Multifamily Building Electric Heating Demand Profile Analysis

Final Report

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Acronyms and Abbreviations

AC	air conditioner
BR	bedroom
CCHP	cold climate heat pump
CDI	cooling demand intensity
CFM	cubic feet per minute
COP	coefficient of performance
DOE	Department of Energy
ER	electric resistance
ERBB	electric resistance baseboard
EUI	energy use intensity
F	Fahrenheit
GFA	gross floor area
HDD	heating degree days
HDI	heating demand intensity
HP	heat pump
kBTU	one thousand British thermal units
kW	kilowatts
LSE	least squares error
NHDA	non-heating demand intensity
NYC	New York City
NYSERDA	New York State Energy Research and Development Authority
OAT	outdoor air temperature
PNNL	Pacific Northwest National Laboratory
PTAC	packaged terminal air conditioner
PTHP	packaged terminal heat pump
PV	photovoltaic
SF	square feet
SWA	Steven Winter Associates
TDI	total demand intensity
VRF	variable refrigerant flow
W	Watts
W/SF	Watts per square foot

Executive Summary

Energy demand data for several electrically heated multifamily buildings was analyzed to identify what the heating and cooling loads are for older buildings compared to newer cold climate heat pump buildings. Other than the electric heating systems, these buildings share many heat-load-driving characteristics with fossil fuel-heated buildings that will need to be electrified in the future. In contrast to central fuel-fired heating plants, heating efficiency is 100% in electrically heated buildings, and heating is delivered only where it is needed. As such, the measured heating demand at the electricity meter is the same as the heat load. This building set and analysis can inform heating and cooling demand forecasting for electrifying existing buildings with heat pumps since the relationship between heat pump efficiency and electric resistance efficiency can be reasonably estimated. This analysis does not include domestic water heating energy use. The analysis took a different approach than building energy models, focusing on empirical data collected hourly or sub-hourly from actual New York City multifamily buildings. And by leveraging a unique set of real-world data in order to minimize the number of assumptions required to "build up" future state demand profiles, this empirically grounded analysis may be useful in refining other thermodynamics-based modeling studies.

The high-level findings are:

1. Peak heating load in older multifamily buildings was estimated to be 2.2 to 4.6 W/SF at 5°F outdoor temperature, with an average of 3.8 W/SF. The heating peak happened most often in the late afternoon and evening and is presumed to be affected by occupancy (e.g., people coming home from work and activating electrical appliances including turning on heating systems). For both baseloads and heating peaks, occupant behavior may drive what time of day the peaks happen more than when the coldest time of a particular day occurs. This needs to be confirmed, but the evidence suggests that there may be an opportunity for demand response to lower the total peak through short-duration responses, even if a cold snap of weather can last a full day or more. Domestic water heating electrification, which was not analyzed in this study, would be additional to these load profiles, and could affect the ultimate peak, although is likely to have a greater impact in the early morning when the water heating load is usually at its highest.

2. Using an estimated real-world installed cold climate heat pump efficiency[1] of COP = 1.6 at 5°F[2], peak heating demand for the typical electric resistance 1970s-1980s multifamily building after a heat pump retrofit[3] would be 1.4 to 2.9 W/SF at 5°F. If this heating demand range is representative of similar vintage fuel-heated multifamily buildings, which have a peak in the summer based on cooling usage estimated at 0.2 to 1.1 W/SF, the increase from summer cooling peak to winter cold climate heat pump peak is estimated at 1.2 to 1.8 W/SF. For buildings that are currently fuel-heated but would retrofit to use a cold climate heat pump, this would be new demand.
3. Newer building electricity heating demand is not as weather dependent as in existing buildings, so baseload and cooling may be most important for peak sizing. This may be important because if the peak power demand for a new building depends on the cooling peak rather than the heating peak, regardless of heating fuel, then electricity infrastructure planning may be unaffected by the electrification of new construction space heating systems.

Potential next steps to refine and add to these findings are described in *Opportunities for Future Research* and include expanding the empirical data collection to more buildings or investigating discrepancies between measured hourly profiles and typical energy model profiles

[1] See section *Estimating Demand* if Cold Climate Heat Pumps were Used in Older Buildings for details.
[2] The COP of 1.6 is at 5°F outdoor temperature and would be substantially higher in warmer weather. Seasonal COP for New York City using this heat pump performance model could range from 3.1 to 3.7.
[3] And assuming no additional energy efficiency or load reduction measures for this simple case.

Findings

Heating, Cooling, and Whole Building Peak Demand Magnitude

The measured peak demand intensities for the electric resistance buildings – those without cold climate heat pumps – are summarized in Table 1. For buildings with electric resistance heating, the measured heating electricity demand is a one-to-one reflection of the heating load in the building, since the heating efficiency at peak days is assumed to be 100%, a coefficient of performance (COP) of 1.0. Non-cold climate packaged terminal heat pumps (PTHPs) do operate in heat pump mode in very mild weather, but they cut over to electric resistance so quickly that any peak demand – which happens on the coldest days – occurs when the PTHPs are operating as electric resistance equipment. Therefore, they have been grouped with the electric resistance buildings when observing maximum electricity demand.

Table 1. Building electricity demand intensity in Watts per gross square foot of floor area (W/SF).

Power Demand for Electric Resistance Heat Buildings, n=12	**Watts per Square Foot Floor Area [W/SF]**		
	Min	Average	Max
Whole Building – Observed Max (Includes baseload)	2.8	3.8	5.3
Baseload Demand (Not heating or cooling)	0.75	1.2	1.75
Heating Load – Observed Max (Baseload removed)	1.8	2.7	4.1
Cooling – Observed Max (Baseload removed)	0.6	0.9	1.4
Estimated Heating Peak at 5F (Baseload removed)	2.3	3.2	4.6

The whole building peak demand most often occurred at 7-9 pm, with some early morning outliers, on one of the coldest days of the year. When looking only at heating demand by subtracting out baseload, the peak time was more varied, with peak heating most often between 5-9 pm, with some outliers scattered between 4 am and 1 pm.

Table 2 has the demand magnitude from each building for both total demand and heating only and includes the three cold climate heat pump buildings. The buildings that do not have cold climate heat pumps all have peaks at around the same time of day when the total building peak occurs. These are typically the warmest times of the day, so heat loss may not be the maximum at this time. There could be an interaction with resident behavior where they arrive home from being out and turn up the heat, driving up heating demand.

Table 2. Peak whole-building demand observed at fifteen electrically heated buildings.

		Total Building Demand			Space Heating Only		
Heating System Type	Building	Max Demand [W/SF]	Daily Average Outdoor Air Temperature (OAT) when max demand occurred [°F]	Hour of day when Max Demand occurred (0-23h)	Max Heating Demand [W/SF]	Daily Average Outdoor Air Temperature (OAT) when max demand occurred [°F]	Hour of day when Max Demand occurred (0-23h)
Cold Climate HP	Site 01	**1.41**	38	4	**0.45**	18	4
	Site 02*	**0.74**	58	15	**0.49**	28	13
	Site 03*	**1.21**	80	21	**0.51**	24	10
ER Baseboard	Site 04	**3.66**	14	20	**2.48**	22	18
	Site 05	**4.15**	14	20	**2.84**	22	17
	Site 06	**2.93**	14	20	**1.9**	22	18
	Site 07	**3.95**	24	19	**2.89**	24	18
	Site 08	**2.94**	22	19	**1.9**	24	17
	Site 09	**4.63**	24	4	**3.23**	24	13
	Site 10	**2.8**	22	20	**1.78**	22	20
	Site 11	**2.94**	22	20	**1.87**	22	20
PTHP / ER	Site 12	**4.39**	14	21	**3.44**	14	21
	Site 13	**4.53**	14	20	**3.6**	14	20
	Site 14	**5.27**	14	21	**4.14**	14	21
	Site 15	**3.72**	12	20	**2.89**	12	18

**Sites 02 and 03 have direct metered occupant loads except for the heating and cooling systems. All other building loads include occupant loads.*

Figure 1 shows the annual total, heating, and cooling demand peaks for each building. The Peak Demand including Baseload includes occupant use and common area loads. The Peak Heating Demand and Peak Cooling Demand removes the measured occupant and common area non-heating loads using the process in the Methodology, leaving only the winter heating peak.

