

Informed Retrofit Prioritization with Random Forest Regression

Pacific Northwest National Laboratory

Juan Gonzalez Matamoros, Supriya Goel, Richard Fowler

ABSTRACT

With the advent of building performance standard requirements, building owners need to be able to measure their building's performance and identify pathways to reduce energy consumption or carbon emissions. Pacific Northwest National Lab's (PNNL) Audit Template (AT) team investigated an alternative approach for identifying and reporting the relative impacts of various energy efficiency retrofits from audit data to meet these needs. The Department of Energy's (DOE) Audit Template web-based tool collects building energy audit data for cities to submit for local energy audit ordinances with over 15,000 buildings, accounting for over 1 billion square feet of commercial real estate, have been entered into tool since 2018.

This paper investigates the potential of applying machine learning techniques onto AT's audit data to estimate building retrofit potential. Researchers explored the development of prototypical models using information from building energy audit data to inform large-scale building simulation datasets. Drawing on the concept of "retrofitability" — a building's potential to reduce its energy and carbon emissions through retrofit savings — this study explored the advantages and limitations of using random forest regression algorithms to estimate both retrofit prioritization and individual measure impact from audit data. A "retrofitability index", proposed for the Audit Template tool, would provide information to auditors based on their Level 1 or Level 2 audit data, on the potential for energy savings and the systems which could potentially benefit most from a retrofit. The identified retrofits could be tailored to meet the jurisdiction's objective of electrification, strategic decarbonization or maximum energy savings. This data-driven approach to identifying improvement opportunities would help auditors as well as jurisdictions identify ways to meet their policy objectives.

Introduction

Buildings are responsible for nearly 40% of annual global CO₂ emissions (Architecture 2030), and over 32% of the total US energy related CO₂ emissions are associated with coal and natural gas fired power plants (EIA 2020). To reduce carbon emissions due to electricity consumption in buildings, many cities have begun incorporating energy audits, retro-commissioning or retuning into their building performance standards and city ordinances (IMT 2021). Audits assess the current state of energy systems in buildings and inform building owners and operators about possible upgrades to save energy and reduce emissions. Retro-commissioning and tune-up processes assess the operation of existing systems and identify ways to improve the same. Building energy audits and retro-commissioning are often the starting point for capital and operational improvements in buildings.

Critical to the development and enforcement of these policies is the availability of data in a standardized format. Standardization of data is beneficial for building owners, program managers (such as a city or a utility) as well as organizations evaluating and managing a portfolio of buildings. Retrofit measures identified during audits are implemented over a period of time after the audit is completed (Maxwell 2013) and providing a mechanism for data perpetuity supports a continuous cycle of assessment and tracking of savings through

improvements over the building life cycle. Commercial building energy audits are becoming more prevalent with the advent of local ordinances and building performance standards (EPA 2021 IMT 2018). Across the U.S., cities are implementing energy efficiency policies and building performance reporting laws for energy and water use in commercial and multifamily buildings. These efforts would generate significant amount of data which would be valuable if can support future decision making and performance tracking. DOE's ecosystem of data tools has been developed to help with exactly that and support cities meet these ambitious energy goals.

Audit Template

Many cities are currently using or are planning on using the Department of Energy's Audit Template (AT) tool to collect, document, and report existing building audit data to help meet their BPS goals (DOE 2022). The Audit Template is a web-based tool developed by Pacific Northwest National Laboratory to simplify audit data collection. Users are presented with industry standard input fields as designated by ASHRAE/ACCA Standard 211 (ASHRAE 2018), Standard for Commercial Building Energy Audits with an option for additional city specific inputs. Audit Template records generate audit reports which lists all data entered along with calculated tables and charts outlining the building energy use by energy type and end use, and the cost and payback of energy saving opportunities. These metrics help cities track progress toward goals.

The cities with the most audit data entered into the Audit Template to-date include New York City and San Francisco. The city of New York requires the use of the Audit Template for auditors to submit an Energy Efficiency Report to demonstrate compliance with their Local Law 87 (LL87) which mandates that buildings over 50,000 gross square feet undergo periodic energy audit and retro-commissioning measures, as part of their Greener, Greater Buildings Plan (GGBP). The intent of this law is to inform building owners of their energy consumption through energy audits, which are surveys and analyses of energy use, and retro-commissioning, the process of ensuring correct equipment installation and performance. (NYC 2022).

San Francisco requires the use of the Audit Template for building owners to submit a Confirmation of Energy Audit as required by their Existing Commercial Buildings Energy Performance Ordinance as outlined in San Francisco Environment Code Chapter 20. The ordinance requires that buildings 50,000 square feet and larger must conduct an ASHRAE Level II "intermediate" survey and energy analysis, and buildings 10,000 to 49,999 square feet must conduct an ASHRAE Level I - basic energy analysis. The data from this analysis is to be entered into the Audit Template which is then used to submit a confirmation notice to the San Francisco Department of Environment. Large facilities and buildings with complex systems are also encouraged to undergo retro commissioning. (SFE 2022a, SFE 2022b)

Audit reports generated by the Audit Template includes a list of all cost-effective energy efficiency measures identified by auditors. San Francisco has noted in their requirements that these measures should each have a simple payback of 3 years or less; each have a beneficial net present value; comprise an integrated package with an overall simple payback of approximately 3 years; or comprise an integrated package with beneficial net present value.

