THE CARBON EMISSIONS IMPACT OF DEMAND FLEXIBILITY

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ABOUT RMI
RMI—an independent nonprofit founded in 1982—transforms global energy use to create a clean, prosperous, and secure low-carbon future. It engages businesses, communities, institutions, and entrepreneurs to accelerate the adoption of market-based solutions that cost-effectively shift from fossil fuels to efficiency and renewables. RMI has offices in Basalt and Boulder, Colorado; New York City; Oakland, California; Washington, D.C.; and Beijing.

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1. BACKGROUND

Demand Flexibility

Demand flexibility is the ability of a building to shed or shift energy demand from one time to another to reduce cost and carbon emissions while maintaining core building functions (e.g., maintaining thermal comfort, providing electric services).[1] Unlike calls for demand response, which are primarily triggered by utility programs for isolated, time-bounded events, demand flexibility is a continuous optimization of demand based on dynamic building and grid characteristics. Demand flexibility measures span a wide array of energy shedding and shifting strategies.

Traditionally, a building acts as a relatively unsophisticated consumer of power from the electrical grid, paying a particular price for the electricity it uses (kWh) and a charge for its peak power (kW). A building consumes energy whenever needed, without regard to potential generation costs or emissions. Emerging demand flexibility strategies enable buildings to manage their electric demand to provide grid services. Grid services could include capacity reduction (similar to demand response efforts), avoiding renewable curtailment, avoiding high-cost generation resources, or reducing emissions.

Buildings with demand flexibility can shift or shed demand rapidly in response to a signal, or multiple signals, to smooth grid peak or increase demand to avoid grid energy curtailment. These signals can represent consumer electricity price, greenhouse gas (GHG) emissions, or other indicators and can be used to inform building operations. This analysis is specifically focused on the potential impact of a carbon signal.

Grid-optimized demand flexibility is facilitated by two-way communication between buildings and the grid. It is a dynamic and interactive relationship that, when optimized around emissions, enables all parties to align to reduce societal cost for decarbonization from both the grid and buildings.

Emissions Metrics

The following emission factors/signals were used for this analysis. In general, the GHG metric considered in this analysis is carbon dioxide (CO_2) since it is the most significant portion of emissions per unit mass in electricity production. CO_2 emissions can be described in many ways. This analysis does so based upon three different characteristics: signal type, timestep, and level of advance notice.

1. Signal Type

There are two primary emission factor types used to measure electricity generation emissions and as a signal for shifting building demand:

- *Average Emissions*: the GHG emissions per unit of electricity (e.g., $MTCO_2e/kWh$) based on every generation resource operating to meet demand. It averages the emissions of all the generation resources contributing to the electricity being supplied.
- *Marginal Emissions*: the GHG emitted by the generating resource responding to changes of load on the grid.

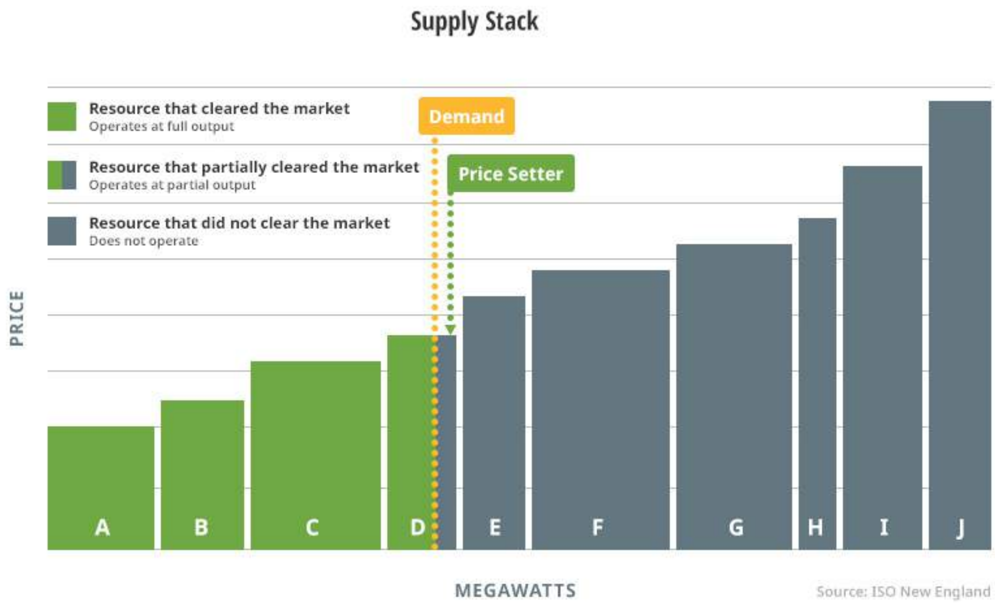


EXHIBIT 1: THIS GRAPHIC ILLUSTRATES THE RELATIONSHIP OF AVERAGE VERSUS MARGINAL SIGNALS IN A GENERIC DISPATCH STACK FROM ISO NEW ENGLAND. PRICE DRIVES PLANT DISPATCH AND RESULTING CARBON EMISSIONS. IN THIS EXAMPLE, AN AVERAGE EMISSION FACTOR WOULD BE THE EMISSIONS OF PLANTS A, B, C, AND D DIVIDED BY THE POWER THEY PROVIDED WHILE OPERATING TO MEET DEMAND. A MARGINAL EMISSION FACTOR WOULD ONLY EVALUATE THE EMISSIONS ASSOCIATED WITH THE POWER PRODUCED BY THE PRICE SETTER, POWER PLANT D, AS IT IS THE LAST RESOURCE NEEDED TO MEET DEMAND.

2. Timestep

Timestep is the interval, or increment, of time between data points in the emissions profiles. For example, a 3-hour timestep would use the average marginal emissions rate over a 3-hour period of time. This analysis used 8-hour, 3-hour, 1-hour, and 15-minute timesteps as examples. In general, even the most high-performance buildings will have a limit to the granularity of the timestep that they can reasonably respond to.

3. Level of Advance Notice

Level of advance notice describes the duration of time between when a forecast is provided and the actual point in time being considered. Examples include real time, 1 hour ahead, 3 hours ahead, 24 hours ahead. Timeframes that are not real time allow for buildings to have more time to shift loads (e.g., preheating, precooling, battery charging). On the other hand, forecasts inherently contain a margin of error, as any prediction of data would.

Demand Flexibility in the Context of Decarbonization Targets

Laws setting building performance targets exist across the country, but Local Law 97 (LL97) in New York City is a notable example because it defines performance expectations based on carbon emissions. Buildings account for nearly 73% of the city's total emissions.[2] This legislation aligns building performance with New York City's targeted city-wide GHG emissions reductions of 40% below 2005 levels by 2030 and 80% below by 2050.

The graphic below shows pathways that the city has forecasted for GHG emissions reductions in buildings.

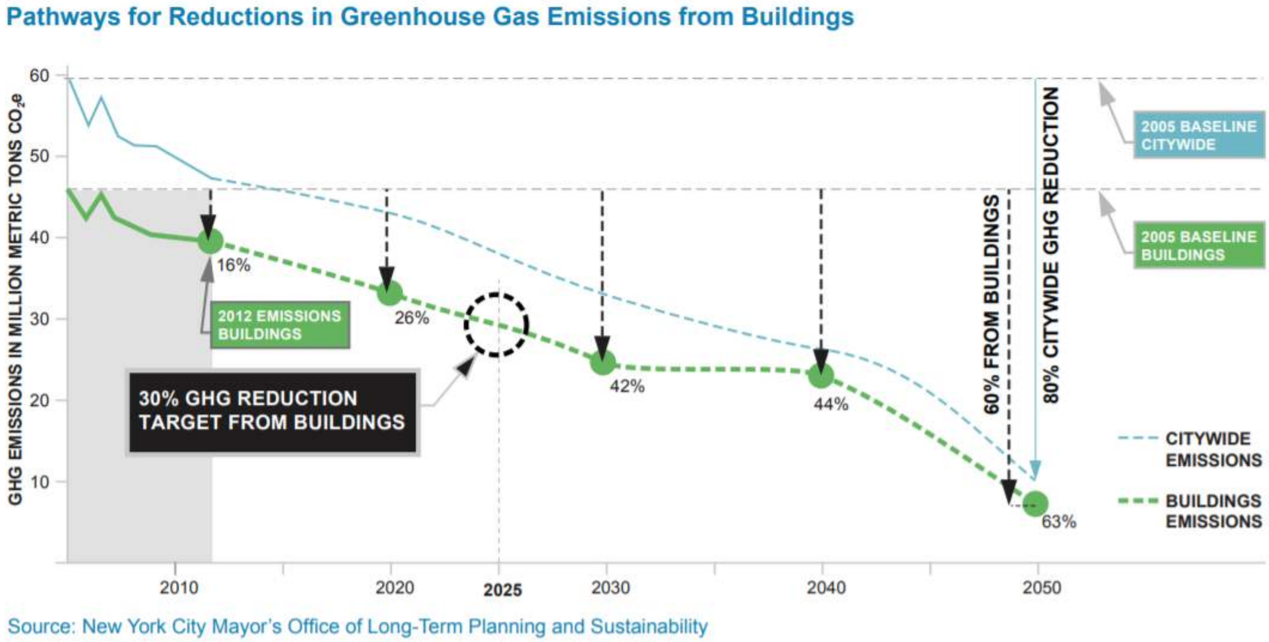


EXHIBIT 2: AN 80X50 PATHWAY (80% TOTAL CITY-WIDE EMISSIONS REDUCTIONS FROM 2005 LEVELS BY 2050) REQUIRES A 30% EMISSIONS REDUCTION IN BUILDINGS FROM 2005 LEVELS BY 2025 AND 60% BY 2050 IN BUILDINGS PER NYC'S *ONE CITY BUILT TO LAST* REPORT.

