

Net-Zero Homes – It's About More than Energy: A Case Study of Power Performance

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Content submitted to and published by:
Proceedings of the 2018 Summer Study on Energy Efficiency in Buildings
American Council for an Energy-Efficiency Economy
Pacific Grove, CA
August 12-17, 2018

U.S. Department of Commerce
Wilbur Ross, Secretary of Commerce



National Institute of Standards and Technology
Walter G. Copan, Director

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ABSTRACT

Numerous deployments of net-zero energy homes have demonstrated the technical feasibility of the concept, yet the power requirements of many net-zero energy homes could have a negative impact on the utility grid or on-site storage applications. Power profiles of net-zero energy homes need to be considered in assessing energy performance and helping electric utilities plan for a proliferation of such homes. This work presents a series of previously-developed analysis methods and metrics to characterize power profiles in net-zero energy homes and applies them to a single-family net-zero demonstration facility. These methods and metrics stress annual and seasonal peak power demand and identify the key loads that contribute to peak power. Additionally, this work describes the temporal variability in power consumed or exported to the grid using a bumpiness metric and standard deviations. The results show that the most significant minute-to-minute variations in power are caused by the heat pump’s defrost cycles and cloud cover on the photovoltaics. This paper also reports the peak derivatives in the power profile and their respective times of occurrence.

Introduction

The concept of net-zero energy construction has been a rallying theme for the building industry and policymakers to reduce the energy consumption in the building sector. For many years, the idea was a stretch goal that inspired designers and builders to imagine ways that homes, and other buildings, could be built with low enough energy demands such that the yearly energy bill could be covered by renewable energy generation. Over the past decade, the proliferation of homes with photovoltaic panels, the increasing stringency of building energy codes, and the demonstration of net-zero energy buildings has made this goal more readily achievable. Still, work remains to make these buildings cost-effective, easy to construct and maintain, and amenable to integration into the electric grid.

To assist in determining the best ways to reach net-zero residences, the National Institute of Standards and Technology (NIST) designed and constructed the Net-Zero Energy Residential Test Facility (NZERTF) on its campus in Gaithersburg, MD, USA (Pettit et al. 2014; NIST 2016). This single-family, detached home, with a floor area of 252 m² and a 135 m² basement within the conditioned space, was designed to exceed the efficiency requirements of the 2012 International Energy Conservation Code (IECC). The facility also has a 10 kW photovoltaic (PV) system on its roof that provides energy to offset the energy consumed in this all-electric home. The facility was fully instrumented to measure energy flows and indoor/outdoor conditions, with a virtual family of four carrying out all activities associated with energy consumption that would be expected in a home.

The facility was operated for two years under this emulated usage pattern. During the first year, the home achieved net-zero operation by generating 13 500 kWh while consuming 13 039 kWh (Fannee et al. 2015). Prior to the second year, adjustments were made to the

thermostat control scheme, dehumidification approach, and ventilation control strategy. The resulting energy balance showed a decrease in energy consumption of over 1200 kWh compared to the first year, with the surplus energy generation amounting to 19 % of the annual energy consumption (Fannee et al. 2016). These results documented in great detail the technical feasibility of net-zero operation in a mixed-humid climate zone when efficient design and construction practices are applied in coordination with a PV system.

In addition to energy performance, the team also examined the economic, indoor air quality (IAQ), and environmental performance of the building. Kneifel (2014) and Kneifel and O'Rear (J. D. Kneifel and O'Rear 2016; J. Kneifel and O'Rear 2015) conducted a life-cycle cost (LCC) and life-cycle assessment comparison of the home to one built to the then-current 2015 IECC, finding that a home built to the specifications of the net-zero house without any government incentives would carry a first-cost premium of approximately \$126 000 compared to a home built to code in a subdivision in Maryland (cost = \$519 000 for the code-compliant house, land costs not included). This premium is dropping quickly with decreasing PV prices. Additionally, Kneifel and O'Rear found that net-zero operation (i.e., with no surplus generation) could be achieved with a life cycle premium over a 10-year study period of \$2392. To maintain the same LCC as a home built to code, it was estimated that the home could achieve 86 % of the path towards net-zero. IAQ performance of the home was investigated through measurements and modeling by Ng et al., who demonstrated the importance of ventilation-associated energy consumption (2016).

While the results to date suggest that a home built to the specifications of the NZERTF would qualify as a success in terms of energy and environmental performance, one topic that has not yet been investigated with the NZERTF relates to the interaction of net-zero energy homes with the utility grid. To consider that issue, one needs to focus on power as a function of time rather than annual energy. A number of authors have discussed metrics for energy performance (Wright et al. 2010; Fairey and Goldstein 2016; Goldstein and Eley 2014), but the purpose of this manuscript is to discuss analysis methods and power metrics that can be used to characterize the impact of net-zero energy homes on the energy generation, distribution, and storage infrastructure. Clear analysis methods and metrics for power performance will help address concerns related to grid stability as net-zero energy buildings become more common.

