	5.7
Vehicle Storage Maintenance (%)	3.1	8.3	5.9	1.1	2.0	4.2	6.1	5.3	2.5	4.2
Other Public Order and Safety (%)	5.0	1.6	3.5	10.1	2.2	0.7	2.2	2.5	1.2	3.9
Vehicle Dealership Showroom (%)	7.6	5.3	2.5	3.9	3.5	-	0.4	-	-	3.8
Fire Station/Police Station (%)	4.5	1.8	1.9	3.7	1.2	8.3	7.5	3.3	-	3.3
Total (%)	**22.1**	**14.7**	**14.3**	**14.3**	**12.3**	**6.2**	**5.5**	**5.5**	**5.1**	**100.0**

The non-building commercial gap models for municipal water and outdoor lighting are summarized in Table F-3 and Table F-4 respectively. The corresponding load shapes for all of the CONUS are depicted in Figure F-1 and Figure F-2.

Table F-3. Municipal Water Gap Model Annual Summary for the CONUS in 2012, Electricity Use and Proportions by Subsector and Census Division

Census Division	Public Water Supply (GWh)	Wastewater Treatment (GWh)	Total (GWh)	Public Water Supply (%)	Wastewater Treatment (%)	Total (%)
Pacific	15,827	4,637	20,465	77.3	22.7	26.2
South Atlantic	7,534	5,802	13,335	56.5	43.5	17.1
East North Central	5,836	4,495	10,331	56.5	43.5	13.2
Mid Atlantic	5,140	3,959	9,099	56.5	43.5	11.6
West South Central	4,576	3,524	8,100	56.5	43.5	10.4
Mountain	2,778	2,140	4,918	56.5	43.5	6.3
West North Central	2,579	1,986	4,565	56.5	43.5	5.8
East South Central	2,318	1,785	4,103	56.5	43.5	5.3
New England	1,817	1,400	3,217	56.5	43.5	4.1
Total	**48,405**	**29,726**	**78,131**	**62.0**	**38.0**	**100.0**

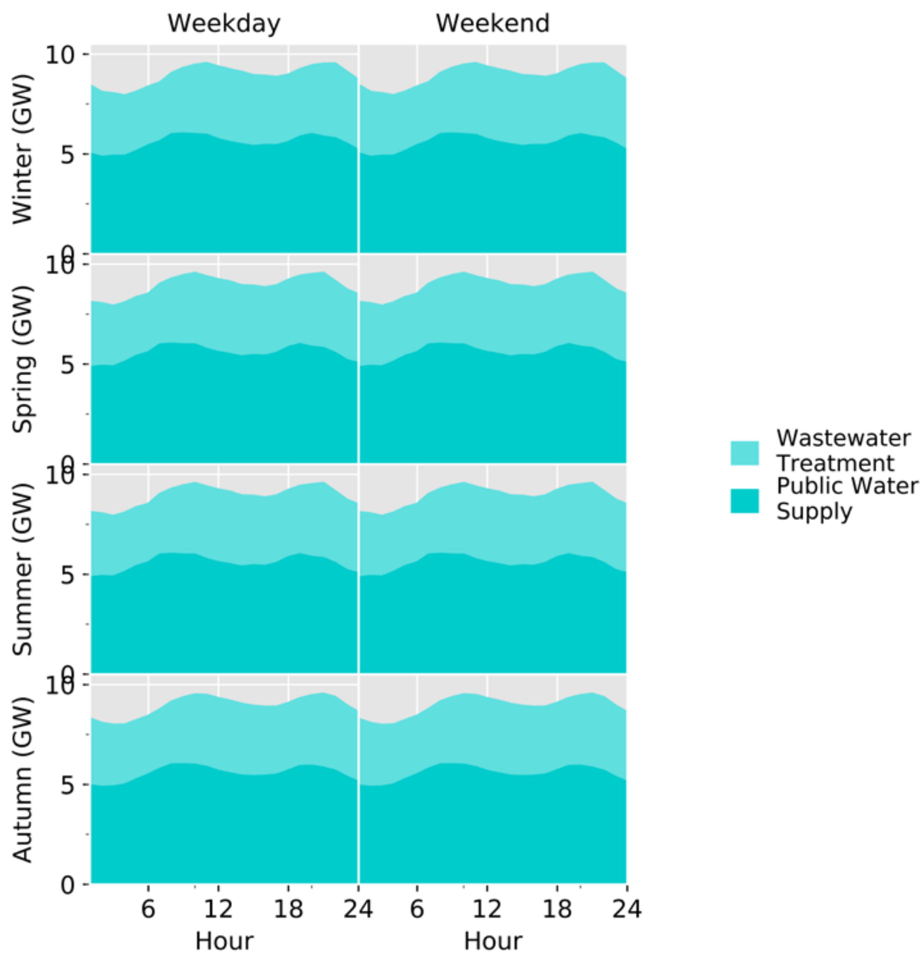

Figure F-1. Municipal water gap model diurnal load shapes

Table F-4. Outdoor Lighting Gap Model Annual Summary for the CONUS in 2012, Electricity Use and Proportions by Subsector and Census Division

Census Division	Parking (GWh)	Roadway (GWh)	Total (GWh)	Parking (%)	Roadway (%)	Total (%)
South Atlantic	20,916	12,406	33,322	62.8	37.2	19.5
Pacific	16,717	9,915	26,633	62.8	37.2	15.6
East North Central	16,203	9,610	25,814	62.8	37.2	15.1
Mid Atlantic	14,271	8,465	22,736	62.8	37.2	13.3
West South Central	12,705	7,536	20,241	62.8	37.2	11.9
Mountain	7,713	4,575	12,288	62.8	37.2	7.2
West North Central	7,159	4,246	11,406	62.8	37.2	6.7
East South Central	6,435	3,817	10,252	62.8	37.2	6.0
New England	5,046	2,993	8,038	62.8	37.2	4.7
Total	**107,166**	**63,562**	**170,728**	**62.8**	**37.2**	**100.0**

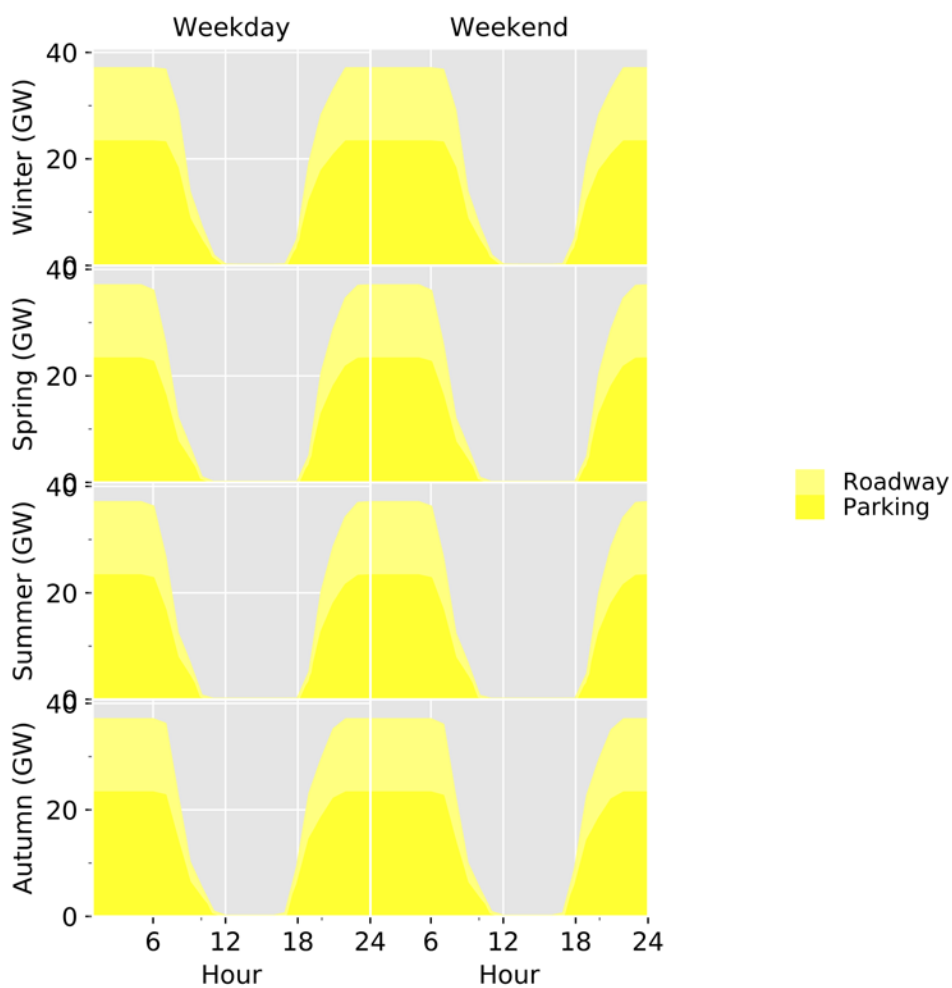

Figure F-2. Outdoor lighting gap model diurnal load shapes for the CONUS in 2012

F.2 Industrial Gaps

Similar to the commercial building gap model, the load shapes for the industrial gap model are essentially the same as the detailed modeling for the industrial sector taken as a whole, and no end-use specificity is provided. And, we summarize this model on an annual basis by census division in Table F-5.

Table F-5. Industrial Gap Model Annual Summary for the CONUS in 2012, Electricity Use and Proportions by Subsector and Census Division

Census Division	Mining, Quarrying, and Oil and Gas Extraction (GWh)	Construction (GWh)	Agriculture, Forestry, Fishing and Hunting (GWh)	Total (GWh)	Mining, Quarrying, and Oil and Gas Extraction (%)	Construction (%)	Agriculture, Forestry, Fishing and Hunting (%)	Total (%)
West South Central	40,738	9,497	3,644	53,879	75.6	17.6	6.8	29.3
South Atlantic	7,229	12,226	7,833	27,288	26.5	44.8	28.7	14.8
Pacific	3,336	9,128	11,720	24,183	13.8	37.7	48.5	13.1
Mountain	14,883	5,335	1,985	22,203	67.0	24.0	8.9	12.1
East North Central	3,941	7,975	2,565	14,481	27.2	55.1	17.7	7.9
Mid Atlantic	4,835	7,886	1,338	14,060	34.4	56.1	9.5	7.6
West North Central	5,220	4,730	2,193	12,144	43.0	39.0	18.1	6.6
East South Central	4,798	3,305	3,194	11,297	42.5	29.3	28.3	6.1
New England	354	2,728	1,356	4,439	8.0	61.5	30.6	2.4
Total	**85,335**	**62,811**	**35,830**	**183,975**	**46.4**	**34.1**	**19.5**	**100.0**

F.3 Transportation Gaps

The transportation gap model for electricity used for passenger rail is summarized in Table F-6. The CONUS load shape is plotted in Figure F-3.

Table F-6. Transportation Gap Model for Passenger Rail Electricity, Annual Summary for the CONUS in 2012 by Census Division

Census Division	Total GWh)	Total (%)
Mid Atlantic	3,304	51.5
South Atlantic	793	12.4
New England	709	11.0
Pacific	706	11.0
East North Central	623	9.7
Mountain	124	1.9
West South Central	114	1.8
West North Central	43	0.7
East South Central	2	0.0
Total	6,417	100.0

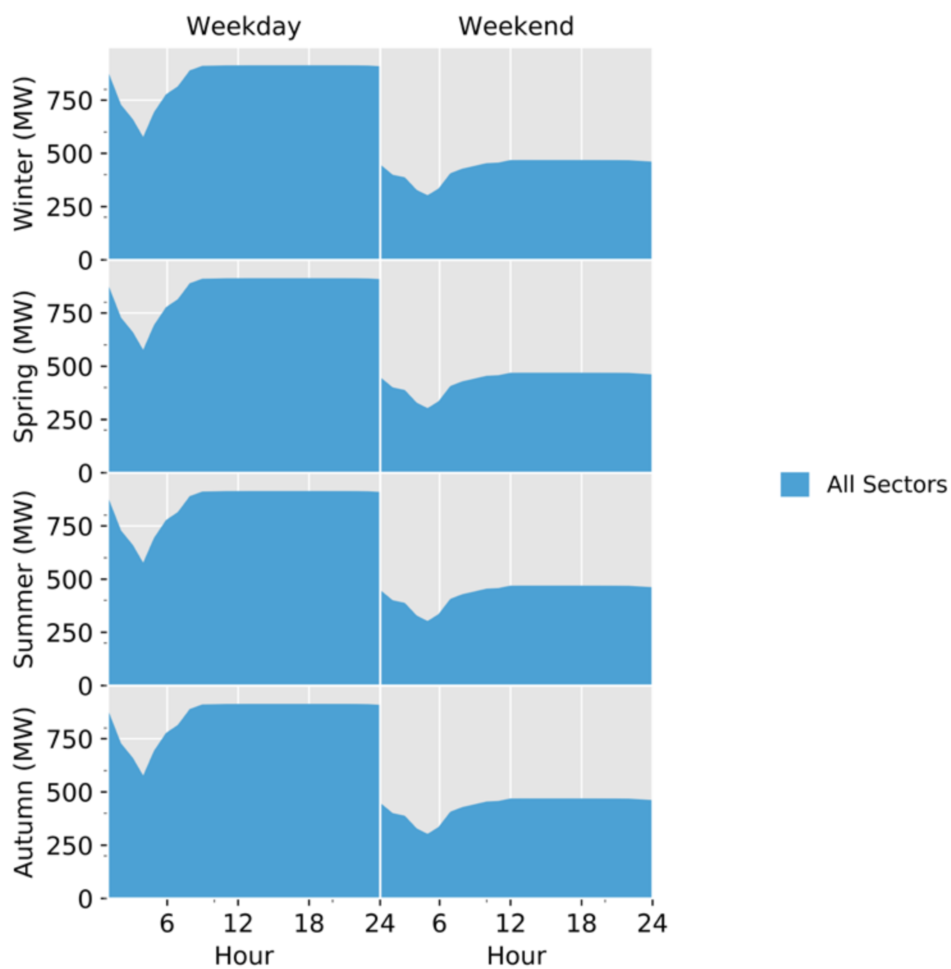

Figure F-3. Transportation gap model diurnal load shapes for the CONUS in 2012

F.4 Distributed Generation

The distributed generation model provides estimates of behind-the-meter generation from CHP plants, other distributed thermal plants, and PV. This is done by sector and by state. The model is summarized for all of the CONUS in Table F-7. The diurnal generation patterns are shown in Figure F-4. CHP and distributed thermal plants are modeled mostly as baseload plants. The solar diurnal pattern is readily apparent in the DPV profiles.

Table F-7. Distributed Generation Model, Annual Summary for the CONUS in 2012

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	194,988	28,457	375	223,820
Thermal DG (GWh)	6,782	561	—	7,343
Distributed PV (GWh)	1,814	1,810	2,386	6,010
Total (GWh)	**203,584**	**30,828**	**2,761**	**237,173**
CHP (%)	95.8	92.3	13.6	94.4
Thermal DG (%)	3.3	1.8	—	3.1
Distributed PV (%)	0.9	5.9	86.4	2.5
Total (%)	**85.8**	**13.0**	**1.2**	**100.0**

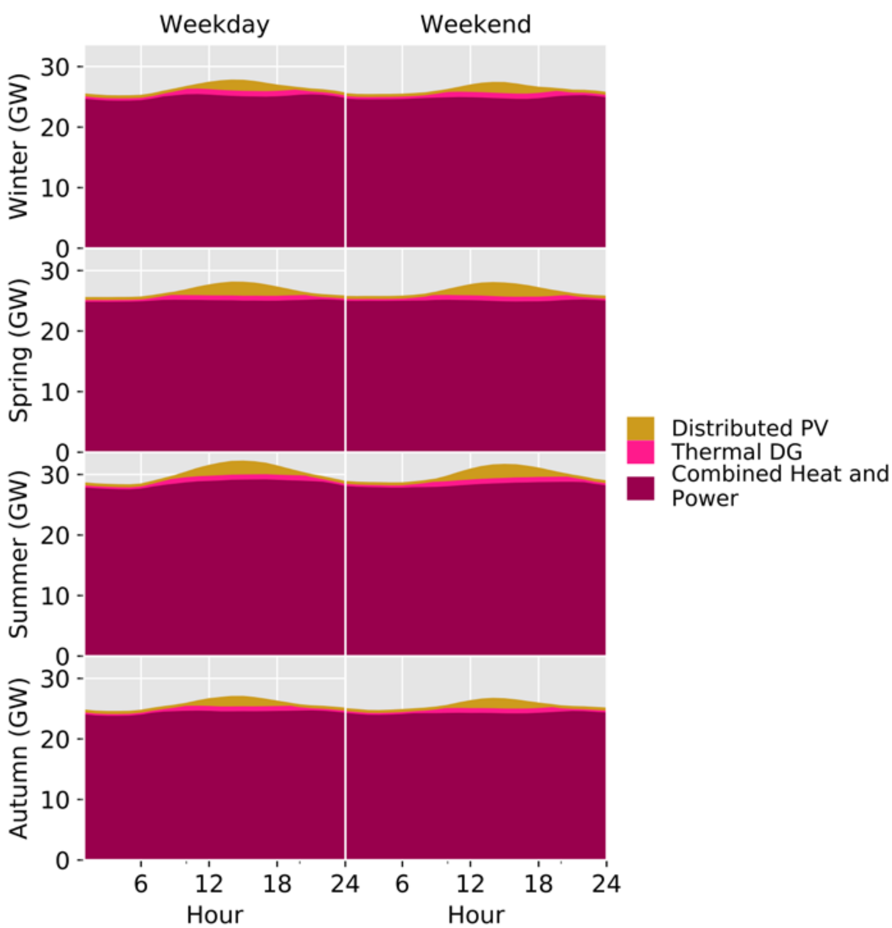

Figure F-4. Distributed generation model diurnal generation patterns for CONUS in 2012

Appendix G. Historical Year Model Results by Census Division

We present results analogous to those in Section 3, but at a finer level of geographic detail, namely at the census division level. The census divisions are defined by the U.S. Census Bureau. For the purposes of this report, we model only the contiguous United States. Those 48 states and the District of Columbia (Washington, D.C.) are listed in Table G-1 next to their corresponding census division and region. The other two states, Alaska and Hawaii, are both in the Pacific census division.

Table G-1. States Listed by Census Region and Division

Census Region	Census Division	States
Midwest	West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
	East North Central	Indiana, Illinois, Michigan, Ohio, Wisconsin
Northeast	New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
	Mid Atlantic	New Jersey, New York, Pennsylvania
South	South Atlantic	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
	East South Central	Alabama, Kentucky, Mississippi, Tennessee
	West South Central	Arkansas, Louisiana, Oklahoma, Texas
West	Mountain	Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming
	Pacific	California, Oregon, Washington

G.1 West North Central

Table G-2. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, West North Central Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					360.6
Derived	T&D losses					21.3
Top-down	Annual energy	102.8	100.6	91.3	0.0	294.8
dsgrid	Distributed generation	–	1.0	4.6	–	5.6
dsgrid-core	Gap models	11.8	27.2	12.1	0.0	51.2
dsgrid-core	Detailed sector models	83.7	65.2	69.3	–	218.2
Derived	Total site energy	102.8	101.6	95.9	0.0	300.4
Derived	Annual sector residuals	7.3	9.3	14.4	-0.0	31.0
Derived	Hourly residuals					75.5

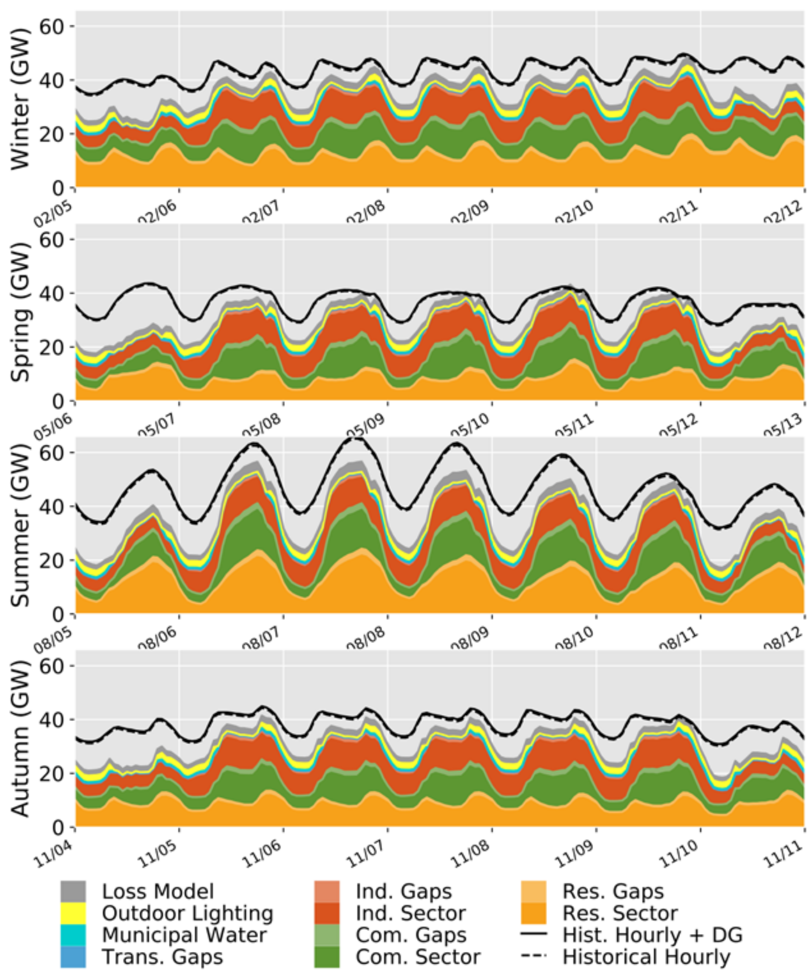

Figure G-1. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the West North Central census division in 2012

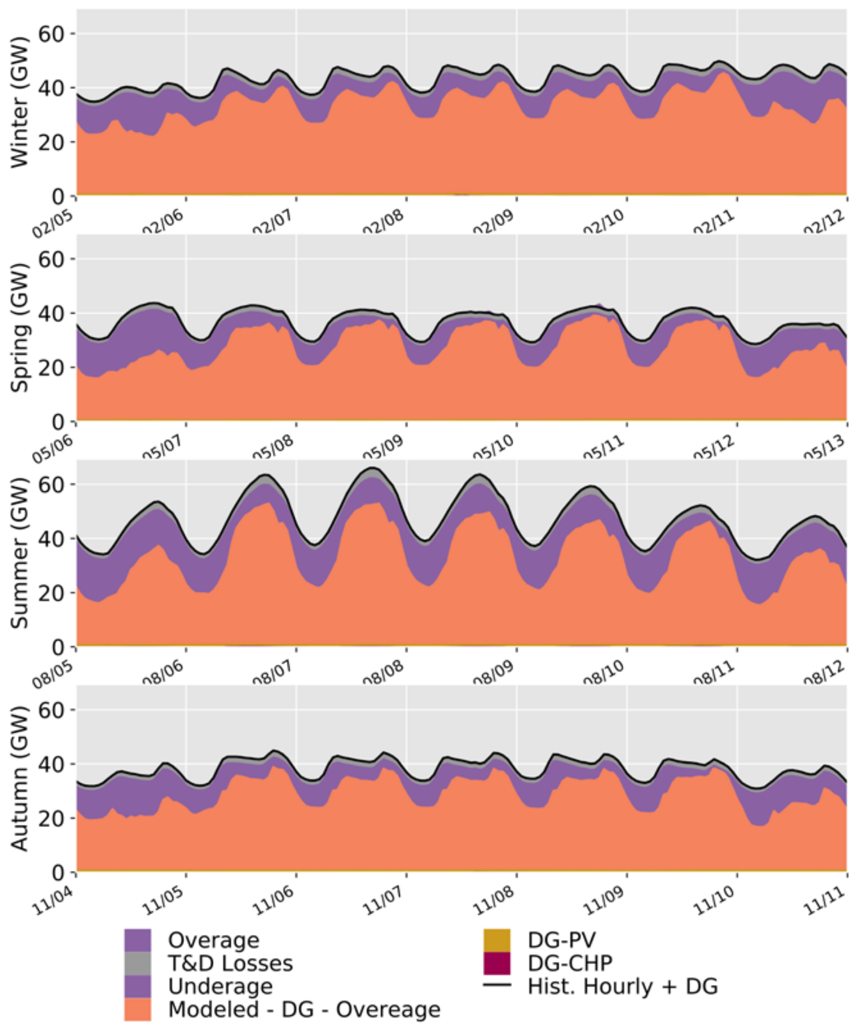

Figure G-2. dsgrid hourly residuals shown in context for the West North Central census division.

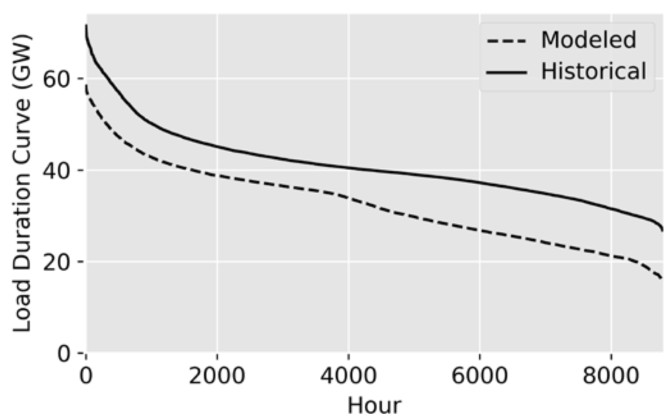

Figure G-3. Historical and dsgrid load duration curves for the West North Central census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-3. Residential Subsectors, Summary of Electricity by End Use for the West North Central Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Interior Lights (GWh)	Space Heating (GWh)	Fans (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	32,662	14,179	10,298	8,672	7,152	7,499	2,092	76	—	82,630
Mobile Home	2,008	717	416	364	342	490	68	4	—	4,409
Single Family Attached	1,730	618	359	313	295	422	58	4	—	3,798
Apartment in Building 2 to 4 Units	1,224	470	463	272	520	—	561	47	16	3,573
Midrise Apartment Building	347	143	144	98	165	—	173	15	5	1,089
Total	**37,970**	**16,126**	**11,680**	**9,719**	**8,474**	**8,411**	**2,952**	**145**	**21**	**95,498**

Table G-4. Residential Electricity Proportions by Subsector and End Use for the West North Central Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Interior Lights (%)	Space Heating (%)	Fans (%)	Water Systems (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	39.5	17.2	12.5	10.5	8.7	9.1	2.5	0.1	—	86.5
Mobile Home	45.5	16.3	9.4	8.2	7.8	11.1	1.5	0.1	—	4.6
Single Family Attached	45.5	16.3	9.4	8.2	7.8	11.1	1.5	0.1	—	4.0
Apartment in Building 2 to 4 Units	34.3	13.2	13.0	7.6	14.6	—	15.7	1.3	0.5	3.7
Midrise Apartment Building	31.9	13.1	13.2	9.0	15.1	—	15.8	1.3	0.4	1.1
Total	**39.8**	**16.9**	**12.2**	**10.2**	**8.9**	**8.8**	**3.1**	**0.2**	**0.0**	**100.0**

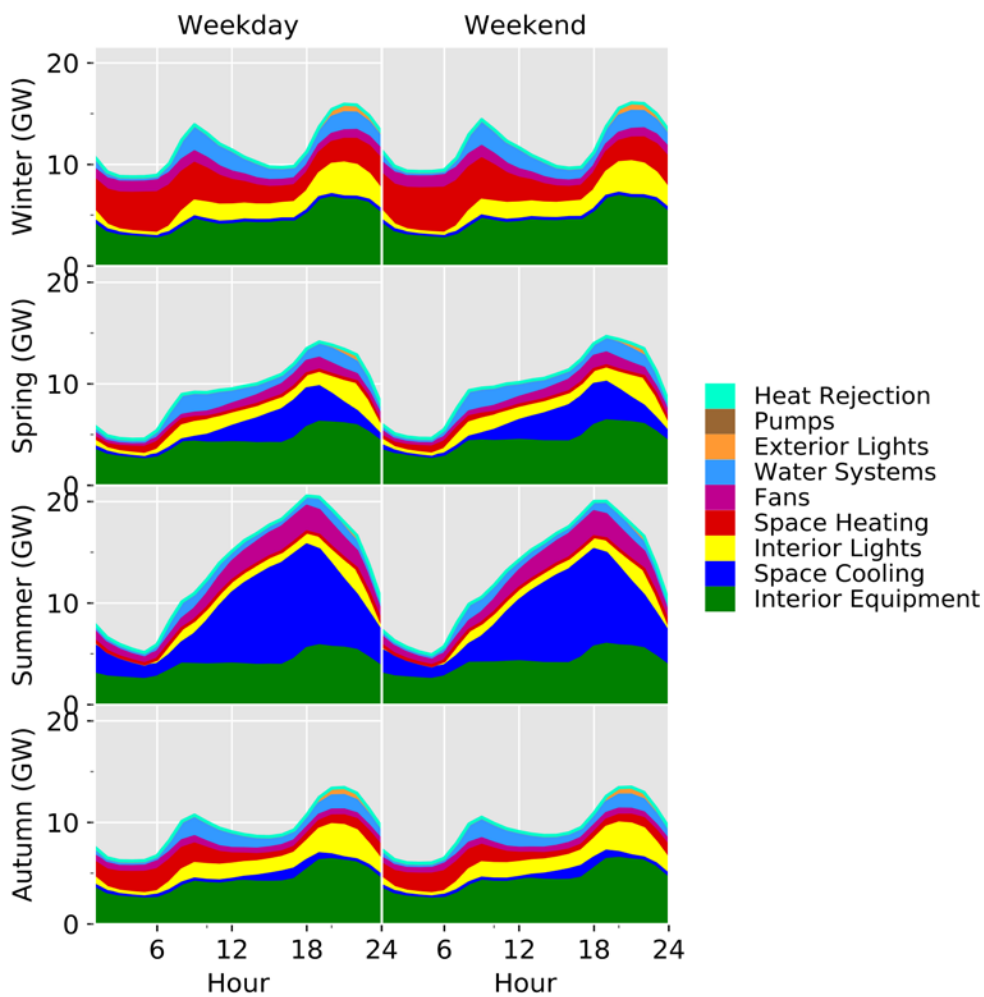

Figure G-4. Residential electricity use diurnal patterns by season, modeled for the West North Central census division 2012

Table G-5. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the West North Central Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Strip Mall	11,541	1,690	3,224	1,578	2,365	701	9	3	21,111
Large Office	4,116	4,746	3,346	2,436	826	114	393	134	16,111
Standalone Retail Store	3,882	1,213	1,452	733	594	715	2	1	8,590
Medium Office	1,139	1,301	941	690	404	67	59	18	4,618
Warehouse	1,175	472	601	120	576	679	5	2	3,631
Small Office	829	1,139	575	382	323	128	5	3	3,385
Full Service Restaurant	597	1,332	331	250	167	93	4	1	2,776
Large Hotel	368	613	405	286	99	71	10	3	1,855
Hospital	391	432	215	182	28	—	35	13	1,296
Primary School	319	252	152	102	40	72	7	3	947
Outpatient Treatment Facility	150	221	89	66	54	—	12	5	596
Small Hotel	52	75	9	6	36	8	1	0	187
Quick Service Restaurant	6	35	12	7	3	1	0	0	64
Total	**24,565**	**13,522**	**11,352**	**6,838**	**5,516**	**2,650**	**541**	**186**	**65,168**

Table G-6. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the West North Central Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Strip Mall	54.7	8.0	15.3	7.5	11.2	3.3	0.0	0.0	32.4
Large Office	25.6	29.5	20.8	15.1	5.1	0.7	2.4	0.8	24.7
Standalone Retail Store	45.2	14.1	16.9	8.5	6.9	8.3	0.0	0.0	13.2
Medium Office	24.7	28.2	20.4	14.9	8.7	1.4	1.3	0.4	7.1
Warehouse	32.4	13.0	16.5	3.3	15.9	18.7	0.1	0.0	5.6
Small Office	24.5	33.7	17.0	11.3	9.6	3.8	0.2	0.1	5.2
Full Service Restaurant	21.5	48.0	11.9	9.0	6.0	3.4	0.2	0.1	4.3
Large Hotel	19.8	33.0	21.9	15.4	5.3	3.8	0.6	0.2	2.8
Hospital	30.2	33.4	16.6	14.0	2.2	—	2.7	1.0	2.0
Primary School	33.7	26.6	16.1	10.8	4.2	7.6	0.7	0.3	1.5
Outpatient Treatment Facility	25.2	37.1	14.9	11.0	9.1	—	2.0	0.8	0.9
Small Hotel	27.7	40.3	4.8	3.0	19.4	4.4	0.3	0.1	0.3
Quick Service Restaurant	9.2	54.4	18.2	11.1	5.4	1.7	0.0	0.0	0.1
Total	**37.7**	**20.7**	**17.4**	**10.5**	**8.5**	**4.1**	**0.8**	**0.3**	**100.0**

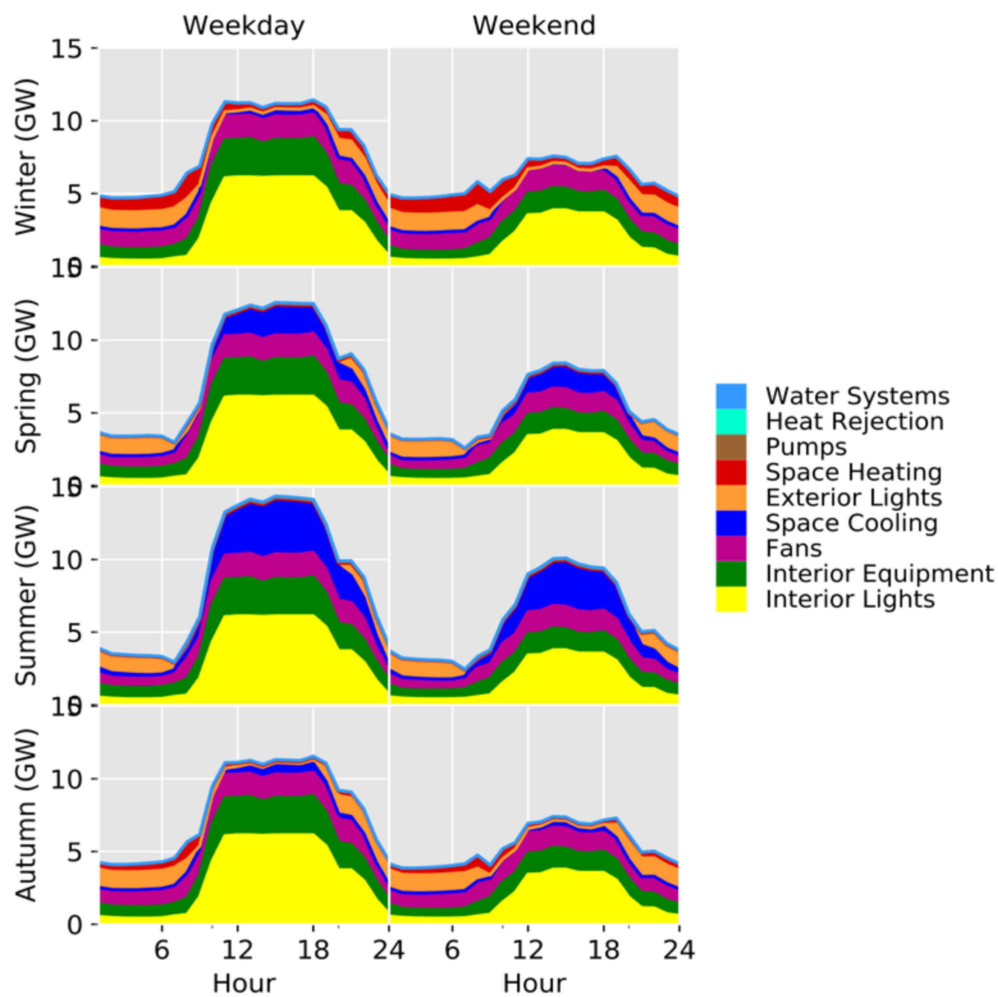

Figure G-5. Commercial electricity use diurnal patterns by season, modeled for the West North Central census division 2012

Table G-7. Industrial Manufacturing Subsectors, Summary of Model Results for the West North Central Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Facility HVAC (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Animal Slaughtering and Processing	2,652	263	1,611	516	454	14	111	123	189	136	57	26	6,151
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	2,790	181	486	319	205	857	78	61	107	69	13	13	5,178
Plastics Product Manufacturing	1,957	586	292	370	346	—	—	83	18	—	16	—	3,668
Petroleum and Coal Products Manufacturing	2,688	113	140	126	84	48	24	33	25	37	0	3	3,321
Iron and Steel Mills and Ferroalloy Manufacturing	859	1,103	47	200	140	734	50	38	15	63	5	9	3,263
Basic Chemical Manufacturing	1,720	111	290	192	124	511	46	36	64	41	8	8	3,150
Converted Paper Product Manufacturing	1,898	99	42	111	97	21	86	27	117	13	5	—	2,515
Grain and Oilseed Milling	961	95	577	185	163	5	40	44	68	49	20	9	2,217
Pulp, Paper, and Paperboard Mills	1,599	83	35	93	81	17	71	23	97	11	4	—	2,115
Animal Food Manufacturing	892	89	548	175	154	5	38	42	64	46	19	9	2,081
Pharmaceutical and Medicine Manufacturing	1,008	65	172	113	73	304	27	22	38	25	5	5	1,856
Other Fabricated Metal Product Manufacturing	741	254	55	263	166	66	61	57	—	—	12	3	1,677
Aerospace Product and Parts Manufacturing	629	179	82	305	204	11	80	64	14	25	23	19	1,634
Architectural and Structural Metals Manufacturing	688	236	51	247	155	62	57	53	—	—	11	3	1,565
Dairy Product Manufacturing	668	66	397	128	113	3	27	30	47	34	14	6	1,534
Printing and Related Support Activities	837	64	116	263	131	18	22	44	13	—	17	—	1,526
Other Nonmetallic Mineral Product Manufacturing	797	378	58	97	74	26	32	23	13	—	6	2	1,506
Cement and Concrete Product Manufacturing	669	318	49	82	62	22	27	19	11	—	5	2	1,267
Foundries	298	381	16	69	48	251	17	13	5	22	2	3	1,125
Other Chemical Product and Preparation Manufacturing	561	36	95	63	40	167	15	12	21	14	3	2	1,029
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	521	34	90	59	38	159	14	11	20	13	2	2	965
Fruit and Vegetable Preserving and Specialty Food Manufacturing	408	40	248	79	70	2	17	19	29	21	9	4	947
Other Food Manufacturing	400	40	239	77	68	2	17	18	28	20	8	4	921
Bakeries and Tortilla Manufacturing	369	37	222	71	63	2	15	17	26	19	8	4	853
Coating, Engraving, Heat Treating, and Allied Activities	351	121	27	127	80	32	30	28	—	—	6	2	803

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Facility HVAC (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Motor Vehicle Manufacturing	294	84	39	145	97	5	38	31	6	12	11	9	773
Motor Vehicle Parts Manufacturing	287	82	37	140	93	5	37	29	6	12	10	9	747
Nonferrous Metal (except Aluminum) Production and Processing	196	250	10	44	31	160	11	8	3	14	1	2	731
Other General Purpose Machinery Manufacturing	308	71	30	151	103	7	17	27	7	—	7	—	729
Glass and Glass Product Manufacturing	385	182	28	46	35	13	15	11	6	—	3	1	724
Agriculture, Construction, and Mining Machinery Manufacturing	297	69	28	143	98	7	16	26	7	—	7	—	697
Semiconductor and Other Electronic Component Manufacturing	148	77	74	155	59	15	47	31	6	14	2	12	639
Other Wood Product Manufacturing	461	39	4	46	37	2	7	10	11	7	2	2	628
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	320	21	54	36	23	95	9	7	12	8	1	1	586
Paint, Coating, and Adhesive Manufacturing	308	20	53	35	23	94	9	7	12	8	1	1	570
Other Miscellaneous Manufacturing	171	60	37	126	73	4	10	25	8	—	3	1	519
Alumina and Aluminum Production and Processing	137	175	7	31	22	113	8	6	2	10	1	1	512
Rubber Product Manufacturing	259	78	39	49	46	—	—	11	2	—	2	—	486
Motor Vehicle Body and Trailer Manufacturing	182	52	24	89	60	3	23	19	4	7	7	6	477
Beverage Manufacturing	171	20	94	56	44	1	12	16	8	36	10	2	470
Other Electrical Equipment and Component Manufacturing	128	105	29	76	45	36	17	10	2	—	3	—	451
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	102	53	52	109	42	10	33	22	4	10	1	9	449
Forging and Stamping	196	67	15	70	44	17	16	15	—	—	3	1	445
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	199	15	7	82	68	1	—	14	5	—	4	2	397
Other Transportation Equipment Manufacturing	136	39	18	67	45	2	17	14	3	6	5	4	356
Sugar and Confectionery Product Manufacturing	151	15	92	29	26	1	6	7	11	8	3	1	351
Industrial Machinery Manufacturing	147	34	14	71	48	3	8	13	3	—	3	—	345
Medical Equipment and Supplies Manufacturing	103	36	22	75	43	2	6	15	5	—	2	1	309
Metalworking Machinery Manufacturing	123	29	12	60	41	3	7	11	3	—	3	—	292

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Facility HVAC (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	122	42	9	44	28	11	10	10	—	—	2	1	279
Commercial and Service Industry Machinery Manufacturing	117	27	11	57	39	3	6	10	3	—	3	—	276
Steel Product Manufacturing from Purchased Steel	73	93	4	16	12	60	4	3	1	5	0	1	272
Communications Equipment Manufacturing	61	32	31	65	25	6	20	13	2	6	1	5	268
Engine, Turbine, and Power Transmission Equipment Manufacturing	112	26	11	54	37	3	6	10	3	—	3	—	263
Lime and Gypsum Product Manufacturing	136	65	10	17	13	5	6	4	2	—	1	0	258
Electrical Equipment Manufacturing	71	58	17	43	25	20	9	6	1	—	2	—	253
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	76	18	7	37	25	2	4	7	2	—	2	—	180
Veneer, Plywood, and Engineered Wood Product Manufacturing	131	11	1	13	10	1	2	3	3	2	0	1	177
Spring and Wire Product Manufacturing	77	26	6	28	17	7	6	6	—	—	1	0	175
Computer and Peripheral Equipment Manufacturing	29	15	15	32	12	3	10	7	1	3	0	3	130
Railroad Rolling Stock Manufacturing	48	14	6	24	16	1	6	5	1	2	2	2	127
Office Furniture (including Fixtures) Manufacturing	60	4	2	25	21	0	—	4	1	—	1	1	121
Other Textile Product Mills	61	8	8	15	12	0	1	3	6	—	3	—	115
Boiler, Tank, and Shipping Container Manufacturing	51	17	4	18	11	4	4	4	—	—	1	0	114
Household Appliance Manufacturing	30	25	7	18	10	8	4	2	0	—	1	—	105
Ship and Boat Building	38	11	5	19	13	1	5	4	1	2	1	1	100
Clay Product and Refractory Manufacturing	44	21	3	5	4	1	2	1	1	—	0	0	84
Seafood Product Preparation and Packaging	27	3	17	5	5	0	1	1	2	1	1	0	63
Cutlery and Handtool Manufacturing	27	9	2	10	6	2	2	2	—	—	0	0	62
Manufacturing and Reproducing Magnetic and Optical Media	14	7	7	15	6	1	4	3	1	1	0	1	60
Fabric Mills	23	3	1	6	3	0	1	1	1	—	0	—	39
Other Leather and Allied Product Manufacturing	24	3	1	4	4	0	0	1	0	—	0	—	38
Audio and Video Equipment Manufacturing	8	4	4	8	3	1	2	2	0	1	0	1	33
Electric Lighting Equipment Manufacturing	9	7	2	5	3	2	1	1	0	—	0	—	31

