

GHG Emissions Reduction Analysis in Commercial Buildings

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ABSTRACT

As the development of new monitoring technology proliferates and the supply of renewable energy grows, reducing greenhouse gas (GHG) emissions from fossil fuel generation has never been more possible. At different times throughout the day and throughout the year, the mix of electricity from clean energy sources vs. fossil fuel sources varies. Calculations of GHG emissions from commercial buildings are based on a general mix of electric loads for individual accounts and include factors such as heating, ventilation, air conditioning (HVAC), lighting, and appliances. It is vital to understand which of these factors are most significant in the production of GHG emissions, so that policymakers and energy efficiency programs are better equipped to target programs and policies in their decarbonization strategy.

This paper seeks to understand the key factors that contribute the most to GHG emissions from commercial buildings through the exploration of GHG emissions patterns based on Michigan utility customers from DTE Energy and another Midwest utility with approximately 8 billion data points collected from 2020 and 2021.... Factors such as industry, building type, number of employees, building size, annual gross margin of companies, and seasonality are also considered. Machine learning algorithms are applied to identify the important factors that contribute to GHG emissions for large electricity users by industry.

This paper further assesses the relative energy efficiency performance by comparing commercial building data across business models, number of occupants, and building-specific features. Results from this study aim to provide data-driven insights to improve energy efficiency policies and programs.

Findings

This paper presents findings based on key contributing factors to greenhouse gas emissions.

- Applying machine learning algorithms, key factors, e.g., season, temperature, business types, geographic location, and energy efficiency technology, are identified to contribute to greenhouse gas emissions of commercial buildings based in DTE Energy and another Midwest utility service territories.
- Findings demonstrate that energy savings and emissions reductions do not have a 1:1 relationship.

- Energy efficiency technology types which save energy when the marginal emissions are the dirtiest, (during peak hours in the Midwest) correlate to lowering a building's overall emissions intensity, although more work is required to isolate these technology types.
- Grid region specific emissions rates should play a large role in determining strategies for decarbonization. Regions with high emissions volatility translate to a divide between a kWh used and the resulting emissions at any given time. For example, California has a high renewable mix, Montana is coal heavy, while the Midwestern regions utilize natural gas with intermittent hydro.

Introduction

With the clean energy transition taking center stage culturally and politically in the United States in 2022, strategies to reduce greenhouse gas (GHG) emissions from existing fossil fuel generation are critically important. President Biden's commitment to cleaner and cheaper energy highlights a critical area of federal focus: modernizing the federal building portfolio to yield a 50 percent reduction in building emissions by 2032 (Statements and Releases 2021; Statements and Releases 2022). Slashing the GHG emissions in buildings is one of the most important actions to protect the living environment, but not all buildings are equal in their energy consumption and potential for emissions reductions. The US Department of Energy estimates that commercial buildings use 35 percent of all electricity consumed in the US, and of that total an average of 30 percent of it is wasted (Buildings 2020). Commercial buildings, then, make an ideal target for their significant energy use, propensity for waste, and proliferation of advanced metering infrastructure with which new machine learning techniques can be leveraged.

The clean energy transition has already precipitated numerous studies on potential methods to reduce GHG emissions using different energy efficiency technologies. Unlike these existing studies, this paper offers a more holistic view of large commercial populations and the myriad factors impacting commercial emissions. The existing landscape of emissions reduction study is narrower in focus, either prioritizing new policy development (Sivaram et al. 2021); forecasting the outcome of current and potential policy impacts (Zhou et al. 2018); or limiting the type of buildings or factors included in the studies (Lou et al. 2021; Zheng and Lai 2018; Zhong et al. 2021). Additionally, no existing study uses machine learning to prioritize the key contributing factors to commercial emissions, and then proceed to unpack the how and why of that impact.

The adoption of machine learning techniques by utilities and their partners means that we can glean new insights into which methods may be most effective to reduce commercial emissions; specifically, how to modify well-established Demand Side Management (DSM) programs to optimize for avoided emissions as much as energy saved. These well-established programs, especially energy efficiency (EE) programs with strong participation history like those of DTE Energy and another Midwest utility, have a great deal to tell us about large energy users – commercial and industrial (C&I) customers – and the factors that have been historically

significant to the reduction of their overall greenhouse gas (GHG) emissions profiles. Existing studies on the key factors contributing to commercial building emissions demonstrate that large datasets are needed to see these GHG emissions patterns (Najafi et al. 2020; Liu, Guo, and Xiao 2019; Zhong et al. 2021). In short, studying the energy use, emissions, firmographic data, and historical program participation across C&I populations from DTE and another Midwest utility may yield a fuller picture than results generated from smaller evaluations.

