Machine Learning for Predicting Annual Electricity Consumption of Unmetered Army Buildings

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Abstract

The U.S. Army has made significant investments in utility meters to improve energy management across its enterprise. However, centralized electricity usage data only exists for about 10,000 of the 78,000 buildings in the Army portfolio. Requirements on facility energy usage become near impossible to plan without energy data for the remaining 68,000 buildings. The lack of energy data for this number of buildings necessitates some kind of modeling. While the Army collects a multitude of data on its buildings, very little of it can be used directly in an equation for a physics-based energy model. Machine learning offers an opportunity to detect and leverage the statistical correlations between the existing data and electricity usage in Army facilities.

The research team utilized a random forest model to generate electricity energy use intensity predictions for unmetered Army buildings. Key findings indicate that machine learning can enhance energy modeling. Preliminary results already show a strong correlation around $R^2 = 0.5$ with facility electricity energy use intensity, especially given the lack of occupant data. These results outperform existing methods for planning policy compliance and energy products within the Army building portfolio. Ongoing research seeks to develop more sophisticated models and achieve results with $R^2 \geq 0.6$.

Introduction

Machine learning (ML) has become very pervasive across many industries. The ML methods available to researchers and engineers have greatly increased in number and quality over the last decade, and this growth has brought significant potential for new ML applications. Decision-makers commonly apply these algorithms in cases with large amounts of data with unclear correlations to ascertain insightful patterns (Jordan & Mitchell, 2015). These analyses, built from existing data, can then be used to bridge gaps in data collection or predict future trends to establish a complete understanding of the data.

ML provides an opportunity for Army decision-makers to leverage existing data to optimize plans across the building portfolio, such as the addition of microgrids for resilience. Furthermore, federal laws and policies often mandate building energy compliance metrics for military installations based on building energy consumption. The Comprehensive Energy and Water Evaluations (CEWE) Policy of 2012 mandates that 75% of facility energy consumption at federal installations should be audited every four years (Hammack, 2012). The Utilities Metering Policy of 2021 directs that energy meters should be installed to meet 60% of consumption by individual utility with a goal of 80% across installations in Department of War components (Gillis, 2021). As of the time of writing, only about 10,000 out of the 78,000 total Army buildings reported regular and usable electricity metering data to a centralized data system, or about 13%. Without building energy modeling (BEM), Army installation energy managers must rely on building count, facility square footage, or reference numbers based on building type and climate zone to perform their planning. These reference numbers summarize findings from the Commercial Building Consumption Survey (CBECS). However, misalignment between commercial buildings and Army buildings poses a fundamental issue with the reference numbers approach (U.S. Energy Information Administration, 2018). The large scale of the Army building portfolio and limited resources available to installation energy managers require deliberate planning to achieve compliance with these policies in a timely and cost-effective manner.

The lack of building electricity data inspired the development of several modeling techniques the Army can use to make more informed energy-related decisions. Many of these techniques rely on physics-driven models, but these models are calculation intensive. Additionally, they frequently require inspections to collect data for use in these physics-based calculations. These models can require “thousands of inputs” and compute for “minutes to hours” (Long, Almajed, von Rhein, & Henze, 2021). The Army cannot currently afford the expensive inspections required to collect the necessary data for physics-based modeling.

However, Army data systems already include building data such as square footage, type, location, climate information, and even mechanical equipment. These data could be statistically correlated with annual building electricity usage using ML. This ongoing study thus seeks to develop an ML model that predicts the “typical” electricity energy use intensity (EUI) of the unmetered Army facilities by using the metered Army facilities as a training and testing dataset. A “typical” electricity EUI would represent the expected annual electricity consumption of a given building based on a “typical” year as defined by the Typical Meteorological Year 3 (TMY3) dataset (National Laboratory of the Rockies, n.d.). To avoid costs from additional data collection, this research correlates available data with annual electricity usage based on the 10,000 buildings that report electricity metering data. The objective of this modeling effort is to generate electricity EUI predictions for the 68,000 unmetered Army facilities as this data is not otherwise available for unmetered facilities.