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Facility HVAC (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Fiber, Yarn, and Thread Mills	13	2	1	3	2	0	0	0	0	—	0	—	21
Textile and Fabric Finishing and Fabric Coating Mills	11	2	1	3	1	0	0	0	0	—	0	—	18
Footwear Manufacturing	11	1	1	2	2	0	0	0	0	—	0	—	18
Cut and Sew Apparel Manufacturing	7	1	0	5	3	—	—	1	0	—	0	—	16
Leather and Hide Tanning and Finishing	9	1	1	1	2	0	0	0	0	—	0	—	15
Tobacco Manufacturing	5	1	3	2	1	0	0	0	0	1	0	0	14
Other Furniture Related Product Manufacturing	6	0	0	3	2	0	—	0	0	—	0	0	13
Sawmills and Wood Preservation	5	0	0	1	0	0	0	0	0	0	0	0	7
Textile Furnishings Mills	3	0	0	1	1	0	0	0	0	—	0	—	5
Hardware Manufacturing	2	1	0	1	0	0	0	0	—	—	0	0	4
Apparel Accessories and Other Apparel Manufacturing	0	0	0	0	0	—	—	0	0	—	0	—	0
Total	**33,716**	**7,201**	**7,007**	**6,863**	**4,852**	**4,080**	**1,492**	**1,440**	**1,201**	**831**	**400**	**222**	**69,305**

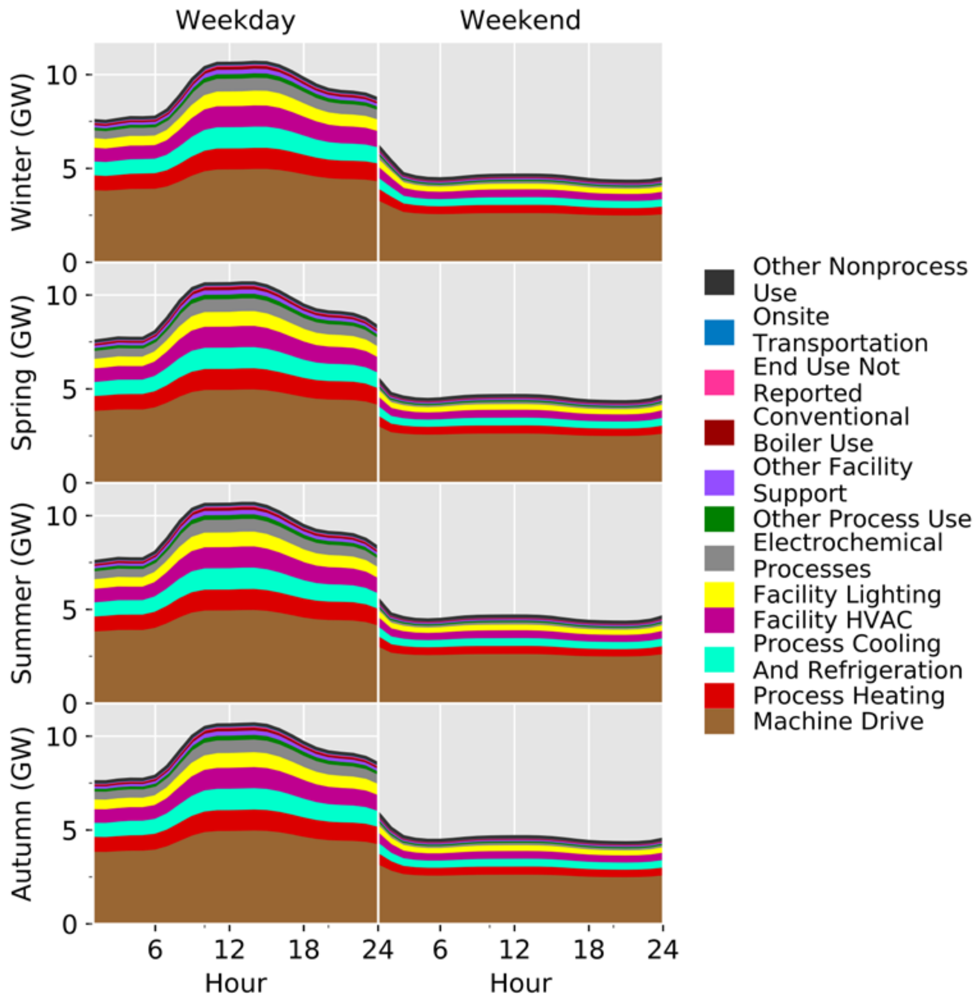

Figure G-6. Industrial electricity use diurnal patterns by season, modeled for the West North Central census division 2012

Table G-8. Distributed Generation Model, Annual Summary the West North Central Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	4,512	938	—	5,450
Distributed PV (GWh)	47	46	29	121
Thermal DG (GWh)	6	7	—	13
Total (GWh)	**4,565**	**991**	**29**	**5,585**
CHP (%)	98.8	94.7	—	97.6
Distributed PV (%)	1.0	4.6	100.0	2.2
Thermal DG (%)	0.1	0.7	—	0.2
Total (%)	**81.7**	**17.7**	**0.5**	**100.0**

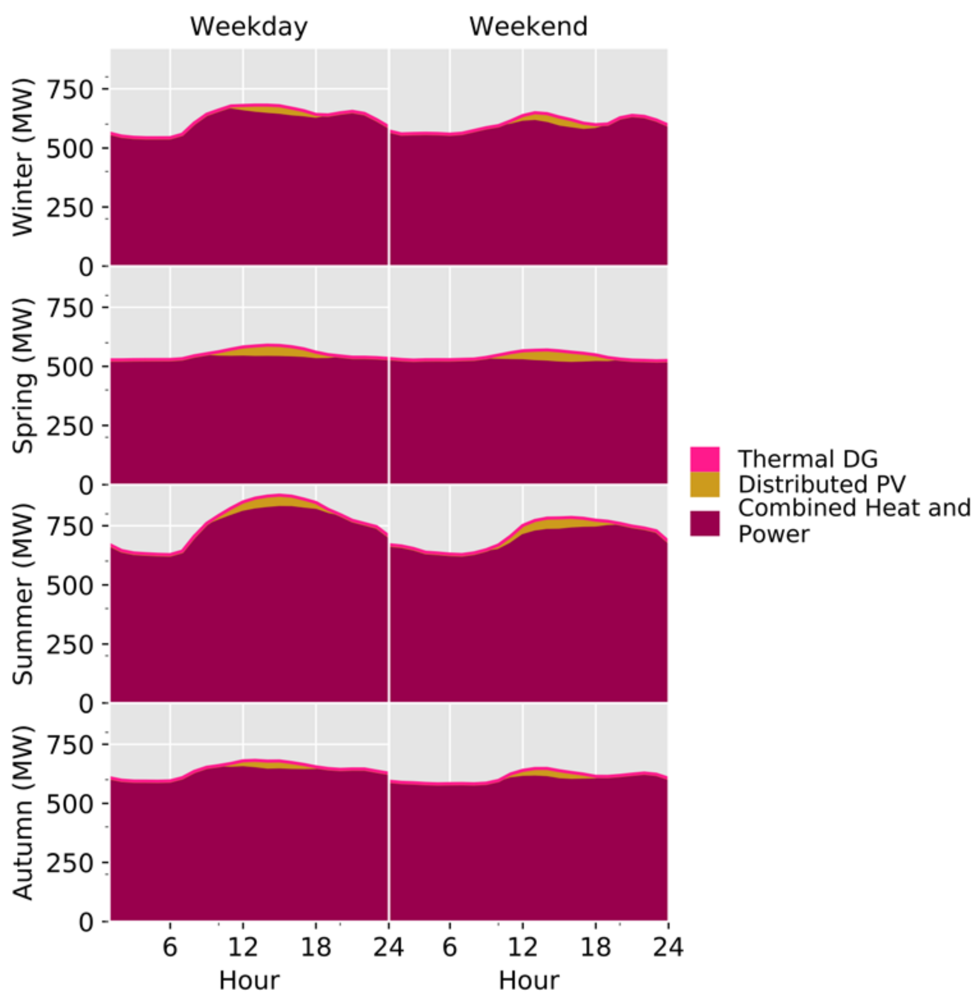

Figure G-7. Distributed Generation Model Diurnal Generation Patterns, West North Central census division 2012

G.2 East North Central

Table G-9. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, East North Central Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					585.4
Derived	T&D losses					27.6
Top-down	Annual energy	188.6	184.9	202.2	0.6	576.4
dsgrid	Distributed generation	0.0	4.8	17.1	–	22.0
dsgrid-core	Gap models	24.6	65.5	14.5	0.6	105.2
dsgrid-core	Detailed sector models	174.5	164.8	190.3	–	529.7
Derived	Total site energy	188.7	189.7	219.4	0.6	598.4
Derived	Annual sector residuals	-10.4	-40.6	14.5	-0.0	-36.4
Derived	Hourly residuals					59.4

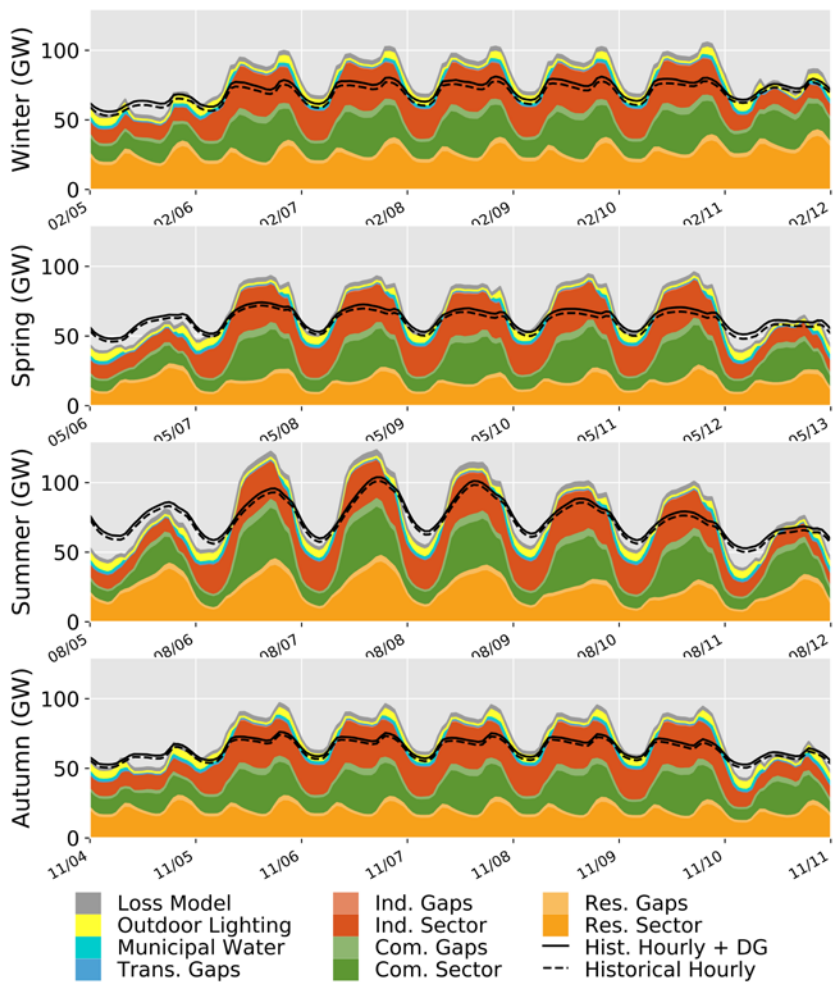

Figure G-8. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the East North Central census division in 2012

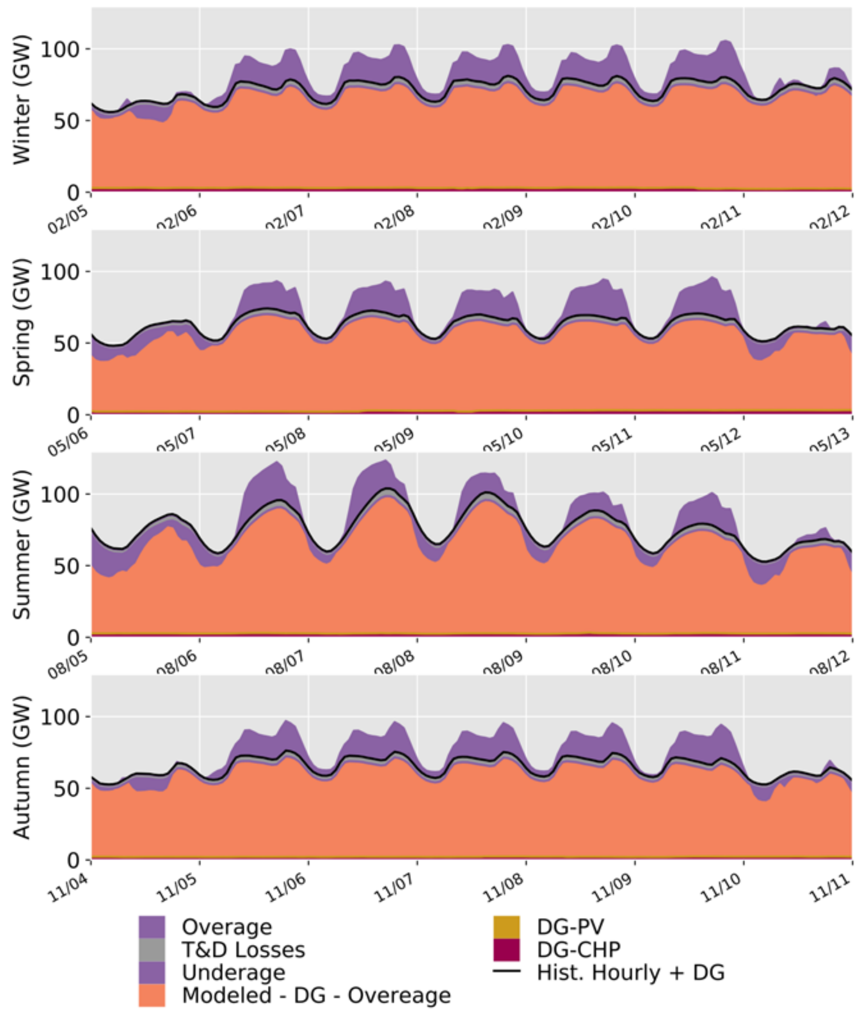

Figure G-9. dsgrid hourly residuals shown in context for the East North Central census division.

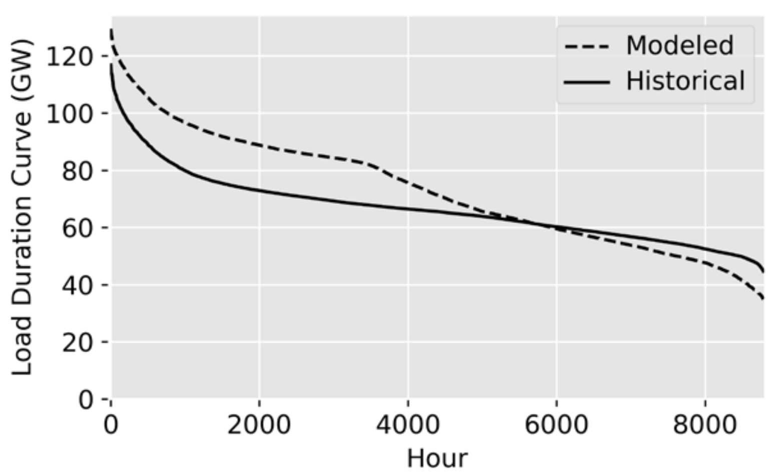

Figure G-10. Historical and dsgrid load duration curves for the East North Central census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-10. Residential Subsectors, Summary of Electricity by End Use for the East North Central Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Interior Lights (GWh)	Space Heating (GWh)	Fans (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	70,344	24,364	22,774	20,152	15,792	13,782	4,612	177	—	171,997
Apartment in Building 2 to 4 Units	4,013	1,169	1,649	1,020	1,501	—	1,987	115	41	11,495
Single Family Attached	3,235	970	698	564	587	616	114	8	—	6,793
Mobile Home	2,995	898	647	522	544	571	105	7	—	6,289
Midrise Apartment Building	821	255	362	233	331	—	433	26	9	2,472
Total	**81,409**	**27,656**	**26,130**	**22,492**	**18,755**	**14,969**	**7,252**	**333**	**50**	**199,046**

Table G-11. Residential Electricity Proportions by Subsector and End Use for the East North Central Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Interior Lights (%)	Space Heating (%)	Fans (%)	Water Systems (%)a	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	40.9	14.2	13.2	11.7	9.2	8.0	2.7	0.1	—	86.4
Apartment in Building 2 to 4 Units	34.9	10.2	14.3	8.9	13.1	—	17.3	1.0	0.4	5.8
Single Family Attached	47.6	14.3	10.3	8.3	8.6	9.1	1.7	0.1	—	3.4
Mobile Home	47.6	14.3	10.3	8.3	8.6	9.1	1.7	0.1	—	3.2
Midrise Apartment Building	33.2	10.3	14.7	9.4	13.4	—	17.5	1.0	0.4	1.2
Total	**40.9**	**13.9**	**13.1**	**11.3**	**9.4**	**7.5**	**3.6**	**0.2**	**0.0**	**100.0**

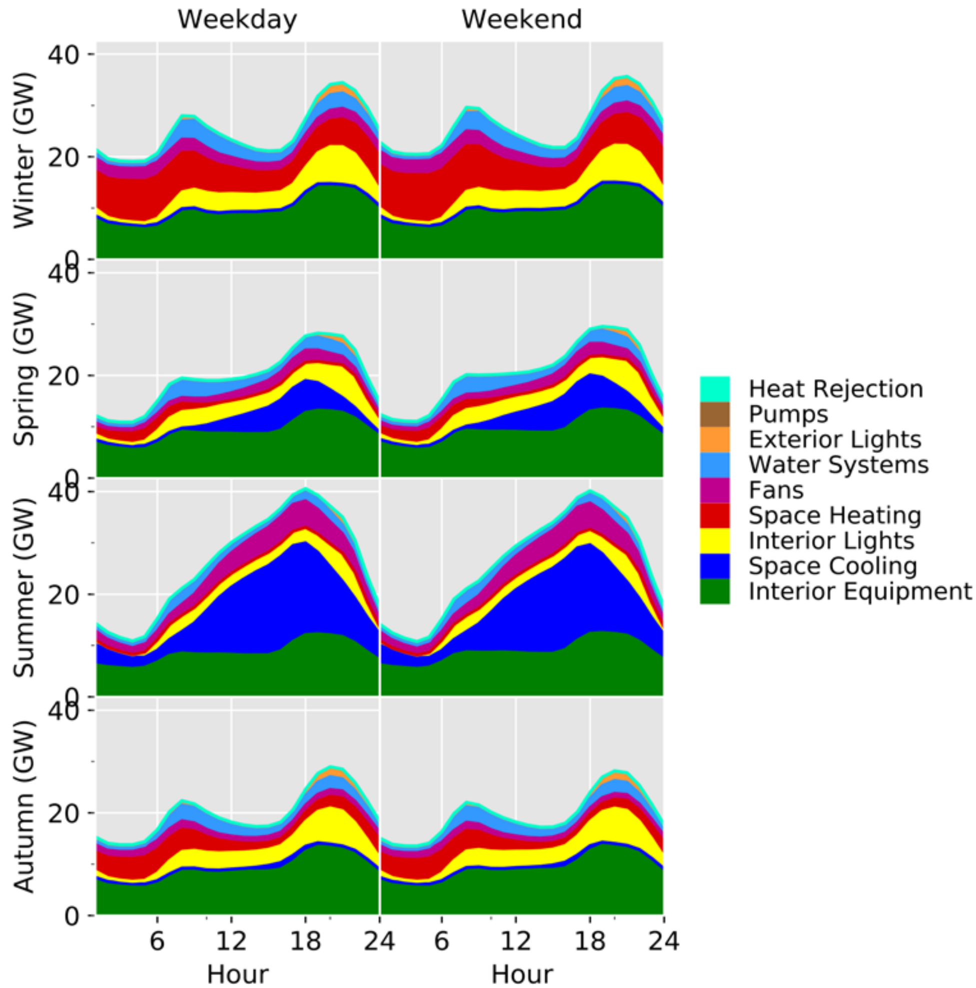

Figure G-11. Residential electricity use diurnal patterns by season, modeled for the East North Central census division 2012

Table G-12. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the East North Central Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Strip Mall	27,091	3,940	7,049	2,755	5,541	1,636	21	8	48,041
Large Office	12,175	13,949	9,235	6,076	2,466	408	916	350	45,574
Standalone Retail Store	11,202	3,460	3,748	1,495	1,702	1,769	11	4	23,390
Medium Office	2,540	2,890	1,975	1,086	903	192	80	29	9,696
Warehouse	3,198	1,271	1,423	164	1,529	1,680	10	4	9,279
Small Office	2,194	3,002	1,429	774	857	318	7	5	8,585
Full Service Restaurant	1,653	3,730	886	556	463	229	8	3	7,527
Large Hotel	952	1,530	862	607	233	105	44	18	4,350
Hospital	1,048	1,475	581	493	81	—	82	32	3,793
Primary School	717	572	309	171	92	111	6	3	1,980
Outpatient Treatment Facility	554	818	218	109	198	—	21	9	1,927
Small Hotel	166	221	20	11	102	14	1	0	537
Quick Service Restaurant	16	96	30	17	9	1	0	0	170
Total	**63,506**	**36,955**	**27,766**	**14,315**	**14,176**	**6,463**	**1,206**	**463**	**164,850**

Table G-13. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the East North Central Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Strip Mall	56.4	8.2	14.7	5.7	11.5	3.4	0.0	0.0	29.1
Large Office	26.7	30.6	20.3	13.3	5.4	0.9	2.0	0.8	27.6
Standalone Retail Store	47.9	14.8	16.0	6.4	7.3	7.6	0.0	0.0	14.2
Medium Office	26.2	29.8	20.4	11.2	9.3	2.0	0.8	0.3	5.9
Warehouse	34.5	13.7	15.3	1.8	16.5	18.1	0.1	0.0	5.6
Small Office	25.6	35.0	16.6	9.0	10.0	3.7	0.1	0.1	5.2
Full Service Restaurant	22.0	49.6	11.8	7.4	6.1	3.0	0.1	0.0	4.6
Large Hotel	21.9	35.2	19.8	13.9	5.4	2.4	1.0	0.4	2.6
Hospital	27.6	38.9	15.3	13.0	2.1	—	2.2	0.8	2.3
Primary School	36.2	28.9	15.6	8.6	4.6	5.6	0.3	0.1	1.2
Outpatient Treatment Facility	28.7	42.5	11.3	5.7	10.3	—	1.1	0.5	1.2
Small Hotel	31.0	41.2	3.7	2.1	19.0	2.7	0.2	0.1	0.3
Quick Service Restaurant	9.4	56.4	18.0	10.1	5.5	0.5	0.0	0.0	0.1
Total	**38.5**	**22.4**	**16.8**	**8.7**	**8.6**	**3.9**	**0.7**	**0.3**	**100.0**

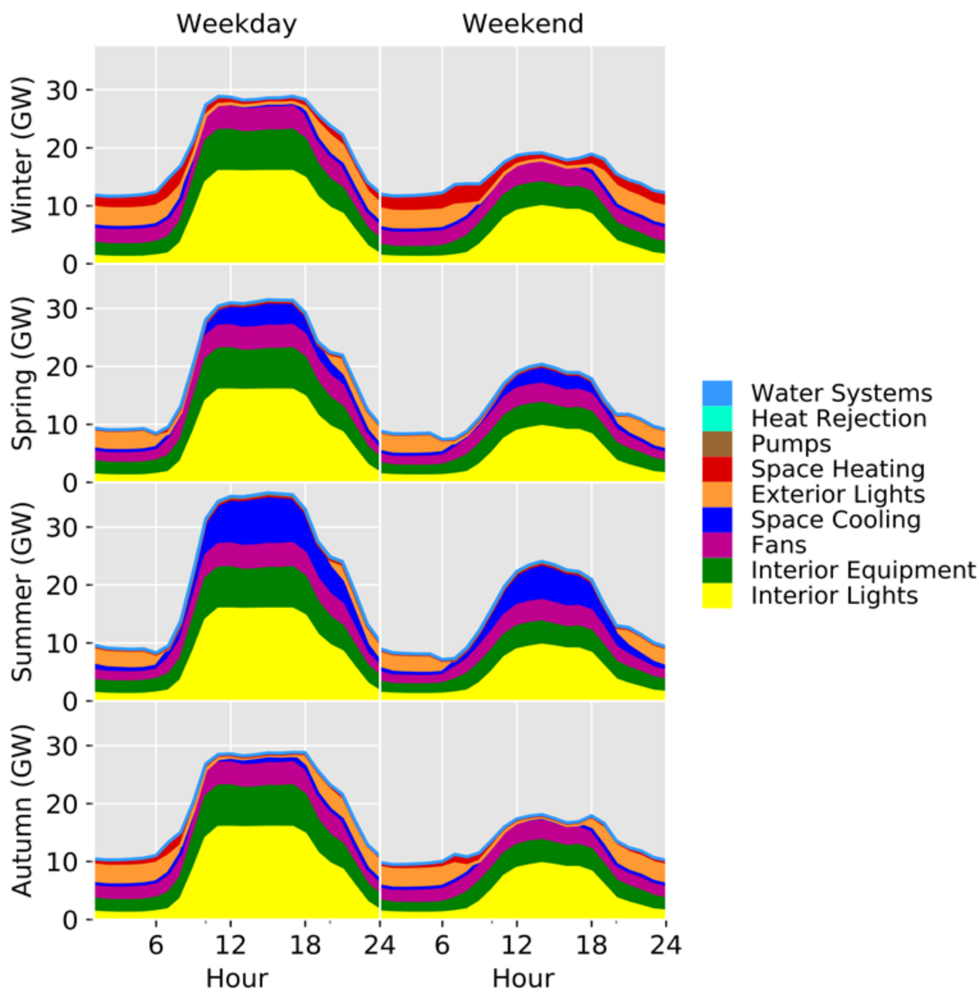

Figure G-12. Commercial electricity use diurnal patterns by season, modeled for the East North Central census division 2012

Table G-14. Industrial Manufacturing Subsectors, Summary of Model Results for the East North Central Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Iron and Steel Mills and Ferroalloy Manufacturing	9,491	12,185	2,205	8,105	1,548	524	549	423	166	694	58	97	36,047
Plastics Product Manufacturing	6,129	1,834	1,157	—	1,082	916	—	261	57	—	49	—	11,484
Motor Vehicle Parts Manufacturing	3,624	1,030	1,760	61	1,178	473	461	371	78	147	132	112	9,429
Basic Chemical Manufacturing	4,544	293	507	1,349	326	765	122	96	169	109	20	20	8,320
Petroleum and Coal Products Manufacturing	6,346	266	298	114	198	331	56	77	58	88	1	8	7,841
Converted Paper Product Manufacturing	5,228	272	306	57	267	117	236	75	322	35	14	—	6,928
Pulp, Paper, and Paperboard Mills	4,913	255	285	53	249	109	219	70	299	32	13	—	6,499
Foundries	1,467	1,879	338	1,237	237	80	84	65	25	106	9	15	5,541
Pharmaceutical and Medicine Manufacturing	2,848	184	321	858	206	486	78	61	107	69	13	13	5,244
Other Fabricated Metal Product Manufacturing	2,081	713	740	184	466	154	172	159	—	—	33	10	4,711
Dairy Product Manufacturing	1,763	174	337	9	297	1,048	72	80	123	89	37	17	4,046
Animal Slaughtering and Processing	1,657	164	322	9	283	1,006	70	77	118	85	36	16	3,843
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	1,994	128	222	593	143	336	54	42	74	48	9	9	3,652
Other Nonmetallic Mineral Product Manufacturing	1,787	848	217	59	166	130	72	51	30	—	13	5	3,377
Motor Vehicle Manufacturing	1,281	366	632	22	422	171	167	134	28	53	48	41	3,364
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	1,689	109	193	519	124	294	47	37	65	42	8	8	3,134
Coating, Engraving, Heat Treating, and Allied Activities	1,363	469	494	124	311	104	115	107	—	—	22	6	3,116
Architectural and Structural Metals Manufacturing	1,359	466	488	122	307	102	113	105	—	—	22	6	3,090
Other Chemical Product and Preparation Manufacturing	1,628	105	182	486	117	276	44	34	61	39	7	7	2,987
Nonferrous Metal (except Aluminum) Production and Processing	793	1,009	178	646	125	42	44	34	13	55	5	8	2,951
Forging and Stamping	1,291	442	461	115	290	96	107	99	—	—	20	6	2,928
Printing and Related Support Activities	1,468	113	462	31	230	203	39	76	23	—	30	—	2,675
Fruit and Vegetable Preserving and Specialty Food Manufacturing	1,063	105	207	5	182	646	45	49	76	55	23	10	2,465
Bakeries and Tortilla Manufacturing	971	96	188	5	165	585	40	45	69	49	21	9	2,244
Other General Purpose Machinery Manufacturing	880	204	431	21	294	85	49	78	20	—	21	—	2,084

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	1,111	72	126	340	81	193	31	24	43	27	5	5	2,058
Steel Product Manufacturing from Purchased Steel	548	697	123	448	87	29	30	23	9	38	3	5	2,042
Glass and Glass Product Manufacturing	1,060	502	127	35	97	76	42	30	17	—	7	3	1,997
Paint, Coating, and Adhesive Manufacturing	1,004	65	114	306	73	174	28	22	38	25	5	5	1,858
Other Food Manufacturing	767	76	148	4	130	459	32	35	54	39	16	7	1,766
Alumina and Aluminum Production and Processing	458	584	103	376	73	24	25	20	8	32	3	5	1,711
Engine, Turbine, and Power Transmission Equipment Manufacturing	707	163	342	17	234	67	39	61	16	—	17	—	1,663
Metalworking Machinery Manufacturing	701	162	342	17	233	68	39	62	16	—	17	—	1,655
Rubber Product Manufacturing	837	251	159	—	148	126	—	36	8	—	7	—	1,571
Cement and Concrete Product Manufacturing	827	393	101	28	77	61	34	24	14	—	6	2	1,566
Grain and Oilseed Milling	672	66	129	3	114	403	28	31	47	34	14	6	1,549
Semiconductor and Other Electronic Component Manufacturing	344	179	361	34	138	172	110	73	13	32	4	29	1,487
Other Wood Product Manufacturing	986	84	100	4	80	9	14	21	24	14	3	5	1,344
Animal Food Manufacturing	513	51	101	3	88	315	22	24	37	27	11	5	1,197
Motor Vehicle Body and Trailer Manufacturing	445	127	218	8	146	59	57	46	10	18	16	14	1,162
Other Electrical Equipment and Component Manufacturing	325	266	192	90	114	74	42	26	5	—	8	—	1,143
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	499	172	180	45	113	38	42	39	—	—	8	2	1,138
Other Miscellaneous Manufacturing	355	125	261	8	150	77	20	53	17	—	6	3	1,076
Industrial Machinery Manufacturing	456	105	220	11	151	43	25	40	10	—	11	—	1,072
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	220	115	235	22	89	112	72	48	9	21	3	19	965
Beverage Manufacturing	342	41	112	2	89	187	24	31	15	73	19	4	938
Other Transportation Equipment Manufacturing	352	100	172	6	115	46	45	36	8	14	13	11	919
Spring and Wire Product Manufacturing	375	129	136	34	85	28	32	29	—	—	6	2	856
Sugar and Confectionery Product Manufacturing	366	36	71	2	63	223	15	17	26	19	8	4	851
Aerospace Product and Parts Manufacturing	309	88	150	5	100	40	39	32	7	13	11	10	804

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	396	29	163	3	135	13	—	27	10	—	9	4	789
Electrical Equipment Manufacturing	221	182	133	63	79	52	30	18	4	—	6	—	787
Commercial and Service Industry Machinery Manufacturing	275	63	133	7	91	26	15	24	6	—	6	—	646
Agriculture, Construction, and Mining Machinery Manufacturing	267	62	129	6	88	25	15	23	6	—	6	—	627
Medical Equipment and Supplies Manufacturing	177	62	129	4	74	38	10	26	9	—	3	1	534
Veneer, Plywood, and Engineered Wood Product Manufacturing	303	26	30	1	24	3	4	6	7	4	1	1	411
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	170	40	84	4	57	17	10	15	4	—	4	—	404
Boiler, Tank, and Shipping Container Manufacturing	175	60	61	15	38	12	14	13	—	—	3	1	392
Clay Product and Refractory Manufacturing	200	95	25	7	19	15	8	6	3	—	1	1	379
Office Furniture (including Fixtures) Manufacturing	185	14	77	1	64	6	—	13	5	—	4	2	371
Household Appliance Manufacturing	100	82	59	27	35	23	13	8	2	—	2	—	350
Lime and Gypsum Product Manufacturing	185	88	22	6	17	13	7	5	3	—	1	1	349
Cutlery and Handtool Manufacturing	91	31	33	8	21	7	8	7	—	—	1	0	208
Communications Equipment Manufacturing	46	24	50	5	19	24	15	10	2	5	1	4	204
Railroad Rolling Stock Manufacturing	77	22	38	1	26	10	10	8	2	3	3	2	203
Ship and Boat Building	76	22	38	1	26	10	10	8	2	3	3	2	203
Other Textile Product Mills	101	13	25	1	20	13	1	5	9	—	5	—	193
Electric Lighting Equipment Manufacturing	49	40	29	14	17	11	6	4	1	—	1	—	173
Fabric Mills	57	8	14	0	7	4	2	1	2	—	1	—	96
Computer and Peripheral Equipment Manufacturing	21	11	23	2	9	11	7	5	1	2	0	2	92
Audio and Video Equipment Manufacturing	18	9	19	2	7	9	6	4	1	2	0	1	77
Seafood Product Preparation and Packaging	31	3	6	0	5	19	1	1	2	2	1	0	71
Manufacturing and Reproducing Magnetic and Optical Media	16	9	17	2	7	8	5	3	1	2	0	1	71
Textile and Fabric Finishing and Fabric Coating Mills	34	5	9	0	4	2	1	1	1	—	1	—	58
Other Leather and Allied Product Manufacturing	36	5	6	0	6	2	0	1	0	—	0	—	57

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Furniture Related Product Manufacturing	25	2	10	0	8	1	—	2	1	—	1	0	49
Fiber, Yarn, and Thread Mills	22	3	6	0	3	1	1	1	1	—	0	—	37
Sawmills and Wood Preservation	21	2	2	0	2	0	0	0	0	0	0	0	28
Cut and Sew Apparel Manufacturing	10	1	7	—	4	0	—	1	1	—	0	—	25
Footwear Manufacturing	11	1	2	0	2	1	0	0	0	—	0	—	18
Tobacco Manufacturing	6	1	2	0	2	3	0	1	0	1	0	0	16
Leather and Hide Tanning and Finishing	8	1	1	0	1	0	0	0	0	—	0	—	12
Textile Furnishings Mills	6	1	1	0	1	1	0	0	1	—	0	—	11
Hardware Manufacturing	2	1	1	0	0	0	0	0	—	—	0	0	5
Apparel Accessories and Other Apparel Manufacturing	0	0	0	—	0	0	—	0	0	—	0	—	1
Total	**85,656**	**29,375**	**18,636**	**16,809**	**13,003**	**12,565**	**4,141**	**3,839**	**2,517**	**2,247**	**954**	**593**	**190,334**

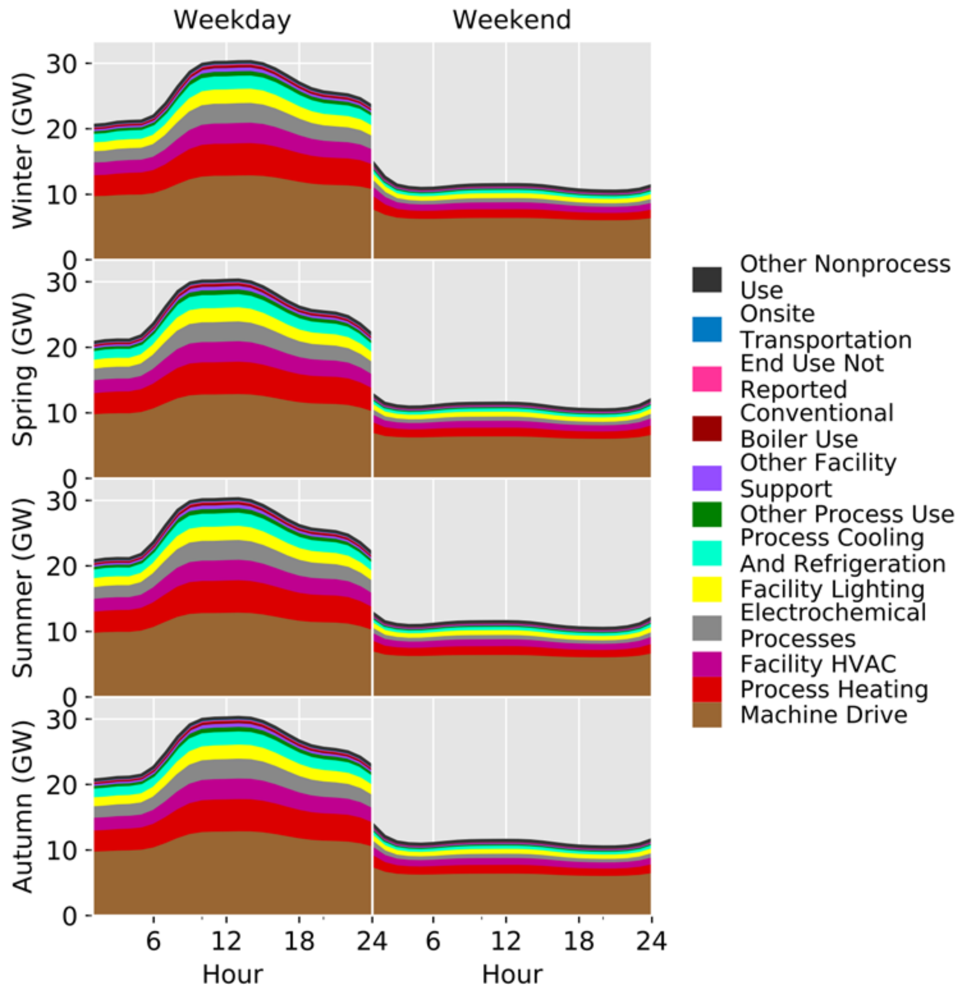

Figure G-13. Industrial electricity use diurnal patterns by season, modeled for the East North Central census division 2012

Table G-15. Distributed Generation Model, Annual Summary the East North Central Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	16,658	4,757	0	21,416
Thermal DG (GWh)	439	32	—	471
Distributed PV (GWh)	39	38	21	97
Total (GWh)	**17,135**	**4,828**	**21**	**21,985**
CHP (%)	97.2	98.5	2.2	97.4
Thermal DG (%)	2.6	0.7	—	2.1
Distributed PV (%)	0.2	0.8	97.8	0.4
Total (%)	**77.9**	**22.0**	**0.1**	**100.0**

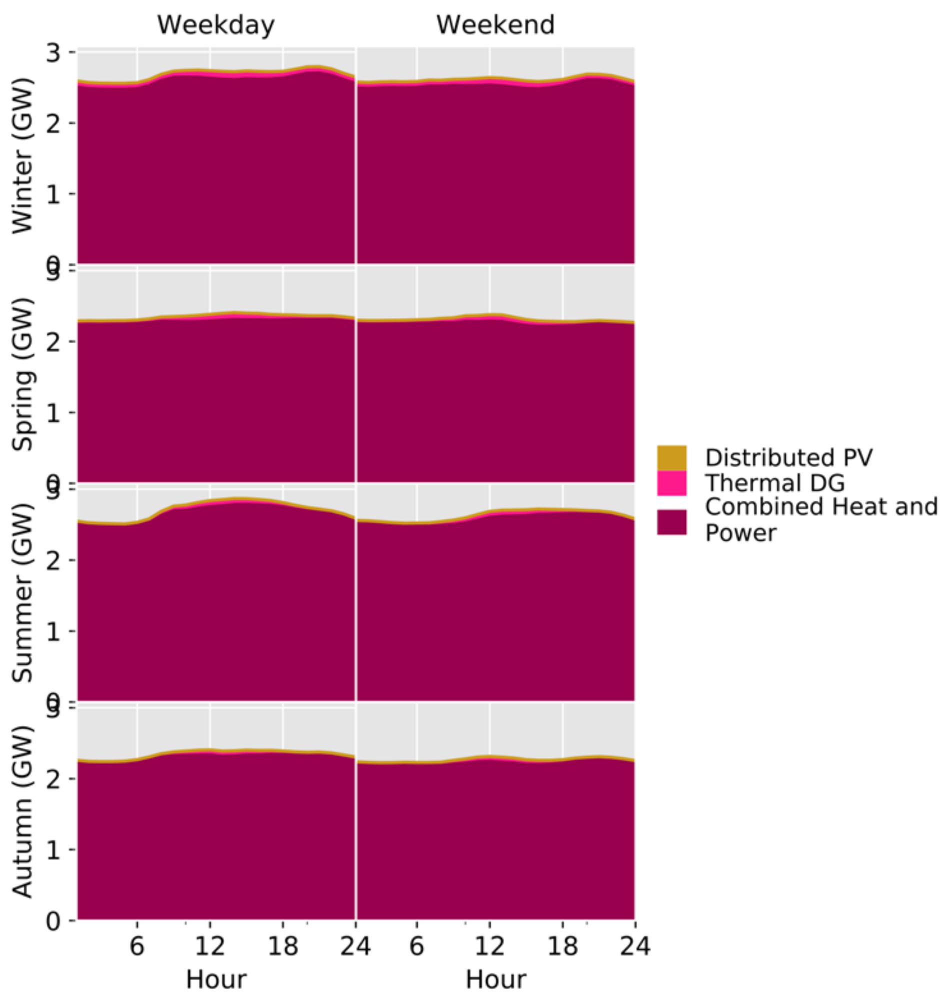

Figure G-14. Distributed Generation Model Diurnal Generation Patterns, East North Central census division 2012

G.3 New England

Table G-16. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, New England Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					126.0
Derived	T&D losses					3.5
Top-down	Annual energy	47.2	45.4	27.8	0.6	121.0
dsgrid	Distributed generation	0.1	2.7	7.5	–	10.3
dsgrid-core	Gap models	8.0	23.9	4.4	0.7	37.1
dsgrid-core	Detailed sector models	42.7	58.7	30.4	–	131.8
Derived	Total site energy	47.3	48.1	35.4	0.6	131.4
Derived	Annual sector residuals	-3.4	-34.5	0.6	-0.1	-37.5
Derived	Hourly residuals					-36.6

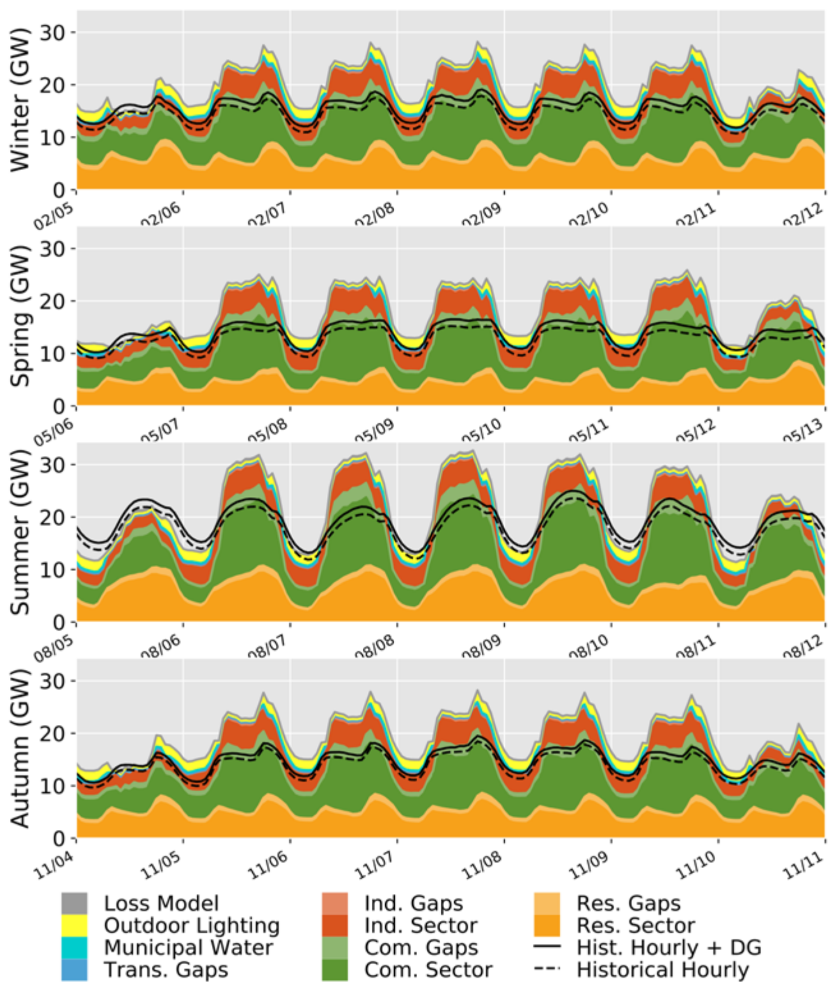

Figure G-15. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the New England census division in 2012

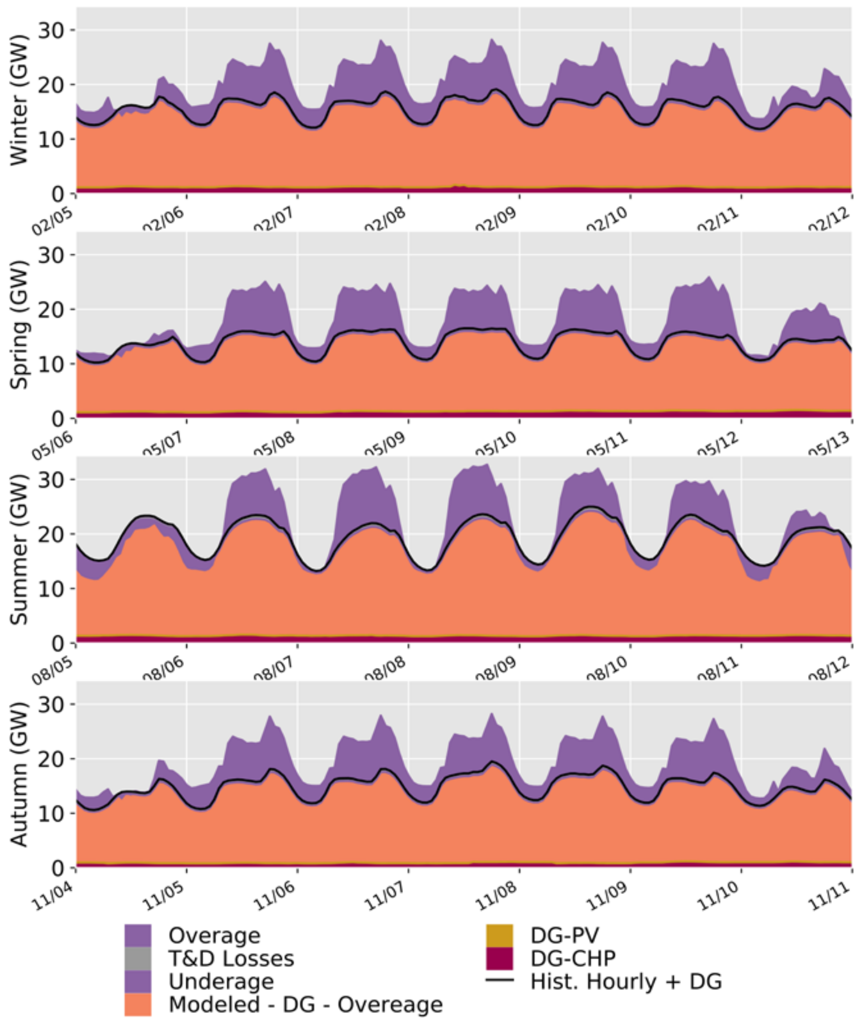

Figure G-16. dsgrid hourly residuals shown in context for the New England census division.

