Implications of electrified residential space heating in California

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ABSTRACT

In order to meet ambitious emission reduction goals in California, greenhouse gas emissions from direct combustion of fossil fuels for residential space and water heating will need to be largely eliminated. If those emission reductions come from fuel switching (natural gas to electricity) then the electricity grid needs to be prepared for the additional load. This paper presents a new method for estimating hourly residential space heating demand using hourly electricity consumption data (smart meter data) and daily natural gas data from 30,000 customer accounts in Northern California. I apply linear regression to hourly, zip-code-averaged whole-home electricity consumption, zip-code-averaged whole-home gas consumption, and outdoor air temperature data to determine both the hours when heating is more active and the outdoor temperature dependence of that consumption. Using piecewise regression, I find that natural gas space heating begins, on average, when the daily outdoor temperature average drops below 59°F, with a mean temperature responsiveness of 0.13 therms per heating degree day (HDD). Therefore, when converting an 80% efficient natural gas furnace to an air source heat pump with a coefficient of performance (COP) of 3, we could expect an additional electric load of 1kWh of energy use per HDD below 59 F. Using a fixed effects model, I estimate the hourly pattern of this new heating load for each zip code analyzed.

Introduction

About 6% of total US greenhouse gas emissions, or 329.9 million metric tons of CO_2-equivalent come from direct combustion of fossil fuels in the residential sector, with approximately two thirds of this coming from space heating (EPA 2016). California has ambitious carbon emission reduction goals, and in order to meet those goals all aspects of the energy system will require significant changes. Impressive progress is already being made, with a rapidly expanding share of renewable electricity generation, exciting advancements on electric vehicles and lower carbon fuels, and almost 40 years of pioneering energy efficiency policy.

But to achieve deep carbon reductions in California, natural gas demand will also need to decrease. In 2009, about 7.2 million of the 12.2 million housing units in California used natural gas for space heating, and on average each of those households used 226 therms of natural gas for heating (EIA 2009). While this study is focused on California, such numbers point to a far greater opportunity for emission reductions in colder climates.

The electrification of heating systems has multiple benefits for the energy system. First, it potentially decarbonizes heating, depending on the fuel sources for electricity generation. Second, in some climates electrified heating with high COP heat pumps can have lower emissions than efficient gas furnaces, even if the electricity is coming entirely from natural gas. While the common perception is that natural gas furnaces have a higher system efficiency than electric heating, if we assume a 40% efficient natural gas power plant and heat pump with a COP of 3, then the electric heat pump will have lower emissions than the gas furnace. Third, since California is a summer-peaking system, electricity infrastructure can be better utilized with additional winter loads. Fourth, with proper control, electrified space and water heating can be useful for integrating large fractions of renewable energy on the grid. As the fraction of variable and uncertain renewable generation increases, more flexibility from electricity loads to maintain balance will be needed. Buildings naturally store energy in their indoor air, thermal mass, and hot water supply which makes these loads flexible in when they consume electricity (Mathieu et al. 2012; Dyson and Mandel 2015).

If fuel switching from natural gas to electricity occurs at a large scale, the grid needs to be prepared for the additional load. Studies such as this are important to characterize what that future load might look like. Furthermore, the building stock is large and slow to change, so if electrification is a serious goal, then smart policies must be put in place to encourage adoption as well as prepare transmission and distribution systems for these new loads. If electrified heating is to be used as flexible load, it will be beneficial to include control technologies in electrified heating from their onset to prevent costly retrofits. Presently, substantial barriers stand in the way of electrification. The Time Dependent Valuations (TDV) that are used to meet Title 24 building codes tend to favor gas space and water heating. Furthermore, the California Public Utilities Commission currently prohibits energy efficiency programs that encourage fuel switching unless the programs pass a three-part test that includes cost effectiveness, emissions, and source energy (California Public Utilities Commission 2013). Given the relative prices of natural gas and electricity, the cost effectiveness test would be challenging to pass.

There is a body of literature that looks at future scenarios of renewables penetration, optimization of renewables and transmission portfolios, and potential studies of what is possible to drastically reduce carbon emissions. Heating electrification is a lever consistently used across studies to meet California’s deep decarbonization goal of 80% below 1990 levels by 2050 (Wei et al. 2013; Williams et al. 2012). However, this prior work has not taken an empirical approach in estimating what the new electrical heating loads would be. Existing studies rather rely on a small set of representative building energy models to create hourly load profiles, or use very coarse load profiles. The empirical approach offered here has the potential to not only account for the thermal properties of buildings but also human behavior.