This paper takes the lessons learned from emissions studies and applies Decision Tree Regression and SelectKBest modeling to identify key contributing factors to commercial emissions. We then isolate these key contributing factors and unpack them to discuss their unique patterns. By viewing each factor in isolation and in concert with the other top contributing factors, we highlight how energy efficiency policies and programs can best contribute to decarbonization.

Methods

Tools and Platforms

For the data extract, transformation, and load (ETL) of both historical participation and firmographic data, we use a combination of Transact-SQL and Python. This data, in the form of relational tables, is then loaded into Delta Tables within our Databricks environment which we prepare for ingest into our Decision Tree and SelectKBest models. The WattTime Marginal Operating Emissions Rates (MOERs) are pulled from WattTime's Historical Data Application Programming Interface (API) with corrected time zones by Python. Then this dataset is joined to the Advanced Meter Infrastructure (AMI) data using PySpark. All modeling is performed in Databricks using PySpark, and then visualized using either Microsoft Power Business Intelligence (BI) software or Python.

Data Source Considerations

Multiple data sources are applied in this study. The datasets, which are from 2020 and 2021, used in this study can be segmented into four main sources:

- Historical Energy Efficiency (EE) program participation data including EE technology types
- Customer firmographic data including but not limited to industry, location, business type, and employee count
- AMI data, smart meter hourly energy data with hourly temperature
- MOERs data, hourly marginal emission rate which is provided by WattTime.org

This paper uses WattTime's MOERs over traditional emissions rates. WattTime, a mission-driven nonprofit subsidiary of the Rocky Mountain Institute, champions the use of

marginal emissions rates over average emissions rates. Basing the rate on the marginal emissions of a given grid region, a MOER measures the impact demand has on a grid based on time of day, geography, time of year, temperature, generation efficiency, and generation fuel mix. A MOER gauges the impact that an energy-saving decision has on a power grid by apportioning GHG emissions to customers based on when and where they are increasing or decreasing their demand on the grid. Because this study is focused on key contributing factors and utilizes time series data as one of its primary inputs, capturing emissions volatility in this impact framework more clearly highlights these differences compared to a traditional emissions accounting framework. Traditional accounting frameworks have limited effectiveness in this type of study, as emissions rates are averaged across a region's generation mix and multiplied by the sum of energy use apportioned to a given energy user. To get a better understanding of the key factors related to commercial emissions, we need an emissions rate that captures the impact a kWh has on a grid during a specific time in a specific geography.

The grid region and grid sub-regions data from WattTime used in this study also warrant a brief explanation. Although we believe a MOER is the most effective way to distinguish the various contributing factors for commercial emissions, we are limited to the WattTime grid region in which our two sample utilities occupy: the Midcontinent Independent System Operator (MISO) and its sub-regions: MISO Grand Rapids and MISO Detroit. Visualized below are the raw MOER values for MISO Detroit compared to the raw values for NV Energy (NVE) and NorthWestern Energy (NWE) for 2020 and 2021. The NVE and NWE grid regions for comparison are selected in this study because of their distinct marginal generation mixes and unique emissions profiles.

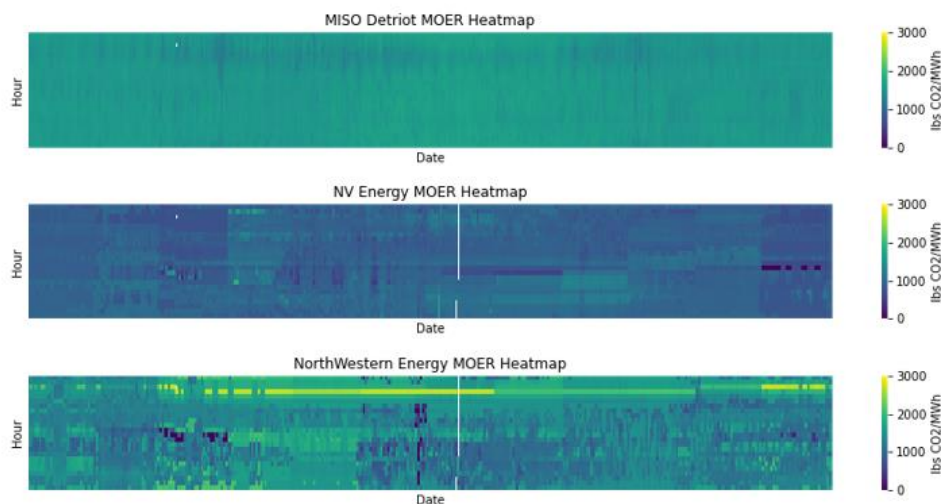


Figure 1. Marginal Operating Emissions Rate (MOER) comparison by balancing authority or Independent System Operator (ISO), 2020 and 2021.

