Distribution of potential savings from urban-scale energy modeling of a utility Building Simulation 2021 Conference

Joshua R New[1], Brett Bass[2], Anne S Berres[3]
[1]Grid Interactive Control Group, Oak Ridge National Laboratory, Oak Ridge, TN, USA
[2]University of Tennessee, TN, USA
[3]Computational Urban Sciences Group, Oak Ridge National Laboratory, Oak Ridge, TN, USA

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Abstract

While urban-scale building energy modeling is growing increasingly mature in data sources, algorithms, and empirical validation, there is still a need for best practices, guidelines, and standards for industry-accepted decision metrics relevant to specific use cases. Case studies are needed to inform such efforts. In addition, successful applications are need to motivate investment by, and in partnership with, utilities to scale grid-interactive efficient building technologies, realize aspirations of smart homes and cities, and dynamically dispatch load (rather than generation) in a way that stabilizes and reduces the cost of critical energy infrastructure. In partnership with the Electric Power Board of Chattanooga, TN, OpenStudio and EnergyPlus models were created of over 178,000 buildings and empirically validated against 15-minute whole-building electrical consumption of each building. Eight energy and demand-related measures relevant to nine utility-defined use cases are evaluated in over 2 million simulations of individual buildings to showcase statistical distributions over the entire building stock of potential savings for energy and demand.

Key Innovations

- AutoBEM (Automatic Building Energy Modeling) software suite developed to synthesize multiple data sources, generate building energy models, simulate, and statistically summarize simulation results for large geographical regions.

- Theta, world's 39^{th} most powerful supercomputer, used to perform over 2 million annual simulations.

- Distribution of annual energy efficiency savings reported for a full utility service area using four building energy efficiency technologies.

- Distributions of annual and monthly peak demand savings reported using four demand reduction building technologies.

Practical Implications

Findings could serve to motivate utility or private-sector investment in energy efficient building retrofits. Distribution of savings for specific areas can be used to inform prioritization, marketing, and testing program rollout of technologies for individual buildings.

Introduction

Most urban-scale building energy modeling projects lack scalability due to use of geographically-limited data sources (e.g. tax assessors data). Lessons learned from categorizing and analyzing 37 data sources have been contrasted with tax assessor data. This study helped define 19 fields that may be useful in developing a comparison matrix with examples comparing/contrasting traditional vs. non-traditional urban-scale data sources (New et al. (2020)). The authors leverage generally informative performance metrics for energy and demand,but acknowledge that urban-scale energy modeling efforts should first consider the appropriate fidelity necessary to address the use case (Ang et al. (2020)). This study required development of building-specific energy analysis. New data sources and algorithms were applied iteratively to create digital twins of each building in the 8-county, 1400 km^2 service area of the Electric Power Board of Chattanooga, Tennessee in the United States of America (EPB). By comparing the simulated energy use of each digital twin to actual 15-minute energy data from each building's advanced metering infrastructure, the authors were able to prioritize the value of data source and algorithm combinations that tended to result in energy models that more closely match the true electrical consumption. These baselines were then modified to quantify energy and demand savings prior to potential program rollout, targeted marketing, and business model decisions for utility-prioritized use cases (Bass and Copeland (2020)). Previous work on savings distributions leveraged the Oak Ridge Leadership Computing Facility's Titan supercomputer, at the time the world's fastest, with data sources used to generate models in 2018. This study updates that analysis by leveraging improved data and algorithms in 2019-

2020 and simulations on Argonne Leadership Computing Facility's Theta supercomputer, currently the 39^{th} fastest supercomputer in the world. However, it is the 2^{nd} fastest supercomputer in the world, after the German-only SuperMUC-NG, leveraging the Central Processing Unit for its computing power, as needed by the simulation engine used in this study. While the data sources, algorithms, and scalable compute for building simulations are beyond the scope of this paper, this study will provide distributions of potential savings for various building technologies across all buildings in a large, city-sized geographical region.

While empirical validation is increasingly common, high-resolution measured energy data is still relatively difficult to attain and is typically done for dozens to 200 buildings in previous literature. This study performs empirical validation of 179,000 buildings, providing a larger sample size with greater statistical confidence in the final results.

Instead of reporting average savings for energy (kWh), this study will focus primarily on the contributions involving the distribution (e.g. box-and-whisker plots) of savings not only for energy but also for electrical peak demand (kW).

Multiple building technologies are evaluated including roof insulation, envelope sealing, more efficient lighting, smart thermostats, more efficient HVAC, and smart water heaters. As an example, smart-thermostat for utility-signaled pre-conditioning of buildings by 4.4C two hours prior to peak demand saves on average 27% of a buildings electrical demand but varies significantly from 0 to 93% across the 179,000 buildings. Aggregation of building-specific savings to utility-scale savings offers reduced risk for the financing and implementation of utility-scale savings. Upon approval by the utility, savings will be presented as average/building or percent to allow rough estimation of potential savings by other utilities.

