TA-23-C067

An Energy Consumption Intensity Ranking System for Rapid Energy Efficiency Evaluation of a Cluster of Commercial Buildings

Aditya Ramnarayan *Student Member ASHRAE*   **Andres Sarmiento, PhD**   **Armin Gerami**   **Michael Ohadi, PhD** *Fellow ASHRAE*

ABSTRACT:

Buildings in the U.S. account for roughly 74% of electricity usage and about 40% of all primary energy use associated with greenhouse gas (GHG) emissions. The Nationally Determined Contribution (NDC) for the U.S., as determined in the Paris Agreement, sets a goal of reducing GHG emissions by ~50% compared to 2005 levels by 2030 while working towards achieving net-zero emissions by 2050. To meet these carbon reduction targets, the U.S. must substantially reduce of energy consumption and improve buildings' energy efficiency. To this end, this study introduces an energy consumption ranking tool that can be used to analyze the energy consumption profile of a cluster of buildings/campuses and provide an efficient tool to measure, monitor, and reduce end-use energy and CO_2 emissions. The tool bases its rankings on a standard benchmark or a targeted energy efficiency goal. The tool generates a band of ranking, from the best to the worst energy efficiency performance, which directs the attention of building designers, operators, and government regulation/enforcement agencies to buildings having subpar energy efficiency performance. The proposed methodology is extrapolated to encompass a broad range of energy and CO_2 consumption metrics in various building types and climate zones, thus having local, regional, and international applications. Using end-use energy utility data from the relevant database for the selected cluster of buildings and campuses, a total square footage area of ~26 million square feet of buildings and campuses was taken as the sample set for performing virtual audits using the custom-developed software. Using dynamic scatter plots and several ranking metrics, buildings with an underwhelming energy performance are identified for detailed energy audits. Once the outliers are spotted, energy modeling is performed to identify and delineate the root cause for the high energy use pattern for the facility. A breakdown of utilities and their corresponding energy analytics are visualized, thus highlighting the range of energy efficiency improvements and the potential for electrification. For the case example studied, the virtual audits are projected to result in minimum annual energy savings of 1,280,461 MMBtu and a corresponding minimum annual GHG reduction of 91,309 metric tons of CO_2.

Keywords: GHG emissions, energy benchmarking, energy audit, energy efficiency, building energy performance ranking, electrification

1. INTRODUCTION

Buildings in the US are liable for 40% of all U.S. energy consumption and contribute a similar percentage of greenhouse gas emissions (GHGs) [1]. Given the national goals of net-zero emissions by 2050 [2], it is imperative to improve buildings' energy efficiency [3]. The building category, i.e., industrial, commercial, or residential, dictates the energy consumption patterns and the subsequent energy sources of these buildings [4]. A building's energy performance can be determined by comparing it with its respective energy benchmarks based on the primary function

Aditya Ramnarayan is a Ph.D. student in the Department of Mechanical Engineering, University of Maryland, College Park. **Dr. Andres Sarmiento** is a Research Scientist at the University of Maryland, College Park. **Armin Gerami** is a master's student in the Department of Computer Science, University of Maryland, College Park. **Dr. Michael Ohadi** is a Professor and Fellow ASHRAE Member in the Department of Mechanical Engineering, University of Maryland, College Park.

and nature of activities carried out within the facilities [5]. Energy benchmarks are quantified using the Energy Use Intensity (EUI) measured in kBtu/sq. ft., which measures a facility's overall energy consumption over its gross floor area.

The Maryland Climate Solutions Now Act of 2022 requires the Maryland Department of Environment (MDE) to develop Building Energy Performance Standards (BEPS) for buildings in Maryland that are 35,000 square feet (3,251 m^2) or larger to achieve a 20% reduction in net direct GHG emissions by January 1, 2030, as compared with 2025 levels, and subsequently net-zero direct GHG emissions by January 1, 2040 [6]. To address this problem, this study demonstrates a custom-made software package that performs virtual energy audits using end-use energy data to calculate savings metrics. The software also ranks facilities based on their energy performance. This powerful tool will help organizations and institutions save labor and overhead costs by demarcating outlier buildings based on their energy performance. By ranking their buildings' energy performance, organizations will be able to prioritize the allocation of resources for further energy audits and mitigation strategies [7]. The most straightforward technique to assess the overall energy performance of a building is to use end-use energy data [8]. By using end-use energy data to calculate the monthly EUI [9], it is possible to determine the energy efficiency evaluation gap for different buildings and segregate buildings into different energy efficiency grades. Further analysis and use of energy modeling software can subsequently help identify critical problems in the building energy consumption patterns and model the savings that can be achieved when site-specific EEMs are employed [10].