As shown in Figure 1, both NVE and NWE use multiple fuel sources for their marginal generation, yielding a volatility between 2,000 and 3,000 lbs. of CO₂ per MWh. MISO Detroit,

however, has a much tighter range of approximately 600 lbs. of CO₂ per MWh over the same period. This is to say that for a given change on the MISO grid the resulting impact will be less noticeable than having made that same change on a grid region with more marginal volatility. The lower volatility of the MISO subregions means the results of this study show less variation between comparisons than had the same study been applied in grid regions with different mixes of marginal fuel sources.

Measure Metrics

When comparing GHG emissions by all categories input into our modeling, it would be difficult to accurately compare building emissions by calculating the total apportioned lbs. of CO₂ by category. Due to different commercial energy use tiers, different business operation behaviors, and the different size and purpose of buildings, total lbs. of CO₂ would be wildly different across categories and customers – tied directly to the total kWh consumption by category. A manufacturing facility with significant energy use would be weighted significantly more in our modeling compared to a small retail outlet. To standardize these values for all categories, we apply a GHG emissions intensity ratio, which is the total lbs. of CO₂ divided by the total kWh for a given category, where each hourly lbs. of CO₂ value is calculated by its respective hourly emissions rate. By using a ratio of lbs. of CO₂ per kWh we help remove the model skew caused by extremely high energy users compared to businesses several magnitudes smaller. The higher the emissions intensity ratio is, the dirtier the electric use; the lower the emissions intensity ratio, the cleaner the electricity use for any given category we calculate.

Data Preparation

As mentioned, we collect our data from various sources. The pre-processing steps are shown in Figure 2 below. Figure 2 details the process of how to prepare the data. The account data is retrieved from customer data, business data, project data, and building data. The final time series dataset is comprised of four diverse sources: raw AMI data from clients, MOERs data from the WattTime API, weather data from the National Oceanic and Atmospheric Administration (NOAA) API, and peak hours for different clients from their own documentation. The data is then extracted, transformed, loaded, NOAA processed, and feature engineered to check for completeness and accuracy. Following that check, the data is aggregated to an hourly granularity, joined with the raw AMI data with weather data, GHG emission rates, and peak hour data. Then, the time features, the distributions, and the velocity changes are retrieved. After this process, the account data and AMI data are joined to get the final data set for our prediction and analysis.

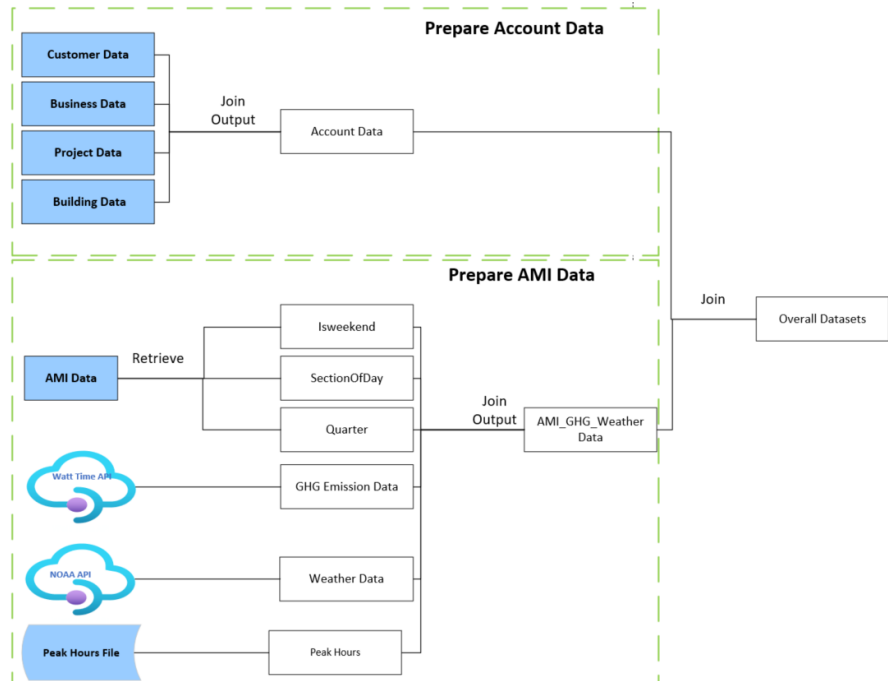


Figure 2. Data preparation process

Feature Selection

After preparing the AMI data for buildings, different groups of features that relate to a building's energy consumption are considered.

- Time features, such as year, season, month, weekend/weekday, section of day, and peak hour
- Customer information, such as utility, customer use tiers, industry sector, customer utility type, electric rate code, annual electric usage, and annual electric cost
- Business details, like business types, total employees, year opened, and business size
- Project data including technology types, electric savings for each technology, project size bin, and technology name
- Building features such as building size by square feet and building location (service city and zip code)
- Time series data such as hourly energy usage, hourly GHG emission by pounds, peak hours, temperature, and hourly timestamp

Within these features, the category data gets encoded¹. Then, the multicollinearity² of each pair of features is observed by calculating the variance inflation factor (VIF). If the VIF is greater than 4, it means the observed features are more likely to have multicollinearity. In other words, they are more likely to be dependent on each other. Otherwise, the observed features are more independent. After this step, the features that have strong dependencies from the observation list are removed.