Ideally, an improved understanding of building-specific EUI enables strategic planning to achieve cost-efficient compliance with policies like the CEWE and Utilities Metering Polices (Hammack, 2012; Gillis, 2021). This team has anecdotally seen building audit lists decrease from thousands of buildings to hundreds of buildings when applying an energy-driven approach rather than a square-footage-driven approach at Army installations. This process can further be applied beyond the military to model the energy usage of any large portfolio that has significant data gaps. This work is ongoing, and preliminary methods and results are discussed in the following sections.

Literature Review

Previous techniques for BEM generally relied on physics-based models. A myriad of such modeling tools have been developed, to the extent that guides have been created to categorize them to simplify the selection process. However, these tools either require large amounts of user input to characterize buildings or they depend heavily on engineering assumptions for their calculations (Long, Almajed, von Rhein, & Henze, 2021). The calculations are then frequently resource intensive, requiring much computing power or time to generate results (Long, Almajed, von Rhein, & Henze, 2021). Statistical models developed using ML provide a faster, less resource-intensive alternative to physics-based BEM. However, physics-based BEM techniques are termed “white box” since they rely on clear causality through their equations. By contrast, statistical modeling techniques are termed “black box” since they rely entirely on correlation, with no guarantee of causality (Long, Almajed, von Rhein, & Henze, 2021). This lack of causality complicates the calculation of energy savings, but it offers great speed in preparing portfolio-level energy planning efforts.

A common set of ML used in these projects are Classification and Regression Tree (CART) algorithms. This category includes algorithms such as Random Forest. These algorithms rely on decision trees created through “recursive, binary splitting of the predictor space into non-overlapping regions” (Østergård, Jensen, & Maagaard, 2018). Abbasabadi et al. (2019) utilized ML techniques for urban planning in Chicago. The model predicted both building energy usage and transportation energy usage at a scale prohibitively difficult using physics-based techniques. Other research using ML produced models in which 41% of the variance in building EUI could be explained by the features in the model ($R^2 = 0.41$) (Abbasabadi, Ashayeri, Azari, Stephens, & Heidarinejad, 2019).

Similar efforts attempted EUI modeling nationally, relying on CBECS. These results showed promise when utilizing gradient boosting and support vector machine algorithms. However, researchers suspect that missing data on occupant behavior, building thermal performance, and more prevent more accurate results (Deng, Fannon, & Eckelman, 2018). Several studies have identified building type to be a key feature when relying on statistical modeling for building energy consumption or EUI (Bass, et al., 2022; Chen, Gao, Zhou, Wang, & Yan, 2024). Golafshani, et al. (2024) identified building shape and temperature to be key features. While Army occupancy data is difficult to gather across the Army building portfolio, many of the other variables explored in the literature are already available in Army databases. The availability of these data suggests a tremendous opportunity for ML.

Methods

The effort described herein focuses on the development of an ML model to predict the electricity component of building EUI. The Army Meter Data Management System (MDMS) previously collected energy metering data for approximately 10,000 Army buildings, but it has since shut down. MDMS collected interval meter data every 15 minutes from electricity meters since late 2018 until its shutdown in early 2025. However, MDMS offered limited insights into unmetered buildings. The platform calculated EUIs by individual commodity per Army Category Code (classifications of Army buildings), but these calculated EUIs frequently relied on only a few buildings (<10). As such, these insights were of limited statistical significance. Even these insights are no longer easily available since the total shutdown of the system. The research team relies on stagnant copies of the data to proceed with this work. For this effort, the team uses monthly electricity consumption reported in MDMS prior to system shutdown.

