An Open-Source Decarbonization Analytics Framework: Designing for Low-Carbon Emission Districts and Communities

Preprint

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An Open-Source Decarbonization Analytics Framework: Designing for Low-Carbon Emission Districts and Communities

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Abstract

This paper introduces an open-source analytics framework designed to assist in creating low or net-zero carbon buildings and urban districts. Integrated within URBANopt™, an open-source platform for energy analysis in districts and communities, this framework equips researchers, architects, engineers, and other stakeholders with tools to evaluate the carbon footprint implications of their design choices. The framework enables the analysis of various scenarios, incorporating both historical and future emission factors, and can span across different climate zones, each with distinct grid and emissions characteristics. The results showcase the framework's capability to evaluate the impact of design upgrades and control strategies on carbon emissions in districts and communities. An illustrative analysis using a hypothetical district in Denver, Colorado, shows reduced emissions from energy efficiency upgrades and control strategies, highlighting the sensitivity in their effects on emissions and energy use.

Introduction

The built environment accounts for a large share of related global greenhouse gas (GHG) emissions (IEA 2022). Cities are pledging to limit GHG emissions to address climate change and setting associated carbon reduction targets (IISD 2021) (EnviroLab 2020). Under these plans, the building sector is tasked with contributions to decarbonization efforts. New building technologies are also emerging, introducing opportunities for decarbonizing the existing building stock through upgrades, as well as reducing emissions in new buildings (e.g., through net zero carbon design). To support these efforts, there is a need for tools to assess the impact of such technologies on emissions. These tools will assist engineers, architects, planners, and building managers in understanding the impact that design decisions have on a building's carbon footprint, thus guiding building and system design and operations to lower emissions.

Key metrics in this effort are operational carbon emission factors, which quantify the carbon impact associated with the energy that is either used or saved in the operation of the building (does not include embodied carbon in building construction materials and systems). Numerous operational carbon factors exist for both electricity and other fuel types, each tailored to guide various kinds of decision-making processes.

Emissions associated with electricity use in buildings often result from energy production at power plants that use energy sources such as coal and natural gas. Emissions associated with buildings can also come from the combustion of fuels onsite (e.g., natural gas, propane, fuel oil) that emit pollutants directly at the point of use. A distinct characteristic of electricity emissions is the carbon intensity fluctuation, which varies in time with the renewable to non-renewable energy sources ratio. Additionally, electricity emissions can be attributed to energy lost as heat during transmission from power plants to end-users. Because electricity emissions vary based on the energy mix and correlate closely with the energy source and grid transmissions, calculating electricity factors is generally more complex than for other fuels, where emissions are more direct and exhibit less variability in nature and source.

For the purposes of many building design use cases, fuel emission factors, excluding electricity, are not presumed to vary by location or time, so it is often assumed that there is a single emission factor for each fuel type. Due to this simplicity, many sources provide straightforward factors for other fuel types. A common example is the ENERGY STAR technical reference for Greenhouse Gas Emissions, which lists an emission factor value for each fuel (ENERGY STAR 2023). The remainder of this section will focus on the various types of electricity emission factors.

Average and marginal electricity emissions

Emission factors for electricity consumption can be classified into two categories (Brander 2022): (a) average emission factors, which are attributional in nature, detailing the current state of the grid and assigning responsibility for emissions, and (b) marginal emission factors, which are consequential as they estimate the emissions that result from actions that add, reduce, or alter electrical load.

Average emissions rates (AER) for electricity represent the typical emissions per unit of electricity across an entire grid within a specific region and timeframe, encompassing all generation sources. These rates are derived by dividing the total emissions by the total electricity generation and adjusting for losses (Azevedo et al. 2020) (eGrid 2021). Therefore, they are attributional, distributing the emissions equally across every unit of electrical consumption. Although AER is straightforward in concept, it encounters a limitation when used to assess the impacts of new interventions, because changes within a system typically affect its margins, not its average. As a result, the generation mix arising from new loads often differs from the existing average generation mix. In contrast, marginal emissions rates (MERs) for electricity quantify the change in emissions resulting from a unit increase or decrease in electrical demand (Zheng et al. 2015) (Hawkes 2010). These factors are capturing the emissions effects at the margin of power generation, which are influenced by actions that modify the electrical load.

Emission metrics

Emissions data often include measurements for three gases: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). A commonly used metric emerged that can capture all three gases in one metric called CO_2 equivalent (CO_2e) (US EPA, 2020). CO_2e values aggregate the impacts of the three gases using 100-year global warming potential (GWP) values sourced from the IPCC's fifth assessment report. Marginal CO_2 equivalent (CO_2e) and average annual CO_2e are increasingly being recognized and utilized as comprehensive measures for encapsulating emissions associated with buildings' operational energy consumption. These metrics provide a holistic view of environmental impact by combining the effects of various greenhouse gases into a single indicator, reflecting their relative contributions to global warming (Present et al. 2022) (Gagnon et al. 2021).

Marginal CO_2e is quantified using hourly marginal emission factors, reflecting the additional emissions resulting from energy consumption changes at a site over a year or several years. The marginal approach, employing time-sensitive emission factors, aims to assess the impact of variations in building energy use attributable to factors like energy efficiency improvements, demand flexibility, or electrification.

Total CO_2e, on the other hand, is calculated using annual average emission factors and represents the cumulative CO_2e for a facility annually or over multiple years. This broader metric is designed for evaluating the overall emissions of buildings for purposes such as buildings stock analysis which require working with data of lower temporal resolution.