After the independent observation variables are retrieved from VIF calculation, these variables are fed into two machine learning algorithms: Decision Tree Regression and SelectKBest. Decision Tree Regression is a supervised/unsupervised machine learning algorithm for predicting the value of a target feature by learning calculation patterns from all the input features. SelectKBest is a feature selection algorithm that retrieves the important features by k highest scores. An $F_{\text{regression}}$ function is applied to calculate a score that measures how important the feature is for the SelectKBest algorithm. The specific procedure of feature selection is explained in Figure 3.

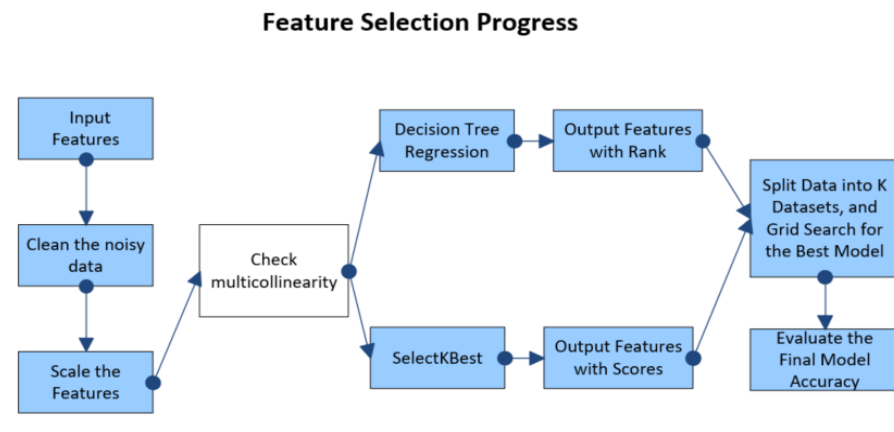


Figure 3. Feature selection process

As described in Figure 3, the input features are cleaned, encoded, normalized, and filtered at the beginning. Then, the remaining features are trained and tested through Decision Tree Regression and SelectKBest, and output by ranking or scores with individual features. Then the individual input features are filtered with certain rules to keep the most key features that contribute to commercial building emissions. The model accuracy is measured with a mean squared error (MSE) of 0.05, which means the model is accurate enough to predict GHG emissions, and the features selected from the model are directly correlated to emissions.

¹ There are a few different methods to encode a string (text) in machine learning. In this paper, encoding replaces string values with a count of the frequency for each string. If there are more dimensions to a string, it then encodes the string into a binary Yes or No value.

² Multicollinearity is applied for checking the correlation of multiple independent variables in regression analysis.

From the twenty-three original input features, our Decision Tree Regression modeling flagged twelve as notable features with a ranking. The SelectKBest algorithm flagged fourteen key features with k-highest scores.

Data Finalization for Analysis

After retrieving the key features, the data is cleaned again to keep only the important features and GHG emissions intensity ratio. Because the different business users have different business behaviors – some commercial buildings operate twenty-four hours a day while others operate from 8 a.m. to 5 p.m., and some businesses have more focused energy use on the weekends and evenings - it is important to separate these customers into distinct groups for analysis. Therefore, all the energy users in this data set are classified into three energy use tiers based on a 9-box potential model. The system divides customers into either a highest impact group, high impact group, or moderate impact group, and further subcategorizes them into large energy users (top 1% of overall users), medium energy users (2% -10% of overall users), or small energy users (remaining 90% of overall users).

After modeling, cleaning the data a second time, and segmenting the commercial accounts into use tiers, 570,897,460 rows of data remain for analysis. According to the overlapping features between our two modeling methods, the data is grouped into four observation groups by type: time features (seasonality, section of day, weekdays vs weekend, and peak hours vs none-peak hours); industries based on The North American Industry Classification System (NAICS 2021); previously installed EE technologies; and business types that describe the business sectors and business size. Because of the data size and visualization platform limitations to observe this volume of AMI data, four groups are pre-aggregated prior to piping into Microsoft Power BI.

Findings and Analysis

The following sections describe the key factors contributing the most to the GHG emissions metrics of commercial buildings. Visualizations are also provided to show the emissions patterns using GHG emissions intensity ratios.

Key Factors Contribute to the GHG Emissions

As described in the output of both the Decision Tree Regression and SelectKBest methods, the key features that affect the GHG emissions are retrieved and shown in Figure 4 below. From the feature selection results, the important features from the Decision Tree Regression algorithm are marked with a rank of 1.