To support these ambitious GHG emissions reduction goals, NYC's Local Law 97, signed into law in May 2019, sets annual emissions limits for all buildings greater than 25,000 square feet, starting in 2024. Under this law, emissions limits are calculated using predefined emissions intensity (tons of CO_2 equivalent (CO_2e) per square foot of building space). Buildings have different emissions limits based on occupancy type and compliance period. The fine for a building that exceeds its baseline emissions limit is $268 per ton CO_2e.

Annual emissions are calculated based on fuel sources for each end use, including electricity, natural gas, fuel oil, utility-provided steam, and others. Currently the annual average electricity emission factor in LL97 is based on EPA eGRID 2016 data for the 2024–2029 compliance period and is not yet defined for 2030 and beyond.[3] The emission factors are multiplied by the building's fuel consumption, divided by square footage, and compared to the intensity limit based on the building type to determine compliance.

Annual average emissions only encourage behavior that reduces energy consumption over the year. This limits the impact of the law because it does not value behavior that is optimized around the timing of electricity consumption. NYC addressed this limitation in a recent amendment to LL97 which added an option for building owners to comply using time-of-use (TOU) emission factors for electricity use. The amendment to the law (December 2019)[4] requires the City to provide an option for compliance based on TOU for 2024–2029, allowing for time-of-use factors and alternative compliance pathways as long as they achieve, at a minimum, the intended reductions overall.

A TOU emission factor would value GHG emissions based on the time at which the electricity is consumed, which the annual average factor does not. This amendment to the law allows for the investigation of various approaches to compliance based on time of use. Time-valued emissions present a mechanism for demand flexibility-enabled GHG emissions reduction. This would allow LL97 to encourage buildings to shift electricity demand to hours when emissions from generation resources are lower.

2. OBJECTIVES

Demand flexibility in buildings may play an important role in decarbonizing the grid, but its emissions reduction potential has not yet been quantified. The purpose of this study is to provide context for the potential impact of using time-of-use emission factors to reduce emissions associated with electricity use in buildings. It evaluates the technical potential of optimally deployed demand flexibility in an office building and a multifamily building. Specifically, we analyzed:

- the technical potential for carbon emissions-optimized demand flexibility to reduce emissions at the building level;
- how the behavior of a building and related carbon emissions reduction change when the type, timestep, and level of advance notice of the signal is modified;
- the signal characteristics that contribute to the highest potential carbon emissions reduction;
- if measuring and optimizing on a marginal basis versus an annual average basis make a difference; and
- how carbon emissions reduction differs when providing buildings with various timestep granularities and levels of advance notice.

By comparing emissions signals of different types, timesteps, and levels of advanced notice, RMI seeks to identify the signal with the highest potential emissions impact. This quantification of demand flexibility's emissions potential impact could be used to help design LL97's time-of-use option or other means of incentivizing demand flexibility.

3. METHODOLOGY

The methodology used to evaluate the emissions impact potential from demand flexibility combines both grid-level analysis (using proxy grids to simulate Zone J characterization projections) and building-level analysis (using typical load profiles). The steps in Exhibit 3 are described in more detail below.

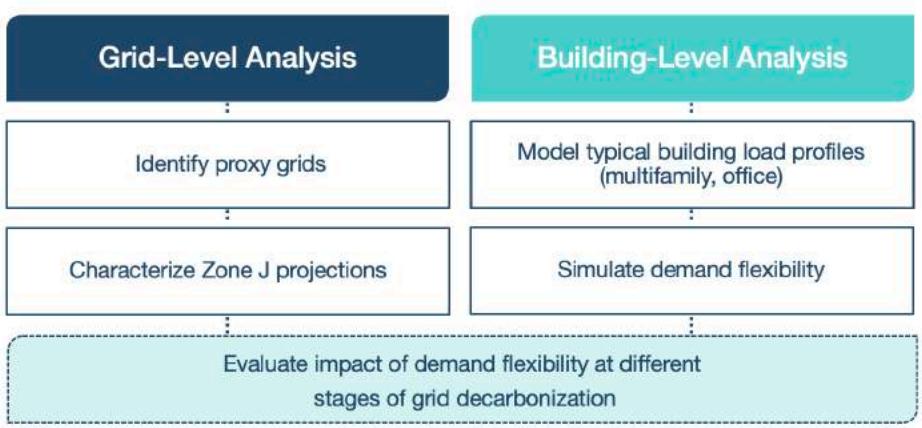


EXHIBIT 3: ANALYSIS PROCESS SHOWING THE STEPS FOR BOTH THE GRID-LEVEL ANALYSIS AND THE BUILDING-LEVEL ANALYSIS.

The results of our analysis isolate the potential emissions savings provided by demand flexibility. Emissions savings from traditional energy efficiency and electrification were calculated separately, the assumptions for which can be viewed in Appendix B. Emissions savings were calculated based on specific grid conditions that were applied to both the baseline and the optimized scenarios. Thus, the results are expressed as a percent reduction compared to baseline, not an absolute emissions reduction value (tons of CO_2).

1. Grid-Level Analysis: Characterize Zone J Projections

Since LL97 is specific to New York City, grid characterization was focused on data from the New York City subregion of NYISO Zone J. Today, the power generated for New York City has minimal variable renewable generation and significant contributions from natural gas and nuclear. See below for more detail on current and projected NYISO Zone J characteristics.

GENERATION TYPE	NYISO ZONE J TODAY[i]	2030 PROJECTION (WIND ONLY)[ii]	2030 PROJECTION (WIND + HYDRO)[iii]
Variable Renewable (Wind and Solar)	2%	36%	35%
Carbon Free (Nuclear and Hydro)	30%	12%	25%
Fossil Fuel	65%	47%	36%
Other	3%	5%	3%

EXHIBIT 4: GRID MIX AND FUTURE PROJECTIONS FOR ZONE J BASED ON THE MAYOR'S OFFICE OF SUSTAINABILITY PUBLIC POLICY TRANSMISSIONS NEEDS (PPTN) DATA.

2. Grid-Level Analysis: Identify Proxy Grids

For the grid emissions projections in 2030 and 2040, actual New York Independent System Operator (ISO) Zone J projections weren't available. Therefore, we used "proxy grid scenarios" to represent future emissions profiles for different points in time for Zone J as the grid moves toward decarbonization. The proxy grid scenarios provide granular carbon emissions data pulled from ISOs across the United States and Canada, with different fuel mixes and generation patterns. While not perfect, they simulate potential grid characteristics expected in a decarbonized future. Note that to truly evaluate NYC potential scenarios, detailed assessments would be needed for Zone J generation under future conditions as well as imported power.

Proxy grids also provide carbon emissions data with shorter timesteps (15 minute) taken from actual, in-operation grids elsewhere in the world, leveraging specifically those grids that have characteristics projected for the forecast for the Zone J fuel mix. This characterization is based on a framework of variable renewable energy (VRE) integration provided by the IEA and described in Exhibit 7.[5]

The proxy grids that most closely resemble Zone J projections include the ISO New England (ISO NE), Southwest Power Pool (SPP), California ISO (CAISO), and Independent Electricity System Operator (IESO) that serves Ontario, Canada. Details can be found in Exhibits 5 and 6.

The intent of evaluating multiple proxy grids was to target specific characteristics that could be expected in the future of Zone J. The ISONE, SPP, and CAISO proxy grids each offer different characteristics that could resemble 2030 NYISO Zone J conditions. IESO roughly maps to a 2050 NYISO Zone J condition. Our analysis emphasizes these grid characteristics rather than specific NY state decarbonization timelines. The proxy grid data does not include imports in the dispatch stack.

[i] Zone J 2020 Draft update of the MOS PPTN 2018 study.
[ii] Zone J 2030 Projection (including 4,500 MW offshore wind). Draft update of the MOS PPTN 2018 study.
[iii] Zone J 2030 projection (including 4,500 MW offshore wind + 1,000 MW Canadian Hydropower). Draft update of the MOS PPTN 2018 study.