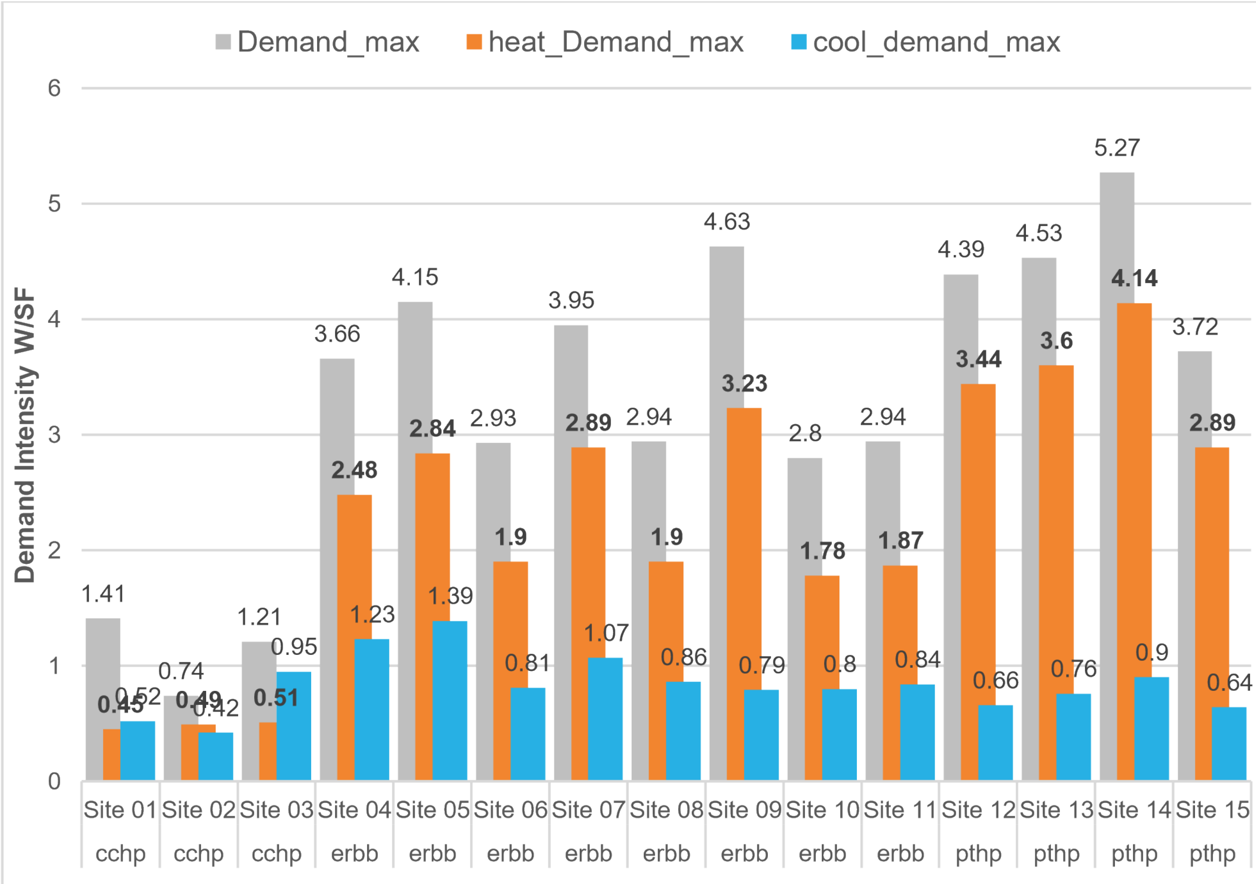

Figure 1. Measured peak demand values for the analyzed buildings. "cchp": cold climate heat pump, "erbb": electric resistance baseboard, "pthp": packaged terminal heat pump (not cold climate, likely 100% electric resistance at design conditions).

Heating Peak - Duration

The peak demand duration was defined in this study as the period of time when the demand is at 75% or higher of the maximum demand. Length of the peak period was observed to be up to multiple days in the electric resistance buildings. This multiple-day duration is displayed in Figure 2. The top row ("cchp") is the newer heat pump buildings, all of which have solar and much lower heating loads in general, which could contribute to the visibly more scattered peaks. The markers are more pronounced where the heating peak is at or above 75% of the maximum peak.

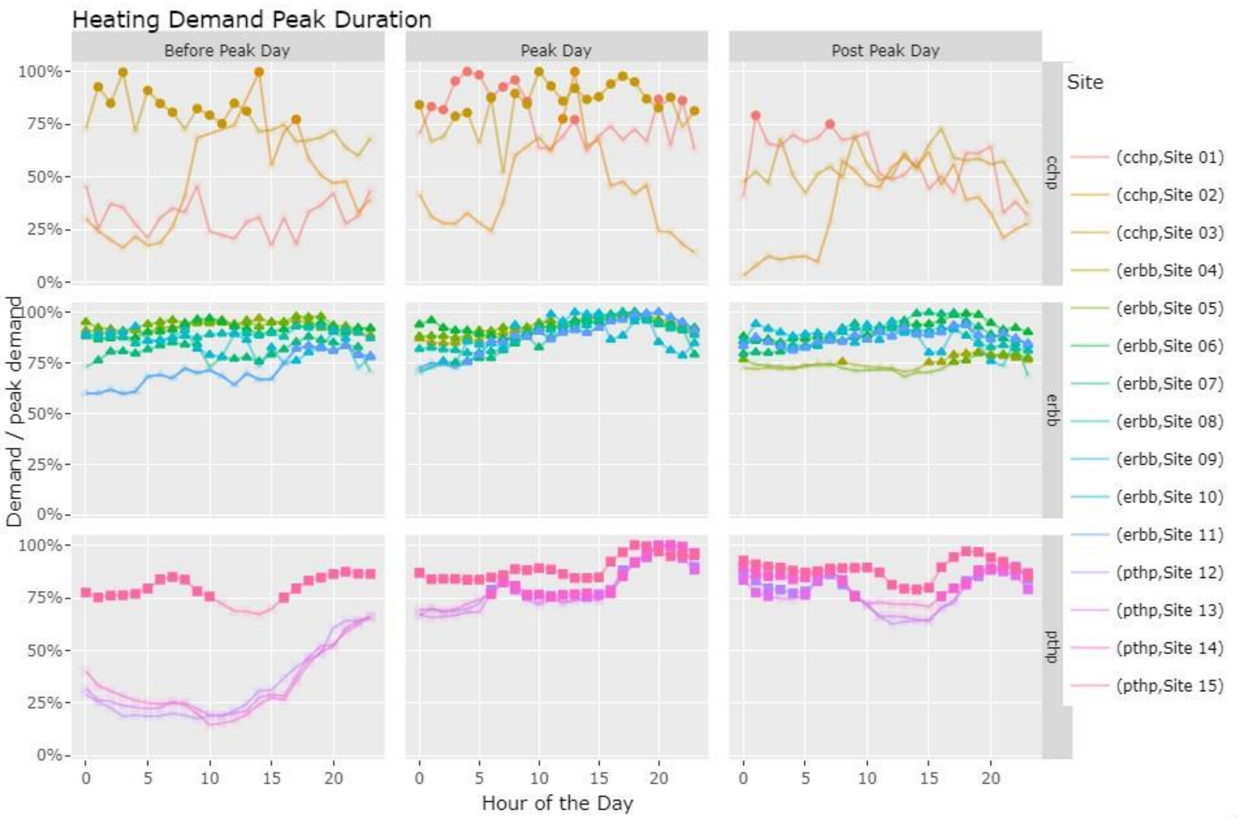

Figure 2. Heating peak lengths using normalized demand profiles for each building.

Heating Peak – Typical Time of Day

Filtering for days colder than 32°F outdoor air temperature, Figure 3 shows a graphical summary of when the peaks happen in each building during cold weather, with some frequency in the morning (~7am) for some buildings and more frequency in the evening (~6-10pm) for most buildings. The chart shows that for some buildings, the peak nearly always happens in the evening (e.g., the submetered buildings) while others frequently have peaks in the morning (e.g., "Site 04" and "Site 13").