Methods

Every building in EPB's 8-county service area is modeled using the "Automatic Building Energy Modeling" (AutoBEM) software suite (New et al. (2018)); a collection of methods, data sources, and algorithms to synthesize data for, generate, simulate, analyze, and visualize urban-scale building energy models and related analysis.

The first step in this process is obtaining individual building physical characteristics. Building geometries were selected from the Chattanooga region from Microsoft's dataset of more than 125 million building 2D footprints across the United States (Microsoft (2018)). In comparison to pixel-based computer vision classification or LiDAR-based building footprint estimation, this dataset provided more regular geometry with potential challenges involving grouping of attached buildings into one building footprint due to the polygonal simplification method used. Building heights were found using statewide LiDAR of the state of Tennessee and acquisition of LiDAR for a small region in the state of Georgia. Description of data sources considered, selected, and processed in the creation of this digital twin for a utility is beyond the scope of this paper, but the interested reader is referred to New et al. (2020), Garrison et al. (2019), Wang et al. (2021), Bass and New (2021).

To mitigate potential privacy concerns, assignment of a prototype building type and vintage is used to assign all internal building details. This assignment is a meta-parameter that leverages building code requirements to define the remaining parameters required for building energy modeling such as heating, ventilation and air conditioning (HVAC) type, water heating, lighting, insulation, glazing fraction, and occupancy schedule. This study leverages the U.S. Department of Energy's flagship whole-building simulation engine, EnergyPlus, which has an average of approximately 3,000 parameters per building. This study, as with many urban-scale studies, has very little information about the internal characteristics of a building. Due to the significant source of uncertainty with such assumptions, 15-minute whole-building electricity consumption from each building is used to reduce prediction error, empirically validate results to the extent possible, and results are still provided as an anonymized-through-aggregation statistical distribution of potential savings. This study leveraged 17 prototype buildings with 6 vintages representing about 75% of commercial building in the US were used for this analysis (US Department of Energy (2019)). In order to capture residential buildings, the multi-rise apartment was modified to correct water usage, lighting (interior and exterior), and related properties to capture single family detached, apartments (2-4 units) and apartments (5+ units). In this study, larger multi-family dwellings are captured by commercial (aka non-domestic) buildings of mid-rise and high-rise apartments. Combinations of every valid building type and vintage, shown in Table 1, were used to develop 97 unique building energy models. To minimize associated errors, the authors compared the fingerprint of each building's actual energy use with each of the 97 unique models' simulations to assign building type and vintage. Specifically, each building's actual 15-minute electrical use intensity (EUI), whole-building electricity consumption from each building's utility-grade advanced metering infrastructure was normalized by square feet of conditioned area. This results in a 35,040-element vector (15-minute EUI for a year) that was compared using Euclidean distance to assign the best-matching building type and vintage (Garrison et al. (2019)). Once assigned, the unique geometry of each of the 178,000 buildings is used to generate a model that populates all internal characteristics based on building type and vintage. Any additional characteristics, known or inferred (e.g. tax assessor or utility data), about each building can then be automatically used to override any default, prototypical assignments.

All buildings are converted to all-electric HVAC which allows an estimate of maximum total energy savings potential with the tradeoff that this may overestimate electricity savings. The synthesized building descriptors from such underlying data sources and algorithms are used to generate OpenStudio (US Department of Energy (2020b)) and EnergyPlus (US Department of Energy (2020a)) models of each building and immediately simulate them on high performance computing resources. AutoBEM uses the OpenStudio standards gem to generate and modify OpenStudio building energy models. The time to generate a model was comparable to the time required to simulate it, resulting in generation-and-execution compute time being twice the number of core-hours awarded on high performance computational resources. Urban-scale energy modeling at the scale of a city or larger would benefit greatly from more efficient building generation than current standard practice.

The model baseline simulations were compared to the measured data to empirically validate the models. While building improvements are generally referred to as Energy Conservation Measures (ECMs), there is growing interest in applying these to demand, water, or other building performance characteristics. As such, we apply the general term "measures" to mean modifications of any kind to a building energy model. Calibration using 15-minute data has been conducted for specific buildings, but computational requirements for reputable automated calibration methods at the current time are computationally infeasible for 178,000 buildings even with modest HPC resources. Instead, each building was simulated with meteorological variables from calendar year 2015, baseline simulated compared to 15-minute energy consumption of each building for the same year, and used to generate building-specific bias adjustments (normalized mean bias error) to close the building energy performance gap.

Table 1: Building type and vintage are assigned by comparing each building's actual energy use to prototype buildings (Garrison et al. (2019)). While not all building types support all vintages, every valid combination of prototype Building Types and Vintages were generated, resulting in 97 unique models.