To construct a dataset for ML, it had to be determined what data would be available and accessible for all unmetered facilities. The Army centralizes real property characteristics of its buildings in the Headquarters Installation Information System (HQIIS). These data include features such as square footage, building type, year built, and location. Similarly, the BUILDER™ Sustainment Management System platform contains centralized mechanical equipment data for most Army facilities (U.S. Army Engineer Research and Development Center (ERDC), 2021). These two systems contain a trove of data, but much of the data requires transformation for usage in an ML model. Unification of these data requires a central identifier to produce one final dataset for ML. HQIIS contains this unique identifier as the Real Property Unique ID (RPUID). Metrics characterizing individual buildings were compiled at the RPUID level.

The BUILDER™ Sustainment Management System categorizes equipment in Army facilities at four different levels through three separate tables (U.S. Army Engineer Research and Development Center (ERDC), 2021). The data in these three tables create a hierarchical categorization system, reflected in Figure 1. Creating a streamlined data model with data from the BUILDER™ database required joining these tables together to compile all classifications of equipment in a single table. Please note that Figure 1 shows the classifications in BUILDER™, not the tables in BUILDER™.

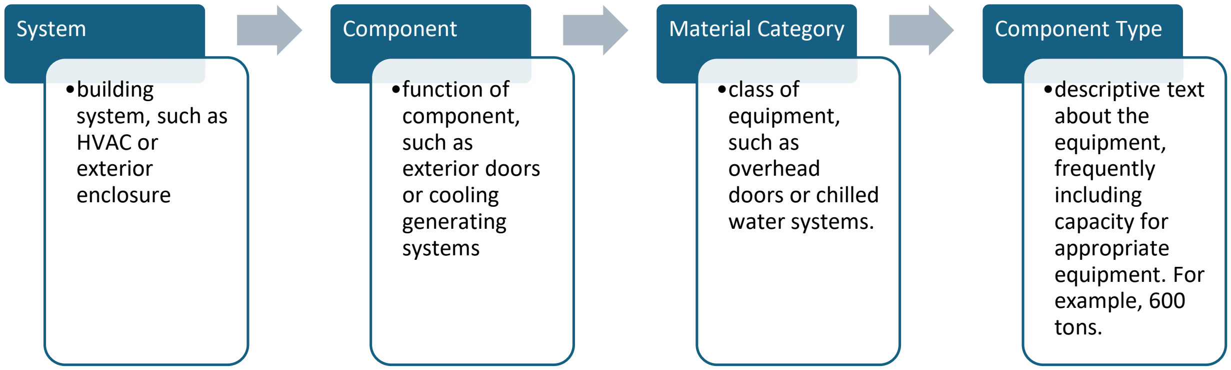

Figure 1. BUILDER™ Classifications

Nominal equipment capacities could be manually extracted from the Component Type field by researchers. This manual processing enables the generation of summary metrics at the building level, such as plant cooling power and plant heating power. These fields represent the capacity of the mechanical equipment in a building to generate cooling and heating respectively. Researchers were able to parse the differences between the following equipment types as shown in Table 1.

Table 1. Equipment Configurations

Equipment Configuration	**Meaning**	**Example(s)**	**Contributes to Building Plant Capacity**
Load	Equipment that directly serves a building thermal load	Fan coil units	No
Rejection	Equipment that rejects unwanted heat from a building system to the environment	Cooling towers	No
Source	Equipment that generates, stores, or provides heating or cooling for downstream load equipment	Boilers, chillers	Yes
Zone	Equipment that generates and serves heating or cooling locally	Window A/C unit	Yes

Accordingly, Army researchers summed up the capacities of source and zone equipment to generate building plant cooling and heating capacities. However, the lack of design information in BUILDER™ creates the potential for error, as Army researchers could not distinguish between parallel and redundant equipment capacity for heating and cooling equipment.