Building energy benchmarking allows facility managers to perform energy accounting, evaluate opportunities for improvement, and estimate energy and cost savings [11]. Roughly 25% of commercial buildings in the U.S. are benchmarked on the EnergyStar Portfolio Manager, which derives its benchmark EUI values from the CBECS database [12]. The benchmark EUI values reflect the national median of energy use for different property types. The benchmarks can be used to identify facilities with poor energy performance, helping facility managers prioritize in-depth auditing to improve the facilities' energy performance [13]. Energy modeling can be carried out to examine further retrofits and EEMs that would improve the facility's energy performance and aid in subsequent GHG reduction [14].

While it is vital to filter out the outliers and analyze their energy performances, the metrics on which they are ranked and audited play a crucial role in achieving the decarbonization of buildings. Different industries are bound by the GHG emission regulations set by the Environmental Protection Agency (EPA) [15], which poses various metrics for facility owners and managers to meet. Access to exhaustive data is therefore needed to analyze and plan for greater energy efficiency to mitigate climate change [16]. To the best of the authors' knowledge, none of the aforementioned studies implement comprehensive ranking schematics, including energy and dollar savings, GHG emission reduction, but not limited to peak demand reduction, and electrification percent, among others.

2. METHODOLOGY

The methodology for this study comprises a three-step process: (i) data collection and filtering, (ii) data analysis, and (iii) data visualization. The availability of energy data from the database EnergyCAP [17] facilitates each process and accelerates the buildings' virtual audit and ranking process. The facilities used in this study comply with the Building Energy Performance Standards (BEPS) defined by the Maryland Department of Environment (MDE) [6]. Due to a lack of submetering for certain facilities, campuses are assessed as a whole rather than as individual buildings.

2.1. Data Collection and Filtering

The first step involved gathering the end-use energy data from the database [17], including the utility quantity and corresponding dollar amount for the facilities. Our analysis software, developed using Python, uses these parameters to classify each site and to apply calculations specific to each building. Utility data and bills for four fiscal years FY 2018 – 2021 were used to evaluate the reliability of the data and check for anomalous values. While the COVID-19 pandemic resulted in an overall energy consumption decrease of 7.3% in 2020 in the US [18], building energy consumption for the examined dataset was found to be relatively consistent. The starting year of analysis was chosen as 2018 based on the "Maryland Leads by Example" Executive Order 01.01.2019.08 signed by Governor Larry Hogan in 2019 [19]. This executive order requires the Maryland Department of General Services (DGS) and the Maryland Energy Administration (MEA) to set the energy savings goal at 10% savings over a 2018 baseline by the year 2029. End-use energy data for ~26 million square footage (~2,415,480 m^2) of facilities was used as the sample set comprising 52 buildings and 39 campuses. The primary use of each facility was then mapped with the Broad Category and Primary Function defined by the EnergyStar Portfolio Manager for further analysis [20].

2.2. Data Analysis and Visualization

With respect to the CBECS benchmarks and the sites' characteristics, the software calculates various criteria, such as their energy performance and energy-saving potential. The assimilated energy data is converted to kBtu, and the EUI is calculated over the square footage of the building. Although the benchmark EUI is the goal for buildings to achieve, this doesn't imply that buildings can't and shouldn't achieve EUIs lower than the benchmark while working toward becoming Net-Zero Energy Buildings (NZEB) [21]. Hence, this metric is the minimum energy savings potential calculated annually based on the EUIs for the four fiscal years, as shown in Equation (1).

$$MAESP\ (kBtu) = (Site\ EUI - Benchmark\ EUI)\ x\ Facility\ Area \tag{1}$$

For facilities performing better than their benchmark EUI, i.e., at the 75th percentile or above, the MAESP is calculated at a 2% reduction in their site EUI, based on a benchmarking study in Chicago, similar to their approximation of energy reductions for three different percentiles using lower and upper boundary estimates [22]. A flat 2% reduction in site energy consumption is a relatively straightforward and reasonable estimate of minimum potential energy savings, making it easier to convey to facility managers and building managers than more complex energy modeling or retrofit options.