Building Types	Vintages
Full Service Restaurant	DOE-Ref-Pre-1980
High-rise Apartment	DOE-Ref-1980-2004
Hospital	90.1-2004
Large Hotel	90.1-2007
Large Office	90.1-2010
Medium Office	90.1-2013
Mid-rise Apartment	
Outpatient	
Primary School	
Quick Service Restaurant	
Retail Standalone	
Retail Stripmall	
Secondary School	
Small Hotel	
Small Office	
Warehouse	
Residential	

Energy Efficiency

Energy efficiency ECMs focus on lowering energy consumption within a building. These ECMs are mostly efficiency improvements and technology retrofits. They are useful to both a utility and the energy consumer by simply reducing the amount of energy used. The energy efficiency ECMs are shown in Table 2.

Table 2: International Energy Conservation Code (IECC-2012) served as the basis for energy efficiency measures. These measures, including photovolatics, focus on reducing annual electricity end-use but can impact demand.

Measure Type	Definition
Lighting	Reduce lighting power density to 0.85 W/sf
Infiltration	Reduce infiltration by 25% from baseline
Insulation	Roof insulation from R-16.12 to R-28.57
HVAC Efficiency	COP to 3.55 (heating), 3.2 (cooling)
PV	70% of roof area with cell efficiency of 15%

Peak Demand Reduction

EPB is an electrical distributor that purchases energy from the generation services of the Tennessee Valley Authority (TVA). By better managing demand in a generator's territory, the most expensive and dirtiest generation assets can be avoided. By better managing demand on its distribution network with advanced control and sensing technologies, EPB was able to avoid three consecutive rate increases for itself and its ratepayers. At generation and distribution electrical scales, mitigating energy use for peak loads during hot summers or cold winter hours can significantly reduce the cost of owning and maintaining generation or responsive load facilities necessary for meeting those loads. In the United States, there are approximately 125 million buildings, 96% of which are residential and consume electricity nearly equivalent to the 4% of commercial (non-domestic) buildings; however, demand charges are typically assessed solely on commercial buildings. While most utilities offer a time-of-use structure for residential buildings that considers demand, the subscription rate is currently below 1%. As buildings and cities become smarter, with connected and controllable devices that can impact behind-the-meter loads, there is a growing interest in the ability to develop and deploy new hardware, software, communication standards, and business models that leverage Grid-interactive Efficient Building (GEB) technologies that deliver more advanced flexibility for modernization of critical infrastructure (esp. the electric grid).

Peak demand for a utility is generally defined based on the utility-scale peak hour of energy use in a calendar month, but can vary by utility based on different time-windows or related definitions. How corresponding demand rate charges are assessed against rate payers is defined by a more complicated tariff for different peaks. For EPB, there is a TVA (generator) peak and an EPB (distributor) peak that involves different peak rate charges along with building-specific peak demand use that defines a block rate demand cost within the tariff. While EPB has integrated these results with its production database to assess related costs based on rate classes, block rates, and tariffs associated with individual customers, the authors simplify this by reporting the distributions of solely energy and demand in hopes the results are more useful to utilities with different costing structures.

Measures related to GEB technologies for demand management used in this study (Table 3) focus on reducing energy use during the peak hour, even if they increase energy usage during the hours prior to or after the peak hour. Smart thermostats for utility-signaled pre-conditioning of buildings allows their use as thermal batteries to coast through the hour of critical generation. In this study's implementation, the thermostat changes are applied to all space conditioning types which may be one to hundreds of individual thermal zones throughout the buildings.

Table 3: Measures focused on demand reduction during monthly peak-hour demand, regardless of any synergies or tradoffs with overall energy efficiency.

Measure Type	Definition
Smart Thermostat (2.2)	Pre-heat/pre-cool by 2.2°C for 2 hours prior to peak
Smart Thermostat (4.4)	Pre-condition by 4.4°C for 4 hours prior to peak
Dual Fuel HVAC	Swap to natural gas heating for peak hour
Smart Water Heater	Turn off heating coil for peak hour

Results

Results are split into electricity and demand savings. While energy efficiency measures often reduce demand, this is not the primary function of these measures. Demand reduction measures can, and often do, result in an annual increase in energy use, though the peak demand reduction is typically worth the increase. For utilities that make money for selling energy (kWh, or more specific kVAR) and are charged based on demand (kW), these measures are financially lucrative. The analysis includes one baseline and nine measures, with several reruns, simulated for each of the 178,000 buildings thereby resulting in over 2 million simulations. While this study assessed other measures, ones that resulted in either negative or 0 annual energy or demand savings were omitted from this study and related analysis as they were not to be considered by the utility for implementation.