For the purpose of this study, audit data from office buildings in San Francisco was used because these building entries offered the best variety of building sizes, HVAC systems entered, and efficiency measures identified useful for this analysis.

Existing Methodologies for Retrofit Assessment

Building owners, utility companies, engineers, and policy makers all have many approaches and perspectives to consider when making selections for building retrofits. Existing strategies tend to fall into three conventional methods of retrofit selection —energy efficiency design guides, simulation informed analysis, and mathematical models.

Energy Efficiency Design Guides

Industry provides a handful of energy efficiency design guides to inform building professionals on best practices for achieving high performance building design. Examples include New York City’s (NYC) Deep Energy Retrofit Plan Analysis (DERPA) and the series of Advanced Energy Design Guides (AEDG) published by the American Society for Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE).

Like many cities, NYC has BPS goals to reduce their carbon emissions over the next few decades. NYC is endeavoring to meet an aggressive goal of reducing emissions by 80% by 2050, with existing buildings requiring roughly 40% to 60% energy reduction (Kerr 2016). The DERPA tool was developed to help meet NYC’s energy efficiency goals as set forth by Local Law 87 (LL87) (NYC 2022). LL87 mandates that buildings with square footage over 50,000 square feet perform periodic energy audits to inform building owners of their building’s performance with the goal of pushing the market toward higher performance buildings. The DERPA tool utilizes Excel to read in an ASHRAE Level II audit data, document savings opportunities, and recommends best practices. Retrofits are identified in the audit process and documented in the DERPA tool (NYC 2009).

For more generalized guidance, ASHRAE documented pathways for energy reduction goals in their Advanced Energy Design Guides (AEDG). This documentation provides practitioners with building measures across different climate zones and building types to meet goals ranging from 30%, 50%, and zero-energy energy reduction levels (ASHRAE 2020). Researchers generated large-scale simulations based on prototypical buildings, representing common construction and systems found in the U.S. Sixteen commercial building types in 17 climate locations were developed as the base models to support energy codes analysis, design guides, and other similar applications (DOE 2018). Similar prototype models have been developed in other countries to support local building energy performance evaluation and design recommendations. Hong, Y. et al. (2020) developed four prototypical buildings as representative standards for low-rise office buildings in Shanghai, and Gui, et al. (2020) developed eleven commercial building prototype models in Beijing.

Design guides provide a quick and easy way to look up the promising energy reduction measures for a specific building type, however, their applications are limited by the configurations of the prototypical building models. When the actual configuration of a building greatly differs from a “typical” building, the energy efficiency measures and savings from the prototypical building models become less applicable or accurate. Therefore, design guides are more useful for new constructions when there is more flexibility in modifying building design and system selections. In contrast, existing building retrofits are constrained by their structure, layout, and legacy electrical and mechanical systems. These legacy building systems are often obsolete in the newer design guides. Therefore, policy makers cannot directly reference these design guides when developing energy programs for existing buildings.

Simulation-based Recommendations

Simulation-based retrofit selection informs building energy practitioners looking for a detailed, tailored look at their building's energy performance. This approach utilizes the power of whole building energy simulation to provide a closer approximation of a specific building's energy performance using physics-based simulation engines like EnergyPlus and OpenStudio (DOE 2021 a, b). Examples include the U.S. Department of Energy's Building Energy Asset Score (Asset Score) and Commercial Building Energy Saver (CBES) (Hong, et al 2015). These tools will evaluate a building's existing energy performance parameters, perform an energy simulation, and provide retrofit recommendations for practitioners to compare pre- and post-retrofit configurations.

Asset Score (DOE 2019) is a web-based software application designed to benchmark a building's existing energy performance based on its as-designed, physical assets and identify potential retrofit opportunities. The tool requires inputs for a building's geometry, use types, envelope, HVAC systems, lighting, and service hot water parameters. It uses standard loads (plug loads, ventilation loads and people density) and schedules to create an energy model for the building. Asset Score also includes a recommendation engine which considers the building's existing parameters and provides applicable retrofit options to estimate the building's potential energy savings (Wang 2016). The Asset Score engine uses OpenStudio and EnergyPlus to simulate both the proposed and retrofitted versions of the buildings and generate a PDF report for the user with a current and potential score for the building along with the list of recommended measures and their estimated energy savings.

CBES is an analysis toolkit developed by Lawrence Berkeley National Laboratory to help small commercial building owners in California and select large U.S. cities evaluate and identify cost-effective energy retrofit strategies. The CBES toolkit provides users with the flexibility to explore retrofit opportunities at a variety of levels tailored to the user's experience. The toolkit provides features such as load shape analysis, Energy Star score benchmarking, preliminary retrofit analysis and ultimately a detailed retrofit analysis using EnergyPlus simulation results from 7 different prototypes across 25+ different U.S. and California based climate zones. Retrofit selection is handled by first evaluating a buildings utility data, calibrating it, and then running either singular retrofit measures or users defined packages. Potential outputs include the annual site energy, CO2 emissions, annual economic analysis, and annual energy cost savings.

As demonstrated by both these tools, simulation based retrofit selection can tailor specific energy retrofits when provided with enough inputs. The challenge with simulation based retrofit selection is two-fold. First, practitioners must have enough information to simulation engines to produce a complete energy simulation. This requires collecting a lot of building system information and, often, engineering expertise. Secondly, these simulation-based methodologies are unable to take into account actual site constraints in their recommendation process and oftentimes might suggest improvements which are not feasible on-site.