Marginal emissions short-and long-run factors

Marginal emissions factors are categorized into:

(1) Short-Run Marginal Emission Rates (SRMER): These rates calculate the immediate emission changes expected from a short-term variation in electricity demand, assuming no change in grid and power generation infrastructure. SRMER determine which power generators will adjust their output in response to load changes, without considering the potential influence on local resource planning or investment in capital assets (Gagnon et al. 2022). They are typically used for operational decisions to optimize energy use in the short term (e.g., building control optimization).

(2) Long-Run Marginal Emission Rates (LRMER): These rates consider the potential long-term changes in grid and power generation infrastructure due to variations in electricity demand (Hawkes 2014). For instance, a sustained increase in demand during daylight hours may lead to the construction of more solar power facilities. LRMER are calculated using models that predict changes in the grid's composition over time, factoring in how electric load shifts could influence grid development and capacity.

Time resolution and grid year

Electricity emissions metrics can be derived retrospectively using historical data or projected based on potential future grid conditions, and they can be computed for any given hour or on an annual basis.

Average and marginal emissions factors are typically provided as a singular annual factor or as an extensive array of 8,760 hourly factors throughout the year. Utilizing annual factors offers convenience and simplicity in application. In contrast, hourly factors reveal the extent to which carbon emissions are influenced by the timing of load fluctuations. This detail is crucial for studies involving demand flexibility, such as those assessing grid-interactive efficient building technologies, where understanding the impact of timing on emissions is essential.

The composition of electricity generation substantially influences carbon emissions, which is particularly relevant given the rapid evolution of the energy mix. Tools like AVERT and eGRID host historical emissions factors that capture the grid's past characteristics but does not reflect potential future changes of the grid.

The Cambium dataset was developed by (Gagnon et al. 2021) to project potential future grid scenarios, which are beneficial for long-term decision-making. The Cambium datasets are based on the outputs of two models, briefly described below. More details on these models can be found in the literature cited for each.

(1) The Regional Energy Deployment System (ReEDS) model, a mathematical programming model of the electric power sector, projects structural changes in the U.S. electric sector under various potential futures (Ho et al. 2021).

(2) PLEXOS, a commercial production cost model, is utilized to simulate the hourly operation of future electric systems as projected by ReEDS (Energy Exemplar 2019).

Geographic resolution

The granularity of emissions factors varies from broad regional levels to specific local areas (e.g., the power plant). Emissions calculations are tied to the electrical grid and its generators, necessitating an understanding of the geographical area to which these generators belong in order to define the emissions rate for that area. In the US, the electrical grid is a complex network comprising electrical generators interconnected locally and on a much larger scale, not confined by most state boundaries. Detailed geographic resolution reveals significant subtleties; for example, Texas, which primarily relies on natural gas for electricity generation, has different emissions factors compared to Vermont, which predominantly uses renewable energy sources. However, opting for more granular emissions factors over larger areas introduces complexities in accurately accounting for indirectly-caused emissions, particularly when employing long-term factors that anticipate infrastructural evolution. Typically, emissions factors in the contiguous United States are segmented into various regions corresponding to the boundaries of organizations responsible for electric grid management and operation.

These organizations, which include the North American Electric Reliability Corporation (NERC), Independent System Operators (ISOs), Regional Transmission Operators (RTOs), and Balancing Authorities (BAs), define geographic boundaries for emissions accounting. NERC Regions, defined by NERC, are a few large regions within the contiguous U.S. representing portions of the electrical grid. For finer resolution, there are Balancing Authority Regions, consisting of 66 BAs within the contiguous U.S., tasked with maintaining a balance between supply and demand on the grid in real time.

To delineate boundaries that encompass generation and emissions from plants within a region while mitigating the accounting effects of imported and exported electricity, the U.S. Environmental Protection Agency (EPA) established eGRID Subregions. These 27 regions are designated for emissions reporting. In a separate effort, Cambium defined Geographic Emissions Allocation (GEA) regions. These are based on the EPA's eGRID regions but differ due to the geographic structures of Cambium's models. Cambium's method involved creating GEA regions by grouping 134 ReEDs BAs. More information on this method is available in Cambium Scenario Descriptions and Documentation.

The sizing of the GEA regions strikes a balance between capturing important differences in LRMER across different parts of the US and addressing challenges in attributing induced emissions and projecting significant structural changes at finer resolutions. (Gagnon et al. 2021)

Weather files

One key element when conducting building emissions analysis is choosing the weather file. In theory, ensuring that the weather data used for analysis is consistent with the weather conditions assumed for carbon emission factors is ideal to ensure that the electricity generation and building load profiles are derived using the same weather file. For instance, during a thunderstorm with complete cloud coverage, solar photovoltaic (PV) generation will be significantly reduced. Typically, peak electricity loads in summer often occur simultaneously with high PV generation due to sunny conditions. However, achieving this weather data alignment can be challenging and needed information might not be available in certain cases. In building energy modeling, two common types of weather files are commonly utilized:

(1) TMY (Typical Meteorological Year) weather files are synthesized from several years of historical weather data to create a 'typical' year that represents weather conditions for the location (Ren et al. 2021).

(2) AMY (Actual Meteorological Year) weather files, on the other hand, contain actual weather data from a specific historical year. AMY data is of course not available for future conditions that align with future emission factors.

With this complexity, the weather assumptions are considered when applying emission calculation frameworks.

For example, Cambium data was produced using resources and load data that corresponds to the weather in 2012. Therefore, the resolution of the hourly emission factors of Cambium are processed to month-hour averages that are then re-casted to an 8760 vector. This approach helps to reconcile the misalignment that may occur when this data is combined with buildings load data derived from different weather assumptions (Gagnon et al. 2022).