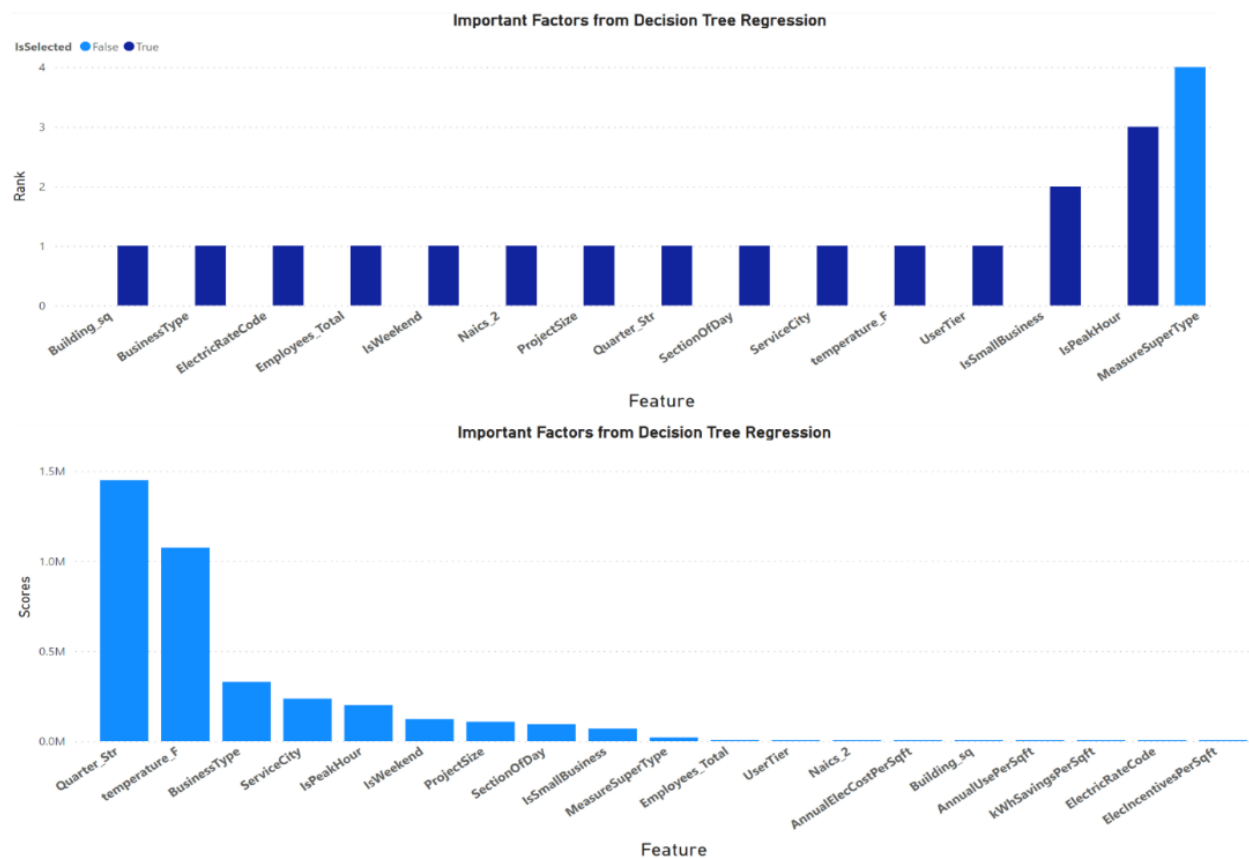


Figure 4. Feature selection results

As shown above, building square footage (Building_sqft), business type (BusinessType), electric rate code (ElectricRate), total employees (Employees_total), weekend or weekday (IsWeekend), industry sector (Naics_2), project size (ProjectSize), season (Quarter_str), service city (ServiceCity), ambient outdoor temperature (temperature_F), and use tier (UserTier) are the principal factors for the GHG emissions in commercial buildings. However, a limitation of the output of Decision Tree Regression is that it is not clear on the importance order of the individual features. In the output list of the SelectKBest algorithm, the results are ordered with scores, which indicate the importance of each feature. From Figure 4, season (Quarter_str) is the most important feature, then use tier, service city, business type, project size, and so on. The conclusion derived from the overlapping of these two algorithms is that season, use tier, and business type are the most important features to be considered for further analysis of commercial building emissions.

Further analysis into these features prompted an additional run of the SelectKBest algorithm separately for each energy use tier. Based on the different business formats and behaviors, the top factors change when applied individually. The output is shown in Figure 5.

In the top bar chart in Figure 5, season and temperature are the most closely correlated to the GHG emissions of the top 1% of commercial energy users. Ambient temperature is the most important key factor to the next 9% and the remaining 90% use tiers.



