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Five Years Later: Second Round Institutional Energy Retrofit Analysis Procedure

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ABSTRACT

This paper provides a continuation of the results and efforts to continuously maintain and use a fleet of 120 detailed Building Energy Models (BEM) of the Sandia National Laboratories New Mexico and California sites. The fleet has continued to be used in new applications beyond its 1st round of site-wide energy retrofit and climate assessments in 2014-2017. These include resilient energy systems assessments in 2018-2019 and institutional peak electric load characterization in 2020. The most recent work is a 2nd round site-wide energy retrofit assessment that is being planned. This paper shows the 10 step procedure planned for this 2nd assessment and contrasts it to the 1st round of institutional energy retrofit analyses. The procedure involves calculating difference metrics between the various steps in the procedure that highlight the accuracy of the energy retrofit decisions being made. Here, energy retrofit decisions involve deciding what specific building and energy retrofit is the next best choice based on metrics such as total energy saved, carbon offset, or energy cost savings minus the energy retrofit implementation cost. The first difference metric Δ_{11} assesses the robustness of energy retrofit decisions with respect to historical, climate change, and extreme event weather futures, the second Δ_{15} assesses the robustness of energy retrofit decisions by comparing results before and after BEM calibration. This provides information that helps to show if the retrofit is very sensitive to other BEM input parameters that are also uncertain. The third metric Δ_{19} involves empirical validation of energy savings or other metrics used based on actual metered results. A demonstration of calculating Δ_{11} shows how important climate and future weather is to energy retrofit decisions for a 96 BEM study with 2 energy retrofits involving roof insulation and external wall insulation. Weather files for 2017-2020, Typical Meteorologic Year 3 (TMY3), and 3 extreme event scenarios were included for different weather futures. The results show that variations in energy savings are significant and the optimal decision set with baseline year 2020 is only stable to 30 decisions of the 192 potential energy retrofit decisions. This shows that using a single weather future is likely to lead to sub-optimal choices.

INTRODUCTION

Energy efficiency (EE) is an important part of a clean-energy, carbon-balanced future. Studies are increasingly focused on the complex tradeoffs between EE and renewables (Alqahtani and Patino-Echeverri, 2019; Almasari et. al., 2021). Sustainability of materials and renewables versus EE are important as well (Oliveira et. al., 2021). Depending on the situation, EE ranges from being the best investment in terms of life cycle cost within interconnected systems to having high cost because there is minimal energy savings potential. Discerning the potential for energy savings can vary widely with slight differences in modeling approach. This is especially true for existing buildings where understanding the actual state of sub-systems within a building is difficult and costly to assess leaving a high probability of modeling errors.

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Institutions that own hundreds to thousands of existing buildings face significant challenges in decision making concerning many issues interrelated with EE including: 1) How to perform energy retrofits within large groups of complex, aged buildings with on-going critical operations (Maia et. al., 2020); 2) How to address climate change (Villa, 2021) and resilience (Jeffers et. al., 2020; Sun et. al., 2020) issues while performing energy retrofits; 3) How to understand tradeoffs between installing renewables to offset generation versus energy retrofits; 4) How to optimize decisions based on current and expected future energy prices; and 5) How to maximize occupant satisfaction and comfort before and after energy retrofits. Though studies concerning the aforementioned issues abound in the literature, combining all of them can become prohibitively difficult and is highly dependent on the priorities of a given institution.

We propose that intensive modeling and data analytics should be united into a continuous process (Villa, 2019) to give actionable answers to many of these challenges. This is not achievable via conventional building energy modeling practices but requires automation of processes such as building energy model (BEM) calibration, weather data acquisition, running BEM, and post processing results. In accord with this proposition, Sandia National Laboratories (SNL) has invested since 2012 in a fleet of 120 BEM. The 120 BEM were wrapped into a software framework called Institutional Transformation (IX) and were used for a set of energy retrofit analyses that guided upper level management for SNL's energy management goals. The final results of these energy retrofit analyses was a decision to reduce the EE goal of 25% reduction in energy use baselined to 2011 consumption to 19% because SNL would have to engage operational issues likely to interfere with institutional productivity and occupant comfort in addition to capital investment to achieve the goal. In making such a decision, EE was deprioritized and thermal comfort was given the highest value. Even so, the original analyses were undocumented and the results contained in spreadsheets were found to be significantly flawed with no documentation concerning compliance to ASHRAE Guideline 14 (G-14) (ASHRAE, 2014). An audit of the 120 BEM found that 44 BEM had not been calibrated—including the entire California site of 23 BEM and 39 did not meet G-14. Only 37 BEM complied to G-14 (Villa et. al., 2017). Five years later, SNL facilities has requested a second round of energy retrofit. These shortcomings have led to the design of a more thorough institution-wide energy retrofit assessment that enables evaluation of accuracy and continued refinement of model inputs throughout the entire assessment cycle.