Role of Power in Net-Zero Energy Buildings

Net-zero energy operation is an important goal towards achieving energy efficient operation, but it does not consider the temporal nature of energy delivery to and from a building. In the extremes, a home could draw a constant power throughout the year or consume all energy in short, high-power time spans and still be a net-zero energy building. However, such buildings are not equivalent in terms of energy impacts, and consideration needs to be given to the time distribution of the energy flows.

Temporal variation is of interest to utilities based on their goal of maintaining power quality (i.e., stable voltage, frequency, and waveform) as significant changes in power draw or supply occur. When aggregated among the buildings served by a utility, power fluctuations may lead to the need to ramp up or down generating assets and to make other adjustments.

Photovoltaics began to be connected to the grid starting about 30 years ago. To encourage such installations, governments enacted net-metering laws and other incentives that allow a PV owner to be compensated for supplying excess electricity generation back to the grid.

While the grid was not originally designed to accept energy from end users, the extremely small number of these installations did not raise concerns with utilities.

This story has changed with the proliferation of PV installations on commercial and residential buildings. This penetration of solar has had a marked impact on overall power demands in many communities with the emergence of the so-called “duck curve” that shows the ramp-up in power demand in late afternoon as loads increase and generation decreases (California Independent System Operator 2016). These changes in power profiles have led to concerns about net-metering laws or additional charges from electric utilities to customers with solar panels. In part due to concerns that PV proliferation is disrupting the grid, so called “Smart Grid” technologies are being proposed to better balance the demand of electricity with supply. One aspect of these technologies is the curtailment of loads at end uses when it may be advantageous to the grid and appropriate for the building function. Another technology is localized energy storage (e.g., batteries). Development and application of these technologies requires an understanding of power flows required to be delivered to and from buildings.

As homes become more efficient, these profiles will change. Certain equipment will use less power, and peak demands may also change given more efficient envelopes and equipment. If one is to add in a new major load like an electric vehicle or a generation source such as PV, more significant changes in power profiles will result. To help understand these challenges, options for describing the power performance of homes are being proposed to clarify the impact of a net-zero energy building on the power grid.

As an isolated example, consider the power draw by a water heating system. For the NZERTF, an efficient system consisting of a solar thermal preheat tank feeding a heat pump water heater (HPWH) was selected due to its high efficiency (Balke, Healy, and Ullah 2016). Given the high costs of solar thermal and the efficiency of HPWHs, however, some have suggested that a more cost-effective approach would have been to replace the solar thermal panels with more photovoltaics and produce hot water with a HPWH alone. From an economic and net-energy point of view, this approach could have merit, but a look at the power profile raises questions regarding the relative value of the two systems. Figure 1 displays the power profile of both systems during a typical spring day. Data for the solar thermal+HPWH are actual measured minutely data; the data on the PV+HPWH were generated from a laboratory test of the

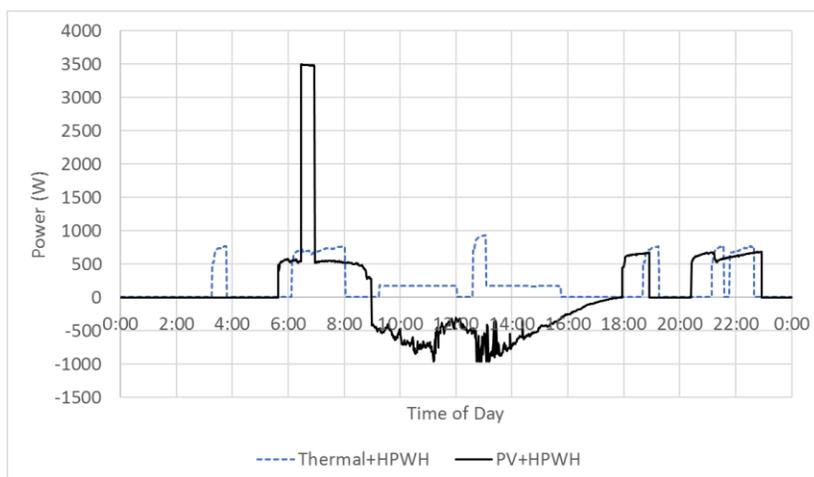


Figure 1. Power profile on a typical spring day for (a) solar thermal preheat with heat pump water heater backup and (b) a simulated heat pump water heater powered by grid-integrated photovoltaic panels.