While prior work has been very important to show what is possible in terms of deeply reducing carbon emissions, a large gap remains in how we might actually arrive at a decarbonized future. This paper presents a simple, novel method to estimate new electrified heating loads empirically, using real natural gas and electricity data from a large number of California households. While there is no guarantee that this empirical approach will provide a more accurate estimate of how future electrified loads will perform, it is grounded in current patterns of energy use from many customers and offers an alternative way to model a future with electrified heating.

Methodology

The narrow goal of this study is to estimate the new hourly electricity demand if gas space heating were converted to electric heating. In order to do this, I use hourly whole-home electricity consumption data (smart meter data) and daily natural gas data from 30,000 customer accounts in the service territory of Pacific Gas and Electric. This data was provided by the Wharton Business School’s Customer Analytics Initiative. The data set consists of 10,000 customers randomly sampled from three geographic zones (Coastal, Inland Hills, and Central Valley) between 2008 and 2012. I currently include only those residences that have both gas and electric service. I estimate when gas is currently used for space heating and estimate future heating electricity demands. If hourly residential gas usage were available, this would be a trivial task. However, only daily residential natural gas consumption data is available in approximately 1 therm resolution which makes this problem more challenging. To estimate the hourly natural gas use for heating, I make use of information that exists in the hourly electricity data.

Three key assumptions are made in this model. First, from a planning perspective, we do not necessarily care about the electrified heating load of an individual house, but rather what the total new load would be for a region. With this relaxed goal, we are able to average over a zip code–though in the future I intend on performing the same analysis over an entire climate zone. The zip code was chosen for the scale of analysis to speed computation and because weather data (gathered from the Weather Underground API) was gathered per zip code. Zip code averaging smooths out the 1-therm resolution issue in natural gas data. Second, I make the assumption that it is not the hourly outdoor temperature that directly drives space heating loads, but rather the time of day together with the average outdoor daily temperature. This assumption is a coarse way of taking into account higher-order thermal dynamics in buildings, and the effects of human behavior such as set-point changes or occupant driven heat gains. Third, while I only include houses that have both natural gas and electricity service, I also assume that consumers either use natural gas for heating or that their pattern of electric heating is the same as their pattern of gas heating. Future work will aim to further classify residences as electrically or gas heated.

The first step in the model is to determine the change point—the daily average temperature at which heating turns on—for the zip-code-average building. I do this by performing a piecewise regression; where daily gas use is regressed onto outdoor temperature, fitting separate coefficients for when outdoor temperature is above or below a change point temperature, T_{cp}. The change point selected is that which reduces the sum of squared errors of predictions (Muggeo 2008).

Using the change point that is identified in this regression using the gas data, I apply it to electricity data. Heating Degree Days are calculated for each day of data using this change point. The regression formulation is below, where y is the hourly electricity use, α_h is an hourly fixed effect for each of the 24 hours of the day (h), and β_h is an hourly temperature responsiveness coefficient, also for each of the 24 hours.

$$y = \alpha_h + \beta_h HDD + \varepsilon$$

I perform this regression twice for each zip code: first using all days with a daily average temperature below the change point (HDD is always positive) and second using all days with a daily average temperature below the change point plus 5 degrees. Including some days with an average temperature warmer than the change point leads to an HDD regressor of zero for some days. I selected a 5-degree threshold to avoid days when cooling might also be occurring. If simply all data were used, then the cooling energy use would enter into the hourly fixed effects estimates (α_h) and doing so would impact β_h. The β_h estimates are the output of interest, which show, on days with heating, which hours are more temperature responsive in their electricity use.

Because I know the daily therms used per HDD from the piecewise regression – call this β_{gas} – and the temperature responsiveness of electricity for each hour, I can estimate the hourly gas use for space heating. β_{gas} is calculated using the difference in slopes above and below the changepoint in the natural gas data. After normalizing the β_h estimates to sum to 1, they will represent the proportion of heating occurring in each hour of the day. In this way, the product of β_{gas}, HDD, and each normalized β_h should represent the hourly gas use. I can use this estimate of hourly gas use, together with assumptions about gas and heat pump efficiencies, to estimate what the new hourly electricity load would be. By adding this new estimate to the prior estimate of electricity use, I arrive at the new total hourly electricity demand. Existing temperature responsive electricity demands (such as resistance heating or furnace fans) are included in the baseline.