Energy assessors also use whole building simulation tools such as Trane, eQUEST, EnergyPlus or OpenStudio to develop whole building energy models. Retrofit opportunities are then identified through an on-site audit modeled parametrically through these tools to quantify energy savings through each.

Mathematical Models

Advances in mathematical models have also begun informing retrofit selection. Several studies have used different machine learning techniques including artificial neural network, support vector machine, gaussian based regression and clustering to forecast building energy use using historical loads for input data (Bourdeau, et al 2019). Zong et al. (2020) predicted household energy consumption by applying a random forest approach to quantify the influence of 87 variables of life choices on electricity, gas, kerosene, gasoline, and diesel consumption in Japan. In 2014, a focused study on quasi-steady state models and interval-based inverse modeling found that both mathematical models accurately estimate savings levels for early-stage retrofit analysis (Gaash 2014). All these studies proved the value of estimating retrofit savings using limited data and this study looks to expand on those principles by predicting retrofit savings from Audit Template data utilizing random forest regression.

Retrofitability

Introduction

EUI is often used to benchmark building performance and evaluate savings potential through retrofits. Despite their widespread use, neither EnergyStar Portfolio Manager scores nor EUI provide the accuracy or granularity required to prioritize buildings based on their energy efficiency savings potential. Gaash et al found that while both ratings had widespread adoption, neither had strong correlation to the building's energy savings potential, especially across large building portfolios. (Gaash 2014). Similarly, Wang et al investigated the relationship between EUI and retrofit potential for the City of Seattle and arrived at the same conclusion (Wang et al 2020). Through this research, authors introduced a concept of retrofitability.

'Retrofitability' for the purpose of this application, is defined as a measure of the energy savings or emission reduction potential for a building to meet the specific objectives of a jurisdiction or program. Several jurisdictions and agencies are requiring the use of Audit Template tool for reporting detailed Level 2 audit data including the city of San Francisco and New York City. The tool is also being evaluated by several additional cities to support the prescriptive pathways within their Building Performance Standards. The reported audit data is rich in detailed building asset information (including building use types, envelope properties, lighting, and HVAC systems), annual building energy use, energy use by end use and fuel type as well as estimate energy efficiency measures (EEM) recommended by the auditors. Through this study, the project team investigated the feasibility of using this data set to develop dynamic prototypes for the different building types in a jurisdiction. Representative building geometries and systems typically found in the jurisdiction being evaluated were used to build dynamic prototypes and train jurisdiction specific random forest regression models.

These regression models serve as the basis for estimating retrofitability for a building. An estimation for retrofitability using machine learning could take as few as a dozen or so inputs, or even fewer inputs if investigating retrofits individually. This opens opportunities for identifying building retrofit opportunities without having to run detailed whole building energy models. Through the regression-based capability proposed in this paper, an auditor could be informed of the savings potential of a building's systems and a list of EEMs with potential energy savings to guide focused analysis. This paper looks to investigate the potential of estimating measure level

savings using random forest regression with as few as 2 inputs. With fewer inputs, practitioners would have the opportunity to EEM savings potential with minimal effort.

Methodology

A random forest regression requires a training using a large, well-sampled dataset. To demonstrate and pilot this capability, researchers used Level 2 audit data reported for San Francisco, to design a large-scale simulation, set to inform the random forest regressions which would be used to predict retrofitability. The simulation set was designed around 25 different inputs compatible with the Asset Score simulation engine for office buildings in San Francisco. The reason for this was two-fold. First, limiting the study to a single use type kept the experiment within the scope of a pilot study. Secondly, the regression model results could be compared against the data for real, audited buildings to quantify the accuracy and relevance of this capability. This study chose to use a random forest regression engine to predict the retrofit potential of the 3000-building data in this study over other conventional forms of regression.

In 2001, Breiman's introduced the concept of random forest analysis (Breiman 2001). Random forests work by aggregating the results of an ensemble of decision trees. Each tree in the forest predicts an output variable (e.g. retrofit potential) by classifying the effects of input variables (e.g. building characteristics) using forking decision points called branches. Furthermore, each tree is uniquely created by randomly selecting a subset of input variables for consideration at each decision point before branching. The random nature of each tree increases the likelihood of capturing complex interactions and reduces the risks of overfitting data (Denisko 2018). By following a decision tree and sequentially considering variables, each tree considers multiple variables, capturing interactive effects better than conventional linear regressions (see Figure 1).