HPWH using the same water use profile and a scaled profile of the PV power generation on this same day. Power values less than zero mean that power is exported to the grid. One can see that the solar thermal+HPWH profile is much smoother than the PV profile. First, the solar preheat minimizes the need for resistance heating by the HPWH that occurs near 06:30, behavior that could also be achieved by preheating a HPWH overnight. Second, the power draw by the solar thermal system's pumps is more stable than PV generation, particularly under partly cloudy conditions. These data suggest potential variations in power quality at the site when using PV for water heating that would not be observed with the solar thermal systems.

Methods and Metrics

This study introduces metrics and analysis approaches for assessing power profiles in residences and then applies them to a full year of data from the NZERTF to examine their applicability. Data on the power usage by the entire facility and by key end uses that were collected on a one-minute basis during the second year of operation are used for this analysis. These examples serve as a base case against which other homes, whether designed to be energy efficient or not, can be compared. The following features of power performance are assessed:

Distribution of Power Consumption

Data on the range of powers measured on a minutely basis over the year are provided as histograms of the overall power. These plots are separated by meteorological season since the heating and cooling operation varies greatly in the mixed-humid climate. These plots provide an overview of the range of power values as well as typical power values observed at different times of the year. Observations of the peaks in the histograms identify those devices that tend to be energized for the longest duration.

Peak Power

This value is the maximum power over the course of the year and by season, determined simply by finding the maximum power at any minute. This value is important in assessing the capacity required by the home, for designing both internal electrical wiring and distribution grids. Saturation factors, obtained by dividing the average power over a timeframe by the peak power observed during that timeframe, provide a metric for assessing where typical power consumption falls across the distribution. Peak and average generation are also tabulated as the maximum and average net export of energy from the house to the grid over the seasons.

End Uses Contributing to Peak Power

This analysis identifies those devices in the home that are most responsible for large overall power draws, which is valuable in assessing options for shedding load. A number of approaches are used to assess these contributors. First, a list is provided of those devices with the highest nameplate power ratings. This list, however, only tells part of the story, since some pieces of equipment are operated sporadically, or they contain multiple stages and the highest power stage only energizes intermittently (e.g., resistance heaters in heat pump). The amount of time that they are on has an impact on whether they are key contributors to overall peak power.

An alternative approach to identifying the key contributors to peak power uses a correlation between individual power uses and the total power consumption using, for example, the Spearman correlation coefficient. In this approach, linear regressions between total power data points and power of each individual appliance across all minutes are developed. Because the correlation coefficients tended to be small, another option was investigated. All minutes of the year were grouped into different bins based on the overall power consumption. Bins were selected for power levels above 10 kW, between 5 kW and 10 kW, and at other levels below 5 kW. Since the investigation focused on instances of high power, the end uses active during minutes when the total power fell in the two highest bins were identified. The average power for all minutes in those bins along with the average power from the end uses during those minutes was determined. This approach leads to the average percentage of the power during these high demand minutes drawn by particular end uses. This analysis was also done by season.

One further approach to identify key contributors to large power draws used machine learning principles, namely feature selection. Feature selection is the process of identifying key variables that should be part of a model that describes performance of a system; in this case, that performance is the power bin. A univariate selection method, in which the chi-squared value between the power level of each individual end use and the power bin for each minute as noted in the previous paragraph was determined. A scaled univariate selection score is then determined by dividing the chi-squared value for each end use by the maximum chi-squared value. The resulting score is between 0 and 1 for each end use, with a value of 1 meaning that it contributes the most to the power bin while numbers closer to zero suggest that the end use has little impact on the bin into which the overall power falls.

Typical Daily Power Profiles

While not providing a single metric, a distribution of the power profile over the course of a day is valuable to understand when power is used and how that power is changing. Simple averages over the many days of study can provide typical power levels, but this approach tends to smooth out changes in power levels that could stress battery or generator backups or a distribution transformer. Instead, it is proposed that an approach similar to how Typical Meteorological Years are constructed is used to develop a typical daily profile for a particular time frame (S. Janjai 2009).

To construct a typical daily profile, cumulative energy consumption throughout the day is compiled on a minutely basis for each day in the period of interest. An average cumulative energy consumption at each minute is then generated by averaging across all days. The difference between the average cumulative energy at each minute and the cumulative energy consumption at each minute for every day is compiled, and the square of that difference is summed across the 1440 minutes of the day. The day of the season with the lowest sum of squared errors between its cumulative energy values and those of the average day is selected as the most representative day for that time period. A plot of this typical day provides expected power draws and time rates of change of those power levels.

