Valuing Residential Energy Efficiency: Technical Appendix

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I. Introduction

This study assessed the untapped potential for cost-effective residential energy efficiency (EE) for a prototypical Southeastern U.S. utility and the new program and policy initiatives that can access the untapped potential.[1] Using GridSIM, The Brattle Group's capacity expansion modeling platform, as well as EE characterizations informed by National Renewable Energy Laboratory (NREL) and Berkeley Lab datasets, we:

1. Constructed and benchmarked a model of a prototypical vertically-integrated utility in the Southeastern U.S.;
2. Forecasted the evolution of the utility's power supply mix over a 20-year time horizon;
3. Estimated the total cost and greenhouse gas emissions associated with serving electricity needs with and without EE deployment over the modeling horizon; and
4. Examined the cost-effective, achievable EE potential under a variety of different economic and policy scenarios.

This technical appendix describes the key modeling inputs and assumptions. Specifically, it:

- Describes GridSIM, Brattle's capacity expansion model;
- Characterizes the prototypical Southeastern utility system simulated in this study and shows that the utility's performance reasonably represents Southeastern utilities;
- Details our assumptions about EE performance and system impacts; and
- Describes our approach for modeling residential EE measures in GridSIM.

II. GridSIM Modeling Framework

GridSIM is Brattle's proprietary capacity expansion model. It optimizes chronological hourly market operations, capacity investment, and retirement within a specific market structure over a multi-decade time horizon. GridSIM forecasts energy, capacity, ancillary service, and, if applicable, renewable energy credit (REC) prices, given investment and operating cost

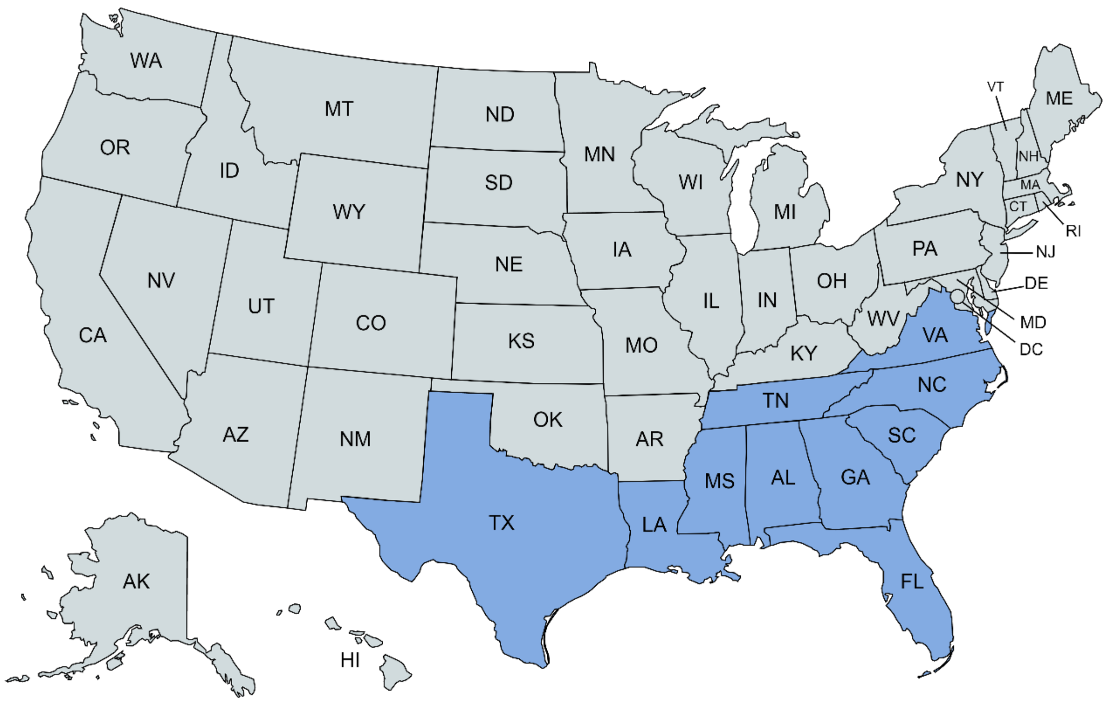
[1] "Cost-effective" is defined as EE potential that will bring a net positive economic benefit to the power system, such that program incentive, marketing, and administrative costs will be outweighed by system energy, capacity, and other benefits. Achievable EE potential accounts for aggressive but realistic participation rates.

assumptions. In co-optimizing investment and operations in multiple regulatory contexts, GridSIM captures the interplay between prices and investment – and the value of EE across multiple value streams.

III. Prototypical Utility Characteristics

We constructed a prototypical Southeastern U.S. utility with summer peaking load. The prototypical utility is characterized using input assumptions consistent with system physical and operating characteristics observed across the Southeastern U.S. and Texas (see **FIGURE 1**). We include Texas as a "Southeastern" state for the purposes of this study in order to incorporate the potential impacts of significant wind additions into the analysis.

FIGURE 1: STATES CONSIDERED WHEN DEVELOPING THE REPRESENTATIVE SOUTHEASTERN UTILITY



A. Load

Customer Base

We assume that the prototypical utility's customer base is composed of approximately 1.5 million customers, growing 1.2% annually. We assume that the population grows at a slightly faster rate than electricity: a 1.0% annual growth in total energy and peak demand (discussed below) reflects an expectation that customers will become more energy efficient over the forecast horizon (e.g., due to naturally occurring energy efficiency and/or building codes and appliance efficiency standards). **TABLE 1** summarizes the customer base, demand, and energy. Residential demand accounts for 45% of the peak coincident demand, and for 34% of the total annual demand.

TABLE 1: PROTOTYPICAL UTILITY CUSTOMER BASE AND DEMAND

	Count (# cust)	Peak Coincident Demand (MW)	(kW/cust)	Annual Energy Demand GWh	(kWh/cust)
Residential	1,327,500	4,500	3.4	17,000	12,806
Small C&I (0 to 20 kW)	142,500	1,400	9.8	7,500	52,632
Medium C&I (20 to 500 kW)	29,250	2,900	99	18,000	615,385
Large C&I (>500 kW)	750	1,200	1,600	7,500	10,000,000
Total	1,500,000	10,000		50,000	

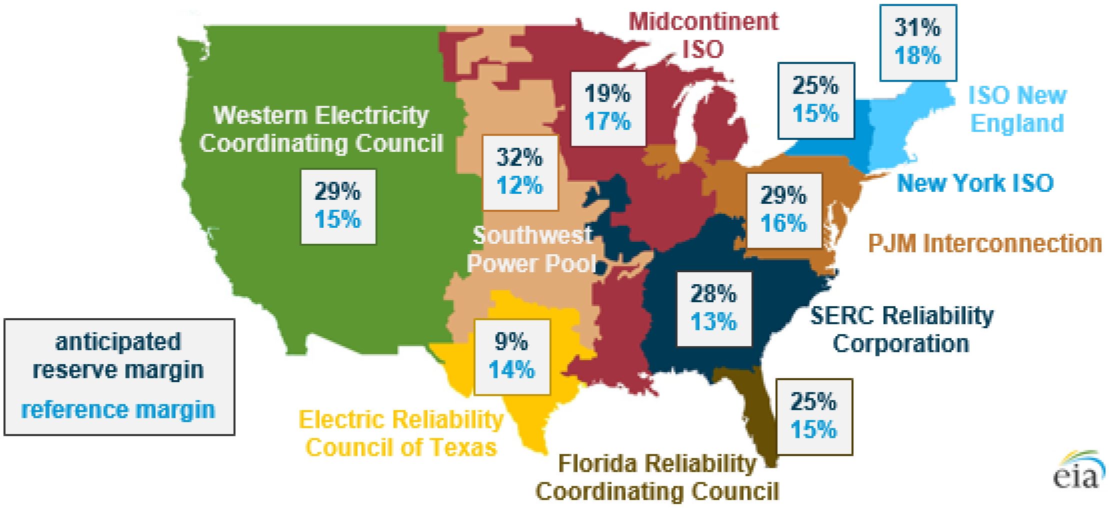
Load Forecast

We assume the utility's peak coincident demand is 10 GW and the total energy demand is 50,000 GWh for the base forecast horizon year. Peak demand of 10 GW is generally consistent with that of a large investor-owned utility.[2] We model the representative utility as planning for a 15% reserve margin, consistent with Southeastern and nationwide target reserve margins in 2019 (see **FIGURE 2**).[3]

2 For example, Alabama Power Company's forecasted system peak demand (after existing EE impacts) for its service territory is 11,998 MW in 2019, according to the utility's 2019 IRP.