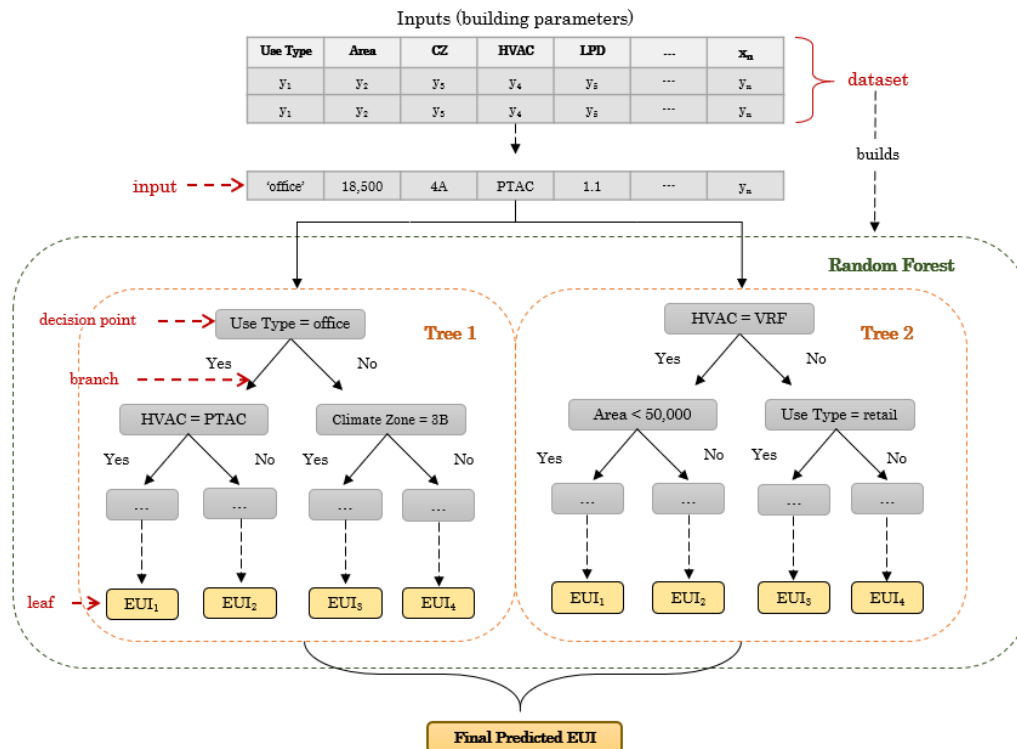


Figure 1. A simplified diagram of a random forest used to predict energy usage intensity (EUI). An initial dataset with a predetermined set of inputs is used to build a random forest. Random forests are comprised of an ensemble of decision trees. Each tree is uniquely created by randomly selecting a subset of input variables for consideration at each decision point. Each forking decision point utilizes branches to further classify the building EUI using the building's parameters. The end of these branches gives the tree's final prediction and is known as a leaf. While the diagram only shows two trees, random forests are typically comprised of hundreds or thousands of trees. The predictions of each tree are then averaged to give the random forest's best prediction for the building's EUI.

In addition to capturing interactive effects, a random forest provides more rigorous insight into feature importance. The “feature importance” metric of random forest separates variables with significant impact from those with negligible impact on a measured value. This metric helps researchers select features to include in their random forest regression models. Removing variables with negligibly low importance reduce the total number of variable inputs. This study utilize percent increase in mean square error (MSE) when a variable is excluded as their metric for importance. From an application perspective, feature importance provides an advantage by reducing the number of building inputs required to complete a retrofit-ability study.

Given the nature of our dataset, its advantages over linear regression, and proven effectiveness at predicting building energy use, random forest regression was chosen for this study. The sections below explain the methodology for defining the simulation training dataset, the prototypes developed to represent office building in San Francisco, the building parameters used to generate the random forest regression model, and the EEMs analyzed through this pilot study.

Constructing the Baseline Simulation Dataset

The audit template database has over 500 buildings submitted to the City of San Francisco. Querying the Audit Template database for single use type, office building submissions resulted in 194 buildings from which to build characteristic seed models. This data was used to establish predominant HVAC system types, building geometries and vintages, and how often audits included certain parameters. Based on the results, office buildings in San Francisco buildings were categorized into 3 categories as shown in Table 1 and Figure 2—

Table 1. San Francisco Prototype Geometries

Model Name	Square Footage	Number of Floors	Thermal Layout
Small Office	12,000 ft ²	1	Perimeter and core
Medium Office	30,000 ft ²	3	Perimeter and core
Large Office	100,000 ft ²	10	Perimeter and core

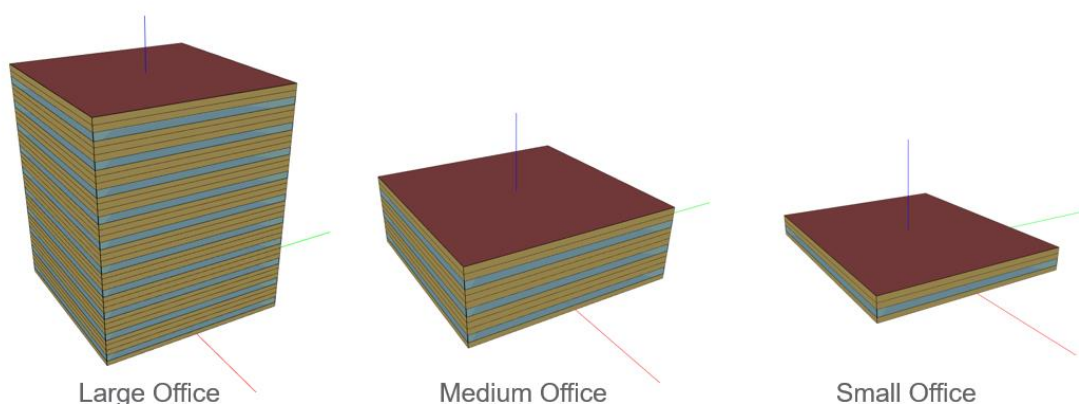


Figure 2. The 3 prototypical geometries used to build the San Francisco dataset

Selecting the HVAC system types also required careful consideration. The 4 most prevalent HVAC system types (Table 2) in the San Francisco audit data were selected as options and their relative inputs were added as input parameters. A combination of building simulation expertise, HVAC system requirements, simulation engine limitations and EEM requirements determined the 25 total inputs used to create the large-scale simulation dataset. Many of these inputs had dependencies on other inputs. For instance, furnace efficiency values were sampled differently for electric and natural gas fired furnaces. The input sampling took these relationships into consideration and ensured any dependency or coupling requirements between inputs were considered. A list of the input parameters and their values can be found in Table 2.