$$MAESP\ (kBtu) = 0.02\ x\ Site\ EUI\ x\ Facility\ Area \tag{2}$$

Similarly, the minimum annual dollar savings potential is calculated using the minimum energy savings potential, as shown in Equation (3).

$$MADSP\ (\$) = \frac{MAESP\ (kBtu)}{TAEC\ (kBtu)}\ x\ Annual\ money\ spent\ on\ Energy\ (\$) \tag{3}$$

The classifier holding the data of zip codes of the facilities is then coupled with the EPA Power Profiler [23] to obtain the GHG emission coefficients per utility. Maryland predominantly occupies the RFC East (RFCE) part of the electric grid, with a small part falling in the RFC West (RFCW), each having different emission rates for electricity based on the electric service provider. The emission rates for other utilities, such as natural gas, crude oil (oil #2), propane, steam, chilled water, and diesel, are obtained from the EPA Emissions Hub database [24], since they undergo constant updating, as the energy conversion systems for each fuel are dynamic and improve with time and infrastructure changes [25]. Traditionally, GHG emissions are documented in units of carbon dioxide equivalent (CO_{2e}). At the same time, other greenhouse gases such as methane (CH_4) and nitrous oxide (N_2O) are transformed into CO_{2e} by multiplying them by their global warming potential (GWP) [26].

$$AGE\ (metric\ tons\ of\ CO_2) = \sum [Utility\ consumption\ (kBtu) * GEC\ (metric\ tons\ of\ CO_2/kBtu)] \tag{4}$$

Using the end-use energy data, a weighted average of every utility is calculated to compute the minimum annual GHG reduction potential by reducing the emissions of a particular utility in that proportion.

$$MAGRP\ (metric\ tons\ of\ CO_2) = \sum [\%\ of\ Utility\ consumption * MAESP * GEC] \tag{5}$$

Once the aforementioned metrics are calculated, they are visualized using a dynamic scatter plot, as shown in Figure 1. The ‘EUI Standing’ bar shows several tolerance bands classifying the energy performance of facilities, and Table 1 shows the energy-saving potential for each tolerance band.

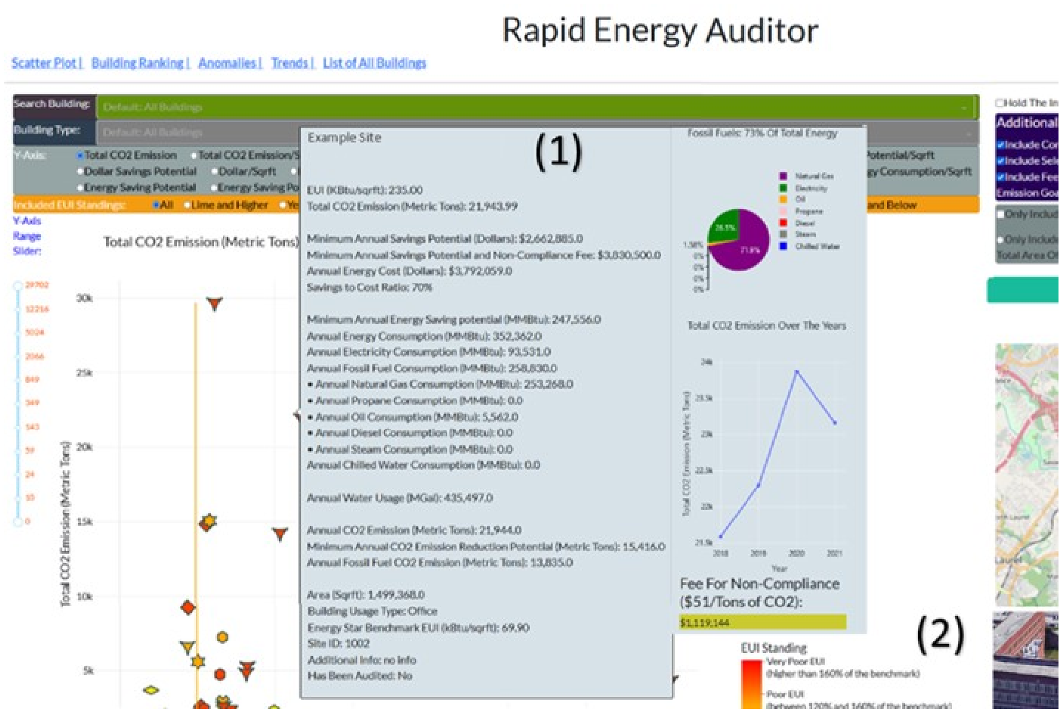

Figure 1 Snapshot of the UMD software’s Dynamic Scatter Plot where (1) shows a summary of site analysis, (2) the EUI Standing Bar, (3) the location of the site, and (4) the image of the site.