GENERATION TYPE	SOURCE	NYISO ZONE J 2019	ISONE	SPP	CAISO	IESO	2030 PROJECTION (WIND ONLY)[iv]	2030 PROJECTION (WIND+ HYDRO)[v]
Variable Renewable Generation	Wind	2%	2%	38%	21%	8%	36%	35%
	Solar	0%	0%	0%	19%	0%		
Carbon Free	Hydro	20%	5%	7%	15%	26%	12%	25%
	Nuclear	33%	30%	3%	6%	59%		
Fossil Fuel	Coal	0%	0%	28%	0%	0%	47%	36%
	Natural Gas	35%	55%	22%	38%	6%		
	Other	1%	7%	1%	0%	1%	5%	3%

EXHIBIT 5: NYISO ZONE J AND PROXY GRID GENERATION.

INDEPENDENT SYSTEM OPERATOR (ISO)	SUB-REGION	SERVICE LOCATION DETAILS	SIMILARITIES TO NYISO ZONE J PROJECTIONS	DIFFERENCES FROM NYISO ZONE J PROJECTIONS
ISONE	NEMA	Primarily Boston metro area	**Gas is the primary fossil fuel resource on the margin.** The balance between wind/carbon free and natural gas could make the variability be like future Zone J grid conditions.	The percentage of production from nuclear facilities is higher than Zone J projections.
SPP	RZ2	Southern Central US (OK, AR, MO, KS)	**High penetration of wind energy**. Wind energy is characterized by inconsistency in generation according to season and time of day.	**Coal is a common fossil fuel resource on the margin**, so SPP variability is high (i.e., the highest marginal emissions are higher on SPP than they would be on NYISO).
CAISO	NP15	Northern California (SF, Bay Area, etc.)	**CAISO has the highest penetration of solar of the proxy grids chosen.** Solar energy is characterized by generation that aligns with the daytime. It is a resource that can be more consistent (a consistent eight hours of renewable on a sunny day) than wind.	Higher carbon-free generation than Zone J projections.
IESO	N/A	Ontario	**A portion of carbon-free energy in Ontario comes from hydro.** It is common on this grid to have entire days with zero emissions. This proxy is meant to represent a high portion of zero emissions electricity, where demand flexibility provides an essential service to the grid in responding when those zero-emissions sources are unable to serve all demand.	**Nuclear is a significant portion of carbon-free energy production, unlike future Zone J projections.** Nuclear and hydro are characterized by similar limitations, their variability is primarily driven by energy constraints (not typically short-term weather). This means the events when demand flexibility is needed by the grid will be different in timing and duration.

EXHIBIT 6: SUMMARY OF PROXY CHARACTERISTICS AND SIMILARITIES AND DIFFERENCES TO NYISO ZONE J PROJECTIONS.

[iv] Zone J 2030 projection including 4,500 MW offshore wind). Draft update of the MOS PPTN 2018 study.
[v] Zone J 2030 projection including 4,500 MW offshore wind + 1,000 MW Canadian hydropower). Draft update of the MOS PPTN 2018 study.

For this study, the proxy grid selection is not an exact science. RMI and WattTime focused on certain aspects of the fuel mix, knowing that no outside grid would perfectly fit the characteristics expected for Zone J. One vital characteristic from this analysis is that higher penetration of wind and solar in Zone J will increase the number of days with highly variable carbon emissions. No proxy grid available had the variability expected in Zone J based on the projections. To better quantify the impact of variable renewable energy on demand flexibility, we focused on the days within the proxy grids with the highest hourly variation in carbon intensity.

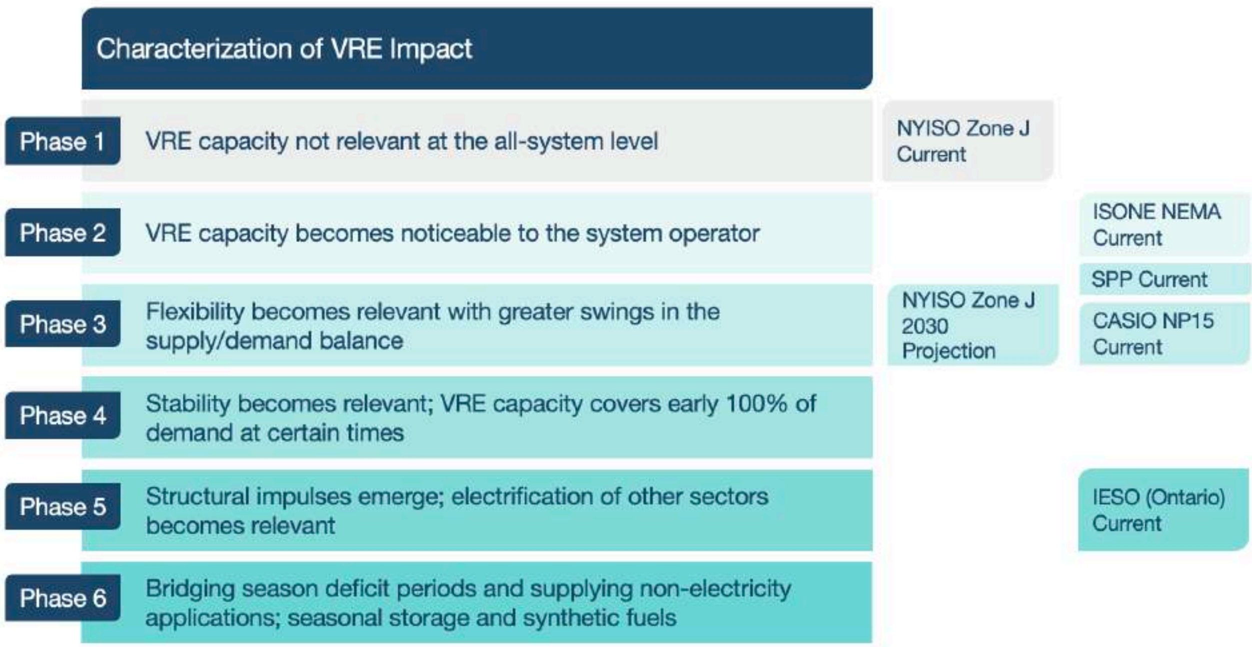


EXHIBIT 7: INTERNATIONAL ENERGY AGENCY VARIABLE RENEWABLE ENERGY (VRE) FRAMEWORK WITH THE PROXY GRIDS USED IN THIS ANALYSIS MAPPED TO EACH PHASE.

To calculate average emissions for a grid, WattTime totals the emissions in a region and divides it by the total generation in that region, based on data provided by the EPA, EIA, and various ISOs. To calculate marginal data for these proxy grids, WattTime used a proprietary empirical model that extends the basic methodology used by both Siler-Evans and Callaway but adapted for real-time use.[6] The model uses regression-based modeling to identify, every time a rise or fall in electricity demand occurs in a given place and time, which power plants actually increase or decrease their output in response.

Inputs for this regression analysis include grid data from the respective ISO and five years of historical Continuous Emissions Monitoring Systems data from the US EPA. The model output is real-time marginal operating emissions rates down to the five-minute increment. For the different timestep options, we used 15-minute average and marginal emissions for the ISO subregions of the proxy grid regions for this analysis.

3. Building-Level Analysis: Model Typical Building Profiles (Office, Multifamily)

RMI created building load profile scenarios for a dual-fuel multifamily building, an all-electric multifamily building, a dual-fuel office building, and an all-electric office building. Office and multifamily buildings were chosen because they are the most greenhouse gas emissions-intensive types in NYC's building stock, making up 58% percent of all NYC's GHG emissions from buildings.[7]

We leveraged DOE reference models and anonymized data from participants in the Real Time Energy Management (RTEM) program offered by NYSERDA to identify end-use breakdown by type and typical schedules. DOE reference models were updated in EnergyPlus to align with New York building stock and recent weather conditions (a NYC TMYx weather file) to generate 15-minute load profiles. Detailed assumptions of the load profiles and energy-end use breakdowns by type can be found in Appendix A.

To identify typical building stock, we compared Local Law 84 benchmarking data and PNNL reference models against the 2018 RTEM data. We then calculated the carbon emissions associated with the 2018 energy consumption based on LL97 factors for 2024 and compared the total annual emissions against the 2024 carbon limits for office buildings. Based on that benchmarking exercise, we determined this RTEM building likely represents a moderate to high-performing building that will comply with LL97 in 2024, if its energy consumption behavior remains relatively stable.[8]

Once the all-electric and dual-fuel scenarios for the two building types were established, energy efficiency measures were applied to each scenario based on measures from the *One City Built to Last* report.

4. Building-Level Analysis: Simulate Demand Flexibility

Demand flexibility measures were applied to the efficient building scenarios defined above. Demand flexibility was evaluated separately from efficiency to isolate the benefits. Demand flexibility measures applied in this analysis included:

- plug load staging (office only),
- appliance load shifting (multifamily only),
- space preheating (all-electric cases only),
- space precooling,
- thermal energy storage for cooling,
- thermal energy storage for heat pump water heating (multifamily all-electric only), and
- battery storage.

Detailed assumptions are based on previous RMI analysis of grid-interactive efficient building potential in NYC and can be found in Appendix C.