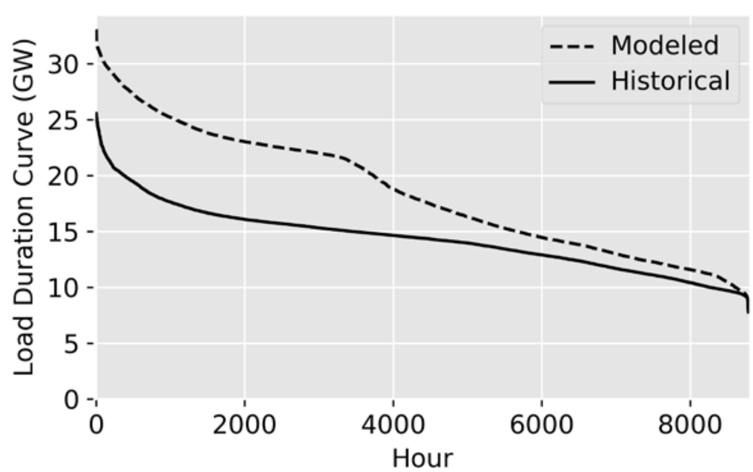

Figure G-17. Historical and dsgrid load duration curves for the New England census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-17. Residential Subsectors, Summary of Electricity by End Use for the New England Census Division in 2012

Subsector	Interior Equipment (GWh)	Interior Lights (GWh)	Space Cooling (GWh)	Water Systems (GWh)	Fans (GWh)	Space Heating (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	20,595	6,646	4,302	3,476	2,620	2,089	1,369	384	—	41,481
Apartment in Building 2 to 4 Units	1,812	780	417	—	672	624	936	54	17	5,312
Single Family Attached	1,115	232	200	194	106	85	38	14	—	1,984
Midrise Apartment Building	403	182	92	—	147	130	216	12	4	1,186
Mobile Home	421	88	76	73	40	32	14	5	—	748
Total	**24,347**	**7,927**	**5,086**	**3,743**	**3,584**	**2,959**	**2,574**	**470**	**21**	**50,712**

Table G-18. Residential Electricity Proportions by Subsector and End Use for the New England Census Division in 2012

Subsector	Interior Equipment (%)	Interior Lights (%)	Space Cooling (%)	Water Systems (%)	Fans (%)	Space Heating (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	49.6	16.0	10.4	8.4	6.3	5.0	3.3	0.9	—	81.8
Apartment in Building 2 to 4 Units	34.1	14.7	7.8	—	12.6	11.7	17.6	1.0	0.3	10.5
Single Family Attached	56.2	11.7	10.1	9.8	5.3	4.3	1.9	0.7	—	3.9
Midrise Apartment Building	34.0	15.3	7.8	—	12.4	10.9	18.2	1.0	0.3	2.3
Mobile Home	56.2	11.7	10.1	9.8	5.3	4.3	1.9	0.7	—	1.5
Total	**48.0**	**15.6**	**10.0**	**7.4**	**7.1**	**5.8**	**5.1**	**0.9**	**0.0**	**100.0**

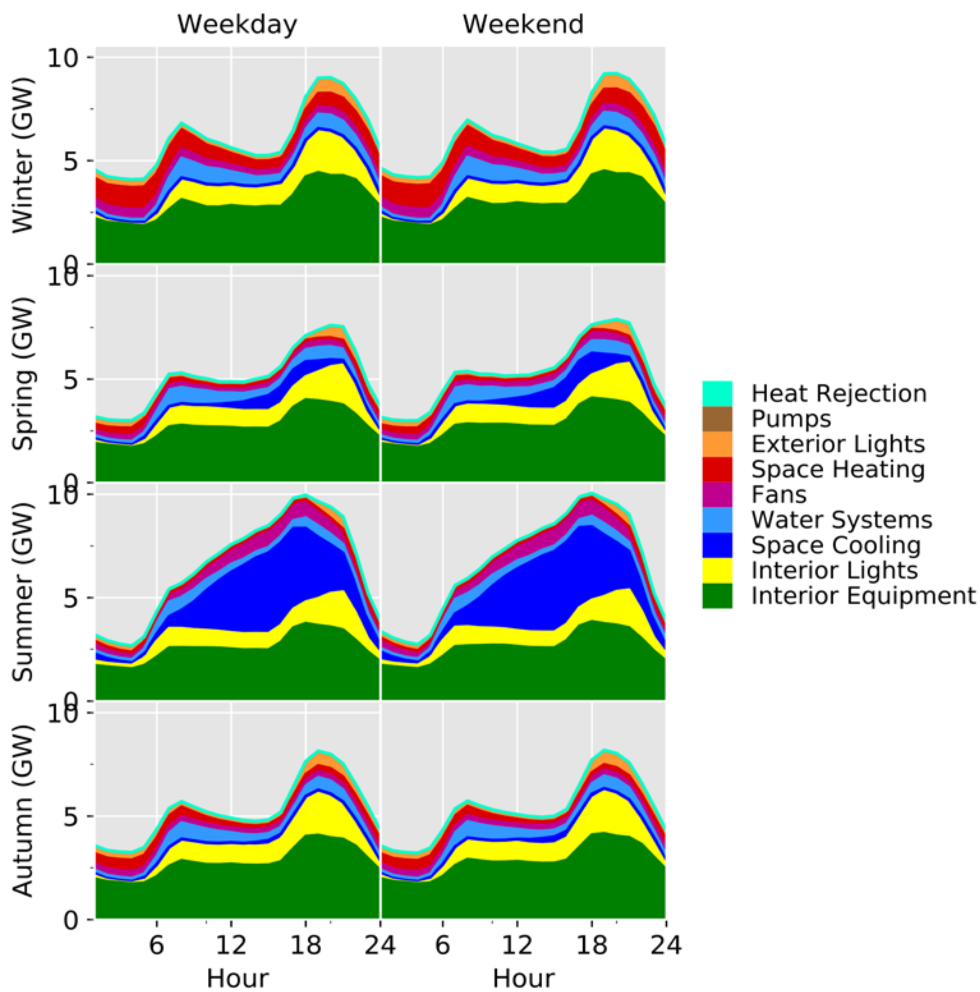

Figure G-18. Residential electricity use diurnal patterns by season, modeled for the New England census division 2012

Table G-19. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the New England Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Exterior Lights (GWh)	Space Cooling (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Large Office	5,538	6,426	4,104	1,108	2,274	134	362	126	20,070
Strip Mall	8,646	1,265	2,163	1,771	603	546	5	2	15,000
Standalone Retail Store	3,729	1,190	1,051	567	334	602	4	1	7,478
Medium Office	1,401	1,598	1,026	499	497	87	43	14	5,164
Small Office	798	1,100	492	312	228	112	3	2	3,047
Warehouse	808	313	293	383	27	418	2	1	2,244
Full Service Restaurant	474	1,063	252	132	113	68	2	1	2,105
Large Hotel	312	502	287	77	175	35	15	5	1,407
Hospital	261	372	191	20	116	—	23	9	992
Outpatient Treatment Facility	174	256	81	62	40	—	8	3	624
Primary School	154	123	82	21	35	12	2	1	429
Small Hotel	49	72	4	36	2	4	0	0	168
Quick Service Restaurant	2	11	4	1	1	0	—	—	19
Total	**22,347**	**14,290**	**10,029**	**4,989**	**4,445**	**2,017**	**468**	**163**	**58,748**

Table G-20. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the New England Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Exterior Lights (%)	Space Cooling (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Large Office	27.6	32.0	20.4	5.5	11.3	0.7	1.8	0.6	34.2
Strip Mall	57.6	8.4	14.4	11.8	4.0	3.6	0.0	0.0	25.5
Standalone Retail Store	49.9	15.9	14.1	7.6	4.5	8.1	0.0	0.0	12.7
Medium Office	27.1	30.9	19.9	9.7	9.6	1.7	0.8	0.3	8.8
Small Office	26.2	36.1	16.1	10.2	7.5	3.7	0.1	0.1	5.2
Warehouse	36.0	14.0	13.0	17.1	1.2	18.6	0.1	0.0	3.8
Full Service Restaurant	22.5	50.5	11.9	6.3	5.4	3.2	0.1	0.0	3.6
Large Hotel	22.2	35.7	20.4	5.5	12.4	2.5	1.0	0.3	2.4
Hospital	26.3	37.5	19.3	2.0	11.7	—	2.3	0.9	1.7
Outpatient Treatment Facility	28.0	41.1	12.9	9.9	6.4	—	1.3	0.5	1.1
Primary School	35.9	28.6	19.1	4.9	8.1	2.7	0.5	0.2	0.7
Small Hotel	28.9	43.0	2.5	21.6	1.3	2.4	0.2	0.1	0.3
Quick Service Restaurant	9.4	55.5	19.4	5.6	7.6	2.4	—	—	0.0
Total	**38.0**	**24.3**	**17.1**	**8.5**	**7.6**	**3.4**	**0.8**	**0.3**	**100.0**

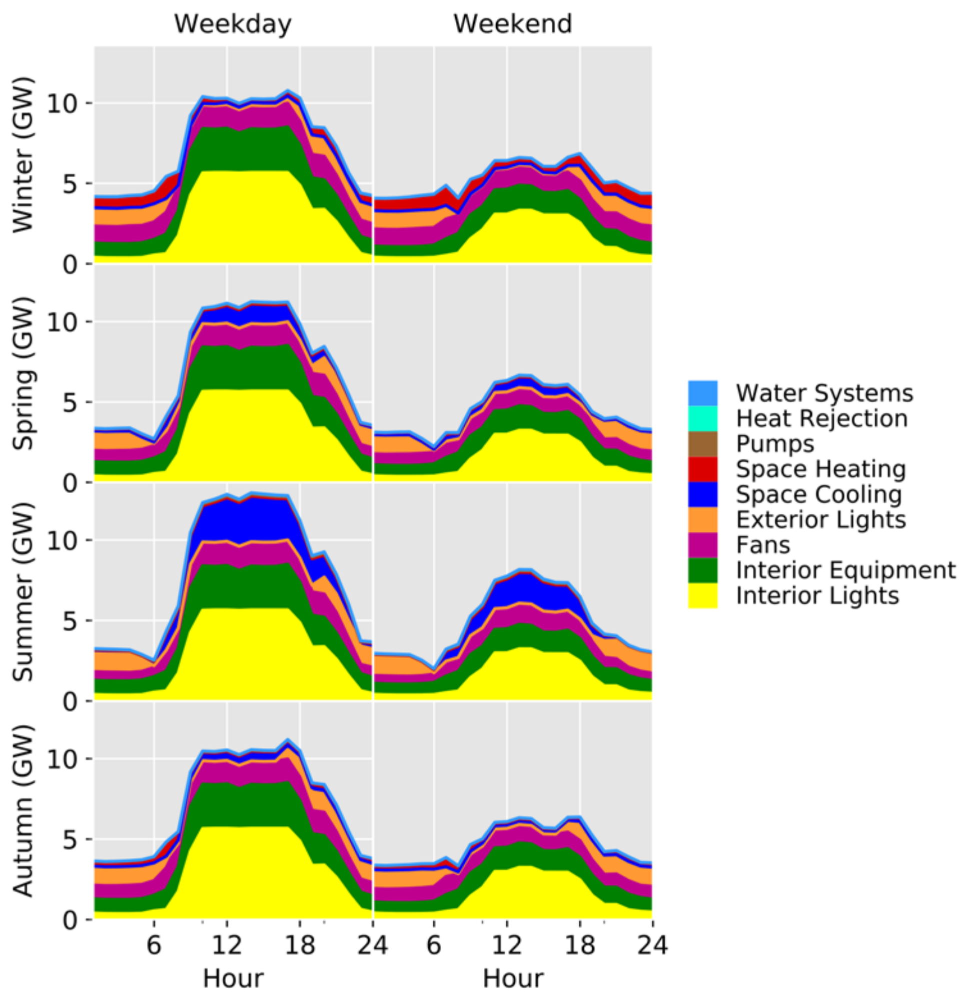

Figure G-19. Commercial electricity use diurnal patterns by season, modeled for the New England census division 2012

Table G-21. Industrial Manufacturing Subsectors, Summary of Model Results for the New England Census Division in 2012

Subsector	Machine Drive (GWh)	Facility HVAC (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Pharmaceutical and Medicine Manufacturing	2,044	230	132	349	615	148	56	44	77	50	9	9	3,763
Pulp, Paper, and Paperboard Mills	1,458	85	76	32	16	74	65	21	89	10	4	—	1,929
Basic Chemical Manufacturing	830	92	53	140	246	60	22	17	31	20	4	4	1,519
Plastics Product Manufacturing	760	143	227	114	—	134	—	32	7	—	6	—	1,424
Converted Paper Product Manufacturing	1,029	60	54	23	11	53	46	15	63	7	3	—	1,363
Other Chemical Product and Preparation Manufacturing	626	70	40	106	187	45	17	13	23	15	3	3	1,149
Semiconductor and Other Electronic Component Manufacturing	245	257	127	122	24	98	78	52	9	23	3	20	1,059
Other Nonmetallic Mineral Product Manufacturing	543	66	258	39	18	50	22	16	9	—	4	2	1,026
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	542	60	35	91	161	39	15	11	20	13	2	2	993
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	192	205	100	98	19	78	63	42	7	19	2	16	843
Aerospace Product and Parts Manufacturing	322	156	92	42	5	105	41	33	7	13	12	10	838
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	355	40	23	62	109	26	10	8	14	9	2	2	658
Printing and Related Support Activities	351	110	27	48	7	55	9	18	5	—	7	—	639
Nonferrous Metal (except Aluminum) Production and Processing	168	38	214	9	137	27	9	7	3	12	1	2	625
Paint, Coating, and Adhesive Manufacturing	333	38	22	58	102	24	9	7	13	8	2	2	617
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	330	38	21	58	101	24	9	7	13	8	2	2	613
Petroleum and Coal Products Manufacturing	486	23	20	25	9	15	4	6	4	7	0	1	600
Other Wood Product Manufacturing	437	44	37	4	2	35	6	9	10	6	1	2	596
Other Electrical Equipment and Component Manufacturing	169	100	139	39	47	59	22	14	3	—	4	—	594
Other Miscellaneous Manufacturing	158	116	56	34	3	67	9	23	8	—	3	1	478
Beverage Manufacturing	173	57	21	95	1	45	12	16	8	37	10	2	476
Iron and Steel Mills and Ferroalloy Manufacturing	121	28	155	7	103	20	7	5	2	9	1	1	459
Glass and Glass Product Manufacturing	243	29	115	17	8	22	10	7	4	—	2	1	458

Subsector	Machine Drive (GWh)	Facility HVAC (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Dairy Product Manufacturing	191	37	19	113	1	32	8	9	13	10	4	2	438
Fabric Mills	236	60	34	15	0	29	7	6	8	—	3	—	399
Other Fabricated Metal Product Manufacturing	176	63	60	13	16	39	15	13	—	—	3	1	399
Ship and Boat Building	133	67	38	18	2	45	18	14	3	6	5	4	353
Architectural and Structural Metals Manufacturing	142	51	49	11	13	32	12	11	—	—	2	1	322
Cement and Concrete Product Manufacturing	168	20	80	12	6	16	7	5	3	—	1	1	318
Coating, Engraving, Heat Treating, and Allied Activities	137	50	47	10	12	31	12	11	—	—	2	1	313
Bakeries and Tortilla Manufacturing	119	23	12	72	1	20	5	5	8	6	3	1	275
Medical Equipment and Supplies Manufacturing	89	65	31	19	2	37	5	13	4	—	2	1	268
Other General Purpose Machinery Manufacturing	112	55	26	11	3	37	6	10	3	—	3	—	265
Foundries	67	15	86	4	57	11	4	3	1	5	0	1	253
Fruit and Vegetable Preserving and Specialty Food Manufacturing	102	20	10	62	1	17	4	5	7	5	2	1	237
Communications Equipment Manufacturing	50	53	26	26	5	20	16	11	2	5	1	4	219
Industrial Machinery Manufacturing	90	44	21	9	2	30	5	8	2	—	2	—	212
Fiber, Yarn, and Thread Mills	123	31	18	8	0	15	4	3	4	—	2	—	208
Textile and Fabric Finishing and Fabric Coating Mills	123	31	18	8	0	15	4	3	4	—	2	—	208
Commercial and Service Industry Machinery Manufacturing	87	42	20	8	2	29	5	8	2	—	2	—	205
Forging and Stamping	86	31	29	6	8	19	7	7	—	—	1	0	194
Computer and Peripheral Equipment Manufacturing	42	46	22	22	4	18	14	10	2	4	1	4	189
Steel Product Manufacturing from Purchased Steel	50	11	64	3	41	8	3	2	1	4	0	0	186
Metalworking Machinery Manufacturing	68	33	16	7	2	23	4	6	2	—	2	—	162
Electrical Equipment Manufacturing	40	24	33	9	11	14	5	3	1	—	1	—	143
Animal Slaughtering and Processing	61	12	6	37	0	10	3	3	4	3	1	1	140
Other Food Manufacturing	58	11	6	34	0	10	2	3	4	3	1	1	132
Motor Vehicle Parts Manufacturing	49	24	14	6	1	16	6	5	1	2	2	2	129
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	53	22	4	2	0	18	—	4	1	—	1	1	105
Alumina and Aluminum Production and Processing	28	6	35	1	23	4	2	1	0	2	0	0	103

Subsector	Machine Drive (GWh)	Facility HVAC (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Seafood Product Preparation and Packaging	41	8	4	25	0	7	2	2	3	2	1	0	97
Rubber Product Manufacturing	48	9	14	7	—	9	—	2	0	—	0	—	91
Sugar and Confectionery Product Manufacturing	37	7	4	23	0	6	2	2	3	2	1	0	86
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	37	14	13	3	3	8	3	3	—	—	1	0	85
Engine, Turbine, and Power Transmission Equipment Manufacturing	35	17	8	3	1	11	2	3	1	—	1	—	81
Electric Lighting Equipment Manufacturing	23	13	19	5	6	8	3	2	0	—	1	—	81
Audio and Video Equipment Manufacturing	18	19	9	9	2	7	6	4	1	2	0	2	78
Spring and Wire Product Manufacturing	32	12	11	2	3	7	3	3	—	—	1	0	73
Lime and Gypsum Product Manufacturing	32	4	15	2	1	3	1	1	1	—	0	0	60
Veneer, Plywood, and Engineered Wood Product Manufacturing	38	4	3	0	0	3	1	1	1	1	0	0	51
Cutlery and Handtool Manufacturing	18	6	6	1	2	4	2	1	—	—	0	0	41
Grain and Oilseed Milling	16	3	2	10	0	3	1	1	1	1	0	0	38
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	16	8	4	2	0	5	1	1	0	—	0	—	38
Other Textile Product Mills	19	5	3	2	0	4	0	1	2	—	1	—	37
Motor Vehicle Body and Trailer Manufacturing	14	7	4	2	0	5	2	1	0	1	1	0	37
Animal Food Manufacturing	15	3	2	9	0	3	1	1	1	1	0	0	35
Household Appliance Manufacturing	10	6	8	2	3	3	1	1	0	—	0	—	34
Clay Product and Refractory Manufacturing	18	2	8	1	1	2	1	1	0	—	0	0	34
Manufacturing and Reproducing Magnetic and Optical Media	6	6	3	3	1	2	2	1	0	1	0	0	26
Agriculture, Construction, and Mining Machinery Manufacturing	10	5	2	1	0	3	1	1	0	—	0	—	24
Other Transportation Equipment Manufacturing	9	4	2	1	0	3	1	1	0	0	0	0	23
Motor Vehicle Manufacturing	9	4	2	1	0	3	1	1	0	0	0	0	22
Office Furniture (including Fixtures) Manufacturing	8	3	1	0	0	3	—	1	0	—	0	0	16
Cut and Sew Apparel Manufacturing	5	3	1	0	—	2	—	0	0	—	0	—	12

Subsector	Machine Drive (GWh)	Facility HVAC (GWh)	Process Heating (GWh)	Process Cooling And Refrigeration (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Sawmills and Wood Preservation	8	1	1	0	0	1	0	0	0	0	0	0	11
Other Leather and Allied Product Manufacturing	7	1	1	0	0	1	0	0	0	—	0	—	10
Tobacco Manufacturing	4	1	0	2	0	1	0	0	0	1	0	0	10
Boiler, Tank, and Shipping Container Manufacturing	4	1	1	0	0	1	0	0	—	—	0	0	9
Other Furniture Related Product Manufacturing	3	1	0	0	0	1	—	0	0	—	0	0	7
Footwear Manufacturing	4	1	0	0	0	1	0	0	0	—	0	—	6
Railroad Rolling Stock Manufacturing	2	1	1	0	0	1	0	0	0	0	0	0	5
Textile Furnishings Mills	1	0	0	0	0	0	0	0	0	—	0	—	2
Hardware Manufacturing	1	0	0	0	0	0	0	0	—	—	0	0	1
Leather and Hide Tanning and Finishing	1	0	0	0	0	0	0	0	0	—	0	—	1
Total	**15,143**	**3,214**	**3,020**	**2,280**	**2,168**	**2,022**	**758**	**641**	**528**	**329**	**144**	**110**	**30,356**

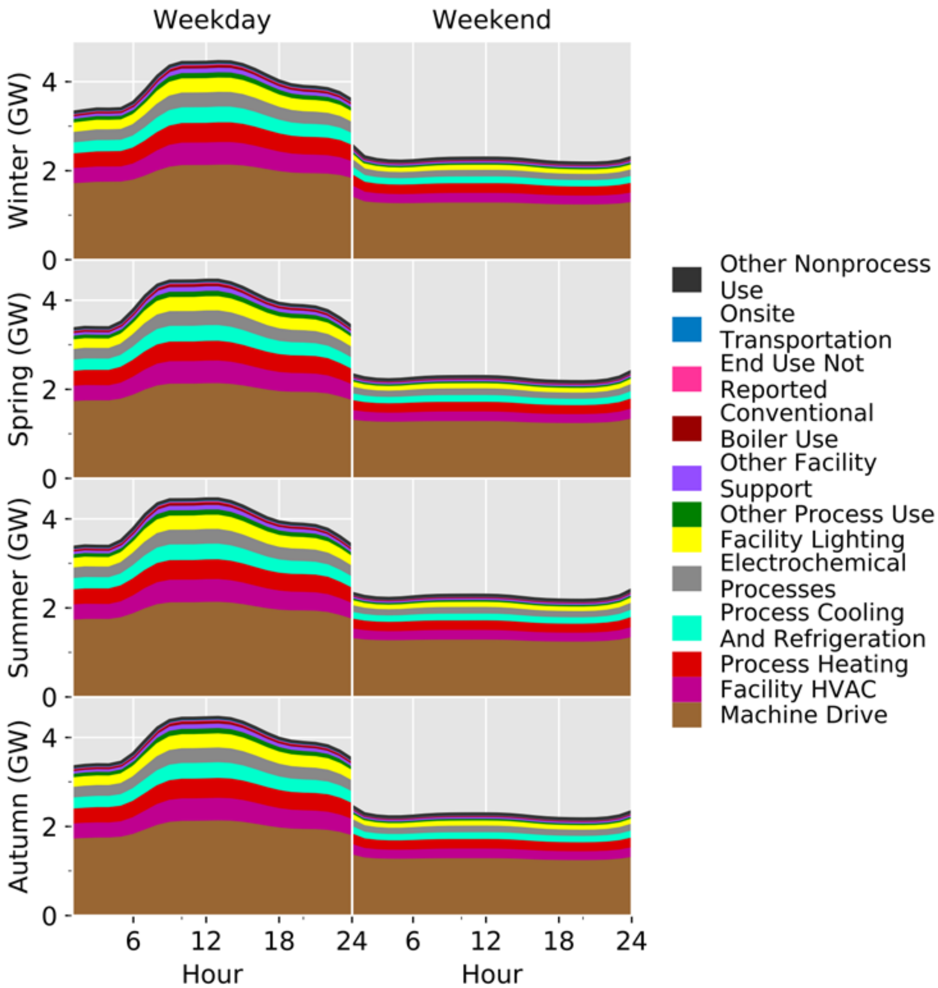

Figure G-20. Industrial electricity use diurnal patterns by season, modeled for the New England census division 2012

Table G-22. Distributed Generation Model, Annual Summary the New England Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	7,412	2,581	20	10,013
Distributed PV (GWh)	110	109	66	284
Thermal DG (GWh)	18	9	—	28
Total (GWh)	**7,540**	**2,699**	**85**	**10,325**
CHP (%)	98.3	95.6	23.1	97.0
Distributed PV (%)	1.5	4.0	76.9	2.8
Thermal DG (%)	0.2	0.4	—	0.3
Total (%)	**73.0**	**26.1**	**0.8**	**100.0**

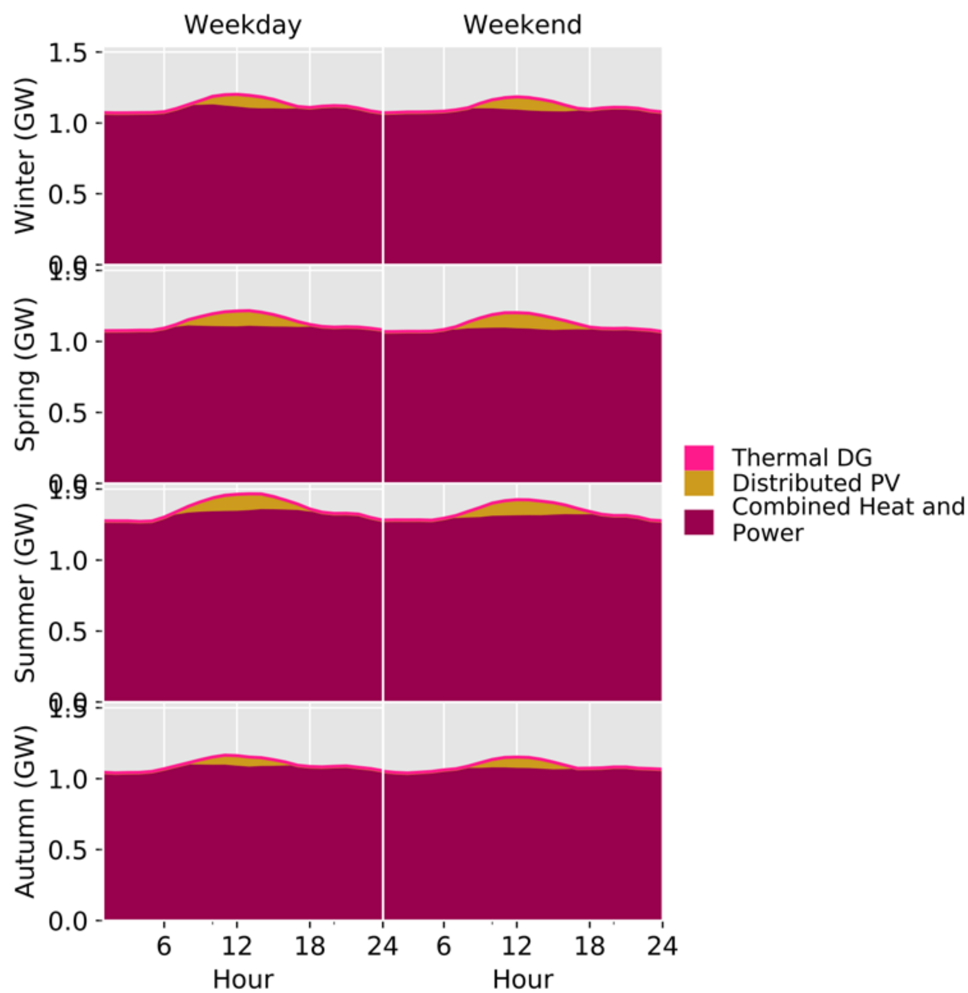

Figure G-21. Distributed Generation Model Diurnal Generation Patterns, New England census division 2012

G.4 Mid Atlantic

Table G-23. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, Mid Atlantic Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					395.0
Derived	T&D losses					17.3
Top-down	Annual energy	132.2	161.5	69.5	3.9	367.2
dsgrid	Distributed generation	0.7	9.6	33.7	–	43.9
dsgrid-core	Gap models	30.6	57.0	14.1	3.3	105.0
dsgrid-core	Detailed sector models	110.2	145.2	89.7	–	345.0
Derived	Total site energy	132.9	171.1	103.2	3.9	411.1
Derived	Annual sector residuals	-7.9	-31.1	-0.5	0.6	-38.9
Derived	Hourly residuals					-28.4

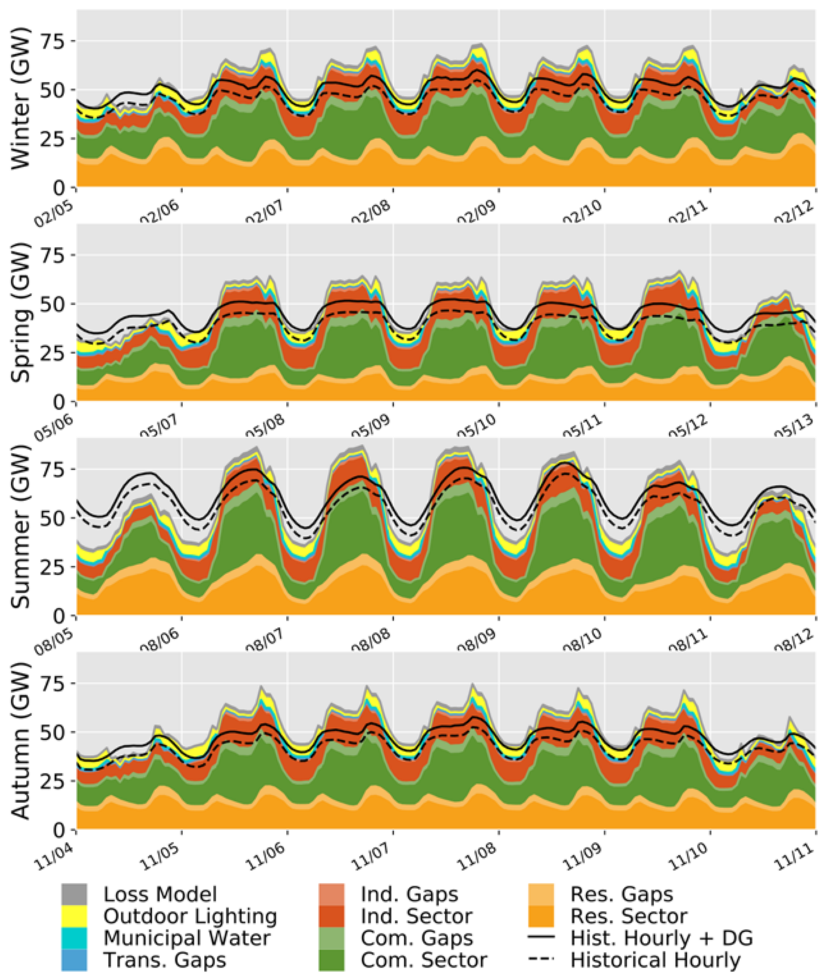

Figure G-22. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the Mid Atlantic census division in 2012

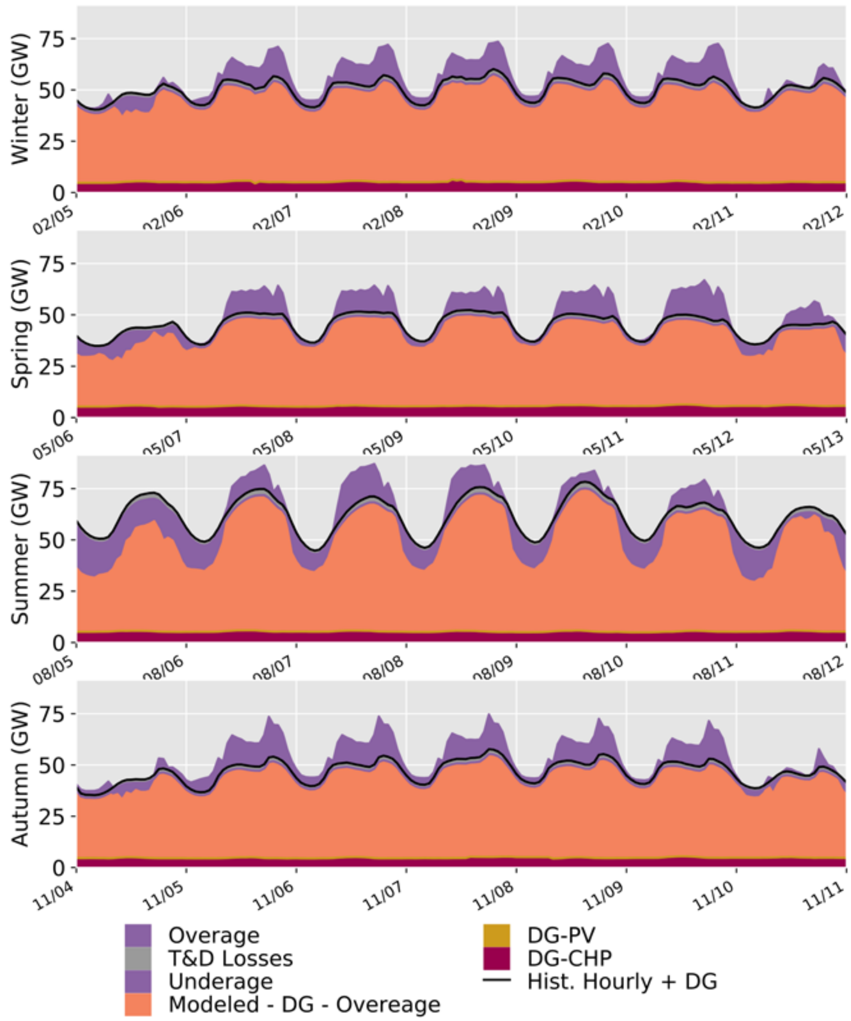

Figure G-23. dsgrid hourly residuals shown in context for the Mid Atlantic census division.