Table 1. Energy Saving Potential for Each Tolerance Band

EUI Standing	Band Range	Energy Saving Potential	Color
Very Poor	Higher than 160% of the benchmark	(Site EUI - Benchmark EUI) * Site Area	Red

Poor	Between 120% and 160% of the benchmark	(Site EUI - Benchmark EUI) * Site Area	Orange
Acceptable	Between 80% and 120% of the benchmark	Max {(Site EUI - Benchmark EUI) * Site Area, 0.02 * Site Energy Consumption}	Yellow
Good	Between 40% and 80% of the benchmark	0.02 * Site Energy Consumption	Lime
Very Good	Lower than 40% of the benchmark	0.02 * Site Energy Consumption	Green

3. RESULTS

Virtual audits using end-use energy data can be a powerful tool for determining energy baselines and determining facility energy efficiency. Using the tool to filter through different metrics, facility managers/organizations can prioritize their resources to meet different energy codes and standards. With ambitions directed towards decarbonization and net-zero emissions [2], having a tool that can detect sites with underwhelming performance and prioritize energy audits can significantly augment the large-scale deployment of retrofits and EEMs [27]. Another tool from the software is showcased in Figure 2, where sites are ranked based on deliberately chosen criteria.

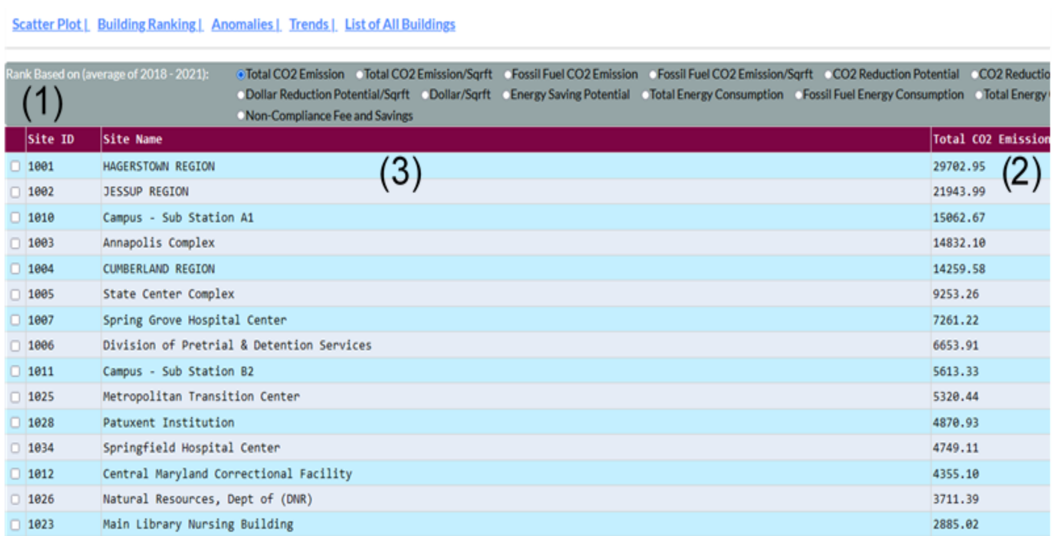

Figure 2 Snapshot of UMD software's ranking capability where (1) is the set of criteria chosen, (2) is the site list ranked based on the selected criteria, and (3) is the value of the selected criteria for each site.

3.1. Energy Modeling

Once the poorest-performing sites are identified, and ASHRAE Level I and II energy audits are performed, facility managers can model the building's energy use to analyze potential savings from retrofits. Using this approach, we identified an office building (EnergyStar Benchmark EUI – 52.9 kBtu/sq. ft. [166.84 kWh/m^2]) having an EUI of 116 kBtu/sq. ft. (365.84 kWh/m^2) with a square footage of 63,481 sq. ft. (5,898 m^2) for FY2021. We then modeled the facility's energy use (as shown in Figure 3) to examine the reasons for its energy consumption of nearly 2.2 times the benchmark value.