In this analysis we focused on the technical potential of demand flexibility by evaluating the potential impact that bundles of optimally deployed flexibility measures could have on the emissions profile of the building scenarios. We bundled individual demand flexibility measures to model them based on their technical potential to shift each energy end use; these bundles represent likely measures for a "typical" commercial and multifamily building based on technology available today and in the near term.

5. Evaluate Impact

Finally, the grid- and building-level analyses were combined to evaluate the impact across the four building scenarios. The load flexibility for each scenario was optimized based on the carbon emissions data with a 15-minute timestep from each proxy grid. The modeling tool shifted load from the highest carbon emissions times to lowest carbon emissions times over a 24-hour period, with each day having a unique optimization output. The quantity of load shifted and the timeframe that was shiftable was based on assumptions at the end-use level. These assumptions can be found in Appendix C. Each day for each proxy grid has different optimized behavior because the patterns of carbon emissions vary.

Sensitivity analyses, found in Appendix D, were performed to understand potential variation in end-use load profiles such as load increases from changes in climate/temperature in the years to come and advances in technology that would allow more demand to be shifted. The results of the sensitivity analysis demonstrated that there is significant carbon emissions reduction potential in the heating end uses in multifamily buildings, including domestic hot water and space heating. In the office scenario, equipment power density is the most significant end use that swayed reduction potential from demand flexibility.

6. Limitations of Analysis

There are limitations to this analysis and how the carbon emissions reduction potential can be considered. This analysis reflects the technical potential for carbon emissions reduction due to demand flexibility as applied to four individual building cases.

- This analysis does not represent the potential impacts to the grid or decarbonization efforts from the entire building stock of NYC.
    - Changes in demand, especially peak power, shift the way generation resources are allocated and operated. This analysis does not project the ways that a shift in resources would change the cost, resilience, and efficiency of Zone J and of imported power. This will be very dependent on how grid providers adjust generation in response to shifting load and how the grid evolves as it incorporates increasing levels of renewable electricity.
    - Since hourly NYISO Zone J and imports projections were not available, we used proxy grid scenarios to represent future carbon emissions profiles for different points in time which may be similar to NYISO Zone J as the grid moves toward decarbonization. These proxy grids generally simulate some grid characteristics expected at different points moving toward a decarbonized future but should only be seen as examples of the types of behavior which may result.
    - The calculations used to determine carbon emissions for the proxy grid data do not explicitly include imports in the dispatch stack but are accommodated by how they affect the local marginal resource.
- This analysis does not look at grid-level impacts from high adoption levels of demand flexibility and how it may alter load peak(s).
- This analysis does not provide a specific path or cost-effective measures for these building examples to comply with LL97. The potential annual impacts represent the behavior were a building to respond to a signal in an ideal manner. The TOU pathway in Local Law 97 would encourage load-shifting behavior but would not result in any additional emissions savings, only provide another compliance alternative.
- This analysis does not evaluate whether LL97 incentivizes or disincentivizes electrification nor the bulk system impacts due to adoption.
    - We modeled all-electric scenarios for samples of multifamily and office building types to determine the carbon emissions reduction potential that demand flexibility could provide for these buildings with increased electrical heating loads.
- We optimized flexibility based on carbon emissions and not cost so this analysis does not evaluate cost-effectiveness from an operational or capital investment perspective. Full implementation achieving these

levels would depend on those full costs (i.e., first cost, return on investment, or operational cost savings).

- Only carbon emissions were considered in this analysis. Other types of emissions contribute to global warming, including (but not limited to) N_2O and CH_4. The results presented in this paper are considered by mass of CO_2. Because CO_2 is the primary global warming pollutant caused by electricity generation, most emissions are accounted for. The result is that the demand flex emissions savings potential is likely conservative, but it would require more analysis to determine confidently.
- The analysis was performed using emissions rates produced by the WattTime model. The model may not capture the full variation in emissions present in a grid region due to the modeling methodology. Furthermore, the model may not fully capture when imports are marginal, but the impact of imports on the marginal resource is included.

4. FINDINGS

Key Findings

1. **Emissions Reductions over the Continuum of Decarbonization:** Demand flexibility in buildings can provide limited emissions reductions based on the electricity generation mix in the current grid—up to 3%. However, demand flexibility in an all-electric office building could reduce emissions up to ~10% from buildings relying on grids similar to the expected generation supplying NYC by 2030, when more variable renewable generation will be included in the mix. And it could reduce emissions up to ~40% as the grid approaches full decarbonization.
2. **Benefits across Grid Conditions:** Demand flexibility could provide benefits across different grid conditions that Zone J may see in its transition to a decarbonized future grid. Regardless of the type of variable renewable generation resources added to Zone J, demand flexibility can provide increasing fractions of emissions reductions for buildings.
3. **Selection of Emissions Signal Matters:** The important characteristics of a time-of-use emissions signal are type, timestep, and level of advance notice. The selection of these criteria will define the demand flexibility response of a building. This analysis shows that the highest emissions reductions come from a marginal emissions signal with the shortest possible timestep and shortest level of advance notice.

Demand flexibility shows significant potential to reduce carbon emissions and could be enabled under LL97 with the right signal structure. These findings are described in detail in the following sections.

1. Emissions Reductions over the Continuum of Decarbonization

Demand flexibility in buildings can provide limited emissions reductions based on the electricity generation mix in the current grid—up to 3%. However, demand flexibility in an all-electric office building could reduce emissions up to ~10% from buildings relying on grids similar to the expected generation supplying NYC by 2030, when more variable renewable generation will be included in the mix. And it could reduce emissions up to ~40% as the grid approaches full decarbonization.

Demand flexibility has a limited potential to reduce carbon emissions today due to a fairly consistent carbon emission rate from generation resources serving Zone J. Shifting load in prototypical multifamily and office buildings, similar to those found in NYC, from high- to low-carbon times with the current grid characteristics only shows a potential of about 3% overall reduction in carbon emissions. This is measured independently from savings provided by energy efficiency. The current generation mix serving Zone J is predominately based on natural gas (35%) and nuclear (33%) with very little variable renewables (2%), so even on the days with the most variability in emissions, shifting load from one hour to another doesn't provide significant reduction. This is fairly consistent over the course of a day, month, and even season.

However, when the Zone J generation mix becomes more reliant on variable renewable generation (36% based on 2030 projections), demand flexibility will become increasingly valuable, providing up to 10% emissions reduction for these prototypical buildings, based on the proxy-grids. As the grid approaches full decarbonization, there will likely still be a few hours that require fossil fuel-based generation to meet peak demand, and demand flexibility could provide up to 40% emissions reduction. Demand flexibility would allow buildings to shift load away from peak hours, further reducing the grid's reliance on gas generation.

When the grid becomes fully decarbonized the generation on the margin will always be zero emissions and a new signal will be needed. Until then, shifting away from dirty generation is important and can be done so with increasing efficacy as Zone J moves toward higher VRE saturation.

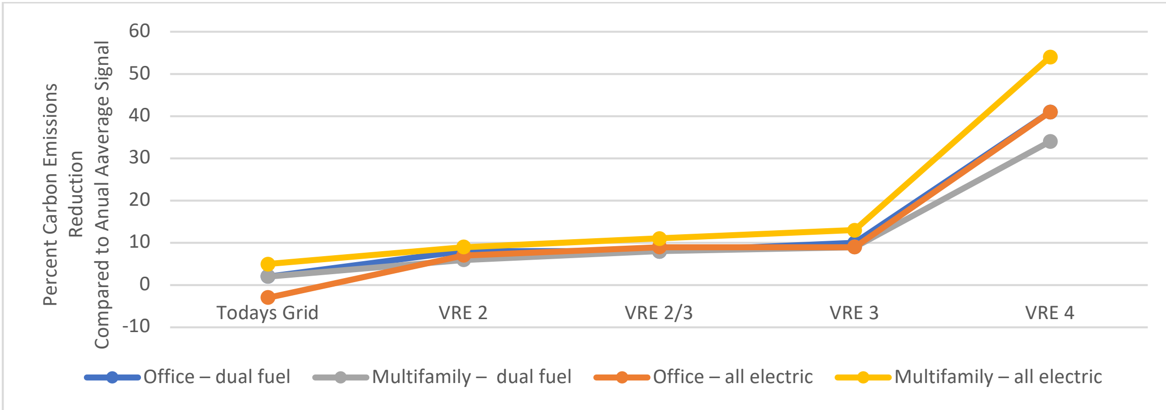


EXHIBIT 8: THE PERCENT REDUCTION IN MARGINAL CARBON EMISSIONS OF DIFFERENT BUILDING TYPES ACROSS DIFFERENT STAGES OF THE GRID TRANSITION. NEGATIVE VALUES IN TODAY'S GRID REPRESENT A BUILDING PROFILE (ALL-ELECTRIC) THAT HAS HIGHER CARBON EMISSIONS THAN A BASELINE DUAL-FUEL BUILDING. VRE PHASES ARE USED TO DESCRIBE THE PROXY GRIDS BASED ON THEIR VARIABLE RENEWABLE PENETRATION. FOR MORE INFORMATION ON VRE PHASES SEE EXHIBIT 7 IN THE METHODOLOGY SECTION.