Results

I tend to see a clear change point in the 285 zip codes that I analyzed, as shown for an illustrative zip code in Figure 1. The amount of natural gas used at and above the change point can be thought of as the baseline gas use, which is the portion of gas that is less responsive to outdoor temperature. This is likely the gas used for water heating or for cooking. I do see some temperature response—this is perhaps due to changes in cold water supply temperatures, or to lower heat losses at warmer outdoor temperatures. Water heaters and stoves need to be electrified to reduce emissions from this portion of household gas use.

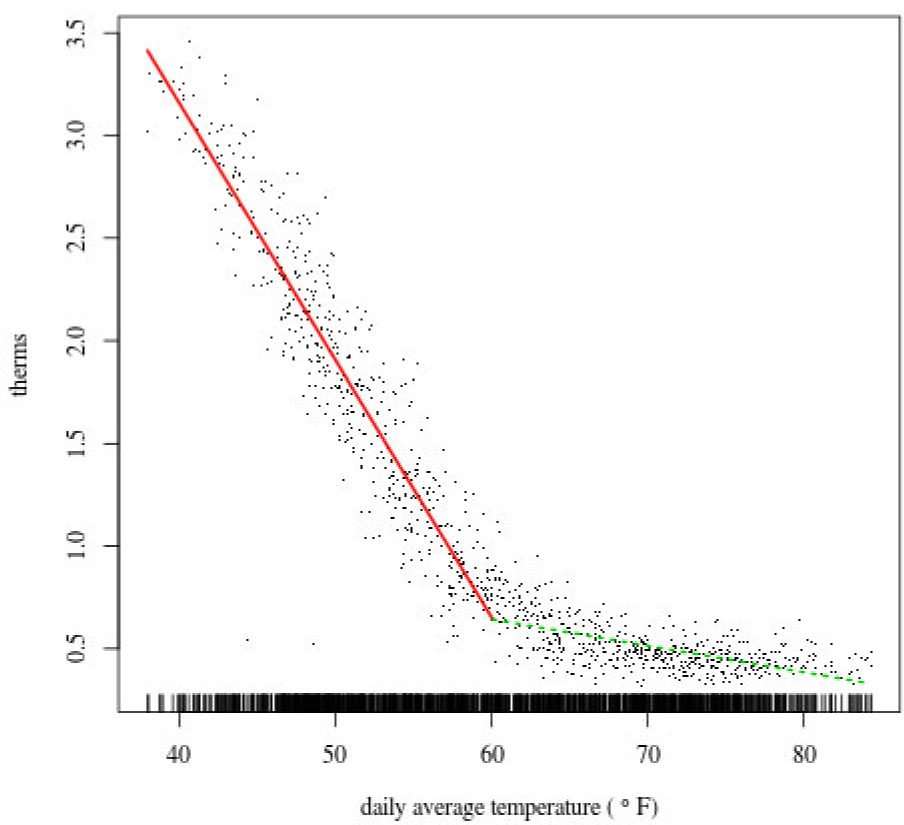


Figure 1. This shows an illustrative example of piecewise regression to identify the change point (60°F) and temperature responsiveness for the zip code average house in Stockton, CA. Over 70 houses were averaged in this analysis.

We can use the information embedded in the hourly resolution electricity data to estimate when heating is occurring. Past efforts have used smart meter data to identify when cooling is occurring, but here I am trying to make use of the much smaller signal that comes from the furnace fan within the electricity data (Dyson et al. 2014). Figure 2 shows hourly zip-code-averaged electricity use versus outdoor hourly temperature. The negative slope at low outdoor temperatures, and the variability of this slope between hours, is what this model aims to capture.