3 Based on NERC *2019 Summer Reliability Assessment* report, summarized by the EIA: https://www.eia.gov/todayinenergy/detail.php?id=39892. Anticipated reserve margin quantifies the region's expected generation resources as a portion of the anticipated peak load.

FIGURE 2: SUMMER 2019 REFERENCE MARGINS AND ANTICIPATED RESERVE MARGINS IN SELECT NORTH AMERICAN ELECTRIC RELIABILITY CORPORATION (NERC) REGIONS



Source: EIA. NERC report highlights potential summer electricity issues for Texas and California. 2019. https://www.eia.gov/todayinenergy/detail.php?id=39892

We assume that over the 20-year forecast horizon, peak and annual energy demand both grow at a rate of 1.0% per year (in the absence of new utility EE programs). These assumptions are based on a review of load forecasts for each U.S. Regional Transmission Organization (RTO) and a sample of more than 80 utilities nationwide.[4] Some regions are expecting peak demand to grow faster than total electricity demand and other regions are expecting the opposite. However, there was not a clear bias across the sample in either direction, so we assume that both peak and energy grow at the same rate.

Load Shape

The prototypical utility's 8,760 (annual hourly) system load shape is based on actual 2016 load data for the Duke Energy Carolinas service territory. The year 2016 was selected because it was a recent year without abnormal weather conditions and reflects relatively up-to-date adoption and impacts of historical EE programs and codes & standards. The load factor for this system is 58%, which is in the middle of the range observed for other Southeastern utilities.[5] This hourly

4 These data came from the NERC Electricity Supply and Demand (ES&D) database, Form EIA-411 data, and FERC-714 filings. Annual peak and total demand growth rates ranged from -1% to nearly 4%.

5 We calculated the following load factors using 2016 load data for utilities around the Southeastern U.S.: Florida Power & Light (57%), Southern Company (59%), South Carolina Electric & Gas (59%), and Tennessee Valley Authority (62%).

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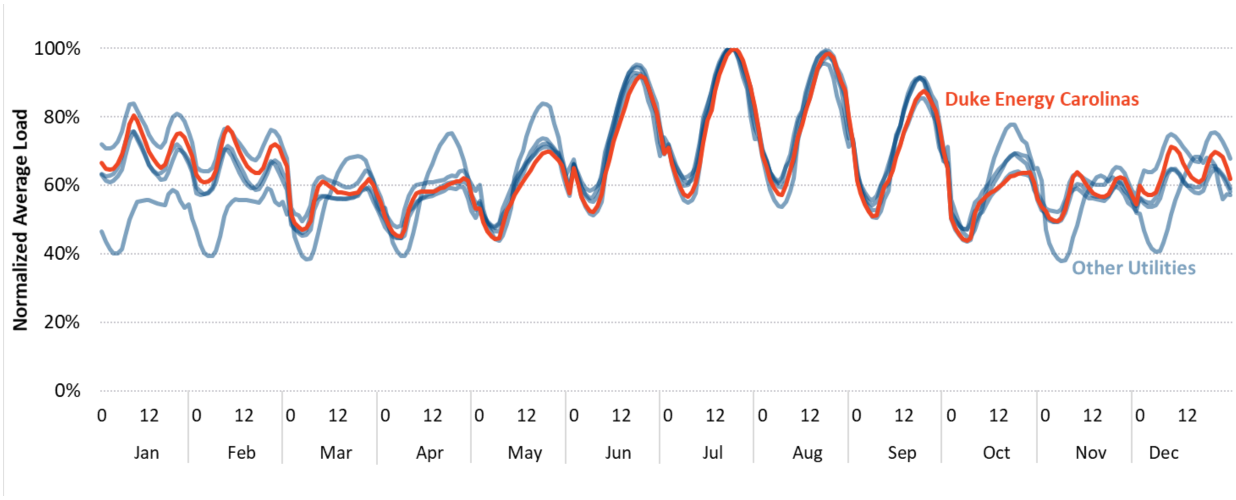
load pattern also falls within the range of patterns observed in other Southeastern utilities (see **FIGURE 3**). [6]

FIGURE 3: NORMALIZED AVERAGE HOUR OF MONTH LOAD PROFILE FOR SOUTHEASTERN UTILITIES



GridSIM utilizes a “typical days” representation of load conditions, which is a common approach for capacity expansion models. The 365 days of the year are clustered based on similarities in daily load level and hourly shape. Reducing the number of days modeled to a subset based on these representative clusters allows the model to capture the full range of load conditions that are necessary to consider from a planning standpoint, while keeping the model runtime low. Using typical days also allows the model to retain intra-day hourly chronology, which is important to accurately account for the impact of the hourly profiles of EE programs.

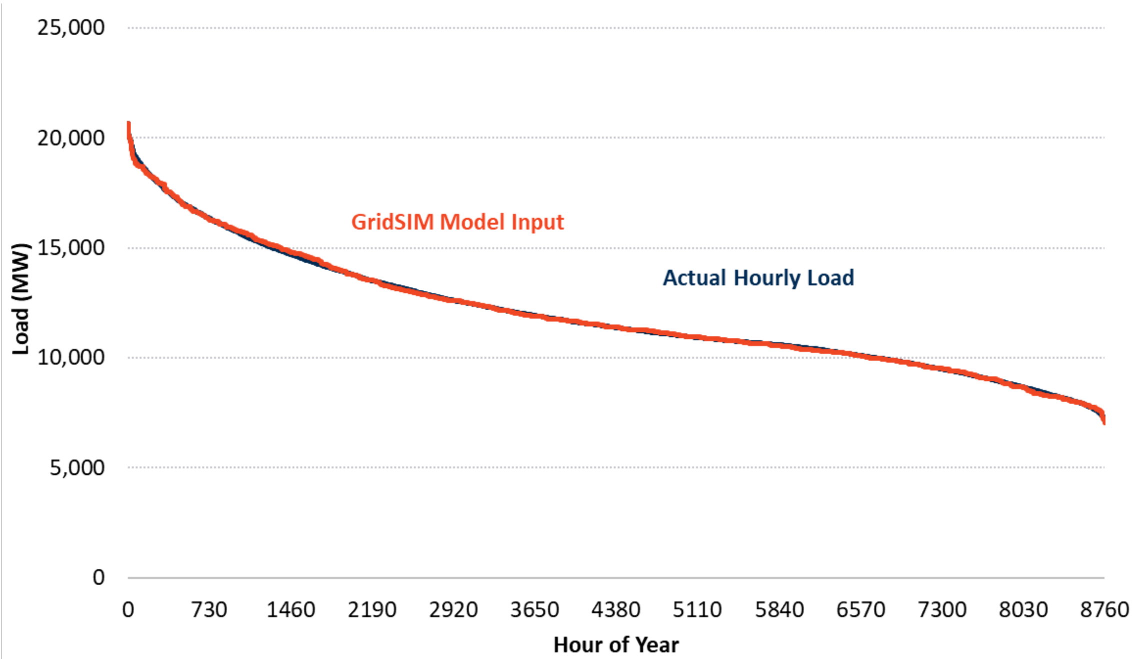
In this study, we model 45 typical days.[7] There are 15 days each for summer (June through August), winter (December through February), and the shoulder seasons (March through May and September through November). We chose these typical days to represent the peak and minimum load conditions in each season, as well as a representative range of typical seasonal days.

[6] Comparisons with a broader range of electric utilities, including Bonneville Power Administration, Idaho Power Company, Arizona Public Service Company, Nevada Power Company, Portland General Electric, Public Service Company of New Mexico, and Public Service Company of Colorado, indicated that the 8,760 hourly load shape we assumed for the modeled prototypical Southeastern utility was reasonable.

[7] We scale these 45 days’ load shapes to match the peak and total energy demand values described earlier.

FIGURE 4 shows that the load duration curve resulting from a simplified "typical day" approach captures the range of conditions represented in the actual 8,760 hourly load duration curve upon which the model inputs are based.

