Targeting Building Energy Efficiency Opportunities: An Open-source Analytical & Benchmarking Tool

Han Li
Associate Member ASHRAE

Carolyn Szum

Sara Lisauskas

Ahmed Behkit, PhD

Clay Nesler
Member ASHRAE

Steven C. Snyder, PE
Member ASHRAE

ABSTRACT

In general, U.S. municipal and state benchmarking and disclosure programs have proven effective in encouraging the development of a strong market for building energy efficiency. Available data for select cities in the United States shows that energy savings per unit of floor space for these programs range between 6% and 8% over a two-year period (Pan et al. 2016, 10). Despite the merit of these programs, however, several shortcomings have been identified, including the need for: (1) more efficient and cost-effective assessment of buildings for retrofit opportunities, and (2) greater standardization and automation of the benchmarking and disclosure processes. To address these shortcomings, Lawrence Berkeley National Laboratory, Johnson Controls, and ICF International are developing a free, on-line, open-source, building energy analysis and retrofit targeting tool. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Inverse Modeling Toolkit (IMT), and Johnson Controls' LEAN Energy Analysis, serve as the technical basis for the tool, which will automatically regress monthly energy usage versus ambient temperature; compare model coefficients to quantify energy and cost-savings potential; and analyze model coefficients to identify energy conservation measures (operational or equipment) for a single building or portfolio. The tool is unique in its open-source, modular, online, and 100% automated format. The source code will be published on GitHub and thus available for use and modification by the buildings community. This paper discusses: (1) the market's need for the tool; (2) the tool's analytic methodology, based on a combination of ASHRAE's IMT and Johnson Controls' LEAN Energy Analysis; (3) tool innovations with industry impact, including a fully automated approach for building change-point selection; (4) and the outcomes of early pilot applications of the tool among 36 hotel buildings. Future work and potential applications are also discussed.

INTRODUCTION

In today's buildings marketplace, there are hundreds of billions of dollars of untapped energy efficiency (EE) opportunities (SEE Action 2012; EDF 2016). According to the U.S. Department of Energy (DOE) Building Technologies Office (BTO), by 2030, at least 60% of commercial floor space in the United States will have been built before 2014 and be in need of retrofit (U.S. DOE EERE 2016). In other major markets, such as China, almost 3 billion square meters of building floor space will have been built before 2010 and require retrofit (Zhou et al. 2016).

Han Li is a scientific engineering associate, **Carolyn Szum** is a program manager with the Energy Technologies Area at Lawrence Berkeley National Laboratory, Berkeley, CA. **Sara Lisauskas** is a principal, **Ahmed Behkit** is a senior associate with ICF International, Fairfax, VA. **Clay Nesler** is vice president of Global Sustainability and Industry Initiatives, **Steve Snyder** is an engineer at Johnson Controls, Washington, DC.

Building energy performance assessment is usually a prerequisite for capturing untapped EE opportunities. Building energy assessment methods can be classified into three main categories (Zhao and Magoulès 2012): (1) first-principle method, which uses physical principles to calculate the thermal properties and energy consumption in buildings; (2) data-driven method, which uses measured data and statistical and/or machine learning models to predict building energy performance; and (3) hybrid method, which uses measured data to improve the accuracy of first-principle calculations. Although the physical principle-based approaches are usually effective and accurate, the requirements for detailed input data and complicated modeling processes make them cost-inefficient and time-consuming (Server et al. 2011; Lee et al. 2015). A review of the 18 commonly-used building energy performance assessment tools shows that: (1) tools developed in the private sector usually offer no free public access, and (2) tools that are freely available often suffer from complex data input and simulation run time (Lee et al. 2015).

Therefore, the gap in the market is clear – a public access, data-driven tool requiring minimal inputs and short run time to benchmark against peers, quantify energy- and cost-savings, and recommend EE improvements. At the same time that this gap exists, in recent years, jurisdictions in the United States and China have begun implementing building energy performance benchmarking and disclosure policies (Burr et al. 2013). Today, there are approximately 27 jurisdictions in the United States and several in China that mandate benchmarking and disclosure (BuildingRating 2018). The rationale is that publicizing building energy performance provides valuable information to market actors, allowing them to incorporate the cost of building operation when making purchase, lease, and financing decisions, thereby spurring a stronger market for EE (Palmer and Walls 2015).

The data suggests that these policies are effective. For instance, available data for select cities in the United States shows that energy savings per unit of floor space for these programs range from 6% to 8% over a two-year period (Pan et al. 2016, 10). Yet, despite the success of these programs, shortcomings have been identified, including the need for: (1) greater standardization and automation of the benchmarking and disclosure processes, and (2) more efficient and cost-effective assessment of buildings for retrofit opportunities (Dunsky et al. 2009; Palmer and Walls 2015; Pan et al. 2016; Todd et al. 2012; Hsu 2013, 266; Kontokosta 2013; Pan et al. 2014).