The previous institution-wide energy retrofit assessment procedure did not convey any information concerning the certainty of the analysis provided. As seen by the region surrounded by red dashed lines in Figure 1, the original procedure involved running the DOE2 (Hirsch, 2021; York and Capiello, 1982) BEM models through several energy retrofit analyses in the IX software (Villa et. al., 2017). The results were accepted with no further scrutiny concerning the accuracy of the BEM predictions for each energy retrofit. Though this is not good modeling practice it is a ubiquitous error among inexperienced or hurried modelers that are under pressure. The failure to meet G-14 error metrics by the majority of the models previously discussed provides strong evidence that the certainty of the predictions were not very good. The new methodology, seen in the region surrounded by blue dashed lines in Figure 1, provides multiple steps that assist in assessing the stability and accuracy of energy retrofit decisions. This is especially important for cases where competing energy retrofits nearly tie with each other. If a near tie has high uncertainty, then there is little importance in choosing one retrofit over another and other considerations should guide the decision rather than the resulting energy savings. This new procedure greatly exceeds the requirements of G-14.

This paper provides an overview of the procedure being proposed which combines manual BEM modeling practices and some new automated techniques. It then provides a demonstration for the first step of this process which involves precalibration analysis of two energy retrofits on 96 BEM and calculation of the decision priority metric Δ_{11}.

METHODS

In this section, we provide details for each step of the new methodology seen in Figure 1 by the number within each rectangle. Rectangles denote procedure steps, ellipsoids represent data resources used in the assessment, and the lone diamond represents data products that inform the accuracy of the process. Though Figure 1 shows a once through cycle to emphasize the entire process, many feedback steps may be necessary as more is discovered. For example, Step 1 may be completed only to discover major flaws in a model in Step 2 requiring repetition of Step 1. This intensive repetition that can occur makes it critical that the calculations be automated. At SNL this has been handled by scripting the process in Python 3.8.5 (Python Software Foundation, 2021) heavily relying on the Numpy (Harris et. al., 2020), Pandas (McKinney, 2010) and Matplotlib (Hunter, 2007) libraries.

Institutional Energy Retrofit Decision Metrics

A family of metric are derived here that guide the decisions needed for institutional energy retrofit assessments. The derivation involves the following steps: 1) A baseline weather year must be chosen that is assumed to represent the most probable future for the coming year. This can be the last year's weather data if no better information is available. 2) Energy savings need to be calculated. Energy savings are counted as the difference in energy between the BEM run without and with energy retrofit changes for a given weather history w.

$$\Delta E_{s,w,b,r} = E_{s,w,b} - E_{s,w,b,r} \tag{1}$$

Here, $E_{s,w,b}$ is the total energy (sum of electric, gas, etc..) expended in 1 year by a building b for weather history w for the s^{th} step of this procedure. The r index indicates what retrofit has been added to building b. The baseline weather file is designated as ω. 3) The energy savings for the baseline year $\Delta E_{s,\omega,b,r}$ must be sorted from greatest to least for all buildings, b, and energy retrofits, r, normalized by the area of the building (kWh/yr/m^2 or BTU/yr/ft^2). The resulting sets of indices form a set of decisions $D = \{ (b_1, r_1), (b_2, r_2), \dots, (b_n, r_n)\}$ where n is the sum of the number of retrofits available over all buildings. These decisions contract the b and r indices into a single decision index d. This set of decisions, D, range from the best choice for energy retrofit and building (d_1) to the worst choice (d_n) for the baseline weather ω. A metric $\Delta_{1s_{w,d}}$ that enables evaluation of the level of variation across weather and decisions is shown below.

$$\Delta_{1s_{w,d}} = \frac{\sum_{k=d_1}^{d} A_k\left(\Delta E_{1,w,k} - (1-\delta_{1s})\Delta E_{s,w,k}\right)}{\sum_{k=d_1}^{d_n} A_k\left(\Delta E_{1,\omega,k} - (1-\delta_{1s})\Delta E_{s,\omega,k}\right)} \tag{2}$$

Here δ is the Kronecker delta and A_k is the area of the building included in decision k. The areas are included to provide greater weight to decisions made concerning larger buildings. This metric indicates the fractional difference between energy savings predicted for Step 1 and another step s. If $s = 1$ (calculating Δ_{11}), δ contracts the formula to the sum of energy savings for weather w up to decision d divided by the total energy savings for all decisions for the baseline weather ω.