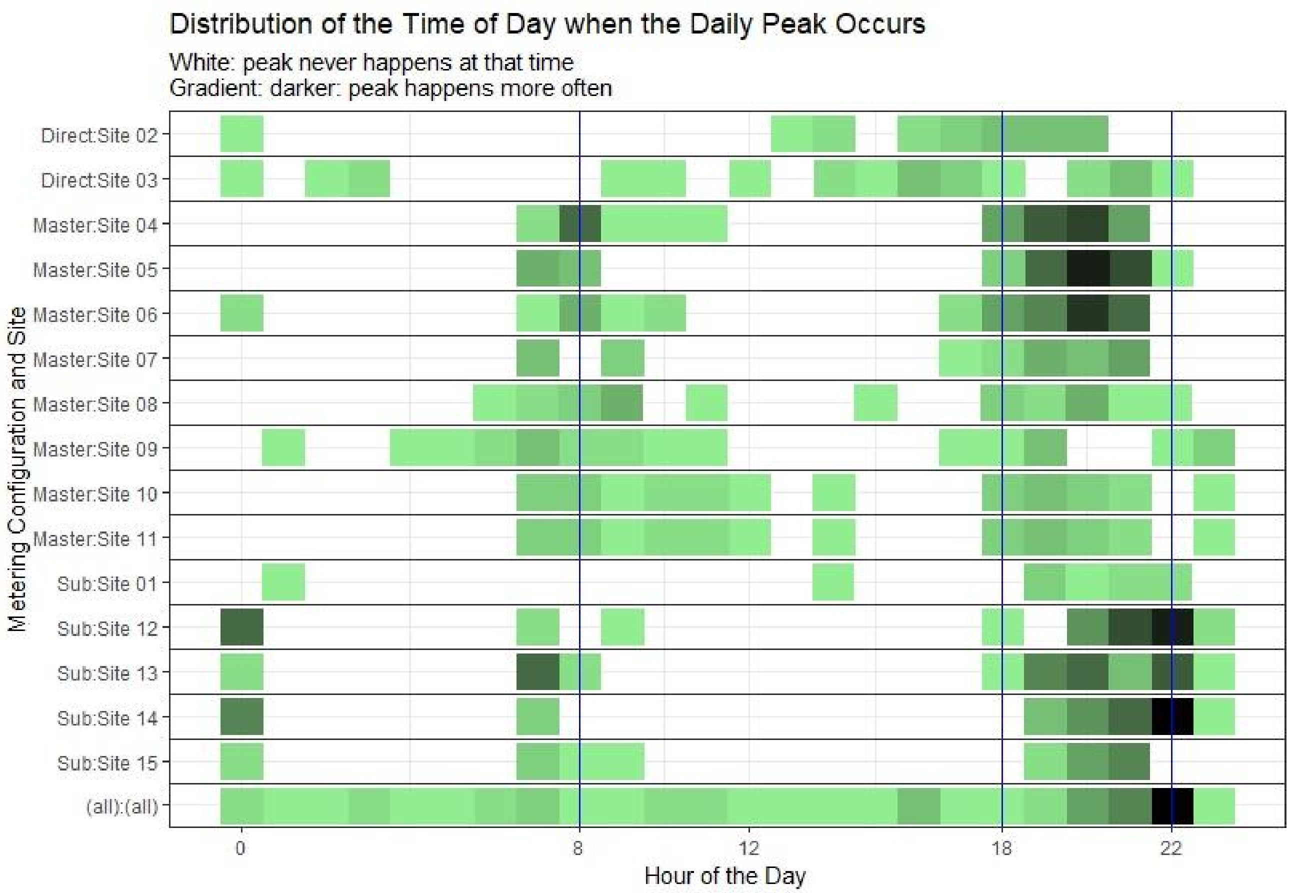

Figure 3. A summary of when the daily peaks happen at each building when the outdoor temperature is less than 32°F. Dark tiles indicate that the peak happens at that hour more often than in light tiles. This does not show magnitude of demand peaks. The vertical lines represent the times when a voluntary time of use electric rate switches. The most expensive time under the Con Edison time of use rates is 18:00-22:00 in the evening, with 8:00-18:00 being less expensive and 22:00-8:00 being the least expensive.

Measured heating peak demand intensity is much less than modeled heating peak demand intensity

SWA modeled heating load for a variety of NYC multifamily buildings using the Manual J method – one modeling method among multiple options when sizing heating equipment in a building. The results from the Manual J analysis are compared to the empirical demand data collected for this study. Figure 4 shows the heating load for the buildings in the Manual J analysis, which are a wider range of ages than what this study included (the Manual J analysis was not confined to electrically heated buildings). Two buildings are in both data sets: Site 04 and Site 02, built in 1973 and 2018 as a Passive House building, respectively. The 1973 building (Site 04) has a Manual J modeled peak heating load of 6 W/SF at 5°F outdoor temperature, more than twice the magnitude of that building's measured heating peaks and 30% higher than the highest recorded peak from all buildings extrapolated to a 5°F estimate. Similarly, the 2018 PH building (Site 02) has a Manual J modeled peak heating load of 2.3 W/SF at 5°F outdoor temperature, which is nearly four times the magnitude of that building's measured heating peak of 0.49 W/SF (See Figure 1), even though the Manual J calculations are modeling a slightly colder 4°F outdoor temperature. This difference could be based on multiple factors, including but not limited to 1) conservative modeling assumptions, 2) diversity of heating loads because of orientation and physical characteristics, and 3) diversity of heating loads because of occupancy and occupant behavioral differences. The range of heating demand from the Manual J analysis based on building age could be extrapolated to older or newer buildings.

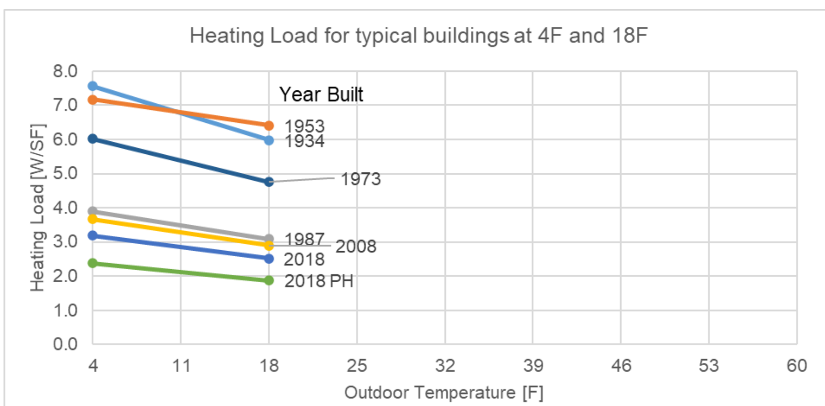

Figure 4. Design load calculations for various building vintages to show how the above demand results could be extrapolated to older or newer buildings. The "2018 PH" building is a Manual J load model for a Passive House certified envelope.

There may be diversity in heating energy demand that is not captured adequately in energy modeling of single apartments but is captured by empirical data analysis of the whole building. Forecasting building and community scale heating demand should consider such diversity and any other discrepancies that can be found between modeled and measured buildings. See *Example of Room-by-Room Heating Demand* for a comparison between apartment level and whole building demand.

Predicting heating peak demand intensity (representative peak demand)

Peak heating demand appears to be driven by multiple factors:

1) Peak demand appears to scale linearly with floor area. Hence, most demand values in this report are shown as Watts per square foot of floor area (W/SF). The average apartment size has a negative correlation with demand intensity: heating demand per square foot is slightly lower in larger apartments. This could be due to larger apartments having a lower surface-to-volume ratio and losing less heat as a result. It could also be that larger apartments have more internal gains relative to heat loss. A third possibility is that heating equipment is less oversized in larger apartments, resulting in lower peak demands when equipment is turned on. See Table 5 for the correlation between apartment size and heating load intensity.
2) The electric resistance buildings were all built in the 1970s and 1980s (summarized in Table 3). Compared to newer construction from the 2010s, buildings from the 1970s and 1980s are predicted to lose more heat through the windows, walls, and roof. Figure 4 shows a downward trend in modeled heat load with more recent construction.
3) Within a building age group, ventilation characteristics affect peak demand. While period-applicable building codes dictate the amount of air required to be provided, buildings vary greatly in how much air is actually supplied and exhausted in the winter. The variation is caused by operational choices and mechanical equipment condition. Adding a larger amount of outdoor air – and heating it with electricity – creates a higher heating load. Modern ventilation systems – which can be retrofit into these buildings – do not carry as much of an energy penalty and can recover heat from exhausted air. There are many buildings that have imbalanced, poorly sealed ventilation systems. By exchanging less air throughout the building, the heating demand is lower than if the fresh air circulation was increased (unless heat recovery is used). See Table 5 for an estimate of the relative importance of electrically heated supply air on demand in a few of these measured buildings.
4) A fourth important factor is the number and size of penetrations in the building envelope, which drives conductive and convective heat loss as well as infiltration rates. The older buildings in this study were all built in the 1970s and 1980s and have similar insulation and window characteristics. One way they differ is in the number and size of penetrations in the exterior wall. The number of penetrations in the exterior wall has a positive correlation with peak heating demand intensity, as summarized in Table 5.

The above factors were tested with a multiple linear regression model and did not result in a statistically significant outcome, meaning that the above factors could not be used to create a refined prediction of peak heating demand intensity using this sample set. A more refined model may be possible with a larger sample set of audited buildings if more buildings can be identified through future research (see *Opportunities for Future Research*).

Given those factors, Figure 9 and Figure 10 show the demand profile for electrically heated buildings at different outdoor temperatures with measured and fitted data, respectively.

Electric Heating Demand Has a Strong Relationship with Outdoor Temperature

Heating demand has a linear relationship with outdoor temperature for electrically heated buildings. Linear models of peak demand versus outdoor air temperature were created for all buildings.

Electric resistance heating is the most linear: efficiency of the heating system does not change with outdoor temperature, so demand is driven only by heating load, which would vary linearly with temperature in a building with a properly functioning heating system.

Non-cold-climate PTHPs are less linear, but still linear enough to predict peak demands: at very mild temperatures, there is some amount of time when the PTHPs are in heat pump mode, but the PTHPs cut over to electric resistance so quickly that any peak demand – which happens on the coldest days – occurs when the PTHPs are operating as electric resistance equipment.

Cold climate heat pumps are the least linear with temperature of the group: heat pump capacity and efficiency changes with outdoor temperature, as does building heating load. The resulting relationship of heating demand is non-linear with outdoor temperature, making peak demand more difficult to predict without a more complicated model.

Newer buildings have much lower heating demand than older buildings

The newer buildings analyzed have peak heating demand at just 10-20% of the electrically heated older buildings, as shown in Figure 9. The newer buildings have cold climate heat pumps while the older buildings use electric resistance for heating. The COP of the heating systems in the CCHP buildings is likely much greater than 1.0 even at 5°F outdoor temperature, which means the measured demand is much lower than the electric resistance heated buildings.

In addition, the heat pump buildings included in this analysis have low heating loads (due to more insulation, controlled infiltration, and better ventilation including energy recovery) and therefore the heating demand is low across all temperatures, making fluctuations based on non-weather variables a larger influence (such as occupant loads or other one-time events like drops in solar PV output that result in a surge of electricity demand). This lower dependence on temperature means that predicting demand is harder if using outdoor temperature information alone.

Comparing peak heating to peak cooling demands

In the older electric resistance buildings, heating demand averaged 2.6 W/SF higher (range: 1.6-4.4W/SF) than peak cooling demand as shown in Figure 1. The duration of a peak event was different for heating versus cooling peaks, which can be seen by comparing Figure 2 and Figure 8. Heating peaks lasted most of a day and across days, while cooling peaks tended to be less than 8 hours long. With an assumed cold climate heat pump retrofit, the heating demand may be higher than the cooling peak demand, at a calculated average of 0.9 W/SF higher (range: 0.4-1.8 W/SF). However, no forecasting was done to model the expected additional cooling in existing buildings as a result of more cooling equipment and rising temperatures, which would increase cooling peaks regardless of heat pump retrofit impacts on heating peaks.