Variability in Power Draws

To capture the time rate of change of power draws, a number of metrics are applied to the data. A simple way to assess the variability is to calculate the standard deviation of all power readings. Another metric is the autocorrelation with a lag of 1, where a time series of powers is

correlated with the same time series shifted by one minute. This metric provides an estimate of the “bumpiness” of a profile. A lower value suggests more significant changes in the data minute-to-minute, whereas a value close to 1 suggests that the value for each minute is dependent upon that of the previous minute in a regular manner. This metric is determined for each season, both for the entire day and also during the periods of sunlight to capture the impact of PV on the variability of power to or from the house.

The time rate of change in power sheds light on potential impacts on power quality and demands on battery storage. A number of approaches were examined to obtain representative “dP/dt” metrics. First, minutely power changes for the typical profiles obtained in the previous section were evaluated. The maximum and minimum values were obtained, corresponding to the times when the power drawn from the grid is increasing or decreasing the most. The times of these extremes were also recorded. Because the minutely data collection resulted in extreme fluctuations, a 15-minute boxcar smoothing method was used on the dP/dt values.

Results

Power Distribution

Power data from all end uses and the PV system in the NZERTF were collected on a minutely basis during the period from February 2015 through January 2016. Density plots of the power demand in the house (Figure 2) across the four meteorological seasons are multi-modal and heavily skewed to the left. The skewness demonstrates how infrequently the peak power levels are achieved, and modes in the plots are observed due to standby loads and discrete operating points of the HVAC system. The peak associated with standby power on the left side of the plot is most pronounced in the swing seasons, Fall and Spring, as the relatively small run time of the HVAC system leads to more minutes when only the standby loads are operational.

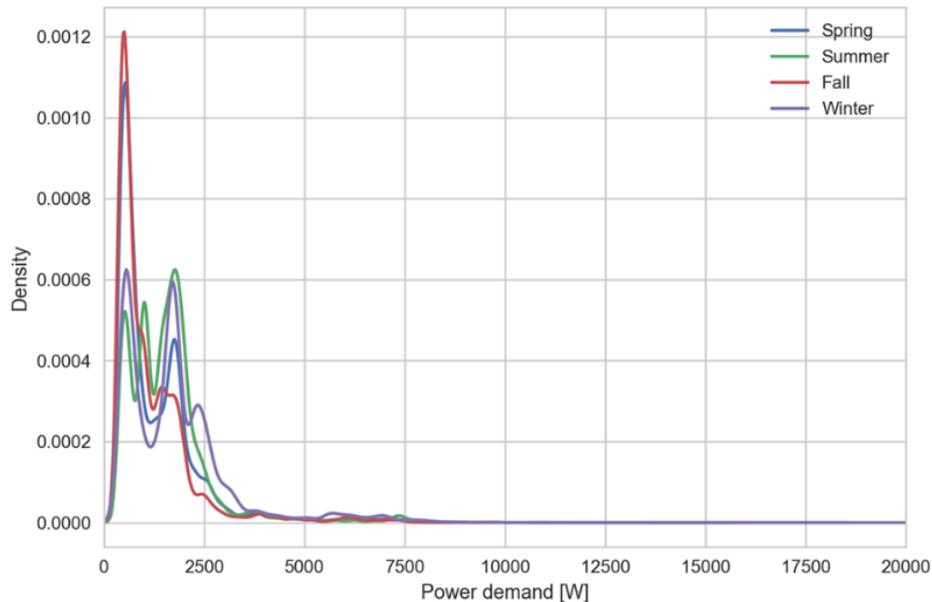


Figure 2. Density plot of minutely power demand across four seasons.

Peak Power

Key values related to the power consumed and generated at the home are provided in Table 1. Considering measured powers during the year, the sum of the peak draws of all appliances is 40 kW. This amount of power draw, however, never occurs. During the year, the peak total measured power consumption was 16.1 kW. The load saturation factor, which estimates how typical it is for this power to be approached, was found to be less than 15 % throughout the year, with the highest value occurring in the summer. The maximum power generation by the PV system observed was 10 kW, and the maximum net power sent to the grid was 9.6 kW. The maximum power generation is uniform across all seasons and closely matches the rated power for the array (10.24 kW), but the average power generation across all minutes of the season is dependent upon the hours of daylight. The average export is negative in the winter months due to the lower hours of daylight and higher energy consumption, while it is positive in the other three seasons.