Institution-wide Energy Retrofit Procedure

Many pre-existing resources must exist before the proposed institution-wide energy retrofit procedure can be carried out. These resources are expressed as ellipsoids in Figure 1. First, there must be a set of BEM or other models that have been shown to predict a reasonably good estimate of institution-wide energy consumption. These models must have relevant parameters to form a set of energy retrofit measures. See Villa et. al. (2016) for the set of energy retrofit measures available in the IX software. Second, energy meter data, weather data, and climate information from reliable sources has to be available and must be curated for the analysis. The process in Figure 1 excludes feedbacks that are likely to occur in the steps as BEM are refined and steps have to be repeated so that the flow of the entire process as a cycle can be emphasized. With these resources in place, the process steps are as follows:

1. Precalibration analysis of energy retrofits: The new process starts with the same step as the previous institutional energy retrofit analysis. A parameter study tool is needed for running BEM over many energy retrofits. At SNL, the IX software is run using all relevant energy retrofit models available in each BEM. To use IX, other institutions must create a fleet of DOE2 models and check them into the IX Microsoft Acccess® database (Villa et. al., 2017). This is a significant investment that costs tens of thousands of dollars per model followed by thousands of dollars per year of maintenance. The Step 1 analysis includes assessing the energy retrofit results across as many years of historical weather as available. Weather data products used here include on-site weather data for 2017-2020 that SNL has access to, TMY3 data (Wilson, 2008), and weather files that have expected increases in extreme events added. For this study extreme events using the Multi-scenario Extreme Weather Simulator (MEWS) open-source software (Villa, 2021: 3). The complexities of adding climate trends and extreme events to BEM weather files are not discussed here but can be explored in the ASHRAE Fundamentals new chapter 21 on climate change (ASHRAE, 2021) and throughout the BEM literature (Villa, 2021: 1-2; Rastogi and Andersen, 2016; Thrasher et. al., 2013). A plan concerning what retrofit decisions to make is formulated from the analysis of retrofits by calculating the previously derived site-wide energy assessment decision metric Δ_{11}.

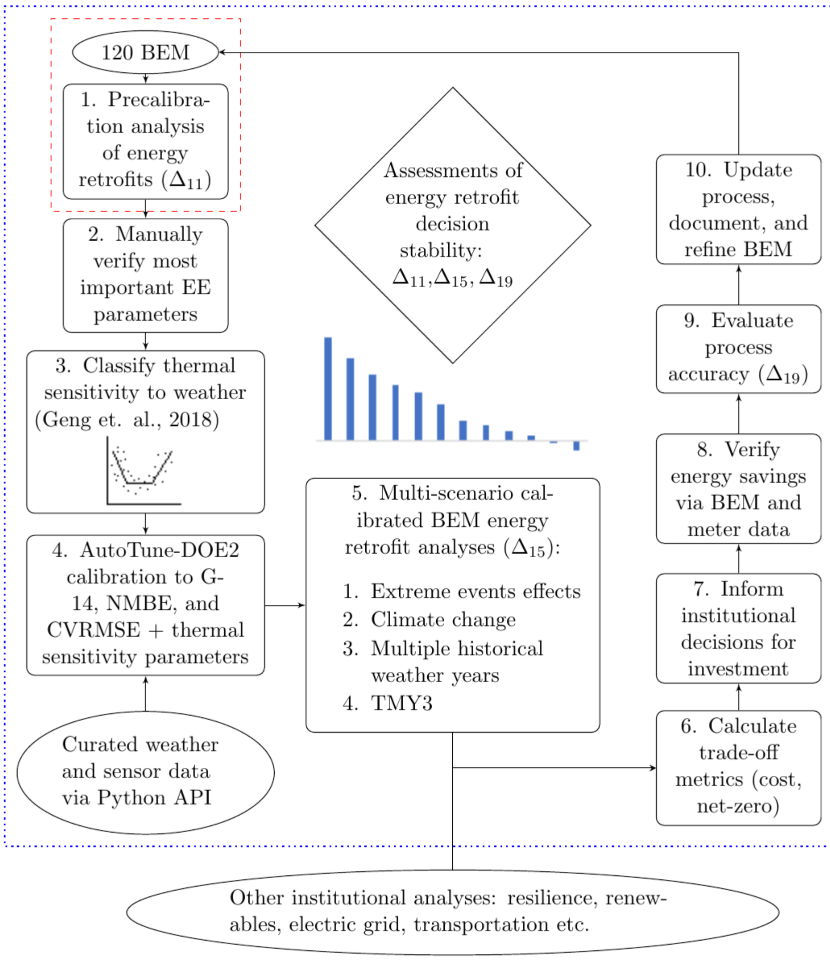
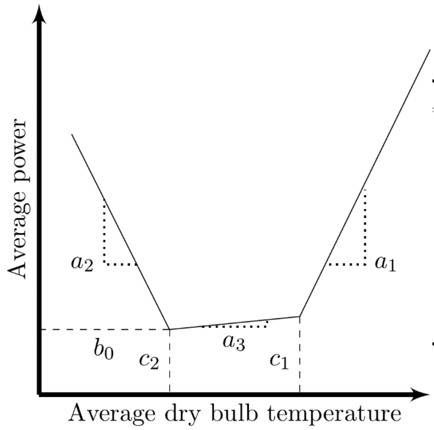