To simultaneously address market gaps in data-driven, public-access building energy analysis tools and the need for more efficient and cost-effective assessment of buildings and greater standardization and automation in U.S. and Chinese benchmarking and disclosure programs, Lawrence Berkeley National Laboratory (LBNL) is partnering with Johnson Controls and ICF International (ICF) to develop an open-source, empirical data-driven, virtual building energy analysis and retrofit targeting tool (hereafter referred to as the "open-source tool" or "open-source EE targeting tool.") The open-source tool will provide a fully-automated, "no-cost/no-touch" approach to screen large volumes of buildings for operational improvement and equipment upgrade opportunities and quantify associated potential energy and cost savings. The tool is being developed under the U.S.-China Clean Energy Research Center Building Energy Efficiency (CERC-BEE) program and is intended to accelerate commercial building retrofit activity in both the United States and China. It will provide analysis for different building types, beginning with hotels, commercial offices, hospital, and university campuses, and gradually expand to other space types. Its key features are:

(1) **Data-driven:** the tool requires simple data inputs including basic building information and energy consumption data.

(2) **Open-source:** developers can adopt, re-develop, or re-distribute the tool freely under an open-source license.

(3) **Modular:** tool contains individual modules that can be used as-is or customized for specific purposes.

(4) **Automatic:** the tool automatically processes data, fits inverse-models, and gives efficiency recommendations.

(5) **Cross-platform:** the tool can be easily deployed on different platforms including cloud computing platforms.

The remainder of this paper provides an introduction to the open-source EE targeting tool's analytical methodology and software architecture. It also presents a preliminary comparison between the open-source tool and Johnson Controls' LEAN Energy Analysis (on which it is based), which indicates the general accuracy and future improvement opportunities of the open-source tool. Finally, potential applications and future work are discussed.

NEW OPEN-SOURCE TOOL

Tool Methodology

The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Inverse Modeling Toolkit (IMT), developed under project RP-1050 (Kissock et al. 2002; Kissock et al. 2003; Haberl et al. 2003), and Johnson Controls' LEAN Energy Analysis (Donnelly et al. 2013; Snyder 2016), serve as the technical basis for the open-source EE targeting tool. Previous research (e.g., Kissock and Mulqueen 2008; Abels et al. 2011; and Server et al. 2011) introduced Lean Energy Analysis for buildings (an allusion to Lean Manufacturing) which utilizes a combination of statistical modeling and understanding of the behavior of buildings to systematically identify EE opportunities in buildings (Kissock and Mulqueen 2008; Abels et al. 2011; Server et al. 2011). Johnson Controls' LEAN Energy Analysis is an enhancement of this previous work in that it introduced robust benchmarking approaches and extended the physical interpretation of the model coefficients into identifying 14 EE measures for commercial buildings (Donnelly et al. 2013; Snyder 2016). The open-source EE targeting tool presented here builds on the ASHRAE IMT and Johnson Controls' LEAN Energy Analysis to automatically regress commercial building monthly energy usage versus ambient temperature; compare inverse model coefficients to identify EE measures (operational or equipment); and analyze inverse model coefficients to quantify energy and cost savings potential for a single building or portfolio (Snyder 2016). Figure 1 below shows the workflow of the open-source EE targeting tool.