Table 1. Key power metrics by season.

| Season | Maximum Consumption (kW) | Average Consumption (kW) | Saturation Factor | Maximum Generation (kW) | Average Generation (kW) | Maximum Net Export (kW) | Average Export (kW) |
|--------|--------------------------|--------------------------|-------------------|-------------------------|-------------------------|-------------------------|---------------------|
| Winter | 16.1 | 1.8 | 0.11 | 10.0 | 0.94 | 9.6 | -0.87 |
| Spring | 12.4 | 1.3 | 0.11 | 10.0 | 1.89 | 9.6 | 0.55 |
| Summer | 10.5 | 1.6 | 0.15 | 10.0 | 2.03 | 9.5 | 0.43 |
| Fall | 11.0 | 1.2 | 0.11 | 10.0 | 1.41 | 9.4 | 0.22 |

End Uses Contributing to Peak Power

To identify those end uses that most contribute to instances of highest power consumption, nameplate ratings or measured values of peak powers of end uses were considered. For the NZERTF, those key end uses are (with nameplate ratings in parentheses): heat pump indoor unit (6 kW), dryer (5.4 kW), heat pump water heater (4.1 kW), oven (3.5 kW), heat pump outdoor unit (1.9 kW), and stove top (1.7 kW). Various smaller appliances draw powers in excess of 1 kW over short durations, specifically the iron, hair dryer, microwave oven, and toaster.

Spearman correlation coefficients of the actual power data show the largest correlations to total power were found with the dryer in Spring and Fall, the heat pump indoor unit in Winter, and the heat pump outdoor unit in Summer. The highest Spearman correlation coefficients, however, ranged from relatively small values of 0.50 to 0.57. As an alternative to the Spearman coefficients, Figure 3 demonstrates the bin approach to categorizing power usage during the three winter months. On the leftmost bar in the graph, the maximum conditions are shown assuming all equipment are energized. Actual power draws never reach this maximum of 40 kW. During the instances of highest total power consumption (second vertical bar from left), the large contributors are the heat pump indoor unit (34 % of total power), dryer (33 % of the total power), and HPWH (24 % of total power). These three devices alone make up 91 % of the typical power consumption during these high-power minutes. If the outdoor unit of the heat pump is added to this calculation, 96 % of the power during these high use times is accounted for. This result suggests that peak powers are attained when those three devices are energized at the same time at their highest power levels (e.g., resistance heating in both the heat pump and HPWH).

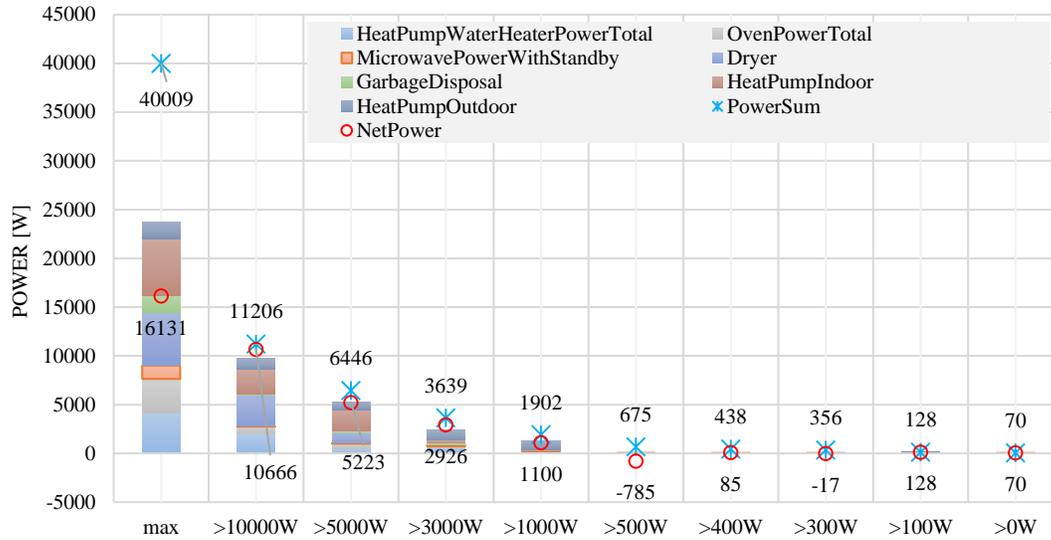


Figure 3. Contributions of different end uses to total power draws, Winter months, Year 2.

Figure 4 shows the same distribution during the summer months. The average observed power in the largest bin is lower than in winter due to the reduced amount of resistance element heating by the heat pump and HPWH. In the summer, the largest contributors to these peak power demands above 10 kW are the oven (32 % of total power) and plug loads in the kitchen (21 % of total power). Considering powers between 5 kW and 10 kW, the dryer accounts for 31 % of the total power, with the oven (18 % of total power) and heat pump (17 % of total power) contributing the next highest amounts. These results suggest that control strategies that aim to reduce peak loads in the summer for this house should focus on the oven, dryer, kitchen plug loads, and heat pump.