Previous work mapped Army sites to ASHRAE climate zones. However, the research team recognizes that numerical characterizations of climate would be superior for use in ML. The TMY3 dataset provides a “typical” year of weather data by selecting a representative month from the 30 years of data available (National Laboratory of the Rockies, n.d.). Thus, the team created mappings of weather stations to Army sites by finding the shortest distance based on site coordinates and weather station coordinates. The research team used the resulting data to generate climate statistics for each site, such as cooling degree days and minimum relative humidity. The research team used various combinations of the features listed in Table 2 to explore whether certain combinations had greater effects on the R^2 than the individual effects of the features on their own.

Table 2. Features Tested by Army Researchers

Feature Name	Meaning
Cooling W/ft^2	Building plant cooling capacity in Watts per square foot
ASHRAE 100 Electric EUI	Actual (not target) electricity component of EUI listed in the tables of ASHRAE 100, split using ratios from CBECS (ASHRAE, 2018) (U.S. Energy Information Administration, 2018)
Facility ft^2	Square footage of the building
Year Built	The year of construction of the building
Power Capacity Intensity (W/ft^2)	The total electrical capacity of the building in Watts per square foot
CERL EUI Category	A categorical field summarizing Army Category Codes into generic building types
CFM/ft^2	Ventilation capacity of the building in cubit feet per minute normalized by building area in square feet
Cooling Degree Days	The expected cooling degree days of a location calculated using the TMY3 data and a baseline of 65°F
Heating Degree Days	The expected heating degree days of a location calculated using the TMY3 data and a baseline of 65°F
Site Latitude Coordinate	The latitude coordinate of the Army site where the building is
Site Longitude Coordinate	The longitude coordinate of the Army site where the building is
Heating W/ft^2	Building plant heating capacity in Watts per square foot

Heating Ratios	These features calculated the fraction of building plant heating capacity attributed to different types of heating
Cooling Ratios	These features calculated the fraction of building plant cooling capacity attributed to different types of cooling
Site Relative Humidity Minimum	The minimum relative humidity observed in the TMY3 dataset for a given Army site
Cooling Hours	Number of hours in the TMY3 dataset above a cooling threshold of 65°F
Heating Hours	Number of hours in the TMY3 dataset below a heating threshold of 65°F
Pump Count	Number of pumps in a building
Max Temperature	The maximum dry bulb temperature reported in the TMY3 for a given site
Min Temperature	The minimum dry bulb temperature reported in the TMY3 for a given site
Temperature Swing	The difference in the maximum and minimum temperatures

For brevity, some features are grouped together in Table 2. The heating ratios calculated and tested were direct-fuel (hydrocarbon burning) heating, electric heating, heat pump heating, and hydronic heating. The cooling ratios calculated and tested were air cooling, direct expansion cooling, evaporative cooling, and water cooling. Note that only the site relative humidity minimum was considered, as both average and maximum relative humidities tended to be at or near 100%.

The ML model was developed in Python for the ease of use and access associated with Python (Python Software Foundation, n.d.). The popularity of Python ensured that documentation would be available online and in the literature. Development relied primarily on Jupyter Notebooks (Kluyver, et al., 2016). Functions were written in one Notebook to be shared across model types. This Notebook defined all necessary functions for running the EUI predicting models, including a function that produces model statistics and plots that visualize results and performance. The research team developed a model testing script to evaluate the performance of different ML algorithms. The script performed a simple 80/20 training and testing split on the 10,000 buildings with electricity data. The script then assessed the performance of different ML model types on the same 80/20 train/test split. The team selected Random Forest for its performance in R^2 and ease of configuration. Table 3 shows results of a model comparison script comparing generic models. Note the performance of the random forest model.

Table 3. Model Comparison (untuned models)

ML Algorithm	R^2
K-Nearest Neighbors	-0.0508
Support Vector Machine	-0.00309
Random Forest	0.458
Extra Trees	0.447
Gradient Boosting	0.443
Ridge Regression	0.427
Kernel Ridge Regression	0.420

Results

Results changed greatly as preprocessing steps were modified and data quality improved through researcher effort. Preprocessing changed iteratively as the research team improved the methodology to generate electricity EUIs from monthly consumption data. Train/test splits were then created by using the "train_test_split" from Scikit-learn. A "random_state" argument was passed to the "train_test_split" function to ensure reproducible results across trials (Pedregosa, et al., 2011). This procedure ensured consistent splitting of the 10,000 metered buildings across experiments. The most recent results as of the time of writing produce the metrics in Table 4.