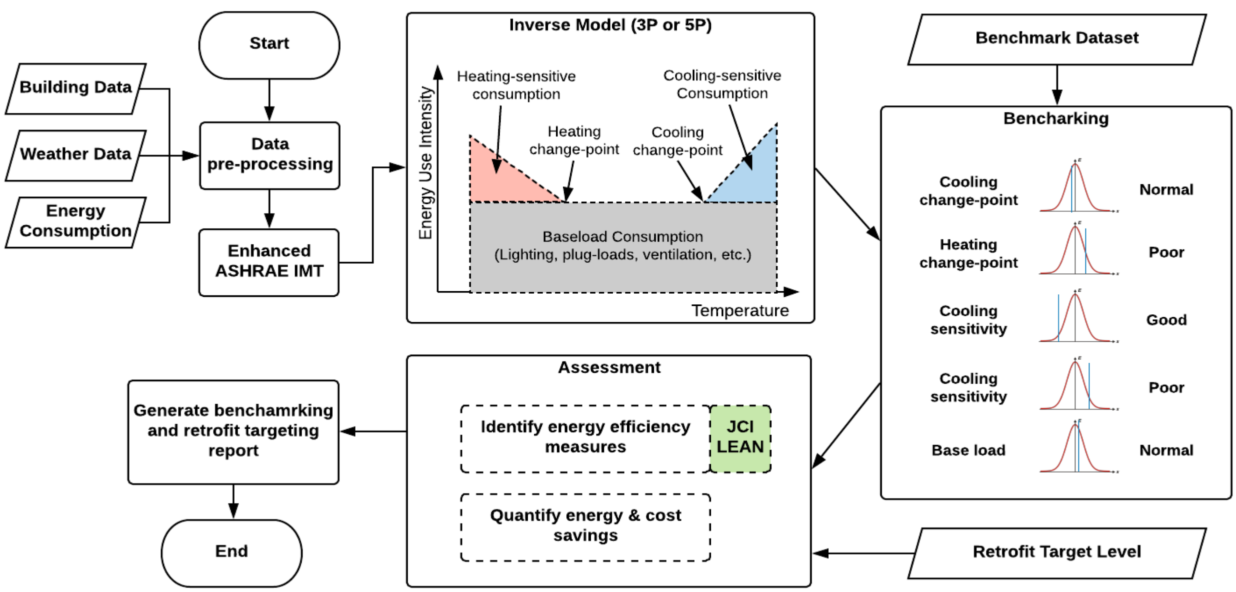

Figure 1. Workflow of the open-source EE targeting tool

As shown in the EE targeting tool workflow chart above, the tool starts with basic building information, raw utility bill data, and weather data inputs. Further details are described in Table 1 below. The tool handles the raw inputs to prepare the data for the inverse modeling. Then a change-point model is fitted, with a three-parameter (3P) model used for fuels that provide only heating or cooling, and a five-parameter (5P) model used for fuels that provide both heating and cooling. The inverse model coefficients for the building being analyzed are then compared to benchmarking statistics from a reference dataset to assess the performance of the building. Next, the tool picks the EE measures and estimates the energy and cost savings for the building based on the benchmarking results and user-selected retrofit target level (see descriptions in the software architecture section). Finally, a report is generated to summarize the building energy consumption, benchmarking results, EE recommendations, and energy- and cost-savings potential. The software architecture and the individual module functionality of the tool are summarized in the following sub-section.

Software Architecture

The tool is composed of three parts – (1) data collection forms; (2) Python-based data processing, inverse modeling, and benchmarking engine; and (3) analytics and reporting. The data collection form provides a template for the required data and its format. Table 1 shows the summary of the required input data.

Table 1. Required Data for the EE Targeting Tool

Name	Type	Format / Unit	Purpose
Building address	Necessary	Minimum: city name	Selecting weather data
Building type	Necessary	Primary and secondary space type	Comparing to peers of the same building type
Gross floor area	Necessary	Square meters	Calculating energy use intensity
Primary cooling fuel	Optional	Electric / Fossil Fuel	Facilitating retrofit assessment
Primary heating fuel	Optional		Facilitating retrofit assessment
Electric utility bills (usage/cost)	Necessary (if electricity used at property)	12-36 months of energy usage/cost and start-/end-dates for monthly utility billing periods	Fitting the change-point models
Fossil fuel utility bills (usage/cost)	Necessary (if fossil fuel used at property)		

For the analytical engine, the open-source EE targeting tool implements an object-oriented programming (OOP) paradigm which has the advantages of code reuse and recycling, data encapsulation, and software maintenance. The tool consists of eight modules (i.e., Python class). Each module has its data fields and behaviors. Figure 2 shows the unified modeling language (UML) diagram of the tool.