FIGURE 4: LOAD DURATION CURVE COMPARISON OF ACTUAL LOADS AND TYPICAL MODELED DAY REPRESENTATION



B. Generation

Existing Unit Characteristics

We assume the prototypical utility's supply mix is similar to the average supply mix for Southeastern utilities. A mix of coal, gas, nuclear, hydro, solar, and onshore wind generation serves demand. **FIGURE 6** compares the modeled capacity mix with those from three other Southeastern utilities.

The existing unit characteristics, including capacities, heat rates, and O&M costs come from a comprehensive national database of individual generating units.[8] Fixed O&M costs are scaled

8 Data from EIA-860, EPA CEMS, and various federal, state, and ISO sources, accessed through ABB Velocity Suite

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according to assumptions made in the EPA Integrated Planning Model.[9] Other operating assumptions come from public NYISO reports.[10] To reduce model runtime, units have been aggregated based on similarities in efficiency and cost. **TABLE 2** summarizes the existing generation mix and their assumed operational and cost characteristics.

TABLE 2: EXISTING UNIT CHARACTERISTICS

Type	Fuel	Capacity (MW)	Heat rate (Btu/kWh)	Variable O&M ($/MWh)	Fixed O&M ($/kW-yr)
Combined Cycle	Gas	3,690	6,939	$2.88	$22
Combined Cycle	Gas	1,095	8,040	$2.88	$22
Combustion Turbine	Gas	967	10,234	$7.43	$25
Combustion Turbine	Gas	941	12,659	$7.43	$25
Steam Turbine	Gas	863	10,219	$5.20	$69
Steam Turbine	Gas	262	11,733	$5.20	$69
Steam Turbine	Coal	1,232	9,474	$5.20	$69
Steam Turbine	Coal	1,300	10,623	$5.20	$69
Nuclear	Uranium	912	10,636	$2.41	$105
Hydro	Water	433	0	$0.00	$32
Solar	Solar	431	0	$0.00	$13
Wind	Wind	964	0	$0.00	$45

New Unit Characteristics

New units are available for addition to the system over the forecast horizon. Their efficiency and cost inputs are based on the 2020 NREL Annual Technology Baseline (ATB) database.[11] **TABLE 3** summarizes the operational and cost assumptions for each new generation unit type.

[9] 2013 EPA Base Case Integrated Planning Model. https://www.epa.gov/sites/production/files/2015-07/documents/documentation_for_epa_base_case_v.5.13_using_the_integrated_planning_model.pdf

[10] EFORd values are from the 2018 Comprehensive Area Review of Resource Adequacy. The minimum generation levels are from NYISO's 2019 Reliability and Market Considerations for a Grid in Transition report.

[11] NREL (National Renewable Energy Laboratory). 2020. 2020 Annual Technology Baseline. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/analysis/data-tech-baseline.html. All values in 2019$USD.

Capital investment costs reflect an adjustment for regional differences in the Southeast consistent with NREL ATB adjustment factors.

TABLE 3: NEW UNIT CHARACTERISTICS

Type	Fuel	Heat rate (Btu/kWh)	Variable O&M ($/MWh)	Capital Investment Cost ($/kW)	Fixed O&M ($/kW-yr)
Combined Cycle	Gas	6,450	$2.25	$1,042	$13.38
Combustion Turbine	Gas	9,820	$4.68	$947	$11.86
Solar	Solar	0	$0.00	$1,145	$16.73
Wind	Wind	0	$0.00	$1,642	$44.58

C. Renewables – Hourly Generation Shapes

Hourly wind and solar generation profiles are based on ERCOT-wide historical data. Texas was chosen as the basis for wind and solar profiles because it has wind speeds and solar radiation levels spanning the middle- to upper-range of those observed across the U.S.[12] Although, we acknowledge the ERCOT renewable hourly shapes may not be necessarily consistent with all Southeast locations.

D. Fuel Prices

Natural gas prices are based on an average of historical basis differentials and OTC Global Holdings Basis Futures through 2022, and then extrapolated using the annual growth rate from the 2019 EIA Annual Energy Outlook (AEO) through the remainder of the forecast horizon. We modify forecasted Henry Hub prices with an average of basis differentials for Transco Z 4 and FGT Z 3 hubs to adjust for Southeastern regional gas price differences, and include a $0.20/MMBtu delivery adder. Coal prices are based directly on the 2019 EIA AEO using steam

[12] See https://www.nrel.gov/gis/wind-geospatial-data-tools.html and https://www.nrel.gov/gis/solar-resource-maps.html. Using wind and solar profiles from a different geographic location than the hourly load shape is conceptually sufficient for this analysis, as distributed wind and solar resources in most parts of the US have not yet reached deployment levels that will materially affect metered load. As sensitivity cases, it may be possible to test the impacts of assumptions that the utility has significantly higher wind or solar potential than the national average.

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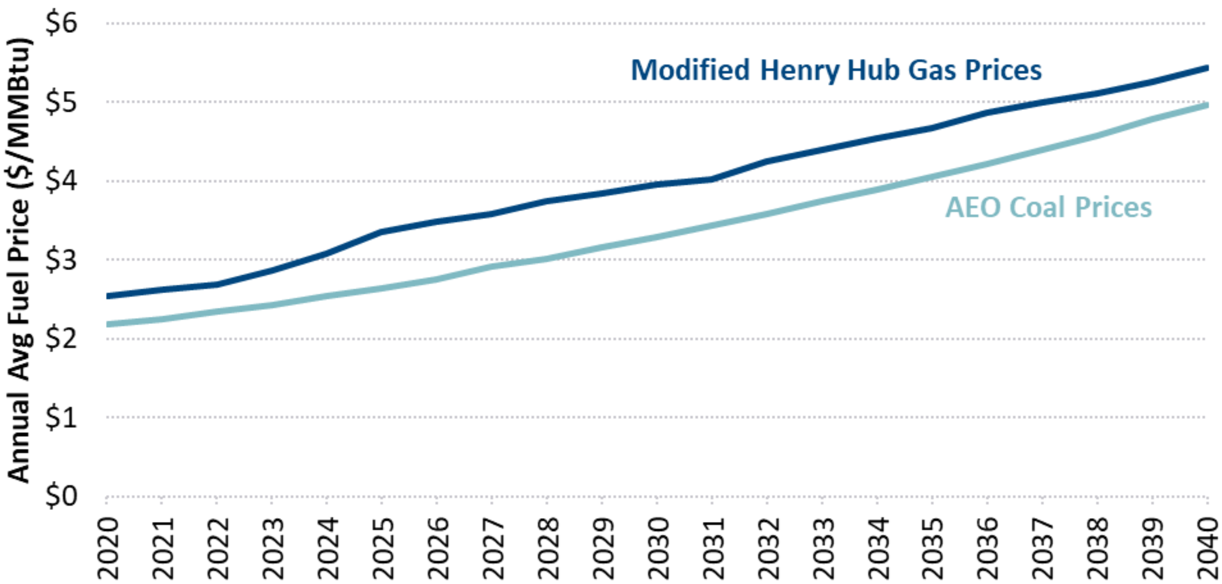
coal prices for electric power generation in the East South Central region.[13] **FIGURE 5** summarizes the gas and coal price forecasts used in this study.

FIGURE 5: NATURAL GAS AND COAL PRICE FORECASTS



E. Renewable Portfolio Standard (RPS)

In the business-as-usual (BAU) scenario, we do not model an RPS because most Southeastern states do not have an explicit renewables procurement requirement. Therefore, all BAU renewables additions are economic in the model simulations. One of the policy levers we consider in this study explores a clean energy standard scenario, which requires that 40% of generation come from carbon-free sources by 2040.

IV. Benchmarking and Calibration

To ensure that GridSIM accurately captures key characteristics of a Southeastern utility, we ran the model with historical input data and compared those results to recently observed system conditions in the Southeastern U.S. In particular, we compared the generation mix and energy prices resulting from the model simulations to those of five Southeastern utilities.