Trane Trace 3D Plus generated a baseline model to outline the current energy performance alongside four EEMs and their corresponding savings. The model was based on the building's existing architectural and mechanical drawings. The baseline model was then compared with the four EEMs following further analysis.

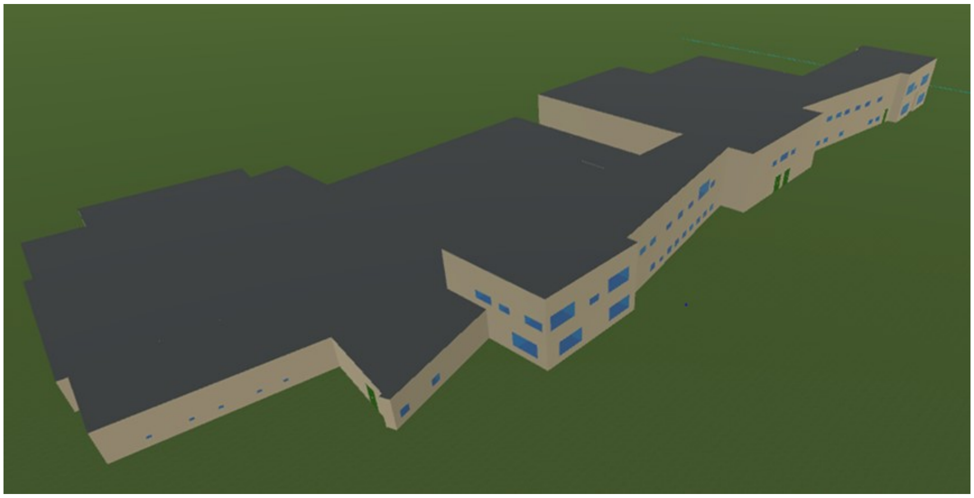

Figure 3 Energy model of the office building

3.2. Energy Efficiency Measures (EEMs) and Savings

From the walkthrough, it was observed that the HVAC systems of the facility were original to the building (dated 1990) and, being far past their useful life, requiring replacement. Moreover, the facility's lighting was predominantly provided by CFLs and incandescent bulbs, which are highly inefficient. The office building also had a roof area of ~54,000 sq. ft. (5,017 m^2) that could be used to implement rooftop solar PV. The building cost $152,861 to operate in FY2021 in energy utilities alone. Implementing EEMs and retrofits would greatly reduce energy consumption and improve the facilities' overall energy performance, resulting in savings as high as 25% and beyond [28]. The first EEM we modeled was variable refrigerant flow (VRF) systems as viable alternatives for HVAC equipment replacement due to the presence of VAVs in the facility. Additionally, VRF systems are known for their high energy performance, thus improving energy efficiency over conventional HVAC systems such as rooftop systems (RTUs) and central chiller and boiler systems. The heat pump VRF models show a potential of 14 –39% annual HVAC site energy savings potential over the RTU-VAV models for different climate locations in the US [29]. If the VRF system were to be deemed economically unviable, an alternative for a like-for-like replacement of HVAC systems was also demonstrated with its subsequent savings. LEDs were the final EEM modeled, owing to the ease of retrofitting them with advanced technological features such as daylight dimming and occupancy sensors. LEDs have the additional benefit of providing more lumen per watt consumed, thus reducing overall energy consumption with the benefits of a longer useful life [30]. Based on the overall analysis of the building, four EEMs were formulated and modeled to calculate their corresponding savings, as shown in Table 2.

Table 2. Energy and Cost Savings Summary

Energy Efficiency Measures (EEMs)	Modeled Annual Consumption		Projected Energy Savings		Utility Savings		
	E (MWh/yr) [MMBtu/yr]	NG (therm/yr) [MMBtu/yr]	E (MWh/yr) [MMBtu/ yr]	NG (therm/yr) [MMBtu/yr]	E ($/yr)	NG ($/yr)	Total ($/yr /ft^2)
HVAC Equipment Replacement	1,586 [5,413]	37,968 [3,797]	61[208]	4,580 [458]	6,030	45,351	0.81

Lighting Upgrades	1,589[5,423]	43,050 [4,305]	58[198]	-502 [-50]	5,812	-4,971	0.01
Solar PV Panels	1,495[5,102]	42,548 [4,255]	152[519]	0 [0]	15,158	0	0.24
VRF System	993[3,389]	0 [0]	654[2,23]	42,548 [4,255]	65,372	42,131	1.69