In the newer buildings, the heating peaks were the same or smaller than the cooling peaks. The newer buildings analyzed in this study appear to have different thermal characteristics than the older buildings due to different insulation levels, infiltration rates, ventilation strategies, and heating/cooling system efficiencies, all of which drive down heating loads. However, cooling loads between older and newer buildings do not appear to be as different as heating loads.

The effect of occupancy changes on heating demand is unknown

Only one building had data available from before and during the COVID-19 pandemic, which caused fairly widespread occupancy changes in multifamily buildings. The data for this building only spanned a few months into the pandemic, but appears to show a drop in overall demand, likely due to the residents leaving. There was insufficient data collected in this study to further quantify the effect of the pandemic or other occupancy changes.

Opportunities for Future Research

1. Identify more buildings across the state, potentially with on-site metering
2. More granular analysis of building characteristics using different analysis techniques to refine a peak demand predictive model
3. Investigate why the heating peak demand does not increase as much at night as typical energy models. A first step could be to directly compare PNNL energy model prototypes[4] hourly profiles to these hourly profiles.

[4] DOE / PNNL's prototype energy models were used in Urban Green Council's "Grid Ready", discussed on page 41: https://www.urbangreencouncil.org/sites/default/files/2021.12.07_grid_ready.pdf

Buildings Used in Analysis

Data from 15 buildings has been collected and analyzed. All buildings are located in New York City. Table 3 provides a basic description of the buildings, and Figure 5 shows the data collection period for each building.

Table 3. Summary characteristics of buildings used in this analysis.

Site #	Year Built	Heating/Cooling System; Metering Configuration; onsite generation	Gross Floor Area (GFA) [square feet]	Number of Apartments	Height [number of stories]
Site 01	2017	Air source VRF (CCHP); Submetered	266,964	356	26
Site 02	2019	Ground Source HP (CCHP); Direct metered except heating/cooling; solar PV	121,433	127	9
Site 03	2014	1 air source HP per Apt (CCHP); Direct metered except heating/cooling; solar PV	89,760	101	11
Site 04	1975	Electric resistance baseboard (ERBB) / sleeve AC; Master metered	665,747	555	38
Site 05	1975		795,110	710	42
Site 06	1975		693,459	578	40
Site 07	1969		804,200	1,017	16
Site 08	1974		680,000	600	34
Site 09	1974		43,941	64	9
Site 10	1972		360,418	306	13
Site 11	1974		343,006	341	32
Site 12	1975	PTHP/electric resistance (PTHP); Submetered	447,431	360	40
Site 13	1975		447,431	360	40
Site 14	1973		341,981	370	37
Site 15	1983		1,881,612	1712	34

**Site 01 is on a meter that is part of a larger campus electricity setup, so it does not have an electricity meter of its own to share access to. This building also has a submeter for just the heating and cooling system, but that data was not accessible, so the data is for whole-building usage like the rest of the buildings in this study.*

The raw demand data is for the entire building, including common areas and resident appliance and plug load electricity use. The exceptions to this are Site 14 and Site 15, which have direct-metered resident appliance and plug loads not included in this data set. The heating and cooling loads are on the owner's account, which was shared and analyzed for this study.

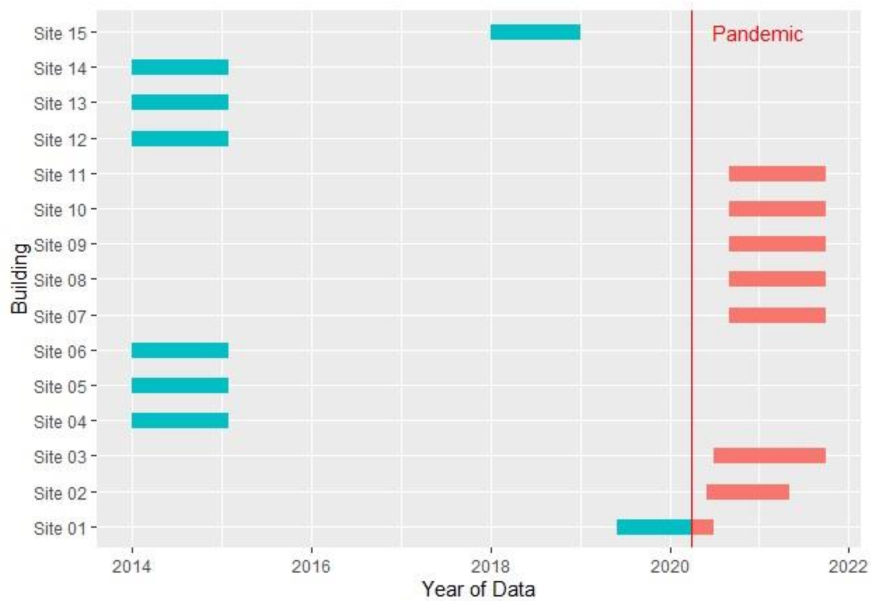

Figure 5. Data collection period for each site in the analysis. The beginning of the pandemic is shown for reference, as it may impact demand use in these buildings.

Methodology

The analysis began with formatting all interval demand data for each building in Watts per square foot of floor area served by that meter. Each building had the following information compiled, mostly from past energy audits, consulting, and prior relationships with the building owners:

Attributes tagged to each building
Sampling rate of interval data (15 minutes or hourly)
Floor area served by the electricity meter
Number of apartments
Number of bedrooms
Building height in number of floors
Electricity metering configuration
Year built
Size of through wall air conditioner sleeves, including PTHPs/PTACs
Count of air conditioner sleeves
Measured exhaust air flow from bathrooms, kitchens, and hallways, where applicable
Measured supply air flow to corridors, where applicable

Attributes tagged to each time sample
Year
Month
Day
Hour
Day of the week (Monday – Sunday)
Weekend or weekday
Time of day (Day: 8am-6pm, Evening: 6pm-10pm, Night: 10pm-8am)[5]
Pre-pandemic (before April 2020) or during pandemic

A summary of the data organization to perform the analysis:

1. Building electricity demand data was merged with outdoor air temperature (OAT) data and binned to 2°F increments

[5] These align with Con Edison voluntary time of use schedules, though the Evening (6pm-10pm) rate is not typically different than the Day (8am-6pm) rate for the current residential rates.

2. Normalized electricity demand per 15 minutes to W/SF, equivalent to kW/1000SF
3. Inspect demand distribution for each OAT bin and identify the maximum demand
4. Calculate average electricity demand for each OAT bin
5. Identify maximum demand during the monitored period for heating (coldest times) and cooling (hottest times), and the maximum when neither heating nor cooling are needed (mild weather).

   Calculate non-heating demand by:

   - Find days in November through April with an outdoor temperature of 55-65°F
   - Average the hourly profile for those days, by building, weekday/weekend, and pandemic state

   The average profile per building is the non-heating-cooling demand (“baseload”)

   - Calculate heating demand by subtracting baseload from total demand when OAT is less than 65°F[6]
   - Calculate cooling demand by subtracting baseload from total demand when OAT is higher than 65°F

   Add a flag for samples where the total demand is zero, missing, or less than the baseload. These are likely data errors coming from missing periods in the interval data. These data points were removed for all analyses except where total consumption was being calculated in section.

Parameter	Calculation method	Units
Total Demand Intensity (TDI)	Metered demand / gross floor area	W/SF or kW/1000SF
Non-heating demand Intensity (NHDI) “baseload”	Hourly demand curve taken from non-heating periods of the year, indicating non-heating use only	
Heating demand intensity (HDI)	TDI-NHDI when OAT <65	
Cooling demand intensity (CDI)	TDI-NHDI when OAT >65	

6. Compare heating demand intensity across buildings to identify trends and correlation with other building characteristics.
7. Using heat pump performance from industry research[7], include an estimate of the peak demand if the electric resistance buildings used market tested heat pumps instead (a simulated retrofit).
8. Where data is available for buildings before and during the Covid pandemic shutdown, analyze the year-on-year difference in demand intensities. If the building can share some details on estimated occupancy, this will be incorporated and discussed. Many of the older buildings may give residents

[6] Although the outdoor air temperature threshold for heating versus cooling was 65°F for this study, some buildings likely do not need heating until the outdoor temperature is colder, such as 50-55°F. The method used in this study may overestimate heating usage in mild weather, but this should not impact the demand peaks at very cold temperatures.
[7] See Section *Estimating Demand if Cold Climate Heat Pumps were Used in Older Buildings* for details.

limited control over the heating system. As a result, heating demand intensity may not drop as much as resident driven loads.