This paper does not primarily concentrate on assessing the impact of weather alignment on the analysis of building emissions. Nonetheless, it is important for users to be aware of the underlying assumptions related to the emissions rates data they utilize in their analysis.

Gap and proposed framework

In recent years, several entities have produced estimates of emission factors covering the variety of time resolutions, geographic resolution, grid compositions, and variety of emissions use cases and scenarios. The following are a set of resources that include one or more of these emissions factor types: U.S. Energy Information Administration (EIA); U.S. Environmental Protection Agency (EPA) through resources like the Emissions & Generation Resource Integrated Database (eGRID) (US EPA 2020b 2021); EPA's AVoided Emissions and geneRation Tool (AVERT) (US EPA 2020a 20201); WattTime; Resurity; Electricity Map; and the National Renewable Energy Laboratory's (NREL) Cambium dataset (Gagnon et al. 2021). However, due to the complexity involved in emissions metrics and data, building designers and engineers are not widely employing this data to analyze operational energy emissions from buildings. At present, there is a need for analytical tools and capabilities that utilize developed metrics for decarbonization analytics.

To address this gap, these metrics for operational carbon can be implemented in an analytical framework where they can be used by engineers and designers in the built environment to drive deeper emissions reductions. This paper presents a novel framework built within URBANopt™ (Polly et al. 2016) (El Kontar et al. 2020) an open-source advanced analytics platform for district and community energy analysis, that enables users to design for low- and net-zero carbon buildings, neighbourhoods, and urban districts. The developed capabilities provide urban planners, architects, engineers, building operators, and other key players with tools to understand the impact of their design decisions on buildings' carbon footprints.

As a part of this work, we conducted an illustrative analysis for one mixed-use district design located in multiple climates using the URBANopt workflows. The developed automated framework is demonstrated by evaluating the effect of multiple energy efficiency measures on carbon emissions at a district-scale in different locations across the U.S. The evaluated measures include envelope efficiency measures, building equipment efficiency measures, and demand flexibility measures.

First, we collected hourly and annual data for various emissions metrics over multiple years from different sources. Next, we analyzed and integrated this data into a simulation workflow to calculate different carbon emissions metrics. The emissions data implemented in this analysis, along with the associated analytical work, is specific to the US and encompasses a range of selected emission datasets. However, the structure of the framework is designed to enable users to integrate other additional emission data they acquire into the workflow. This flexibility allows users to test new emissions datasets, facilitating new research tasks and broadening the application to various locations of interest.

We applied this workflow to our case study, resulting in modeled CO2e emissions data at both building and district/community scales. These results facilitate carbon emissions analysis and allow for comparisons across various emissions scenarios. Subsequently, we conducted a sensitivity analysis to demonstrate the impact of different building technology upgrades, energy efficiency strategies, and demand flexibility and control strategies on emissions versus energy use reductions. This framework can be utilized to inform the selection of the most effective strategies and upgrades for optimal reductions in emissions and energy use.

These new open-source capabilities enable users to analyze and compare various scenarios, reflecting either historical or potential future emission factors, across different locations with unique grid and emissions characteristics. This framework has been integrated into the URBANopt platform, facilitating the analysis of various energy efficiency measures, and aiding in the identification of optimal design decisions based on a carbon emissions reduction target. Users can automatically create, run, and analyze emissions scenarios for their projects. The reported emissions results and metrics are intended to help guide design and control decisions. The paper highlights how users can assess upgrades and load shifting/control strategies in building and community systems, and examine their impacts on carbon emissions at a community-and district-scale.

Methodology

Figure 1 illustrates the integration of operational emissions calculation and analysis within URBANopt (UO). Users define top-level inputs for the emissions calculations based on the year, location, and emissions type of interest. These inputs/options are defined based on the datasets in the OpenStudio® (OS) Measure resources directory. Users define these options in the UO GeoJSON file and UO Mapper Classes defined in (El Kontar et al. 2020) and URBANopt documentation (https://docs.urbanopt.net). This structure allows for the addition of user inputs/options for emissions analysis as OS Measure resources are extended in the future with new datasets. The emissions calculations are then executed within the OS Measure using data from the Measure's datasets that reflect the user-defined options. Calculated hourly and annual emissions for the buildings are then be reported in UO feature and scenario reports. These reports can be compared through figures that plot the resulting emissions across buildings and scenarios.

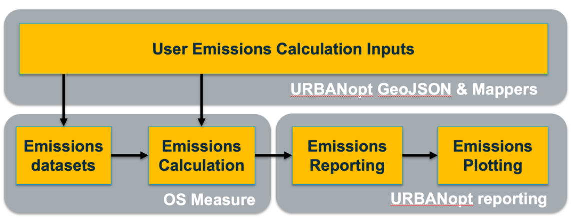

Figure 1 - Framework for integrating operational emissions calculations in URBANopt platform.

The following sections describe each of the elements mentioned above in detail.

OS Measure integration

An OS Measure "add_ems_emissions_reporting" was developed and integrated in the UO workflow. The developed measure includes the emissions factors data and the functionality to utilize these factors as multiplier to corresponding energy use results to calculate the emissions. The "add_ems_emissions_reporting" OS measure is published in OS Building Component Library (BCL) (https://bcl.nrel.gov) and openstudio-common-measures-gem (https://github.com/NREL/openstudio-common-measures-gem).