Figure 5. Top features for each use tier

GHG Emissions from Small Commercial Users are More Sensitive to Seasonal Change

For the individual use tiers, the GHG emission intensity ratio is contrasted by quarter to determine what trends of GHG emissions change for each use tier according to four seasons.

Figure 6 shows the intensity ratio change with the different seasons for different use tiers. It is clear to see that these three use tiers have the highest intensity ratio in the third quarter (Q3). The large users changed slowly from the second quarter (Q2) to Q3, and the intensity ratio of medium users changed a bit faster than that of the large user. Small users are more sensitive to seasonality, as the intensity ratio dramatically climbs from 1.14 lbs. CO₂ / kWh to 1.19 lbs. CO₂ / kWh. It is also interesting to see that the medium users have the largest intensity ratio overall compared to large users and small users. And in Q3 and Q4, the large users balance the GHG emission better than medium business and small business. Of note here is that, while the SelectKBest model selected quarter/season as the top contributing factor to the top 1 percent of users, this does not translate to these users having the largest quarterly swings. As evidenced below in subsequent examples, while the SelectKBest model can differentiate between crucial factors, large energy users are still relatively impervious to these factors compared to small and medium energy users.

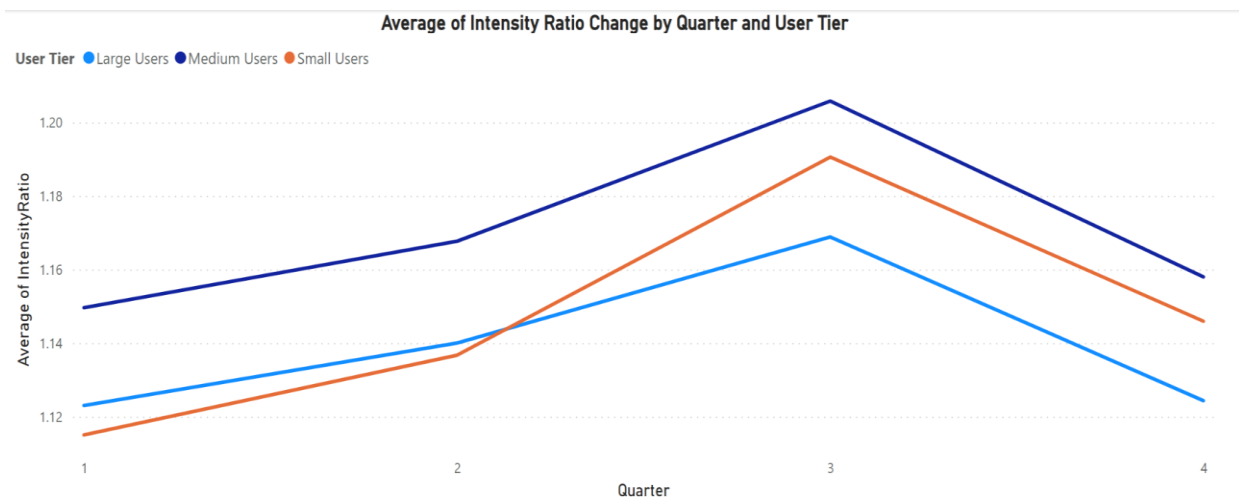


Figure 6. Intensity ratio trend by use tier and quarter

Heavy Energy Consumption Industry not the Dirtiest GHG Emission Industry

As noted in the Measure Metrics section, the use of a standard emissions intensity ratio allows for the comparison of a single value of lbs. of CO₂ per kWh. Using that metric, the larger the intensity ratio, the dirtier the overall energy use is. The lower the ratio, the cleaner the energy use.

To answer how clean or dirty each industry's electric use is, we visualize average emissions intensity ratio by total kWh annual consumption in Figure 7. Each bubble represents an industry sector, while the bubble size is based upon the count of account premise combinations belonging to that industry. From this bubble chart, we can see the Manufacturing sector is the leading energy user but also has one of the lowest intensity ratios. This means manufacturing is not the dirtiest energy-using industry. The intensity ratio of the Utilities sector, made up of electric power generation, natural gas supply, steam supply, water supply, and sewage removal, is a much higher value of 1.54 lbs. CO₂ / kWh. Even though the total energy usage is much smaller compared to Manufacturing, the Utilities sector is the dirtiest when considering when and where that energy is used. Moving down the visual, the Information, and Management of Companies and Enterprise sectors have the next highest intensity ratios, both with similarly low overall annual energy use. Noting the Manufacturing sector as an outlier, we can draw a trending line of decreasing intensity ratios from the Utilities sector to the Retail Trade sector as overall energy use increases.