Electricity Savings

The distribution of potential urban-scale electricity savings are broken down by building type and vintage in the box-and-whisker plots of Figure 2. Decreasing the lighting power density results in the greatest annual electricity savings, and is typically one of the most cost-effective measures to enable financing and deployment of other, less cost-effective measures. There is a trend for two of the measures in terms of building vintage. In older buildings (DOE-Ref-Pre-1980, DOE-Ref-1980-2004), the HVAC efficiency upgrade and reduction of space infiltration all had more savings than newer buildings (90.1 vintages). For this specific data and analysis, the typical lifespan of 20 years was not used to replace/upgrade HVAC systems. As such, this result should match the reader's intuition as the technology in older buildings would typically be less efficient, but should be informative by providing quantitative ranges around potential energy savings from such common measures.

When considering energy efficiency savings across building types, the lighting measure is especially effective in the warehouse, retail standalone, and retail strip mall while being more effective than other measures in the two prototype restaurants (Quick-service, Full-service).

Currently, energy efficiency of 20% to 50% is commonly a cost-effective first fuel prior to renewable generation. Nevertheless, many homeowners and building owners express interest in potential energy and cost savings of producing their own power from rooftop photovoltaics. Unfortunately, most such interests starve from lack of relevant information to justify additional effort. Modeling capabilities and tools today are sufficiently advanced to give reasonable estimates of PV potential for a given roof, and can sometimes accommodate shading from other buildings or trees. EnergyPlus uses PVWatts and can natively simulate/assess PV generation impacts on

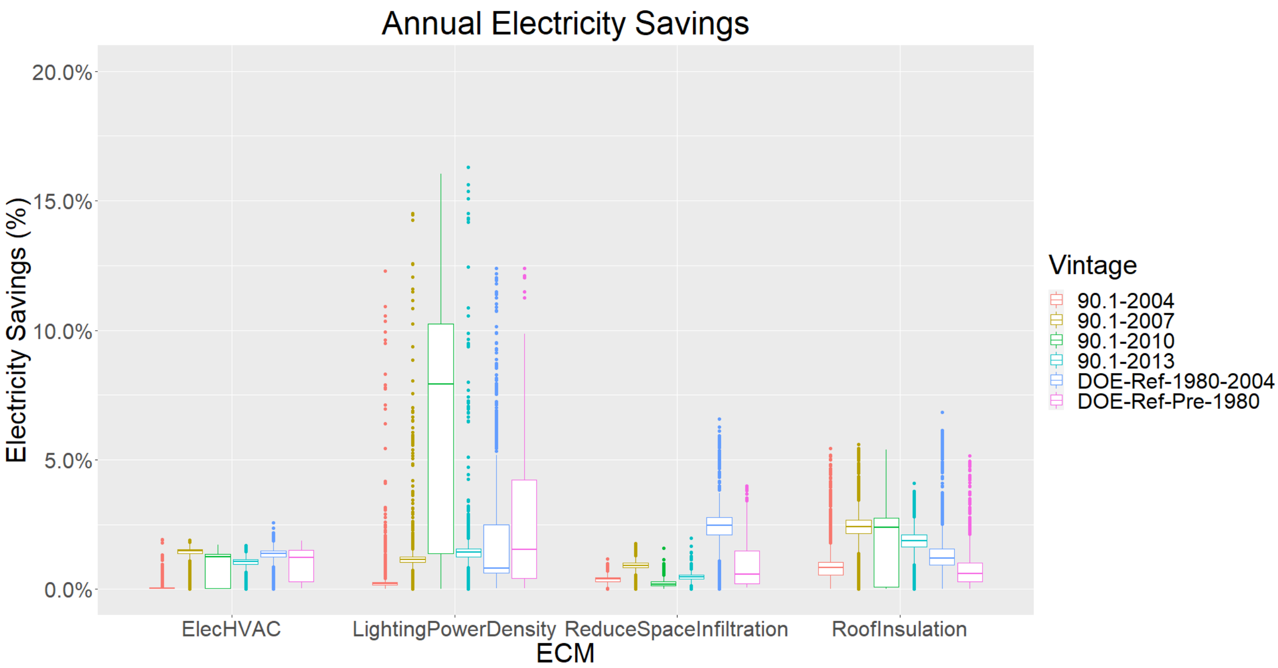

Figure 1: Older vintage buildings had the greatest average savings for the space infiltration ECM while electric HVAC efficiency savings were consistent across vintages.