2. Benefits across Different Grid Conditions

Demand flexibility could provide benefits across different grid conditions that Zone J may see in its transition to a decarbonized future grid. Regardless of the type of variable renewable generation resources added to Zone J, demand flexibility can provide increasing fractions of emissions reductions for buildings.

Demand flexibility can be beneficial to carbon reduction efforts throughout all stages of the grid transition. The quantity of emissions reductions varies depending on the generation fuel mix and variability in marginal emissions rate. The following are examples of responses that a building might have to a marginal 15-minute signal in grid conditions with different types of high renewable generation. These specific days reflect high opportunity conditions for demand flexibility because of high variability in the renewable generation (e.g., wind penetration being high during some hours causing curtailment).

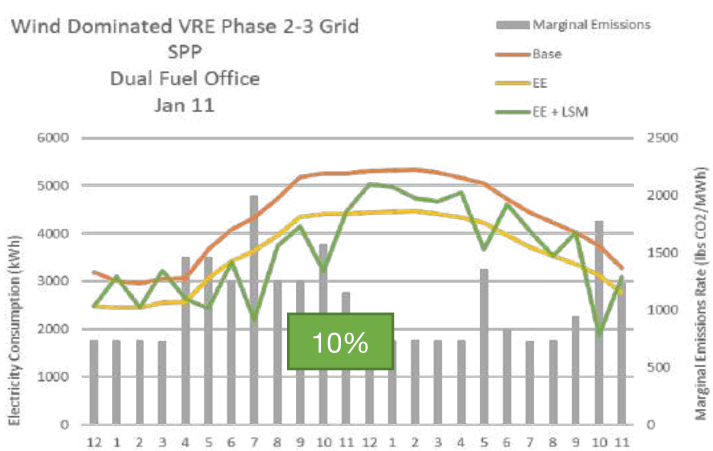


Exhibit 9 demonstrates a 10% reduction in emissions due to demand flexibility in an office building on a day with a highly variable emissions pattern. The orange line represents the baseline hourly energy demand. The yellow line shows an energy efficient case (i.e., a typical building's response to LL97 without a TOU emissions signal). The green line represents the behavior expected with load-shifting measures (LSMs) that are shifting energy use away from high-emissions periods to low-emissions periods. In this case with a wind-dominated grid the emissions profile is more sporadic.

EXHIBIT 9: DEMAND FLEXIBILITY BEHAVIOR ON A DAY WITH VARIABLE WIND GENERATION. THE GREEN BOX SHOWS THE DAILY CARBON REDUCTION FROM THE OPTIMIZED DEMAND FLEXIBILITY. AS SHOWN, THE TIMES WITH LOWER EMISSIONS (SHORTER GREY BARS) HAVE AN INCREASE IN DEMAND (HIGHER POINTS IN THE GREEN LINE).

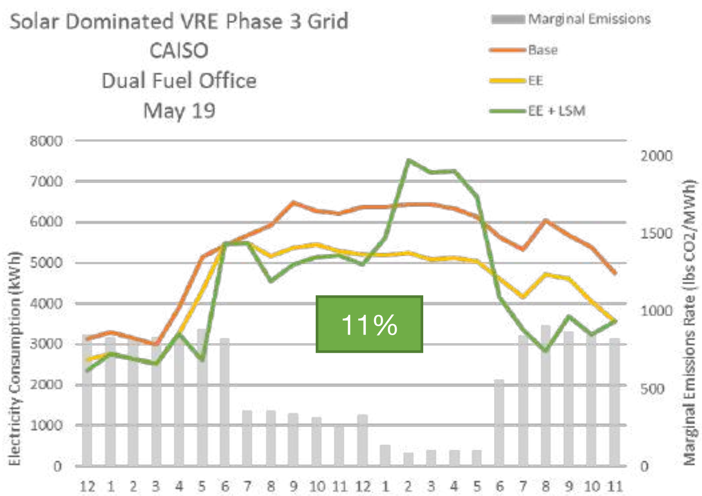


EXHIBIT 10: DEMAND FLEXIBILITY BEHAVIOR ON A DAY WITH HIGH SOLAR GENERATION, LIKELY INCLUDING CURTAILMENT.

Exhibit 10 shows demand flexibility optimized in an office building on a day with high solar generation on the grid. The grid emissions are low in the day and high at night and thus the load profile shifts to absorb the midday solar generation. In this scenario, demand flexibility reduces 11% of emissions beyond efficiency alone.

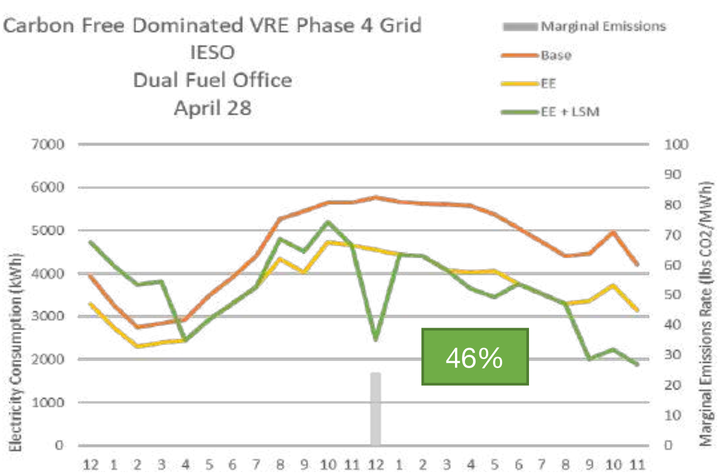


EXHIBIT 11: DEMAND FLEXIBILITY BEHAVIOR ON A DAY WITH MOSTLY EMISSIONS-FREE GENERATION MIX.

Exhibit 11 shows demand flexibility in an office building in a grid with high carbon-free generation. While almost all hours are carbon free, there is one isolated hour where fossil fuel generation was needed to keep up with demand. Under these generation conditions, the value of demand flexibility increases. In this instance, it reduces emissions by 46% beyond efficiency alone.

As shown, demand flexibility provides emissions benefits by reducing emissions at specific key times (the highest emissions hours), as opposed to energy efficiency which often reduces energy use (and corresponding emissions) across all hours. Demand flexibility could be considered an alternative (or additive) to traditional energy efficiency since not all hours have equal emissions.

3. Selection of Emissions Signal Matters

The important characteristics of a time-of-use emissions signal are type, timestep, and level of advance notice. The selection of these criteria will define the demand flexibility response of a building. This analysis shows that the highest emissions reductions come from a marginal emissions signal with the shortest possible timestep and shortest level of advance notice.

Signal Type: An emission-based signal is most often based on a marginal or an average factor, as defined above. Marginal and average emission rates are fundamentally different, irrespective of any other characteristics of the signal. A marginal signal more clearly indicates the emissions benefit of avoided load. For example, in a grid with high renewables penetration, the marginal signal would indicate when renewables are being curtailed (i.e., a good time to shift load into) and times when dirty peaker plants are running (i.e., a good time to avoid consuming electricity). This means that marginal emissions better capture the real grid emissions impact of any load-shifting activities.

It should be noted that if many or all buildings shift their load to respond to a signal, there would likely be a reshaping of the grid's load curve and the creation of new peaks at different times. The secondary implications of sector-wide adoption were not analyzed but were recommended for follow-on analysis.

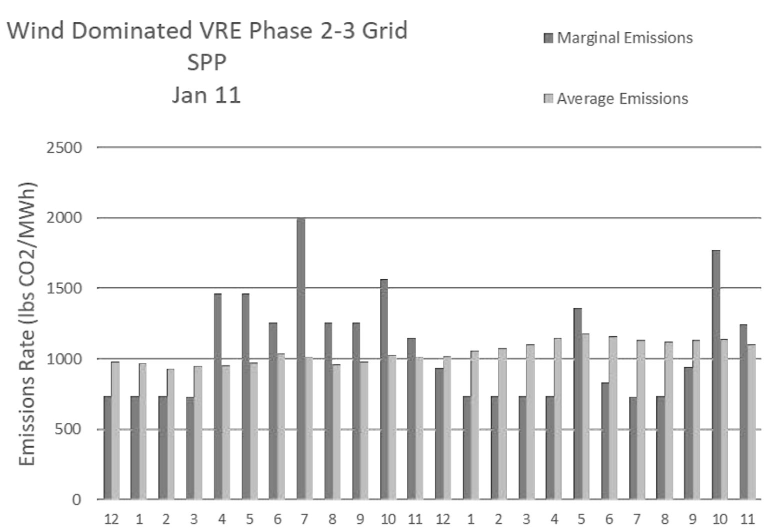


EXHIBIT 12: EXAMPLE OF A COMPARISON OF AN AVERAGE HOURLY SIGNAL TO A MARGINAL HOURLY SIGNAL. THE PATTERN OF EMISSIONS OVER THE COURSE OF THE DAY IS VERY DIFFERENT.