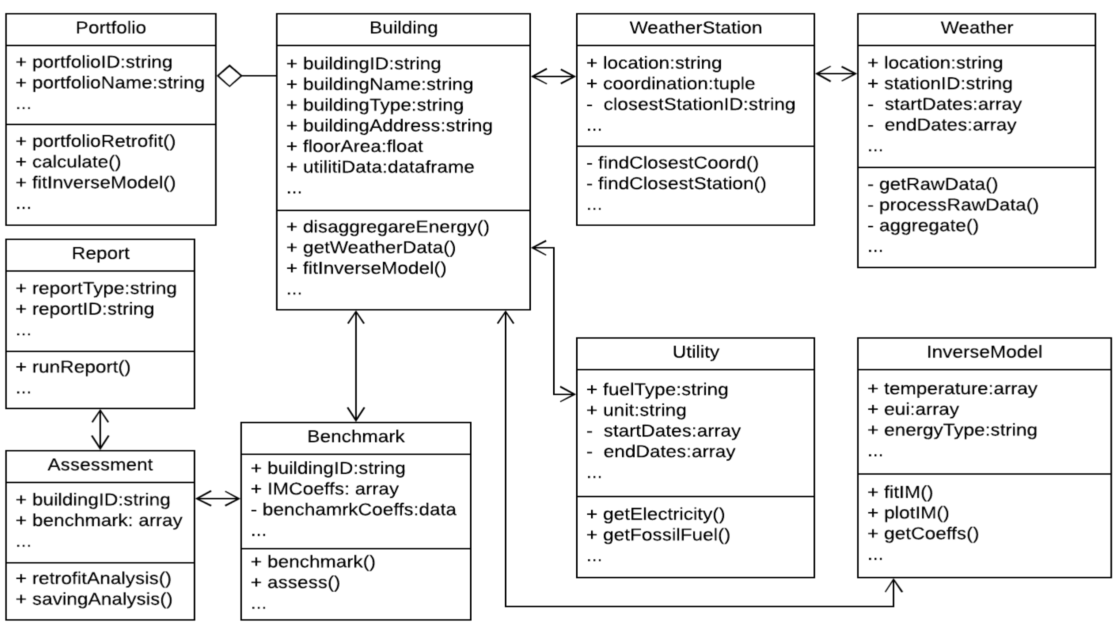

Figure 2. UML diagram of the EE targeting tool

Building. The Building class is used to store information for a particular building (building type, address, and monthly energy usage and cost data from utility bills) for inverse modeling and benchmarking. The geocoding function automatically generates the geocoded address and the building's latitude and longitude based on user-entered address.

Portfolio. In addition to individual buildings, the tool has a Portfolio class which allows users to add, update, or delete individual building(s) from a portfolio. It also provides a ranking of buildings across the portfolio based on their energy- and cost-saving potentials (high-savings potential to low-savings potential); the average building energy- and cost-performance of the portfolio; and the total energy- and cost-savings potential for the portfolio.

Utility. The Utility class handles the energy consumption and cost data processing. After reading the energy consumption and cost raw data collected from the data input forms, this class cleans up the data, converts the units of electricity and fossil fuel consumption to kWh, and combines different types of fossil fuel consumption.

WeatherStation. The tool allows users to use pre-downloaded weather files or on-line historical weather data from National Oceanic and Atmospheric Administration (NOAA) for the inverse modeling. The WeatherStation class searches for the closest weather station of the entered building address based on the distance calculated with the latitude and longitude of the building and a list of available weather stations.

Weather. The Weather class helps to download weather files from the specified weather station and prepares the data for inverse modeling. Utility bill data often doesn't align with calendar months. This class automatically processes the sub-daily weather files to aggregate and synchronize them to the same time intervals as the utility bill data.

InverseModel. The InverseModel class is built upon the ASHRAE IMT which fits the least squares piece-wise linear regression models with outdoor air dry-bulb temperature and building energy consumption data. The tool automatically searches the optimal change-point ranges and conducts statistical tests to reject insignificant heating or cooling sensitivities. The outputs of the InverseModel class are the piece-wise linear regression model coefficients including: (1) the cooling and/or heating change-points (the balance point temperatures for the building), (2) cooling and/or heating sensitivities (slopes), and (3) the baseload consumption. Research has shown that the coefficients of change-point regression models of building energy usage have physical meaning, i.e., they are algebraic combinations of building parameters (derived using an energy balance on the building) (Kissock and Mulqueen 2008). For example, the baseload coefficient may be interpreted as the weather-independent load of a building and is a function of internal loads (e.g., lights, plug loads). A high baseload for a building may indicate a need for a lighting retrofit (Kissock and Mulqueen 2008; Snyder 2016).

Benchmark. The Benchmark class takes the inverse model coefficients of an individual building generated from the InverseModel class and compares them to the benchmarking statistics (robust mean and standard deviation of the coefficients from a larger number of buildings with similar functions). It then compares the values of the coefficients of the individual building being analyzed to the benchmark statistics. A coefficient can be classified as "inefficient", "typical", or "efficient" depending on how it compares to the benchmark statistics. Generally, lower values mean better performance, except for the cooling change-point where higher value means better performance (Snyder 2016).

Assessment. After the benchmarking, the Assessment class identifies the EE upgrade measure(s) that are recommended for an individual building, and quantifies the potential energy and cost savings. The target model coefficients need to be established first. The tool allows three levels of target values -- "conservative", "nominal", and "aggressive". A "conservative" target means the model coefficient is one standard deviation worse than the benchmark dataset mean. A "nominal" target means the model coefficient is the same as the benchmarking dataset mean. An "aggressive" target means the model coefficient is ½ standard deviation better than the benchmark dataset mean. The module selects the potential EE measure(s) for the building being analyzed based on the pattern of "efficient" and "inefficient" coefficients for the building compared to the target levels from the benchmark statistics dataset (Snyder 2016). Next, the tool re-runs the model with each model coefficient moved to the target coefficient level (only if previously worse than the target) to estimate the energy consumption with the improvements. Finally, energy savings are quantified by comparing the current consumption and estimated consumption with modified coefficients.