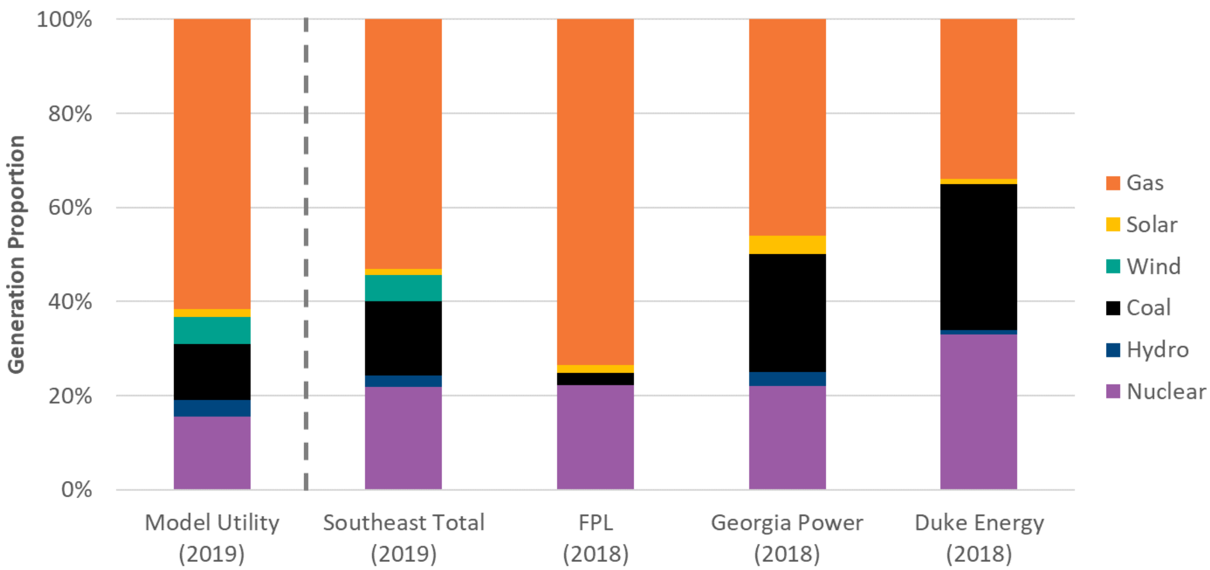
13 EIA Annual Energy Outlook: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=15-AEO2019&cases=ref2019&sourcekey=0

A. Generation Mix

Annual Generation Mix

Using 2019 system inputs[14], the prototypical utility's annual generation mix is generally consistent with the generation mixes of other Southeastern utilities (see **FIGURE 6**). [15] This consistency confirms that we are modeling a reasonable system base state.

FIGURE 6: ANNUAL GENERATION MIX BY FUEL TYPE



Hourly Generation Profiles

During our model calibration, we also confirmed that the system's marginal generation resource is gas or coal, much like what would be observed in a gas- and coal-dominated Southeastern utility. **FIGURE 7** shows the 2019 hourly system operations for nine representative days across the three seasons and load conditions we model.[16] In 2019, gas and coal units are

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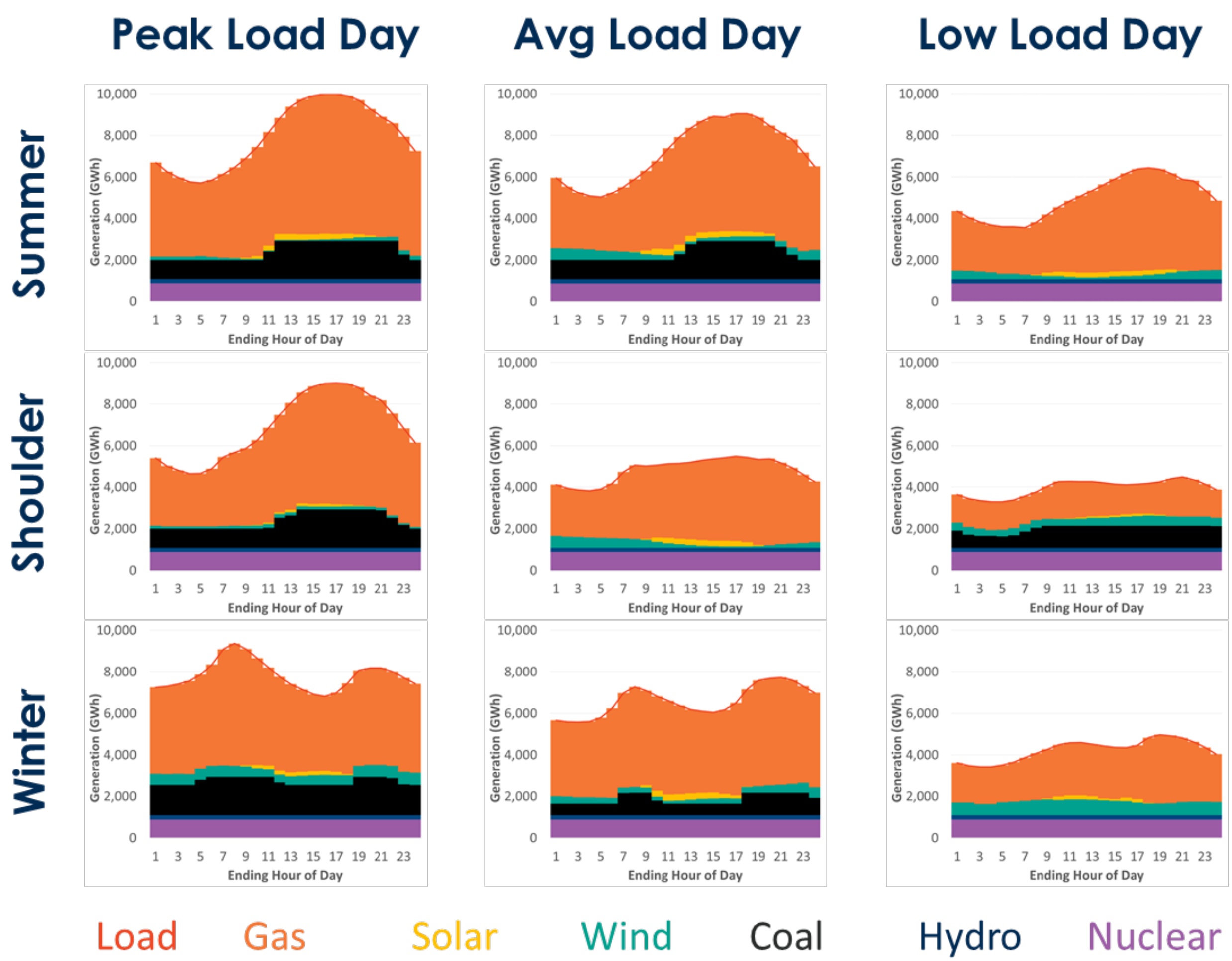
[14] Inputs include 2019 fuel prices and EE deployment (included in the hourly load shape for Duke Energy Carolinas).

[15] Data sources: Duke Energy Carolinas: https://sustainabilityreport.duke-energy.com/introduction/duke-energy-at-a-glance/ FPL: https://www.fpl.com/news/2019/energy-news-q2-2019.pdf . GA Power: https://www.georgiapower.com/company/about-us/facts-and-financials.html . Southeast Total: 2019 EIA-923 data for Alabama, Florida, Georgia, Louisiana, Mississippi, North and South Carolina, Tennessee, Texas, and Virginia.

[16] We model 45 representative days total. Since there are multiple representative days with "average" load conditions, we have shown days demonstrating a range of observed system behaviors.

typically on the margin, depending on load levels, seasonal fuel costs, and unit efficiencies. The trade-off between marginal resource types is especially apparent in the shoulder season, when coal units run either at significant levels or not at all.