Table 4. Performance Metrics of ML Model

R^2	Adjusted R^2	RMSE	Mean Percent Error
0.483	0.472	18.3	57.2

The adjusted R^2 accounts for the number of features included in training as it follows the formula in Equation (1):

$$Adjusted\ R^2 = 1 - \frac{(1-R^2)(N-1)}{N-p-1} \quad (1)$$

where R^2 was previously calculated as 0.483, N is the total sample size, and p is the number of features. The adjusted R^2 attempts to penalize the number of unnecessary variables and signal potential overfitting. Figure 2 visualizes these results on an identity plot. Red dashed lines represent $\pm 5\%$ error bounds from the ideal one-to-one line of an identity plot, which is shown as a black dashed line.

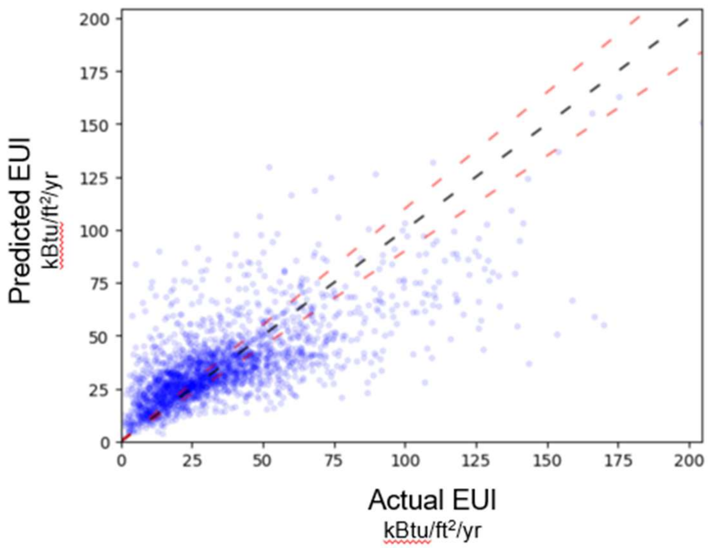

Figure 2. Identity Plot for Random Forest Results

While the research aims to achieve $R^2 = 0.6$, the current results show a strong ability to predict the variance in EUI. Particularly important to note is the lack of occupancy data, which other researchers have noted as a key feature in predicting building energy consumption (Abolhassani, et al., 2024; Deng, Fannon, & Eckelman, 2018). Both the goal of 0.6 and current results exceed the results in the literature without occupancy data (Abbasabadi, Ashayeri, Azari, Stephens, & Heidarinejad, 2019). These results outperform using ASHRAE 100 reference numbers, which have an R^2 value near 0. Similarly, the method using ASHRAE 100 reference numbers results in a mean percent error of 119%, over double the results from using machine learning. Army Energy Managers previously relied on the approach based on reference numbers, so machine learning represents a valuable improvement in planning energy projects across Army sites. The results of a tabular method based on ASHRAE 100 are shown in Figure 3.