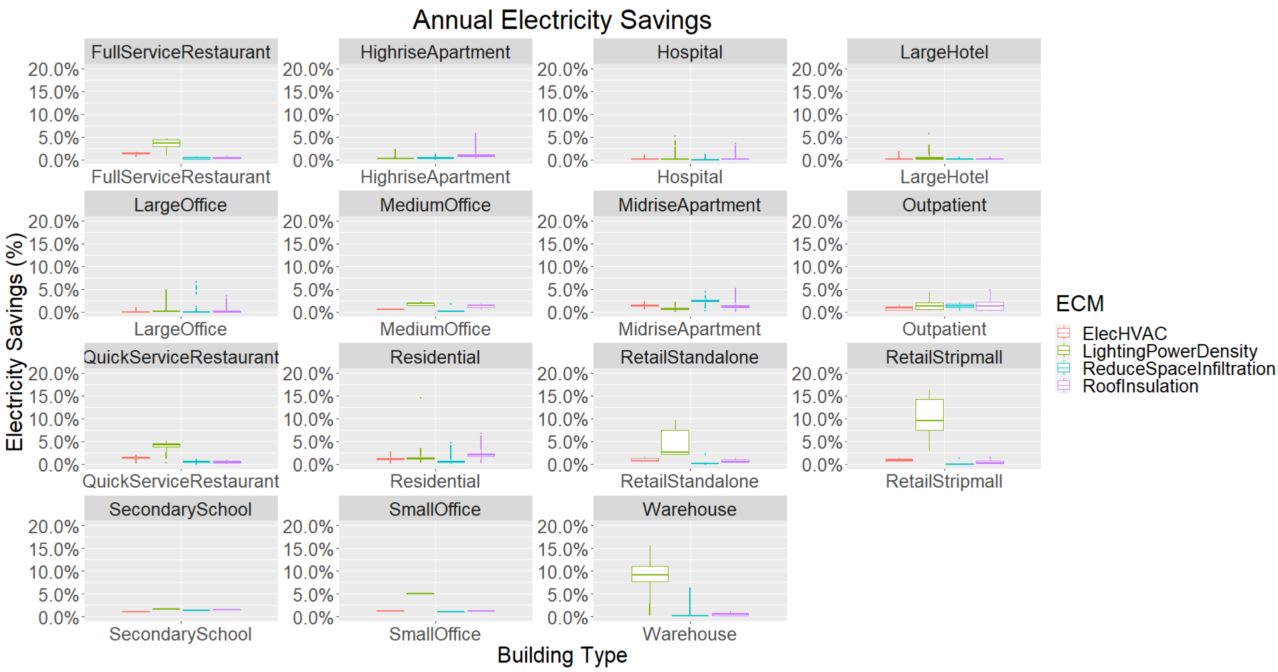

Figure 2: Reducing lighting power density had the most savings across all building type especially effective on warehouses and retail strip-malls.

whole-building energy consumption.

In this study, we simulated PV deployed on 70% of the roof with 15% cell efficiency and 98% microinverter efficiency for every building in EPB's service territory of over 178,000 buildings. This maximum technical adoption potential for PV is shown in Figure 3. This generated electricity can be viewed as savings with buildings that generate more than the building used, resulting in negative values. In some cases, this can turn the meter backward but in many cases, building owners are surprised that these are dual-metered and do not allow them to operate for a time off-the-grid in the case of an outage. PV installation results in demand savings for some months when the peak hour is during daylight, but does not contribute to demand reduction when the peak hour is before sunrise or after sunset; typically in the winter months.

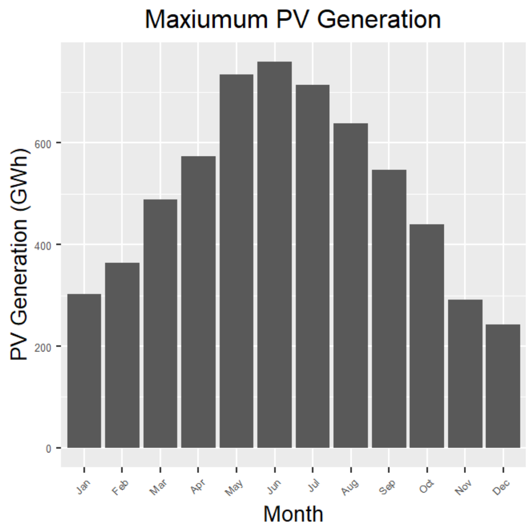

Figure 3: Total PV potential in EPB's service area correlates to total roof area and daylight hours of each month, with maximum PV generation in July when days are longest and minimum PV generation in December when days are shortest.

Demand Savings

The demand savings are similarly broken down by vintage and building type in Figure 5. The 4.4°C offset smart thermostat measure results in the greatest savings with an average of 29.3% across all building types and vintages. The 2.2°C offset resulted in 22.3% annual demand savings across all building types and vintages. This difference is significant but should be considered if employing the smart thermostat as comfort levels may wain more for an 4.4°C difference compared to a 2.2°C difference. Thermal comfort level considerations and percent of potential overrides is not considered in this total technical adoption potential study. Annual demand savings of the dual fuel measure, that emulates fuel-switching from electricity to natural gas for heating, is limited in this study since it only results in demand savings during the winter months for the climate zone of this utility.