FIGURE 7: 2019 HOURLY GENERATION SHAPE ACROSS SEASONS AND REPRESENTATIVE DAYS



B. Energy Price Benchmarking

We used marginal energy prices to verify that the system's hourly operations and economics realistically represent those of a Southeastern utility. Our review of historical load data suggested that 2018 had anomalous load and weather conditions, so we used 2016 and 2017 as reference years. Using 2017 gas prices, we simulated utility operations in the base model year.[17]

Marginal Energy Prices

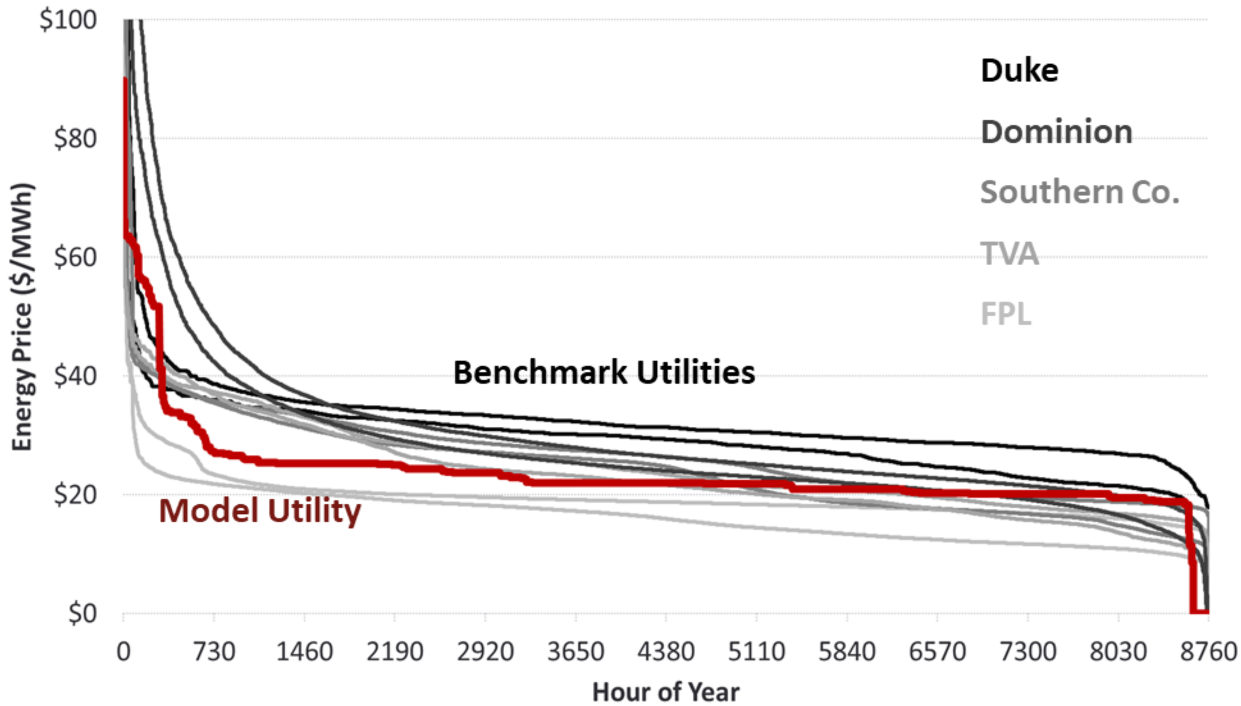
FIGURE 8 shows that the price duration curve of our model utility falls within the range observed among five major Southeastern utilities.[18] The benchmark energy prices are color coded by utility, with data for both 2016 and 2017 shown in the same color for each utility. Duke Energy Carolinas' energy prices were higher than the model utility's because natural gas prices in the Carolinas are higher than the rest of the Southeastern U.S. Dominion exhibits more price volatility and higher peak prices because the data shown are based on observed PJM market prices, which are generally more volatile than the "system lambdas," which are reported for vertically integrated utilities that do not operate in wholesale electricity markets.

The modeled energy prices fall in the middle of historical prices for more than half of the year and within the historical range for the rest of the year. This price similarity indicates that the model utility's hourly operations roughly match those of historical utilities. Capacity expansion models such as GridSIM are inherently limited in their ability to reproduce the full level of volatility observed in market prices, as these models assume "perfect foresight" into market conditions and therefore do not capture unexpected factors (such as transmission or generation outages) that otherwise would drive greater volatility in prices and marginal costs.

[17] Since any changes to the Southeastern resource mix between 2016-2019 were minor, we did not re-calibrate the prototypical model's resource mix for this test.

[18] Marginal energy costs for Duke, Southern Co., TVA, and FPL are based on system lambdas available in FERC Form 714 data. Dominion marginal energy costs are historical prices for Dominion's location within PJM.

FIGURE 8: BENCHMARKING PRICE DURATION CURVES

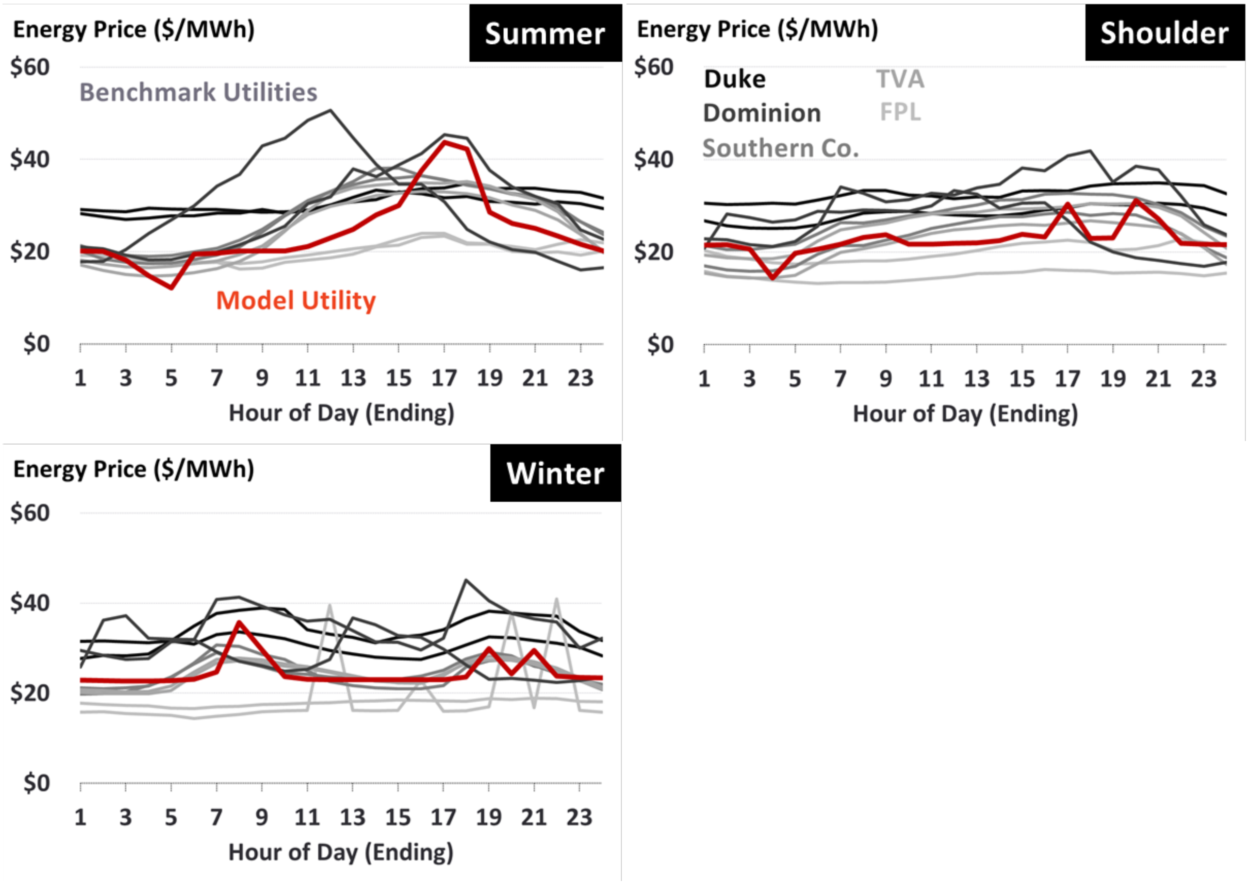


Seasonal Average Hourly Energy Prices

We also benchmarked the seasonal[19] marginal energy price patterns to verify that the prototypical utility represents the seasonal utility economics seen in the Southeastern U.S. **FIGURE 9** compares seasonal average hourly energy prices in the prototypical utility with the same set of Southeastern utilities as in **FIGURE 8**. The shapes of the modeled prices are generally consistent with historical data, and display key seasonal features, including a peak pricing event in the summer evening hours, and a slight price spike in the winter morning hours.

19 Summer is June through August, winter is December through February, and shoulder is all other months.

FIGURE 9: SEASONAL AVERAGE HOURLY ENERGY PRICES



V. EE Measure Detail

Utilities deploy a variety of residential EE programs, involving many different EE technologies available today. To keep the modeling tractable and focus our analysis, we model a set of EE packages that represent commonly deployed EE programs. The modeled residential EE packages were selected in coordination with DOE, to focus on those considered likely to have the highest value to the power system. This appendix section discusses the technological, economic, and participation assumptions for the modeled EE measures.