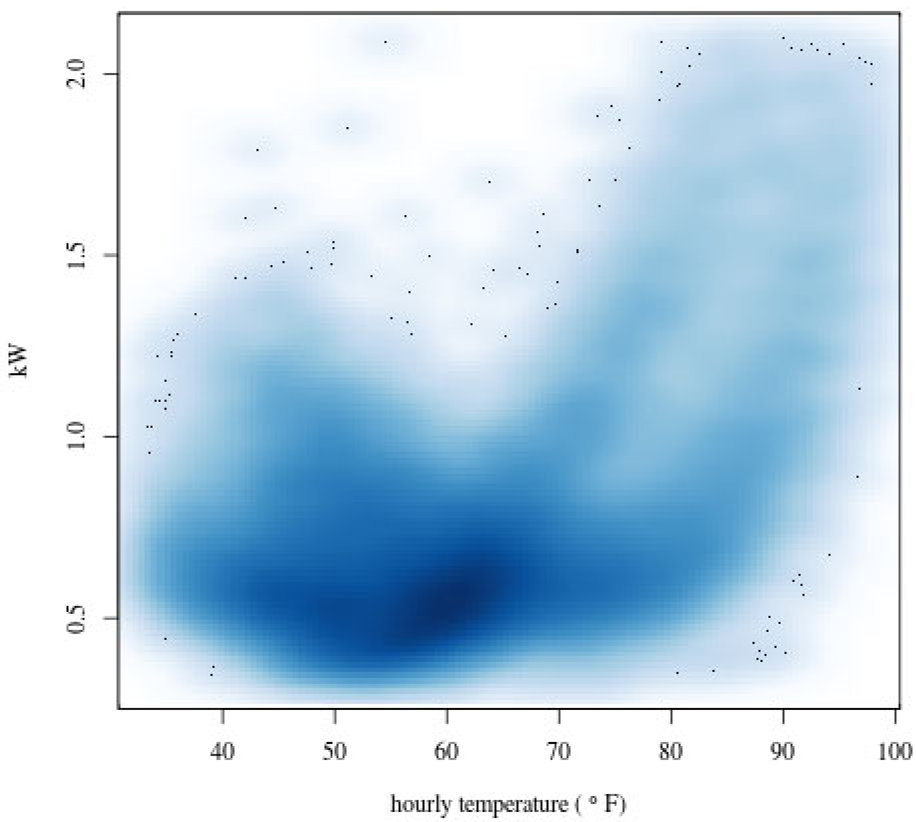
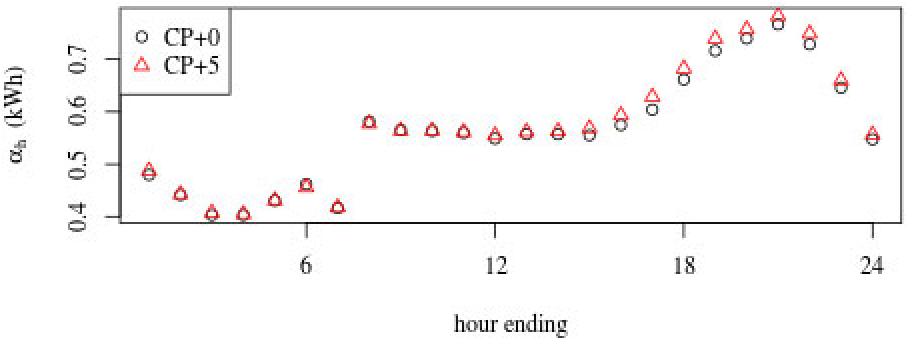


Figure 2. For the same zip code as Figure 1, the hourly average power vs the hourly outdoor temperature is plotted here. Shading indicates density of points. The positive slope shows electricity used for cooling, and the negative slope shows electricity used for heating. Three years of data are included in this plot.

We can see the results of the regression of this zip code in Figure 3. Note that the hourly fixed effects are largely unaffected when days above the change point are added (although days that would be warm enough for cooling are still most likely omitted). The temperature responsiveness coefficients also remain largely unchanged in this illustrative example. There are a couple of notable features in these plots. First, the fixed effects show a sharp rise during the hour ending at 8am, as people wake up, with non-heating electricity peaking around the hour ending at 9pm. The shape of the lower plot shows that, in this zip code, most heating occurs in the evening, peaking around the hour ending at 7pm. For 75% of the zip codes analyzed, the adjusted R^2 of the regression, using only hour of day and heating degree days on the right hand side, was 0.58 or better.