Exhibit 12 shows an example of the difference between an average hourly metric (in light grey) and a marginal hourly metric (in dark grey) over the course of a day. The variation between signals encourages very different behaviors in buildings, load shifting at different times. Also, the magnitude is very different and at times, the marginal emissions rates are two times the average emissions rate. This also drives different behavior (see Exhibit 13).

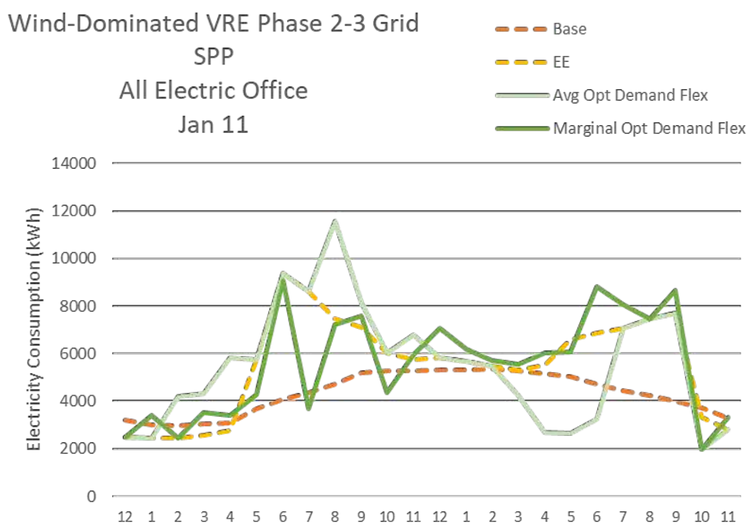


EXHIBIT 13: A COMPARISON OF DEMAND FLEXIBILITY BEHAVIOR WHEN OPTIMIZED FOR A MARGINAL SIGNAL COMPARED WITH AN AVERAGE SIGNAL.

Exhibit 13 shows the demand profiles from the same building when flexibility is optimized around an average hourly signal (light green) and a marginal hourly signal (dark green). The load is shifted based on the energy efficiency case in yellow. It is an efficiency case derived from the baseline in orange. The response to the signals is very different. An average hourly signal encourages shifting load from the late afternoon to the early morning. On the other hand, the marginal signal encourages shifting the early morning loads to late afternoon/evening. In this case, the responses are the exact opposite.

Signal Timestep: The timestep of the signal refers to the interval/increment of time between data points in the emissions profiles. Examples of selections for this characteristic include (but are not limited to) 15-minute, 1-hour, 8-hour, and 24-hour. Greater emissions reductions are possible with a shorter timestep (i.e., 15-minute) because that kind of metric captures the true variability in a highly renewable grid and reduces the number of opportunities for buildings to flex their demand. Exhibits 13 and 14 represent the diminishing potential of a larger timestep on CAISO and SPP.

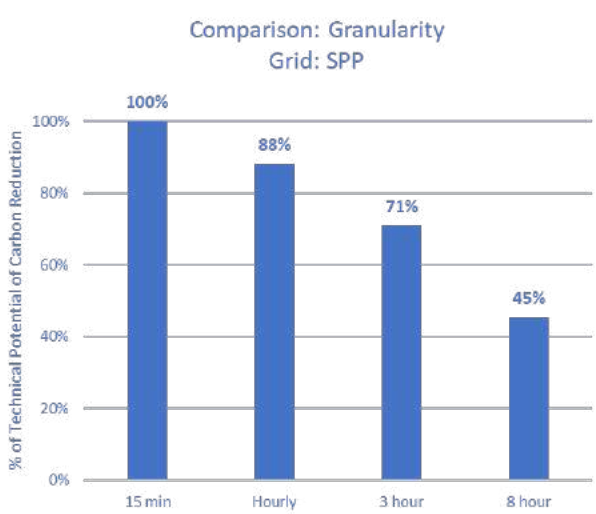


EXHIBIT 14: THIS GRAPH SHOWS A COMPARISON OF THE EMISSIONS REDUCTION POTENTIAL IN AN OFFICE BUILDING OF SIGNALS WITH VARYING GRANULARITIES IN SPP. THE PERCENTAGES REPRESENT THE PORTION OF THE 15-MINUTE CARBON REDUCTION POTENTIAL THAT THE VARIOUS SIGNALS CONTRIBUTE (I.E., HOURLY HAS 88% OF THE TECHNICAL POTENTIAL OF A 15-MINUTE SIGNAL).

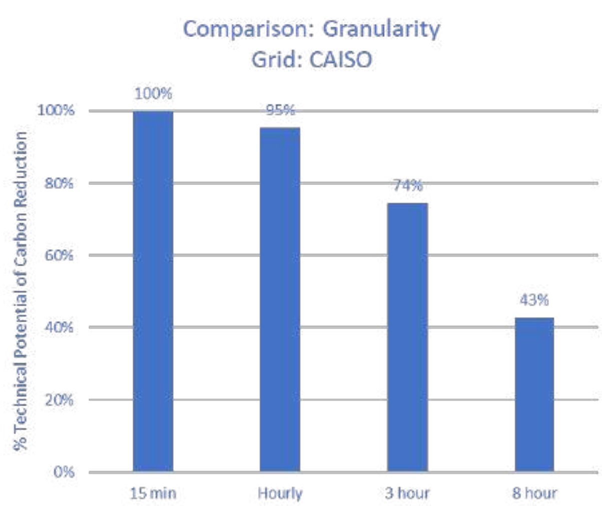


EXHIBIT 15: THIS GRAPH SHOWS THE DIMINISHING POTENTIAL IN AN OFFICE BUILDING EXAMPLE OF A SIGNAL WITH A LONGER TIMESTEP THAN 15 MINUTES. PERCENTAGES REPRESENT THE PORTION OF EMISSIONS REDUCTION POTENTIAL OF EACH SIGNAL (I.E., HOURLY REDUCES 95% OF EMISSIONS COMPARED WITH A 15-MINUTE SIGNAL).

Signal Level of Advance Notice: This characteristic refers to the use of forecast data for carbon emissions compliance calculations. A predicted signal can be provided ahead of time to give buildings more time to determine operational changes. Forecasts inherently contain error compared with what happens in real time, therefore the shorter the forecast horizon (closer to actual events), the higher the emissions reduction potential. Day-ahead advance notice is common today for demand response programs whereas an hour-ahead or real-time signal would require advanced levels of sophistication not only on the grid side to provide the signal but also in buildings to be able to respond to the signal.

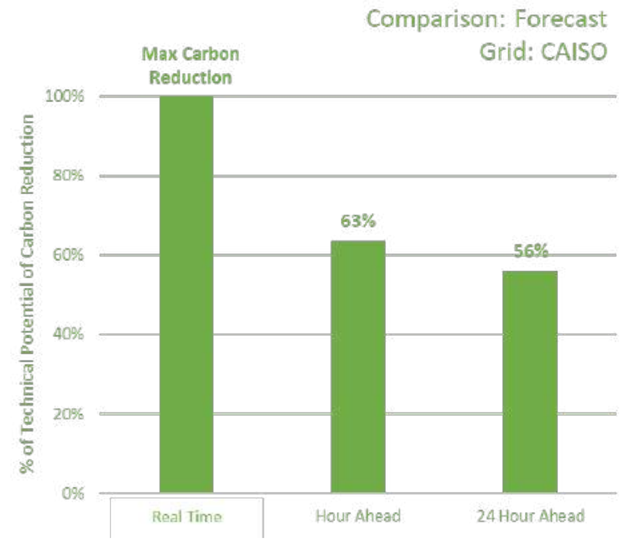


EXHIBIT 16: THIS GRAPH COMPARES THE CARBON REDUCTION POTENTIAL OF SIGNALS WITH VARYING LEVELS OF ADVANCE NOTICE. PERCENTAGES REPRESENT THE POTENTIAL COMPARED WITH A REAL-TIME SIGNAL (I.E., HOUR AHEAD PRESENTS 63% OF THE POTENTIAL OF REAL-TIME).

Behavior is important to identifying the emissions-based signal that maximizes the benefits of demand flexibility for grid decarbonization. A marginal signal optimizes demand flexibility to effectively integrate it with the grid and enable using buildings as a grid resource. An average signal would not trigger the same behavior and would therefore not have the same positive implications on grid decarbonization.

For signal-optimized demand flexibility, this analysis shows that the highest emissions reductions can come from a marginal emissions signal with the shortest possible advance notice and timestep.

This assumes buildings have the intelligence and automation to respond to such signals. While many large commercial buildings have some level of automation, there is still a notable gap in most buildings' ability to respond to a signal with short level of advanced notice and short signal timestep.

While emissions impact is maximized with short timesteps and short level of advanced notice, longer forecasts and timesteps could be easier to implement and easier for building owners to respond to (less dynamic shifting). All steps in the process from communication of the signal, to response to the signal, to tracking of emissions impact will be less complex with longer forecasts and timesteps for even the most high-performance buildings. Programs, including LL97 TOU compliance, will need to find the signal that balances tradeoffs between program complexity, potential for emissions reduction, and the ability for buildings to respond today and in the future.