A. Residential EE Measure Performance Details

We model four broad categories of residential EE measures, representing seven technologies selected for study by DOE. **TABLE 4** summarises the EE measure packages and performance assumptions.

TABLE 4: MAPPING OF MODELED RESIDENTIAL EE PACKAGES TO INDIVIDUAL EE MEASURES

EE Package	EE Measure	Description
Envelope	Air Sealing	25% air leakage reduction applied from current ACH50 levels
	Attic Insulation	Insulate vented attics to R-49, reduce duct leakage to 10%, and all ducts located in attic insulated to R-8
	Cool Roofs	Properties derived from BEopt database using “light” materials, by roofing type (data originally sourced from FSEC publication) and all roofing material types are ENERGY STAR qualified
	Windows	Windows with U-factor 0.27 and SHGC 0.2
HVAC	EE CAC and ASHP	Central AC CEE Tier 2 (SEER 16, 1 stage) ASHP CEE Tier 2 (SEER 16 HSPF 9.0)
Thermostat DR	Smart Thermostat	Simulate dispatch to curtail load during limited number of events per year. All curtailed load assumed to be offset with pre-cooling
Water Heating	EE HPWH	ENERGY STAR Heat Pump Water Heater (EF 2.4, 80 gallon)

B. EE Package Costs

We use the Berkeley Lab Cost of Saving Electricity (COSE) database to source cost assumptions for HVAC-related EE packages (Envelope and HVAC). Data in this database are based on reported utility program costs in aggregate, reflecting a range of EE technologies and energy savings levels. The BAU package cost assumptions are based on national median costs observed in the COSE data. We assumed that “Whole Home Retrofit” data from COSE apply for the Envelope package given the breadth of EE measures, and the “HVAC” data from COSE apply for the HVAC package.

EE costs modeled in this study are inclusive of incentive, marketing, and administrative costs (i.e., program administrator costs), but exclude the share of the EE measure cost borne by the participating customer. The administrative cost is assumed to be equal to 10% of the sum of the equipment, installation, and marketing costs.

To calibrate the assumed cost of heat pump water heaters (HPWH) specifically to recent market data, we assumed a cost of $1,400 per-water heater.[20] Table 5 summarizes the cost assumptions on a per-household basis.

[20] The DOE’s Scout model assumes a $1,447/unit cost for a “best available” HPWH. Source: https://scout.energy.gov/ecms.html. Additionally, Berkeley Lab’s *Grid-Interactive Efficient Building Technology Cost, Performance, and Lifetime Characteristics* report reports a $1,327/unit cost for HPWH, assuming a 20-year lifetime. Source: https://eta.lbl.gov/publications/grid-interactive-efficient-building.

TABLE 5: EE PROGRAM COST ASSUMPTIONS

	Incremental Technology Cost $/HOUSEHOLD	Marketing and Administrative Cost $/HOUSEHOLD
Envelope	$3,046.80	$442.91
HVAC	$1,387.18	$199.60
Thermostat DR	$ 380.61	$ 57.30
HVAC + Envelope + Water Heating	$4,092.41	$555.01
Water Heating	$1,400.00	$210.77

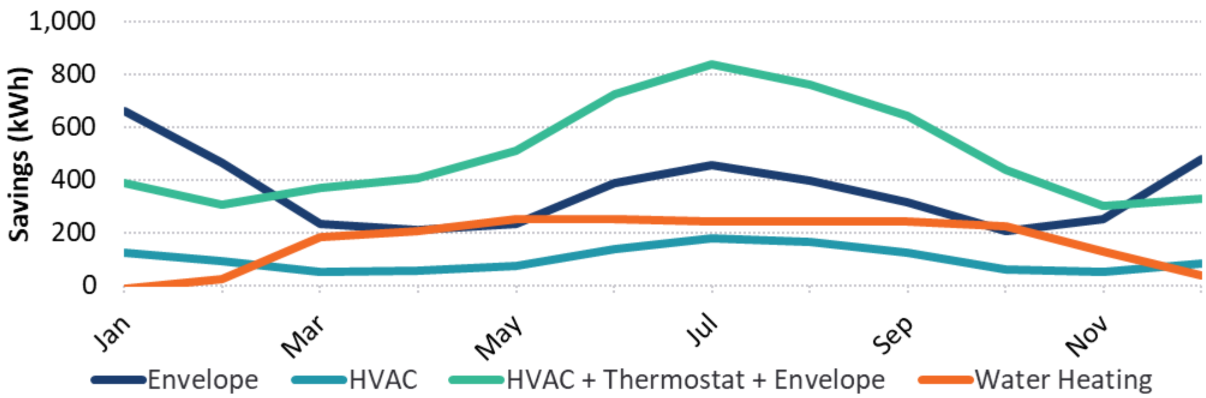
C. EE Electricity Saving Profiles

We model EE energy savings using output from NREL's ResStock model.[21] The energy savings profiles we use in this study are based on Duke Energy Carolinas weather locations in 2016 to ensure consistency between weather affecting utility loads and EE shapes. EE electricity savings profiles[22] are represented on an hourly basis. In some hours, the EE packages increase consumption relative to the baseline (though all packages decrease usage over the year). Figure 10 displays the assumed monthly total per-household energy savings profiles for each measure considered.

[21] ResStock™ is a physics-based simulation model of the U.S. residential building stock, developed by NREL with support from the U.S. DOE Building Technologies Office. More information available at: https://www.nrel.gov/buildings/resstock.html

[22] Hourly electricity savings profiles were generated using a version of ResStock that incorporated 1 of 5 phases of model calibration performed as part of the End-Use Load Profiles (EULP) project (see: https://www.nrel.gov/buildings/end-use-load-profiles.html); however, the final published EULP data use a more recent version of ResStock that incorporates additional model calibration not available at the time of this study. ResStock calibration as part of EULP is detailed in: https://www.nrel.gov/docs/fy22osti/80889.pdf.

FIGURE 10: TOTAL ASSUMED MONTHLY PER-HOUSEHOLD ENERGY SAVINGS



D. EE Program Eligibility, Adoption, and Participation

Household Eligibility

Eligibility for the modeled EE programs is limited to those customers with a baseline end-use that is qualified for an efficiency upgrade. We rely on the EIA's 2015 Residential Energy Consumption Survey[23] for our household EE program eligibility assumptions. In the EIA data, we identified the proportion of South Atlantic Census Region residential housing units with electrified HVAC and water heating.[24] We made a conservative assumption that eligibility for the modeled HVAC measures (Envelope, Thermostat, and HVAC) was the smaller of the proportions of homes with electrified heating and cooling. We based the water heating measure eligibility on the proportion of homes with electric water heating. **TABLE 6** summarizes our eligibility assumptions.

23 U.S. Energy Information Administration, Office of Energy Consumption and Efficiency Statistics. *2015 Residential Energy Consumption Survey (RECS)*. Revised May 2018. Tables HC1.8 and HC8.8.

24 Data range from August 2015 to April 2016.

TABLE 6: HOUSEHOLD ELIGIBILITY ASSUMPTIONS

	Incremental Technology Cost PORTION OF ELIGIBLE HOUSEHOLDS
Envelope	65%
HVAC	65%
Thermostat	65%
HVAC + Envelope + Water Heating	65%
Water Heating	72%

Achievable Adoption Potential Assumptions

Achievable EE adoption rates, defined as the total portion of eligible customers participating in EE programs, regardless of incentive level, are a significant driver of untapped potential for residential EE. In our modeling, we scale each EE package's per-participant savings profile by an assumed adoption rate, expressed as the portion of eligible households adopting each EE measure, to find the total impact of EE on the system. Since the relationship between energy savings and adoption assumptions is linear, the latter can significantly change the amount of potential for residential EE.

We base our maximum cumulative EE adoption assumptions in the BAU and high-adoption scenarios on an extensive review of regional EE potential studies across the U.S., conducted for the DOE's report, *A National Roadmap for Grid-Interactive Efficient Buildings*.[25] The reviewed studies use methods like primary market research (customer surveys), reviews of achieved participation in successful demand flexibility programs, interviews with customer account managers, review of utility DR plans, and expert judgment to establish maximum achievable household participation rates for the base and high-adoption scenarios. **TABLE 7** summarizes our achievable adoption rate assumptions for each modeled EE package.