According to this analysis, it appears the oldest "DOE-Ref-Pre-1980" buildings have the least potential for demand savings for the measures assessed. Annual demand savings broken down by building type carry the same general trends with smart thermostat (4.4°C) resulting in the greatest annual demand savings. The smart water heater has the least annual demand savings for all building types except for the hospital since standby losses for tank-based water heaters common in the United States are not significant in comparison to whole-building energy use.

The demand results can be viewed through a monthly aggregation which provides a better picture of the savings throughout the year. The monthly demand savings for the 2.2°C smart thermostat measure are shown in Figure 6. January and February have fewer lower demand savings as the smart thermostat is less effective in residential buildings in the winter months which is approximately 80% of the building stock in the utility's service area. Commercial buildings (Figure 7), illustrate the demand savings difference by limiting the analysis to only commercial buildings where the greatest savings are in the winter months. This increased savings is likely due to the all-electric heating assumption. The opposite is true in the summer months, where commercial buildings save less.

The year being analyzed (2015) had a particularly cold January through March but a mild November and December; leading to the difference in these months compared to the first three of the year. The summer months have the lowest average demand savings with the spring and fall months in the mid-range.

The smart thermostat with the 4.4°C offset was not shown as it mirrors the 2.2°C offset; scaled to a 7% greater savings that stays constant throughout the year.

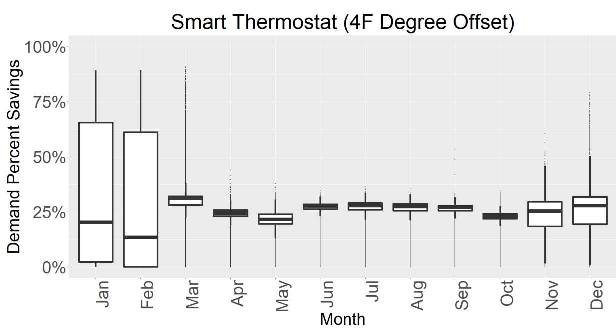

Figure 6: Smart thermostat (2.2° C) offset for all buildings. Demand savings are relatively consistent through the warm months and vary drastically in winter months.

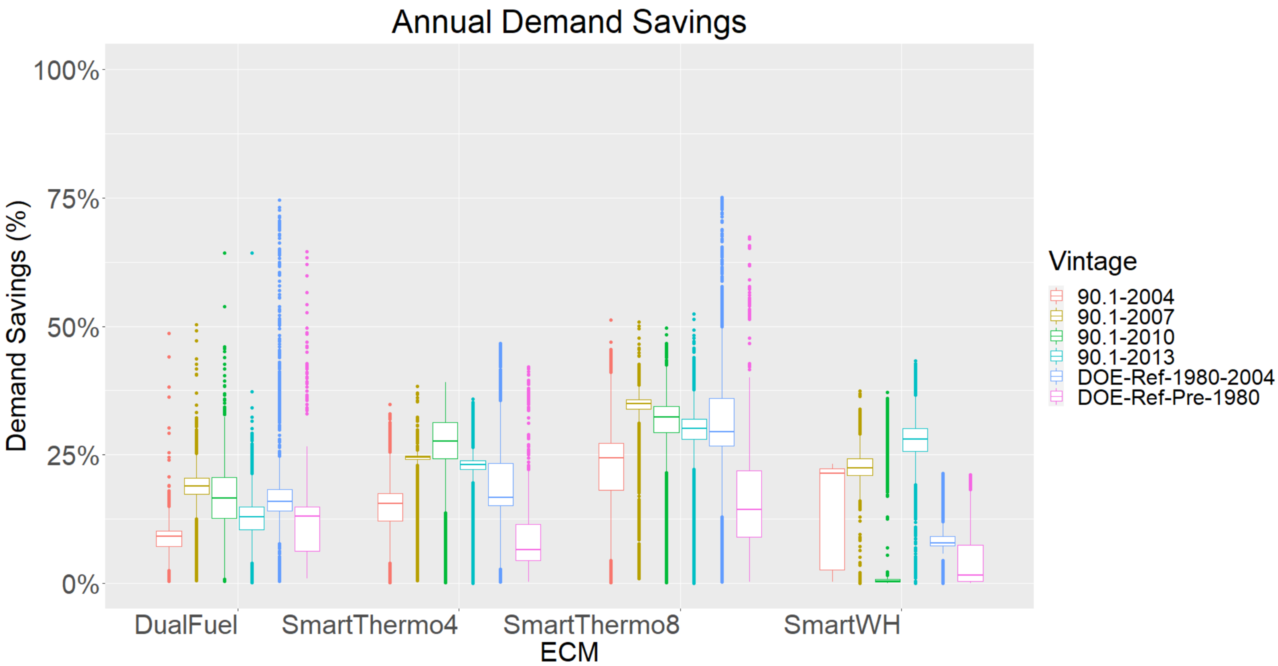

Figure 4: The smart thermostat 4.4° C offset measure had the most simulated savings with the 2.2° C offset mirroring it at a lesser savings rate. Older vintages have lower average simulated demand savings compared to newer vintages.