Data Supporting the Primary Findings: Answering the Research Questions

Baseload Electricity Demand Profiles

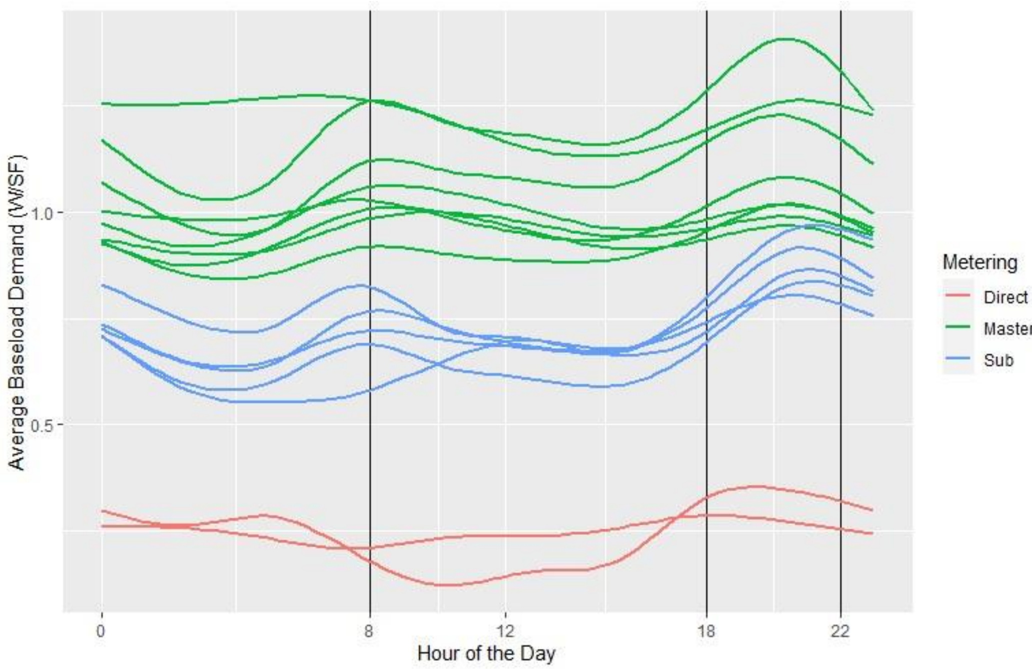

Figure 6. Calculated non-heating demand profiles for each building, color coded by electric metering configuration. The vertical lines represent the times when a voluntary time of use electric rate switches. The most expensive time under the Con Edison time of use rates is 18:00-22:00 in the evening, with 8:00-18:00 being less expensive and 22:00-8:00 being the least expensive.

Metering configuration appears to have an impact on baseload electricity consumption, as shown in Figure 6. The direct-metered buildings are newer and may have more efficient lighting and appliances than the older buildings do, but there is still a clear distinction where sub-metered buildings tend to have lower baseload demand than master metered buildings do.

Peak Demand Relative to Annual Heating Energy Consumption

For each of the older buildings, the total heating energy consumption was summed, then weather normalized using total measurement period and heating degree days (base 65°F) during that period. All buildings were weather normalized to 4,500 HDD65, which is the approximate recent ten-year average for New York City. The buildings were grouped into the PTHP submetered buildings and the ERBB master metered buildings, shown in Figure 7, which demonstrates that the PTHP submetered buildings have lower heating energy consumption given the same peak heating demands. This could be from conservation by occupants and/or different heating load dynamics of the PTHP systems' forced air delivery compared to the ERBB's natural convection.

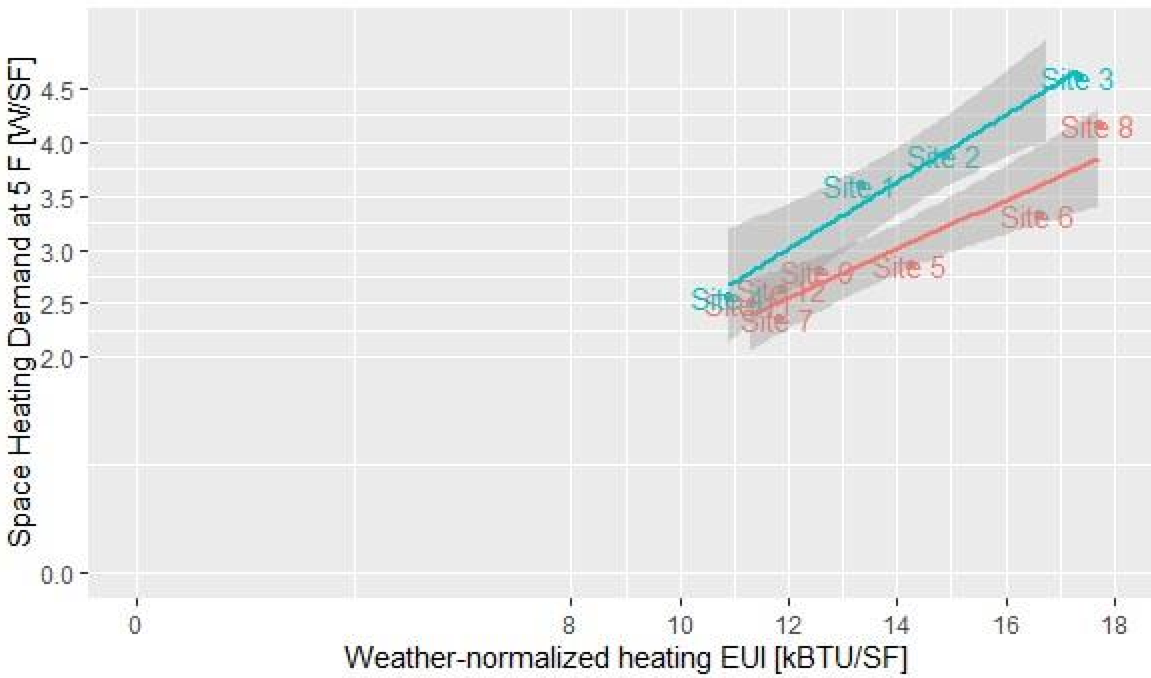

Figure 7. Comparison of heating energy consumption and heating energy demand. PTHP/submetered buildings in blue, ERBB/master metered buildings in red. Grey ranges indicate the 95% confidence interval of the linear trend line for each group.

Peak Duration

Cooling peak lengths appear to be shorter than heating peaks, ramping up and down more quickly.

Figure 8. Cooling peak lengths using normalized demand profiles for each building.

Relationship with Outdoor Temperature

The measured heating demand intensity shown in Figure 9 indicates a clear trend with outdoor temperature. There is a bit of spread across the buildings and a fair amount of noise given to be expected from measured data, but the peak demand at each temperature appears to have a fairly linear relationship with outdoor temperature.

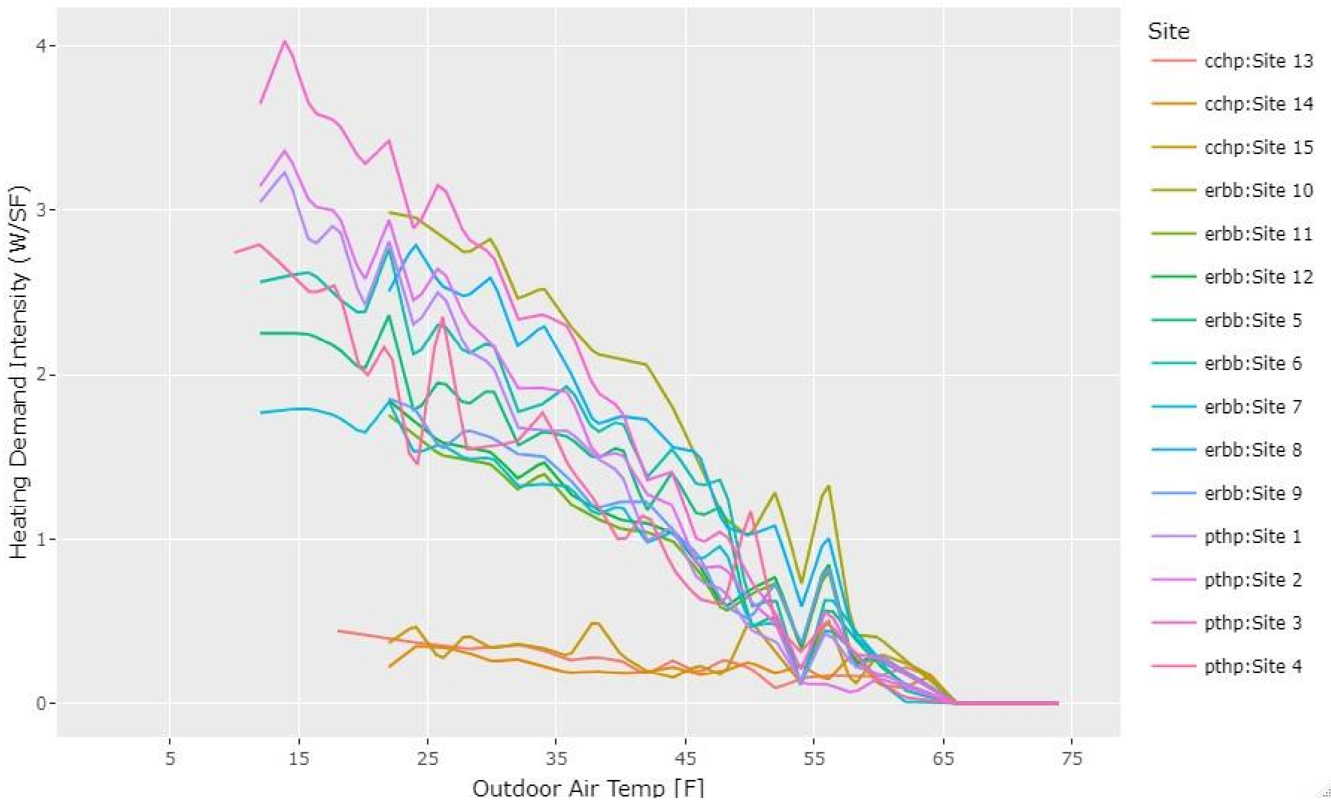

Figure 9. Peak heating demand intensity at each outdoor air temperature for all buildings. For each building, the line represents the 95th percentile heating demand intensity, not the average.