Figure 1 Institution-wide energy retrofit continuous process that is repeated once every several years. The blue dotted line outlines the updated process for SNL whereas the red dashed lines shows the original process for the first energy assessment. The entire process is still being completed at SNL.

2. Manually verify most important EE parameters: The bar chart at the center of Figure 1 shows tallest bars on the left with decreasing bars toward the right until some bars even go below zero. This signifies the most common output of IX calculated in Step 1 where buildings are sorted by the energy savings per area for a given retrofit. Typically, the highest EE potential building should be scrutinized the most. This step involves making efforts to verify that the highest energy savings potentials are accurate predictions through walk-throughs, review of energy audit reports and change orders, review of Building Automation System (BAS) data, quality checks on associated BEM, and interviews with building engineers. Only the highest consequence energy retrofit decisions will be able to be scrutinized in this way. When discrepancies are found through this process, the BEM are updated and Step 1 repeated. Comprehensiveness in this step can be a significant financial investment that institutions must carefully weigh. Also, organization of information concerning a building's state can allow this step to become more efficient.

3. Classify thermal sensitivity to weather: This step involves applying the work presented by Geng et. al. (2018) to fit up to 6 parameters as seen in Figure 2. For this step, curated hourly meter data and output from each BEM are both fit to the tri-linear model shown in Equation 3 with physical constraints seen in the right hand side of Figure 2. Here T is average temperature over the time duration being used, P is average power over the time duration being used, T_{min} is the minimum temperature within the curated data, and T_{max} the maximum.



Parameter	Description	Constraints
a_1	Cooling system efficiency	$a_1 \geq 0$
a_2	Heating system efficiency	$a_2 \leq 0$
a_3	Economization system efficiency	$a_2 < a_3 < a_1$
b_0	Base load of non-thermally driven electricity use	$b_0 \geq 0$
c_1	Change point to active cooling	$c_1 > c_2 > T_{min}$
c_2	Change point from active heating	$c_2 < c_1 < T_{max}$

Figure 2 Regression parameters for classification of building thermal response.

$$P = \begin{cases} a_2(T - c_2) + b_0 & c_2 > T \\ a_3(T - c_2) + b_0 & c_1 > T \geq c_2 \\ a_1(T - c_1) + b_0 + a_3(c_1 - c_2) & c_1 \leq T \end{cases} \quad (3)$$

The $a_1, a_2, a_3, b_0, c_1,$ and c_2 parameters provide a gray-box type model that distinguishes important attributes of a building's performance as seen in the description column of Figure 2. It is proposed here that the residual between these parameters fit to the meter data and BEM model output provides an important additional metric for optimizing BEM fits. The G-14 measures Normalized Mean Bias Error (NMBE) and Coefficient of Variation for Root Mean Square Error (CVRMSE), are purely statistical measures for the 1st (average) and 2nd (standard deviation) goodness of fit between timeseries. On the other hand, the difference in a_1 between measured and modeled thermal performance is an indicator of whether cooling systems between the models are aligned to actual data with filtering on the noise typically exhibited by operations in a building. Similar analogies exist for the other parameters.