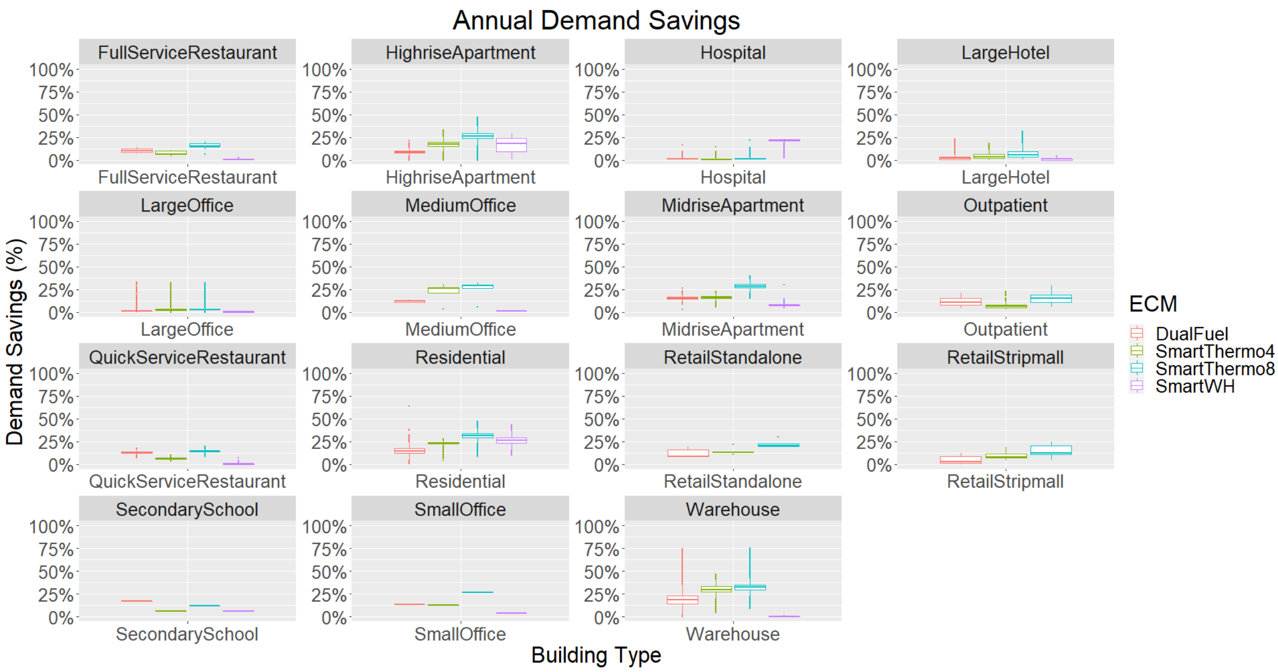

Figure 5: Annual demand savings for dual-fuel HVAC are limited due to heating demand only in winter months for this climate zone. Warehouses, high-rise apartments, and residential buildings are the building types with the greatest average savings across all ECMs.

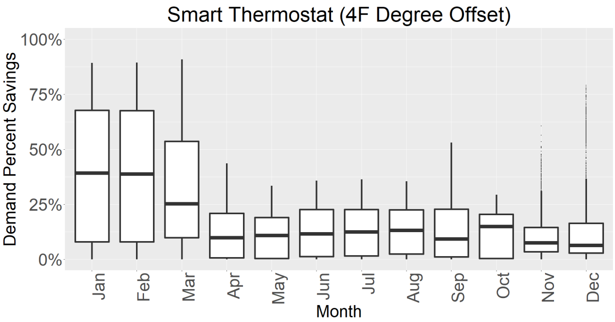

Figure 7: Smart thermostat (2.2° C) offset for commercial buildings shows different seasonal variability than the previous image dominated by residential performance. Demand management uses cases often benefit from enhanced segmentation provided by building-specific urban modeling.

Monthly demand savings for the dual fuel measure are summarized in Figure 8. Demand savings are significant in winter months as the electric HVAC heating is replaced by natural gas for the peak hour. The relative warmth in the final months of calendar year 2015 in the area is evidenced again as little demand savings were seen in the typically-cold November or December. Since this study was conducted in service to an electrical distributor, it should be noted that these are electricity savings, not total energy savings.