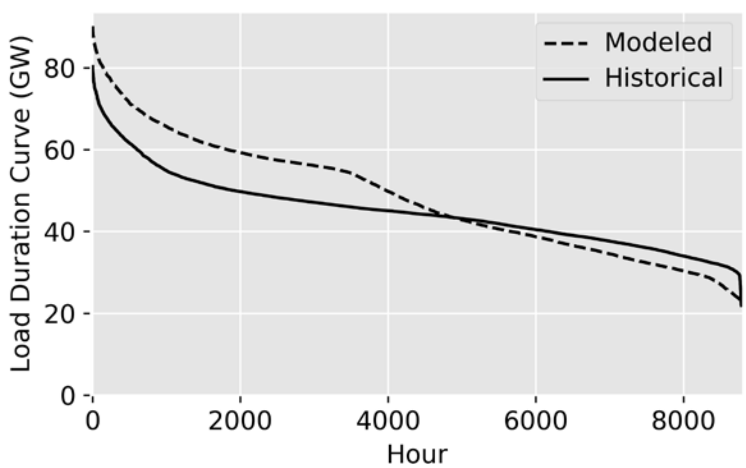

Figure G-24. Historical and dsgrid load duration curves for the Mid Atlantic census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-24. Residential Subsectors, Summary of Electricity by End Use for the Mid Atlantic Census Division in 2012

Subsector	Interior Equipment (GWh)	Interior Lights (GWh)	Space Cooling (GWh)	Space Heating (GWh)	Fans (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	44,354	15,035	14,443	10,818	8,646	7,692	3,095	586	—	104,668
Single Family Attached	6,916	1,514	2,042	899	1,024	1,082	247	64	—	13,788
Apartment in Building 2 to 4 Units	4,415	1,797	1,542	1,120	1,829	—	2,161	159	54	13,076
Midrise Apartment Building	1,775	785	688	435	791	—	935	80	25	5,514
Mobile Home	1,866	409	551	242	276	292	67	17	—	3,719
Total	**59,325**	**19,540**	**19,266**	**13,515**	**12,566**	**9,066**	**6,505**	**906**	**79**	**140,766**

Table G-25. Residential Electricity Proportions by Subsector and End Use for the Mid Atlantic Census Division in 2012

Subsector	Interior Equipment (%)	Interior Lights (%)	Space Cooling (%)	Space Heating (%)	Fans (%)	Water Systems (%)a	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	42.4	14.4	13.8	10.3	8.3	7.3	3.0	0.6	—	74.4
Single Family Attached	50.2	11.0	14.8	6.5	7.4	7.8	1.8	0.5	—	9.8
Apartment in Building 2 to 4 Units	33.8	13.7	11.8	8.6	14.0	—	16.5	1.2	0.4	9.3
Midrise Apartment Building	32.2	14.2	12.5	7.9	14.3	—	17.0	1.4	0.5	3.9
Mobile Home	50.2	11.0	14.8	6.5	7.4	7.8	1.8	0.5	—	2.6
Total	**42.1**	**13.9**	**13.7**	**9.6**	**8.9**	**6.4**	**4.6**	**0.6**	**0.1**	**100.0**

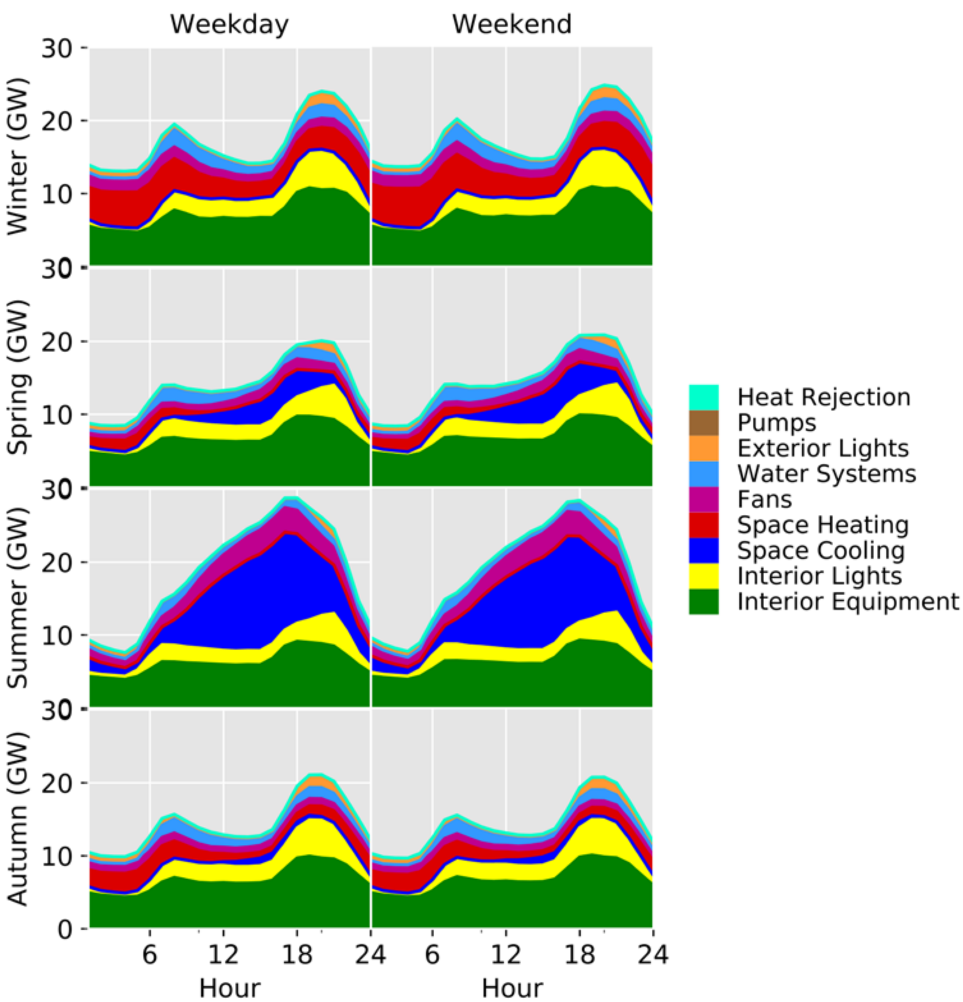

Figure G-25. Residential electricity use diurnal patterns by season, modeled for the Mid Atlantic census division 2012

Table G-26. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the Mid Atlantic Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Exterior Lights (GWh)	Space Cooling (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Strip Mall	33,372	4,833	7,535	6,797	2,980	1,995	25	10	57,547
Large Office	9,146	10,950	6,715	1,859	5,378	187	819	267	35,320
Standalone Retail Store	7,303	2,311	2,240	1,102	906	1,012	5	2	14,882
Medium Office	2,735	3,117	2,044	974	1,288	159	109	34	10,458
Small Office	1,918	2,621	1,237	750	702	258	8	5	7,500
Warehouse	1,954	785	758	957	103	927	6	2	5,491
Full Service Restaurant	1,208	2,720	669	338	371	174	6	2	5,489
Large Hotel	780	1,237	567	196	469	62	36	13	3,360
Hospital	494	686	315	39	246	8	45	17	1,850
Primary School	531	427	236	70	137	72	6	3	1,482
Outpatient Treatment Facility	393	592	173	141	101	—	19	8	1,426
Small Hotel	87	133	22	60	12	12	1	0	326
Quick Service Restaurant	7	39	12	4	6	0	0	0	69
Total	**59,927**	**30,452**	**22,523**	**13,287**	**12,699**	**4,865**	**1,085**	**362**	**145,200**

Table G-27. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the Mid Atlantic Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Exterior Lights (%)	Space Cooling (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Strip Mall	58.0	8.4	13.1	11.8	5.2	3.5	0.0	0.0	39.6
Large Office	25.9	31.0	19.0	5.3	15.2	0.5	2.3	0.8	24.3
Standalone Retail Store	49.1	15.5	15.1	7.4	6.1	6.8	0.0	0.0	10.2
Medium Office	26.2	29.8	19.5	9.3	12.3	1.5	1.0	0.3	7.2
Small Office	25.6	35.0	16.5	10.0	9.4	3.4	0.1	0.1	5.2
Warehouse	35.6	14.3	13.8	17.4	1.9	16.9	0.1	0.0	3.8
Full Service Restaurant	22.0	49.6	12.2	6.2	6.8	3.2	0.1	0.0	3.8
Large Hotel	23.2	36.8	16.9	5.8	14.0	1.8	1.1	0.4	2.3
Hospital	26.7	37.1	17.0	2.1	13.3	0.4	2.4	0.9	1.3
Primary School	35.9	28.8	15.9	4.7	9.2	4.9	0.4	0.2	1.0
Outpatient Treatment Facility	27.5	41.5	12.1	9.9	7.1	—	1.3	0.5	1.0
Small Hotel	26.5	40.8	6.7	18.4	3.6	3.5	0.4	0.1	0.2
Quick Service Restaurant	9.7	57.5	18.1	5.7	8.3	0.5	0.0	0.1	0.0
Total	**41.3**	**21.0**	**15.5**	**9.2**	**8.7**	**3.4**	**0.7**	**0.2**	**100.0**

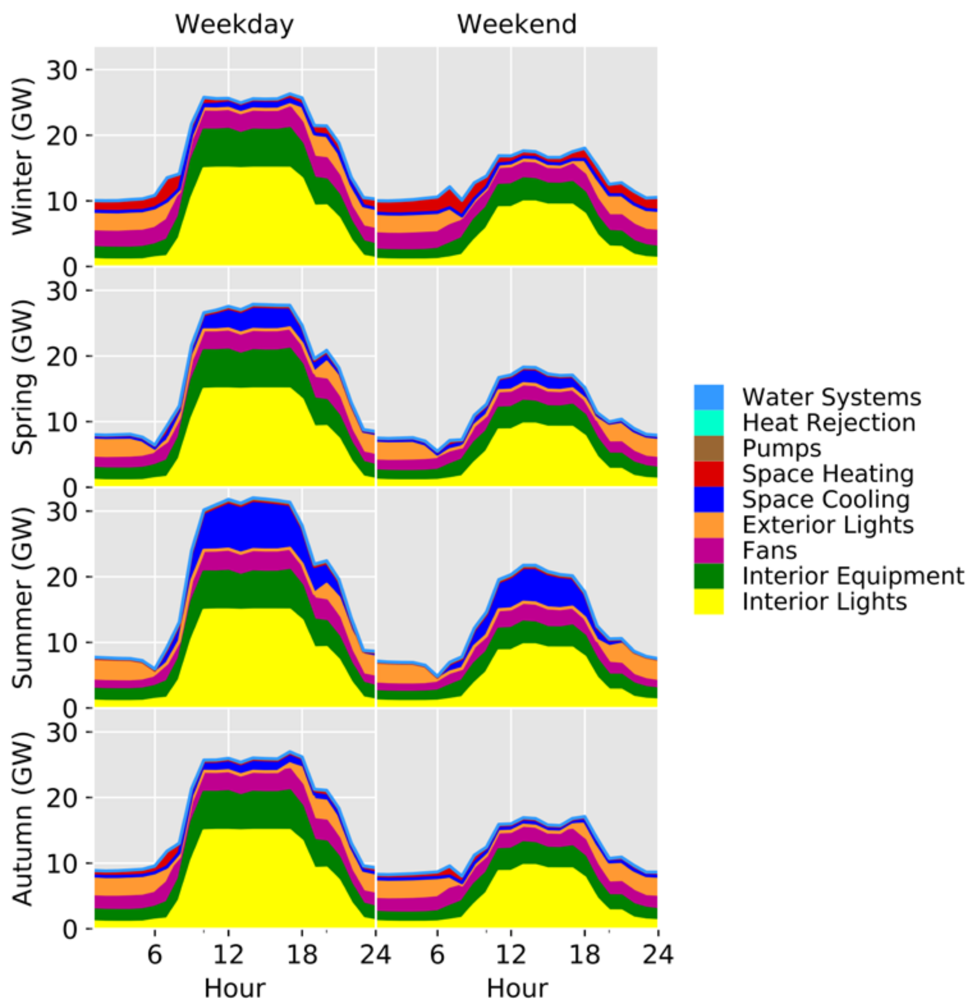

Figure G-26. Commercial electricity use diurnal patterns by season, modeled for the Mid Atlantic census division 2012

Table G-28. Industrial Manufacturing Subsectors, Summary of Model Results for the Mid Atlantic Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Pharmaceutical and Medicine Manufacturing	7,779	502	2,342	876	1,328	564	212	293	166	189	35	35	14,322
Basic Chemical Manufacturing	5,090	328	1,511	567	857	366	137	189	107	122	23	22	9,320
Iron and Steel Mills and Ferroalloy Manufacturing	2,341	3,006	2,000	544	129	382	135	41	104	171	14	24	8,893
Pulp, Paper, and Paperboard Mills	3,538	184	38	205	78	180	158	216	50	23	9	—	4,680
Plastics Product Manufacturing	2,025	606	—	382	303	357	—	19	86	—	16	—	3,794
Converted Paper Product Manufacturing	2,785	145	30	163	62	142	125	171	40	19	8	—	3,690
Other Chemical Product and Preparation Manufacturing	1,769	114	528	198	299	127	48	66	37	43	8	8	3,245
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	1,749	113	535	199	303	128	48	67	38	43	8	8	3,241
Petroleum and Coal Products Manufacturing	2,075	87	37	97	108	65	18	19	25	29	0	3	2,563
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	1,369	88	407	153	231	98	37	51	29	33	6	6	2,507
Other Nonmetallic Mineral Product Manufacturing	940	446	31	114	68	87	38	16	27	—	7	3	1,775
Printing and Related Support Activities	917	71	19	288	127	144	24	14	48	—	19	—	1,671
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	842	55	258	96	147	62	23	32	18	21	4	4	1,562
Semiconductor and Other Electronic Component Manufacturing	336	175	33	352	168	134	107	13	71	32	4	28	1,452
Glass and Glass Product Manufacturing	691	327	23	83	49	63	27	11	19	—	5	2	1,301
Paint, Coating, and Adhesive Manufacturing	695	45	212	79	120	51	19	27	15	17	3	3	1,287

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Nonferrous Metal (except Aluminum) Production and Processing	340	433	277	76	18	54	19	6	14	24	2	3	1,266
Other Wood Product Manufacturing	799	68	3	81	8	64	12	19	17	12	3	4	1,089
Dairy Product Manufacturing	461	45	2	88	274	78	19	32	21	23	10	4	1,058
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	213	111	21	228	109	87	70	8	46	21	2	18	934
Beverage Manufacturing	337	40	2	110	184	87	23	15	31	72	19	4	925
Other Miscellaneous Manufacturing	302	107	6	222	66	128	17	15	45	—	5	2	916
Other Electrical Equipment and Component Manufacturing	260	213	72	153	59	91	34	4	21	—	6	—	913
Architectural and Structural Metals Manufacturing	374	128	34	134	28	84	31	—	29	—	6	2	851
Foundries	220	281	185	51	12	36	13	4	10	16	1	2	830
Bakeries and Tortilla Manufacturing	345	34	2	67	208	59	14	24	16	18	7	3	797
Other Fabricated Metal Product Manufacturing	339	116	30	120	25	76	28	—	26	—	5	2	767
Cement and Concrete Product Manufacturing	395	188	13	48	29	37	16	7	11	—	3	1	749
Fruit and Vegetable Preserving and Specialty Food Manufacturing	317	31	2	62	192	54	13	23	15	16	7	3	734
Animal Slaughtering and Processing	297	29	2	58	180	51	12	21	14	15	6	3	689
Other Food Manufacturing	244	24	1	47	146	41	10	17	11	12	5	2	561
Motor Vehicle Parts Manufacturing	208	59	3	101	27	68	27	4	21	8	8	6	542
Other General Purpose Machinery Manufacturing	208	48	5	102	20	70	12	5	18	—	5	—	493
Medical Equipment and Supplies Manufacturing	156	55	3	114	33	66	9	7	23	—	3	1	470

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Steel Product Manufacturing from Purchased Steel	124	157	101	28	7	20	7	2	5	9	1	1	461
Fabric Mills	257	37	0	65	16	32	8	9	7	—	4	—	433
Forging and Stamping	185	64	17	66	14	42	15	—	14	—	3	1	421
Coating, Engraving, Heat Treating, and Allied Activities	184	63	17	67	14	42	16	—	14	—	3	1	420
Communications Equipment Manufacturing	93	49	9	100	48	38	31	4	20	9	1	8	409
Aerospace Product and Parts Manufacturing	150	43	3	73	20	49	19	3	15	6	5	5	390
Clay Product and Refractory Manufacturing	204	97	7	25	15	19	8	3	6	—	1	1	388
Electrical Equipment Manufacturing	107	89	31	65	25	38	14	2	9	—	3	—	383
Fiber, Yarn, and Thread Mills	225	32	0	56	14	27	7	8	6	—	3	—	378
Industrial Machinery Manufacturing	159	37	4	77	15	52	9	4	14	—	4	—	373
Alumina and Aluminum Production and Processing	97	124	80	22	5	15	5	2	4	7	1	1	364
Sugar and Confectionery Product Manufacturing	150	15	1	29	92	26	6	11	7	8	3	1	349
Commercial and Service Industry Machinery Manufacturing	144	33	3	69	14	47	8	3	12	—	3	—	338
Metalworking Machinery Manufacturing	140	32	3	68	14	47	8	3	12	—	3	—	332
Engine, Turbine, and Power Transmission Equipment Manufacturing	135	31	3	65	13	45	7	3	12	—	3	—	318
Railroad Rolling Stock Manufacturing	106	30	2	52	14	35	14	2	11	4	4	3	278
Animal Food Manufacturing	119	12	1	23	73	20	5	9	6	6	3	1	277
Textile and Fabric Finishing and Fabric Coating Mills	162	23	0	41	10	20	5	6	4	—	2	—	273

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Rubber Product Manufacturing	142	42	—	27	21	25	—	1	6	—	1	—	266
Veneer, Plywood, and Engineered Wood Product Manufacturing	172	15	1	17	2	14	2	4	4	2	1	1	233
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	105	8	1	43	4	36	—	3	7	—	2	1	209
Lime and Gypsum Product Manufacturing	97	46	3	12	7	9	4	2	3	—	1	0	184
Motor Vehicle Body and Trailer Manufacturing	67	19	1	33	9	22	9	1	7	3	2	2	175
Other Transportation Equipment Manufacturing	66	19	1	32	9	22	9	1	7	3	2	2	174
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	73	25	7	26	6	17	6	—	6	—	1	0	167
Computer and Peripheral Equipment Manufacturing	36	19	4	40	19	15	12	1	8	4	0	3	163
Grain and Oilseed Milling	70	7	0	14	42	12	3	5	3	4	1	1	162
Agriculture, Construction, and Mining Machinery Manufacturing	66	15	2	32	6	22	4	1	6	—	2	—	155
Spring and Wire Product Manufacturing	57	20	5	21	4	13	5	—	5	—	1	0	131
Manufacturing and Reproducing Magnetic and Optical Media	30	15	3	31	15	12	10	1	6	3	0	2	129
Electric Lighting Equipment Manufacturing	34	28	9	20	8	12	4	1	3	—	1	—	120
Audio and Video Equipment Manufacturing	25	13	2	26	12	10	8	1	5	2	0	2	108
Cut and Sew Apparel Manufacturing	36	5	—	26	2	15	—	2	3	—	1	—	90
Ship and Boat Building	34	10	1	17	5	11	5	1	4	1	1	1	90

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	36	8	1	17	3	12	2	1	3	—	1	—	84
Boiler, Tank, and Shipping Container Manufacturing	34	12	3	12	2	7	3	—	3	—	1	0	76
Other Textile Product Mills	38	5	0	9	5	8	0	4	2	—	2	—	73
Motor Vehicle Manufacturing	27	8	0	14	4	9	4	1	3	1	1	1	72
Office Furniture (including Fixtures) Manufacturing	35	3	0	15	1	12	—	1	2	—	1	0	71
Tobacco Manufacturing	23	3	0	7	12	6	2	1	2	5	1	0	61
Cutlery and Handtool Manufacturing	22	8	2	8	2	5	2	—	2	—	0	0	50
Seafood Product Preparation and Packaging	16	2	0	3	10	3	1	1	1	1	0	0	36
Household Appliance Manufacturing	10	8	3	6	2	3	1	0	1	—	0	—	35
Sawmills and Wood Preservation	19	2	0	2	0	2	0	0	0	0	0	0	26
Other Leather and Allied Product Manufacturing	12	2	0	2	1	2	0	0	0	—	0	—	19
Other Furniture Related Product Manufacturing	8	1	0	3	0	3	—	0	1	—	0	0	16
Footwear Manufacturing	4	1	0	1	0	1	0	0	0	—	0	—	7
Textile Furnishings Mills	4	0	0	1	0	1	0	0	0	—	0	—	7
Leather and Hide Tanning and Finishing	2	0	0	0	0	0	0	0	0	—	0	—	4
Hardware Manufacturing	1	0	0	0	0	0	0	—	0	—	0	0	3
Apparel Accessories and Other Apparel Manufacturing	0	0	—	0	0	0	—	0	0	—	0	—	1
Total	**44,898**	**9,637**	**9,001**	**7,770**	**6,633**	**5,134**	**1,823**	**1,565**	**1,553**	**1,055**	**349**	**249**	**89,667**

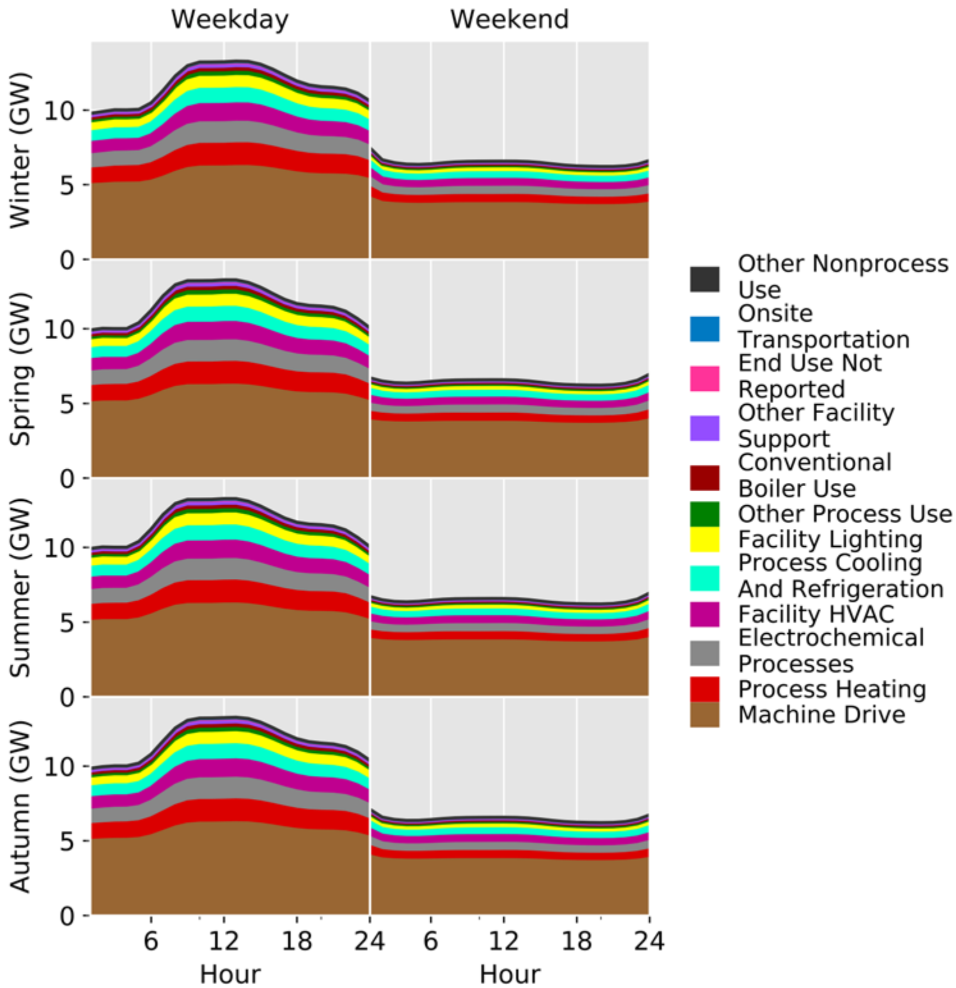

Figure G-27. Industrial electricity use diurnal patterns by season, modeled for the Mid Atlantic census division 2012

Table G-29. Distributed Generation Model, Annual Summary the Mid Atlantic Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	33,096	9,015	349	42,460
Distributed PV (GWh)	542	544	318	1,403
Thermal DG (GWh)	36	40	—	76
Total (GWh)	**33,674**	**9,599**	**667**	**43,940**
CHP (%)	98.3	93.9	52.3	96.6
Distributed PV (%)	1.6	5.7	47.7	3.2
Thermal DG (%)	0.1	0.4	—	0.2
Total (%)	**76.6**	**21.8**	**1.5**	**100.0**

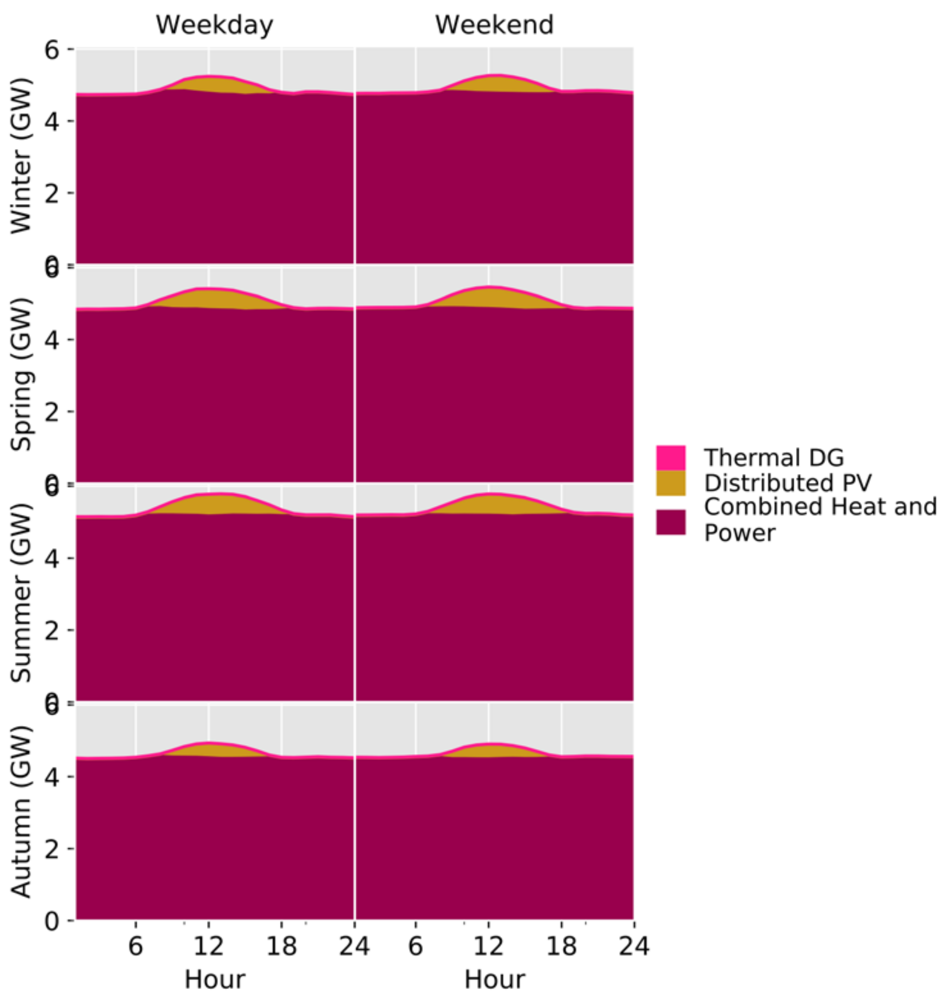

Figure G-28. Distributed Generation Model Diurnal Generation Patterns, Mid Atlantic census division 2012

G.5 South Atlantic

Table G-30. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, South Atlantic Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					810.7
Derived	T&D losses					41.8
Top-down	Annual energy	336.8	305.6	139.4	1.3	783.0
dsgrid	Distributed generation	–	3.0	30.7	–	33.6
dsgrid-core	Gap models	63.8	91.8	27.3	0.8	183.7
dsgrid-core	Detailed sector models	271.1	251.1	174.0	–	696.2
Derived	Total site energy	336.8	308.6	170.0	1.3	816.7
Derived	Annual sector residuals	1.9	-34.4	-31.3	0.5	-63.3
Derived	Hourly residuals					-79.2

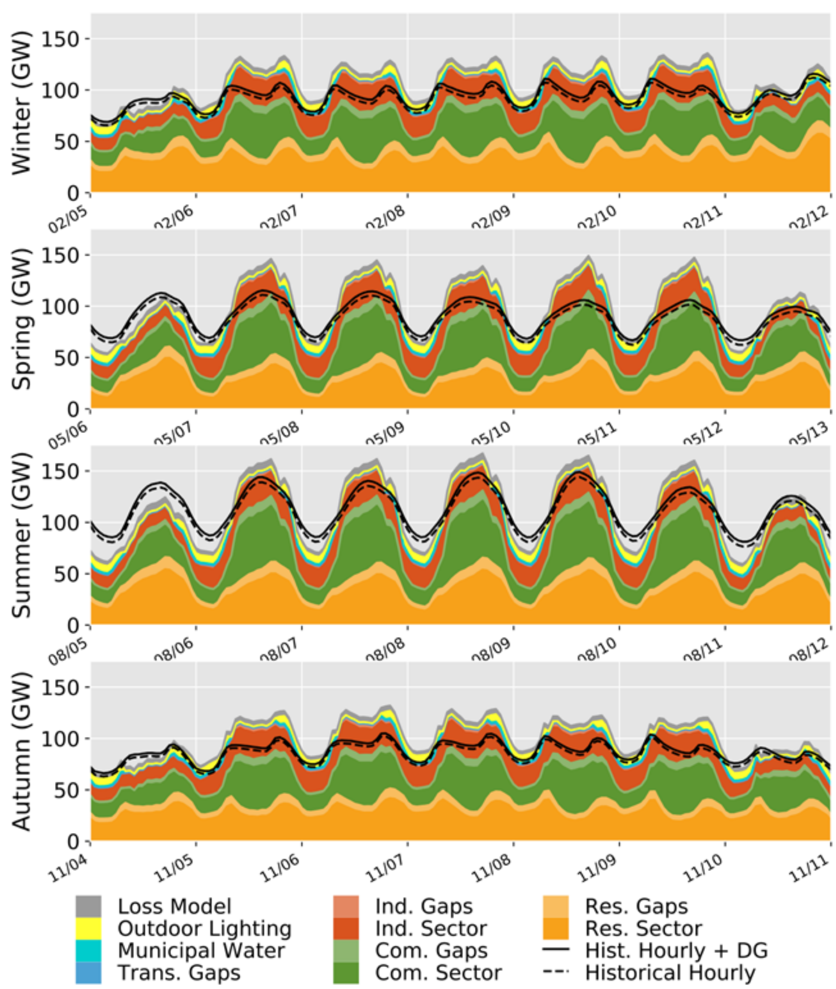

Figure G-29. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the South Atlantic census division in 2012

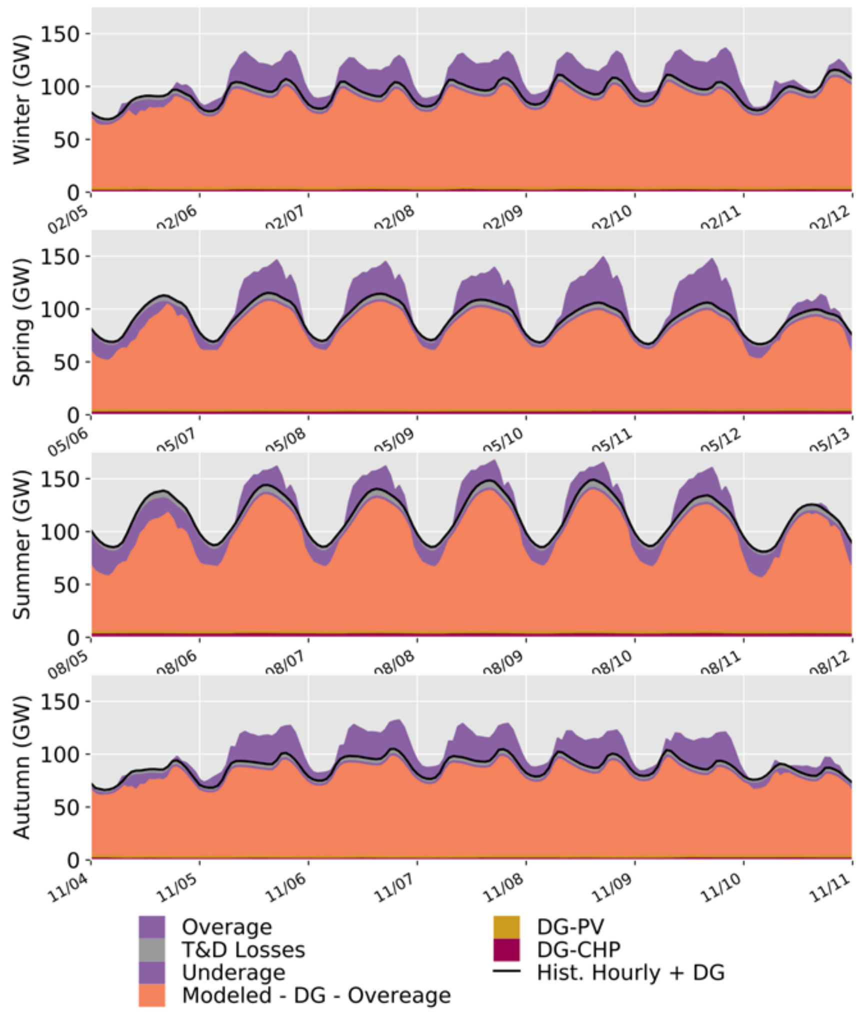

Figure G-30. dsgrid hourly residuals shown in context for the South Atlantic census division.

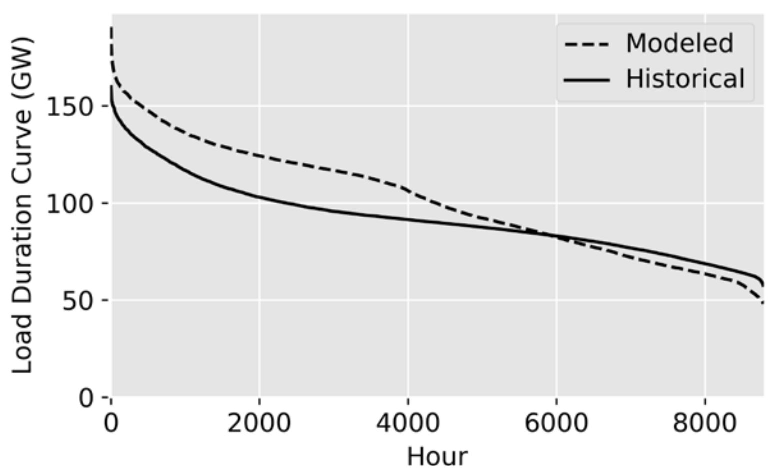

Figure G-31. Historical and dsgrid load duration curves for the South Atlantic census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-31. Residential Subsectors, Summary of Electricity by End Use for the South Atlantic Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Space Heating (GWh)	Interior Lights (GWh)	Water Systems (GWh)	Fans (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	89,096	61,900	32,942	28,115	27,691	22,142	5,716	39	—	267,640
Mobile Home	11,787	6,684	2,873	2,423	3,965	2,322	394	7	—	30,454
Single Family Attached	8,164	4,630	1,990	1,678	2,747	1,608	273	5	—	21,094
Apartment in Building 2 to 4 Units	4,030	2,083	466	1,735	—	1,640	2,083	164	74	12,274
Midrise Apartment Building	1,081	613	131	485	—	461	578	52	24	3,424
Total	114,157	75,909	38,402	34,435	34,403	28,173	9,043	266	98	334,886

Table G-32. Residential Electricity Proportions by Subsector and End Use for the South Atlantic Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Space Heating (%)	Interior Lights (%)	Water Systems (%)	Fans (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	33.3	23.1	12.3	10.5	10.3	8.3	2.1	0.0	—	79.9
Mobile Home	38.7	21.9	9.4	8.0	13.0	7.6	1.3	0.0	—	9.1
Single Family Attached	38.7	21.9	9.4	8.0	13.0	7.6	1.3	0.0	—	6.3
Apartment in Building 2 to 4 Units	32.8	17.0	3.8	14.1	—	13.4	17.0	1.3	0.6	3.7
Midrise Apartment Building	31.6	17.9	3.8	14.2	—	13.5	16.9	1.5	0.7	1.0
Total	**34.1**	**22.7**	**11.5**	**10.3**	**10.3**	**8.4**	**2.7**	**0.1**	**0.0**	**100.0**

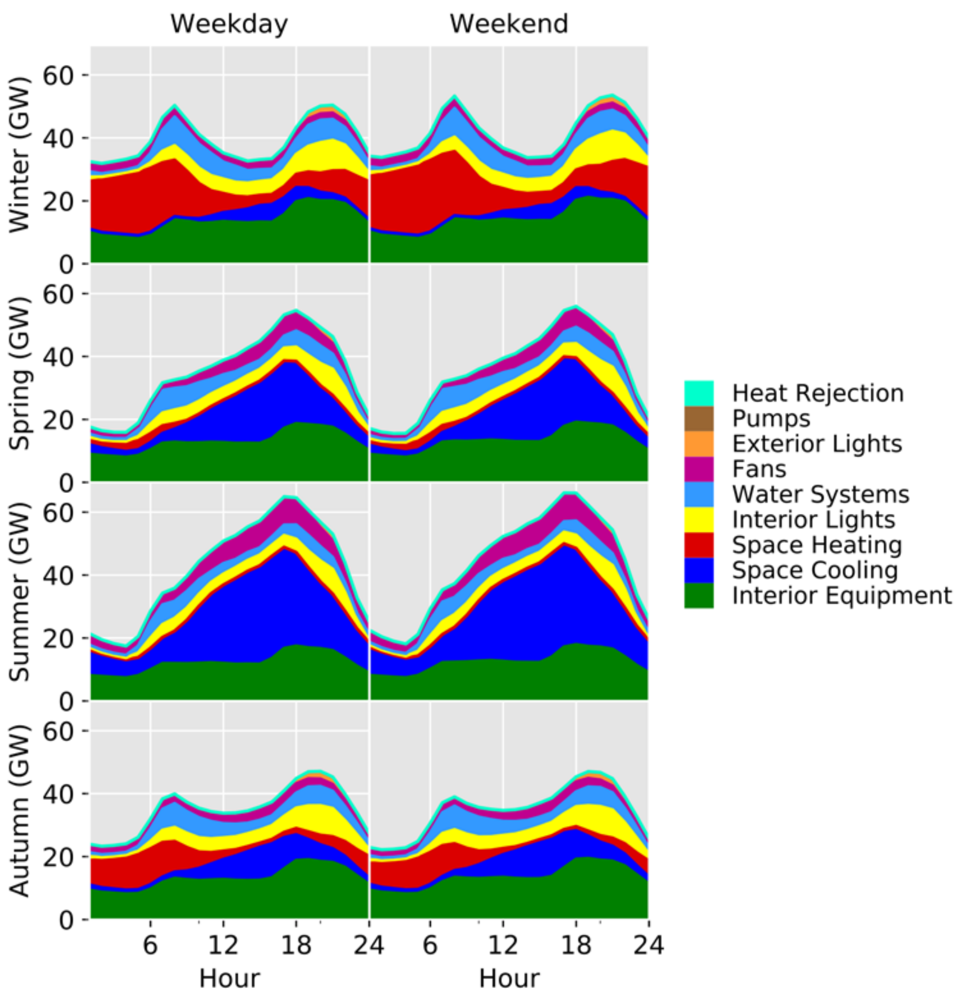

Figure G-32. Residential electricity use diurnal patterns by season, modeled for the South Atlantic census division 2012

Table G-33. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the South Atlantic Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Space Cooling (GWh)	Fans (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Large Office	18,354	21,049	16,108	14,570	3,736	255	2,149	915	77,135
Strip Mall	30,416	4,409	5,428	5,947	6,198	1,019	26	13	53,456
Standalone Retail Store	17,273	5,332	4,287	4,651	2,607	915	13	6	35,085
Medium Office	4,289	4,902	3,473	3,017	1,528	85	208	89	17,591
Small Office	4,150	5,696	2,808	2,813	1,622	196	25	18	17,328
Large Hotel	2,961	4,783	3,259	2,694	761	76	168	74	14,774
Warehouse	4,398	1,746	513	1,140	2,099	631	10	8	10,544
Full Service Restaurant	2,122	4,733	1,377	1,193	592	105	14	6	10,143
Hospital	1,678	2,131	1,715	1,153	126	—	258	146	7,206
Primary School	1,160	925	625	558	149	46	21	13	3,496
Outpatient Treatment Facility	912	1,340	311	338	328	—	48	26	3,303
Small Hotel	248	343	45	39	163	11	5	3	857
Quick Service Restaurant	19	115	33	37	11	1	0	0	217
Total	**87,979**	**57,504**	**39,982**	**38,150**	**19,920**	**3,340**	**2,943**	**1,318**	**251,137**

Table G-34. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the South Atlantic Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Space Cooling (%)	Fans (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Large Office	23.8	27.3	20.9	18.9	4.8	0.3	2.8	1.2	30.7
Strip Mall	56.9	8.2	10.2	11.1	11.6	1.9	0.0	0.0	21.3
Standalone Retail Store	49.2	15.2	12.2	13.3	7.4	2.6	0.0	0.0	14.0
Medium Office	24.4	27.9	19.7	17.2	8.7	0.5	1.2	0.5	7.0
Small Office	24.0	32.9	16.2	16.2	9.4	1.1	0.1	0.1	6.9
Large Hotel	20.0	32.4	22.1	18.2	5.1	0.5	1.1	0.5	5.9
Warehouse	41.7	16.6	4.9	10.8	19.9	6.0	0.1	0.1	4.2
Full Service Restaurant	20.9	46.7	13.6	11.8	5.8	1.0	0.1	0.1	4.0
Hospital	23.3	29.6	23.8	16.0	1.7	—	3.6	2.0	2.9
Primary School	33.2	26.5	17.9	16.0	4.3	1.3	0.6	0.4	1.4
Outpatient Treatment Facility	27.6	40.6	9.4	10.2	9.9	—	1.4	0.8	1.3
Small Hotel	28.9	40.0	5.3	4.5	19.0	1.3	0.6	0.3	0.3
Quick Service Restaurant	8.9	53.0	15.2	17.0	5.2	0.4	0.1	0.1	0.1
Total	**35.0**	**22.9**	**15.9**	**15.2**	**7.9**	**1.3**	**1.2**	**0.5**	**100.0**

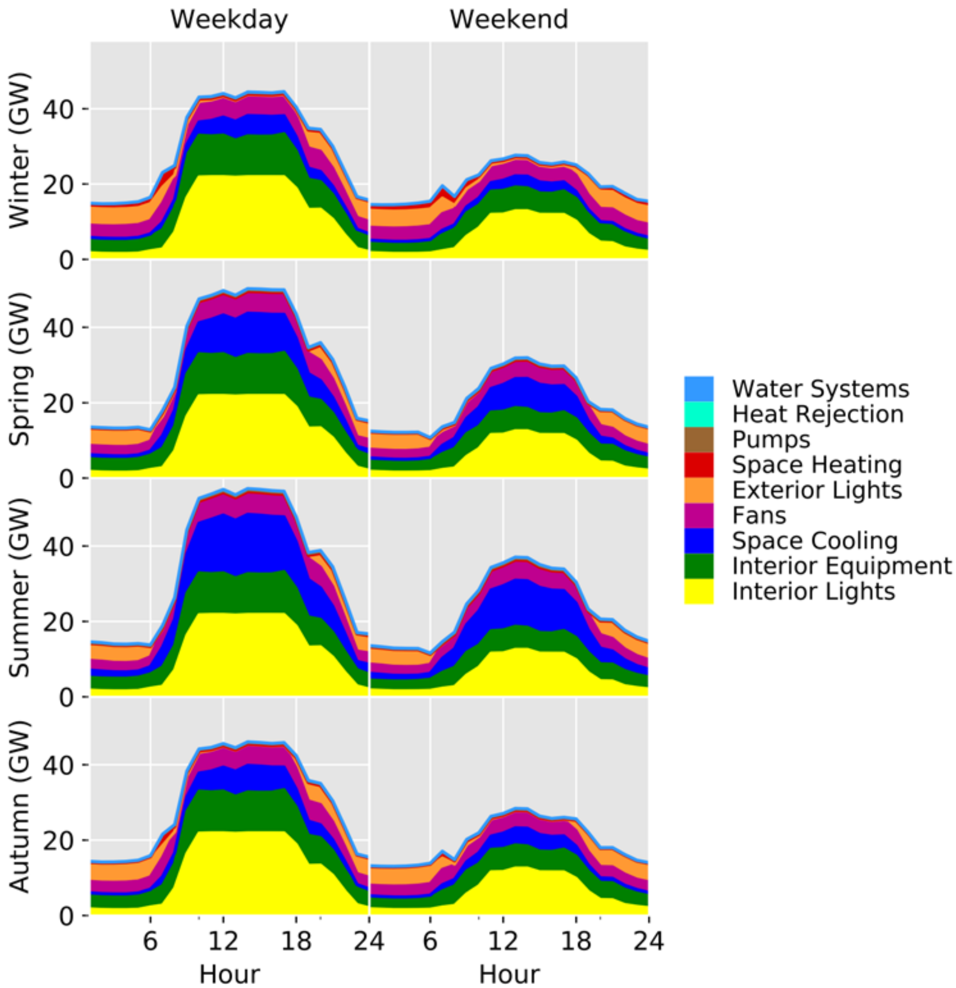

Figure G-33. Commercial electricity use diurnal patterns by season, modeled for the South Atlantic census division 2012

Table G-35. Industrial Manufacturing Subsectors, Summary of Model Results for the South Atlantic Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Pulp, Paper, and Paperboard Mills	15,867	824	921	172	351	805	708	967	225	105	43	—	20,988
Iron and Steel Mills and Ferroalloy Manufacturing	3,372	4,329	784	2,879	186	550	195	59	150	247	21	35	12,806
Petroleum and Coal Products Manufacturing	9,798	410	460	176	512	306	86	90	119	136	1	12	12,106
Basic Chemical Manufacturing	6,211	400	692	1,844	1,046	446	167	231	131	149	28	27	11,372
Plastics Product Manufacturing	5,056	1,513	955	—	756	893	—	47	215	—	40	—	9,475
Converted Paper Product Manufacturing	6,491	338	380	71	145	331	293	400	93	43	18	—	8,603
Pharmaceutical and Medicine Manufacturing	4,378	283	493	1,318	748	317	119	165	94	106	20	20	8,060
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	2,691	173	300	800	454	194	72	100	57	65	12	12	4,930
Fiber, Yarn, and Thread Mills	2,849	408	709	0	176	348	86	98	71	—	41	—	4,788
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	2,470	160	282	759	430	181	69	95	54	61	11	11	4,584
Animal Slaughtering and Processing	1,919	190	373	10	1,165	328	80	137	89	98	41	19	4,450
Other Wood Product Manufacturing	3,222	274	325	13	31	260	47	77	69	47	11	15	4,389
Other Chemical Product and Preparation Manufacturing	1,938	125	217	578	328	140	52	72	41	47	9	9	3,556
Printing and Related Support Activities	1,936	149	609	41	267	304	51	30	101	—	39	—	3,527
Other Nonmetallic Mineral Product Manufacturing	1,728	820	209	57	126	160	70	29	49	—	12	5	3,266

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	1,397	90	159	427	242	102	39	54	30	35	6	6	2,588
Fabric Mills	1,526	219	385	0	96	189	47	53	39	—	23	—	2,576
Nonferrous Metal (except Aluminum) Production and Processing	648	824	145	527	34	102	36	11	28	45	4	6	2,410
Motor Vehicle Parts Manufacturing	851	242	413	14	111	277	108	18	87	35	31	26	2,214
Rubber Product Manufacturing	1,113	333	211	—	167	197	—	10	48	—	9	—	2,088
Architectural and Structural Metals Manufacturing	869	298	312	78	65	196	72	—	67	—	14	4	1,975
Veneer, Plywood, and Engineered Wood Product Manufacturing	1,408	119	140	5	13	112	20	33	29	20	5	6	1,910
Paint, Coating, and Adhesive Manufacturing	1,011	65	115	308	175	74	28	39	22	25	5	5	1,871
Aerospace Product and Parts Manufacturing	702	199	340	12	91	228	89	15	72	28	26	22	1,824
Other Fabricated Metal Product Manufacturing	735	252	261	65	54	165	61	—	56	—	11	3	1,664
Other Electrical Equipment and Component Manufacturing	470	385	278	130	107	164	61	8	38	—	12	—	1,653
Cement and Concrete Product Manufacturing	847	403	103	28	62	79	34	14	24	—	6	3	1,605
Beverage Manufacturing	580	69	190	3	317	150	40	26	53	123	33	7	1,591
Alumina and Aluminum Production and Processing	400	510	90	328	21	64	22	7	17	28	2	4	1,494
Glass and Glass Product Manufacturing	774	366	93	25	55	71	31	13	22	—	5	2	1,458