Table 2. Input Sampling

Input	Values	Units	Dependencies	Notes
Geometry	small, medium, or large office	-	-	See Table 1

System Type	PSZ AC, PSZ HP, VRF, VAV with Hot Water Reheat	-	-	-
Furnace Fuel Type	electricity, natural gas	-	System Type	Sampled for relevant system types
Furnace Efficiency	0.6 - 0.985, 1.0	thermal efficiency	Furnace Fuel Type	Electric furnace efficiency rated at 100%
Cooling DX Efficiency	2.0 - 4.1	COP	System Type	Only sampled for relevant system types
Boiler Efficiency	0.700 - 0.985, 1.0	thermal efficiency	System Type	Electric boiler efficiency rated at 100%
Chiller Efficiency	2.2 - 4.2	COP	System Type	Sampled for relevant system types
Heat Pump Heat Efficiency	2.0 - 4.4	COP	System Type	Sampled for relevant system types
Heat Pump Cool Efficiency	2.0 - 4.4	COP	System Type	Sampled for relevant system types
VRF Heat Efficiency	3.0 – 6.0	COP	System Type	Sampled for relevant system types
VRF Cool Efficiency	3.0 – 6.0	COP	System Type	Sampled for relevant system types
Air Handler Fan Performance	0.4 - 1.2	W/CFM	System Type	Sampled for relevant system types
Zone Equipment Fan Performance	0.15 – 0.60	W/CFM	System Type	Sampled for relevant system types
Boiler Pump Performance	12 – 22	W/GPM	System Type	Sampled for relevant system types
Chiller Pump Performance	12 – 22	W/GPM	System Type	Sampled for relevant system types
Economizer	True / False	-	System Type	Sampled for relevant system types
Energy Recovery Ventilation (ERV)	True / False	-	System Type	Sampled for relevant system types
ERV Type	Plate, Wheel	-	ERV	Requires an ERV
ERV Bypass Control	True / False	-	ERV	Requires an ERV
Lighting Power Density	0.6, 0.8, 1.0, 1.2, 1.4, 2.4	W/ft2	-	LPD based on code requirements and different lighting fixture types.
Roof R-Value	R-5 to R-20 in R-2.5 increments, R-20 to R-50 in R-5	R-Value	-	-
Wall R-Value	R-5 to R-20 in R-2.5 increments, R-20 to R-30 in R-5	R-Value	-	-
Window-to-wall Ratio	0.01 - 0.90	-	-	-
Window Thermal Performance	U-Values: [0.37, 0.4, 0.6], SHGC: [0.22, 0.33, 0.7]	U-Value / SHGC	Coupled	Window U-Value and SHGC values paired together

All 25 variables were randomly sampled and paired based on their dependencies 3000 times to create a baseline input data set. This resulted in 250 combinations for each geometry and HVAC system type combination. A baseline set of annual energy consumption results were simulated from these 3000 input combinations using the Building Energy Asset Score simulation engine.

Measure Selection

A limited set EEMs were selected to keep this retrofitability analysis within the scope of a pilot study. An effort was made to pick high impact, Tier 1 and Tier 2 measures as identified by the Pathways to Carbon-Neutral NYC study (NYC Mayor’s Office of Sustainability 2021). Researchers selected 5 of these EEMs to layer onto the 3000-building data set. These 5 were as follows:

1. Upgrade to LED bulbs
2. Upgrade to high performance windows
3. Upgrade constant air volume (CAV) fans to variable air volume (VAV) fans in air handlers
4. Install air side economizer on air handling units
5. Replace single zone systems with a high-performance unitary heat pump (PSZ HP) with dedicated outdoor air system (DOAS) with an ERV

Considerations were made to ensure only relevant systems received each EEM. For example, VRF systems would not be eligible for the air side economizer measure as they do not utilize a central air handling unit. Researchers applied these measures onto the 3000-building dataset to measure the individual savings of each of these measures. These new sets of simulation results were compared against their respective baseline buildings to quantify the EUI savings for each. With the measures applied and simulated, random forest regressions could be trained to estimate EUI savings for these measures.

The distribution of savings for these data sets can be found in Figure 3.

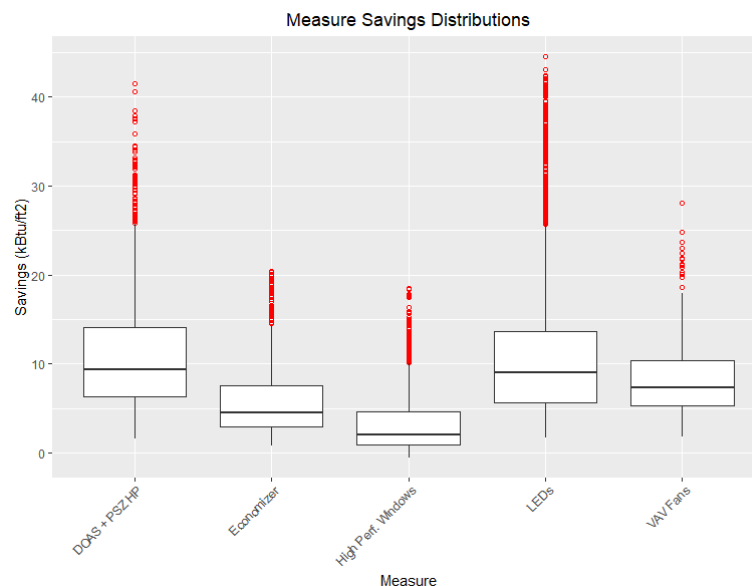


Figure 3. Measure savings in kBtu/ft² for the EEMs ran in this analysis for San Francisco offices. As demonstrated by its high median value, lighting proved to be a very impactful measure when appropriate. Likewise, replacing existing HVAC with a high efficiency DOAS and packaged heat pump also proved comparatively impactful, albeit much more difficult to implement.