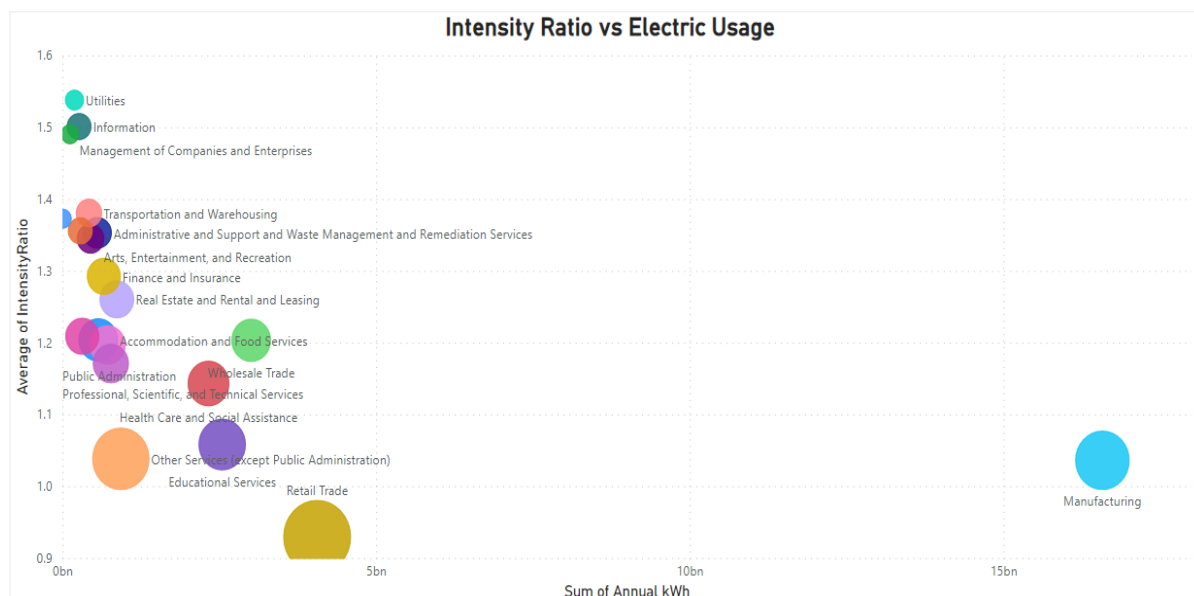


Figure 7. Intensity ratio by industry sector

Considering the pattern noted above, the business modes of these various industries are worth consideration. For the two largest energy use industries, both with overall low intensity ratios, Manufacturing and Retail Trade typically operate 7 days a week, 18 hours each day. The operations and energy use during non-peak hours when the grid marginal emissions are cleaner (5 p.m. to 8 a.m.) balance the intensity during normal business hours (8 am to 5 pm). That is, heavier energy use industries are more likely to have cleaner emission intensity ratios due to their consistent energy use when the grid marginal emissions are both clean and dirty. The opposite also proves that small businesses operating during typical business hours (especially during peak) are more likely to have higher intensity ratios and overall dirtier energy consumption.

Top Technologies Contributing to GHG Emission

The distinct EE technologies installed across these C&I populations in 2020 and 2021 demonstrate a unique relationship between the installation of a given technology and the average emissions intensity ratio of accounts tied to those installations. In the tree map visual below, the emissions intensity ratio for accounts associated with each EE technology type is visualized as the area of the block, with the average emissions intensity ratio value is displayed in the bottom of each block. Process technologies, which includes high efficiency boilers, regenerative thermal oxidizers, oxygen trim controls, energy recovery, snow melt controls, and boiler tune-ups, are the top installed technologies that correlate to accounts with high emissions intensity ratios. Lighting technologies, correlated to accounts with an average intensity ratio of just 0.34 lbs. CO₂ / kWh, has the clearest connection to lowering the overall emissions intensity ratios of commercial

buildings. Further analysis into technology load shapes would be required to verify when these technology improvements save energy, but in the aggregate of this study, technology types such as lighting help to lower a building's emissions intensity ratio by saving energy when the marginal emissions are the dirtiest, during peak hours, when the business is in operation.