Report. The report class is responsible for the post-processing and data visualization. It collects and organizes the outputs from the previously-described modules such as the building information, change-point model coefficients, recommended EE measures, and estimated energy- and cost-savings. The Report module can compile HTML and PDF reports, which can be adopted by web-based or standalone applications.

PRELIMINARY TEST

This section presents the preliminary test of the open-source EE targeting tool. The goal of the test was to evaluate how accurate the open-source tool is in fitting the change-point models, benchmarking, and identifying EE improvement opportunities (operational and equipment) under the fully automatic condition. The change-point model coefficients and improvement measures suggested by Johnson Controls' LEAN Energy Analysis (which is semi-automated with manual adjustments) and the new open-source EE targeting tool (which is fully automated) are compared and analyzed. Data for a collection of 36 hotel buildings in China was used, including outdoor air temperature, electricity use intensity, and fossil fuel use intensity. Table 2 summarizes the data used in the test.

Table 2. Summary of the validation data

Item	Number
Number of building	36
Buildings with electricity consumption data available	36
Buildings with fossil fuel consumption data available	33
Average number of electricity billing periods	17.3
Average number of fossil fuel billing periods	16.9

The test was conducted by comparing the open-source EE targeting tool with Johnson Controls' LEAN Energy Analysis in terms of the change-point models and recommended EE measures. Figure 3 shows the comparison between the five change-point model coefficients generated by LEAN and the new open-source tool. The horizontal and vertical axes stand for the coefficient from the new open-source tool and LEAN, respectively. Each dot represents a building. A shorter distance of a point to the diagonal line means the better agreement of the two tools on that coefficient.

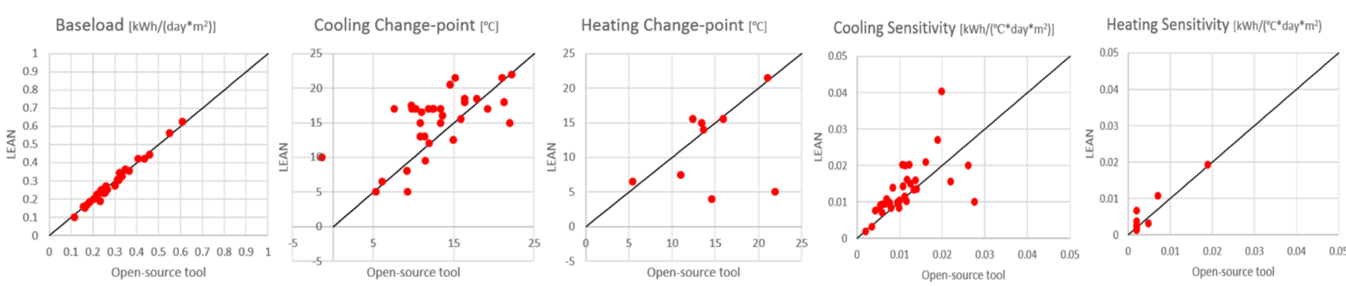

Figure 3. Change-point model coefficients comparisons between LEAN and the new open-source EE targeting tool

It can be seen that the two tools produce similar values for the baseload and heating sensitivities of the buildings. For cooling sensitivity, the two tools produce similar results when the value is below 0.02 kWh/(ºC·day·m²). For cooling change-points, the estimations from LEAN tends to be higher than the new open-source tool. The estimations of the heating change-points of some buildings tends to be lower than the estimations by the new open-source tool.

Another important comparison is the EE measure recommendations. The EE measures are selected based on the model coefficients and the benchmarking settings including the benchmarking statistics and upgrade target levels. For the comparison, the same benchmarking dataset (the set of 36 hotels) and upgrade target levels (set to be "nominal") were selected for both tools. For each building, the two tools picked a combination of EE measures from a total of 14 available measures. Figure 4 below shows a comparison of the results using cosine similarity to quantify the similarity of EE measure recommendations. A pair of vectors of EE measures is constructed for each building. It is marked as one when the EE measure at the corresponding position in the vector is picked. Otherwise the value for that EE measure is marked as zero.