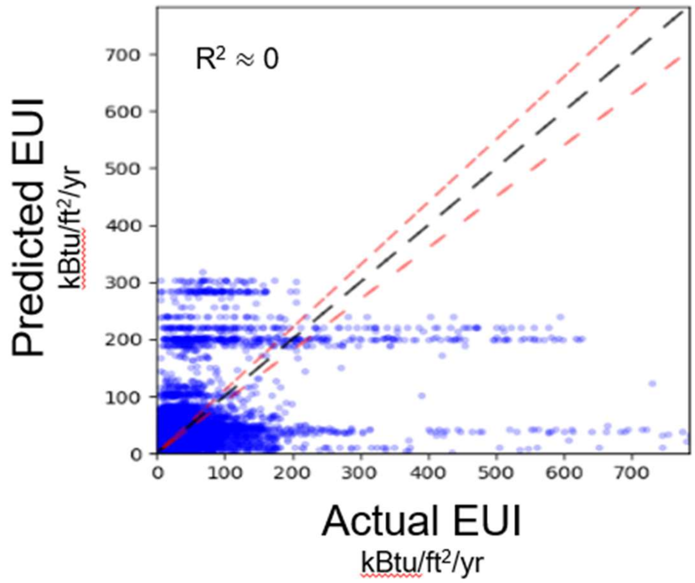

Figure 3. Identity Plot for ASHRAE 100 Electric EUIs versus Metered EUIs

Shapley Additive Explanation (SHAP) is a technique used to increase the interpretability of ML models (Chen, Xiao, Guo, & Yan, 2023). The research team used SHAP plots like Figure 4 to better understand the model.

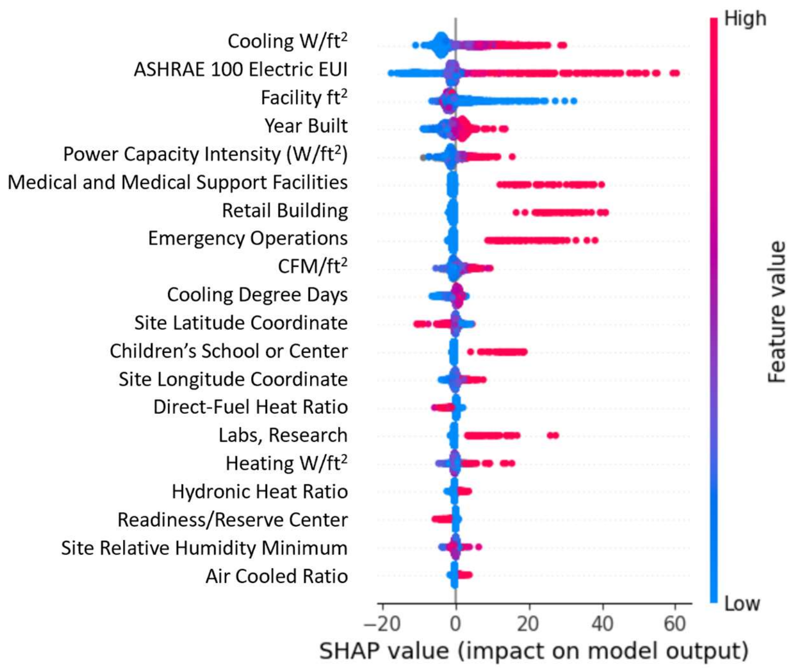

Figure 4. SHAP Plot

The maximum value for each feature is set to red. The minimum value for each feature is set to blue. Binary fields, such as building category, appear with only red or blue as they can only be true or false. Other values such as the cooling power intensity in W/ft^2 are continuous and thus show a continuous range of colors. The SHAP value reflects the impact of a feature value on the output predicted electricity EUIs. Negative SHAP values represent reducing a prediction below the average prediction. Positive SHAP values represent bringing an individual prediction above the average prediction. Through these characteristics, Figure 4 visualizes how individual values in a given feature affect the output predicted electricity EUI.

Discussion

While this research project is ongoing, preliminary results already show progress in informing Army stakeholders. Figure 4 empirically confirms some intuitive correlations. For example, a high value in the direct-fuel heat ratio indicates that the building relies primarily on burning a hydrocarbon for heating. Logically, this decreases the reliance on electricity, which the model confirms as a decrease in the predicted electricity EUI. The more fuel a building uses for heat, the less electricity it must use. The energy input used for cooling technologies is usually solely electricity. Logically, this would indicate that more cooling capacity per square foot of the building would increase the electricity consumption per square foot. Figure 4 confirms this, as high values in the Cooling W/ft^2 field lead to higher predicted electricity consumption in kBtu/yr/ft^2. One advantage of machine learning is the ability to rapidly identify and confirm these correlations and their impacts on predicted variables.