This Measure was integrated into UO Mapper classes and base workflow. A new UO Mapper class was developed to integrate this OS Measure. This Mapper has the functionality to map top-level user options defined in the UO GeoJSON file to the arguments of the OS Measure. Users can activate and define the inputs for this Measure from the GeoJSON file or customize the developed Mapper class to specify the inputs.

Utilized emissions datasets

The OS measure resources folder hosts the emission rates datasets. These datasets include hourly and annual data for multiple years and multiple emissions metrics. The emission metrics utilized are a measure of the total CO_2e for a facility over the course of a year or multiple years.

Total emissions are calculated by summing up emissions from grid electricity, fuels burned on site, and district utilities. Hourly and annual emission factors are considered for electricity, while only annual factors are considered for other fuel types and district utilities. Emissions factors cover historical and future years and are collected from different emissions data sources.

Integrated Electricity Emissions Data Sources:

1) Historical annual CO_2e average emission rates are extracted form EPA's Emissions & Generation Resource Integrated Database (eGRID) and use eGRID subregions as the geographic resolution.
2) Historical hourly CO_2e marginal emission rates are based on data from EPA's AVoided Emissions and geneRation Tool (AVERT). Only 2019 hourly data is available and added in the UO – OS measure.
3) Future annual and hourly average emissions rates (AER) are extracted from Cambium LowRECost scenario and follow GEA regions. The LowRECost scenario models a baseline grid current scenario but assumes lower costs for renewable energy and batteries.
4) Future annual and hourly long-run marginal emissions rates (LRMER) are extracted from Cambium and use GEA regions as geographic resolution. The data was extracted from the LowRECost scenario.

For (3) and (4) we note that the Cambium emission factors are not CO_2e, so they are adjusted based on the ratio of CO_2e to CO_2 from eGRID for each subregion.

Integrated Other fuels Data Source:

5) Single CO_2e emission rates for other fuel type are extracted from the ENERGY STAR Portfolio Manager Technical Reference for Greenhouse Gas Emissions. These rates incorporate the 100-year global warming potential (GWP) of each gas (CO_2=1, CH_4=25, and N_2O=298), which compares the radiative forcing ability of each gas relative to CO_2,

which serves as the reference gas. (https://portfoliomanager.energystar.gov/pdf/reference/Emissions.pdf)

Emissions factors may change over the years. The current data sets that are implemented are considered as the current "default" or "starting point" data for UO modeling, however, the best practices on emission data sets and calculations are still evolving. The developed framework gives the flexibility for users to use their own data (e.g., of alternative emission rates and/or for other geographic locations) and integrate it in the workflow.

Emissions data application

This section discusses the application of specific factors, to enhance users' understanding on how to utilize the integrated emissions datasets. As new use cases and research emerge, users are afforded the flexibility to select and apply these factors in various innovative ways that best support their tasks.

The Average Emissions Rates (AERs) and Long-Range Marginal Emission Rates (LRMERs) are provided in both hourly and annual formats. Annual rates are suitable for studies focusing on annual totals without time-of-use concerns, while hourly rates are typically used for more detailed time-sensitive analysis.

In projects that focus on assessing the long-term impact of measures or upgrades, future impact evaluations are common. For such evaluations, Future Long-Run Marginal Emission Rates (LRMERs), based on projected electric grid scenarios, are commonly utilized.

Annual AERs are suitable for developing existing baseline scenarios for future carbon emissions planning or analyzing changes in the aggregate emission footprint of a home or city. Conversely, hourly AERs are suitable for Time-of-Use (TOU) dependent scenarios, particularly those involving Distributed Energy Resources operating with TOU electricity rates, such as retrofit interventions that are tied to temporal energy use and TOU energy costs. Users can opt for either annual or hourly AERs based on the specific needs of their task, or the detail required in their models.

Future LRMER can be used to evaluate the potential emissions impacts of building upgrades and potential future scenarios that include the application of energy efficiency, electrification, and demand flexibility measures.

Cambium Emissions Scenarios: To manage future uncertainties in grid-related analyses, a variety of potential grid scenarios have been developed to calculate emission factors corresponding to these scenarios. Future Cambium emissions data include emissions rates for multiple potential emissions scenarios. The scenarios are described here and can be utilized for different use cases. The OS measure currently includes only the Low RE Cost scenario. Users can extend the data set to include other emissions data scenarios that are provided in Cambium. Existing Cambium emissions data scenarios, organized by increasing emissions reduction/renewable energy targets, include: (1) High RE Cost (2) MidCase (3) Low RE Cost (4) 95% Decarb by 2050 - 95% Decarb by 2035.

The choice of scenario depends on the analyst's perspective on the grid's future. For instance, the Mid-case scenario is suitable for analyses based on current policies and technology cost estimates. To analyze potential futures with differing renewable energy costs, either the Low or High RE Cost scenarios can be employed. Lastly, for examining aggressive, nationwide power sector decarbonization policies, the decarbonization scenarios can be considered. More detailed information of these scenarios can be found at Cambium website. (Gagnon et al. 2021)

Emissions calculation

The OS measure has the functionality to calculate the emissions for a specific building. The user-specified inputs are passed to the arguments of this measure. Based on the arguments' input, the measure calculates the emissions by multiplying the electricity, other fuels, and district utility energy uses by the corresponding emission factors defined in the datasets. Unit conversion is managed to ensure accurate calculation; for example, Hourly CO_2e emissions is reported (in Kg) by multiplying an hourly emission factor (in kg/MWh) by the hourly energy use (converted to MWh). The measure reports the generated hourly and annual emissions results variables in the EnergyPlus™ output SQL database, which are then extracted and saved in URBANopt results reports. The calculations for emissions are as follows:

1- *Total Emissions*: We estimate the total emissions by accounting for all energy sources used within a certain period, typically over a year. Each type of energy has its own characteristic emission factor that reflects how much pollutant is produced per unit of energy consumed.