Building	A1		A2		A3		A4		A5		A6		A7		A8		A9		A10		A11		A12	
Tool (1 -- LEAN, 2 -- New tool)	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Increase Cooling Setpoints		X			X								X	X				X	X	X				
Decrease Heating Setpoints	X	X							X	X			X	X	X						X	X		X
Reduce Equipment Schedules	X	X			X	X			X	X	X		X	X	X	X	X	X	X	X	X	X		X
Decrease Ventilation	X	X								X									X	X	X	X	X	X
Eliminate Any Electric Heating																			X	X				
Decrease Infiltration	X	X								X									X	X	X	X	X	X
Reduce Lighting Load	X	X			X	X					X		X	X	X	X	X	X	X	X	X	X		
Reduce Plug Loads	X	X			X	X					X		X	X	X	X	X	X	X	X	X	X		
Add/Fix Economizers		X			X								X	X				X	X	X				
Increase Cooling System Efficiency	X											X	X	X	X	X	X	X	X	X	X	X	X	X
Increase Heating System Efficiency	X	X	X	X						X							X	X	X	X	X	X	X	X
Add Wall/Ceiling Insulation		X								X									X	X	X	X	X	X
Upgrade Windows																			X	X				
Check Fossil Baseload	X	X									X		X	X					X					
Cosine similarity	0.8		1		0.8		NA		0.6		0		1		0.9		0.8		1		1		0.8	
Average cosine similarity	0.828																							

Building	A13		A14		A15		A16		A17		A18		A19		A20		A21		A22		A23		A24	
Tool (1 -- LEAN, 2 -- New tool)	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Increase Cooling Setpoints		X							X		X	X	X	X	X	X						X	X	X
Decrease Heating Setpoints		X					X				X		X	X						X	X	X		
Reduce Equipment Schedules		X					X		X	X	X	X	X	X	X	X		X		X	X	X	X	X
Decrease Ventilation		X					X	X					X	X					X	X	X	X		
Eliminate Any Electric Heating																			X					
Decrease Infiltration		X					X	X					X	X					X	X	X	X		
Reduce Lighting Load									X	X	X	X	X	X				X					X	X
Reduce Plug Loads									X	X	X	X	X	X				X					X	X
Add/Fix Economizers		X							X		X	X	X	X	X	X						X	X	X
Increase Cooling System Efficiency							X	X	X	X	X	X			X		X	X	X	X	X	X	X	X
Increase Heating System Efficiency	X	X	X	X			X	X				X	X	X					X	X	X	X	X	X
Add Wall/Ceiling Insulation		X					X	X					X	X					X	X	X	X		
Upgrade Windows																						X		
Check Fossil Baseload			X	X					X			X	X	X			X	X			X	X	X	X
Cosine similarity	0.4		1		NA		0.8		0.8		0.8		1		0.9		0.6		0.8		0.9		1	

Building	A25		A26		A27		A28		A29		A30		A31		A32		A33		A34		A35		A36	
Tool (1 -- LEAN, 2 -- New tool)	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Increase Cooling Setpoints	X	X	X	X	X	X			X	X	X	X	X	X	X	X	X	X	X	X			X	X
Decrease Heating Setpoints			X	X	X				X	X		X					X			X	X	X		
Reduce Equipment Schedules	X	X	X	X	X	X			X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Decrease Ventilation			X	X					X	X		X								X	X	X		X
Eliminate Any Electric Heating																								
Decrease Infiltration			X	X					X	X		X								X	X	X		X
Reduce Lighting Load					X	X					X	X	X	X					X	X			X	X
Reduce Plug Loads					X	X					X	X	X	X					X	X			X	X
Add/Fix Economizers	X	X	X	X	X	X			X	X	X	X	X	X	X	X	X	X	X	X			X	X
Increase Cooling System Efficiency	X	X	X		X	X						X				X					X			X
Increase Heating System Efficiency	X	X	X	X			X	X	X	X	X	X							X	X	X	X	X	X
Add Wall/Ceiling Insulation			X	X					X	X		X								X	X	X		X
Upgrade Windows																								
Check Fossil Baseload	X	X	X	X		X			X	X					X		X	X	X					X
Cosine similarity	1		0.9		0.9		1		1		0.7		1		0.8		0.9		0.7		0.9		0.7	

Figure 4. EE measure recommendations comparison

From the comparison, excluding the two buildings (A4 and A15) where no EE measure is recommended, 11 of the total 34 buildings have the exact same EE measure recommended from the two tools. And 27 of the total 34 buildings have the cosine similarity greater than 0.8. The average cosine similarity of the 34 buildings is 0.828, which means the new open-source EE targeting tool has achieved a relatively high agreement with LEAN.

The comparison of change-point model coefficients shows that the initial version of the new open-source tool is producing similar results to the Johnson Controls LEAN Energy Analysis, but differences between the two exist. The comparison of EE measure recommendations shows that differences in the model coefficients directly translate to differences in recommended EE improvements. It is important to select the right change-point model coefficients in order to have confidence in the resulting EE recommendations and savings estimates. The reason why the model coefficients for some buildings vary between the two tools is based on the selection criteria for the inverse model. One factor in selecting a model is statistical measures. The table below shows a comparison of the standard error and R-squared value of the change-point model for each building.