Another advantage is the ability to identify unexpected correlations. For example, the model selects geographic coordinates as high importance in addition to features relating to weather, such as cooling degree days. The geographic coordinates may reflect behavioral differences across locations in addition to weather effects. One may not have expected facility square footage to have a notable impact on electricity EUI, as electricity EUI should already be normalized for square footage. However, the results in Figure 4 suggest that electricity consumption and square footage are not cleanly proportional, as implied by EUI. Equipment features were fed to the model as either ratios or intensities normalized by square footage. As such, the strong importance associated with square footage in Figure 4 is surprising, suggesting a more complicated relationship between energy usage and building size than linearity.

Figure 4 identifies several CERL EUI Categories as high importance. Medical and Medical Support Facilities and Labs or Research Buildings increase the predicted electricity EUI, as expected. These buildings would be expected to house specialized equipment with high electrical loads. Readiness/Reserve Center Buildings show a negative SHAP value, decreasing the predicted electricity EUI. These buildings usually experience intermittent, seasonal occupancy rather than full-year occupancy, resulting in lower electricity consumption. The remaining categories warrant further investigation. Emergency Operations Buildings led to greater predicted electricity EUI, possibly indicating a near constant operation of these buildings. Both Children’s School or Center Buildings and Retail Buildings also led to greater predicted electricity EUI, suggesting high electricity consumption needing further study.

The unique situation of the Army as an organization with a large building portfolio but many unmetered buildings poses an opportunity to test and leverage ML. Training across the Army portfolio allows the ML model to observe the impact of local climates on electricity EUI. The size of the dataset enables an ML model to learn the correlations between the various available building characteristics and electricity EUI. The research team believes other large real property holders could attempt similar projects, strengthening the role of ML in managing the energy consumption of large building portfolios.

Ongoing research explores expert models that train on clusters of buildings instead of the complete portfolio. Researchers create clusters by grouping buildings of the same category or with similar climate data. However, cluster models will be limited by the size of the datasets after the splits. Future publications will include the details of these more sophisticated models. The research team hopes that findings produced through this ongoing effort will guide future metering efforts in the Army. An increase in Army building metering would expand the training and testing dataset, hopefully improving the predictive power of this ML model for the remaining unmetered buildings.

The Army meters much more building electricity usage than building gas usage. The research team believes that expanding gas metering would enable the construction of an ML model for gas EUI as well as providing a more holistic insight into how Army buildings consume energy. Most Army buildings still rely on direct fuel firing for heating. Without more gas metering data, heating energy consumption poses a blind spot. This blind spot is observable in the identification of direct fuel heat ratio as an important feature in Figure 4. However, the research team currently lacks sufficient data to see how much the gas EUI increases to compensate.

Conclusions

ML provides an ideal technique for modeling annual-level energy usage of unmetered facilities in large portfolios. Physics-based models require extensive auditing to collect the necessary data, but ML can leverage commonly available data that should be present in large building portfolios. This technology is ideal for an organization such as the Army; much data is available, but cost limitations prevent extensive energy metering or thorough inspections to gather data for physics-based modeling.

The Army research team utilized preexisting tools available through Scikit-learn to quickly develop a random forest model to predict the electricity component of EUI. The ease of use through Scikit-learn enables quick iteration both on input features and hyperparameters for the model (Pedregosa, et al., 2011). The team discovered that certain derived features, such as the temperature swing, are more powerful than the individual features used in calculation. Ongoing research seeks to develop cluster-based models or mixture-of-expert ML models.

The team expects that the sharing of results with Army stakeholders will accelerate building energy planning at the portfolio level. The research team has begun sharing modeling predictions through data visualization tools to help Energy Managers more quickly and efficiently plan energy projects at their installations. Initial feedback has been positive.

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