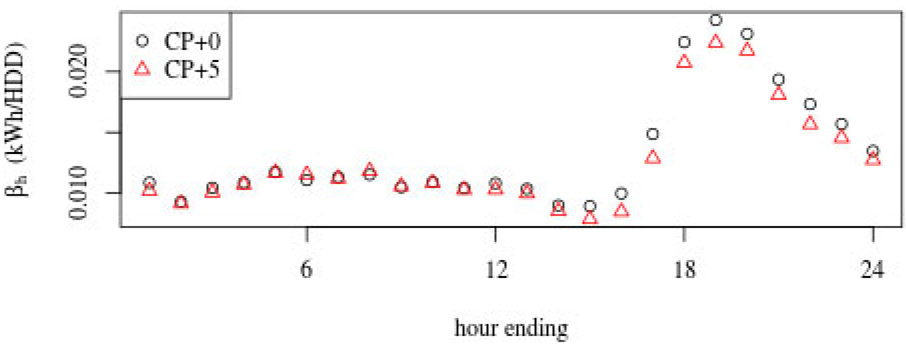


Figure 3. The upper plot shows the estimates of the fixed effects, α_h, for each hour of the day using only days with an average temperature below the change point or days with an average temperature below 5 degrees higher than the change point. The lower plot shows the estimates for β_h, the hourly temperature responsiveness.

By normalizing the hourly temperature coefficients to sum to 1 and using the slope from the piecewise regression in Figure 1, I can estimate what a new electrified heating load would be with a few assumptions. Figure 4 shows those results with HDD=5, COP=3, and $\eta_{furnace}$=80%.

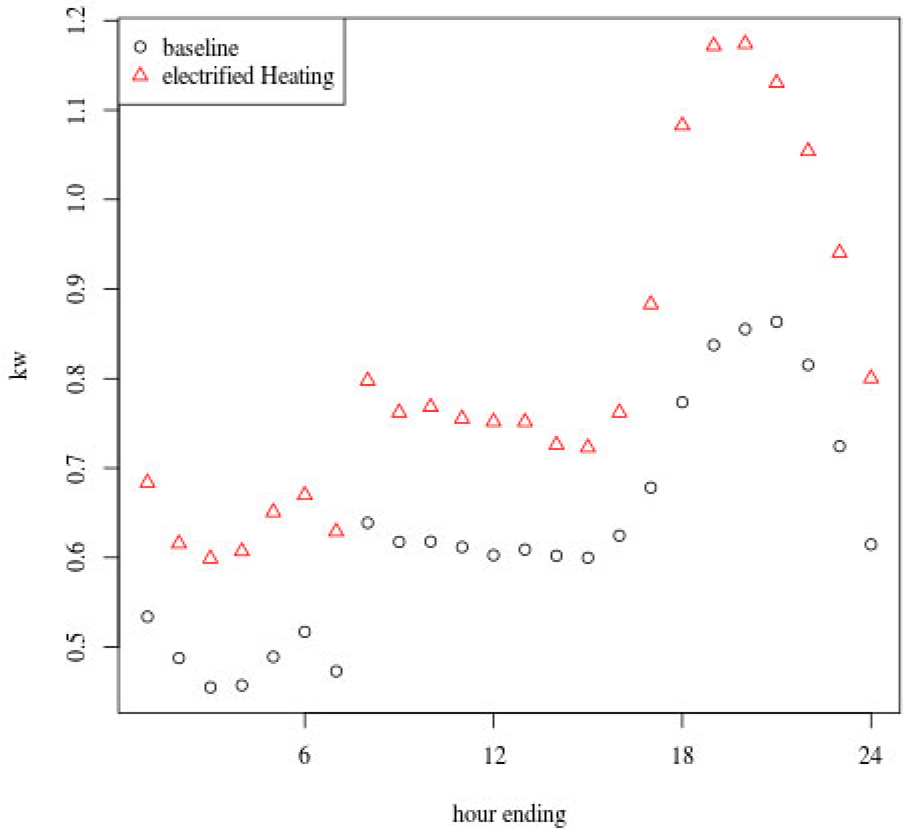


Figure 4. Baseline and electrified heating load shapes assuming a day with an average daily temperature of around 55 degrees, an 80% efficient gas furnace in the baseline and a COP 3 heat pump in the electrified case.

This analysis was performed on many other zipcodes other than this illustrative one in Stockton, CA. Results from two of these, from two other climate zones, are shown below in Figure 5.