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Food Manufacturing	588	58	113	3	352	100	24	41	27	30	12	6	1,353
Textile and Fabric Finishing and Fabric Coating Mills	746	107	189	0	47	93	23	26	19	—	11	—	1,262
Bakeries and Tortilla Manufacturing	541	54	105	3	326	92	23	38	25	28	12	5	1,250
Semiconductor and Other Electronic Component Manufacturing	287	149	301	28	143	115	91	11	61	27	3	24	1,241
Foundries	322	412	74	271	18	52	18	6	14	23	2	3	1,216
Fruit and Vegetable Preserving and Specialty Food Manufacturing	512	51	100	3	311	88	21	36	24	26	11	5	1,187
Motor Vehicle Manufacturing	441	126	218	8	59	145	57	10	46	18	16	14	1,158
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	539	40	221	4	18	183	—	13	37	—	12	5	1,072
Dairy Product Manufacturing	458	45	88	2	272	77	19	32	21	23	10	4	1,052
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	236	123	252	24	121	96	77	9	51	23	3	20	1,034
Other Miscellaneous Manufacturing	322	114	237	7	70	137	19	16	48	—	6	2	976
Other Textile Product Mills	490	65	121	3	61	98	4	46	23	—	23	—	933
Ship and Boat Building	307	88	155	5	42	103	41	7	33	13	12	10	815
Other General Purpose Machinery Manufacturing	309	72	151	8	30	103	17	7	27	—	7	—	732
Coating, Engraving, Heat Treating, and Allied Activities	320	110	116	29	24	73	27	—	25	—	5	2	731

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Electrical Equipment Manufacturing	201	166	121	57	47	71	27	3	17	—	5	—	715
Communications Equipment Manufacturing	160	84	172	16	83	65	53	6	35	16	2	14	707
Animal Food Manufacturing	292	29	57	2	179	50	12	21	14	15	6	3	681
Steel Product Manufacturing from Purchased Steel	179	227	40	146	9	28	10	3	8	13	1	2	666
Engine, Turbine, and Power Transmission Equipment Manufacturing	274	63	132	7	26	90	15	6	24	—	6	—	644
Industrial Machinery Manufacturing	262	60	126	6	25	86	14	6	23	—	6	—	615
Tobacco Manufacturing	211	25	68	1	112	54	14	9	19	44	12	2	571
Commercial and Service Industry Machinery Manufacturing	219	51	106	5	21	72	12	5	19	—	5	—	515
Medical Equipment and Supplies Manufacturing	167	59	121	4	36	70	9	8	24	—	3	1	502
Lime and Gypsum Product Manufacturing	265	126	32	9	19	25	11	4	8	—	2	1	501
Forging and Stamping	198	68	71	18	15	44	16	—	15	—	3	1	449
Sugar and Confectionery Product Manufacturing	183	18	36	1	111	31	8	13	9	9	4	2	424
Clay Product and Refractory Manufacturing	222	106	27	8	16	21	9	4	6	—	2	1	422
Motor Vehicle Body and Trailer Manufacturing	141	40	69	2	19	46	18	3	15	6	5	4	368
Grain and Oilseed Milling	158	16	30	1	95	27	7	11	7	8	3	2	364
Agriculture, Construction, and Mining Machinery Manufacturing	134	31	65	3	13	44	7	3	12	—	3	—	315

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Textile Furnishings Mills	164	22	41	1	21	33	1	15	8	—	8	—	313
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	128	30	63	3	12	43	7	3	11	—	3	—	303
Seafood Product Preparation and Packaging	126	13	25	1	78	22	5	9	6	7	3	1	294
Computer and Peripheral Equipment Manufacturing	66	35	72	7	35	27	22	3	15	7	1	6	294
Cut and Sew Apparel Manufacturing	111	14	80	—	5	47	—	6	9	—	2	—	274
Metalworking Machinery Manufacturing	106	25	52	3	10	35	6	2	9	—	3	—	251
Spring and Wire Product Manufacturing	106	36	38	10	8	24	9	—	8	—	2	1	242
Other Transportation Equipment Manufacturing	85	24	42	1	11	28	11	2	9	3	3	3	223
Household Appliance Manufacturing	62	51	36	17	14	22	8	1	5	—	2	—	217
Electric Lighting Equipment Manufacturing	57	46	33	15	13	20	7	1	5	—	1	—	198
Boiler, Tank, and Shipping Container Manufacturing	80	27	28	7	6	18	6	—	6	—	1	0	180
Sawmills and Wood Preservation	126	11	13	0	1	10	2	3	3	2	0	1	171
Railroad Rolling Stock Manufacturing	65	18	32	1	9	21	8	1	7	3	2	2	170
Office Furniture (including Fixtures) Manufacturing	84	6	35	1	3	29	—	2	6	—	2	1	168
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	47	16	17	4	4	11	4	—	4	—	1	0	107

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Conventional Boiler Use (GWh)	Other Facility Support (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Furniture Related Product Manufacturing	47	3	19	0	2	16	—	1	3	—	1	0	93
Audio and Video Equipment Manufacturing	16	8	17	2	8	6	5	1	3	2	0	1	70
Manufacturing and Reproducing Magnetic and Optical Media	15	8	16	1	7	6	5	1	3	1	0	1	64
Cutlery and Handtool Manufacturing	23	8	8	2	2	5	2	—	2	—	0	0	52
Other Leather and Allied Product Manufacturing	16	2	3	0	1	3	0	0	1	—	0	—	26
Footwear Manufacturing	5	1	1	0	0	1	0	0	0	—	0	—	9
Hardware Manufacturing	4	1	1	0	0	1	0	—	0	—	0	0	8
Apparel Accessories and Other Apparel Manufacturing	2	0	2	—	0	1	—	0	0	—	0	—	6
Leather and Hide Tanning and Finishing	2	0	0	0	0	0	0	0	0	—	0	—	4
Apparel Knitting Mills	1	0	1	—	0	0	—	0	0	—	0	—	2
Total	**94,480**	**17,959**	**15,331**	**11,431**	**11,302**	**10,543**	**3,599**	**3,354**	**3,047**	**1,788**	**787**	**409**	**174,029**

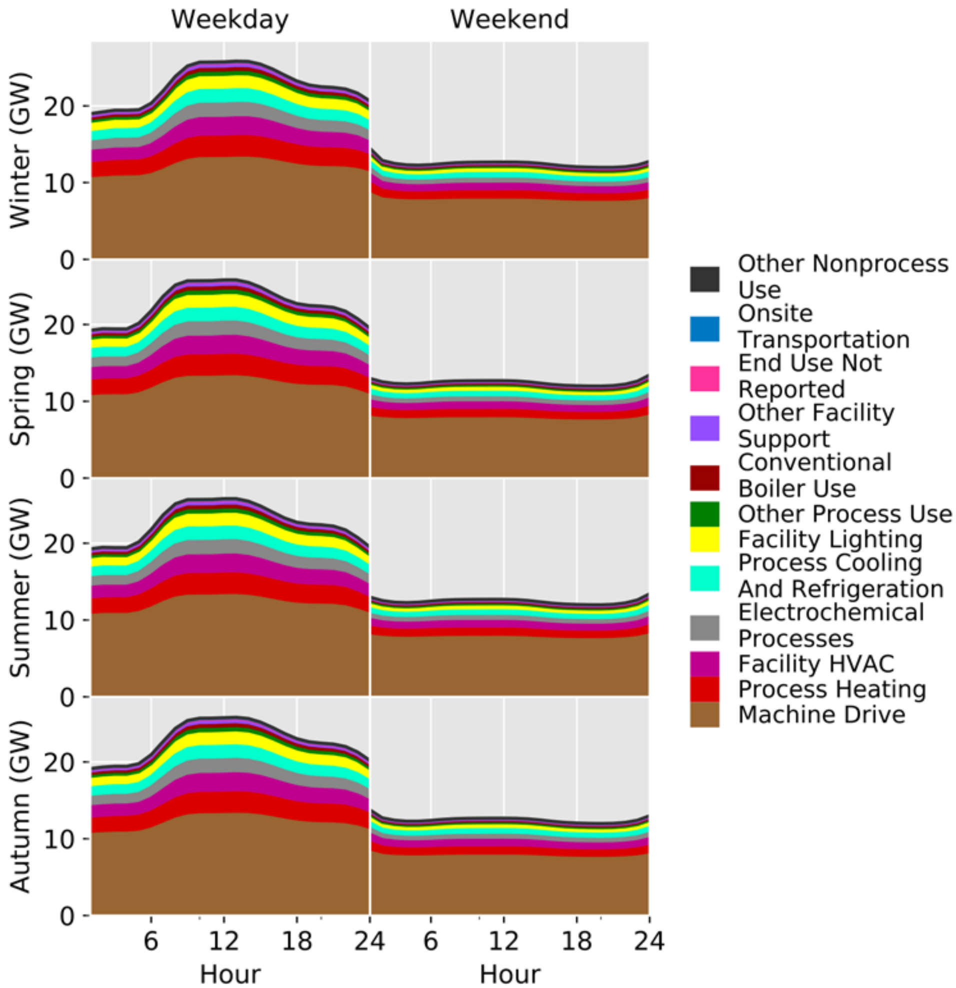

Figure G-34. Industrial electricity use diurnal patterns by season, modeled for the South Atlantic census division 2012

Table G-36. Distributed Generation Model, Annual Summary the South Atlantic Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	30,000	2,751	—	32,752
Thermal DG (GWh)	553	111		664
Distributed PV (GWh)	114	114	86	314
Total (GWh)	**30,667**	**2,976**	**86**	**33,730**
CHP (%)	97.8	92.4	—	97.1
Thermal DG (%)	1.8	3.7	—	2.0
Distributed PV (%)	0.4	3.8	100.0	0.9
Total (%)	**90.9**	**8.8**	**0.3**	**100.0**

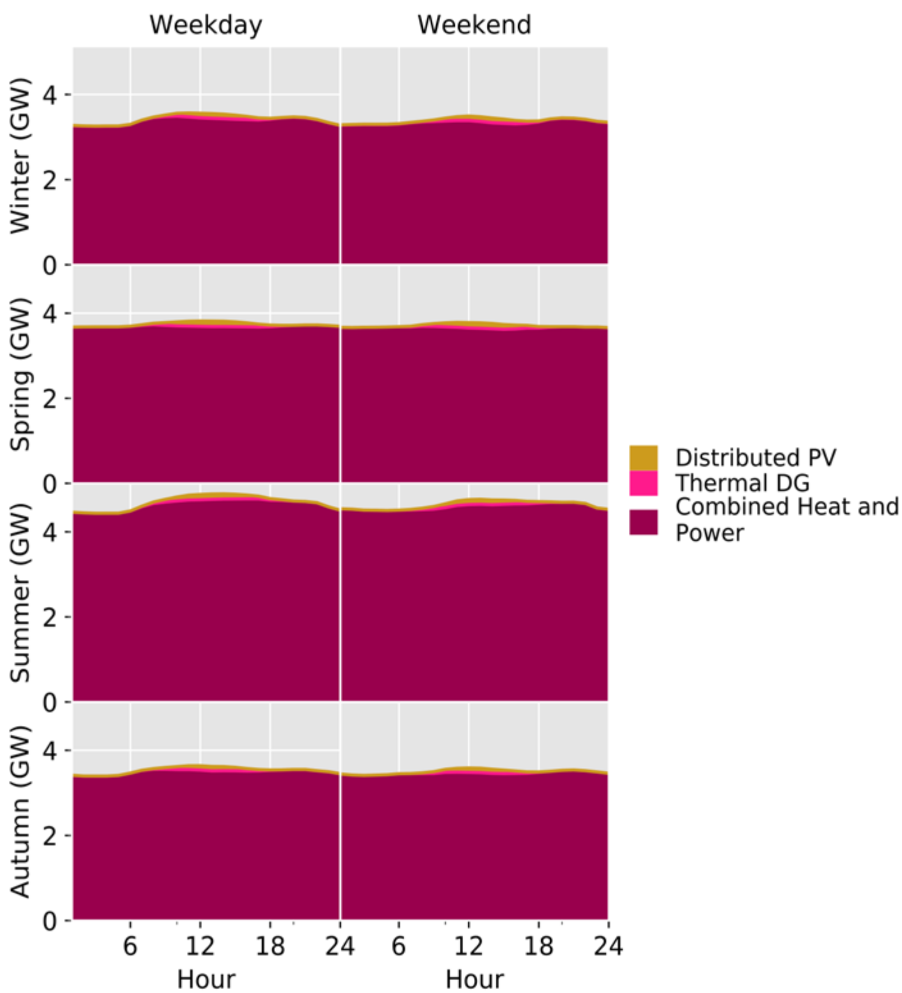

Figure G-35. Distributed Generation Model Diurnal Generation Patterns, South Atlantic census division 2012

G.6 East South Central

Table G-37. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, East South Central Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					332.8
Derived	T&D losses					17.8
Top-down	Annual energy	114.5	82.8	123.2	0.0	320.5
dsgrid	Distributed generation	–	0.5	17.9	–	18.3
dsgrid-core	Gap models	16.6	25.6	11.3	0.0	53.5
dsgrid-core	Detailed sector models	88.8	54.7	89.4	–	232.9
Derived	Total site energy	114.5	83.2	141.1	0.0	338.8
Derived	Annual sector residuals	9.0	3.0	40.4	0.0	52.4
Derived	Hourly residuals					33.2

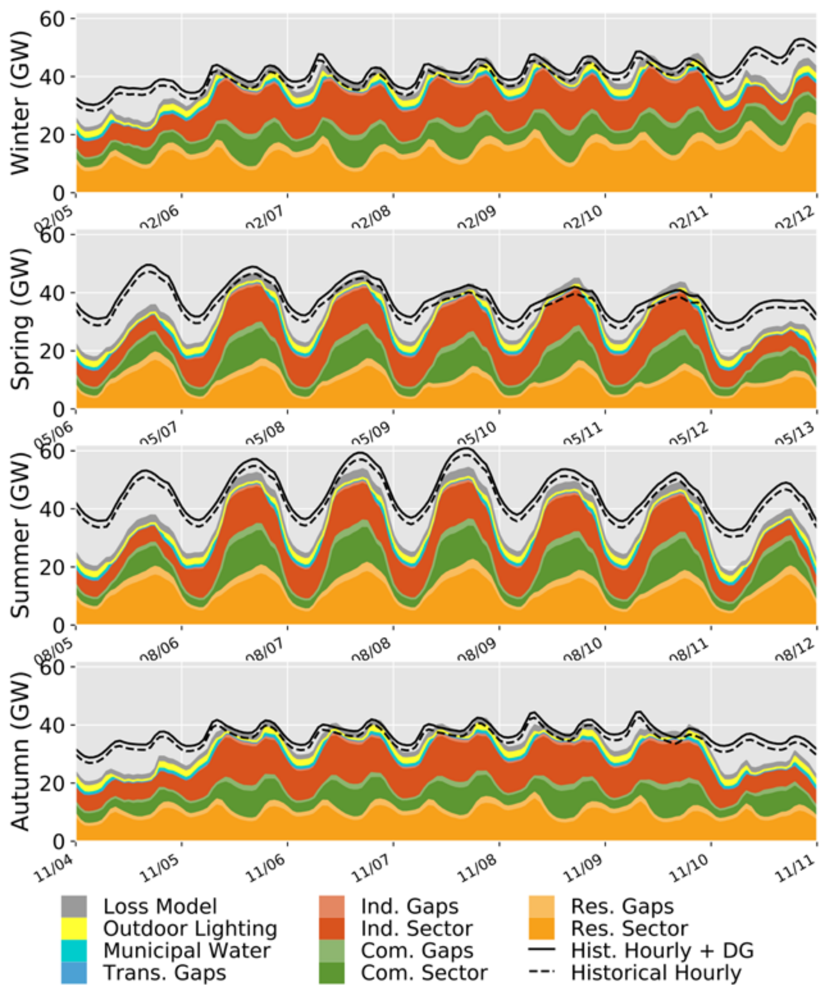

Figure G-36. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the East South Central census division in 2012

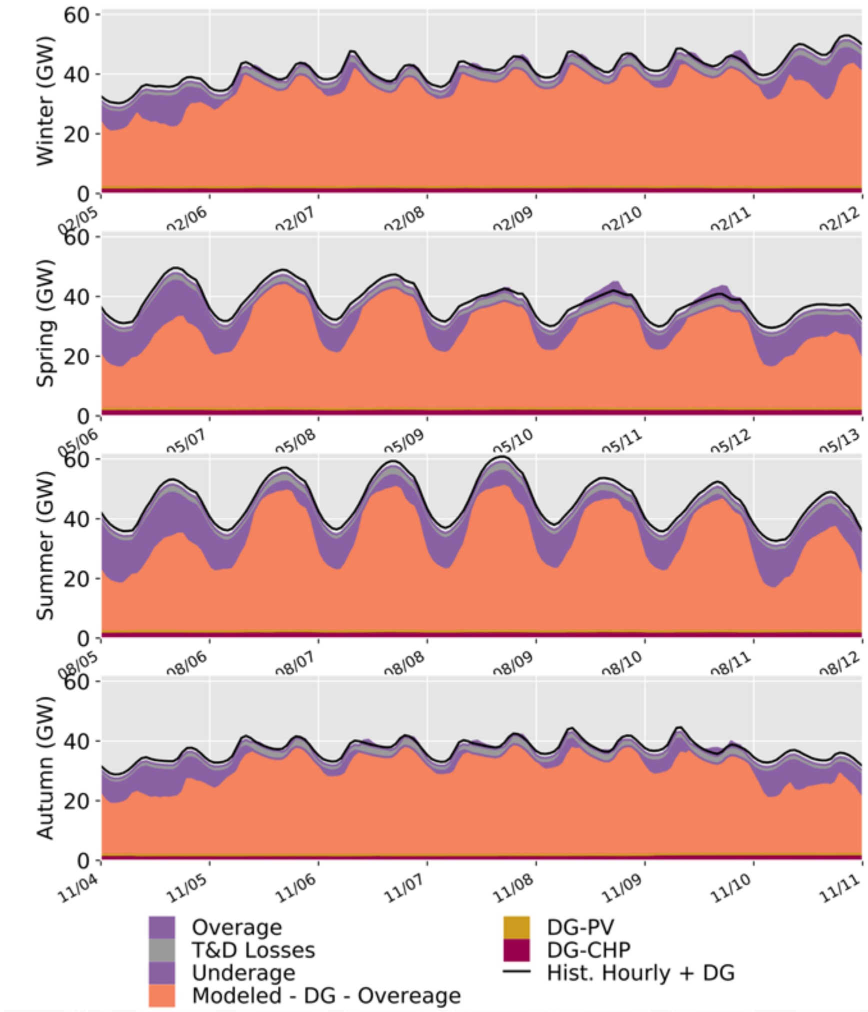

Figure G-37. dsgrid hourly residuals shown in context for the East South Central census division.

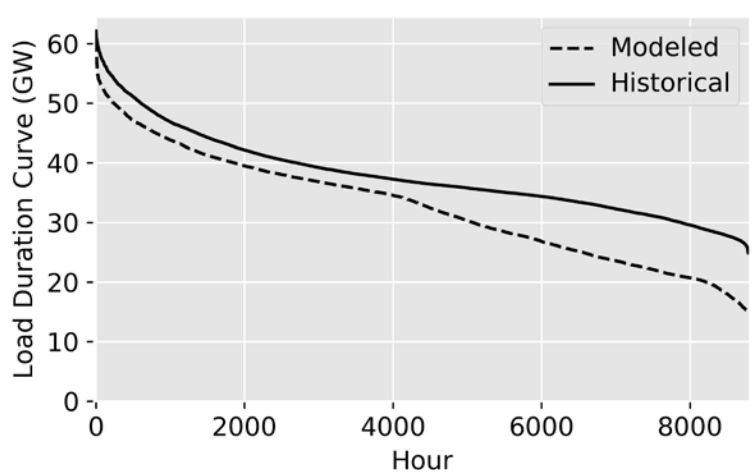

Figure G-38. Historical and dsgrid load duration curves for the East South Central census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-38. Residential Subsectors, Summary of Electricity by End Use for the East South Central Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Space Heating (GWh)	Interior Lights (GWh)	Water Systems (GWh)	Fans (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	29,574	17,358	14,166	9,205	8,997	7,185	1,864	10	—	88,359
Mobile Home	4,398	2,137	1,464	906	1,402	852	147	2	—	11,307
Apartment in Building 2 to 4 Units	1,144	577	120	490	—	502	592	46	15	3,485
Single Family Attached	716	348	238	147	228	139	24	0	—	1,841
Midrise Apartment Building	145	79	15	64	—	71	76	7	2	459
Total	**35,977**	**20,498**	**16,003**	**10,811**	**10,628**	**8,749**	**2,704**	**64**	**17**	**105,451**

Table G-39. Residential Electricity Proportions by Subsector and End Use for the East South Central Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Space Heating (%)	Interior Lights (%)	Water Systems (%)	Fans (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	33.5	19.6	16.0	10.4	10.2	8.1	2.1	0.0	—	83.8
Mobile Home	38.9	18.9	12.9	8.0	12.4	7.5	1.3	0.0	—	10.7
Apartment in Building 2 to 4 Units	32.8	16.6	3.4	14.1	—	14.4	17.0	1.3	0.4	3.3
Single Family Attached	38.9	18.9	12.9	8.0	12.4	7.5	1.3	0.0	—	1.7
Midrise Apartment Building	31.7	17.2	3.2	13.9	—	15.5	16.6	1.5	0.5	0.4
Total	**34.1**	**19.4**	**15.2**	**10.3**	**10.1**	**8.3**	**2.6**	**0.1**	**0.0**	**100.0**

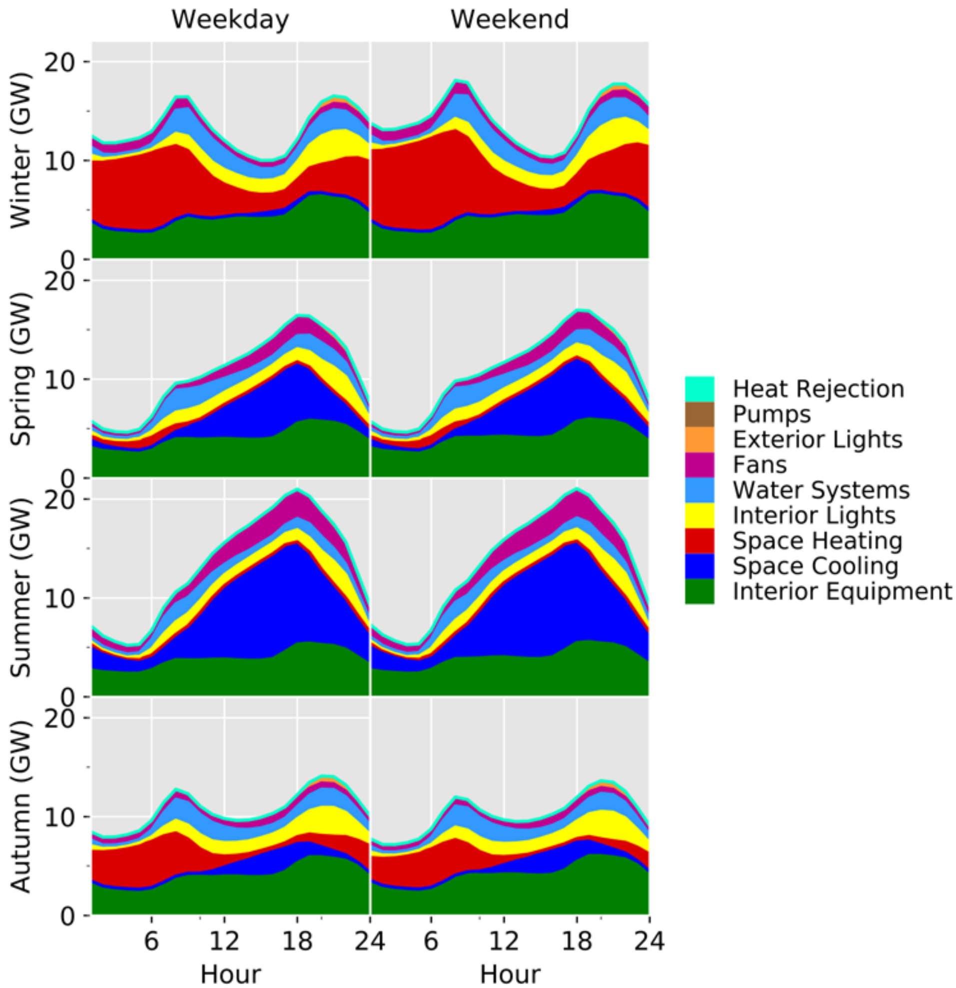

Figure G-39. Residential electricity use diurnal patterns by season, modeled for the East South Central census division 2012

Table G-40. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the East South Central Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Strip Mall	8,545	1,240	1,875	1,419	1,750	442	7	3	15,281
Standalone Retail Store	5,387	1,778	1,613	1,270	819	350	5	2	11,224
Large Office	2,289	2,642	1,635	1,758	441	40	239	87	9,131
Small Office	1,060	1,456	744	647	414	72	6	4	4,403
Medium Office	861	985	605	619	305	18	44	16	3,452
Warehouse	1,045	416	330	102	514	267	2	1	2,678
Full Service Restaurant	517	1,172	303	295	145	45	3	1	2,481
Large Hotel	516	793	442	477	131	26	24	9	2,419
Hospital	372	521	294	338	30	—	59	30	1,645
Primary School	325	256	147	144	41	27	4	2	946
Outpatient Treatment Facility	213	312	60	43	76	—	7	3	714
Small Hotel	72	97	4	3	42	6	1	0	225
Quick Service Restaurant	6	34	13	10	3	0	0	0	66
Total	**21,209**	**11,702**	**8,064**	**7,124**	**4,710**	**1,292**	**401**	**160**	**54,663**

Table G-41. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the East South Central Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Strip Mall	55.9	8.1	12.3	9.3	11.5	2.9	0.0	0.0	28.0
Standalone Retail Store	48.0	15.8	14.4	11.3	7.3	3.1	0.0	0.0	20.5
Large Office	25.1	28.9	17.9	19.3	4.8	0.4	2.6	1.0	16.7
Small Office	24.1	33.1	16.9	14.7	9.4	1.6	0.1	0.1	8.1
Medium Office	24.9	28.5	17.5	17.9	8.8	0.5	1.3	0.5	6.3
Warehouse	39.0	15.5	12.3	3.8	19.2	10.0	0.1	0.0	4.9
Full Service Restaurant	20.9	47.2	12.2	11.9	5.9	1.8	0.1	0.0	4.5
Large Hotel	21.3	32.8	18.3	19.7	5.4	1.1	1.0	0.4	4.4
Hospital	22.6	31.7	17.9	20.5	1.8	—	3.6	1.8	3.0
Primary School	34.4	27.0	15.5	15.3	4.3	2.8	0.5	0.2	1.7
Outpatient Treatment Facility	29.8	43.7	8.3	6.0	10.7	—	1.0	0.5	1.3
Small Hotel	32.1	43.0	1.9	1.5	18.7	2.5	0.2	0.1	0.4
Quick Service Restaurant	8.7	51.8	19.3	15.0	5.1	0.0	0.1	0.0	0.1
Total	**38.8**	**21.4**	**14.8**	**13.0**	**8.6**	**2.4**	**0.7**	**0.3**	**100.0**

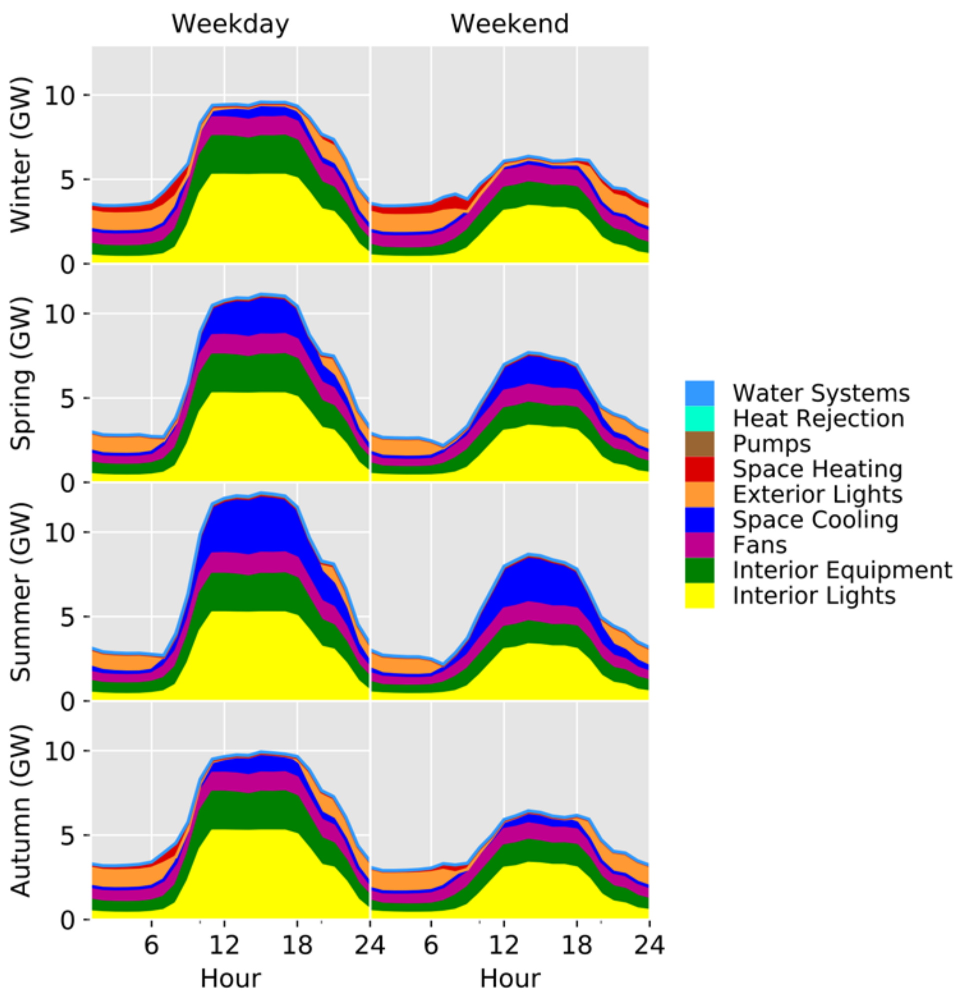

Figure G-40. Commercial electricity use diurnal patterns by season, modeled for the East South Central census division 2012

Table G-42. Industrial Manufacturing Subsectors, Summary of Model Results for the East South Central Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Iron and Steel Mills and Ferroalloy Manufacturing	3,749	4,813	871	3,202	612	207	217	167	66	274	23	38	14,239
Pulp, Paper, and Paperboard Mills	6,809	354	395	74	345	151	304	97	415	45	18	—	9,006
Petroleum and Coal Products Manufacturing	5,907	247	277	106	185	308	52	72	54	82	1	8	7,299
Basic Chemical Manufacturing	3,437	221	383	1,021	247	579	92	72	128	82	15	15	6,294
Converted Paper Product Manufacturing	3,477	181	203	38	178	78	157	50	214	23	9	—	4,608
Plastics Product Manufacturing	2,103	629	397	—	371	314	—	89	20	—	17	—	3,941
Motor Vehicle Parts Manufacturing	1,292	367	628	22	420	169	165	132	28	52	47	40	3,362
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	1,819	117	203	541	131	307	49	38	68	44	8	8	3,333
Animal Slaughtering and Processing	988	98	192	5	169	600	41	46	70	51	21	10	2,291
Other Wood Product Manufacturing	1,666	141	168	7	134	16	24	36	40	24	6	8	2,269
Foundries	489	626	113	412	79	27	28	22	8	35	3	5	1,846
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	966	63	110	297	71	168	27	21	37	24	4	4	1,792
Motor Vehicle Manufacturing	676	193	334	12	223	90	88	71	15	28	25	21	1,776
Nonferrous Metal (except Aluminum) Production and Processing	433	551	97	352	68	23	24	18	7	30	3	4	1,611
Alumina and Aluminum Production and Processing	413	526	93	339	66	22	23	18	7	29	2	4	1,541

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Chemical Product and Preparation Manufacturing	696	45	78	208	50	118	19	15	26	17	3	3	1,276
Rubber Product Manufacturing	666	199	126	—	118	100	—	28	6	—	5	—	1,250
Printing and Related Support Activities	664	51	209	14	104	92	18	35	10	—	13	—	1,210
Other Nonmetallic Mineral Product Manufacturing	587	279	71	19	54	43	24	17	10	—	4	2	1,110
Steel Product Manufacturing from Purchased Steel	232	295	52	189	37	12	13	10	4	16	1	2	864
Pharmaceutical and Medicine Manufacturing	447	29	50	134	32	76	12	10	17	11	2	2	822
Architectural and Structural Metals Manufacturing	352	121	126	32	79	26	29	27	—	—	6	2	801
Other Fabricated Metal Product Manufacturing	332	114	118	29	74	25	27	25	—	—	5	2	752
Cement and Concrete Product Manufacturing	392	186	48	13	37	29	16	11	7	—	3	1	743
Beverage Manufacturing	251	30	82	1	65	137	17	23	11	53	14	3	688
Veneer, Plywood, and Engineered Wood Product Manufacturing	505	43	50	2	40	5	7	11	12	7	2	2	685
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	357	23	41	109	26	62	10	8	14	9	2	2	662
Bakeries and Tortilla Manufacturing	273	27	53	1	46	164	11	13	19	14	6	3	630
Fiber, Yarn, and Thread Mills	362	52	90	0	44	22	11	9	12	—	5	—	609
Household Appliance Manufacturing	163	134	96	45	57	37	21	13	3	—	4	—	571

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Paint, Coating, and Adhesive Manufacturing	285	18	32	87	21	49	8	6	11	7	1	1	527
Glass and Glass Product Manufacturing	263	124	32	9	24	19	10	7	4	—	2	1	495
Motor Vehicle Body and Trailer Manufacturing	179	51	88	3	59	24	23	19	4	7	7	6	468
Other Electrical Equipment and Component Manufacturing	128	105	76	36	45	29	17	10	2	—	3	—	452
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	223	17	92	2	76	8	—	15	5	—	5	2	444
Other Food Manufacturing	189	19	36	1	32	113	8	9	13	10	4	2	436
Animal Food Manufacturing	183	18	36	1	32	113	8	9	13	10	4	2	427
Fruit and Vegetable Preserving and Specialty Food Manufacturing	178	18	35	1	30	108	7	8	13	9	4	2	413
Dairy Product Manufacturing	176	17	34	1	30	105	7	8	12	9	4	2	404
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	91	47	97	9	37	46	30	20	4	9	1	8	398
Other General Purpose Machinery Manufacturing	165	38	81	4	55	16	9	15	4	—	4	—	391
Textile and Fabric Finishing and Fabric Coating Mills	224	32	57	0	28	14	7	6	8	—	3	—	380
Aerospace Product and Parts Manufacturing	145	41	70	2	47	19	18	15	3	6	5	4	377
Forging and Stamping	160	55	57	14	36	12	13	12	—	—	3	1	362
Coating, Engraving, Heat Treating, and Allied Activities	152	52	55	14	35	12	13	12	—	—	2	1	347

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Miscellaneous Manufacturing	113	40	83	2	48	24	6	17	5	—	2	1	341
Grain and Oilseed Milling	143	14	27	1	24	86	6	7	10	7	3	1	329
Other Textile Product Mills	169	22	42	1	34	21	1	8	16	—	8	—	322
Electrical Equipment Manufacturing	78	64	47	22	28	18	10	6	1	—	2	—	277
Lime and Gypsum Product Manufacturing	141	67	17	5	13	10	6	4	2	—	1	0	267
Semiconductor and Other Electronic Component Manufacturing	60	31	63	6	24	30	19	13	2	6	1	5	258
Ship and Boat Building	90	26	46	2	30	12	12	10	2	4	3	3	241
Sawmills and Wood Preservation	176	15	18	1	14	2	3	4	4	3	1	1	240
Clay Product and Refractory Manufacturing	119	57	15	4	11	9	5	3	2	—	1	0	226
Industrial Machinery Manufacturing	80	18	38	2	26	8	4	7	2	—	2	—	187
Engine, Turbine, and Power Transmission Equipment Manufacturing	76	17	37	2	25	7	4	7	2	—	2	—	178
Fabric Mills	105	15	27	0	13	7	3	3	4	—	2	—	178
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	73	17	36	2	24	7	4	6	2	—	2	—	172
Metalworking Machinery Manufacturing	68	16	33	2	23	7	4	6	2	—	2	—	161
Spring and Wire Product Manufacturing	67	23	24	6	15	5	6	5	—	—	1	0	152
Agriculture, Construction, and Mining Machinery Manufacturing	65	15	31	2	21	6	4	6	1	—	2	—	152

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Medical Equipment and Supplies Manufacturing	46	16	33	1	19	10	3	7	2	—	1	0	139
Sugar and Confectionery Product Manufacturing	57	6	11	0	10	35	2	3	4	3	1	1	132
Seafood Product Preparation and Packaging	55	5	11	0	9	34	2	3	4	3	1	1	128
Commercial and Service Industry Machinery Manufacturing	54	12	26	1	18	5	3	5	1	—	1	—	126
Tobacco Manufacturing	44	5	14	0	11	24	3	4	2	9	2	1	120
Cut and Sew Apparel Manufacturing	40	5	29	—	17	2	—	3	2	—	1	—	100
Computer and Peripheral Equipment Manufacturing	22	11	24	2	9	12	7	5	1	2	0	2	97
Communications Equipment Manufacturing	19	10	20	2	8	10	6	4	1	2	0	2	82
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	35	12	13	3	8	3	3	3	—	—	1	0	81
Office Furniture (including Fixtures) Manufacturing	34	3	14	0	12	1	—	2	1	—	1	0	68
Electric Lighting Equipment Manufacturing	19	15	11	5	6	4	2	1	0	—	0	—	66
Textile Furnishings Mills	32	4	8	0	6	4	0	2	3	—	2	—	61
Railroad Rolling Stock Manufacturing	22	6	11	0	7	3	3	2	0	1	1	1	59
Audio and Video Equipment Manufacturing	13	7	14	1	5	7	4	3	1	1	0	1	57
Boiler, Tank, and Shipping Container Manufacturing	25	9	9	2	6	2	2	2	—	—	0	0	57

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Electro Chemical Processes (GWh)	Facility Lighting (GWh)	Process Cooling And Refrigeration (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Other Transportation Equipment Manufacturing	20	6	10	0	7	3	3	2	0	1	1	1	53
Manufacturing and Reproducing Magnetic and Optical Media	9	5	10	1	4	5	3	2	0	1	0	1	40
Cutlery and Handtool Manufacturing	12	4	4	1	3	1	1	1	—	—	0	0	28
Other Furniture Related Product Manufacturing	7	0	3	0	2	0	—	0	0	—	0	0	13
Other Leather and Allied Product Manufacturing	8	1	1	0	1	0	0	0	0	—	0	—	12
Leather and Hide Tanning and Finishing	1	0	0	0	0	0	0	0	0	—	0	—	2
Footwear Manufacturing	1	0	0	0	0	0	0	0	0	—	0	—	1
Total	**45,442**	**12,010**	**7,491**	**7,487**	**5,293**	**5,113**	**1,850**	**1,538**	**1,505**	**1,060**	**377**	**240**	**89,405**

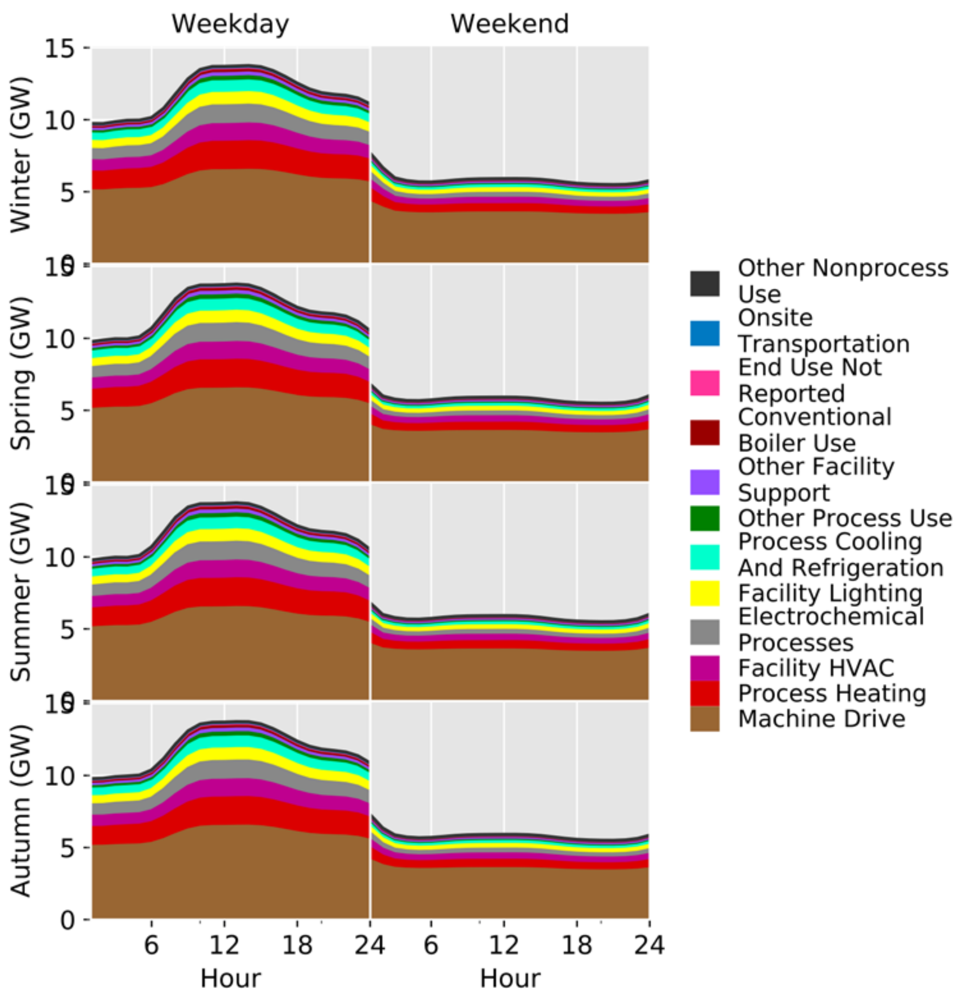

Figure G-41. Industrial electricity use diurnal patterns by season, modeled for the East South Central census division 2012

Table G-43. Distributed Generation Model, Annual Summary the East South Central Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	16,553	450	—	17,002
Thermal DG (GWh)	1,298	—	—	1,298
Distributed PV (GWh)	18	18	6	43
Total (GWh)	**17,869**	**468**	**6**	**18,343**
CHP (%)	92.6	96.1	—	92.7
Thermal DG (%)	7.3	—	—	7.1
Distributed PV (%)	0.1	3.9	100.0	0.2
Total (%)	**97.4**	**2.6**	**0.0**	**100.0**