4. AutoTune-DOE2 calibration to G-14 + thermal sensitivity parameters: In preparation for this new analyses, a proprietary version of the public, open source Autotune Python library (New and Sanyal, 2015) has been created. This upgraded version of Autotune has a few notable changes, including the ability to run on any version of EnergyPlus. The original open source Autotune code is limited to EnergyPlus version 7.0. The authors also added the ability to run DOE2.2 (Winkelman et. al., 2015), which was critical to the work outlined in this paper. The major steps to get DOE2.2 working with Autotune were to create an input file (INP) parser and output file (SIM) parser. A custom recursive descent parser was developed to parse the INP file, which created an internal representation of the input file that Autotune can read, modify, and write back out to a file. The SIM file parser captures the necessary information from the SIM file to properly run Autotune as well as provide additional outputs for reporting at the end of the calibration. These changes allow Autotune to calibrate BEM for the two largest simulation engines, including recent versions. Also, the connection of AutoTune to DOE2.2 has been developed so that every calibration provides a detailed report that fully documents the associated optimization and changes to BEM making the effects of the auto-calibration fully transparent.

The parameters from Step 3 are planned to be interwoven with G-14 NMBE and CVRMSE to create a better solution. Our previous work has shown the benefits and cost savings associated with using auto-calibration for the SNL BEM fleet but has also shown that parameter variations tend to reach unacceptable levels in comparison to expected physical bounds (Villa et. al., 2019). With the addition of the parameters in Step 3, the genetic algorithms of AutoTune-DOE2.2 is grounded more soundly in the physics of the problem and can better penalize unrealistic variations. For this work, the genetic algorithm will be provided with an objective function that makes NMBE, CVRMSE, and the total residual between the parameters of Step 3 equally important. If a model cannot meet G-14 standards, it is rejected and must be manually investigated per the quality check procedure outlined by Villa et. al. (2019).

5. Multi-scenario calibrated BEM energy retrofit: This step is a repeat of Step 1 except that the BEM have undergone steps 2, 3, and 4 such that the accuracy to meter data has been increased. In Step 1, $\Delta_{11}$was calculated. In this step, the analyses from Step 1 and Step 5 are compared to determine a similar metric, Δ_{15}, that provides a second indication that focusses on whether the calibration procedure has changed the set of decisions D.

6. Calculate tradeoff metrics: This step is included as a place holder that emphasizes the need to interface to other analyses that are outside the bounds of the new energy retrofit assessment procedure being proposed as depicted at the bottom of Figure 1. Other competing objectives besides EE should be considered to achieve optimal resilience to climate and man-made threats. Also, many institutions are faced with financial decisions concerning whether to invest in clean generation via renewables or in EE for new and existing infrastructure. These issues are all related by complex cost/benefit relationships that have many parameters that are usually unknown. Even so, research is showing that EE and resilience are not always positively correlated and exclusion of cross issues can lead to suboptimal conclusions (Sun et al., 2020) that overlook the needs of a competing interest. The to-be-determined metrics for such cross cutting analysis can take the form of the Δ metrics presented here but with a different signal than energy such as thermal comfort, grid availability—the percent electric load served by Distributed Energy Resources (DER), carbon emissions avoided, and expected cost of associated solutions. The metrics for a wide range of scenarios could then be used to form pareto fronts of cost-metric tradeoffs.

7. Inform institutional decisions for investment: This step is the least analytical and the most difficult. The combined results of Step 6 must be able to be presented to decision makers such that a clear plan with associated level of confidence from the Δ_{15} assessment can be made. Work is needed to make the complex results understandable.