4. DISCUSSIONS

Comparisons of the calculated results from the software and energy modeling give perspective on how definitive energy savings can be calculated and how they affect the corresponding metrics. The baseline case for the facility is its present energy profile based on the existing systems operating in the facility. Energy modeling was carried out to replicate and understand this baseline case, compare methods to improve the existing performance, and check for accurate equipment sizing. Since EEM #1 – HVAC Equipment Replacement is a like-for-like HVAC replacement and an alternative to EEM #4 – VRF system, the two options are considered separately. The proposed EEMs are an upgrade to the existing systems, with their higher Energy Efficiency Ratios (EER) and modern efficiency values dictated by ASHRAE Standard 90.1. Table 3 shows how these compare to the predicted values by the software. Additionally, Table 4 demonstrates the GHG emissions reduction that can be achieved by implementing these EEMs.

Table 3. Energy Savings Comparison

Minimum Annual Energy Savings Predicted from Software [MMBtu] (MWh)	Energy Savings (with HVAC replacement)		Energy Savings (with VRF system)	
	Electricity [MMBtu] (MWh)	Natural gas [MMBtu] (therms)	Electricity [MMBtu] (MWh)	Natural gas [MMBtu] (therms)
4,005 (1,173)	925 (271)	408 (4,080)	2,949 (864)	4,205 (42,050)

Table 4. GHG Emission reduction

Minimum Annual GHG Reduction Predicted from Software [metric tons of CO_2] (Imperial tons)	Annual GHG Reduction (with HVAC replacement) [metric tons of CO_2] (Imperial tons)		Annual GHG Reduction (with VRF system) [metric tons of CO_2] (Imperial tons)	
	Electricity	Natural gas	Electricity	Natural gas
302 (297)	80 (78)	22 (21)	256 (252)	223 (219)

As expected, the minimum energy savings lies between the best and worst alternatives to improve the facility's energy performance. VRF systems for the facility are modeled to match the facility's heating and cooling loads, thus explaining the overall lower electricity consumption despite being an all-electric system and further displaying the presence of oversized systems in the facility. In contrast, HVAC systems are modeled to have the same capacity as the initial systems with an improvement in their efficiencies based on efficiency guidelines from ASHRAE Std 90.1. This is why the savings in Case #1 (Implementation of EEMs 1, 2, and 3 – with HVAC replacement) aren't as attractive as predicted by the software, which is also corroborated by the fact that the facility has two oversized boilers accounting for large consumption of natural gas, thus resulting in large EUI values. From the walkthrough, it was key to determine if this sizing matched the loads of the facility. Furthermore, based on the predicted energy savings, the facility had a minimum annual dollar savings potential of $83,182 compared to its annual energy cost of $152,861, resulting in possible savings of 46%. The annual GHG reduction potential was found to be 302 metric tons (297 imperial tons) of CO_{2e}, which could be considered as a facility manager/owner as a future scope owing to the noncompliance fees for on-site emissions. With energy modeling, every EEM implementation was modeled, and their effect on energy consumption and subsequent savings was analyzed.

4.1. Limitations and Future Scope

As with any data-driven analysis, the generalization of the techniques and subsequent results apply only to the input data tested. In this case, the process was applied to a large dataset in Maryland. It has the potential to be extrapolated and adopted nationwide and worldwide, subject to data availability; however, this was not done for the present study. While the software has the advantage of rapidly screening through years of end-use energy data, the benchmark EUI it uses is a national median for a specific building type. These benchmark values don't indicate the EUI for a particular climate zone but rather a nationwide metric adoption for a particular building type. The CBECS data set contains a limited number of buildings (6,720) and is updated infrequently (approximately once every four years) [31]. With the advent of machine learning (ML) techniques used in prediction and forecasting, we expect new energy efficiency benchmarks to be developed based on climate zones and ambient temperatures [32]. Building energy simulation models, such as EnergyPlus, quantitatively accounts for several factors that affect energy performance [33]. The minimum savings potential metric gives a ballpark estimate of the savings that can be expected by focusing on energy efficiency but doesn't indicate how to realize those numbers.