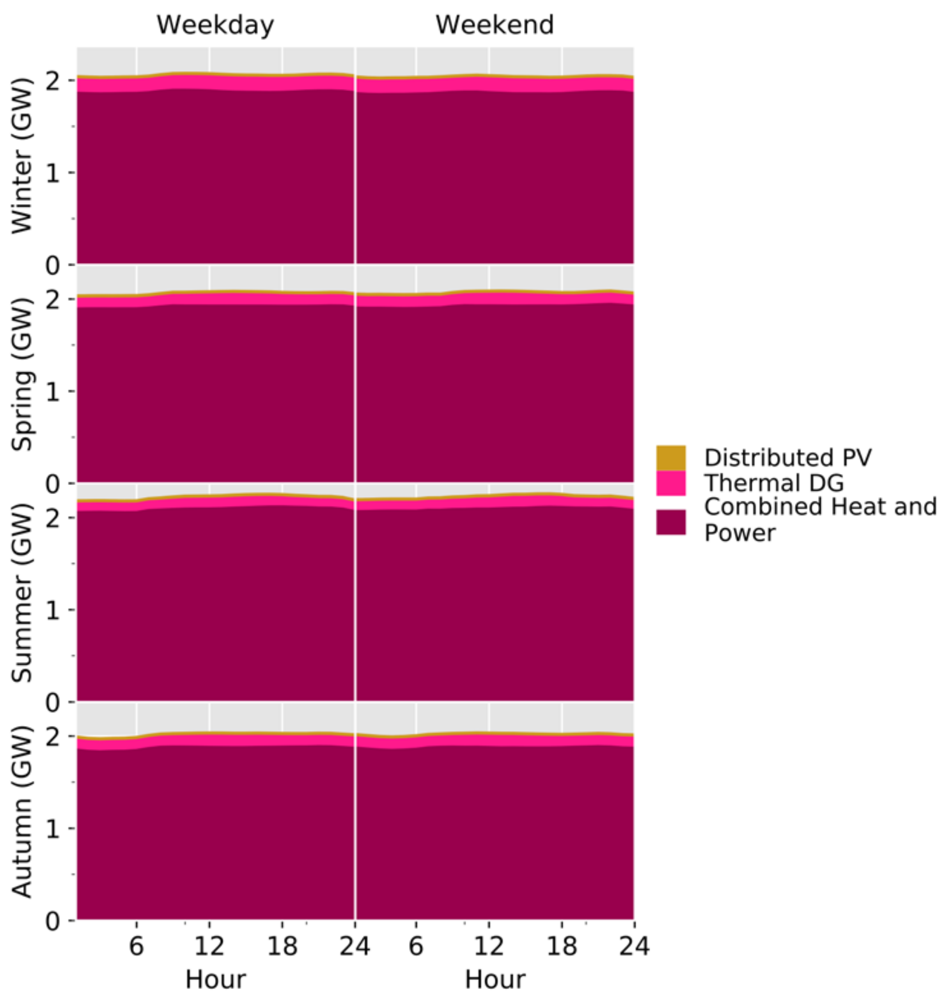

Figure G-42. Distributed Generation Model Diurnal Generation Patterns, East South Central census division 2012

G.7 West South Central

Table G-44. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, West South Central Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					591.1
Derived	T&D losses					32.3
Top-down	Annual energy	208.2	191.4	158.4	0.1	558.0
dsgrid	Distributed generation	0.0	1.8	58.6	–	60.4
dsgrid-core	Gap models	27.1	57.7	53.9	0.1	138.8
dsgrid-core	Detailed sector models	176.8	138.6	130.5	–	445.9
Derived	Total site energy	208.2	193.2	217.0	0.1	618.4
Derived	Annual sector residuals	4.3	-3.1	32.6	-0.0	33.7
Derived	Hourly residuals					13.7

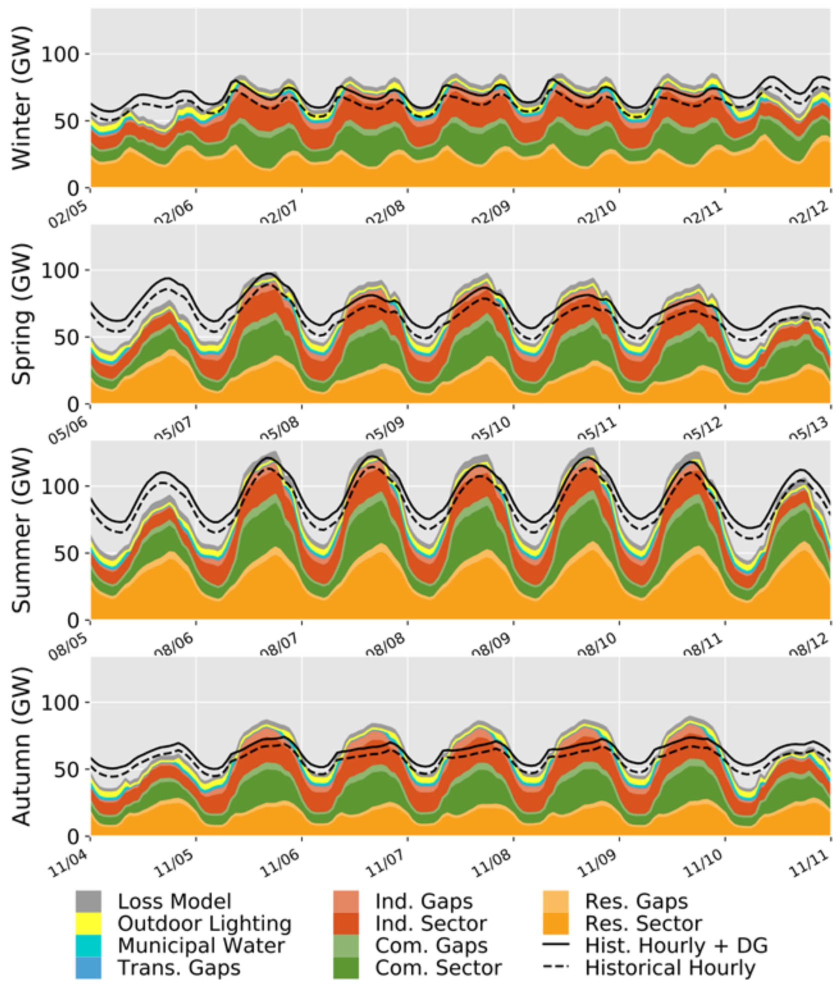

Figure G-43. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the West South Central census division in 2012

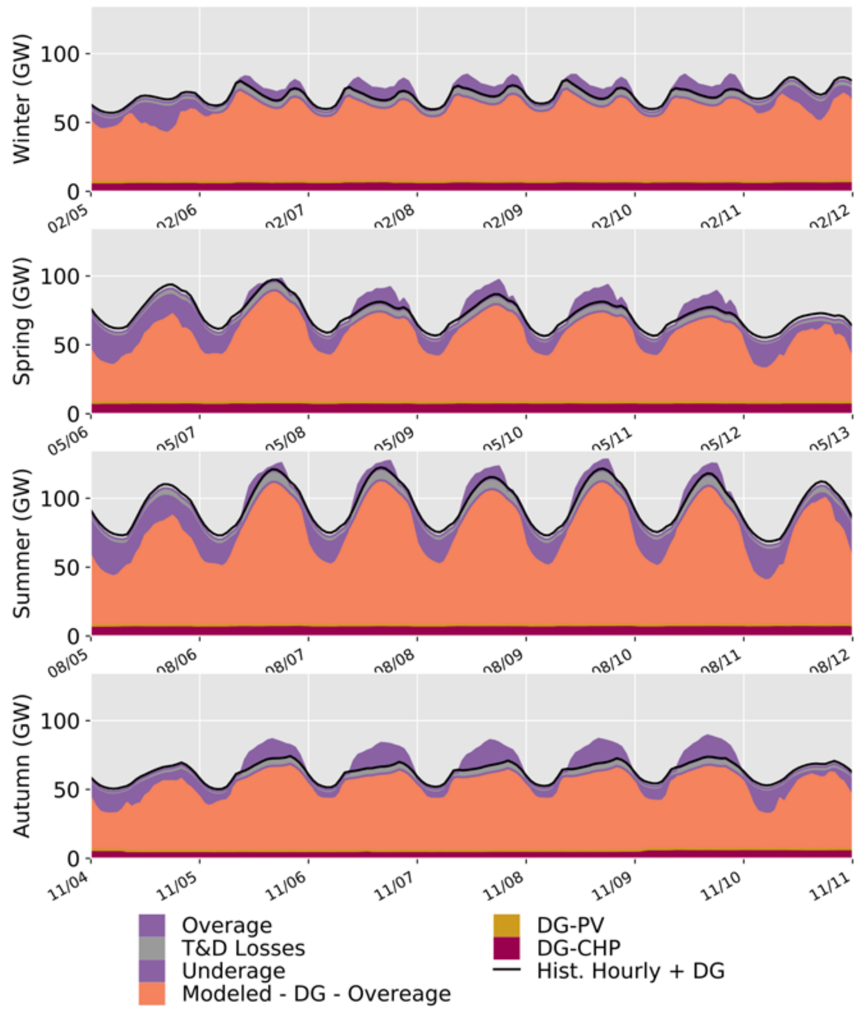

Figure G-44. dsgrid hourly residuals shown in context for the West South Central census division.

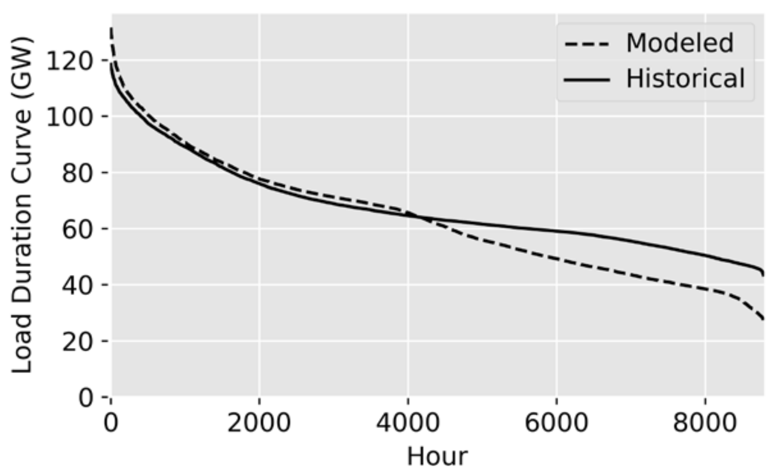

Figure G-45. Historical and dsgrid load duration curves for the West South Central census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-45. Residential Subsectors, Summary of Electricity by End Use for the West South Central Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Interior Lights (GWh)	Fans (GWh)	Space Heating (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	56,869	54,123	17,698	16,906	13,616	12,823	3,560	3	—	175,598
Mobile Home	6,305	5,076	1,316	1,537	889	1,416	214	0	—	16,753
Apartment in Building 2 to 4 Units	2,027	1,320	803	963	168	—	973	76	38	6,369
Single Family Attached	1,495	1,203	312	364	211	336	51	0	—	3,971
Midrise Apartment Building	370	271	158	191	28	—	190	19	9	1,236
Total	**67,066**	**61,993**	**20,288**	**19,961**	**14,911**	**14,575**	**4,988**	**99**	**48**	**203,928**

Table G-46. Residential Electricity Proportions by Subsector and End Use for the West South Central Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Interior Lights (%)	Fans (%)	Space Heating (%)	Water Systems (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	32.4	30.8	10.1	9.6	7.8	7.3	2.0	0.0	—	86.1
Mobile Home	37.6	30.3	7.9	9.2	5.3	8.5	1.3	0.0	—	8.2
Apartment in Building 2 to 4 Units	31.8	20.7	12.6	15.1	2.6	—	15.3	1.2	0.6	3.1
Single Family Attached	37.6	30.3	7.9	9.2	5.3	8.5	1.3	0.0	—	1.9
Midrise Apartment Building	30.0	21.9	12.8	15.4	2.2	—	15.3	1.6	0.7	0.6
Total	**32.9**	**30.4**	**9.9**	**9.8**	**7.3**	**7.1**	**2.4**	**0.0**	**0.0**	**100.0**

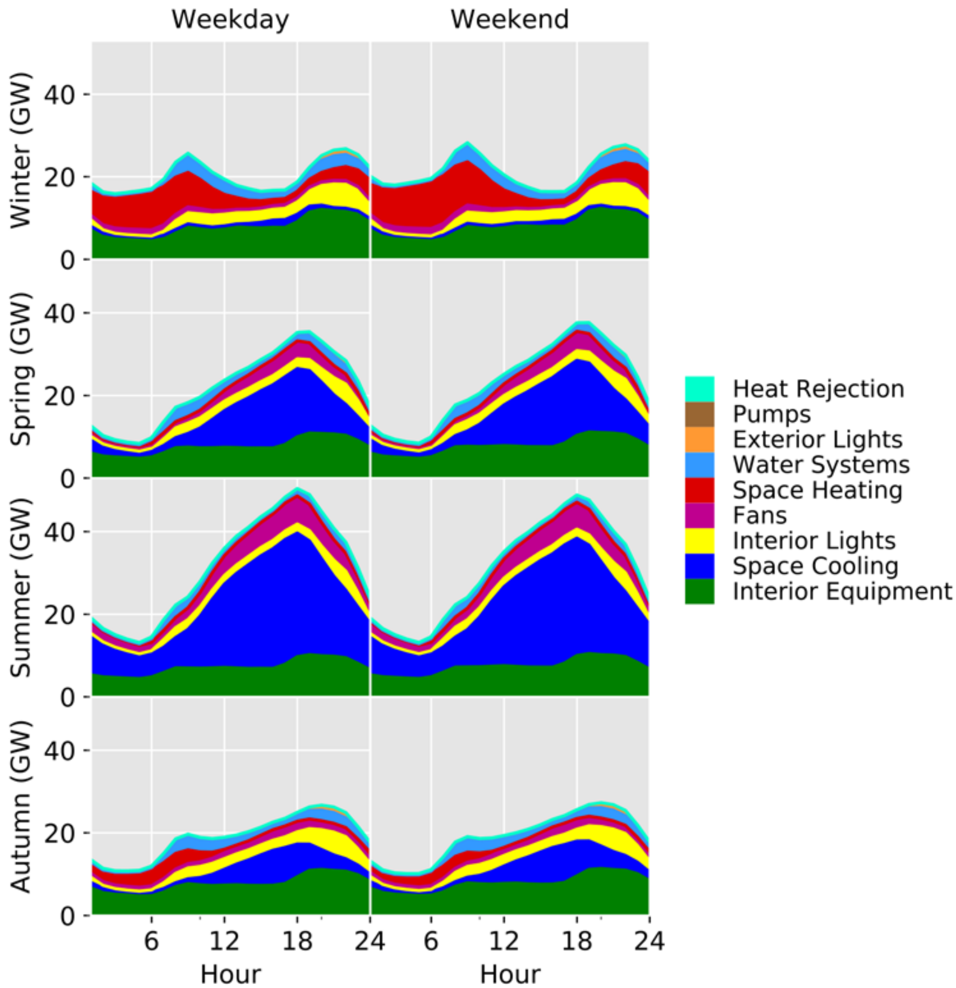

Figure G-46. Residential electricity use diurnal patterns by season, modeled for the West South Central census division 2012

Table G-47. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the West South Central Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Space Cooling (GWh)	Fans (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Space Heating (GWh)	Heat Rejection (GWh)	Total (GWh)
Large Office	10,320	12,109	10,791	8,549	2,103	1,228	38	638	45,777
Strip Mall	16,687	2,427	3,948	3,408	3,418	14	299	8	30,209
Standalone Retail Store	9,816	3,146	3,155	3,009	1,498	10	432	5	21,072
Small Office	1,712	2,347	1,319	1,255	668	11	64	8	7,383
Medium Office	1,682	1,928	1,573	1,256	599	86	19	40	7,182
Warehouse	2,804	1,117	475	828	1,375	7	347	5	6,959
Full Service Restaurant	1,233	2,772	960	725	343	9	48	4	6,094
Large Hotel	1,137	1,854	1,359	1,197	282	38	32	17	5,916
Hospital	1,022	1,280	950	801	77	156	—	81	4,368
Primary School	575	457	344	276	73	15	10	8	1,758
Outpatient Treatment Facility	382	566	147	165	138	23	—	13	1,433
Small Hotel	78	117	11	8	61	1	3	1	280
Quick Service Restaurant	17	99	34	33	10	1	0	0	194
Total	**47,463**	**30,218**	**25,067**	**21,510**	**10,645**	**1,599**	**1,294**	**829**	**138,625**

Table G-48. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the West South Central Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Space Cooling (%)	Fans (%)	Exterior Lights (%)	Pumps (%)	Space Heating (%)	Heat Rejection (%)	Total (%)
Large Office	22.5	26.5	23.6	18.7	4.6	2.7	0.1	1.4	33.0
Strip Mall	55.2	8.0	13.1	11.3	11.3	0.0	1.0	0.0	21.8
Standalone Retail Store	46.6	14.9	15.0	14.3	7.1	0.0	2.0	0.0	15.2
Small Office	23.2	31.8	17.9	17.0	9.0	0.2	0.9	0.1	5.3
Medium Office	23.4	26.8	21.9	17.5	8.3	1.2	0.3	0.6	5.2
Warehouse	40.3	16.0	6.8	11.9	19.8	0.1	5.0	0.1	5.0
Full Service Restaurant	20.2	45.5	15.7	11.9	5.6	0.2	0.8	0.1	4.4
Large Hotel	19.2	31.3	23.0	20.2	4.8	0.6	0.5	0.3	4.3
Hospital	23.4	29.3	21.8	18.3	1.8	3.6	—	1.9	3.2
Primary School	32.7	26.0	19.6	15.7	4.2	0.8	0.6	0.4	1.3
Outpatient Treatment Facility	26.7	39.5	10.3	11.5	9.6	1.6	—	0.9	1.0
Small Hotel	27.7	41.7	3.9	2.9	21.8	0.4	1.2	0.2	0.2
Quick Service Restaurant	8.6	50.9	17.6	17.3	5.0	0.3	0.1	0.2	0.1
Total	**34.2**	**21.8**	**18.1**	**15.5**	**7.7**	**1.2**	**0.9**	**0.6**	**100.0**

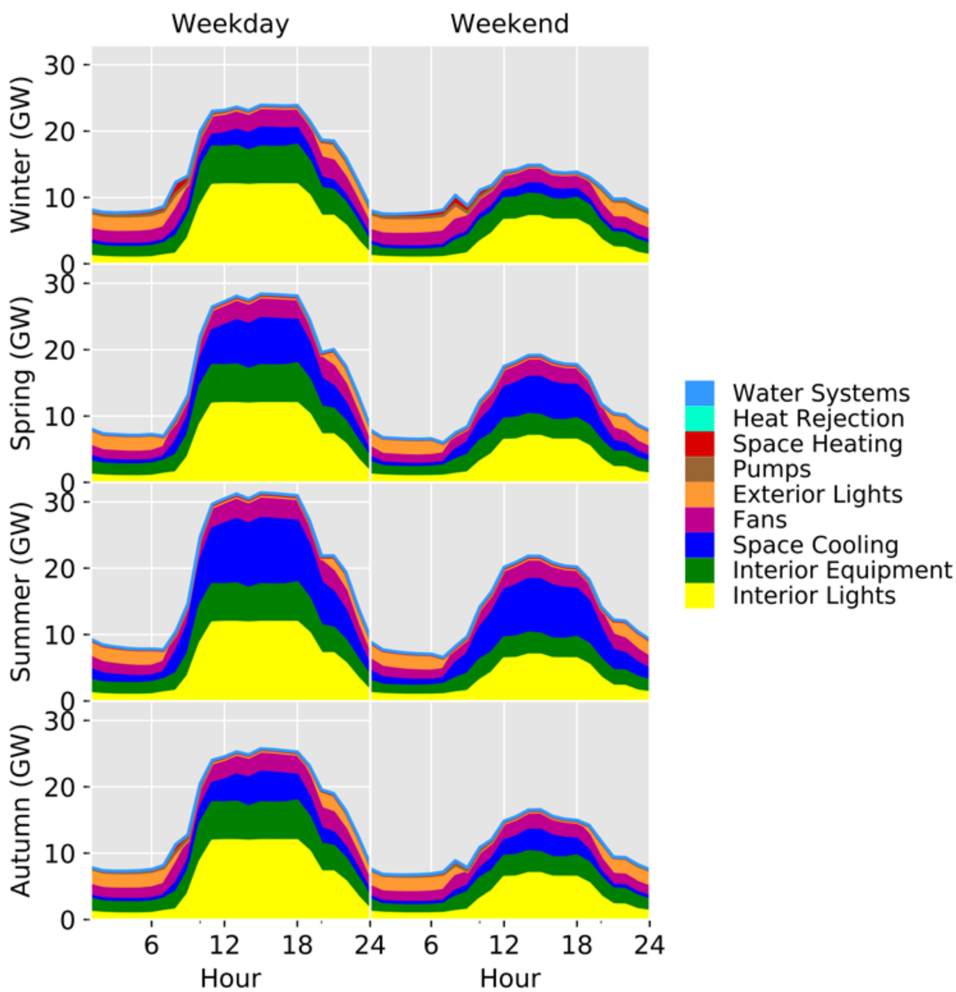

Figure G-47. Commercial electricity use diurnal patterns by season, modeled for the West South Central census division 2012

Table G-49. Industrial Manufacturing Subsectors, Summary of Model Results for the West South Central Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Petroleum and Coal Products Manufacturing	17,126	717	307	804	894	535	151	208	158	237	2	22	21,161
Basic Chemical Manufacturing	10,318	664	3,064	1,150	1,737	741	277	217	384	247	46	46	18,892
Iron and Steel Mills and Ferroalloy Manufacturing	3,482	4,470	2,974	809	192	568	201	155	61	255	21	36	13,224
Pulp, Paper, and Paperboard Mills	5,965	310	65	346	132	303	266	85	364	39	16	—	7,890
Plastics Product Manufacturing	2,990	895	—	565	447	528	—	127	28	—	24	—	5,602
Converted Paper Product Manufacturing	4,049	211	44	237	90	207	182	58	249	27	11	—	5,366
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	2,403	155	715	268	405	173	65	51	89	58	11	11	4,402
Other Chemical Product and Preparation Manufacturing	1,878	121	560	210	318	135	51	40	70	45	8	8	3,445
Animal Slaughtering and Processing	1,425	141	7	277	865	244	60	66	101	73	31	14	3,305
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	1,582	103	486	181	276	116	44	34	61	39	7	7	2,936
Other Wood Product Manufacturing	1,664	141	7	168	16	134	24	36	40	24	6	8	2,266
Steel Product Manufacturing from Purchased Steel	509	648	416	115	27	81	28	22	9	36	3	5	1,897
Printing and Related Support Activities	993	76	21	312	137	156	26	52	16	—	20	—	1,809
Pharmaceutical and Medicine Manufacturing	970	63	292	109	166	70	26	21	37	24	4	4	1,786

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Architectural and Structural Metals Manufacturing	734	252	66	263	55	166	61	57	—	—	12	3	1,670
Other Fabricated Metal Product Manufacturing	720	246	64	256	53	161	59	55	—	—	11	3	1,629
Other Nonmetallic Mineral Product Manufacturing	831	394	28	101	60	77	34	24	14	—	6	2	1,571
Semiconductor and Other Electronic Component Manufacturing	355	185	35	373	177	142	113	75	14	33	4	30	1,535
Nonferrous Metal (except Aluminum) Production and Processing	402	512	328	90	21	64	22	17	7	28	2	4	1,497
Aerospace Product and Parts Manufacturing	549	156	9	266	72	178	70	56	12	22	20	17	1,427
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	764	49	234	87	133	56	21	17	29	19	4	3	1,415
Rubber Product Manufacturing	676	202	—	128	102	120	—	29	6	—	5	—	1,268
Agriculture, Construction, and Mining Machinery Manufacturing	506	117	12	243	48	166	27	44	11	—	12	—	1,186
Cement and Concrete Product Manufacturing	609	289	20	74	45	57	25	18	10	—	4	2	1,152
Foundries	304	390	256	70	17	49	17	13	5	22	2	3	1,149
Alumina and Aluminum Production and Processing	265	338	217	60	14	42	15	11	4	19	2	3	990
Paint, Coating, and Adhesive Manufacturing	531	34	162	60	92	39	15	12	20	13	2	2	983
Beverage Manufacturing	334	40	2	109	182	86	23	31	15	71	19	4	915

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Veneer, Plywood, and Engineered Wood Product Manufacturing	669	57	3	66	6	53	9	14	16	10	2	3	908
Fruit and Vegetable Preserving and Specialty Food Manufacturing	387	38	2	75	235	66	16	18	28	20	8	4	898
Motor Vehicle Manufacturing	307	88	5	151	41	101	40	32	7	13	11	10	806
Other Food Manufacturing	342	34	2	66	205	58	14	16	24	17	7	3	789
Grain and Oilseed Milling	321	32	2	62	192	54	13	15	23	16	7	3	739
Bakeries and Tortilla Manufacturing	319	32	2	62	192	54	13	15	23	16	7	3	736
Glass and Glass Product Manufacturing	384	182	13	46	27	35	15	11	6	—	3	1	723
Other General Purpose Machinery Manufacturing	282	65	7	138	27	94	16	25	6	—	7	—	669
Coating, Engraving, Heat Treating, and Allied Activities	291	100	26	106	22	66	25	23	—	—	5	1	665
Motor Vehicle Parts Manufacturing	252	72	4	123	33	82	32	26	5	10	9	8	657
Other Electrical Equipment and Component Manufacturing	174	143	48	103	40	61	23	14	3	—	4	—	613
Dairy Product Manufacturing	263	26	1	50	156	44	11	12	18	13	6	2	603
Animal Food Manufacturing	251	25	1	49	155	43	11	12	18	13	5	2	586
Other Miscellaneous Manufacturing	191	67	4	141	42	81	11	28	9	—	3	1	580

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	126	66	13	135	65	51	41	27	5	12	1	11	554
Electrical Equipment Manufacturing	146	120	42	88	34	52	19	12	2	—	4	—	519
Lime and Gypsum Product Manufacturing	269	128	9	33	20	25	11	8	4	—	2	1	508
Other Textile Product Mills	238	32	1	59	30	48	2	11	22	—	11	—	454
Communications Equipment Manufacturing	86	45	9	92	44	35	28	19	3	8	1	7	377
Motor Vehicle Body and Trailer Manufacturing	129	37	2	63	17	42	17	13	3	5	5	4	337
Commercial and Service Industry Machinery Manufacturing	139	32	3	67	13	46	8	12	3	—	3	—	328
Railroad Rolling Stock Manufacturing	123	35	2	61	17	41	16	13	3	5	5	4	324
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	160	12	1	66	5	54	—	11	4	—	4	2	319
Ship and Boat Building	118	34	2	60	16	40	16	13	3	5	5	4	315
Spring and Wire Product Manufacturing	124	43	11	45	9	28	10	10	—	—	2	1	282
Engine, Turbine, and Power Transmission Equipment Manufacturing	116	27	3	56	11	38	6	10	3	—	3	—	272
Industrial Machinery Manufacturing	115	26	3	55	11	38	6	10	3	—	3	—	270
Forging and Stamping	115	39	10	41	9	26	10	9	—	—	2	1	261
Computer and Peripheral Equipment Manufacturing	55	29	6	61	29	23	19	12	2	6	1	5	248

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Fabric Mills	143	21	0	36	9	18	4	4	5	—	2	—	241
Sugar and Confectionery Product Manufacturing	103	10	1	20	63	18	4	5	7	5	2	1	240
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	93	22	2	46	9	31	5	8	2	—	2	—	222
Clay Product and Refractory Manufacturing	117	56	4	14	9	11	5	3	2	—	1	0	222
Medical Equipment and Supplies Manufacturing	72	25	2	52	15	30	4	10	3	—	1	1	216
Cut and Sew Apparel Manufacturing	79	10	—	57	3	33	—	7	4	—	1	—	195
Textile and Fabric Finishing and Fabric Coating Mills	104	15	0	26	7	13	3	3	4	—	2	—	177
Seafood Product Preparation and Packaging	71	7	0	14	44	12	3	3	5	4	2	1	165
Metalworking Machinery Manufacturing	54	13	1	26	5	18	3	5	1	—	1	—	128
Boiler, Tank, and Shipping Container Manufacturing	55	19	5	19	4	12	4	4	—	—	1	0	124
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	54	19	5	20	4	12	5	4	—	—	1	0	124
Fiber, Yarn, and Thread Mills	61	9	0	15	4	7	2	2	2	—	1	—	103
Office Furniture (including Fixtures) Manufacturing	45	3	0	19	2	15	—	3	1	—	1	0	89
Other Transportation Equipment Manufacturing	34	10	1	17	4	11	4	3	1	1	1	1	88

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Electro Chemical Processes (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Sawmills and Wood Preservation	54	5	0	5	1	4	1	1	1	1	0	0	73
Electric Lighting Equipment Manufacturing	20	16	5	12	5	7	3	2	0	—	0	—	70
Household Appliance Manufacturing	19	16	5	11	4	7	3	2	0	—	0	—	68
Cutlery and Handtool Manufacturing	19	6	2	7	1	4	2	1	—	—	0	0	43
Other Leather and Allied Product Manufacturing	21	3	0	3	1	4	0	1	0	—	0	—	33
Tobacco Manufacturing	12	1	0	4	6	3	1	1	1	2	1	0	32
Audio and Video Equipment Manufacturing	7	3	1	7	3	3	2	1	0	1	0	1	28
Other Furniture Related Product Manufacturing	14	1	0	6	0	5	—	1	0	—	0	0	27
Textile Furnishings Mills	11	1	0	3	1	2	0	1	1	—	1	—	22
Footwear Manufacturing	8	1	0	1	0	1	0	0	0	—	0	—	12
Manufacturing and Reproducing Magnetic and Optical Media	2	1	0	2	1	1	1	0	0	0	0	0	9
Apparel Accessories and Other Apparel Manufacturing	2	0	—	1	0	1	—	0	0	—	0	—	5
Leather and Hide Tanning and Finishing	2	0	0	0	0	0	0	0	0	—	0	—	3
Hardware Manufacturing	1	0	0	0	0	0	0	0	—	—	0	0	2
Total	**70,703**	**13,876**	**10,661**	**10,395**	**8,684**	**7,160**	**2,422**	**2,155**	**2,102**	**1,516**	**472**	**324**	**130,471**

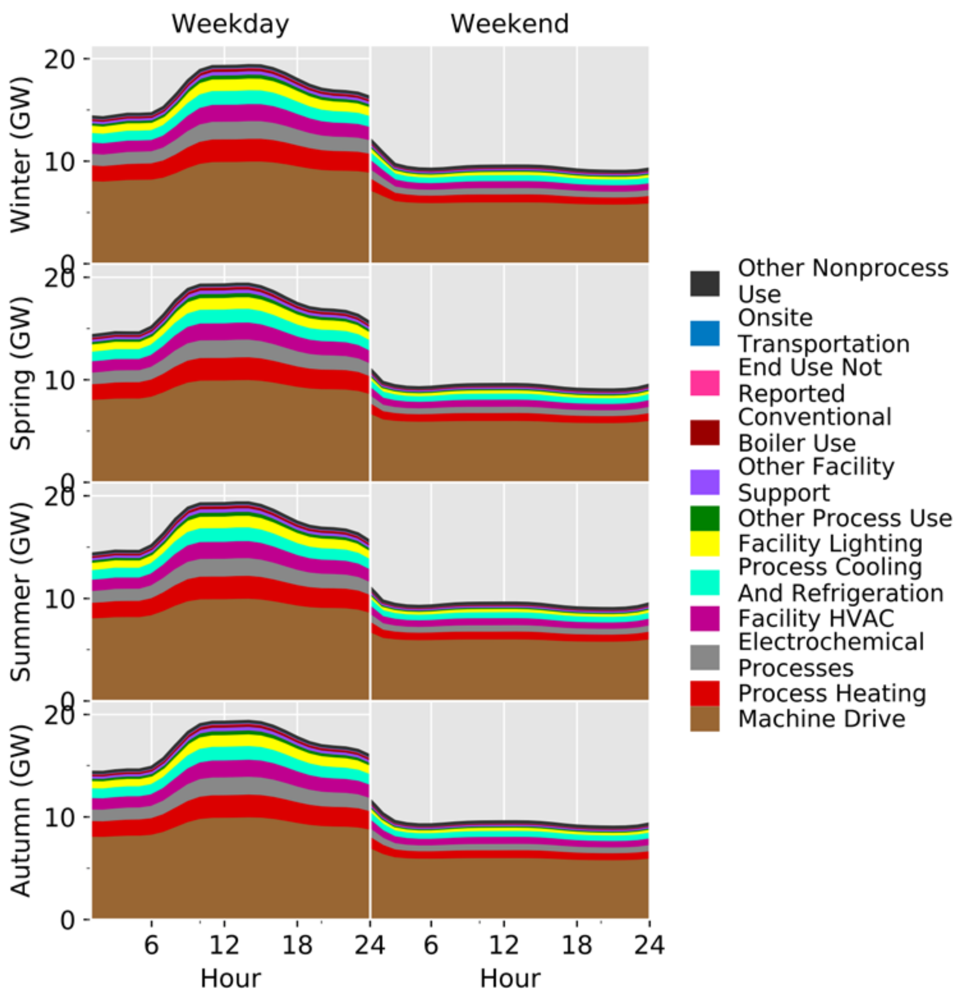

Figure G-48. Industrial electricity use diurnal patterns by season, modeled for the West South Central census division 2012

Table G-50. Distributed Generation Model, Annual Summary the West South Central Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	55,861	1,787	0	57,648
Thermal DG (GWh)	2,692	35	—	2,727
Distributed PV (GWh)	15	14	30	60
Total (GWh)	**58,568**	**1,837**	**30**	**60,435**
CHP (%)	95.4	97.3	0.2	95.4
Thermal DG (%)	4.6	1.9	—	4.5
Distributed PV (%)	0.0	0.8	99.8	0.1
Total (%)	**96.9**	**3.0**	**0.1**	**100.0**

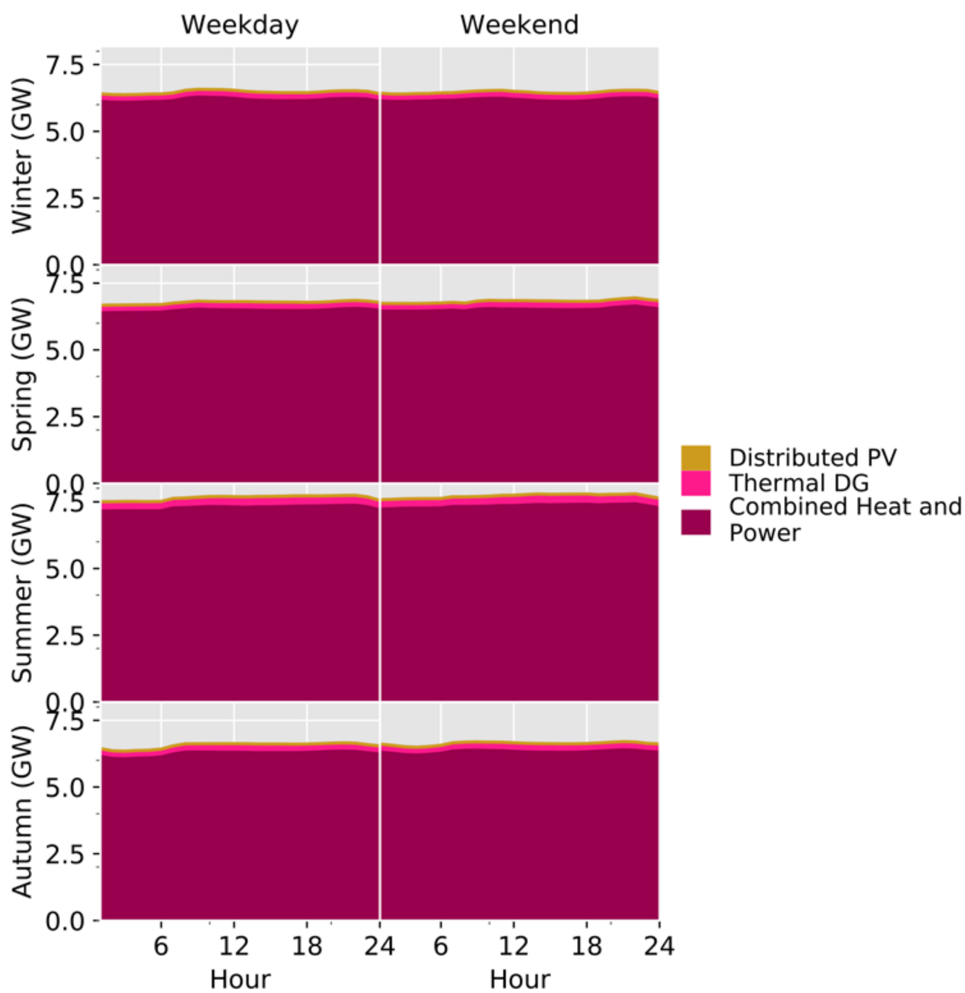

Figure G-49. Distributed Generation Model Diurnal Generation Patterns, West South Central census division 2012

G.8 Mountain

Table G-51. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, Mountain Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					289.4
Derived	T&D losses					15.0
Top-down	Annual energy	94.9	98.2	82.3	0.1	275.4
dsgrid	Distributed generation	–	1.0	3.6	–	4.5
dsgrid-core	Gap models	12.4	27.7	22.2	0.1	62.4
dsgrid-core	Detailed sector models	84.4	65.3	36.5	–	186.1
Derived	Total site energy	94.9	99.1	85.9	0.1	280.0
Derived	Annual sector residuals	-1.9	6.2	27.2	-0.0	31.5
Derived	Hourly residuals					29.1

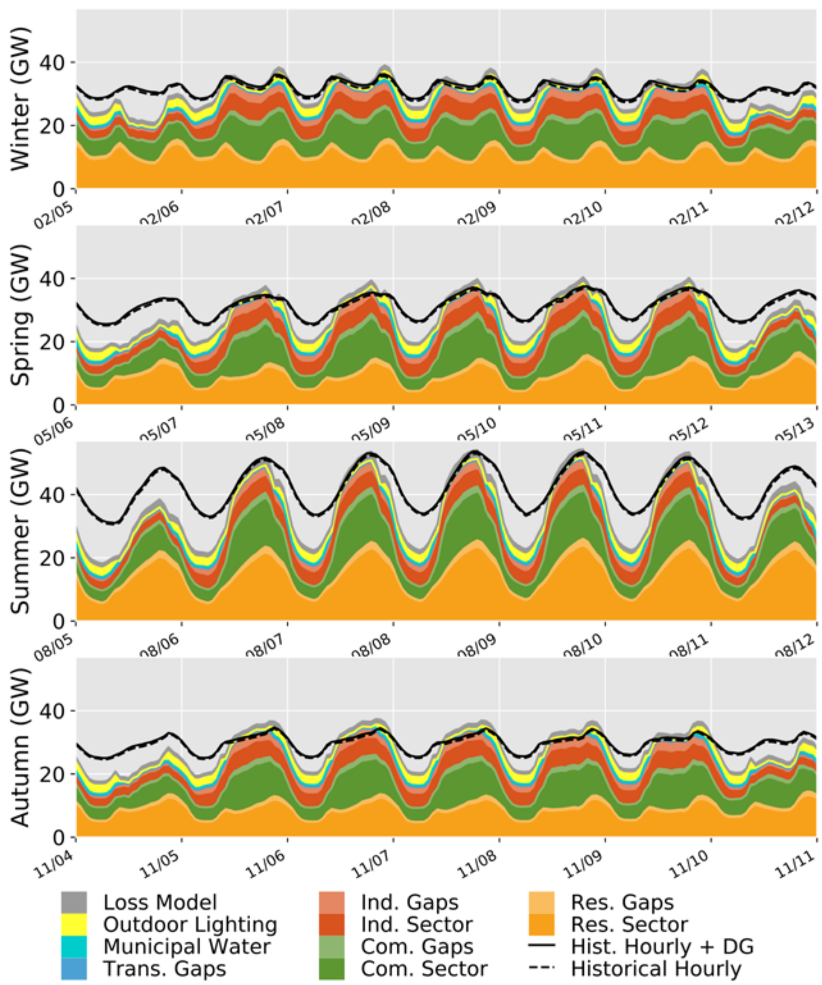

Figure G-50. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the Mountain census division in 2012

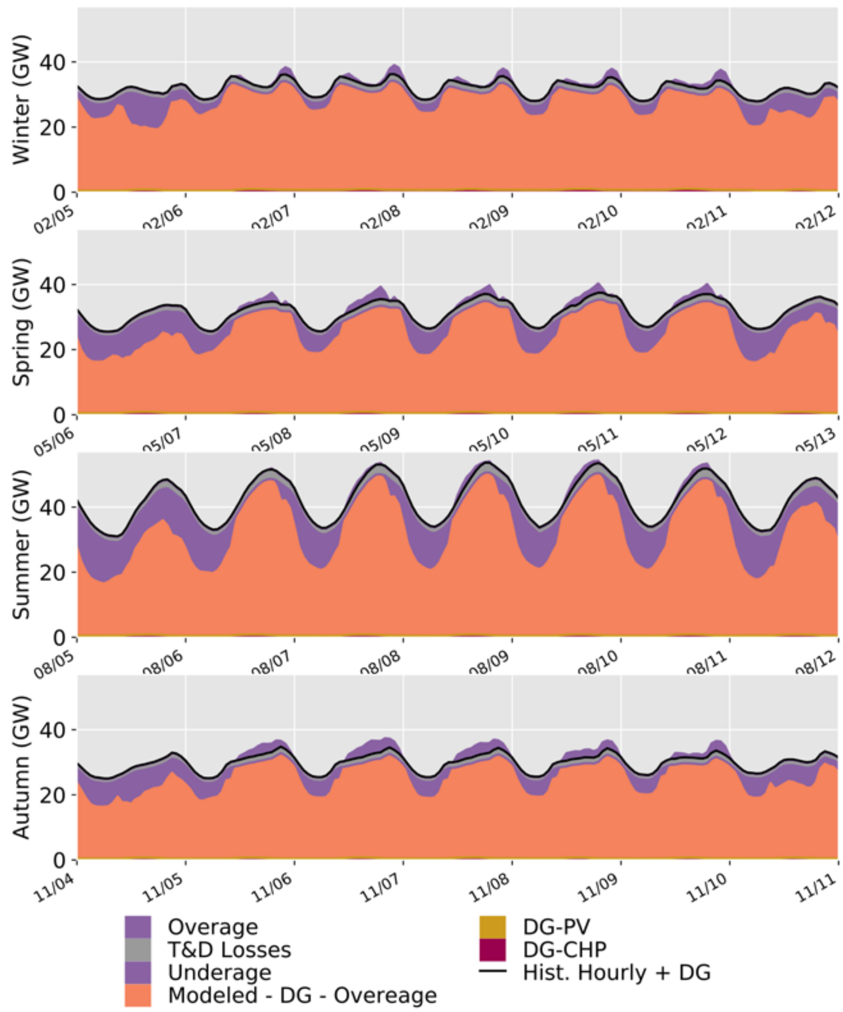

Figure G-51. dsgrid hourly residuals shown in context for the Mountain census division.