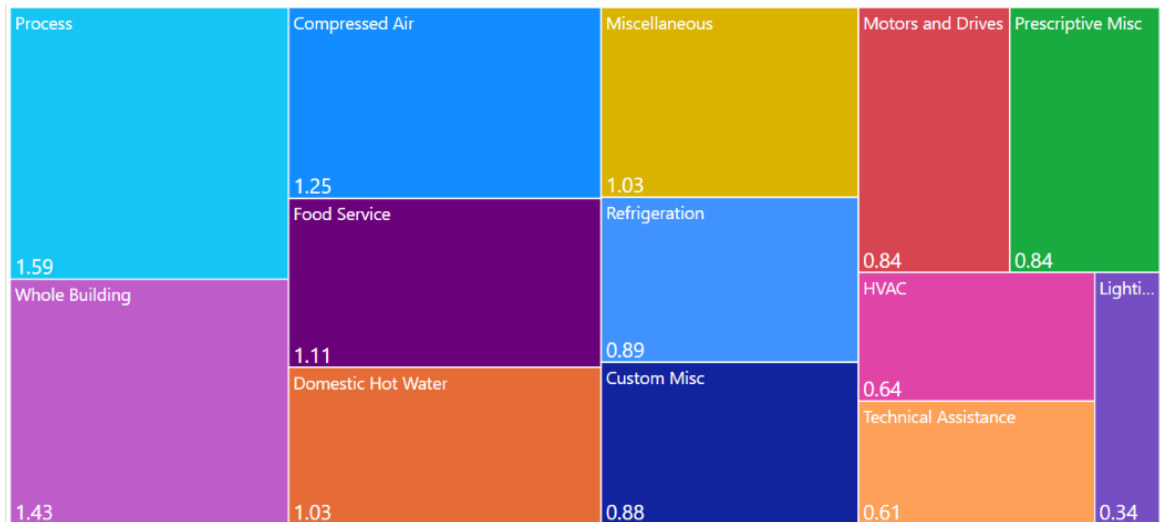


Figure 8. Average emissions intensity ratio for accounts installing EE technologies

Recommendations

The results of this study generate nearly as many questions as we can answer. We believe, however, that our modeling methods allow us to make general recommendations for how to view future decarbonization through the lens of established utility EE programs.

- Energy use matters
 - There are various factors that impact a building's emissions, but chief among them is total annual kWh use. The consistent hourly energy consumption for these highest users yields a lower overall emissions intensity ratio. Our recommendation would be to focus on any EE technology that saves the greatest amount of energy, especially in grid regions with little emissions volatility.
 - For the remaining 90% of the C&I population, factors such as industry, percentage of weekday or weekend energy use, and time of day play a much larger role in the overall emissions intensity for a given building. For the remaining 90%, we recommend technologies that are known to yield the most time-of-day specific energy savings relative to the utility's grid region. For some grid regions, that may equate to more efficient

lighting technologies to lower energy consumption during peak hours, while for others it may mean better air conditioning technologies to lower energy use during evening hours when no renewables are online.

- Separate from segmenting customers by energy use tier, any business operating around the clock, or with no time-of-day dependent energy consumption, would also get the same recommendation of choosing EE technologies saving the greatest energy, with less focus on emissions specifically.
- Combinations of Distributed Energy Resources (DERs) will play an important role in any decarbonization plan, requiring alignment between energy use, energy storage, and grid emissions.
- Technology type matters
 - As noted previously in this paper, further analysis into technology load shapes would be required to verify exactly when technology improvements save energy, but as shown above, technology types such as lighting, which appears to save energy when the marginal emissions are the dirtiest, during peak hours when the business is in operation, correlate to lowering a building's overall emissions intensity.
- Seasonality matters
 - All three energy use tiers showed an increase in their emissions intensity during Q3, or summer. When targeting customers for EE technology improvements, the way in which seasonality changes the behavior of a grid region should be considered. In the visuals above, the higher summer values are likely due to high air conditioning loads. Grid regions experiencing extreme cold could have a similar increase during the winter season, Q1. Technologies related to heating or cooling buildings in these regions would be more impactful than more generic year-round energy savers.
- Industry matters
 - This study shows that industry is one of the clearest ways to segment a customer population by emissions intensity. Following the general trend seen in all visuals, industries with lower annual energy use would benefit from EE technologies intended to save energy when the grid is the dirtiest. As the total energy use trends higher for any given industry, this consideration matters less due to the decreased variability in energy use throughout the day.
- Grid region matters
 - For all the findings specific to this study and DTE and another Midwest utility, the provided examples of NV Energy and Northwestern Energy show that no single solution exists without taking grid region into account. Each ISO or balancing authority has its own mix of marginal fuel sources,

which in turn should inform the larger strategy around tailoring EE technologies by end user.

Conclusion

As evidenced in this paper, the lessons learned from the established EE programs of DTE and another Midwest utility can tell us a great deal about the future of program design with a focus on decarbonization. Applying machine learning effectively to rich data allows us to flag top contributing factors related to the emissions of commercial buildings and helps us see patterns within these factors previously hidden in the sheer volume of this data. These insights point us in directions that are familiar in their outcome – saving energy – with nuances around factors like commercial customer type, size, location, and technology type.

Even when focusing our attention on decarbonization, we cannot separate our findings from the necessarily close relationship energy use has on generated emissions and strategies to avoid them. Utilities that adopt, or continue to leverage, available data and the appropriate data science methodologies to extract additional insights will be best equipped to operate and manage programs that support their goals around energy decarbonization.

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