[25] U.S. Department of Energy, Building Technologies Office. "A National Roadmap for Grid-Interactive Efficient Buildings." May 2021. Figure 8, p. 96. https://gebroadmap.lbl.gov/

TABLE 7: ACHIEVABLE EE ADOPTION RATE ASSUMPTIONS, % OF UTILITY HOUSEHOLD CUSTOMERS

	BAU Adoption	High Adoption
Envelope	30%	50%
HVAC	60%	80%
Thermostat	30%	50%
HVAC + Envelope + Water Heating	50%	70%
Water Heating	60%	80%

In practice, it takes time for utilities to ramp up to maximum achievable participation rates. To reflect this constraint in GridSIM, we assume that 25% of the maximum achievable potential can be added in any given year. As such, it would take at least four years in the simulations for EE participation to reach maximum achievable levels.

Relationship between Program Participation and Incentives

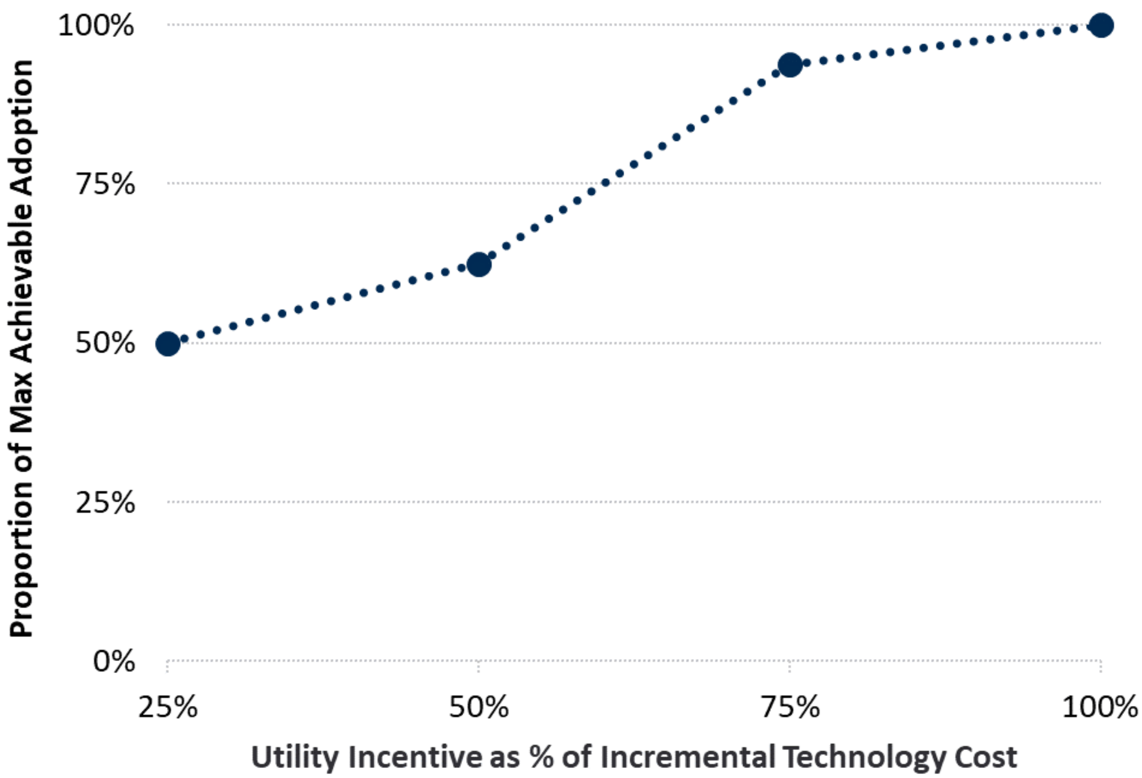
Participation incentives covering portions of the incremental equipment and installation costs of residential EE measures (e.g., in the form of rebates) can boost program participation.[26] Highly cost-effective EE programs, which provide large economic benefits relative to costs, justify larger participation incentives, which lead to higher participation rates (all else equal).

We capture this relationship between participation and incentives by dynamically modeling EE program participation as a function of cost-effectiveness. To do so, we split the total adoption potential for each modeled EE measure into four incentive "tiers." Each tier represents the incremental portion of households willing to join an EE program at a given incentive level. Our adoption assumptions are derived from a 2015 energy efficiency study for Pennsylvania; **FIGURE 11** illustrates the relationship estimated in that study.[27] At a 25% utility incentive level, we assume that half of the maximum achievable adoption rate is reached; if the utility covers 100% of equipment and installation costs, then the maximum achievable adoption rate is reached. This approach allows the model to select the cost-minimizing quantity of each EE measure up to an assumed participation limit.

[26] Most studies reviewed in developing EE adoption assumptions for the Grid-Interactive Efficient Buildings study (referenced above) conduct surveys on customer's willingness to adopt EE at varying incentive payment levels.

[27] The participation-incentive relationship is based on a 2015 study by the Statewide Evaluation Team: *Energy Efficiency Potential For Pennsylvania*. Figure 1-2: Long-term market adoption rates based on residential willingness-to-participate survey results. We used the "Central Air" results for all EE programs.

FIGURE 11: RELATIONSHIP BETWEEN EE PROGRAM INCENTIVES AND PARTICIPATION



E. Characterizing Combination Programs

To spur EE adoption, utilities may bundle and subsidize multiple EE measures into a single combination program. We characterize such a program as an aggregate of the envelope, HVAC, and water heating measures by summing derated envelope + HVAC combination[28] hourly savings profiles with the water heating profiles. We assume a combination package subsidy such that the levelized cost of saved electricity for the entire package is equal to the lowest of the individual programs' costs. We also assume that the maximum adoption for this combination program is equal to the highest of the individual programs' adoption limits.

[28] ResStock data provided energy savings profiles for combined EE programs. Their energy savings profiles were smaller than the sum of the individual component measures, due to measure interactions.

VI. EE modeling approach

To model dynamic EE program deployment, we represent each tier of each EE program as a separate "generating unit" on a fixed output schedule representing the measure's hourly energy savings profile.[29] We convert the units of the aforementioned eligibility, adoption, and participation limits from households to MWh, based on each measure's maximum annual kWh/hour-household values found in the ResStock data. These program participation limits therefore become maximum adoptable MW values represented in GridSIM. We similarly convert each measure's levelized $/kWh saved costs into $/kW-yr costs, as if the EE program were an installable generating facility. Finally, we assign each EE program a capacity value to help capture the benefit of reduced generating capacity requirements.

Having thus represented EE program deployment, we run the capacity expansion simulation in GridSIM, allowing the model either to install traditional generating resources or deploy EE programs to serve utility load and maintain the reserve margin. The modeling simulation therefore selects the cost-effective EE portfolio by allowing it to "compete" with supply side resources. The model weighs the EE benefits, including reduced energy, capacity, and RPS requirements, against the EE costs, including customer participation incentives, administrative costs, and marketing costs when selecting the optimal portfolio. The benefits considered in this study are given in Table 8.

[29] This approach of modeling shaped EE savings as a resource is becoming more popular as the power supply mix evolves toward renewables, which can lead to significant time-differentiated changes in marginal system costs. For more information, see https://emp.lbl.gov/publications/methods-incorporate-energy-efficiency.

TABLE 8. EE VALUE STREAMS CONSIDERED

	Included?	Method
Reduced energy consumption	Yes	Compete as a "generating unit" in capacity expansion model.
Reduced generation capacity	Yes	Assign each EE package a capacity credit (ELCC) based on its energy savings during peak load hours. Capacity credit is considered within GridSIM logic when making economic investment decisions. Gross capacity value up by 15% to represent reduction in target reserve margin.
Reduced line losses	Yes	Scale EE output profiles up by 5% to account for avoided line losses.
RPS fulfilment	Yes	EE energy savings count 1:1 against RPS requirement.
Reduced T&D investment	No	Not included because study focuses on the bulk system, similar to a utility integrated resource plan.
Avoided CO2 emissions	No	Not explicitly included as a monetized benefit, but (1) the environmental value of EE is partly captured by allowing it to satisfy the utility's clean energy standard, and (2) CO2 savings are reported in the final report.
Ancillary service provision	No	Expected to be a modest benefit.