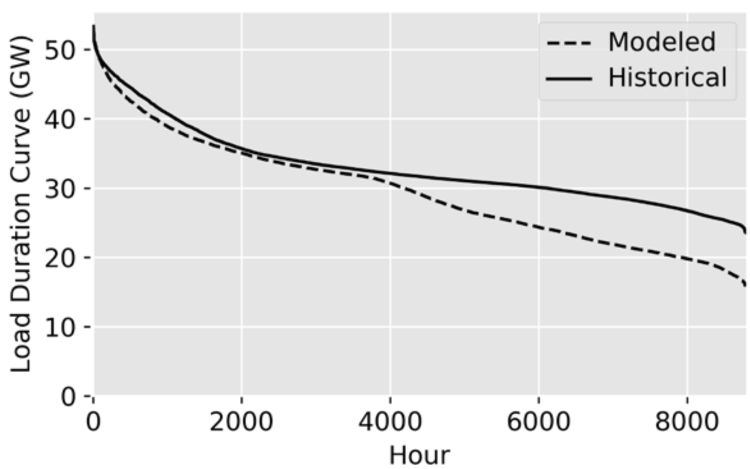

Figure G-52. Historical and dsgrid load duration curves for the Mountain census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-52. Residential Subsectors, Summary of Electricity by End Use for the Mountain Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Cooling (GWh)	Interior Lights (GWh)	Fans (GWh)	Space Heating (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	32,880	15,722	10,540	8,833	7,934	5,447	2,136	58	—	83,551
Mobile Home	2,988	1,046	628	643	502	522	102	4	—	6,435
Apartment in Building 2 to 4 Units	1,009	397	430	519	156	—	514	24	5	3,053
Single Family Attached	1,332	466	280	287	224	233	45	2	—	2,868
Midrise Apartment Building	274	95	123	140	40	—	146	8	2	827
Total	**38,482**	**17,727**	**12,002**	**10,422**	**8,856**	**6,201**	**2,944**	**95**	**6**	**96,735**

Table G-53. Residential Electricity Proportions by Subsector and End Use for the Mountain Census Division in 2012

Subsector	Interior Equipment (%)	Space Cooling (%)	Interior Lights (%)	Fans (%)	Space Heating (%)	Water Systems (%)a	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	39.4	18.8	12.6	10.6	9.5	6.5	2.6	0.1	—	86.4
Mobile Home	46.4	16.3	9.8	10.0	7.8	8.1	1.6	0.1	—	6.7
Apartment in Building 2 to 4 Units	33.0	13.0	14.1	17.0	5.1	—	16.8	0.8	0.2	3.2
Single Family Attached	46.4	16.3	9.8	10.0	7.8	8.1	1.6	0.1	—	3.0
Midrise Apartment Building	33.1	11.5	14.8	17.0	4.8	—	17.7	0.9	0.2	0.9
Total	**39.8**	**18.3**	**12.4**	**10.8**	**9.2**	**6.4**	**3.0**	**0.1**	**0.0**	**100.0**

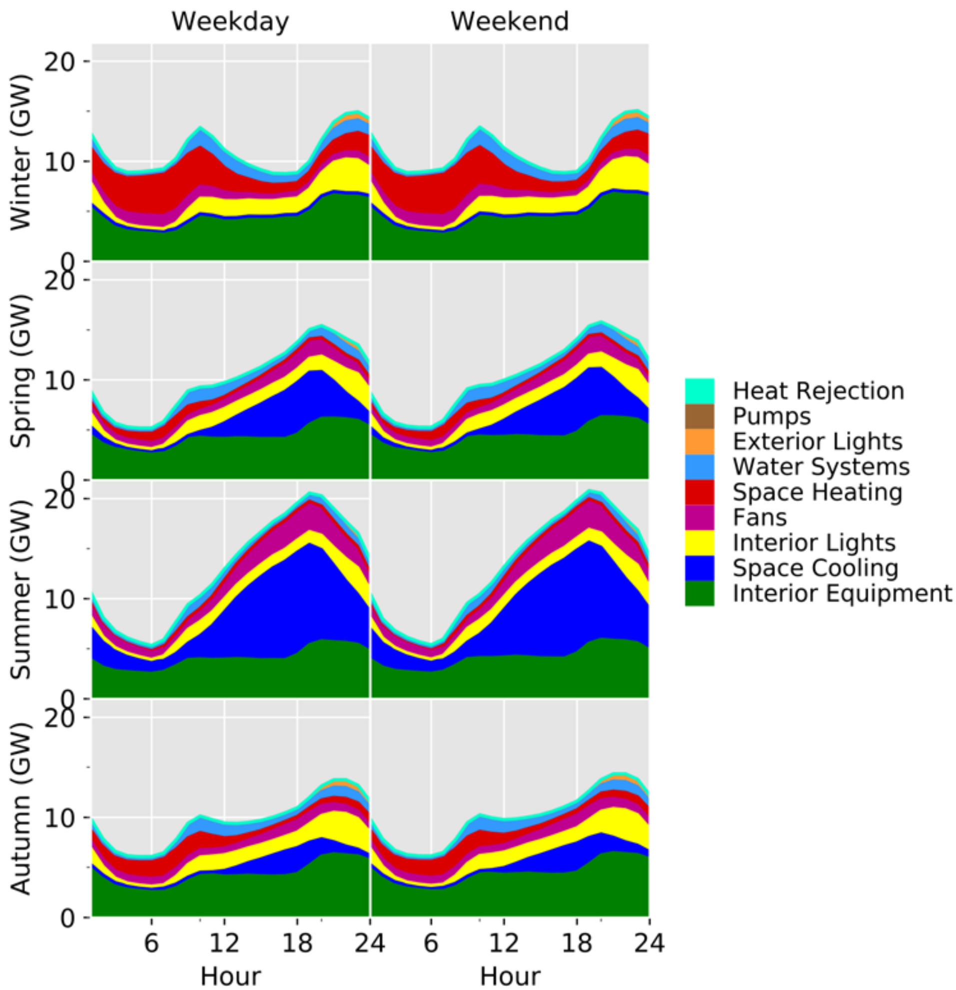

Figure G-53. Residential electricity use diurnal patterns by season, modeled for the Mountain census division 2012

Table G-54. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the Mountain Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Strip Mall	9,437	1,379	2,464	1,231	1,927	399	10	2	16,849
Large Office	3,463	4,073	3,177	1,874	726	62	284	67	13,726
Standalone Retail Store	4,309	1,421	1,715	861	665	544	1	0	9,514
Medium Office	1,357	1,546	1,203	741	482	37	45	11	5,423
Warehouse	1,634	651	716	199	804	630	3	1	4,638
Small Office	1,114	1,523	872	557	435	115	5	2	4,623
Full Service Restaurant	724	1,616	447	310	202	70	3	1	3,372
Large Hotel	648	1,024	718	445	163	60	31	6	3,094
Hospital	460	704	283	189	38	—	32	9	1,714
Primary School	330	266	177	118	43	18	5	1	958
Outpatient Treatment Facility	261	381	123	60	94	—	11	3	933
Small Hotel	97	142	9	4	71	15	1	0	339
Quick Service Restaurant	6	36	13	8	4	0	—	—	67
Total	**23,839**	**14,761**	**11,918**	**6,596**	**5,653**	**1,949**	**429**	**105**	**65,251**

Table G-55. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the Mountain Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Strip Mall	56.0	8.2	14.6	7.3	11.4	2.4	0.1	0.0	25.8
Large Office	25.2	29.7	23.1	13.7	5.3	0.5	2.1	0.5	21.0
Standalone Retail Store	45.3	14.9	18.0	9.0	7.0	5.7	0.0	0.0	14.6
Medium Office	25.0	28.5	22.2	13.7	8.9	0.7	0.8	0.2	8.3
Warehouse	35.2	14.0	15.4	4.3	17.3	13.6	0.1	0.0	7.1
Small Office	24.1	33.0	18.9	12.1	9.4	2.5	0.1	0.0	7.1
Full Service Restaurant	21.5	47.9	13.3	9.2	6.0	2.1	0.1	0.0	5.2
Large Hotel	20.9	33.1	23.2	14.4	5.3	1.9	1.0	0.2	4.7
Hospital	26.8	41.0	16.5	11.0	2.2	—	1.9	0.5	2.6
Primary School	34.4	27.8	18.5	12.3	4.5	1.9	0.5	0.2	1.5
Outpatient Treatment Facility	28.0	40.8	13.2	6.4	10.1	—	1.1	0.4	1.4
Small Hotel	28.5	41.9	2.6	1.3	20.9	4.6	0.2	0.0	0.5
Quick Service Restaurant	9.0	53.4	19.9	12.1	5.3	0.3	—	—	0.1
Total	**36.5**	**22.6**	**18.3**	**10.1**	**8.7**	**3.0**	**0.7**	**0.2**	**100.0**

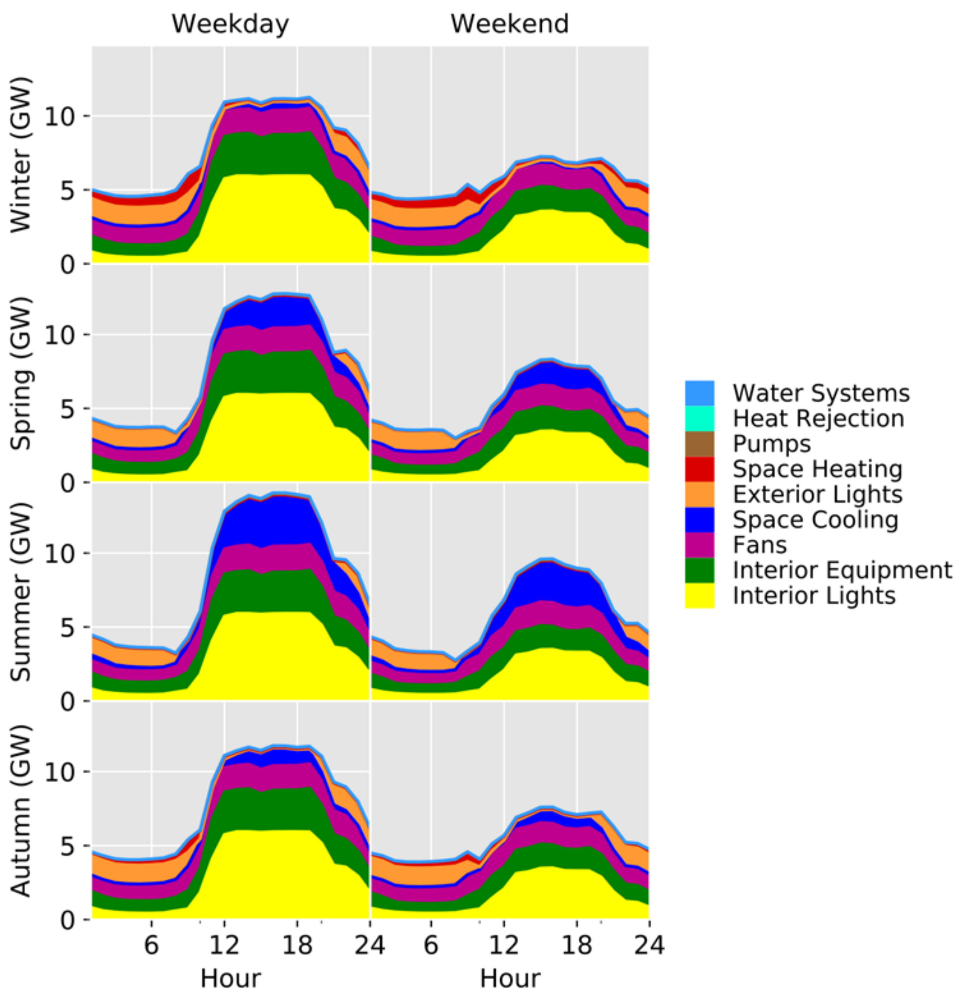

Figure G-54. Commercial electricity use diurnal patterns by season, modeled for the Mountain census division 2012

Table G-56. Industrial Manufacturing Subsectors, Summary of Model Results for the Mountain Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Petroleum and Coal Products Manufacturing	3,212	134	151	168	100	58	28	39	30	45	0	4	3,969
Plastics Product Manufacturing	1,435	429	271	214	253	—	—	61	13	—	11	—	2,689
Iron and Steel Mills and Ferroalloy Manufacturing	697	894	162	38	114	595	40	31	12	51	4	7	2,645
Pulp, Paper, and Paperboard Mills	1,602	83	93	35	81	17	71	23	98	11	4	—	2,119
Converted Paper Product Manufacturing	1,161	60	68	26	59	13	52	17	71	8	3	—	1,539
Semiconductor and Other Electronic Component Manufacturing	313	163	328	156	125	31	100	66	12	29	4	26	1,352
Other Wood Product Manufacturing	892	76	90	9	72	4	13	19	21	13	3	4	1,216
Basic Chemical Manufacturing	644	41	72	108	46	191	17	14	24	15	3	3	1,179
Pharmaceutical and Medicine Manufacturing	620	40	70	106	45	187	17	13	23	15	3	3	1,142
Other Nonmetallic Mineral Product Manufacturing	533	253	65	39	49	18	22	15	9	—	4	2	1,008
Dairy Product Manufacturing	421	42	81	250	71	2	17	19	29	21	9	4	967

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Aerospace Product and Parts Manufacturing	361	103	175	47	117	6	46	37	8	15	13	11	938
Nonferrous Metal (except Aluminum) Production and Processing	250	319	56	13	40	204	14	11	4	17	1	2	932
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	205	107	219	105	83	21	67	45	8	20	2	17	898
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	419	27	48	73	31	129	12	9	16	10	2	2	778
Animal Slaughtering and Processing	325	32	63	197	56	2	14	15	23	17	7	3	753
Beverage Manufacturing	246	29	81	135	64	1	17	23	11	52	14	3	675
Cement and Concrete Product Manufacturing	356	169	43	26	33	12	14	10	6	—	3	1	675
Architectural and Structural Metals Manufacturing	281	96	101	21	63	25	23	22	—	—	4	1	639
Communications Equipment Manufacturing	132	69	142	68	54	13	44	29	5	13	2	11	583
Fruit and Vegetable Preserving and Specialty Food Manufacturing	242	24	47	147	41	1	10	11	17	12	5	2	561
Other Fabricated Metal Product Manufacturing	246	84	87	18	55	22	20	19	—	—	4	1	556
Glass and Glass Product Manufacturing	273	129	33	20	25	9	11	8	4	—	2	1	514
Computer and Peripheral Equipment Manufacturing	114	60	125	61	47	12	39	26	5	11	1	10	511

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	267	17	30	46	20	82	7	6	10	7	1	1	495
Other Chemical Product and Preparation Manufacturing	269	17	30	46	19	80	7	6	10	6	1	1	494
Veneer, Plywood, and Engineered Wood Product Manufacturing	361	31	36	3	29	1	5	8	8	5	1	2	489
Other Miscellaneous Manufacturing	144	51	106	31	61	3	8	21	7	—	3	1	438
Printing and Related Support Activities	230	18	72	32	36	5	6	12	4	—	5	—	419
Bakeries and Tortilla Manufacturing	178	18	34	107	30	1	7	8	13	9	4	2	411
Animal Food Manufacturing	156	15	31	96	27	1	7	7	11	8	3	2	363
Other Food Manufacturing	136	13	26	81	23	1	6	6	10	7	3	1	313
Foundries	80	103	18	4	13	67	5	4	1	6	0	1	302
Coating, Engraving, Heat Treating, and Allied Activities	114	39	41	9	26	10	10	9	—	—	2	1	260
Grain and Oilseed Milling	109	11	21	65	19	1	5	5	8	6	2	1	251
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	117	9	48	4	40	1	—	8	3	—	3	1	232
Motor Vehicle Parts Manufacturing	78	22	38	10	25	1	10	8	2	3	3	2	202
Alumina and Aluminum Production and Processing	52	66	12	3	8	43	3	2	1	4	0	1	194

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Medical Equipment and Supplies Manufacturing	63	22	46	14	27	1	4	9	3	—	1	0	190
Paint, Coating, and Adhesive Manufacturing	91	6	10	16	7	28	3	2	3	2	0	0	168
Lime and Gypsum Product Manufacturing	83	39	10	6	8	3	3	2	1	—	1	0	156
Sugar and Confectionery Product Manufacturing	66	7	13	41	11	0	3	3	5	3	1	1	154
Commercial and Service Industry Machinery Manufacturing	65	15	32	6	22	2	4	6	1	—	2	—	154
Other General Purpose Machinery Manufacturing	57	13	28	6	19	1	3	5	1	—	1	—	134
Other Electrical Equipment and Component Manufacturing	37	30	22	8	13	10	5	3	1	—	1	—	129
Motor Vehicle Body and Trailer Manufacturing	48	14	23	6	16	1	6	5	1	2	2	1	124
Steel Product Manufacturing from Purchased Steel	33	42	7	2	5	27	2	1	1	2	0	0	123
Agriculture, Construction, and Mining Machinery Manufacturing	51	12	25	5	17	1	3	4	1	—	1	—	119
Rubber Product Manufacturing	56	17	11	8	10	—	—	2	1	—	0	—	105
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	54	3	6	9	4	16	1	1	2	1	0	0	100

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Industrial Machinery Manufacturing	38	9	18	4	13	1	2	3	1	—	1	—	90
Other Textile Product Mills	46	6	11	6	9	0	0	2	4	—	2	—	87
Electrical Equipment Manufacturing	23	19	14	5	8	7	3	2	0	—	1	—	83
Clay Product and Refractory Manufacturing	40	19	5	3	4	1	2	1	1	—	0	0	75
Audio and Video Equipment Manufacturing	17	9	18	9	7	2	6	4	1	2	0	1	75
Forging and Stamping	30	10	11	2	7	3	2	2	—	—	0	0	67
Manufacturing and Reproducing Magnetic and Optical Media	11	6	12	6	5	1	4	2	0	1	0	1	49
Engine, Turbine, and Power Transmission Equipment Manufacturing	20	5	10	2	7	0	1	2	0	—	0	—	48
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	21	7	8	2	5	2	2	2	—	—	0	0	47
Other Transportation Equipment Manufacturing	18	5	9	2	6	0	2	2	0	1	1	1	47
Metalworking Machinery Manufacturing	19	4	9	2	6	0	1	2	0	—	0	—	46
Spring and Wire Product Manufacturing	18	6	7	1	4	2	2	1	—	—	0	0	41
Seafood Product Preparation and Packaging	16	2	3	10	3	0	1	1	1	1	0	0	38
Tobacco Manufacturing	10	1	3	6	3	0	1	1	0	2	1	0	28
Boiler, Tank, and Shipping Container Manufacturing	13	4	4	1	3	1	1	1	—	—	0	0	28

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Fiber, Yarn, and Thread Mills	16	2	4	1	2	0	0	0	1	—	0	—	27
Railroad Rolling Stock Manufacturing	10	3	5	1	3	0	1	1	0	0	0	0	25
Sawmills and Wood Preservation	17	1	2	0	1	0	0	0	0	0	0	0	23
Other Furniture Related Product Manufacturing	11	1	4	0	4	0	—	1	0	—	0	0	22
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	7	2	4	1	3	0	0	1	0	—	0	—	18
Ship and Boat Building	7	2	3	1	2	0	1	1	0	0	0	0	18
Office Furniture (including Fixtures) Manufacturing	9	1	4	0	3	0	—	1	0	—	0	0	17
Electric Lighting Equipment Manufacturing	5	4	3	1	2	1	1	0	0	—	0	—	17
Cutlery and Handtool Manufacturing	7	3	3	1	2	1	1	1	—	—	0	0	17
Household Appliance Manufacturing	4	3	2	1	1	1	0	0	0	—	0	—	13
Motor Vehicle Manufacturing	5	1	2	1	2	0	1	0	0	0	0	0	12
Cut and Sew Apparel Manufacturing	5	1	3	0	2	—	—	0	0	—	0	—	12
Fabric Mills	7	1	2	0	1	0	0	0	0	—	0	—	11
Textile and Fabric Finishing and Fabric Coating Mills	4	1	1	0	1	0	0	0	0	—	0	—	7
Other Leather and Allied Product Manufacturing	4	0	1	0	1	0	0	0	0	—	0	—	6

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Onsite Transportation (GWh)	Other Nonprocess Use (GWh)	Total (GWh)
Textile Furnishings Mills	1	0	0	0	0	0	0	0	0	—	0	—	2
Leather and Hide Tanning and Finishing	1	0	0	0	0	0	0	0	0	—	0	—	1
Footwear Manufacturing	1	0	0	0	0	0	0	0	0	—	0	—	1
Apparel Accessories and Other Apparel Manufacturing	0	0	0	0	0	—	—	0	0	—	0	—	0
Total	**18,435**	**4,253**	**3,631**	**2,814**	**2,375**	**1,983**	**864**	**770**	**572**	**455**	**162**	**144**	**36,459**

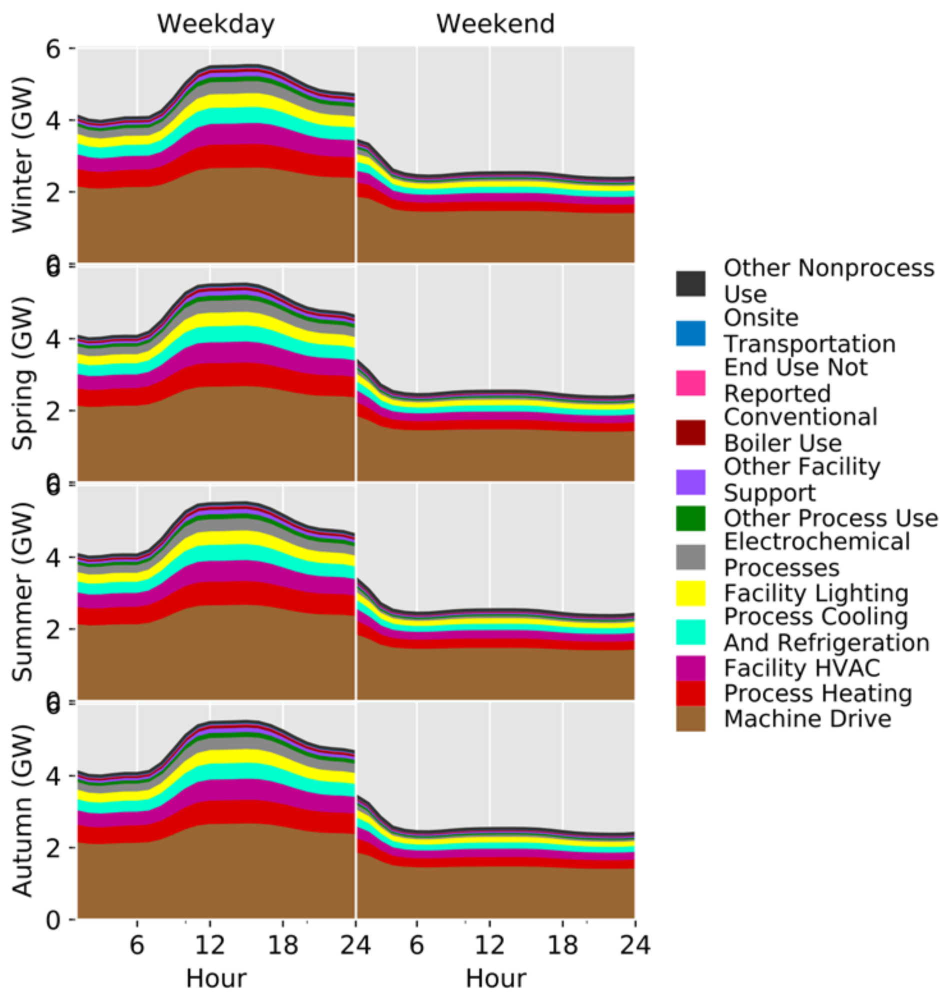

Figure G-55. Industrial electricity use diurnal patterns by season, modeled for the Mountain census division 2012

Table G-57. Distributed Generation Model, Annual Summary the Mountain Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	3,080	669	—	3,749
Distributed PV (GWh)	247	246	445	938
Thermal DG (GWh)	247	38	—	285
Total (GWh)	**3,574**	**953**	**445**	**4,972**
CHP (%)	86.2	70.2	—	75.4
Distributed PV (%)	6.9	25.9	100.0	18.9
Thermal DG (%)	6.9	4.0	—	5.7
Total (%)	**71.9**	**19.2**	**8.9**	**100.0**

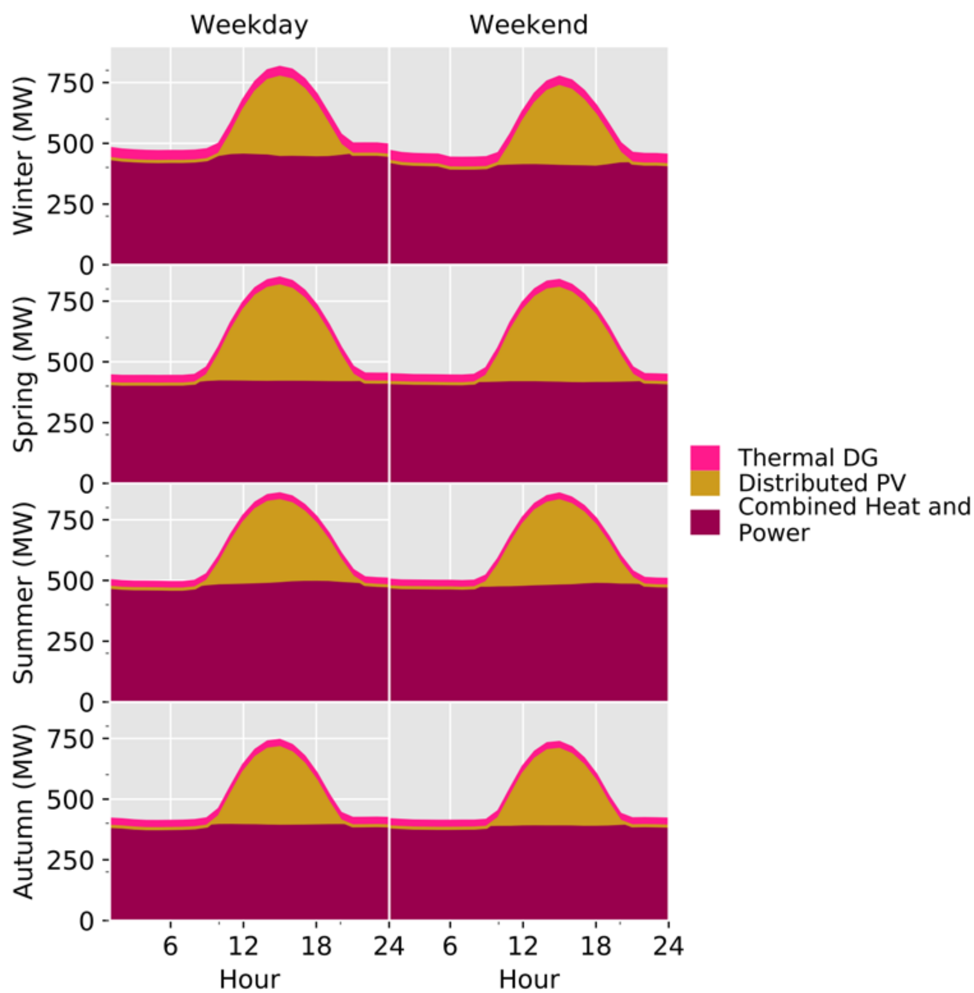

Figure G-56. Distributed Generation Model Diurnal Generation Patterns, Mountain census division 2012

G.9 Pacific

Table G-58. Annual Electricity Load for 2012 in Terawatt-Hours, Top-Down and Represented in dsgrid, Pacific Census Division

Component Type	Component Name	Residential	Commercial	Industrial	Transport	Total
Top-down	Hourly load					418.7
Derived	T&D losses					21.9
Top-down	Annual energy	144.5	179.6	86.5	0.7	411.3
dsgrid	Distributed generation	1.4	6.5	30.0	–	37.9
dsgrid-core	Gap models	23.0	77.2	24.2	0.7	125.1
dsgrid-core	Detailed sector models	137.1	163.4	83.3	–	383.8
Derived	Total site energy	145.9	186.1	116.5	0.7	449.2
Derived	Annual sector residuals	-14.2	-54.5	9.0	0.0	-59.7
Derived	Hourly residuals					-74.2

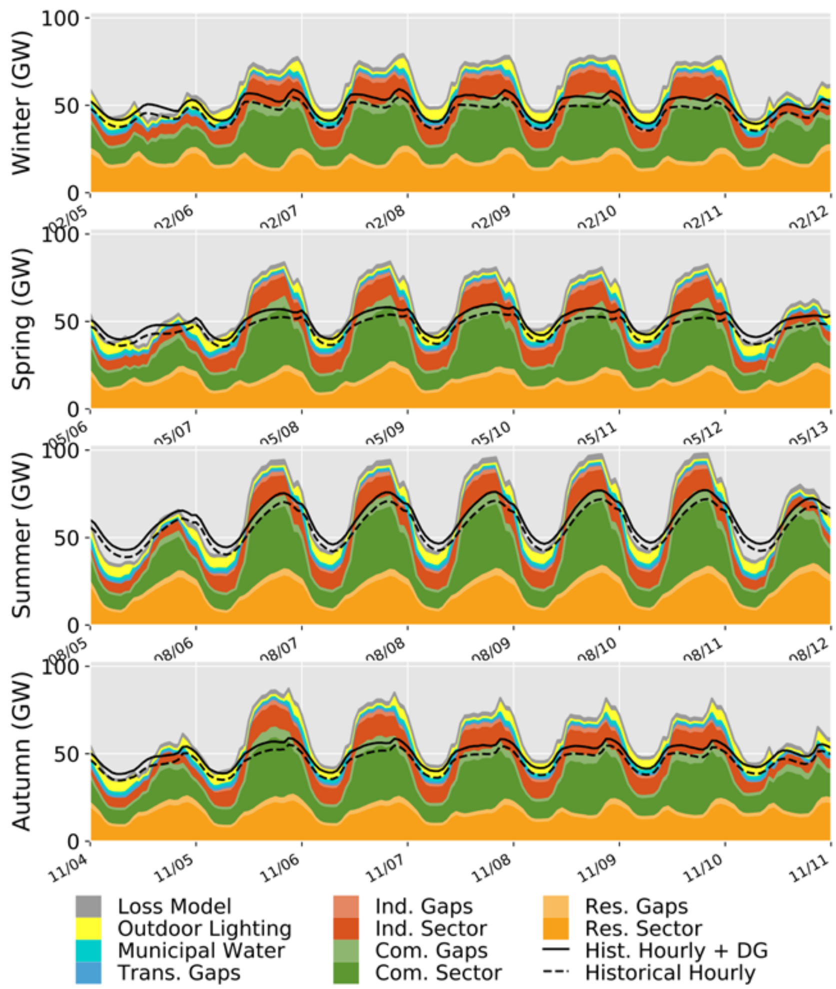

Figure G-57. Bottom-up detailed sectoral and gap model load compared to bulk-level historical hourly load plus DG estimates for the Pacific census division in 2012

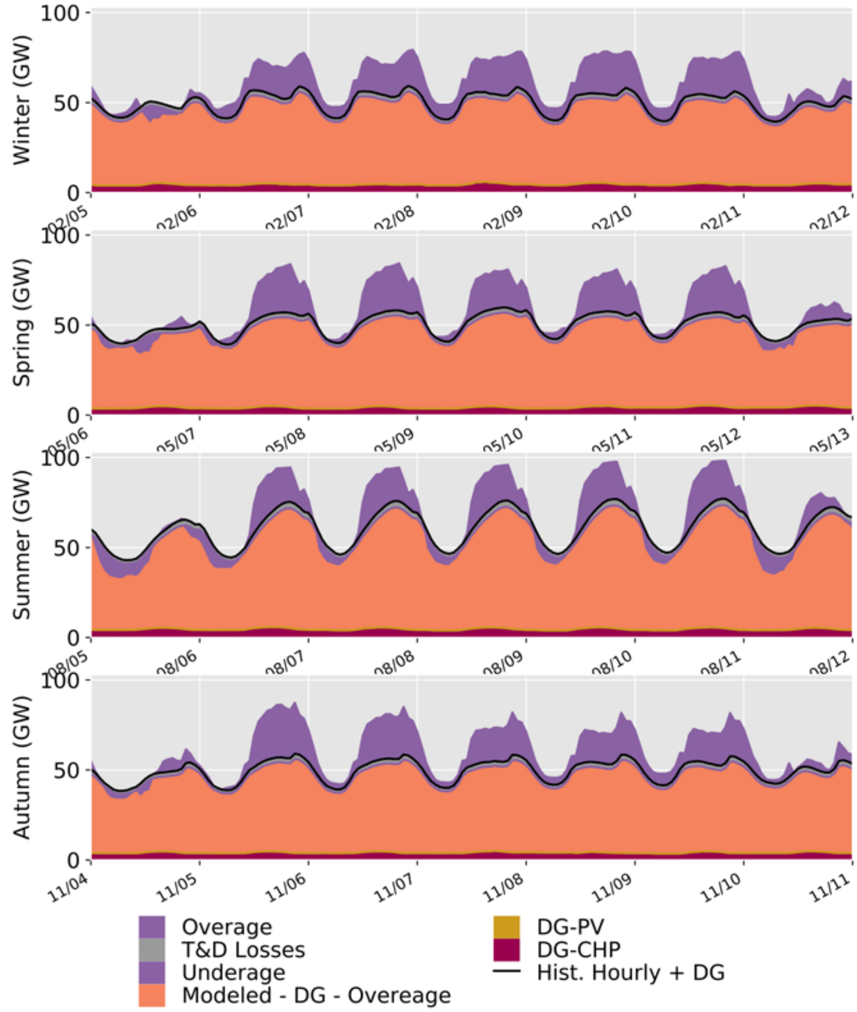

Figure G-58. dsgrid hourly residuals shown in context for the Pacific census division.

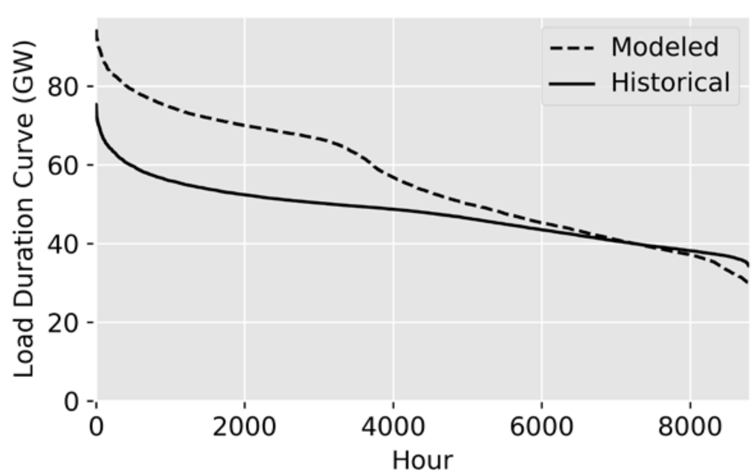

Figure G-59. Historical and dsgrid load duration curves for the Pacific census division in 2012

The dsgrid modeled load duration curve consists of the distributed generation model subtracted from the sum of the detailed sector and gap models.

Table G-59. Residential Subsectors, Summary of Electricity by End Use for the Pacific Census Division in 2012

Subsector	Interior Equipment (GWh)	Space Heating (GWh)	Interior Lights (GWh)	Space Cooling (GWh)	Fans (GWh)	Water Systems (GWh)	Exterior Lights (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Single Family Detached	54,567	21,167	17,893	16,840	11,922	8,438	3,592	9	—	134,428
Mobile Home	3,880	803	876	1,001	673	480	143	0	—	7,855
Single Family Attached	3,783	783	854	976	656	468	139	0	—	7,659
Apartment in Building 2 to 4 Units	2,673	378	1,127	831	1,012	—	1,352	95	19	7,487
Midrise Apartment Building	957	127	419	267	344	—	500	32	6	2,652
Total	**65,861**	**23,257**	**21,168**	**19,915**	**14,606**	**9,386**	**5,725**	**137**	**26**	**160,080**

Table G-60. Residential Electricity Proportions by Subsector and End Use for the Pacific census division in 2012

Subsector	Interior Equipment (%)	Space Heating (%)	Interior Lights (%)	Space Cooling (%)	Fans (%)	Water Systems (%)	Exterior Lights (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Single Family Detached	40.6	15.7	13.3	12.5	8.9	6.3	2.7	0.0	—	84.0
Mobile Home	49.4	10.2	11.1	12.7	8.6	6.1	1.8	0.0	—	4.9
Single Family Attached	49.4	10.2	11.1	12.7	8.6	6.1	1.8	0.0	—	4.8
Apartment in Building 2 to 4 Units	35.7	5.1	15.0	11.1	13.5	—	18.1	1.3	0.3	4.7
Midrise Apartment Building	36.1	4.8	15.8	10.1	13.0	—	18.8	1.2	0.2	1.7
Total	**41.1**	**14.5**	**13.2**	**12.4**	**9.1**	**5.9**	**3.6**	**0.1**	**0.0**	**100.0**

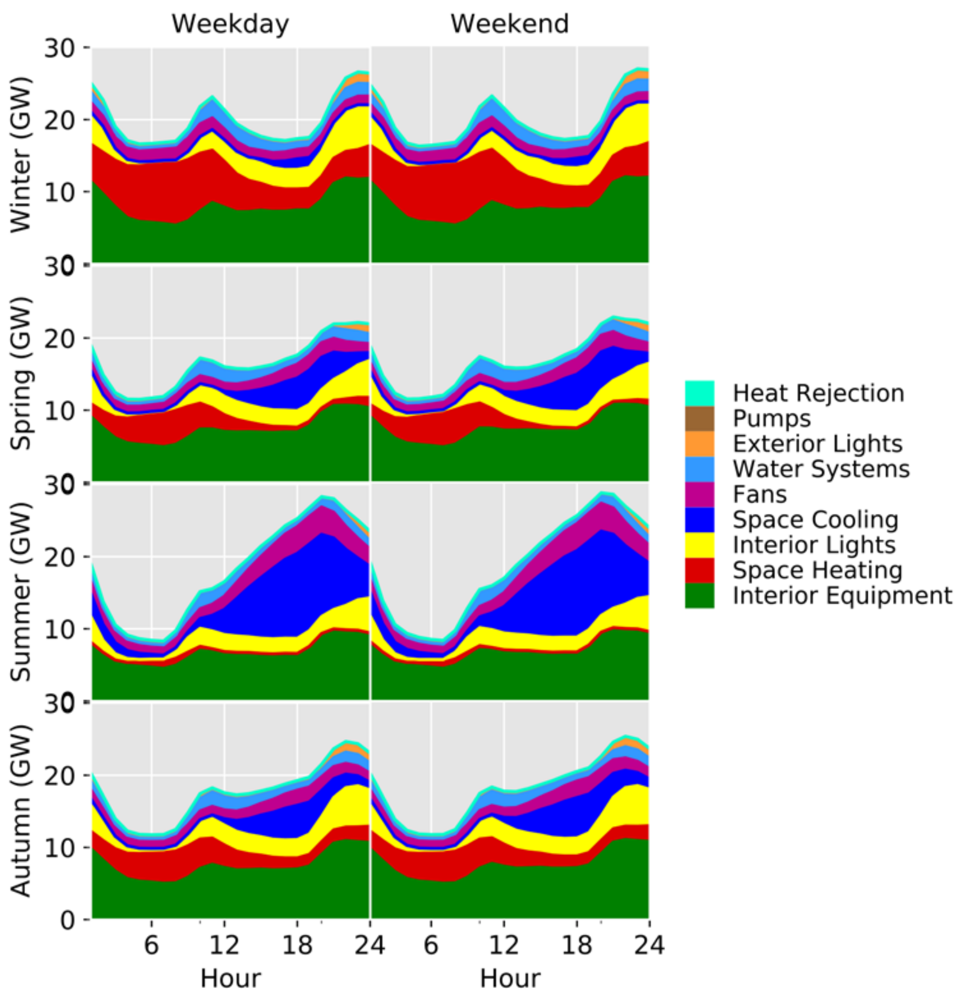

Figure G-60. Residential electricity use diurnal patterns by season, modeled for the Pacific census division 2012

Table G-61. Commercial Subsectors, Summary of Electricity in Detailed Energy Modeling by End Use for the Pacific Census Division in 2012

Subsector	Interior Lights (GWh)	Interior Equipment (GWh)	Fans (GWh)	Space Cooling (GWh)	Exterior Lights (GWh)	Space Heating (GWh)	Pumps (GWh)	Heat Rejection (GWh)	Total (GWh)
Large Office	14,163	16,430	9,870	6,847	2,900	105	1,148	239	51,703
Strip Mall	24,987	3,628	4,582	2,139	5,105	546	14	4	41,006
Standalone Retail Store	9,557	3,110	2,808	1,348	1,462	787	5	1	19,077
Medium Office	3,487	3,971	2,301	1,422	1,241	77	114	25	12,638
Warehouse	3,888	1,550	970	281	1,882	702	5	2	9,279
Small Office	2,187	2,976	1,477	867	854	162	11	4	8,537
Large Hotel	1,516	2,334	1,240	917	368	33	98	19	6,526
Full Service Restaurant	1,378	3,077	785	402	385	82	7	1	6,117
Hospital	975	1,274	621	456	75	—	86	22	3,508
Outpatient Treatment Facility	687	1,017	258	110	243	—	22	6	2,343
Primary School	648	519	304	195	84	53	12	3	1,818
Small Hotel	227	307	32	17	144	13	3	1	743
Quick Service Restaurant	10	57	19	9	6	0	0	0	101
Total	**63,709**	**40,249**	**25,265**	**15,011**	**14,748**	**2,561**	**1,524**	**328**	**163,396**

Table G-62. Commercial Electricity Proportions of Detailed Models by Subsector and End Use for the Pacific Census Division in 2012

Subsector	Interior Lights (%)	Interior Equipment (%)	Fans (%)	Space Cooling (%)	Exterior Lights (%)	Space Heating (%)	Pumps (%)	Heat Rejection (%)	Total (%)
Large Office	27.4	31.8	19.1	13.2	5.6	0.2	2.2	0.5	31.6
Strip Mall	60.9	8.8	11.2	5.2	12.5	1.3	0.0	0.0	25.1
Standalone Retail Store	50.1	16.3	14.7	7.1	7.7	4.1	0.0	0.0	11.7
Medium Office	27.6	31.4	18.2	11.3	9.8	0.6	0.9	0.2	7.7
Warehouse	41.9	16.7	10.4	3.0	20.3	7.6	0.1	0.0	5.7
Small Office	25.6	34.9	17.3	10.2	10.0	1.9	0.1	0.1	5.2
Large Hotel	23.2	35.8	19.0	14.1	5.6	0.5	1.5	0.3	4.0
Full Service Restaurant	22.5	50.3	12.8	6.6	6.3	1.3	0.1	0.0	3.7
Hospital	27.8	36.3	17.7	13.0	2.1	—	2.4	0.6	2.1
Outpatient Treatment Facility	29.3	43.4	11.0	4.7	10.4	—	1.0	0.3	1.4
Primary School	35.7	28.5	16.7	10.7	4.6	2.9	0.7	0.2	1.1
Small Hotel	30.5	41.3	4.2	2.3	19.4	1.8	0.4	0.1	0.5
Quick Service Restaurant	9.5	56.3	19.2	9.0	5.7	0.2	0.0	0.0	0.1
Total	**39.0**	**24.6**	**15.5**	**9.2**	**9.0**	**1.6**	**0.9**	**0.2**	**100.0**