2- *Electricity Emissions*: Since the impact of electricity on emissions can fluctuate based on when it is used and how it is generated, we calculate these emissions by looking at the electricity use every hour. The hourly electricity values are multiplied by the corresponding emission factor for that hour to get a more accurate estimate of emissions from electrical energy.

3- *Other Fuel Emissions*: For fuels other than electricity, such as natural gas or oil, we calculate emissions by multiplying the annual use of each fuel by its average emission factor. This gives us an estimate of the yearly emissions resulting from each non-electric fuel source.

User-defined inputs

Based on the different datasets packaged in the OS measure and the OS measure arguments, emissions analysis options are enabled for the users in the UO GeoJSON and UO Mapper Classes. Users activate the emissions calculations from the GeoJSON file by defining options such as the emission metric and time resolution, region based on the defined regions for each metric, year of analysis, and emission results units (lb, kg). These options match the folder names defined in the OS measure datasets.

When the "emissions calculations" input is set to TRUE, the unspecified emissions calculations option is set to the following default values. Defaults are set to use LRMER Cambium future values and eGRID historical values for year 2022. The corresponding eGRID and GEA subregion will be defined automatically based on mapper that use the location of the UO feature and map it to a corresponding eGRID and GEA subregion.

Users can specify all these inputs for all the features in the GeoJSON file, instead of the default values. The inputs allow users to use historical year emission factors and future emission factors in a single simulation. An example of user-inputs is as the following:

{"emissions": true,
"emissions_future_subregion": "NYSTc",
"emissions_hourly_historical_subregion": "New York",
"emissions_annual_historical_subregion": "NYCW",
"emissions_future_year": "2030",
"emissions_hourly_historical_year": "2019",
"emissions_annual_historical_year": "2019"}

For this example, the framework calculates operational CO_2e emissions from the emissions rates data that corresponds to the specified inputs:

- Hourly future operational emissions will be calculated using hourly LRMER from Cambium for year 2030, extracted from the LowRECost scenario and from the specified GEA subregion which is NYSTc.
- Hourly historical emission will be calculated based on the rates that are taken from AVERT, for year 2019 and from the AVERT region "New York".
- Annual historical emissions will be calculated using eGRID data that correspond to year 2019 and "NYCW" eGRID subregion.

This framework, which includes the integrated datasets and exposed inputs in the GeoJSON file, is customizable. Users can modify the datasets within the resources folder of the OS Measure by setting their own emission factor values for time series and hourly results. Additionally, they can expose new inputs in the GeoJSON file. This flexibility allows for the development of new workflows for emissions analysis within this structure.

Emissions reporting and visualizations

The UO reporting schema was extended to include emissions results. Results are added to both the UO JSON reports and timeseries CSV reports. The UO Reporting Measure was extended to query the timeseries and annual emissions results reported in the EnergyPlus output SQL file for each feature and added to the feature reports. Aggregation methods were also implemented in UO reporting gem to aggregate the features' emissions results to produce scenario-level reports.

The existing UO data plotting functionality was extended to include emissions graphical reports. These graphics show aggregated and time-varying emissions for each feature broken down by fuel type as well as total emissions. Similarly, aggregated emissions results are also be plotted and compared across multiple UO scenarios.

All reported emissions refer to CO_2e emissions. Two primary metrics are reported for each type of emission output: (1) total emissions in metric tons (MT), and (2) emissions intensity, represented in kg/ft^2. Emissions intensity is the emission in kg normalized by the total floor area of the building and is useful for comparing emissions of buildings with varying floor areas.

The list below presents emissions-related outputs variables from a simulation. These outputs are aggregated over the simulation's reporting period and presented as a single value in the UO JSON reports. Additionally, they are provided as time series results for the reporting period in the UO CSV output files.

- Future_Annual_Electricity_Emissions ($mtCO_2e$)
- Future_Hourly_Electricity_Emissions ($mtCO_2e$)
- Historical_Annual_Electricity_Emissions ($mtCO_2e$)
- Historical_Hourly_Electricity_Emissions ($mtCO_2e$)
- Natural_Gas_Emissions ($mtCO_2e$)
- Propane_Emissions ($mtCO_2e$)
- FuelOilNo2_Emissions ($mtCO_2e$)

- Future_Annual_Electricity_Emissions_Intensity ($kgCO_2e$/sqft)
- Future_Hourly_Electricity_Emissions_Intensity ($kgCO_2e$/sqft)
- Historical_Annual_Electricity_Emissions_Intensity ($kgCO_2e$/sqft)
- Historical_Hourly_Electricity_Emissions_Intensity ($kgCO_2e$/sqft)
- Natural_Gas_Emissions_Intensity ($kgCO_2e$/sqft)
- Propane_Emissions_Intensity ($kgCO_2e$/sqft)
- FuelOilNo2_Emissions_Intensity ($kgCO_2e$/sqft)

Case study characterization

This section showcases the developed emissions framework through a case study. For this illustrative example, we constructed a hypothetical mixed-use superblock new construction district as a case study. This designed district comprises 23 buildings, encompassing a diverse mix of building types: 9 residential buildings, 7 office buildings, 4 restaurants, a school, a hotel, and a mall. Figure 2 presents the 3D visualization of the district.