Modeling to Estimate Heating Demand Given Outdoor Temperature

A simple linear regression was performed to allow extrapolation of demand to any temperature for each building.

The measured heating demand used for the linear regression model is the peak demand from each day. The relationship between heating demand and outdoor temperature was examined using the Lambda values from a Box-Cox transform[8,9]. A simple linear regression uses a Least Squares Error (LSE) optimization[10] to identify the parameters of a linear model to estimate heating demand at a given outdoor temperature:

$$E(HDI|OAT) = b_0 + heat\_slope * OAT$$

Where:

E (HDI | OAT) = an estimate of the heating demand intensity at a given outdoor air temperature

HDI = heating demand intensity in W/SF

OAT = outdoor air temperature in degrees Fahrenheit b_0 = intercept (aka demand estimate when OAT = 0°F)

heat_slope = change in demand value for each °F change in OAT

The older buildings had lambda values between 0.6 and 1.1, meaning the data is already fairly normally distributed and a linear regression can provide a decent model. The PTHP buildings had lambda values between 0.6 and 0.7, which means there is some non-linearity and non-normality to the demand vs temperature relationship, likely due to the operation of the PTHPs in heat pump mode during mild temperatures. As mentioned previously, the PTHPs in these buildings are operating as electric resistance heaters, not heat pumps, at temperatures below ~40°F. The subset of buildings with baseboard heating had lambda values between 0.8 and 1.1 indicating that a linear model is a very good approximation for demand and outdoor temperature, even more so than the PTHP subset.

The newer buildings had lambda values that indicate a non-linear relationship with outdoor temperature. Buildings with air source heat pumps, even cold climate ones, lose efficiency and capacity

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8 The Box-Cox transform is a way to convert non-normal data to have a normal distribution. Linear regressions should only be performed on normally distributed data. In a Box-Cox transformation, the Lambda value gives an indication of how much transformation is needed to make the data normal. Lambda values between 0.5 and 1.5 are generally considered close to normal without transformation with 1.0 being the most normally distributed. This page gives a good overview.

9 No transform was applied to this data – the Box-Cox transform was used as a test for normality and linearity only.

10 *Seltman, Howard J. (2008-09-08). Experimental Design and Analysis (PDF). p.222.*

at lower temperatures, at the same time the heating loads are increasing, so the relationship of demand to outdoor temperature may be higher order than linear. The Site 02 building has ground source heat pumps which do not lose as much capacity at colder outdoor air temperatures, and the lambda value for Site 02 is higher than the air-source heat pump buildings. However, all the newer buildings' linear models have poor R^2 values which means a model could not be fit well using outdoor air temperature and measured demand data alone. Given the non-linearity of the relationship found in the lambda test, the poor R^2 value is not surprising.

Table 4 shows the lambda values and the linear regression model parameters for each building. Greyed out values are not used due to poor fit of the model to the measured data. Figure 10 shows the linear regression prediction for each of the older buildings at various outdoor temperatures.

Table 4. Linear regression results for heating demand with outdoor air as the only independent variable. Lambda values close to one indicate more linearity, less than 0.5 indicating a higher order relationship (e.g., demand may be proportional to the square of temperature).

Building	Heating Type	Lambda (Box-Cox transform)	Y-intercept (W/SF at 0°F)	Slope (W/SF/°F)	R^2 of linear regression
Site 01	CCHP	0.5	0.32	0.00	0.26
Site 02	CCHP	0.6	0.28	0.00	0.41
Site 03	CCHP	0.3	0.40	-0.01	0.28
Site 04	ERBB	0.7	3.08	-0.05	0.86
Site 05	ERBB	0.7	3.55	-0.06	0.87
Site 06	ERBB	0.8	2.52	-0.04	0.89
Site 07	ERBB	0.7	4.36	-0.07	0.86
Site 08	ERBB	0.7	2.91	-0.05	0.88
Site 09	ERBB	0.8	4.96	-0.08	0.86
Site 10	ERBB	0.8	2.62	-0.04	0.86
Site 11	ERBB	0.8	2.75	-0.04	0.86
Site 12	PTHP	0.4	3.68	-0.06	0.85
Site 13	PTHP	0.5	4.01	-0.07	0.89
Site 14	PTHP	0.5	4.71	-0.08	0.86
Site 15	PTHP	0.6	2.69	-0.04	0.62

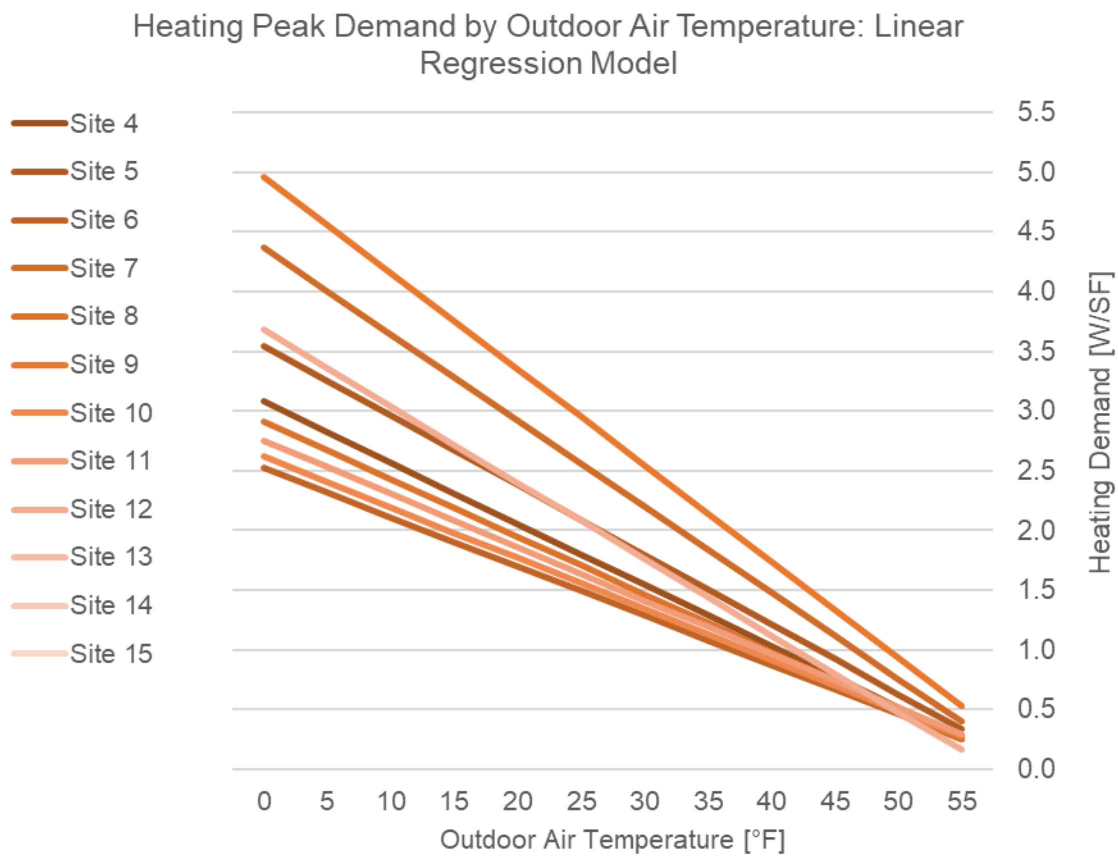


Figure 10. The linear regression models of heating peak demand for each building.

The range of heating demand is large between the low and high values for the older buildings. These buildings, while built in a relatively narrow 13-year range, have various characteristics that may also impact heating demand.

The next section describes how the possible impact of these differences was assessed.

Relationship Between Peak Demand and Building Characteristics

While there is a strong relationship between outdoor temperature and peak demand, building characteristics also play a role. Characteristics that may influence demand peak were compiled for each building to see if there is a correlation between peak demand and these theoretical contributors.

- Floor area: building size could influence peak demand intensity
- Apartment size: densely packed apartments that are smaller on average may have a higher demand intensity than larger apartments
- Bedroom density: more densely packed bedrooms could result in higher demand
- Building footprint: a tall, narrow building may have different demand intensity than a shorter broader building
- Year built: something about construction may have changed in the range of these example buildings
- AC sleeves (wall penetrations): each sleeve could introduce a path for infiltration, driving up heating demand
- Exhaust average flow: unbalanced exhaust pulls in outside air that may drive up heating demand
- Supply average flow: heating outside air with electricity drives up demand if there is no heat recovery

These characteristics were compared to peak heating demand and a correlation coefficient was calculated for each to see how closely demand varied with variations across buildings. The characteristics and results are shown in Table 5. Of the above characteristics, Apartment size, AC sleeves, and Supply average flow have the strongest correlations. Given the relatively strong correlations between the three characteristics and peak heating demand, a multiple regression test was performed to see if a refined model of heating demand could be created that incorporates those characteristics.