Training the Random Forests Regression Models

Random forests were generated to predict the retrofitability of a building given a limited set of inputs. To train these random forests, the cleaned dataset was randomly subdivided into two smaller data sets—a training dataset comprising 80% of the dataset and a second testing dataset comprising 20% of the dataset used to measure the accuracy of the generated regression model. An R-based random forest generating package called random forest (Liaw 2022) trained the random forest regression models on the 80% training dataset's building variables with percent EUI reduction as the predicted output. The remaining 20% testing set's building variables can then be passed through these regressions to get predicted percent EUI reductions for each building in the training set. Comparing these predicted EUI reduction against the known EUI reductions in the 20% training set can measure the accuracy of the random forest. The results of this analysis are discussed in the section below

Feature importance played a role in reducing the required parameters for predicting the impact. The random forest regressions used in this study reduced the original 25 input variables from Table 2 down to only anywhere from 2 to 9 variables. Removed variables were not deemed sensitive enough through a process of trial and error. Inputs were systemically removed when their absence resulted in either an increase in model accuracy or had minimal impact on the accuracy of the model.

Random Forest Results

Each of the 5 EEMs applied to the 3000-building data set had a random forest trained against expected EUI savings. Prior to training the random forests, the training and test data sets were filtered down to only include applicable simulations. For instance, the VAV fan EEM random forest should only include simulations with air handlers. As noted in the previous section, calibrating each random forest required reducing the 25 input parameters to a select few based on feature importance as well. A list of each EEM's important parameters and associated R² values can be found in Table 3 below:

Table 3 – Important input parameters for each measure

Input	PSZ HP + DOAS w/ERV	Economizer	LEDs	VAV Fans	High Performance Windows
AHU Fan Efficiency	✓	✓		✓	
Boiler Efficiency		✓			
Chiller Efficiency		✓			
Cooling Coil DX Efficiency		✓			
Economizer	✓		✓	✓	✓

HP Cooling Efficiency		✓			
Lighting Power Density	✓	✓	✓	✓	
Square Footage	✓	✓		✓	✓
System Type					
Window SHGC	✓	✓		✓	✓
Window U-Factor	✓	✓		✓	✓
WWR	✓				✓
R-squared	0.89	0.82	0.99	0.89	0.88

Table 3. Check marks (✓) indicate that an EEM's random forest regression required this input to predict EUI savings. R² values determined using the test dataset.

As shown by Table 3, the random forests generated by the 3000-building data set resulted in relatively high R-squared values for the 5 EEMs evaluated for this pilot study. The random forest regression algorithm had the hardest time predicting the impact of economizers, with only an R² of 0.82 and required the most inputs. Unsurprisingly, the random forest algorithm predicted savings for LED light replacement very well with an R² of 0.99, as lighting energy consumption is almost entirely due to lamp type with only minor impacts on heating and cooling energy. Note how it could be approximated with just 2 inputs. Window thermal performance also stood out. Apart from LED replacements, including window U-factor and solar heat gain coefficient (SHGC) into the training set improved random forest performance.

The results of this pilot study demonstrate that random forest regression can predict EEM energy savings using substantially fewer inputs than required for a full energy simulation or ASHRAE Level 2 Audit. Next, this paper will discuss potential applications for this capability.

Applications and the Retrofitability Index

Predicting EEM savings has applications for a wide range of building energy practitioners. By requiring fewer inputs, using random forest regression has the added value of savings time and resources when compared to many conventional retrofit selection approaches. This methodology has the potential to add new features into the Audit Template web tool. Retrofitability prediction implementation has applications for both individual auditors and city ordinances managing a portfolio of energy audits.

For energy auditors, retrofitability estimation could provide EEM recommendations and estimations for their impacts for users as they fill out their audit information. In Audit Template for instance, users would have the option to receive EEM recommendations as they populated their city reports. Using random forest retrofitability prediction, energy savings could be estimated for various measures. These EEM savings predictions could then get grouped into categories such as HVAC, envelope, and lighting. Having auditors see retrofit potential prior to doing any EEM analysis of their own has the advantage of providing EEM suggestions and their relative impacts.

This regression engine-based analysis comes with caveats. First, the random forests regression models in this study were trained on Asset Score simulations. Operations in these simulations were standardized and do not reflect operations of the auditor's exact building as the minimum reporting requirements in ASHRAE Standard 211 do not require detailed building operations and schedules of operation to be reported. Hence, EUI savings from these random forests are approximations based on standard operation assumptions. This caveat suggests that

EUI savings from these regression models should be considered relative to others in the dataset rather than exact numerical calculations tailored to the user’s audit template data. To address this, the retrofitability capability uses a qualitative approach when reporting results from these regression engines. EEM savings would be better reflected through a retrofitability index—a grading scale based on relative savings for a building against those found across all buildings in the 3000-building dataset. Secondly, these random forests apply only to San Francisco office buildings with the 4 most common HVAC system types. This could be addressed by running more combinations of use types, HVAC systems, and weather locations but this effort fell outside the bounds for this pilot study.