5. POTENTIAL NEXT STEPS

This report quantifies the potential carbon emissions impact of demand flexibility. Recommended areas for follow-on analysis include iterating impact potential if deployed at scale and assessing the structure and mechanisms for an alternative compliance pathway to LL97.

Impact Potential if Deployed at Scale:

1. Update grid projections from proxy grids to hourly or sub-hourly Zone J projections
2. Analyze the impact of imports on marginal emissions and how NY state's potential future as a net exporter could change the carbon potential for demand flexibility in NYISO
3. Advance understanding of grid-level impacts from high adoption levels of an alternative compliance pathway focused on time-of-use emissions and how it may create a new peak(s)
4. Scale to NY building stock—from two representative buildings to many buildings across zone J

Structure and Mechanisms for an Alternative Compliance Pathway to LL97:

There are additional questions that would need to be answered to build a program that incentivizes demand flexibility. Follow-on analysis would need to determine the best structure and mechanisms by which a program, like the time-of-use alternative compliance pathway of LL97, could be successfully implemented.

6. CONCLUSION

Demand flexibility provides significant potential to decarbonize emissions from buildings as variable renewable generation increases on the grid. It can also reduce emissions over the continuum of the electric grid's decarbonization, delivering benefits across many grid conditions. Finally, it can achieve the highest emissions savings by applying a marginal emissions signal with a short timestep (15 min) provided in real time. This report demonstrates that the creation of a time-of-use compliance pathway in LL97 that is designed to encourage demand flexibility would likely provide buildings with an alternative to reducing some of their energy use emissions for compliance while maintaining overall emissions reductions from electricity generation.

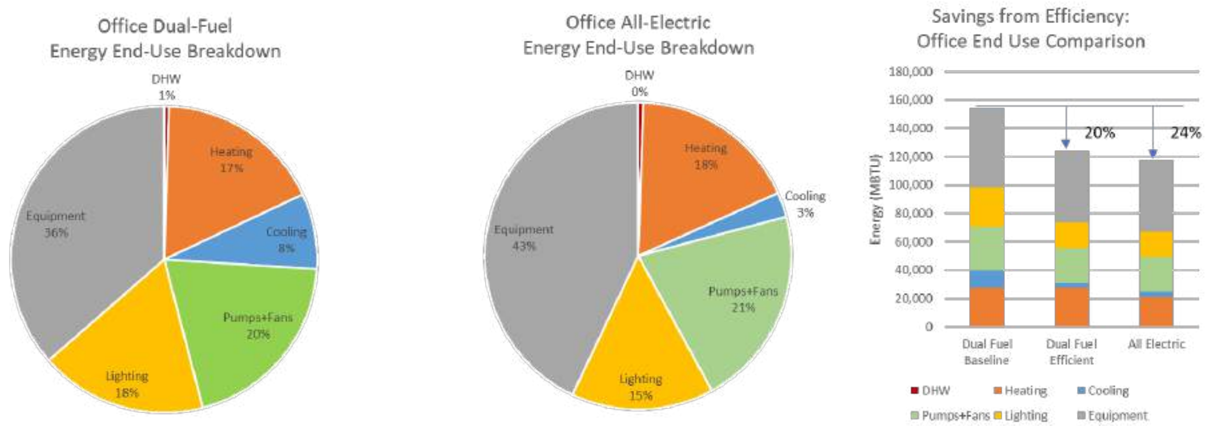
7. APPENDICES: ASSUMPTIONS AND SUPPORTING RESEARCH

A. Building Load Profiles and Assumptions
B. Energy Efficiency Measures Assumptions
C. Demand Flexibility Assumptions
D. Sensitivity Analysis

Appendix A: Building Load Profiles and Assumptions

Building load profiles and assumptions were built from NYC-specific sources.[9] We used multifamily and office buildings as they represent the two most emissions-intensive building types in NYC.[10] In terms of performance, they are relatively moderate to high performing. The prototypical buildings we modeled would most likely comply with LL97 in 2024 without significant upgrades but will need investments for compliance (even with a cleaner grid) to meet the limits in 2030.

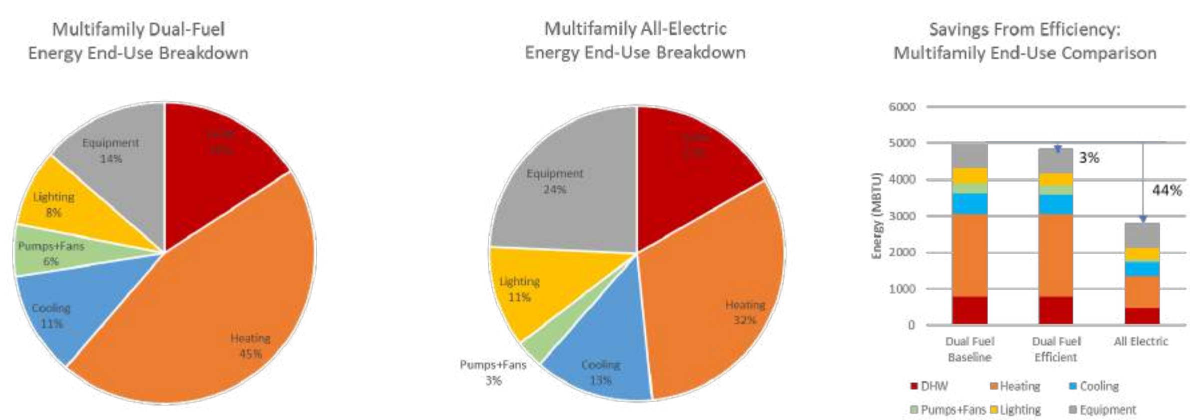
EXHIBIT A1: OFFICE BASELINES



Notes:

- This baseline is represented by the orange line called "base" in the graphics, showing maximum demand flexibility, in the key findings section. The baseline is the raw RTEM data, unchanged by efficiency or demand flexibility measures.
- The load profiles and assumptions are based on an 11.7 million sq. ft. building.
- The baseline was generated from RTEM whole-building meter data, with end-use breakdowns proportional to the DOE reference model for large commercial office buildings.

EXHIBIT A2: MULTIFAMILY BASELINES



Notes:

- This baseline is represented by the orange line called "base" in the graphics, showing maximum demand flexibility, in the key findings section.
- The load profiles are based on a 50,000 sq. ft., three-story building.
- The baseline energy model was created from a DOE reference model, located in NY.

- Natural gas end uses were not considered for efficiency measures. This means that dual-fuel, efficient case savings are low (3%) because heating and domestic hot water (DHW), representing 61% of the total load, are fueled by natural gas.

Appendix B: Energy Efficiency Assumptions

EXHIBIT B1: ENERGY MODELING ASSUMPTIONS FOR FIXED ENERGY EFFICIENCY REDUCTIONS – OFFICE

ENERGY EFFICIENCY MEASURES	OFFICE DUAL-FUEL BASELINE	OFFICE DUAL-FUEL EFFICIENT CASE	OFFICE ALL-ELECTRIC CASE	SOURCES
Heating Efficiency	Efficiency of 85%	Efficiency of 85%	Efficiency of 1	NYC Building Code Minimum
Cooling Efficiency	COP 4	COP 6	COP 6	NYC Building Code Minimum
Lighting Fixture and Control System Upgrade	RTEM baseline end use	35% reduction to lighting loads	35% reduction to lighting loads	Assumption based on Lawrence Berkeley National Laboratory's (Berkeley Lab) reported average savings of 30%–40% for various lighting control types.[11]
Equipment Efficiency and Smart Controls	RTEM baseline end use	10% reduction to EPD	10% reduction to EPD	Case Study[vi]
Schedules	Per RTEM data	RTEM + DOE reference model schedules	RTEM + DOE reference model schedules	

Notes:

- COP stands for coefficient of performance. Efficiency in heating is represented as a percentage. Lighting and equipment percentages represent the percent reduction on the loads compared with the baseline case.
- For office buildings, energy efficiency reduction equates to a 20%–24% reduction in electricity use annually, predominantly through lighting upgrades, cooling efficiency increases, and improved controls.
- Dual-fuel, efficient case savings are low (3%) since heating and DHW, representing 61% of the total load, are fueled by natural gas, which was not optimized.

EXHIBIT B2: ENERGY MODELING ASSUMPTIONS FOR FIXED ENERGY EFFICIENCY REDUCTIONS – MULTIFAMILY

COMMON ENERGY EFFICIENCY MEASURES	MULTIFAMILY DUAL-FUEL BASELINE	MULTIFAMILY DUAL-FUEL EFFICIENT CASE	MULTIFAMILY ALL-ELECTRIC CASE	SOURCES
Nominal Heating Efficiency	1.0	1.0	1.5	Dual-fuel cases assume hot water radiators; all-electric case assumes packaged terminal heat pumps + HRV
Cooling Efficiency	2.5	2.5	3.5	
Lighting Fixture and Control System Upgrade	DOE Reference Models	30% Reduction to Lighting Loads	30% Reduction to Lighting Loads	Assumption based on Berkeley Lab's reported average savings of 30%–40% for various lighting control types[12]
Equipment Efficiency and Smart Controls	DOE Reference Models	15% Reduction to EPD	15% Reduction to EPD	
Water Heating System Efficiency	60%	60%	1 (heat pump)	
Schedules	DOE Reference Model Schedules	No Change	No Change	

[vi] The individual end-use reductions are based on the efficiency measures applied to all paths in the analysis.