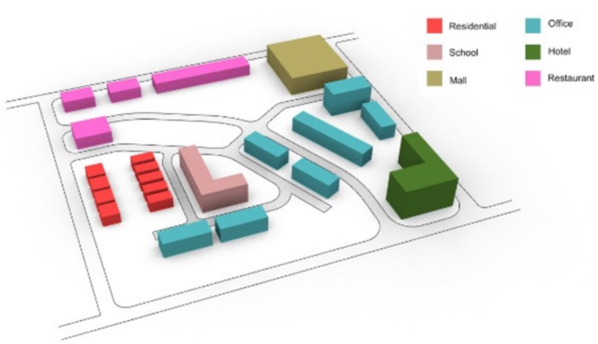

Figure 2 - 3D rendering of the mixed-use case study district.

In the baseline scenario of the new construction district, commercial buildings were modeled using ASHRAE Standard 90.1-2019, while residential buildings followed the 2019 Residential IECC templates. These templates are applied according to building types and climate zones for each location, defining energy models with inputs that align with baseline U.S. standards for commercial and residential buildings within the corresponding climate zones. However, for this analysis, we modified the energy properties for all buildings to utilize electricity exclusively. Specifically, we equipped small commercial buildings with Packaged Single Zone Air Conditioner (PSZ-AC) units and baseboard electric heating, large commercial buildings with Packaged Variable Air Volume (PVAV) systems and Parallel Fan Powered (PFP) boxes, and residential buildings with electric resistance heating and room air conditioners. Note that we used electrical resistance for the HVAC systems for the purpose of creating an all-electric baseline scenario against which higher performance options (like heat pumps) can be evaluated.

The service hot water systems in all buildings, as well as all other equipment and lighting systems, are powered electrically. We also introduced diversity into the operational schedules for each building type to reflect more realistic occupancy and energy use behaviors', to help avoid overestimation of peak loads due to coincident occupancy and occupant-behavior patterns. For residential buildings, stochastic schedules were derived from American Time Use Survey (ATUS) data and modeled following the approach by Chen et al. (Chen et al. 2022) Commercial building schedules were derived from SafeGraph data, following the methodology by El Kontar et al. (El Kontar et al 2022).

After establishing an electrified baseline model, we can run various simulations across different locations and evaluated various efficiency measures to observe their predicted effects on emissions and electricity consumption.

Since this analysis primarily focuses on electrification, energy efficiency, and load flexibility measures, we utilized hourly long-run marginal emission rates in all cases where they are available. For historical years where hourly long-run marginal emissions do not exist, historical annual emission rates are utilized.

The hypothetical district was modeled in multiple locations. These locations map to specific eGRID and GEA emissions subregions: Buffalo, NY (NYCW eGRID, NYSTc GEA), Phoenix, AZ (AZNM eGRID, AZNMc GEA), Denver, CO (RMPA eGRID, RMPAc GEA), and Miami, FL (FRCC eGRID, FRCCc GEA). For details on default mapping to these subregions, visit https://docs.urbanopt.net/workflows/carbon_emissions.html.

Results

We demonstrate various decarbonization analytics capabilities through multiple scenario simulations and a sensitivity analysis. Consequently, we discuss the results and illustrate the impact of various energy efficiency measures (EEMs) and load flexibility measures on the predicted energy and emissions of an all-electric district.

Analysis across different locations

Using the baseline model, we conducted four different sets of simulations for the designed district in four distinct locations: Buffalo, NY; Phoenix, AZ; Denver, CO; and Miami, FL. These simulations involved adapting the baseline hypothetical district model to include weather data and emissions factors for the year 2024 that are specific to each location. We then compared the total aggregated emissions and the hourly emissions profiles across these locations.

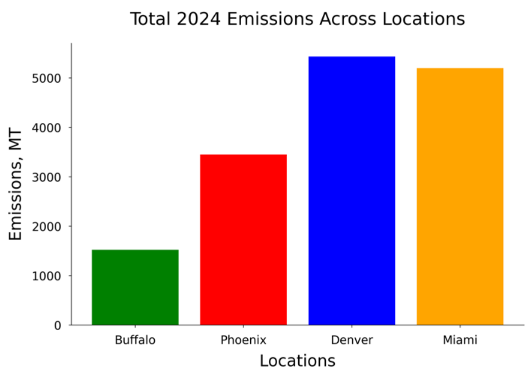

Figure 3 - Case study district modeled 2024 emissions comparison in metric tons across locations.

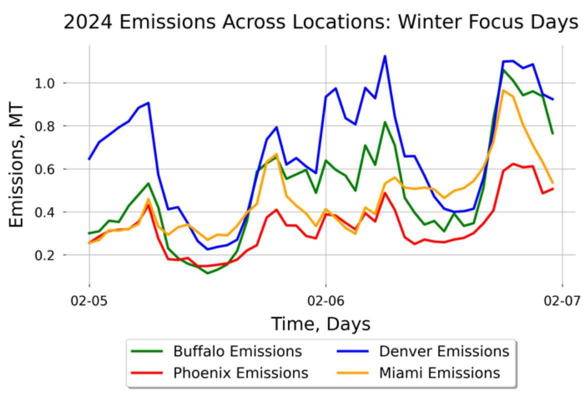

Figure 4 - Case study district modeled hourly emissions profiles comparison for two winter days.

As illustrated in figures 3 and 4, the emissions scenarios can be compared across different locations. The simulations indicate that the hypothetical district, when situated in Denver and Miami, would result in higher operational emissions compared to when located in Buffalo and Phoenix, with Buffalo registering the lowest emissions. The levels of emissions in each case are driven by the predicted electricity consumption of the buildings in the specific climate and the emissions factors used, which reflect the emissions intensity of electricity generation at each emission subregion.