The retrofitability index for this analysis bins EUI savings from EEMs into five distinct categories—very low, low, medium, high, and very high retrofitability. Calculations for these bins is based on aggregating all EEM simulations into one large data set and breaking simulations out into quintiles. Savings in the bottom quintile would map to very low, second quintile to low, and so on (Figure 5). Each applicable EEM in an energy audit would receive a retrofitability index, thereby providing auditors with the relative impacts of each measure with respect to a San Francisco office building under standard operating conditions. This guidance will help auditors weigh EEM selection based on their energy saving properties.

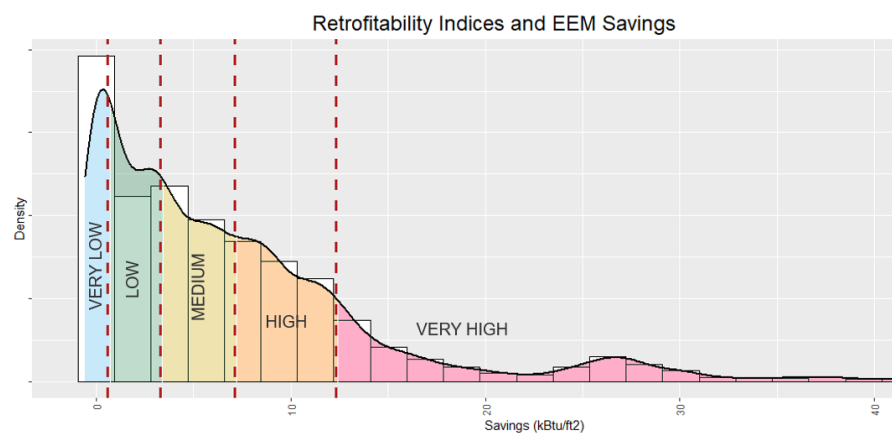


Figure 5. Distribution of retrofitability indices based on the EEMs in this study. These rankings would inform practitioners which savings had the greatest impact for a particular building.

Practitioners that manage a portfolio of buildings in Audit Template could use this approach similarly. Local ordinances and incentives could be shaped by EEMs which consistently produce high levels of energy savings and appear often throughout their Audit Template portfolio. Additionally, if any EEMs appear frequently throughout the portfolio, the retrofitability indices of those buildings would help guide which EEMs to prioritize.

Limitations of Random Forest Analysis for Retrofitability Index

Random forest regression comes with important caveats. As noted in the *Random Forest Results* section, each EEM has a unique set of required inputs. The random forest regression cannot estimate an EEM’s savings unless a user’s building has each of these inputs. This could be remedied using default values for missing required inputs, but each inferred default input would reduce the accuracy of the prediction. Many inputs will also require mapping to values

understood by the random forest. Building geometry, for instance, is difficult to fully capture and would require mapping to the closest approximation used in the random forest simulations. Mixed use buildings challenging for the same reason. One cannot feasibly capture all combinations of use types when generating a dataset upon which to train a random forest. Solutions exist by heuristically pre-processing data. For instance, a mixed-use building could instead pass in the use type with the greatest square footage. While this provides a working solution, the accuracy of a random forest's prediction drops with each of these approximations.

In short, the quality and completeness of data sets used to train the random forest regressions determine the ability to estimate a wide array of inputs. The more limited the data sets used to train the engines, the more limited their capabilities. Practitioners looking to implement their own random forest regressions should carefully consider which inputs to include in their engines and how to map them to values understood by their random forest regressions.

Future Developments and Application

The retrofitability capability proposed through this paper would provide a convenient and reliable approach for auditors to identify and priorities retrofits for the facility being audited. The fact that the regression-based savings are estimated using the building systems and equipment specifications for that specific facility and tailored to meet the city's objectives and goals, would make this capability highly useful. Measures could be prioritized based on the metric and overarching target for emissions reduction or energy savings. For cities and programs targeting strategic decarbonization strategies, equipment remaining useful life could be considered to give electrification recommendations for the future. Similarly, programs targeting deep emissions reduction or energy savings to meet a performance target could receive envelope and HVAC replacement recommendations in addition to the low-cost controls and lighting. A prioritized list which indicates potential energy savings that is based on the buildings existing systems has tremendous benefits and provides guidance to auditors and engineers. The Retrofitability Index capability in Audit Template tool is simple as it integrates into the existing audit workflow, and without requiring any additional information about the building, uses its existing equipment inventory to identify and prioritize retrofits with estimated energy savings potential.