Notes

- RTEM was used for the whole-building profiles, end uses were broken out proportionally based on previous modeling efforts from DOE Reference models.
- Energy efficiency provides a 3% reduction in electricity use compared with a dual-fuel baseline (low since heating and hot water are fueled by natural gas and not optimized but represent a significant portion of the load). Efficiency provides a 44% reduction in electricity use in an all-electric scenario.

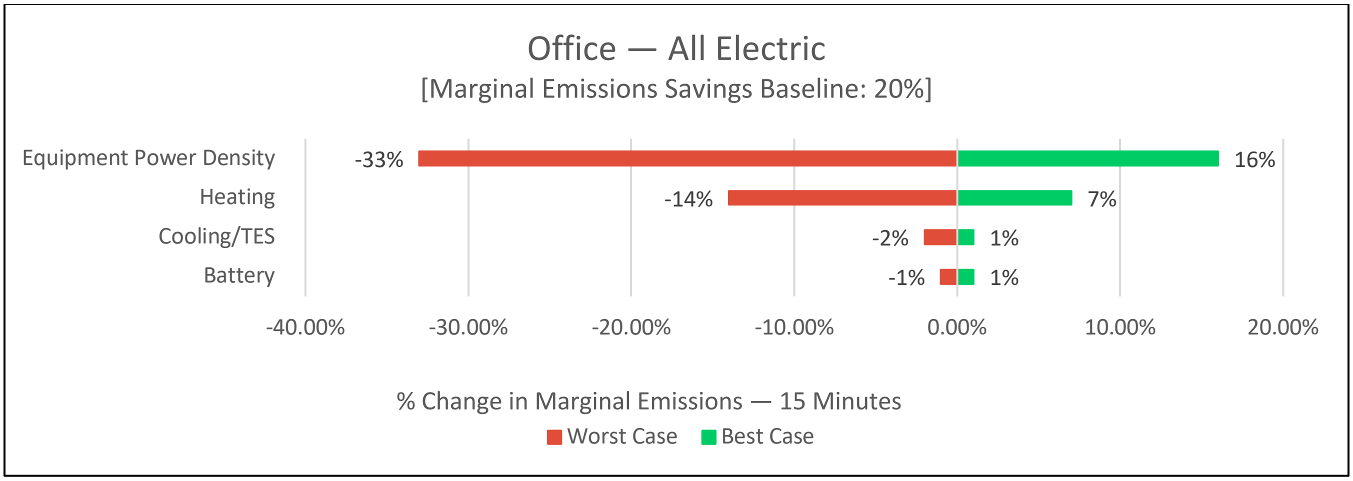
Appendix C: Demand Flexibility Assumptions

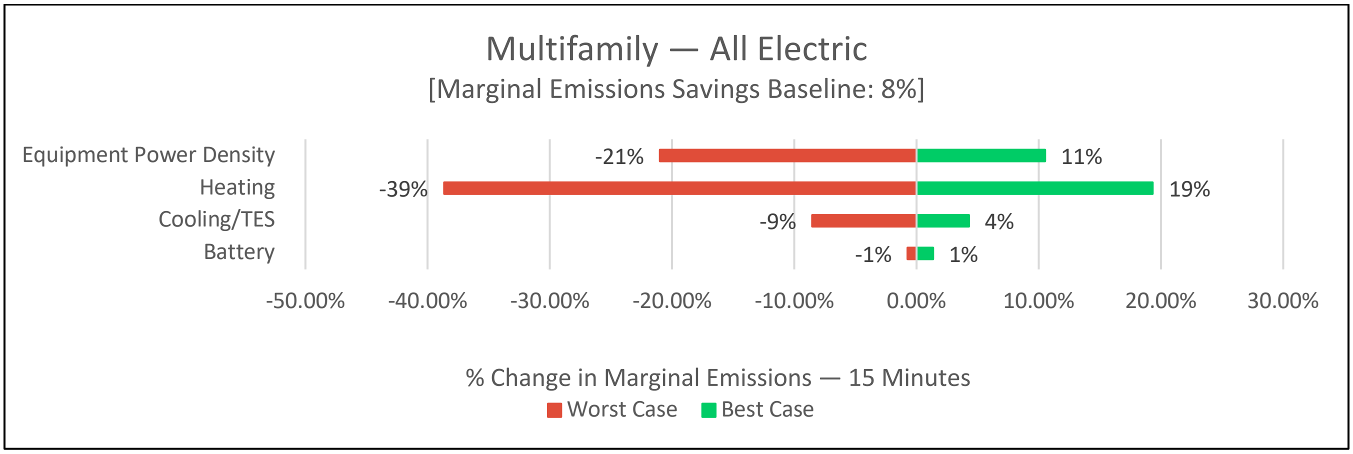
EXHIBIT C1: DEMAND FLEXIBILITY MEASURES

DEMAND FLEXIBILITY MEASURE	FLEXIBLE LOAD (% OF END USE PEAK)	DAILY WINDOW OF SHIFT OPPORTUNITY (TIME OF DAY)	CHARGE TIME (BEST HOURS)	DISCHARGE TIME (WORST HOURS)	NOTES
Office Plug-Load Staging	30% of Equipment Load	8:00–17:00	3 Hours	3 Hours	e.g., Staging laptop charging[13]
Multifamily Appliance Shifting	20% of Equipment Load	22:00–5:00	4 Hours	4 Hours	Previous RMI Analysis used 17% shiftable plug loads by up to four hours, so a future 20% is realistic.[14]
Pre-heat (all-electric cases only)	50% of Heating Load	4:00–20:00	2 Hours	2 Hours	Values from outputs of models run through RMI's portfolio energy optimization tool.
Pre-cooling	50% of Cooling Load	4:00–20:00	2 Hours	2 Hours	Pre-cooling as a strategy can limit the peak cooling load to 75% of the cooling capacity as proven by ASHRAE in 1997.[15]
Thermal Energy Storage for Cooling	20% of Cooling Load	0:00–24:00	4 Hours	4 Hours	According to a Berkeley Lab study,[16] TES systems can provide ~50% of the cooling load. Our flexibility estimates are conservative. Ice Bear's system also supports our estimates.[17]
Battery Storage	40% of Total Building Load	0:00–24:00	2 Hours	2 Hours	Battery size targeted at ~1 MW (roughly the size of a parking space) to address spatial constraints.
Domestic Hot Water Staging (multifamily all-electric only)	100% of DHW Load	0:00–24:00	6 Hours	6 Hours	RMI's previous analysis shows feasibility of 100% load flex to off-peak times with Smart DHW.[18]

Appendix D: Sensitivity Analysis

EXHIBIT D1: SENSITIVITY ANALYSIS





	WORST CASE	BEST CASE
Equipment Power Density Heating Cooling/Thermal Energy Storage (TES)	Low Efficiency High Emissions (x2 kWh) No Shift Changes	High Efficiency Low Emissions (/2 kWh) No Shift Changes
Battery	Low Efficiency High Emissions Shift: 10% Hours: 2	High Efficiency Low Emissions Shift: 80% Hours: 4

Notes:

- A sensitivity analysis was done to measure the variation in potential marginal emissions savings under a range of scenarios where electricity consumption from end uses were higher/lower or on-site storage was deployed/sized differently (i.e., if different amounts of electricity were available to be shifted by our load-shifting measures). It does not represent potential future scenarios; it was built to assess a range of electricity consumption that may be seen outside of the prototypical building load profiles we used.
- The sensitivity analysis was applied on top of energy efficiency, so it reflects demand flexibility potential only.
- The sensitivity results show the additional/subtractive potential marginal emissions savings relative to the baseline that was calculated for our prototypical buildings.
- Each potential scenario was calculated in isolation (i.e., while testing how a variation in the electricity consumed by cooling end uses would affect marginal emissions, the electricity consumed by all other end uses remained the same).
- For example: Heating in the Office—All-Electric Building
    - [Best Case] If the electricity used to heat the all-electric office building was doubled, the potential marginal emissions saving would be 27% rather than the baseline of 20% (shown as a +7%)
    - [Worst Case] If the electricity used to heat the all-electric office building was halved, the potential marginal emissions savings would be just 6% rather than the baseline of 20% (shown as a -14%).

Conclusions from sensitivity analysis:

1. Equipment power density is an important demand flexibility measure since it is a big (and growing) end use for both office and multifamily buildings. There is the potential to flex equipment power density to reduce emissions by an additional 11%–16%.
2. Efficiency targeted at reducing heating is also important, particularly in multifamily buildings. Cutting heating energy use in half would decrease emissions by 19%.
3. Cooling load shifting and efficiency is less important since those end uses for the prototypical buildings used in the analysis were small to begin with.

8. ENDNOTES

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