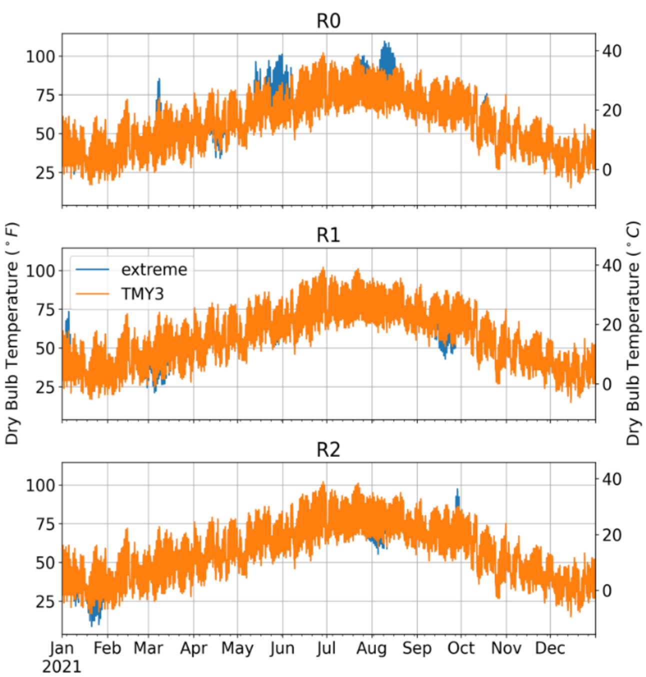
8. Verify energy savings via BEM and meter data: In accord with G-14, a post-mortem review of changes in energy performance must be conducted that shows the actual energy savings associated with combinations of energy retrofits minus weather related variations.

9. Evaluate process accuracy and 10. Update process, document and refine BEM: A final assessment of conclusion accuracy, Δ_{19} is calculated with the same procedure as used for Δ_{15} but using meter data from an energy analytics system and model results from Step 5 with updated weather data to adjust for weather differences. These final steps provide the empirical validation of the energy savings achieved.

RESULTS

The procedure outlined above is not complete because the pieces for its execution are currently in progress. This paper focusses on the New Mexico (NM) site with a demonstration of Step 1 with energy retrofit conclusions assessed by Δ_{11} through multiple historic weather years (2017-2020), TMY3, and three extreme event weather files generated by MEWS from the TMY3 data as seen in Figure 3. The "Insulate Roof" and "Exterior Insulated Finish System (EFIS)" energy retrofits as described in the IX user manual (Villa, 2016) were chosen to illustrate the process of calculating Δ_{11}. Ninety-six NM BEM have these retrofits. Each building was given an increase to an insulated roof R value of 40 hr·ft^2·^{o}F/BTU (7 m^2·^{o}C/W) from the previous state. Most buildings have R30 (5.3 m^2·^{o}C/W) but many have lower values like R19 (3.3 m^2·^{o}C/W) and R12 (2.1 m^2·^{o}C/W). For EFIS, insulation of the walls of the buildings were increased by an R value of 20 hr·ft^2·^{o}F/BTU (3.5 m^2·^{o}C/W). The level of wall insulation also varied across the buildings from 10-20 hr·ft^2·^{o}F/BTU (1.8-3.5 m^2·^{o}C/W). The output of the models was processed to calculate energy savings for electricity, natural gas, and total energy. Failed DOE-2 runs were removed from the results with no further investigation for this demonstration. Figure 4 and Table 1 provide a perspective of the results for the 192 BEM runs. Explicit building names are not included to obfusticate identification of proprietary information.

The demonstration of Step 1 with two energy retrofits and 96 BEM provides a good illustration of the helpful perspective provided by calculating Δ_{11}. The lower right corner of Figure 3 clearly depicts that cooling degree days (CDD) and heating degree days (HDD) vary significantly for Albuquerque and were unprecedentedly high for the baseline year 2020. The TMY3 weather is cooler than all of the historic years providing compelling evidence of a warmer climate in Albuquerque. These variations in CDD and HDD produce wide differences in energy savings as seen by the top 11 decisions for 2020 weather in Table 1. Less intuitive is the non-simple relationship between CDD, HDD, and the associated insulation retrofits. More insulation clearly saves energy for all the top choices but the amount of energy saved is not proportional to CDD and HDD. Figure 4 shows how different the energy savings can be for different weather. Δ_{11} is the ratio of energy savings at the current decision divided by total energy savings potential of the baseline 2020 year. The 2018 and 2019 results outperform 2020 slightly to decision number 46 while the rest of the results underperform and also drop sharply at decision 46. This sharp drop is questionable with respect to the DOE2.2 result which predicted zero energy savings for 2017, 2018, and 2019 and lesser though significant energy savings for the TMY3, R0, R1, and R2 scenarios. Flat regions of the Δ_{11} metric indicate agreement between all weather scenarios concerning what decision to make next. In this demonstration it is clear that decisions past #30 do not have a strong basis for implementation in the buildings due to uncertainty in the model results and insignificant energy savings. An EE decision maker can use these results to proceed to Step 2 of the procedure presented in this paper by ordering work to verify that the DOE2 inputs and modeling results for decision #1 in Table 1 are correct and to make this the highest priority for manual verification followed by decision #2 and so forth. In this case, the drop off in EE achieved per decision quickly drops an order of magnitude making the first few decisions the most critical.