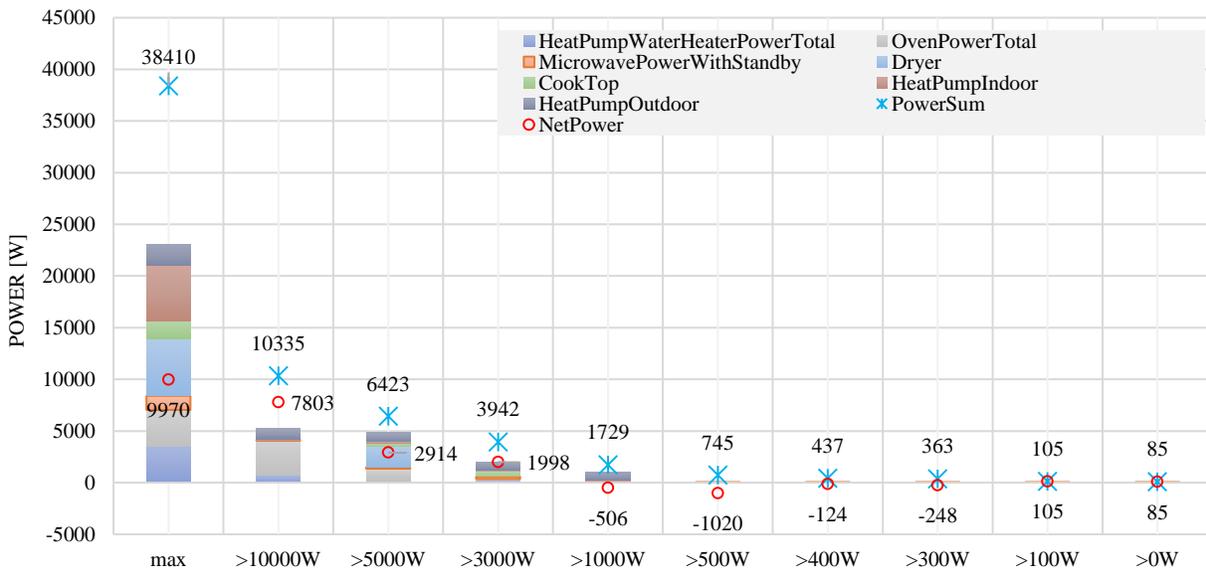


Figure 4. Distribution of Total Power Levels in NZERTF during summer months of Year 2 and components of those power levels.

Table 2 provides the univariate selection scores discussed earlier, which are the chi-squared scores between each end use and the power bin divided by the maximum chi-squared score for any end use. All other end uses (not shown in the table) have scores of 0.01 or below, which indicates that they contribute relatively little to peak power. These results clearly show the impact of the dryer and oven in driving overall power demand. The HPWH scores much lower, as the low power levels when operating in heat pump mode do not necessarily push the overall house power to a high level.

Table 2. Univariate feature selection scores for most significant end uses in total power usage.

| End Use | Univariate Selection Score |
|------------------------|----------------------------|
| Dryer | 1.00 |
| Oven | 0.28 |
| Heat Pump Indoor Unit | 0.16 |
| Heat Pump Outdoor Unit | 0.15 |
| Heat Pump Water Heater | 0.05 |
| Stove Top | 0.05 |

Typical Daily Power Profile

The average power consumption, PV generation, and net-energy impact by hour throughout the year are shown in Figure 5. This plot shows the smooth distribution of power generation from the photovoltaic system over the day as the sun rises and falls. Energy consumption and the resultant net electrical demand have more peaks (e.g., at 6 a.m. and 12 p.m.) for this facility due to the regular schedule imposed during testing that called for certain appliances to be activated at the exact same time each day. A normal profile may still see larger values at those times but would not see such large differences from adjacent hours. This profile presents a good overview of when power is demanded and highlights concerns such as the steep increase in power generation in the morning and the ramp up in energy demand in the afternoon, but they miss out on discrete instances of surges in power draws or supplies by PV.