The future scope of work includes using machine learning (ML) techniques to develop energy efficiency benchmarks and tighter tolerance bands to prioritize performance and energy audit improvements. Incorporating a more extensive dataset would give better prediction models. Identifying outliers and conducting ASHRAE Level I, II, and III audits would enhance their energy performance and drive the state of Maryland toward its energy and GHG goals and directives [6].

5. CONCLUSIONS

This study investigates the functionalities of the custom-built software developed to assess the energy efficiency performance of commercial buildings. By assessing the end-use energy data, it is possible to judge facilities' energy performance using predefined benchmarking metrics. Using the custom-built software, it is possible to perform rapid virtual audits and identify sites with low energy efficiency performance.

Tolerance bands make it possible to pinpoint sites with excellent to egregious overall performance, which can be subjected to energy audits and further investigation through energy modeling. Given the range of savings from both the software and energy modeling, facility managers and owners can choose a solution that is optimal from both environmental sustainability and return on investment perspectives. Further, ranking facilities based on different metrics can be beneficial from an institutional point of view, with the intention of developing extensive energy efficiency improvements and reducing energy consumption. Using the present study's dataset comprising a combination of buildings and campuses of ~26 million square feet (2,415,479 m^2), the potential to reduce the energy consumption by a minimum of 1,280,461 MMBtu (375,172 MWh) with a corresponding minimum annual GHG reduction of 91,309 metric tons (89,867 imperial tons) of CO_2 can be realized while saving the facility owners a corresponding minimum of $19.75 million annually.

ACKNOWLEDGMENTS

The authors would like to thank the Office of Energy Sustainability within the State of Maryland's Department of General Services (DGS) for their support of this project.

NOMENCLATURE

MAESP – Minimum Annual Energy Saving Potential
MADSP – Minimum Annual Dollar Saving Potential
TAEC – Total Annual Energy Consumption
AGE – Annual Greenhouse Gas Emissions
GEC – Greenhouse Gas Emission Coefficient
MAGRP – Minimum Greenhouse Gas Reduction Potential
CBECS – Commercial Buildings Energy Consumption Survey
EEM – Energy Efficiency Measure
GHG – Greenhouse Gas
EUI – Energy Use Intensity
E – Electricity
NG – Natural Gas

REFERENCES

[1] Frequently asked questions (FAQs) - U.S. energy information administration (EIA). https://www.eia.gov/tools/faqs/
[2] The White House. from https://www.whitehouse.gov/wp-content/uploads/2021/10/US-Long-Term-Strategy.pdf
[3] Jacobson M. Review of solutions to global warming, air pollution, and energy security. Energy Environ Sci 01/21 2009;2. https://doi.org/10.1039/B809990C.
[4] Bos´ak L, Palko M. Energy saving building in mountain area. Adv Mater Res 10/01 2014; 1057:27–34. https://doi.org/10.4028/www.scientific.net/AMR.1057.27.
[5] Vaisi, S., Firouzi, M., & Varmazyari, P. (2023). Energy benchmarking for secondary school buildings, applying the top-down approach. Energy and Buildings, 279, 112689. https://doi.org/10.1016/j.enbuild.2022.112689
[6] The Maryland Climate Solutions Now Act (2022), Maryland Department of Environment (MDE)
[7] Chung, W. (2011). Review of Building Energy-use performance benchmarking methodologies. Applied Energy, 88(5), 1470–1479. https://doi.org/10.1016/j.apenergy.2010.11.022
[8] Field, J., Soper, J., Jones, P., Bordass, W., & Grigg, P. (1997). Energy performance of occupied non-domestic buildings: Assessment by analysing end-use energy consumptions. Building Services Engineering Research and Technology, 18(1), 39–46. https://doi.org/10.1177/014362449701800106
[9] Sun, F., & Yu, J. (2021). Improved Energy performance evaluating and ranking approach for office buildings using simple-normalization, entropy-based Topsis and K-means method. Energy Reports, 7, 1560–1570. https://doi.org/10.1016/j.egyr.2021.03.007
[10] Ang, Y. Q., Berzolla, Z. M., & Reinhart, C. F. (2020). From concept to application: A review of use cases in Urban Building Energy Modeling. Applied Energy, 279, 115738. https://doi.org/10.1016/j.apenergy.2020.115738
[11] Building Energy Use Benchmarking. Energy.gov. https://www.energy.gov/scep/slsc/building-energy-use-benchmarking
[12] Scofield JH. ENERGY STAR Building Benchmarking Scores: Good Idea, Bad. Science, 2014:16.
[13] Bosu, I., Mahmoud, H., & Hassan, H. (2023). Energy audit and management of an industrial site based on energy efficiency, economic, and environmental analysis. Applied Energy, 333, 120619. https://doi.org/10.1016/j.apenergy.2022.120619
[14] Deng, Z., Chen, Y., Yang, J., & Causone, F. (2023). AutoBPS: A tool for Urban Building Energy Modeling to support energy efficiency improvement at city-scale. Energy and Buildings, 282, 112794. https://doi.org/10.1016/j.enbuild.2023.112794
[15] Environmental Protection Agency, Regulatory Information by Business Sector. EPA. https://www.epa.gov/regulatory-information-sector
[16] Yajima, N., & Arimura, T. H. (2022). Promoting energy efficiency in Japanese manufacturing industry through energy audits: Role of information provision, disclosure, target setting, inspection, reward, and organizational structure. Energy Economics, 114, 106253. https://doi.org/10.1016/j.eneco.2022.106253
[17] Energy Management Analytics & Sustainability Data Solution Boalsburg: ESG reporting software. EnergyCAP, https://www.energycap.com/
[18] Jiang, P., Fan, Y. V., & Klemeš, J. J. (2021). Impacts of covid-19 on energy demand and consumption: Challenges, lessons and emerging opportunities. Applied Energy, 285, 116441. https://doi.org/10.1016/j.apenergy.2021.116441