A. Converting Household-Level Participation Data to MW-Based Adoption Constraints

Converting household-level adoption constraints to MW-based constraints allows GridSIM to consider both EE and supply-side generation resources in its capacity expansion optimization. We scale assumed total number of residential customers in the final modeled year, 2040, by each measure's customer eligibility and maximum adoption assumptions to get the maximum number of households adopting each EE measure type. We then divide this number of adopting households into four tiers of measures, according to our participation assumptions for each incentive tier. We can express the maximum number of households adopting each measure at each incentive tier as

$$N_{i,j} = H_{2040} * E_i * A_i * P_j$$

Where the sets i and j represent the EE measure types and incentive tiers, respectively, and

- $N_{i,j}$ represents the maximum number of households adopting each measure at each incentive tier;
- H_{2040} represents the total assumed residential customers served by the model utility in 2040;
- E_i represents the portions of residential customers eligible to install each EE measure;
- A_i represents each EE measure's assumed maximum adoption rate among eligible customers; and
- P_j represents the maximum participation among eligible and adopting customers in each incentive tier.

We then multiply $N_{i,j}$ by the maximum energy savings per customer, in kWh/hr-household, as indicated in the ResStock output data, to get a cumulative max build limit for each EE measure, in MW, for input into the model. We scale this maximum cumulative build limit using our adoption rate constraints to find an annual maximum build limit input for GridSIM.

B. Converting Levelized Cost of Saved Electricity to Per-MW Costs

As with the adoption constraints, we express the EE programs' levelized COSE inputs as levelized per-kilowatt-year costs that we can input into GridSIM alongside new generators' capital costs. We start with levelized COSE inputs for installation, equipment, and marketing cost components of the modeled EE programs. We also assume that administrative costs add 10% to these costs. We then use the following equation to convert the levelized COSE ($/kWh) to a per-household capital cost:

$$Capital\ Cost = \frac{Levelized\ COSE * Annual\ Electricity\ Savings\ (Gross - kWh)}{Capital\ Recovery\ Factor\ (CRF)}$$

Where the CRF is

$$CRF = \frac{r(1+r)^N}{(1+r)^N - 1}$$

And

- r is the discount rate (assumed at 6%) and
- N is the estimated EE program lifetime in years, calculated as the savings-weighted lifetime of measures or actions installed by participating customers in a program.

Having calculated the per-household capital cost for each cost component of each EE program, we use the maximum energy savings per customer value to re-express the capital cost in $/kW. We levelize these total costs over the EE measure lifetime, assuming a 6% discount rate, to arrive at program costs expressed as capital investment costs that we can put into GridSIM.[30] Finally, we scale the marginal equipment and installation costs for each EE measure according to our assumed participation incentive tier levels, such that each EE incentive tier for each EE measure has a cost, defined as:

$$Total\ Cost_{i,j} = Equipment\ Cost_i * I_j + Marketing\ Cost_i + Administrative\ Cost_i$$

Where the sets i and j represent the EE measure types and incentive tiers, respectively, and I_j represents the participation incentive for tier j, as a portion of equipment costs to be covered by the utility.

C. EE Capacity Value Calculation

Within GridSIM, we model a target reserve requirement. Resources are chosen based on their ability to economically meet demand, as well as on their contribution toward the target reserve requirement. New generation resources may be built to meet the target reserve margin, even if older generation is available to supply the necessary electricity. EE measures can out-compete traditional generation resources because in addition to reducing electric demand, they can reduce the amount of new generation needing to be built to satisfy the target reserve margin.

We consider the system reliability impact of EE by modeling its estimated load carrying capability (ELCC). Dynamically determining ELCC values in capacity expansion models is still a complicated, open research topic. We therefore assume that the energy savings capacity of all EE measures is small enough that the timing of the system's peak load hour would not dramatically change at maximum deployment levels. In other words, we assume that EE programs do not impact renewables' or each other's ELCC values. These assumptions allow us

[30] This discount rate is representative of a utility's weighted average cost of capital (WACC), which is appropriate to use for the utility planning-focused framework in this study.

to assume the EE ELCC values as model inputs. Further exploration of techniques for dynamically modeling EE ELCC would be a valuable research activity.

Working with the base and high-renewables scenarios separately, we solve for the optimal resource mix with no EE deployment. Assuming these optimal solar and wind penetrations, we solve for the top 100 net load hours in each year.

Then, we individually determine each EE program's average energy saving capability in those hours, assuming that no other EE packages are installed. Normalizing these average energy saving values against each measure's maximum annual output yields the measure's ELCC for the given year. **TABLE 9** summarizes our EE capacity value assumptions for 2040 in the base and high-renewables cases.

TABLE 9: 2040 EE PROGRAM CAPACITY VALUES

	BAU	Higher EE Adoption
Envelope	48%	45%
HVAC	88%	82%
Thermostat	70%	70%
HVAC + Envelope + Water Heating	76%	72%
Water Heating	51%	50%

D. Modeling Thermostat as Demand Flexibility

Smart thermostats shift residential heating and cooling cycles in response to utility price and/or control signals. We model smart thermostats as demand flexibility measures that can shift peak heating and cooling loads to off-peak hours. Practically, we model these programs as operationally-constrained storage units that the model can deploy, up to the cost-effective optimal amount. We assume 1 kW/customer curtailment events, lasting up to four hours.[31] We assume that smart thermostats pre-cool homes (building load before the evening peak). We limit the model to less than ten demand flexibility events per year. These events occur in a patchwork, with the utility staggering interruptions across households. We assume a 70%

[31] Assumptions based on a detailed survey of demand flexibility programs surveyed in: U.S. Department of Energy, Building Technologies Office. "A National Roadmap for Grid-Interactive Efficient Buildings." May 2021. https://gebroadmap.lbl.gov/

capacity value for the thermostat measure, based on a review of recent DR potential studies in the DOE's *A National Roadmap for Grid-Interactive Efficiency Buildings*.

E. Additional Power System Benefits

In addition to the direct benefits from EE energy savings, we model multiple power system benefits of deploying EE, including a reserve margin benefit, reduced line losses, and a renewable portfolio standard (RPS) benefit.

Reserve Margin Benefit

The peak load reduction afforded by EE allows the utility to maintain a lower reserve margin. For example, our study system maintains a 15% reserve margin. If EE reduces the system's peak demand by 1 MW, then the system reserve margin requirement falls by 1.15 MW. We represent this benefit by scaling the calculated EE capacity values up by 15%, the system's target reserve margin. This approach captures this reserve margin benefit as avoided capacity costs.

Line Losses Benefit

Reducing the system electricity demand likewise reduces the line losses associated with T&D. On average, T&D line losses in the US comprise around 5% of total electricity generation.[32] We capture the benefit of reduced losses by scaling the EE hourly savings profiles up by 5% to represent a 5% reduction in the required amount of generation. The model therefore captures this T&D benefit as the economic benefit of avoided energy costs.

RPS Benefit

By reducing system load, EE reduces the amount of investment in renewable generation that is otherwise required to satisfy RPS requirements in the "clean energy standard" scenario. The latter are frequently expressed as a percentage of the total system load, so reducing load reduces the amount of megawatt-hours (MWh) that must come from clean sources. We model

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[32] U.S. Energy Information Administration: *How much electricity is lost in electricity transmission and distribution in the United States?* https://www.eia.gov/tools/faqs/faq.php?id=105&t=3

Continued on next page

this RPS benefit by allowing the energy savings from EE to count 1:1 against the modeled MWh RPS requirement.[33] This approach captures the economic RPS benefits as avoided REC costs.

Other Benefits Not Quantified

We did not capture the benefits of reduced T&D investment in this study, since we model a vertically integrated utility without transmission or distribution constraints. Nor did we capture the economic benefit of avoided CO_2 emissions, which would be heavily dependent on the assumed cost of carbon.

[33] Some states allow EE energy savings to partially fulfill their RPS requirements. For example, a 1 MWh reduction in system demand (due to EE) in a system with a 40% RPS target would reduce the total RPS requirement by 0.4 MWh. Other states allow RPS to count 1:1 against the RPS target, where a 1 MWh reduction in system demand due to EE would reduce the total RPS requirement by 1 MWh. We model the latter scheme in our effort to maximize EE economics and find the maximum cost-effective potential for EE.