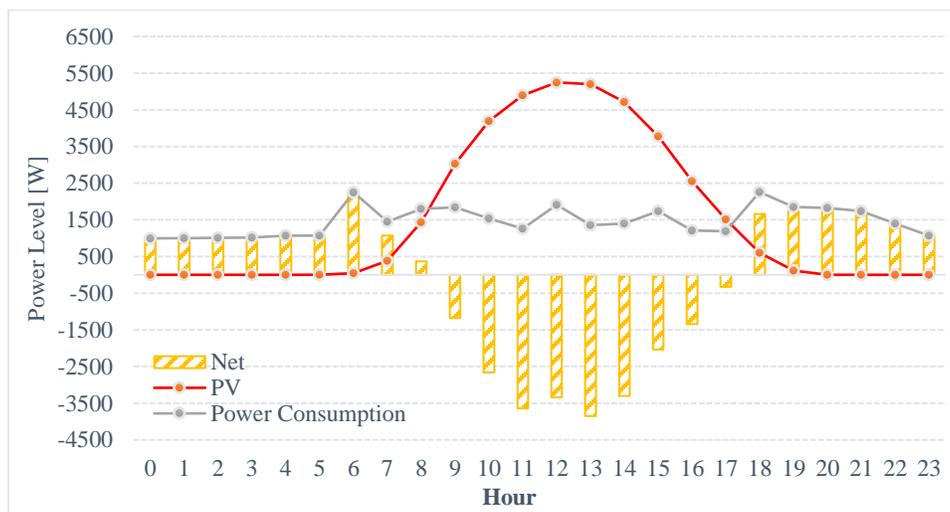
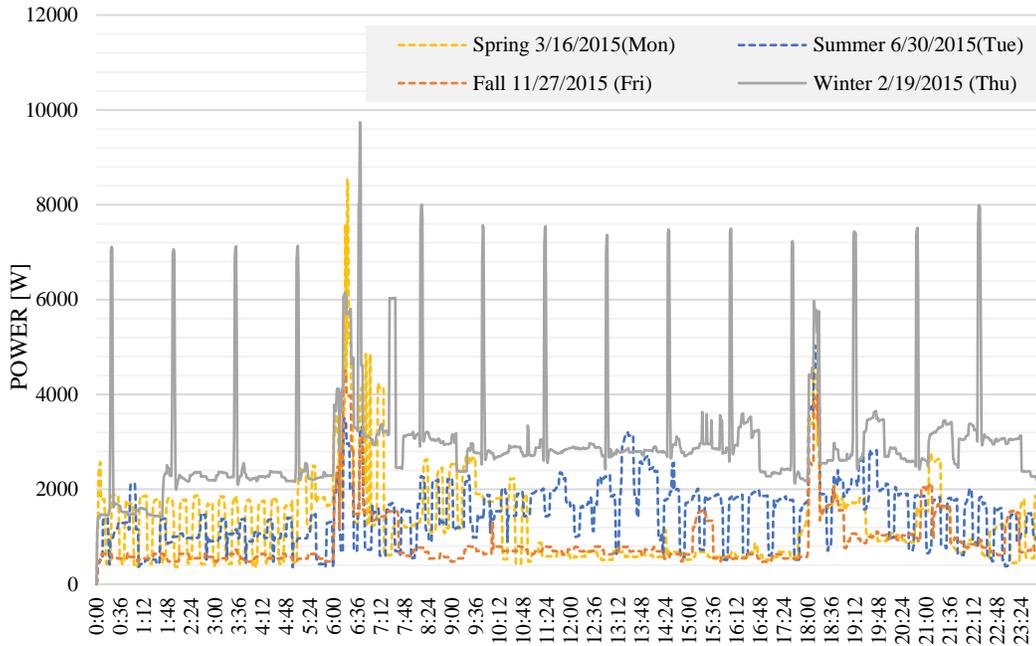
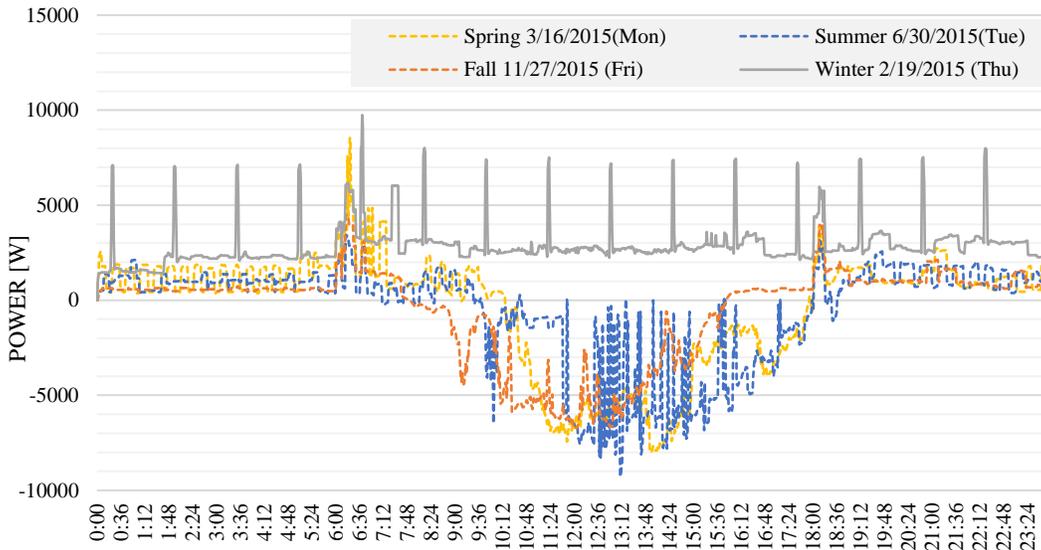


Figure 5. Average Power Consumption, PV Generation, and Net-Energy Import by hour.