Analysis across different years

In this analysis, we examined emissions from the case study district in Denver over several years. For 2010, we used historical annual emissions rates, while for 2024 and 2050, we used hourly long-run marginal emission rates. Figures 5 and 6 illustrate a substantial reduction in emissions from the district buildings in the years 2024 and 2050 compared to 2010, with the significant decrease by 2024 resulting from the rapid deployment of renewable energy and energy-efficient technologies in Denver's district buildings. This overall decrease is attributed to the anticipated advancements in grid electricity generation resources and equipment, which are expected to become more efficient and less emissions-intensive, as modeled in Cambium for future years.

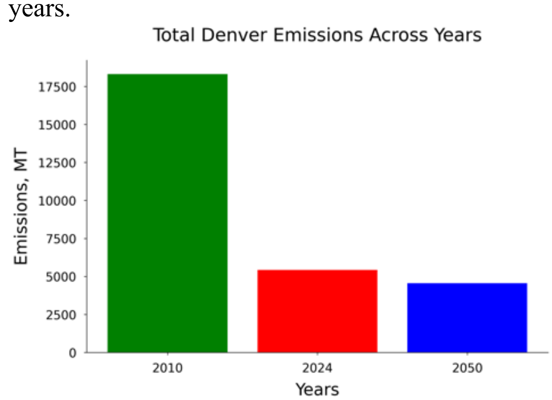

Figure 5 - Case study district total emissions comparisons in metric tons across multiple years (past and future) in Denver.

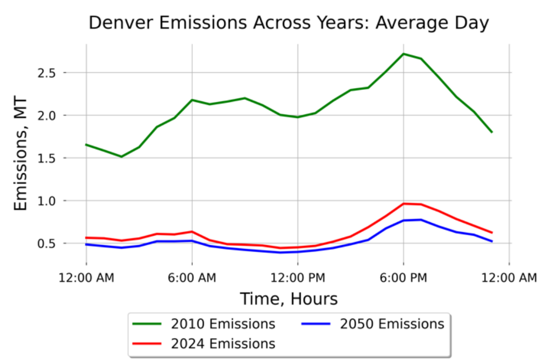

Figure 6 - Case study district average day CO_2e Emissions comparisons in metric tons across multiple years in Denver

Building upgrades sensitivity analysis

In this section, we conduct a sensitivity analysis to showcase the ability of the new workflows to estimate the impact of various building technology upgrades on emissions and electricity usage for the case study district. To facilitate this analysis, we created multiple scenarios in which we applied a range of building technology upgrades to the case study new construction district, including both EEMs and load flexibility measures. The following measures were applied:

1) Energy Efficiency Measures:
(a) Implement demand-controlled ventilation, adjusting building ventilation according to the energy demand profile.
(b) Increase the exterior wall R-value to R-30.
(c) Enhance roof insulation to an R-value of R-50.
(d) Reduce electrical equipment loads by 30% by upgrading to more efficient equipment and minimizing power usage.
(e) Decrease electric loads during peak hours by 30% through robust power management and powering down non-essential equipment.
(f) Lower lighting loads by 30% by transitioning to LED lighting and reducing lighting power density (LPD).
(g) Cut space infiltration by 30% by implementing continuous air barrier systems to curtail air leakage.
(h) Upgrade HVAC systems to Heat pump systems: PSZ-HP for small commercial buildings, PVAV with central air source heat pump reheat for large commercial buildings, and air-to-air heat pumps for residential buildings.

2) Load Flexibility Measures:
(a) Shift heating and cooling schedules by 1 or 2 hours to times when emissions factors are lower, as illustrated by Figure 7. This takes advantage of the lower emissions during intense sun hours due to active renewable resources, aiming to preheat or cool before 6 pm when building electricity demand has a higher emissions impact.
(b) Adjust water heating schedules to align with times of lower emissions, using heat pump water heaters and defining flexible hours for operation to coincide with lower emissions intensity, similar to the approach in (2a).

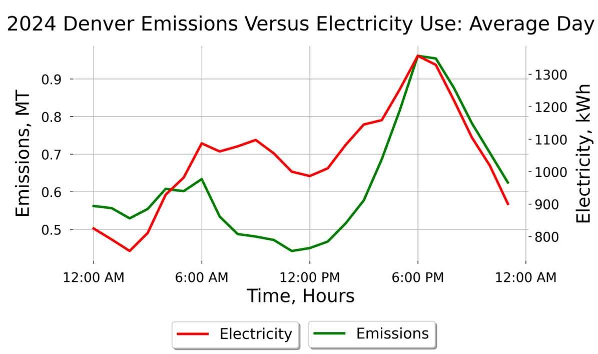

Figure 7 - Denver case study district modeled emissions and electricity use for an average/typical day.

After implementing all the aforementioned design upgrades, we conducted simulations for each upgrade scenario and compared the results with the baseline model. Figure 8 illustrates the modeled reduction in emissions for each upgrade compared to the baseline.

We also performed cumulative simulations, beginning with the baseline model, and sequentially adding upgrades one at a time. Figure 9 displays the correlation between modeled emissions reductions and electricity usage as each upgrade is implemented.