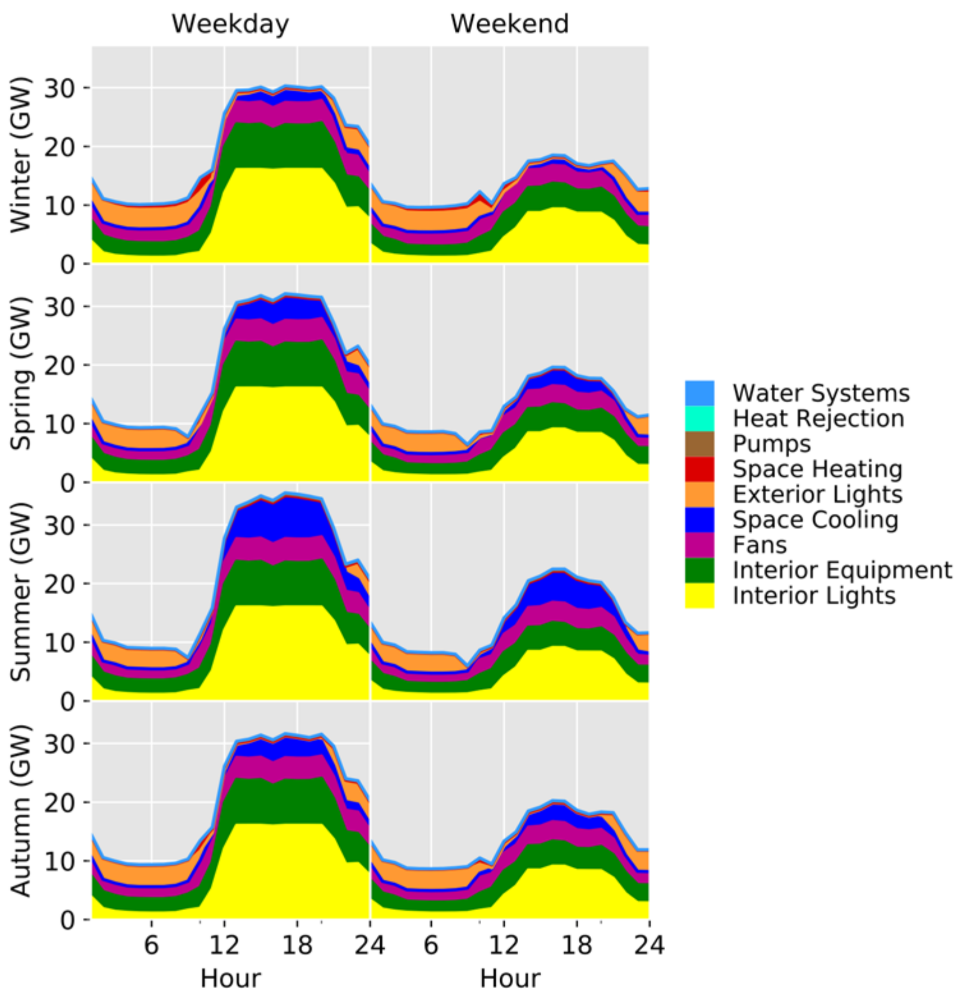

Figure G-61. Commercial electricity use diurnal patterns by season, modeled for the Pacific census division 2012

Table G-63. Industrial Manufacturing Subsectors, Summary of Model Results for the Pacific Census Division in 2012

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Petroleum and Coal Products Manufacturing	6,454	270	303	337	202	116	57	78	59	89	8	1	7,974
Plastics Product Manufacturing	3,389	1,014	640	506	598	—	—	144	32	—	—	27	6,350
Iron and Steel Mills and Ferroalloy Manufacturing	1,628	2,090	378	90	266	1,390	94	73	28	119	17	10	6,184
Semiconductor and Other Electronic Component Manufacturing	1,387	722	1,457	693	555	137	442	295	53	131	116	16	6,003
Converted Paper Product Manufacturing	3,723	194	218	83	190	41	168	53	229	25	—	10	4,934
Pulp, Paper, and Paperboard Mills	3,702	192	215	82	188	40	165	53	226	24	—	10	4,896
Pharmaceutical and Medicine Manufacturing	1,780	115	200	304	129	536	49	38	67	43	8	8	3,276
Aerospace Product and Parts Manufacturing	980	278	475	128	318	16	124	100	21	40	30	36	2,547
Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	578	302	617	295	235	58	189	126	22	56	49	7	2,534
Beverage Manufacturing	887	105	290	485	230	5	61	81	40	188	11	50	2,433
Fruit and Vegetable Preserving and Specialty Food Manufacturing	942	93	183	572	161	5	40	44	67	48	9	20	2,185
Other Wood Product Manufacturing	1,309	111	132	13	106	5	19	28	31	19	6	4	1,783
Other Food Manufacturing	701	69	135	420	119	4	29	32	49	35	7	15	1,615
Dairy Product Manufacturing	680	67	130	404	115	3	28	31	47	34	6	14	1,561
Communications Equipment Manufacturing	320	167	344	165	131	33	105	70	13	31	28	4	1,410
Basic Chemical Manufacturing	693	45	77	117	50	206	19	15	26	17	3	3	1,270
Foundries	327	419	75	18	53	276	19	14	6	24	3	2	1,235

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Veneer, Plywood, and Engineered Wood Product Manufacturing	875	74	87	8	69	3	12	18	20	12	4	3	1,187
Animal Slaughtering and Processing	497	49	97	302	85	3	21	23	35	25	5	11	1,152
Computer and Peripheral Equipment Manufacturing	256	135	281	136	106	27	87	58	10	26	23	3	1,146
Glass and Glass Product Manufacturing	560	265	67	40	51	18	22	16	9	—	2	4	1,055
Architectural and Structural Metals Manufacturing	463	159	166	35	104	41	39	36	—	—	2	7	1,053
Other Nonmetallic Mineral Product Manufacturing	532	252	64	39	49	18	21	15	9	—	2	4	1,005
Nonferrous Metal (except Aluminum) Production and Processing	265	338	60	14	42	216	15	11	4	19	3	2	987
Bakeries and Tortilla Manufacturing	416	41	80	251	71	2	17	19	29	21	4	9	961
Soap, Cleaning Compound, and Toilet Preparation Manufacturing	474	31	54	82	35	145	13	10	18	12	2	2	879
Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	468	30	53	82	34	144	13	10	18	12	2	2	868
Manufacturing and Reproducing Magnetic and Optical Media	191	99	201	96	77	19	61	41	7	18	16	2	828
Other Fabricated Metal Product Manufacturing	337	115	120	25	75	30	28	26	—	—	2	5	763
Printing and Related Support Activities	405	31	127	56	64	9	11	21	6	—	—	8	738
Coating, Engraving, Heat Treating, and Allied Activities	317	109	115	24	72	29	27	25	—	—	2	5	725

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Other Chemical Product and Preparation Manufacturing	368	24	41	62	26	110	10	8	14	9	2	2	674
Cement and Concrete Product Manufacturing	329	156	40	24	31	11	13	10	6	—	1	2	623
Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing	311	20	35	52	22	92	8	7	12	7	1	1	570
Alumina and Aluminum Production and Processing	147	187	33	8	23	120	8	6	2	10	1	1	548
Other Miscellaneous Manufacturing	175	62	129	38	74	4	10	26	9	—	1	3	531
Paint, Coating, and Adhesive Manufacturing	260	17	30	45	19	79	7	6	10	6	1	1	482
Grain and Oilseed Milling	193	19	37	116	33	1	8	9	14	10	2	4	445
Motor Vehicle Parts Manufacturing	167	47	81	22	54	3	21	17	4	7	5	6	435
Rubber Product Manufacturing	224	67	42	34	40	—	—	10	2	—	—	2	420
Steel Product Manufacturing from Purchased Steel	101	129	23	5	16	83	6	4	2	7	1	1	378
Other General Purpose Machinery Manufacturing	159	37	78	15	53	4	9	14	4	—	—	4	377
Audio and Video Equipment Manufacturing	83	43	88	42	33	8	27	18	3	8	7	1	361
Medical Equipment and Supplies Manufacturing	119	42	86	25	50	3	7	17	6	—	1	2	357
Household and Institutional Furniture and Kitchen Cabinet Manufacturing	170	13	70	6	58	1	—	12	4	—	2	4	339
Forging and Stamping	148	51	53	11	33	13	12	11	—	—	1	2	336
Lime and Gypsum Product Manufacturing	168	80	20	12	16	6	7	5	3	—	1	1	318
Animal Food Manufacturing	134	13	26	82	23	1	6	6	10	7	1	3	313

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Seafood Product Preparation and Packaging	129	13	25	79	22	1	5	6	9	7	1	3	301
Other Electrical Equipment and Component Manufacturing	84	69	50	19	29	23	11	7	1	—	—	2	297
Industrial Machinery Manufacturing	125	29	60	12	41	3	7	11	3	—	—	3	294
Commercial and Service Industry Machinery Manufacturing	124	29	60	12	41	3	7	11	3	—	—	3	292
Sugar and Confectionery Product Manufacturing	124	12	24	76	21	1	5	6	9	6	1	3	289
Clay Product and Refractory Manufacturing	149	71	18	11	14	5	6	4	3	—	0	1	284
Ship and Boat Building	97	28	49	13	33	2	13	10	2	4	3	4	258
Motor Vehicle Manufacturing	90	26	45	12	30	2	12	9	2	4	3	3	237
Motor Vehicle Body and Trailer Manufacturing	73	21	36	10	24	1	9	8	2	3	2	3	191
Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	79	27	29	6	18	7	7	6	—	—	0	1	181
Other Transportation Equipment Manufacturing	60	17	30	8	20	1	8	6	1	2	2	2	158
Metalworking Machinery Manufacturing	66	15	32	6	22	2	4	6	2	—	—	2	157
Agriculture, Construction, and Mining Machinery Manufacturing	58	13	28	5	19	1	3	5	1	—	—	1	135
Spring and Wire Product Manufacturing	59	20	21	4	13	5	5	5	—	—	0	1	134
Electrical Equipment Manufacturing	35	29	21	8	13	10	5	3	1	—	—	1	126
Other Textile Product Mills	52	7	13	7	10	0	0	2	5	—	—	2	99
Boiler, Tank, and Shipping Container Manufacturing	40	14	14	3	9	3	3	3	—	—	0	1	90

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Textile and Fabric Finishing and Fabric Coating Mills	53	8	13	3	7	0	2	1	2	—	—	1	89
Sawmills and Wood Preservation	64	5	6	1	5	0	1	1	2	1	0	0	87
Office Furniture (including Fixtures) Manufacturing	41	3	17	1	14	0	—	3	1	—	0	1	82
Cut and Sew Apparel Manufacturing	26	3	18	1	11	—	—	2	1	—	—	0	63
Electric Lighting Equipment Manufacturing	17	14	10	4	6	5	2	1	0	—	—	0	61
Engine, Turbine, and Power Transmission Equipment Manufacturing	25	6	12	2	8	1	1	2	1	—	—	1	59
Fabric Mills	33	5	8	2	4	0	1	1	1	—	—	0	56
Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	23	5	11	2	8	1	1	2	1	—	—	1	54
Fiber, Yarn, and Thread Mills	26	4	6	2	3	0	1	1	1	—	—	0	43
Household Appliance Manufacturing	12	10	7	3	4	3	2	1	0	—	—	0	43
Cutlery and Handtool Manufacturing	17	6	6	1	4	2	1	1	—	—	0	0	38
Other Furniture Related Product Manufacturing	14	1	6	0	5	0	—	1	0	—	0	0	28
Tobacco Manufacturing	6	1	2	3	1	0	0	1	0	1	0	0	15
Textile Furnishings Mills	4	1	1	1	1	0	0	0	0	—	—	0	8
Hardware Manufacturing	4	1	1	0	1	0	0	0	—	—	0	0	8
Other Leather and Allied Product Manufacturing	4	1	1	0	1	0	0	0	0	—	—	0	7
Footwear Manufacturing	3	0	0	0	0	0	0	0	0	—	—	0	4
Railroad Rolling Stock Manufacturing	1	0	1	0	0	0	0	0	0	0	0	0	3

Subsector	Machine Drive (GWh)	Process Heating (GWh)	Facility HVAC (GWh)	Process Cooling And Refrigeration (GWh)	Facility Lighting (GWh)	Electro Chemical Processes (GWh)	Other Process Use (GWh)	Other Facility Support (GWh)	Conventional Boiler Use (GWh)	End Use Not Reported (GWh)	Other Nonprocess Use (GWh)	Onsite Transportation (GWh)	Total (GWh)
Apparel Accessories and Other Apparel Manufacturing	0	0	0	0	0	—	—	0	0	—	—	0	1
Leather and Hide Tanning and Finishing	0	0	0	0	0	0	0	0	0	—	—	0	0
Total	**40,613**	**9,504**	**9,040**	**6,821**	**5,648**	**4,194**	**2,276**	**1,917**	**1,340**	**1,168**	**411**	**385**	**83,319**

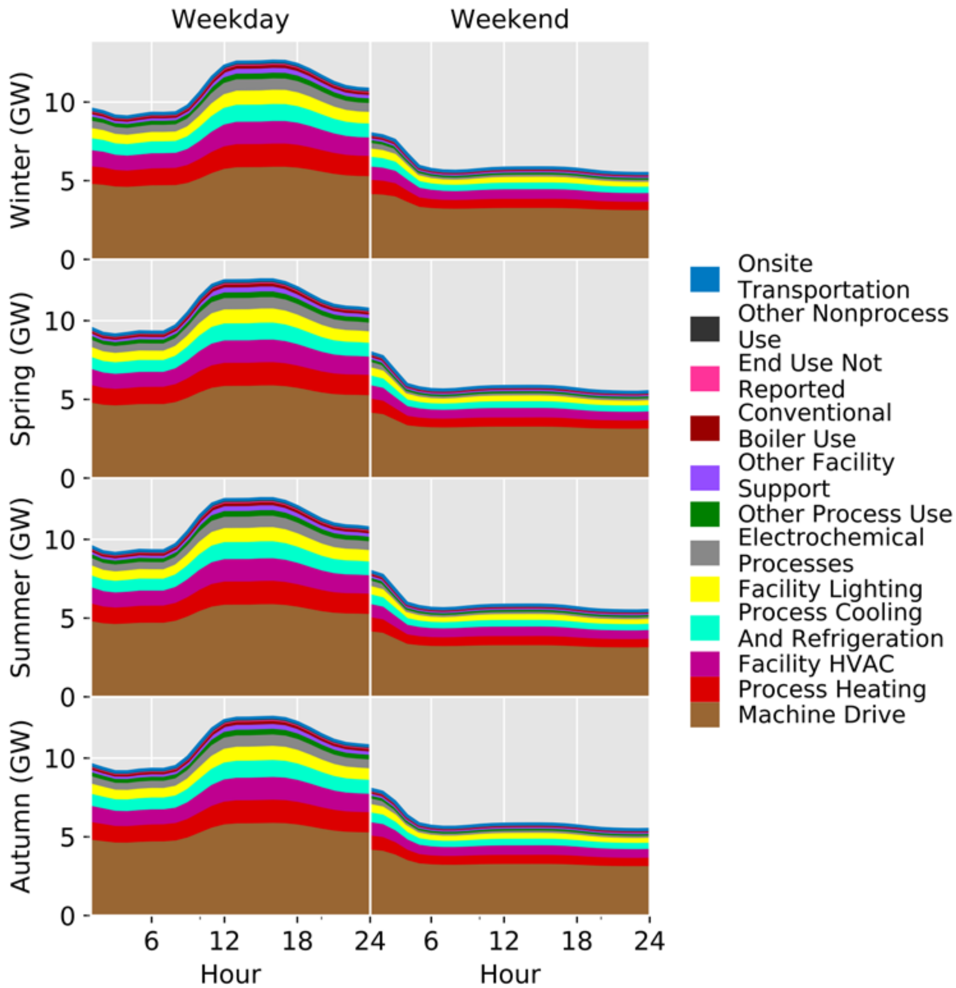

Figure G-62. Industrial electricity use diurnal patterns by season, modeled for the Pacific census division 2012

Table G-64. Distributed Generation Model, Annual Summary the Pacific Census Division in 2012 by Sector and DG Type

Sector/DG Type	Industry	Commercial	Residential	Total
CHP (GWh)	27,816	5,508	5	33,330
Distributed PV (GWh)	683	681	1,385	2,749
Thermal DG (GWh)	1,493	288	—	1,780
Total (GWh)	**29,992**	**6,477**	**1,391**	**37,859**
CHP (%)	92.7	85.0	0.4	88.0
Distributed PV (%)	2.3	10.5	99.6	7.3
Thermal DG (%)	5.0	4.4	—	4.7
Total (%)	**79.2**	**17.1**	**3.7**	**100.0**

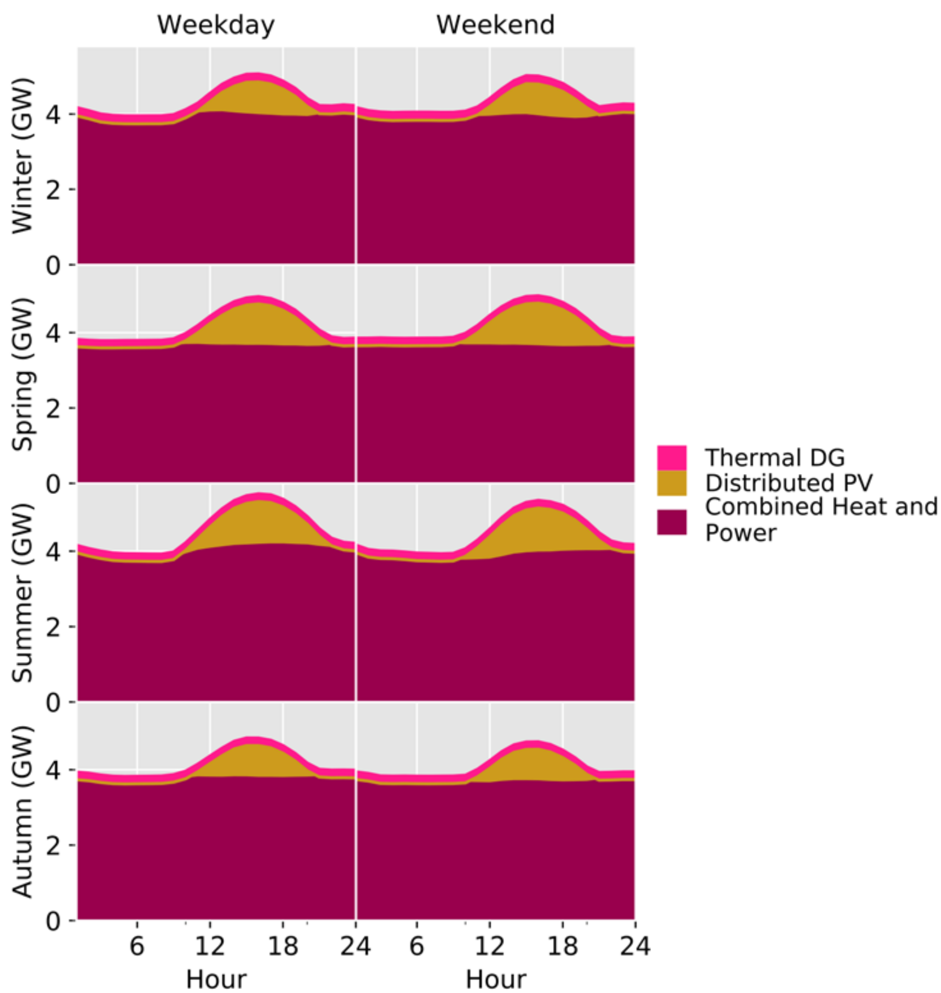

Figure G-63. Distributed Generation Model Diurnal Generation Patterns, Pacific census division 2012

Appendix H. Weather File Methodology

Many building energy analyses rely on typical meteorological year (TMY) weather files to capture expected energy efficiency impacts over long time horizons. Building energy model calibration requires actual meteorological year (AMY) weather files matched to the period for which measured data are available (Hale et al. 2014), but otherwise, analysis with AMY weather files is relatively uncommon.

For this project, to produce load data that are usable in grid models with significant penetrations of wind and solar generation, we require AMY weather files for an appropriate historical year. These files were generated by transforming data from the National Solar Radiation Database (NSRDB)[62] into the format and units required by EnergyPlus weather (EPW) files (Wilcox 2012; DOE 2017c) (Figure H-1).

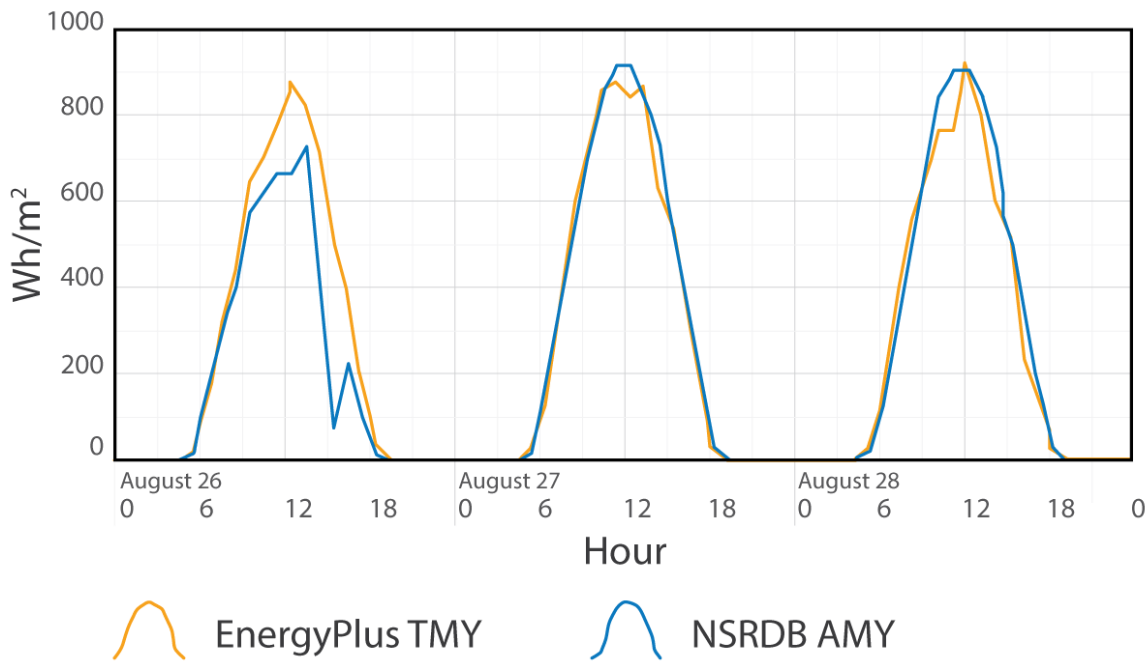

Figure H-1. Example of alignment of integrated AMY NSRDB solar radiation profiles with EPW time conventions as demonstrated using a TMY EPW file

NSRDB data are available at half-hourly resolution and represent an instantaneous measurement. In contrast, EPW files are typically hourly, with an end-of-period interpretation for data points. Thus, we apply trapezoidal rule averaging and integrating methods that use three NSRDB data points to construct every EPW data point. With t representing the time for which we are constructing an EPW data point these methods are:

Average:

$$\mathrm{EPW}(t) = 0.25 \cdot \mathrm{NSRDB}(t - 1\mathrm{h}) + 0.5 \cdot \mathrm{NSRDB}(t - 0.5\mathrm{h}) + 0.25 \cdot \mathrm{NSRDB}(t)$$

Integrate:

$$\mathrm{EPW}(t) = 0.25\mathrm{h} \cdot \mathrm{NSRDB}(t - 1\mathrm{h}) + 0.5\mathrm{h} \cdot \mathrm{NSRDB}(t - 0.5\mathrm{h}) + 0.25\mathrm{h} \cdot \mathrm{NSRDB}(t)$$

[62] See https://nsrdb.nrel.gov/.

The field mappings of EPW and NSRDB, along with the methods used to convert between the two are summarized in Table H-1.

Table H-1. Mapping to EnergyPlus Weather File Fields from NSRDB Fields

EPW Field	EPW Units	NSRDB Field	NSRDB Units	Conversion Factor	Summary Method
Relative Humidity	%	Relative Humidity	%	-	Average
Snow Depth	cm	Snow Depth	m	100 cm/m	Average
Dew Point Temperature	°C	Dew Point Temperature	K	°C = K – 273.15	Average
Surface Pressure	Pa	Surface Pressure	mbar	100 Pa/mbar	Average
Dry Bulb Temperature	°C	Surface Temperature	K	°C = K – 273.15	Average
Precipitable Water	mm	Total Precipitable Water	mm	-	Average
Wind Speed	m/s	Wind Speed	m/s	-	Average
Wind Direction	°	Wind Direction	°	-	Average
Global Horizontal Radiation (GHR)	Wh/m^2	Global Horizontal Irradiance (GHI)	W/m^2	-	Integrate
Direct Normal Radiation (DNR)	Wh/m^2	Direct Normal Irradiance (DNI)	W/m^2	-	Integrate
Diffuse Horizontal Radiation (DHR)	Wh/m^2	Diffuse Horizontal Irradiance (DHI)	W/m^2	-	Integrate

In addition to handling unit and data point interpretation conversions, the weather file time extents were made to match the needs of producing a data set that covers 2012 for the entire CONUS, using EST as our basis for defining the exact extents of the year. To ensure full coverage, an additional day of simulation—December 31, 2011 local time—was added. The EnergyPlus output timeseries were subsequently processed to drop hours falling outside 2012, EST.

Appendix I. Combined Heat and Power and Distributed Thermal Model

To develop an estimate of hourly generation from combined heat and power (CHP) and other distributed thermal generators, we start by merging EIA data available at the plant and unit level. EIA Form 860 provides unit level prime mover and capacity information, with nameplate, summer, and winter capacity specified in MW (EIA 2013a). We aggregate this data to the plant-prime mover level, and then join it with the EIA Form 923 generation and fuel data after aggregating the latter over fuel type. At the end of this process, we have capacity and generation data for each plant-prime mover combination, along with the code for the primary fuel used during the year. EIA Form 923 also provides information on sector—both a coarse specification and a NAICS code—as well as whether the plant provides CHP services, name and location information (EIA 2018, 923).

The source and disposition table of EIA Form 923 provides further details by plant that let us estimate how much generation is used behind-the-meter. Quantities of electricity generated on site and imported from the grid are reported: the sum is the total source electricity. The disposition of that electricity is then reported in terms of station use, direct use on site (this is what we interpret as the behind-the-meter use of electricity), sales (retail and for resale), tolling agreements and other outgoing electricity (EIA 2018). From these data, we estimate the behind-the-meter fraction as

$$f_{\text{behind-the-meter}} = \frac{\text{Direct Use (MWh)}}{\text{Net Source (MWh)}} = \frac{\text{Direct Use (MWh)}}{\text{Total Source (MWh)} - \text{Station Use (MWh)}}.$$

At this point we filter the plants down to just those that are non-utility CHP and other thermal plants. The filters we apply are:

- **Sector** – Plants that are commercial or industrial, CHP and not-CHP
- **Prime mover** – Other, hydro, wind, and PV are removed. All other prime movers are classified as CHP/Thermal DG.[63] PV is covered by the distributed PV model. The other categories we remove are of potential interest but are excluded because of their small capacity and less available data (e.g., at the hourly level). As shown in Table I-1, this is not a severe limitation, as 98% of the generation reported falls in our aggregated CHP/Thermal DG category.
- **Capacity and net generation** – Some plants are reported as having zero capacity. These are removed, as are plants that report negative net generation for those prime movers classified as CHP/Thermal DG. However, we retain plants with zero net generation to represent capacity that is available but not used on a regular basis.

Following the application of the filters, we have data on 847 plants. Next, we determine for which of these plants a CEMS hourly profile is available. This join is done based on the Plant ID and yields 69 plants with a CEMS profile; however, only 23 of those have a non-zero profile. For

[63] The EIA prime mover codes included in our CHP/distributed thermal model are: CA, CS, CT (Combined Cycle), FC (Fuel Cell), GT (Combustion (Gas) Turbine, including Jet Engines), IC (Internal Combustion Engine), and ST (Steam Turbine).

each of those plants we calculate the capacity factor of the profile in two ways. The "standard capacity factor" is calculated by dividing the annual generation represented in the profile by the profile's maximum value, that is, by assuming the plant's capacity is equal to the maximum output achieved in the annual profile. The "alternate capacity factor" is computed by dividing the annual generation in the CEMS profile by the plant capacity reported on EIA Form 860. Both of these capacity factors are retained and used in the process of matching modeled plants to CEMS profiles and then transforming those profiles to match the capacity factors prescribed for each modeled plant.

Table I-1. Commercial and Industrial Power Plant Capacity and Generation by Prime Mover, per EIA Forms 860 and 923

Generator Type	Nameplate Capacity (GW)	Net Generation (TWh)	Generation (%)
CHP/Thermal DG	34.52	154.12	98%
Hydro	0.69	2.37	2%
Other	0.11	0.31	0%
PV	0.12	0.14	0%
Wind	0.04	0.07	0%
Total	**35.48**	**157.02**	**100%**

The DOE Combined Heat and Power Installation Database (ICF Inc. and DOE 2016) lists CHP capacity in kW by city, state, facility name, application, NAICS code, operational year, prime mover, and fuel. For our purposes, we filter out CHP facilities for whom the application is "utilities," and remove units installed after 2012. We also map NAICS codes to sector: residential, commercial, or industrial. At the end of this process, we have information on 3,687 units in place as of 2012. They are fairly evenly split between small (< 1 MW and therefore not eligible for EIA reporting) and large (1 MW or greater) units, coming in at 1,951 units and 1,736 units respectively. In principle, one might expect the number of large CHP units in the CHP DB to be the same as the number of CHP units reported in the EIA data sources explained above. However, the EIA data sources only report 687 CHP plants, that is, 40% of the expected 1,736. The difference between data sources similarly holds if we look at capacity instead of number of installations (Table I-2). Therefore, we model CHP capacity from the CHP DB, and distributed thermal generation units reported in the EIA data sources (as such units are not listed in the CHP DB).

Table I-2. CHP and Thermal DG Capacity Described in EIA Forms 860 and 923 (EIA) and in the DOE Combined Heat and Power Installation Database (CHP DB)[a]

Capacity Type	Commercial (MW)	Industrial (MW)	Residential (MW)	Total (MW)
EIA DG	781	2,499	—	3,280
EIA CHP	2,542	28,032	44	30,618
CHP DB >= 1 MW	9,330	69,088	97	78,515
CHP DB < 1 MW	344	137	29	510

[a] Capacity included in the CHP/Thermal DG model is shaded orange.

We assign behind-the-meter generation quantities to the CHP DB entries by performing a match between the CHP DB and EIA meta-data. In particular, we attempt to match operational data to CHP DB capacity on the basis of

- **Sector information** – First by Residential, Commercial, Industrial, then by increasingly specific NAICS codes (starting with three-digit and progressing up to five-digit if possible)
- **Prime mover and fuel type** – We first attempt to match just on prime mover. If that is successful and there are still multiple potential matches, we then attempt to match on prime mover-fuel type pairs. In both cases, the mapping that is applied between EIA codes and the CHP DB designations are listed in Table I-3.
- **Capacity** – For CHP DB plants of 1 MW or larger, we filter EIA plants based on capacity, for tighter and tighter bounds. For each run of the filter, the EIA plants that are kept are those whose capacities are between $f \cdot C_{\text{CHP DB}}$ and $(1/f) \cdot C_{\text{CHP DB}}$, where f is a fraction that starts at 0.5 and can go as high as 0.99, and $C_{\text{CHP DB}}$ is the capacity of the plant for which we are defining operational data.
- **Location** – The only location filter applied is state

These filters are applied in a particular order, starting with those aspects that we are most interested in matching, and proceeding to match at finer and finer levels as long as multiple potential EIA matches remain (Algorithm 1).

Table I-3. Mapping Between EIA and CHP DB Prime Mover and Fuel Type Codes[a]

EIA		CHP DB	
Prime Mover Code	**Fuel Type Code**	**Prime Mover**	**Fuel Class**
IC	DFO	Reciprocating Engine	OIL
GT	DFO	Combustion Turbine	OIL
ST	SUB	Boiler/Steam Turbine	COAL
CA	NG	Combined Cycle	NG
GT	NG	Combustion Turbine	NG
ST	AB	Boiler/Steam Turbine	BIOMASS
ST	BIT	Boiler/Steam Turbine	COAL
ST	BLQ	Boiler/Steam Turbine	WAST
ST	DFO	Boiler/Steam Turbine	OIL
ST	NG	Boiler/Steam Turbine	NG
IC	NG	Reciprocating Engine	NG
ST	WDS	Boiler/Steam Turbine	WOOD
CS	NG	Combined Cycle	NG
CA	LFG	Combined Cycle	BIOMASS
IC	OBG	Reciprocating Engine	BIOMASS
ST	PUR	Boiler/Steam Turbine	WAST

EIA		CHP DB	
Prime Mover Code	Fuel Type Code	Prime Mover	Fuel Class
ST	OG	Boiler/Steam Turbine	OTR
ST	OTH	Boiler/Steam Turbine	OTR
CT	NG	Combined Cycle	NG
GT	JF	Combustion Turbine	OIL
CA	DFO	Combined Cycle	OIL
ST	WH	Boiler/Steam Turbine	WAST
GT	OG	Combustion Turbine	OTR
ST	BFG	Boiler/Steam Turbine	WAST
ST	MSB	Boiler/Steam Turbine	BIOMASS
ST	LIG	Boiler/Steam Turbine	COAL
ST	RFO	Boiler/Steam Turbine	OIL
CA	BIT	Combined Cycle	COAL
CA	WH	Combined Cycle	WAST
GT	BIT	Combustion Turbine	COAL

All acronyms are defined in the acronyms list on page vi.

Algorithm 1—Match EIA Operational Data to CHP DB Instances

```
Input: CHP DB Instance to Match,
       Set of 687 CHP Plants with EIA Data
```

No additional screens are applied as soon as the filtered subset is down to 1.

```
Screen on 3-digit NAICS
If no matches:
    Screen on sector (Residential, Commercial, Industrial)
Screen on prime mover
If prime mover matched:
    Screen on prime mover and fuel type
If CHP DB Capacity 1 MW or greater:
    Screen capacity with f = 0.5
Screen on 4-digit NAICS
Screen on state
Screen on 5-digit NAICS
While f < 0.99:
    Screen on capacity with f = 1 – (1 – f)/2

Output: Subset of EIA CHP Plants that Match the CHP DB Instance
```

The matching granularity varies quite a bit across instances. Only 3% of instances achieved matches at the closest level possible: a sectoral match at the five-digit NAICS code level, and also matched on prime mover and fuel, state, and capacity (with $f \geq 0.5$). Plants achieving that level of match are generally associated with the most common large-scale CHP applications: pulp and paper, wastewater treatment, refining, chemicals, food processing, and primary metals. Even so, those plants often ended up matched to a few or a handful of EIA plants, rather than a single one. In contrast, 1,369 of the 3,687 CHP DB plants considered did end up with a single match. With only one residential CHP plant in the EIA data, all 233 instances of residential CHP listed in the CHP DB were mapped to that instance. In contrast, getting down to a single match happened in many different ways for commercial and industrial plants. In some cases, there was only one EIA plant matching at the three-digit NAICS code level. In others the state was also matched, or the prime mover and fuel, or just the prime mover. The types of match achieved for each filter category are summarized in Table I-4. Once the final set of matching EIA CHP plants was returned for a given CHP DB plant, a single one was selected at random and the CHP DB plant's capacity factor and behind the meter fraction assigned accordingly.

Table I-4. Results of Matching CHP Plants in the DOE CHP DB with CHP Plant Reports in 2012 EIA Form 860 and Form 923 Data

Sector Match	No. Plants	Plants (%)	Prime Mover Match	No. Plants	Plants (%)	Size Match	No. Plants	Plants (%)	Location Match	No. Plants	Plants (%)
Sector	1,124	30	None	1,055	29	None	2,403	65	None	1,942	53
NAICS three-digit	1,875	51	Prime Mover	431	12	0.5	684	19	State	1,745	47
NAICS four-digit	235	6	Prime Mover & Fuel	2,201	60	0.75	299	8			
NAICS five-digit	453	12				0.875	154	4			
						> 0.875	147	4			

Similar, but abbreviated, matching processes were then applied to select plants with CEMS data from which to derive an hourly generation profile. These processes were slightly different depending on whether the plant being matched was a CHP DB plant, or a distributed thermal plant from the EIA data. The two matching processes used are summarized in Algorithm 2 and Algorithm 3 respectively. In both cases, the final profile is chosen by comparing the capacity factor of the plant being matched to the two capacity factors associated with the CEMS profile. Both the chosen CEMS Plant Id, and which CEMS capacity factor (standard or alternate) should be used as a starting point for generating the modeled plant's profile, are noted.

Algorithm 2—Match CEMS Profiles to CHP DB Instances

```
Input: CHP DB Instance to Match,
       Set of 23 Plants with non-zero CEMS Data
```

No additional screens are applied as soon as the filtered subset is down to 1.

```
Screen on EIA Operational Match is one of the 23 CEMS Plants
Screen on 3-digit NAICS
If no matches:
    Screen on sector (Residential, Commercial, Industrial)
Screen on prime mover
If prime mover matched:
    Screen on prime mover and fuel type

Output: Subset of CEMS Plants that Match the CHP DB Instance
```

Algorithm 3—Match CEMS Profiles to EIA Distributed Thermal Instances

```
Input: EIA Distributed Thermal Instance to Match,
       Set of 23 Plants with non-zero CEMS Data
```

No additional screens are applied as soon as the filtered subset is down to 1.

```
Screen on this plant is one of the 23 CEMS Plants
Screen on 2-digit NAICS
If no matches:
    Screen on sector (Residential, Commercial, Industrial)
Screen on 3-digit NAICS
Screen on prime mover

Output: Subset of CEMS Plants that Match the EIA Distributed Thermal
Instance
```

Finally, a profile for each modeled plant is created by transforming the selected CEMS plant profile to match the modeled plant's capacity factor and then multiplying the result by the behind-the-meter fraction. The CEMS profile transformation proceeds by representing the profile in terms of hourly capacity factors, finding the minimum generation point of the profile (the minimum over all hours when generation is non-zero), and then decomposing the profile into a baseload and non-baseload part. The non-baseload part is equal to the original profile minus the minimum generation point, truncated to be non-negative. This is retained as the "shape" of the profile. We then compute a new minimum generation point such that that level of generation plus the "shape" results in the desired annual capacity factor. And that is the returned profile if the desired capacity factor is large enough. If the desired capacity factor is smaller than that achieved by retaining only the "shape" of the profile, we instead multiply the original profile by a simple scaling factor (that is necessarily less than one).

The CEMS profiles that were used to feed this process are shown in Figure 15. The resulting aggregated CHP and distributed thermal profiles are depicted in Figure F-4 for all of the CONUS. Census division level plots are available in Appendix G.

Appendix J. Raw State-Level System Loss Factors

Table J-1 provides the raw state-level data referenced and plotted in Section 2.3.4.1. Large differences between the so-called Reported and Estimated loss factors indicate some combination of discrepancies in data reported to EIA and FERC, or in our allocation of hourly load data from planning regions, to transmission nodes, and then up to the state level. For one example of the latter type of discrepancy, any load that is metered in a different state than the associated transmission node is almost certain to have been miscounted, that is, assigned to the state in which the transmission node resides rather than the state in which the meter resides.

Table J-1. Raw State-Level Loss Factors (a) Based on EIA Form 861 Data Alone (Reported), (b) Based on Comparing FERC Form 714 and EIA Form 861 Data (Estimated), and (c) Their difference (Estimated – Reported)

State	EIA Annual Site Energy (TWh)	EIA Annual Losses (TWh)	Reported Data Loss Factor (%)	FERC Hourly Load (TWh)	FERC – EIA Loss Estimate (TWh)	Estimated Loss Factor (%)	Estimated – Reported (% pt)
RI	7.7	0.4	5.0	4.9	-2.8	-36.2	-41.1
DC	11.4	1.3	11.2	8.0	-3.4	-29.6	-40.8
WY	17.1	0.3	1.8	11.7	-5.4	-31.5	-33.3
IN	105.3	3.4	3.2	80.4	-24.9	-23.6	-26.8
VT	5.5	0.4	6.6	5.1	-0.4	-7.8	-14.4
CO	57.4	4.3	7.5	56.7	-0.7	-1.2	-8.7
KY	89.1	3.6	4.1	86.1	-3.1	-3.5	-7.6
NM	23.2	1.2	5.4	22.7	-0.5	-2.1	-7.5
FL	221.6	14.0	6.3	220.1	-1.5	-0.7	-7.0
AR	47.0	3.5	7.4	47.7	0.7	1.6	-5.8
UT	29.8	0.3	0.9	28.4	-1.4	-4.7	-5.6
GA	131.3	8.8	6.7	133.0	1.7	1.3	-5.4
NE	30.9	2.3	7.5	31.7	0.8	2.5	-5.0
DE	11.6	0.8	6.9	11.9	0.3	2.2	-4.7
WA	94.2	4.4	4.6	94.3	0.1	0.1	-4.5
CA	269.0	12.9	4.8	271.5	2.5	0.9	-3.9
OR	48.1	6.3	13.2	52.9	4.8	9.9	-3.3
KS	40.5	2.8	6.9	42.1	1.6	4.1	-2.9
ME	11.7	0.1	1.2	11.5	-0.1	-0.9	-2.2
MI	105.0	5.6	5.4	109.4	4.3	4.1	-1.2
OH	153.0	13.1	8.5	164.5	11.5	7.5	-1.0
AL	86.3	4.6	5.3	90.2	3.8	4.4	-0.9
VA	108.0	3.5	3.3	111.1	3.1	2.9	-0.4
LA	84.9	4.0	4.7	88.8	3.9	4.6	-0.1

State	EIA Annual Site Energy (TWh)	EIA Annual Losses (TWh)	Reported Data Loss Factor (%)	FERC Hourly Load (TWh)	FERC – EIA Loss Estimate (TWh)	Estimated Loss Factor (%)	Estimated – Reported (% pt)
PA	144.9	7.7	5.3	152.6	7.7	5.3	0.0
NC	128.4	9.4	7.3	138.0	9.6	7.5	0.1
OK	59.9	5.6	9.4	65.8	5.8	9.8	0.4
SC	78.1	3.0	3.8	81.6	3.6	4.6	0.8
TN	96.5	6.5	6.8	103.9	7.4	7.7	0.9
TX	366.2	19.4	5.3	388.8	22.6	6.2	0.9
NJ	75.1	3.1	4.2	79.2	4.2	5.5	1.4
CT	29.5	0.8	2.7	30.9	1.4	4.7	2.1
MS	48.5	2.9	6.0	52.7	4.2	8.7	2.7
MN	68.3	4.3	6.3	75.5	7.3	10.7	4.4
AZ	75.2	4.8	6.4	83.7	8.6	11.4	5.0
WI	69.0	2.3	3.3	75.2	6.2	8.9	5.6
NV	35.3	1.0	2.9	38.3	3.0	8.5	5.7
IL	144.1	3.6	2.5	156.0	11.9	8.2	5.8
NY	147.2	5.8	3.9	163.1	15.9	10.8	6.9
MA	55.7	1.3	2.3	61.1	5.3	9.6	7.3
MD	61.9	2.3	3.8	69.9	8.0	13.0	9.2
NH	10.9	0.5	4.6	12.5	1.6	14.7	10.1
ID	23.7	1.5	6.1	28.5	4.8	20.1	13.9
ND	14.8	1.8	12.0	19.3	4.5	30.6	18.6
SD	11.9	0.5	3.8	14.7	2.8	23.4	19.6
WV	30.8	0.0	0.0	37.1	6.2	20.3	20.2
MO	82.7	6.2	7.5	107.5	24.9	30.1	22.6
MT	13.9	0.6	4.6	19.5	5.6	40.5	35.9
IA	45.8	1.8	3.9	69.7	23.9	52.1	48.2

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