Table 5. Possible demand-driving characteristics and correlation coefficients. The parameters with the three highest correlation coefficients are in bold.

Building	Peak Heating Demand @5ºF	GFA [SF]	**Apt Size [SF/apt]**	BR Size [SF/BR]	Footprint [SF/floor]	Year built	**AC Sleeves [count/SF]**	Exhaust [CFM/SF]	**Supply [CFM/SF]**
Site 04	2.82	665747	1,200	810	17,520	1975	0.0021	0.0618	0
Site 05	3.25	795,110	1,120	787	18,931	1975	0.0022	0.0618	0
Site 06	2.32	693,459	1,200	814	17,336	1975	0.0021	0.0618	0
Site 07	4	804,200	791	433	50,263	1969	0.0036	0.0750	0
Site 08	2.67	680,000	1,133	518	20,000	1974	0.0018	0.0400	0
Site 09	4.56	43,941	687	687	4,882	1974	0.0029	0.0900	0
Site 10	2.41	360,418	1,178	536	27,724	1972	0.0007	0.0400	0
Site 11	2.53	343,006	1,006	395	10,719	1974	0.0020	0.0700	0
Site 12	3.36	447,431	1,243	836	11,186	1975	0.0020	0.1300	0.0366
Site 13	3.66	447,431	1,243	836	11,186	1975	0.0020	0.1300	0.0366
Site 14	4.31	341,981	924	576	9,243	1973	0.0028	0.0800	0.0366
Site 15	2.46	1,881,612	1,099	896	55,342	1983	0.0019	0.1800	0.0211
Correlation Coefficient	1.00	-0.43	**-0.67**	-0.09	-0.26	-0.39	**0.674**	0.13	**0.34**

Using the three characteristics with the strongest correlation, a multiple linear regression model was investigated to refine the peak demand prediction. However, the relationship between the characteristics and the peak demand was not a good fit for linear regression as the partial linear regressions do not appear to have normal distributions, as shown by the seemingly random scatter plots on the bottom row of Figure 11.

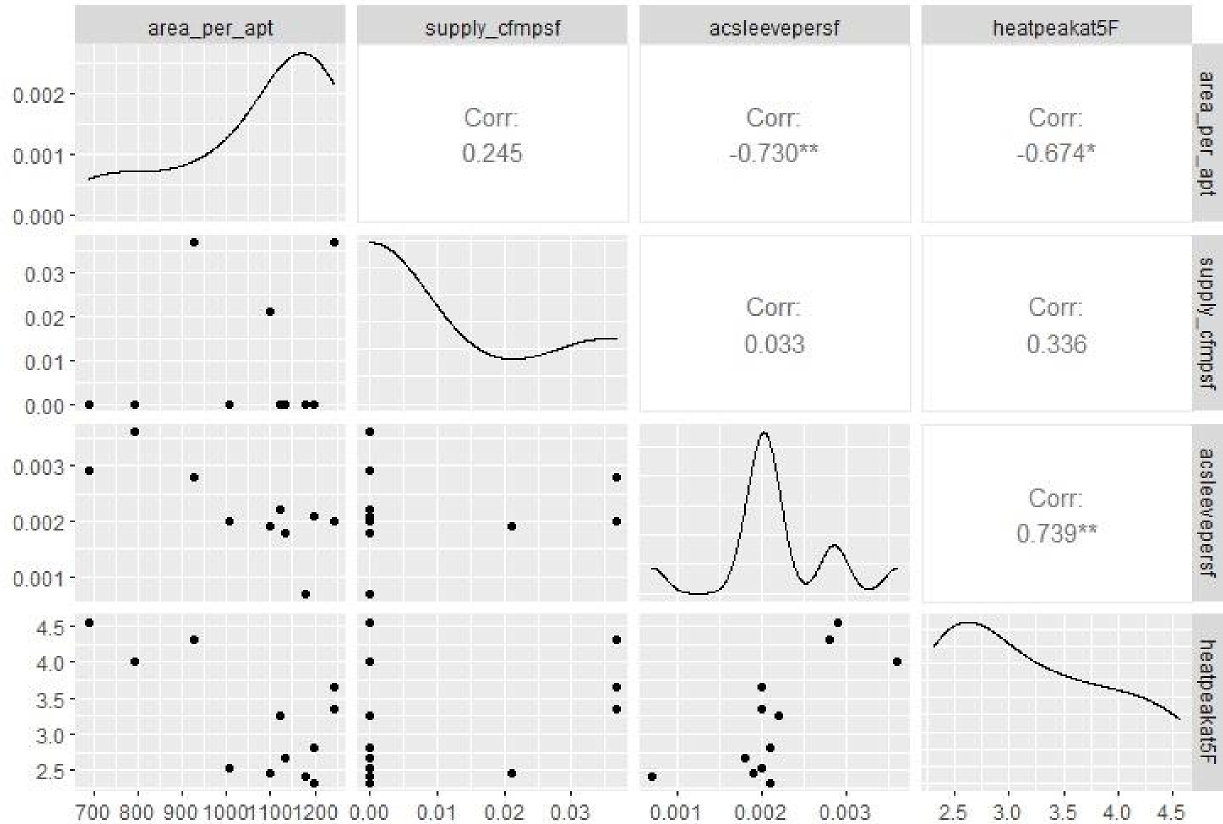


Figure 11. Pairs plot of the response variable (heat peak at 5ºF) to the building characteristics identified in the correlation study. The bottom row shows peak heating demand on the y-axis and the three characteristics on the x-axis going across. None of the charts have a clear trend or a seemingly normal distribution.

A refined model could not be created from this data set. Perhaps a larger sample of buildings with well-known and verified characteristics would yield a more constructive result. The AC sleeve density of a building may be the closest to significance and has a high likelihood of being a significant driver of peak heating demand, but a confounding variable not captured here is the quality of the AC sleeve installation and how many AC units are installed versus the total count of sleeves. In the PTHP buildings, all sleeves have an AC unit in them, but the smaller sleeves in the ERBB buildings may not be filled with equipment and many may be capped.

Estimating Demand if Cold Climate Heat Pumps were Used in Older Buildings

To model cold climate heat pump retrofits in these buildings, a Coefficient of Performance (COP) curve was extracted from a field measurement study of cold climate heat pumps installed in New England homes[10].

Table 6. Cold climate efficiency assumptions.

OAT [°F]	COP
47	4.5
17	2.5
5	1.6
-7	1.25

The resulting curve fit of $COP = 1.50139 + 0.04649 * OAT + 0.00037 * OAT^2$ has an R^2 value of 0.995 and was used to model COP of heat pumps retrofitted into these buildings. For each building with either electric resistance baseboards or non-cold-climate PTHPs, the COP was assumed to be 1.0. No other load reductions were assumed in the heat pump model scenario. Cooling efficiency was not changed as viable assumptions could not be created for all buildings; there is a possibility of increases or decrease in cooling demand with heat pumps compared to the existing air conditioning systems, but that modeling is outside the scope of this study. Measured cooling peaks are shown.

[10]Cadmus, 2017. "Evaluation of Cold Climate Heat Pumps in Vermont". COP extracted from Figure 14, field measured COP.
http://publicservice.vermont.gov/sites/dps/files/documents/Energy_Efficiency/Reports/Evaluation%20of%20Cold%20Climate%2 0Heat%20Pumps%20in%20Vermont.pdf