Table 3. Comparison of the Change-point Model Statistics

	LEAN Energy Analysis	New Open-source EE Targeting Tool
Average Standard Error	0.031	0.027
Average R-squared Value	0.667	0.735

Looking just at these statistical measures, the initial version of the open-source EE targeting tool produces better results for both the average standard errors and R-squared values. However, statistical performance is not the only factor that should be considered. Additional restraints (e.g., limitations on change-point boundaries or slopes) can be added during the model fitting process to ensure that results reflect what would be expected based on a physical interpretation of the data. It is also important to consider assumptions that may be applied in cases where the data is limited and how to account for outliers in the raw data. Some of these non-statistical criteria have been incorporated into the existing open-source EE targeting tool, but additional work is necessary to refine the model selection criteria. Initial steps will be taken prior to release of the open-source tool on GitHub. However, the open-source nature of EE targeting tool will allow others to propose additional refinements once the initial version of the tool is public.

DISCUSSION

The lack of public-access, data-driven tools requiring minimal inputs and short run time to benchmark against peers, quantify energy-/cost-savings, and recommend EE improvements is one of the main barriers to capturing untapped EE opportunities in the United States and China. To fill the gap, and simultaneously address the need for automated, cost-effective, and standardized EE assessment of large volumes of buildings in U.S. and Chinese benchmarking and disclosure programs, an automatic, open-source, virtual building EE targeting tool is being developed. The tool requires very simple building data inputs; minimum manual work; and provides fast, "no-cost/no-touch" building EE upgrade targeting (equipment and operations) with an acceptable accuracy. It implements ASHRAE IMT to find piece-wise linear regression models between building energy consumption and outdoor air temperature. The model coefficients of each individual building are then benchmarked against the coefficients of buildings in the same space type category. Johnson Controls' LEAN Energy Analysis is used to identify the EE measures for the building. Finally, the potential energy and cost savings are estimated with the suggested EE measures. The preliminary open-source tool test shows that the tool produces similar change-point models to Johnson Controls' LEAN Energy Analysis, but additional refinements are necessary to improve the results for the EE measure recommendations. In the next phase of the project, tool refinements will be applied and large amounts of real building data will be assessed.

The tool being developed in this project is at its preliminary stage. Once finalized, it will be utilized to enhance China's Building Energy Saving Tool (BEST). In the United States, it will be available on GitHub for use and further development under an open-source software license. It will be most effective and user-friendly if integrated into existing tools that leverage building energy data. Targeted applications include enhancements to the U.S. DOE ecosystem of tools (e.g., OpenStudio); use in market transformation programs such as the World Resources Institute (WRI) Building Efficiency Accelerator (BEA) and U.S. state/municipal benchmarking/disclosure programs; and/or integration with ENERGY STAR Portfolio Manager®. Opportunities exist for further development and broader applications as well. For instance, accurately quantifying energy savings is critical in measurement and verification (M&V) of building retrofit projects. Energy consumption before- and after- retrofit often needs to be weather-normalized before calculating the savings. The weather processing and inverse modeling modules of the tool can be used to weather-normalize building energy consumption pre-and post-retrofit, which aligns with International Performance Measurement & Verification Protocol (IPMVP) Option C. The tool can also support model calibration for whole-building simulations. It can automatically break down the total building energy consumption into weather-dependent pieces and non-weather-dependent pieces, which can provide more insight into the building's heating, cooling, and baseload consumption as compared to the traditional whole-building energy consumption-based approach. As the tool continues to evolve, opportunities to expand to new property types, mixed-used property types, and to disaggregate energy- and cost-savings by individual EE measures will be explored.

ACKNOWLEDGMENTS

This project is supported by U.S. Department of Energy (Contract No. DE-AC02-05CH11231) and Johnson Controls under the U.S.-China Clean Energy Research Center for Building Energy Efficiency (CERC-BEE) program.

REFERENCES

Abels, B., F. Server, J.K. Kissock, and D. Ayele. 2011. Understanding Industrial Energy Use through Lean Energy Analysis. Mechanical and Aerospace Engineering Faculty Publications. Paper 164. http://ecommons.udayton.edu/mee_fac_pub/164

BuildingRating. 2018. "U.S. Commercial Building Policy Comparison Matrix." Institute for Market Transformation, December 20. http://www.buildingrating.org/graphic/us-commercial-building-policy-comparison-matrix.

Burr, A., C. Majersik, and N. Zigelbaum. 2013. The Future of Building Energy Rating and Disclosure Mandates: What Europe Can Learn from the United States. Washington, DC: Institute for Market Transformation and Natural Resources Defence Council.