Input	Value
Markov chain transition probability matrix	$\begin{bmatrix} 0.99 & 0.01 & 0.01 \\ 0.15 & 0.85 & 0.00 \\ 0.15 & 0.00 & 0.85 \end{bmatrix}$
Weather file	Albuquerque International Airport TMY3
Extreme heat lognormal inputs to produce $^\circ F \cdot hr/hr$ ($^\circ C \cdot hr/hr$)	μ = 1.800 (1.212), σ = 0.5 (0.5)
Extreme cold lognormal inputs to produce	μ = 1.000 (0.412), σ = 0.5 (0.5)
Random seed	434186856231

	CDD ($^\circ F \cdot day$)	HDD ($^\circ F \cdot day$)	CDD ($^\circ C \cdot day$)	HDD ($^\circ C \cdot day$)
2017	1491	-3353	828	-1863
2018	1696	-3840	942	-2133
2019	1485	-4235	825	-2353
2020	2336	-3205	1298	-1780
TMY3	1218	-4278	676	-2376
R0	1613	-4259	896	-2366
R1	1178	-4350	654	-2417
R2	1192	-4401	662	-2445

Figure 3 MEWS weather scenario output (left), inputs (upper right), and weather file degree days (lower right)

It is important to highlight that this demonstration used total energy (electricity + natural gas) as the metric for making decisions. Other alternatives can be used to calculate Δ metrics as well such as carbon avoided, total energy cost, percent availability of a microgrid during outage events (i.e. EE can increase the reliability of microgrids), thermal comfort during power outages, and combinations of these interrelated efficiency and resilience issues.

CONCLUSION

The procedure presented herein is still being executed but has been shown to have the potential to assess the certainty and successfulness of a systematic approach to energy retrofit decisions across a large stock of buildings owned by an institution. The variations seen in EE due to weather differences within the results clearly indicate that EE assessments

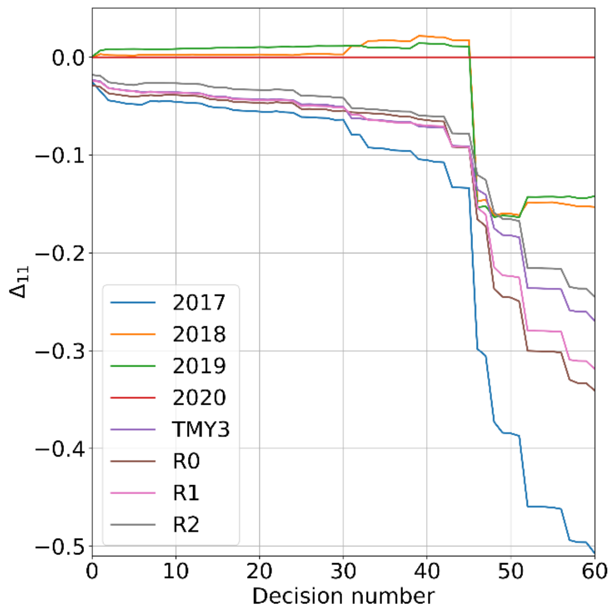


Figure 4 Δ_{11} for the first 60 decisions

must include as much historic weather data as available, climate change scenarios, and extreme event scenarios to understand whether one energy retrofit decision is likely to be better than another one for competing energy retrofit decisions. Also, institutional energy retrofit assessments need to interact with institutional sustainability, resilience, and cost assessments so that better informed decisions can be made. The Δ class of metrics proposed in this paper have been shown via the Δ_{11} demonstration to be useful for discerning whether EE decisions are robust on the basis of weather variations. Future work to complete the procedure will extend this to model stability through calculating Δ_{15} and to empirical validation through Δ_{19}. Only a data and modeling intensive approach like this one will provide a scientific basis to evaluate how well BEM and data driven institutional energy retrofit assessments guide decision makers to the best EE decisions.