[19] (2019). 01.01.2019.08 - Energy expense reduction in State Facilities of 10% reduction by 2029, 2018 base year
[20] ENERGY STAR Portfolio Manager, https://portfoliomanager.energystar.gov/
[21] Albers, S. (2009). Algorithms for energy saving. Lecture Notes in Computer Science, 173–186. https://doi.org/10.1007/978-3-642-03456-5_12
[22] Hart, Z. (2018, May). Analyzing Benchmarking Data, Institute for Market Transformation.
[23] Environmental Protection Agency, Power Profiler. https://www.epa.gov/egrid/power-profiler#/
[24] EPA's Emission Factors Hub. (2022, April). https://www.epa.gov/climateleadership/ghg-emission-factors-hub.
[25] Wang, X. G., & Yan, L. (2022). Driving factors and decoupling analysis of fossil fuel related-carbon dioxide emissions in China. Fuel, 314, 122869. https://doi.org/10.1016/j.fuel.2021.122869
[26] Intergovernmental Panel on Climate Change (IPCC), Fourth Assessment Report (AR4), 2007.
[27] Balaras, C. A. (2022). Building energy audits—diagnosis and retrofitting towards decarbonization and sustainable cities. Energies, 15(6), 2039. https://doi.org/10.3390/en15062039
[28] Asif, M., Ahmed, W., & Alazazmeh, A. (2023). Energy Performance Assessment of a post-retrofit office building using measurement and Verification Protocol: A Case Study from KSA. Energy Reports, 9, 1366–1379. https://doi.org/10.1016/j.egyr.2022.12.061
[29] Kim, D., Cox, S. J., Cho, H., & Im, P. (2017). Evaluation of energy savings potential of variable refrigerant flow (VRF) from Variable Air Volume (VAV) in the U.S. climate locations. Energy Reports, 3, 85–93. https://doi.org/10.1016/j.egyr.2017.05.002
[30] Gayral, B. (2017). LEDs for lighting: Basic physics and Prospects for Energy Savings. Comptes Rendus Physique, 18(7-8), 453–461. https://doi.org/10.1016/j.crhy.2017.09.001
[31] How the 1-100 energy star score is calculated. ENERGY STAR. https://www.energystar.gov/buildings/benchmark/understand_metrics/how_score_calculated
[32] Arjunan, P., Poolla, K., & Miller, C. (2020). EnergyStar++: Towards more accurate and explanatory building energy benchmarking. Applied Energy, 276, 115413. https://doi.org/10.1016/j.apenergy.2020.115413
[33] Crawley, D. B., Lawrie, L. K., Winkelmann, F. C., Buhl, W. F., Huang, Y. J., Pedersen, C. O., Strand, R. K., Liesen, R. J., Fisher, D. E., Witte, M. J., & Glazer, J. (2001). EnergyPlus: Creating a new-generation building energy simulation program. Energy and Buildings, 33(4), 319–331. https://doi.org/10.1016/s0378-7788(00)00114-6