References

- Architecture 2030. architecture2030.org/why-the-building-sector/ Accessed March 25th, 2022
- ASHRAE, 2018. "Standard 211-2018: Standard for Commercial Building Energy Audits". Atlanta, GA
www.ashrae.org/File%20Library/Technical%20Resources/Bookstore/previews_2016437_pre.pdf
- ASHRAE. 2020. Advanced Energy Design Guides. www.ashrae.org/technical-resources/aedgs
- Breiman, Leo, 2001. "Random Forests", *Machine Learning*, 45, 5-32

- Denisko, Daniel, Hoffman, Michael. 2018. “Classification and interaction in random forests.” *Proceedings of the National Academy of Sciences*. 115
- Department of Energy (DOE), 2018. “Commercial Prototype Building Models.”. Washington, DC: DOE. www.energycodes.gov/development/commercial/prototype_models#90.1
- Department of Energy (DOE), 2019. “Asset Score: Overview”. Washington, DC: DOE. help.buildingenergyscore.com/support/solutions/articles/8000026068-overview
- Department of Energy (DOE), 2020. “Audit Template: Overview”. Washington, DC: DOE. help.buildingenergyscore.com/support/solutions/articles/8000053354-overview
- Department of Energy (DOE), 2021 a. “OpenStudio”. Washington, DC: DOE. openstudio.net/
- Department of Energy (DOE), 2021 b. “EnergyPlus”. Washington, DC: DOE. energyplus.net/
- EIA 2020. www.eia.gov/tools/faqs/faq.php?id=77&t=11 . Accessed March 25th, 2022
- EPA. 2018. ENERGY STAR Portfolio Manager Technical Reference. portfoliomanager.energystar.gov/pdf/reference/ENERGY%20STAR%20Score.pdf
- EPA. 2019. Use Portfolio Manager. Washington, DC: U.S. Environmental Protection Agency. Accessed October 1, 2019. www.energystar.gov/buildings/facility-owners-andmanagers/existing-buildings/use-portfolio-manager
- EPA 2021. Building Performance Standards: Overview of State and Local Decision Makers. epa.gov/sites/default/files/2021-02/documents/benchmarking_building_performance_standards_section2.pdf
- Gaash, W.H., Travis, J., Zhao F., Kaplan, M., Muth, C., 2014. “A Comparison of Methods for Early-Stage Retrofit Analyses”, In *2014 ACEEE Summer Study on Energy Efficiency in Buildings* 149-160
- Gui, C., Guo, S., Yan, D., An, J. 2020. “Development of Prototype Building Model in Beijing Based on Actual Energy Consumption.” *Proceedings of the 11th International Symposium on Heating, Ventilation and Air Conditioning* 1187-1196.
- Hong, T., Mary Ann Piette, Yixing Chen, Sang Hoon Lee, Sarah C. Taylor-Lange, Rongpeng Zhang, Kaiyu Sun, Phillip Price., 2015. “Commercial Building Energy Saver: An energy retrofit analysis toolkit.”, *Applied Energy*, 159, 298-309
- IMP 2018, www.imt.org/wp-content/uploads/2018/03/PuttingDatatoWork_ProjectSummary.pdf
- IMT 2021, www.imt.org/wp-content/uploads/2021/01/IMT-Comparison-of-Audit-TuneUp-RCx-Policies-January-2021.pdf

- Kerr, Laurie, 2016. “The Lazy Man’s Guide to 80 x 50 in NYC”, In *2016 ACEEE Summer Study on Energy Efficiency in Buildings*
https://www.aceee.org/files/proceedings/2016/data/papers/9_883.pdf
- Liaw, Andy, Breiman, Wiener, 2022. “randomForest: Breiman and Cutler's Random Forests for Classification and Regression”, <https://cran.r-project.org/web/packages/randomForest/index.html>
- Maxwell, 2013. Auditing Audits: Big Savings Found in Long-Term Assessment, 2013
- International Energy Program Evaluation Conference, Chicago, IL. ers-inc.com/wp-content/uploads/2017/02/Auditing-Audits.pdf
- New York City (NYC), 2009. “LL87 of 2009 Compliance Guidelines”
https://www1.nyc.gov/assets/buildings/pdf/how_to_file_energy_efficiency_report.pdf
- New York City (NYC), 2022. “LL87: Energy Audits & Retro-commissioning” Accessed March.
www1.nyc.gov/html/gbee/html/plan/ll87.shtml
- NYC Mayor’s Office of Sustainability, 2021. “Pathways to Carbon-Neutral NYC: Modernize, Reimagine, Reach”
<https://www1.nyc.gov/assets/sustainability/downloads/pdf/publications/Carbon-Neutral-NYC.pdf>
- SFE, 2022a. sfenvironment.org/article/san-franciscos-existing-commercial-buildings-ordinance Accessed March 2022.
- SFE, 2022b. sfenvironment.org/article/how-to-comply-and-report-to-sf-environment Accessed March 2022.
- Tso, Geoffrey K.f., Kelvin K.w. Yau, 2007. “Predicting Electricity Energy Consumption: A Comparison of Regression Analysis, Decision Tree and Neural Networks.” In *Energy*, vol. 32, no. 9, 1761–1768
- Wang, N., Supriya Goel, Atefe Makhmalbaf, 2013. “Commercial Building Energy Asset Score Program Overview and Technical Protocol”
www.pnnl.gov/main/publications/external/technical_reports/PNNL-22045rev1.1.pdf
- Wang, N. Supriya Goel, Atefe Makhmalbaf, Nicholas Long, 2016. “Development of building energy asset rating using stock modelling in the USA” *Journal of Building Performance Simulation*, SSN: 1940-1493 (Print) 1940-1507 (Online)
- Wang, N., Juan Gonzalez Matamoros, Libu Babu, Richard Fowler, 2020., “Retrofit-ability: A Complementary Metric to Inform Energy Efficiency Policies and Programs” In *ACEEE Summer Study on Energy Efficiency in Building*