ACKNOWLEDGMENTS

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Table 1 First 11 decisions of 192 total (96 Buildings x 2 energy retrofits)

	Description	Area (m2)	2017 (kWh)	2018 (kWh)	2019 (kWh)	2020 (kWh)	TMY3 (kWh)	R0 (kWh)	R1 (kWh)	R2 (kWh)
1	Building 1 EFIS	1.8e+03	5.0e+05	9.5e+05	9.7e+05	9.6e+05	5.4e+05	4.4e+05	5.3e+05	6.3e+05
2	Building 2 EFIS	2.6e+03	3.6e+05	5.3e+05	5.7e+05	4.8e+05	4.6e+05	4.6e+05	4.7e+05	4.7e+05
3	Building 3 EFIS	1.9e+03	1.3e+05	2.7e+05	3.1e+05	2.9e+05	1.7e+05	1.7e+05	1.8e+05	1.8e+05
4	Building 4 Insulate Roof	9.9e+02	2.1e+04	6.1e+04	6.5e+04	6.6e+04	2.8e+04	2.8e+04	2.9e+04	3.1e+04
5	Building 5 Insulate Roof	1.6e+03	3.3e+04	6.7e+04	7.0e+04	6.8e+04	4.4e+04	4.3e+04	4.3e+04	4.6e+04
6	Building 6 EFIS	1.3e+03	1.8e+04	3.2e+04	4.0e+04	3.8e+04	2.2e+04	1.4e+04	2.1e+04	2.0e+04
7	Building 1 Insulate Roof	1.8e+03	4.4e+04	6.7e+04	4.9e+04	5.1e+04	3.3e+04	6.6e+04	2.4e+04	8.2e+04
8	Building 7 EFIS	2.9e+03	1.2e+05	7.9e+04	7.5e+04	8.0e+04	8.5e+04	8.9e+04	8.8e+04	8.9e+04
9	Building 8 EFIS	1.2e+03	1.4e+04	2.9e+04	3.3e+04	3.1e+04	2.1e+04	1.8e+04	2.0e+04	2.2e+04
10	Building 9 EFIS	1.8e+03	5.2e+04	4.6e+04	4.8e+04	4.4e+04	4.1e+04	5.8e+04	4.4e+04	4.0e+04
11	Building 5 EFIS	1.6e+03	2.3e+04	3.8e+04	4.3e+04	3.8e+04	3.4e+04	3.3e+04	3.3e+04	3.6e+04

	Description	Area (ft2)	2017 (BTU)	2018 (BTU)	2019 (BTU)	2020 (BTU)	TMY3 (BTU)	R0 (BTU)	R1 (BTU)	R2 (BTU)
1	Building 1 EFIS	1.9e+04	1.7e+09	3.3e+09	3.3e+09	3.3e+09	1.8e+09	1.5e+09	1.8e+09	2.2e+09
2	Building 2 EFIS	2.8e+04	1.2e+09	1.8e+09	1.9e+09	1.7e+09	1.6e+09	1.6e+09	1.6e+09	1.6e+09
3	Building 3 EFIS	2.0e+04	4.3e+08	9.3e+08	1.1e+09	9.9e+08	5.8e+08	6.0e+08	6.0e+08	6.0e+08
4	Building 4 Insulate Roof	1.1e+04	7.2e+07	2.1e+08	2.2e+08	2.3e+08	9.7e+07	9.6e+07	9.9e+07	1.0e+08
5	Building 5 Insulate Roof	1.8e+04	1.1e+08	2.3e+08	2.4e+08	2.3e+08	1.5e+08	1.5e+08	1.5e+08	1.6e+08
6	Building 6 EFIS	1.4e+04	6.2e+07	1.1e+08	1.3e+08	1.3e+08	7.6e+07	4.9e+07	7.3e+07	6.8e+07
7	Building 1 Insulate Roof	1.9e+04	1.5e+08	2.3e+08	1.7e+08	1.7e+08	1.1e+08	2.3e+08	8.1e+07	2.8e+08
8	Building 7 EFIS	3.1e+04	4.2e+08	2.7e+08	2.6e+08	2.7e+08	2.9e+08	3.0e+08	3.0e+08	3.0e+08
9	Building 8 EFIS	1.3e+04	4.8e+07	9.8e+07	1.1e+08	1.0e+08	7.2e+07	6.3e+07	6.9e+07	7.4e+07
10	Building 9 EFIS	1.9e+04	1.8e+08	1.6e+08	1.6e+08	1.5e+08	1.4e+08	2.0e+08	1.5e+08	1.4e+08
11	Building 5 EFIS	1.8e+04	8.0e+07	1.3e+08	1.5e+08	1.3e+08	1.2e+08	1.1e+08	1.1e+08	1.2e+08

DISCLAIMER

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