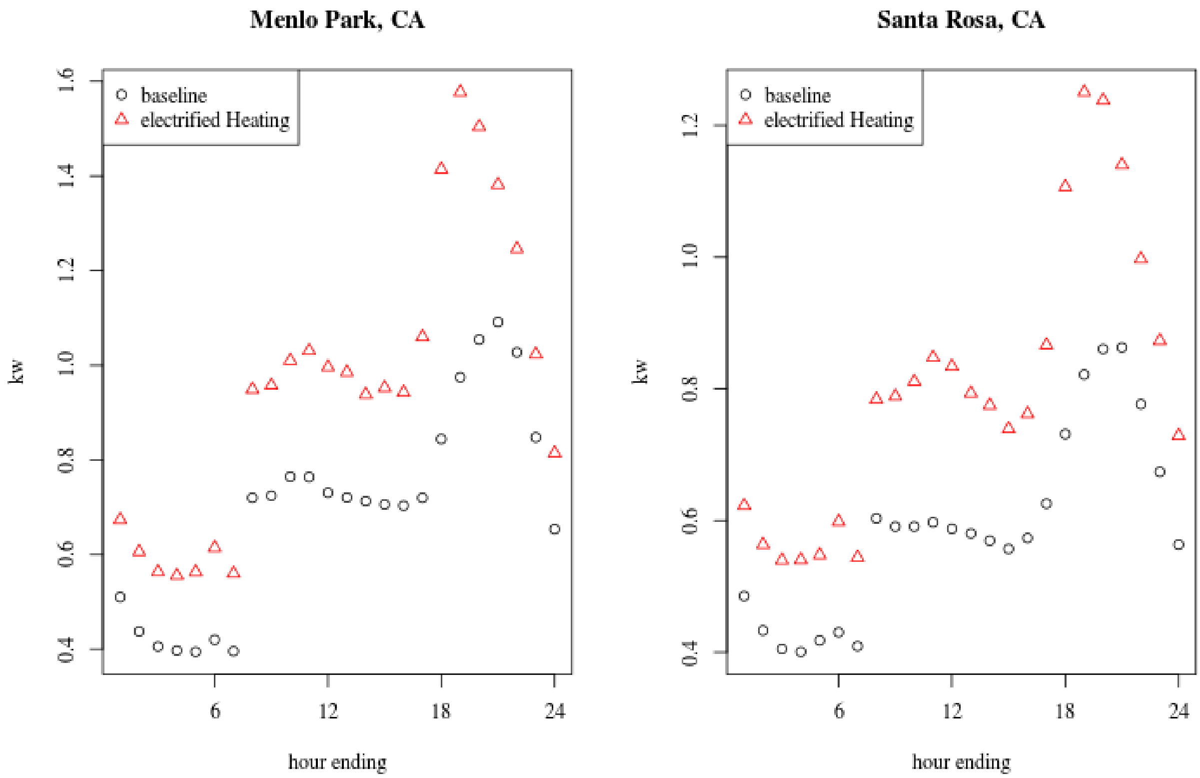


Figure 5. Estimation of new electrified heating loads from two other zip codes in two different climate zones. These results also show an earlier peak and steeper ramp with electrified space heating.

Conclusion

A consistent feature across zip codes is an earlier peak in the temperature responsiveness coefficients than in the fixed effects. This means that as heating systems are electrified, the evening peak will likely shift to earlier in the day. We also see a steep evening ramp up in the temperature responsiveness coefficients, which suggests that the evening ramp will be steeper with electrification, particularly on cold days. This evening ramp is especially concerning; it occurs around the same time that solar power resources are ramping down. Because buildings contain energy storage in their thermal mass, we could likely shift some of this demand to earlier in the day through the intelligent control of electric heating.

Future work will estimate, in aggregate, new electrified heading loads in each climate zone in California. Further work is also necessary to classify residences that might currently have electric heating systems to verify that their schedule is similar to homes with gas heating systems or to exclude them from this analysis. I also aim to control for seasonal and weekday/weekend effects in future iterations of this work.

Electrification is only one option for decarbonizing the space and water heating sector in California. It is perhaps the most promising alternative. However, creating this massive change in the building stock will require technology that consumers find satisfying, policy that speeds their adoption, and system planning that is ready for these new loads.

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