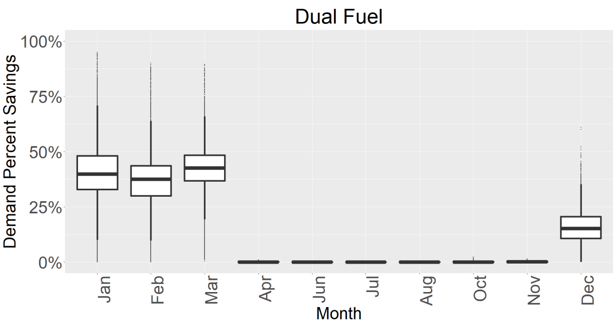

Figure 8: Dual fuel, fuel-switching, electrical demand savings for the entire service area are primarily limited to winter when the HVAC's heating coil is replaced with a natural gas furnace during the peak hour in the early hours of the winter months.

The monthly demand savings for the smart water heater measure are shown in Figure 9. The amount of demand mitigated for each month is correlated directly with the water temperature setpoint. Winter months have the most savings, with summer months having the least.

The smart water heater measure shows significant difference, as one might expect, among buildings in the EPB service territory and is pronounced for commercial buildings that typically require larger amounts of water. The smart water heater measure is shown monthly in 10. While there are notable savings when residential buildings are included, these savings are less for all months when limited to only commercial buildings.

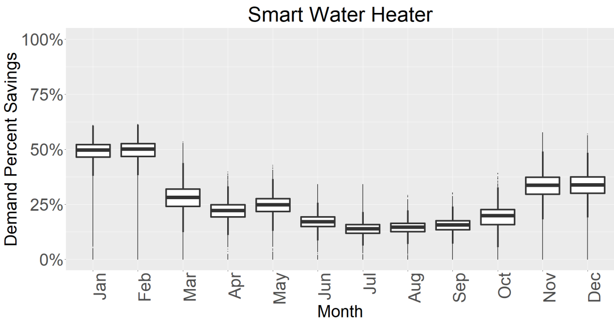

Figure 9: Smart water heater demand savings for all buildings in the service area. The demand reduction correlates to the temperature at that time of the year.

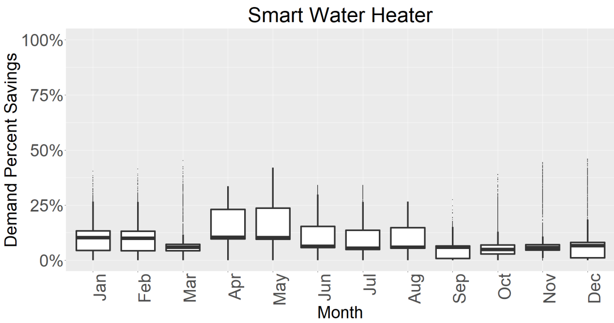

Figure 10: Smart water heater demand savings for commercial buildings in the service area. Savings are relatively constant throughout the year for commercial buildings compared to all buildings.

Conclusion

For this study, over 178,000 OpenStudio and EnergyPlus models were generated, over 2 million annual simulations were performed on high performance computing results, and baseline models were empirically validated against 15-minute electrical consumption of each building. This study elucidates methods and showcases results for statistical distributions of potential energy and demand savings of 8 building technologies under a maximum technical adoption scenario.

Energy efficient building measures were implemented in each building include energy-efficient lighting, space-sealing, roof/attic insulation, improved HVAC efficiency, and rooftop photovoltaics. Lighting was notably impactful in traditionally-lit warehouses and retail stripmalls while maximum rooftop PV potential for the utility's service area was estimated at up to 750 GWh in a single month.

Annual demand savings, defined as the sum of energy use during the peak hour of each calendar month, were shown for four measures including two scenarios for smart thermostat building space pre-conditioning, fuel-switching HVAC, and smart water heaters. The smart thermostat with an 4.4°C offset resulted in the greatest demand reduction. The 2.2°C offset simulated an average of 7% lower annual demand offset but would likely result in fewer customer overrides than the liberal 4.4°C approach. There was a significant difference in the effectiveness of smart thermostats between residential and commercial buildings with greater relative effectiveness for commercial buildings in the winter but residential buildings in the summer. The dual fuel measure reduced demand more than any other technology for a single month, but was limited to applicability only in winter months. Demand savings from a smart water heater were higher overall in the winter than in the summer, but with relatively constant savings for commercial buildings.

These findings are actively informing energy efficient program formulation and rollout for demand-management technologies at this utility. It is hoped that such metrics and savings ranges can be further empirically validated using standard Measurement and Verification (MV) protocols using pre- and post-retrofit energy use estimates compared to actuals. The authors observe a need for empirical validation of urban-scale modeling toward the establishment of best-practices, community-standard testing frameworks, and innovative data/algorithm sources for both external and internal building descriptors for model inputs. It is the hope that such building-specific, urban-scale energy modeling efforts will one day unlock significant investments for the improvement of the world's building stock to a more responsible, sustainable, adaptive, and optimized built environment via actionable steps with investment-grade metrics for financial, environmental, and social impacts.

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