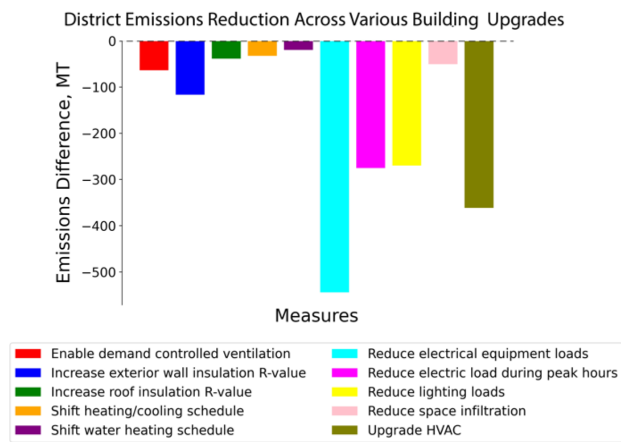

Figure 8 - Modeled emissions reductions across various building design upgrades for case study district in Denver.

According to Figure 8, it is evident that the EEMs considered in this Denver case study analysis have a greater impact on emissions reduction than load flexibility measures. This is primarily because the EEMs reduce the overall demand profile rather than simply redistributing loads across different time periods. Although the EEMs considered would generally be more costly to implement, with higher initial capital costs, they offer a more substantial reduction in energy consumption compared to load flexibility measures, which mainly manage the timing of building system operations.
The distinction between EEMs and load flexibility measures in terms of emissions is further illustrated in Figure 9. In this figure, most points align along a straight line, except for the purple and orange points, which exhibit a greater reduction in emissions relative to reduction in electricity use, and the red point, which shows a marginally larger decrease in electricity than in emissions.
Upon analysis, it is evident that when the EEMs are applied to the case study district, the reduction in emissions is proportionally similar to the decrease in electricity use, resulting in an emission to electricity reduction rate (EERR) that is close to 1. In contrast, the load flexibility measures considered in the case study, which aim to prioritize emission reductions over electricity use, demonstrate an EERR greater than 1. This is observed in our preheating and precooling strategies, as well as in the adjustment of water heating schedules, which contribute more to emission reductions than to electricity savings for the Denver case study district.

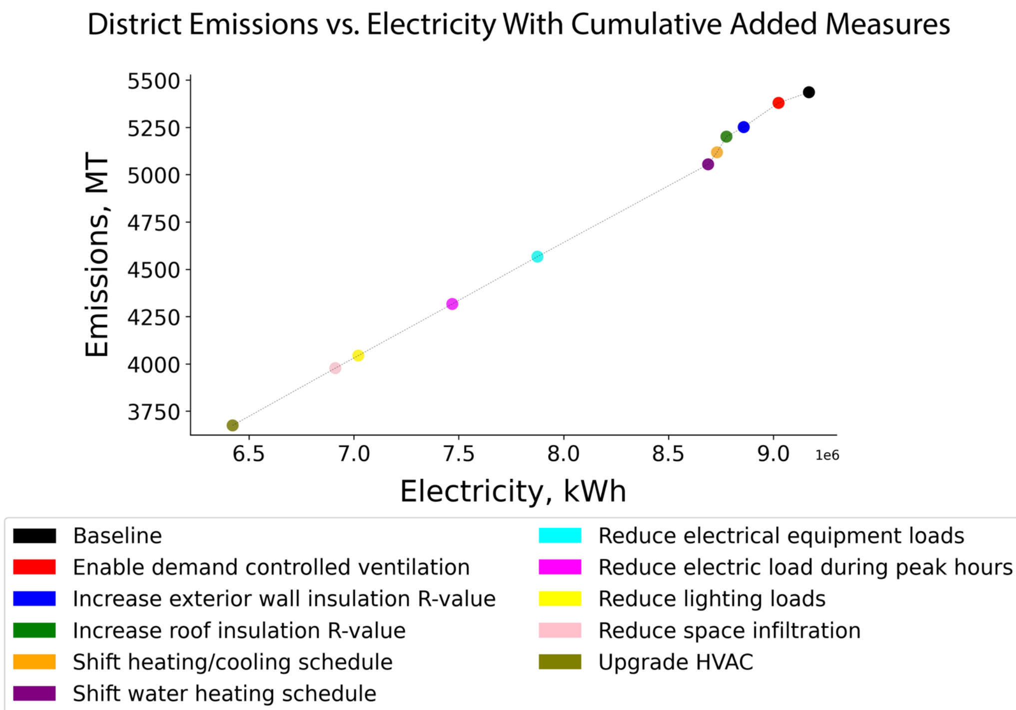

Figure 9 - Denver case study district modeled emissions vs. total annual electricity consumption with EEMs and Load flexibility measures applied on top of the baseline model (baseline is top right point).

The demand control ventilation, indicated by the red point, presents an EERR less than 1. This outcome arises because the ventilation system is controlled based on the electricity load rather than the emissions profile, thus prioritizing electricity reduction without considering the variability in emissions throughout the day.

Conclusion

The integrated open-source URBANopt modeling framework allows users to design and plan for low or net-zero carbon buildings, neighborhoods, and urban districts. It allows users to model emissions using a variety of potential emissions calculation approaches depending on the modeling use cases and compare outcomes across multiple URBANopt scenarios. Further information about the inputs, outputs, and the process for utilizing this capability within URBANopt is available at https://docs.urbanopt.net/workflows/carbon_emissions.html. As demonstrated in the case study district example, users can automatically generate and evaluate emissions scenarios to analyze the potential emissions impact of their projects. This integration not only facilitates new analysis workflows aimed at emissions reductions, but also enables users to utilize buildings emission results to guide design choices and integrate into control and optimization frameworks. For instance, users can assess the efficacy of new upgrades and control strategies for building and community systems, examining their effects on carbon emissions at a neighborhood or district scale.

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