Donnelly, M., J. Krummer, and K. Drees. 2013. LEAN Energy Analysis: Using Regression Analysis to Assess Building Energy Performance. Washington, DC: Johnson Controls.

Dunsky, P., J. Lindberg, E. Piyalé-Sheard, and R. Faesy. 2009. Valuing Building Energy Efficiency Through Disclosure and Upgrade Policies: A Roadmap for the Northeast U.S. Massachusetts, U.S.: Northeast Energy Efficiency Partnerships.

Environmental Defense Fund (EDF). 2016. "ICP Europe Launches Investor Network, Aims to Boost Investment in Energy Efficiency by €1 Billion." https://www.edf.org/media/icp-europe-launches-investor-network-aims-boost-investment-energy-efficiency-eu1-billion

Haberl, J.S., A. Sreshthaputra, D. Claridge, and J.K. Kissock. 2003. "Inverse Modeling Toolkit: Application and Testing." ASHRAE Transactions, Vol. 109: 435-448.

Hsu, D. 2013. "How Much Information Disclosure of Building Energy Performance is Necessary." Energy Policy 64: 263-272.

Kissock J.K., J.S. Haberl, D. E. Claridge. 2002. Development of a Toolkit for Calculating Linear, Change-point Linear and Multiple- Linear Inverse Building Energy Analysis Models. Dayton, OH: University of Dayton, Department of Mechanical and College Station, Texas: Aerospace Engineering and Energy Systems Laboratory Texas Engineering Experiment Station Texas A&M University System.

Kissock J.K., J.S. Haberl and D. E. Claridge. 2003. Inverse Modeling Toolkit: Numerical Algorithms. American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Transactions, Vol. 109, Part 2.

Kissock, J.K. and S. Mulqueen. 2008. Targeting Energy Efficiency in Commercial Buildings Using Advanced Billing Analysis. 2008 ACEEE Summer Study on Energy Efficiency in Buildings. August 17-22, Pacific Grove, California.

Kontokosta, C. 2013. "Energy Disclosure, Market Behavior, and the Building Data Ecosystem. Annals of the New York Academy of Science 1295: 34–43.

Lee, S.H., T. Hong, M. Piette. 2015, S. Taylor-Lange. "Energy Retrofit Analysis Toolkits for Commercial Buildings: A Review." Energy 89: 1087-1100.

Palmer, K. and M. Walls. 2015. Discussion Paper: Can Benchmarking and Disclosure Laws Provide Incentives for Energy Efficiency Improvement in Buildings. Washington, DC: Resources for the Future.

Pan, Z., J. Qian, C. Cui, and H. Firestone. 2014. Benchmarking and Disclosure for Building Energy Efficiency: Insights from New York and Other International Cities. Beijing, China: Natural Resources Defense Council.

Pan, Z., J. Qian, Y. Wang, S. Yiyang, L. Pike, X. Zhou, and Y. Zheng. "Feasibility Study on Building Energy Performance Benchmarking and Disclosure in China." Unpublished report, last modified December 16, 2016. Microsoft Word file.

Server, F., K. Kissock, D. Brown and S. Mulqueen. 2011. Estimating Industrial Building Energy Savings using Inverse Simulation. ASHRAE Transactions, Volume 117, Part 1: 348-355.

Snyder, S. 2016. "Lean Energy Analysis (LEAN)." Unpublished report, last modified October 2016. Microsoft Word file.

State and Local Energy Efficiency (SEE) Action Network. 2012. "Fact Sheet." https://unfccc.int/files/documentation/submissions_from_parties/adp/application/pdf/see_action_network_-_the_state_and_local_energy_efficiency_action_network._submitted_by_the_u.s..pdf

Todd, A., E. Stuart, S. Schiller, and C. Goldman. 2012. Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations. Washington, DC: The State and Local Energy Efficiency Action Network (SEE Action).

U.S. DOE Office of Energy Efficiency and Renewable Energy (EERE). 2016. "Building Technologies Office (BTO) Multi-year Program Plan." https://www.energy.gov/eere/buildings/downloads/multi-year-program-plan

Zhao, Hai Xiang, and Frédéric Magoulès. 2012. "A Review on the Prediction of Building Energy Consumption." Renewable and Sustainable Energy Reviews 16 (6). Elsevier Ltd: 3586–92. https://doi.org/10.1016/j.rser.2012.02.049.

Zhou, N., F. Wei, N. Khanna, C. Szum, Y. Wu, J. Hou, Y. Zhou, and L. Xie. 2016. "50/50 – Accelerating Deep Commercial Building Energy Retrofits in Cities in China." Unpublished proposal, last modified June 19, 2016. Microsoft Word file.