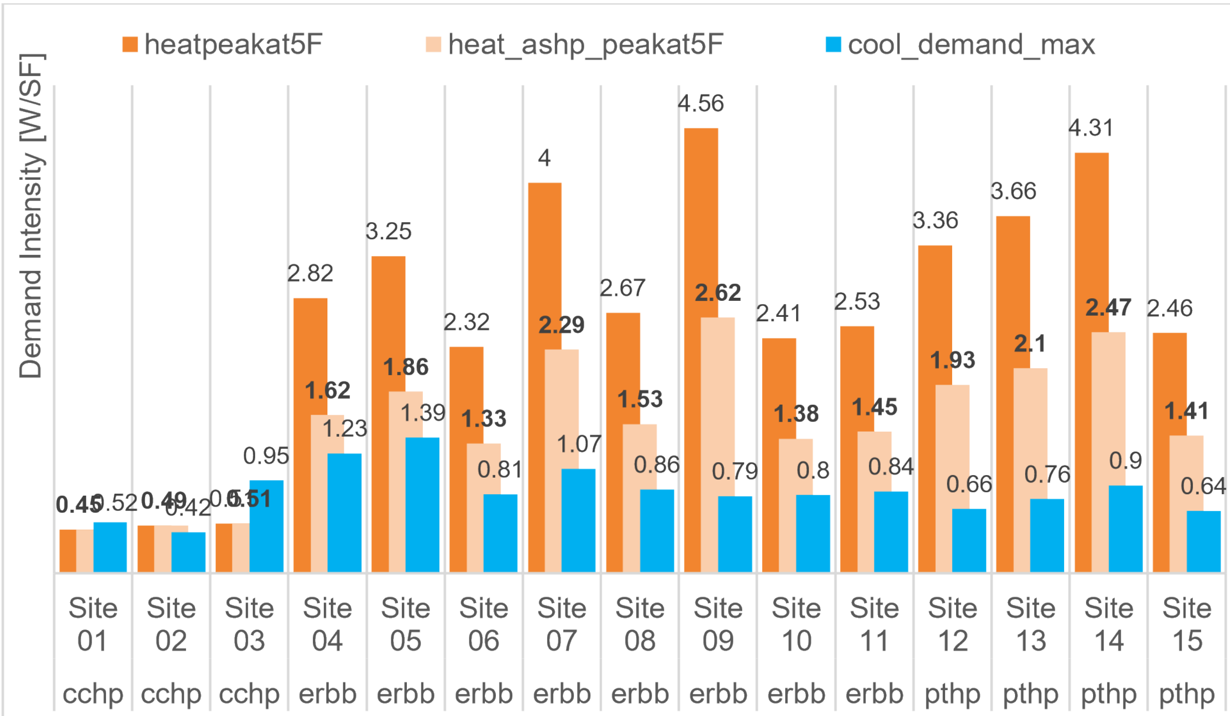
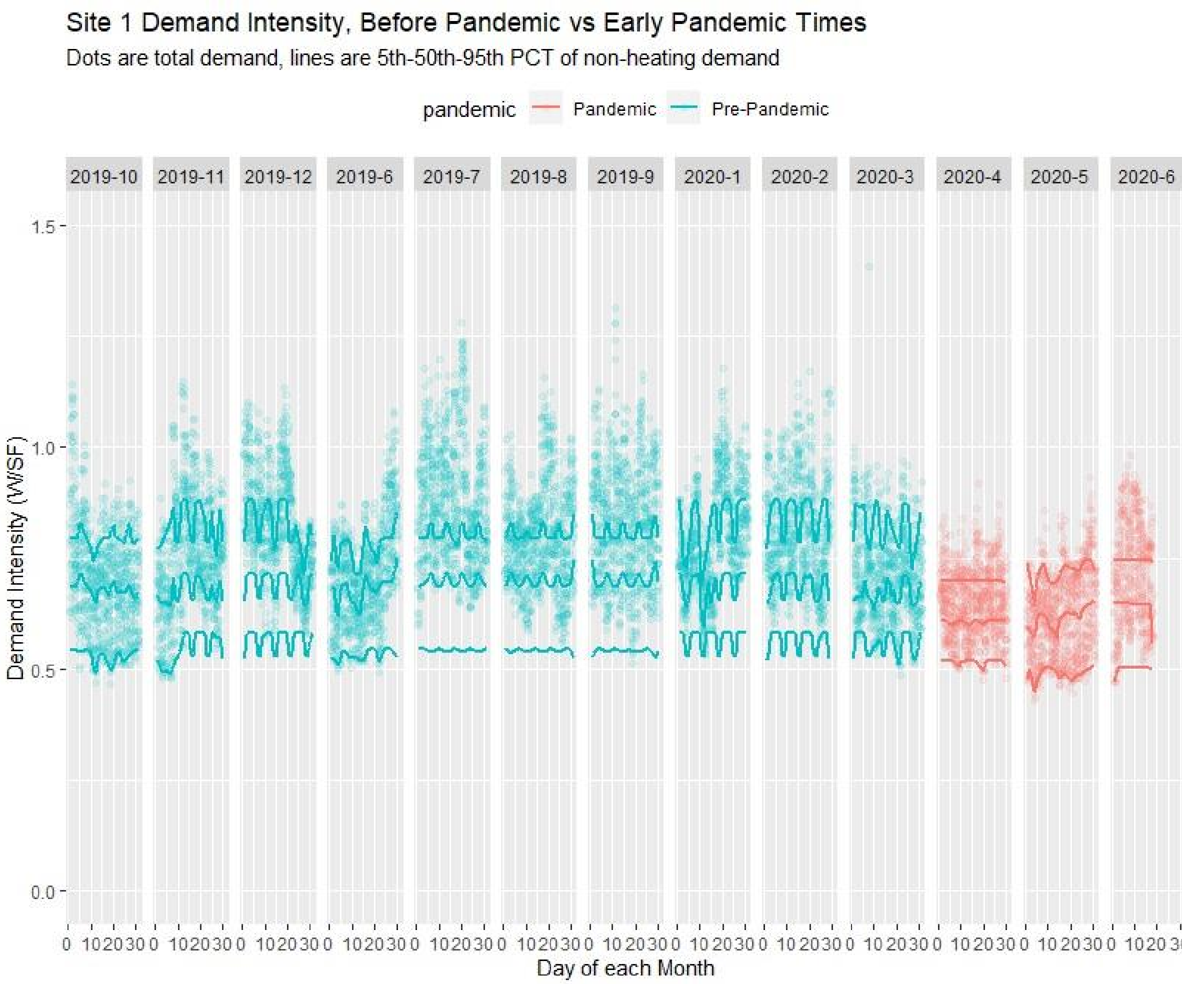


Figure 12. Heating demand with existing systems (heatpeakat5F) and modeled with an air source heat pump at 5°F OAT, with measured cooling demand for comparison.

Occupancy Impact on Multifamily Building Electric Demand

Given the limited data useful to this portion of the analysis, only a small but detectable decrease in one monitored building could be identified. However, this building, Site 01, is a dormitory so it likely emptied out even more than other residential buildings without the counterbalancing of having residents staying at home more. This limited finding is not robust enough to extrapolate to the broader market.



Example of Room-by-Room Heating Demand

While the whole building demand shows what a particular building looks like from the meter and the utility, the demand varies across the different apartments in the building. To explore this, data was analyzed from one of the buildings, Site 09, which has sensors to detect baseboard heating output (in Watts) for each room in each apartment. From this information, Figure 13 shows how there is significant diversity in the heating demand of different apartments, which then aggregate to the median for the whole building compared to outdoor temperature. From the summary in Figure 12, Site 09 has an estimated whole building heating demand of 4.5 W/SF at an outdoor temperature of 5°F. The median calculated across the individual apartments (shown in Figure 13) is around 4 W/SF at 5°F, which is reasonably close to the whole building estimate considering the slight differences between median average and between the whole building (which includes some common area) versus the apartment areas only. The individual apartment level data shows some apartments with significantly higher heating demand, running the heaters nearly flat out even at mild outdoor temperatures, while other apartments keep their heaters off, even at very cold temperatures, and have little-to-no heating demand.

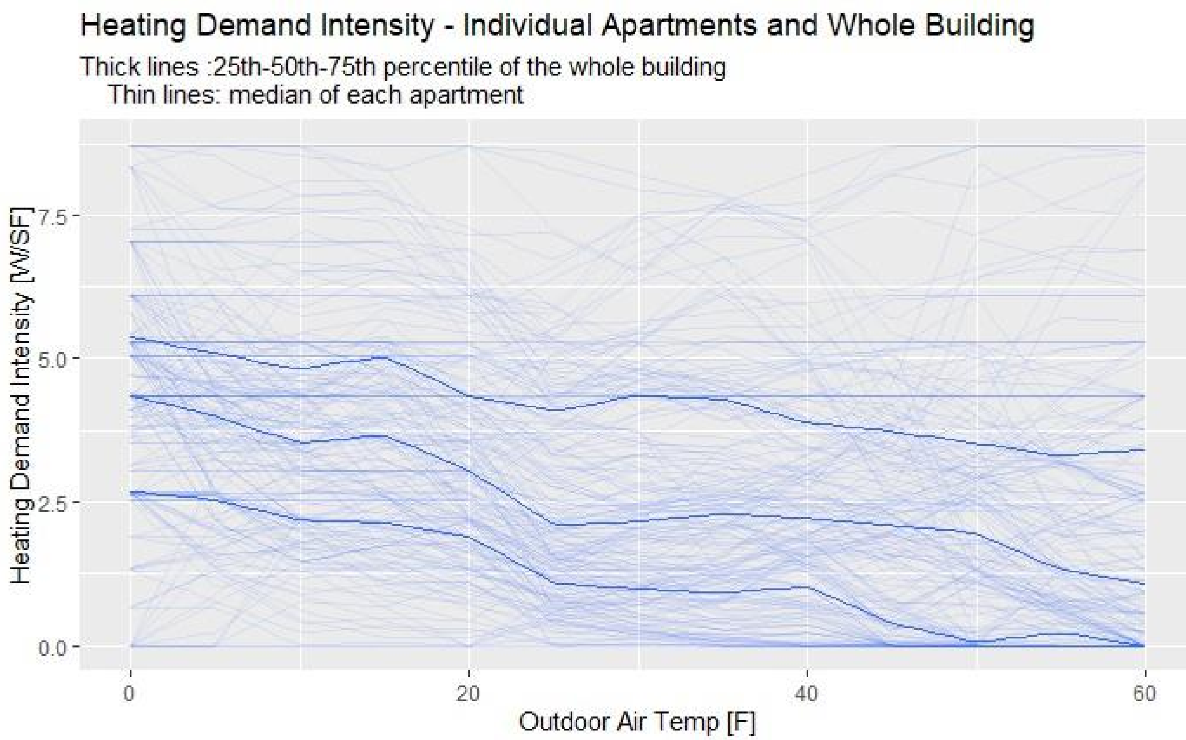


Figure 13. Individual apartment demand compared to outdoor temperature in a single building.

The takeaway from this apartment-by-apartment analysis is that the whole building demand intensity masks significant diversity in heating demand in specific apartments. This does not mean that individual heating equipment sizing could be based on the whole building demand intensity from this study, but it may mean that grid-level planning should consider this diversity of loads within a building. By incorporating this diversity, grid and/or whole building planning activities could potentially use the whole building heating demand from the meter, and not simply sum all apartments' potential heating demand when sizing main electrical equipment.