Figure 6(a) shows the daily power consumption profiles on a minutely basis for the most typical days in all four seasons, while Figure 6(b) shows the most typical net power draw including onsite renewable energy generation. Interestingly, while the determination of the most typical day was done separately for the energy consumption and the net-energy consumption, the most typical days for both situations were the same. This result is reflective of the dominance of



(a) Typical power consumption patterns



(b) Typical Net Power Patterns

Figure 6. Most typical daily electrical profiles by season.

energy consumption over generation in the winter months due to the relative lack of sunlight. The advantage of these plots compared to the averaging plots in Figure 5 are that they capture power changes on a more discrete level. Some key features should be noted. For example, during the winter day, periodic spikes arise due to defrost operation of the heat pump. Also, the most typical winter day involves essentially no PV generation. The large spikes in spring in the morning arise due to activation of the resistance elements of the HPWH. Periodic step jumps in power consumption in summer arise due to activation of the heat pump. The net energy import in summer shows the dramatic variations in power exported to the grid due to cloud cover.

Table 3 provides key statistics on these most typical days. In all cases, peak draws from the grid occur in the morning as the family begins its activities and the sun has not yet risen, and the peak exports occur in early afternoon when the solar resource is greatest. For the typical winter day, there was no export to the grid. Peak power use in the house occurs in early morning for the typical day in Spring, Fall, and Winter and at 18:09 during the Summer.

Table 3. Power statistics for the most typical day in each season.

| Season | Average Power Use [W] | Average Net Power* [W] | Peak Power Use [W] | Peak Power From Grid [W] | Peak Power To Grid [W] | Time of Peak Power Use [hh:mm] | Time of Peak Power from Grid [hh:mm] | Time of Peak Power To Grid [hh:mm] |
|--------|-----------------------|------------------------|--------------------|--------------------------|------------------------|--------------------------------|--------------------------------------|------------------------------------|
| Spring | 1268 | -438 | 8537 | 8537 | 7988 | 06:21 | 06:21 | 13:57 |
| Summer | 1502 | -564 | 5038 | 3438 | 9279 | 18:09 | 06:15 | 13:08 |
| Fall | 881 | -518 | 4503 | 4503 | 6755 | 06:17 | 06:17 | 12:01 |
| Winter | 2945 | 2900 | 9744 | 9744 | n/a | 06:39 | 06:39 | n/a |

Variability in power draw

Table 4 presents statistics on the variability in power for the most typical day in each of the seasons for both the power consumed by the equipment in the house and the net-power drawn from the grid. This discussion will focus on a typical day instead of an average day, so the artificial spikes in the average profile due to the regimented schedule do not come into consideration. The same approaches could be used, however, with averaged data. Additionally, auto-correlations are presented during the period of the day when most occupant activity and solar generation occurs, between 06:00 and 21:00. The smoothest data, as indicated by the highest auto-correlations, appear in the fall, where both the power consumption and net-power consumption vary in a smooth manner. The low auto-correlation coefficients observed in the winter are a reflection of the periodic spikes from the defrost cycles of the heat pump. These variations are also represented by the large standard deviations seen in winter consumption compared to the other seasons, but the lack of sun on the typical winter day keeps the standard deviation of the net-power consumption below those for the other seasons.

Table 4. Metrics for the variability and bumpiness of typical daily power profiles.

| Season | Power Consumption | | | Net Power Consumption | | |
|--------|------------------------|----------------------------|----------------------------------|------------------------|----------------------------|----------------------------------|
| | Standard Deviation [W] | Auto-correlation, Full Day | Auto-correlation, 06:00 to 21:00 | Standard Deviation [W] | Auto-correlation, Full Day | Auto-correlation, 06:00 to 21:00 |
| Spring | 899 | 0.907 | 0.908 | 3001 | 0.991 | 0.991 |
| Summer | 681 | 0.927 | 0.922 | 2313 | 0.925 | 0.914 |
| Fall | 573 | 0.961 | 0.961 | 2470 | 0.994 | 0.994 |
| Winter | 1133 | 0.828 | 0.810 | 1135 | 0.828 | 0.813 |

Table 5 provides the maxima and minima of the time rate of change of power for each season along with the time of day that these peak changes occurred. These numbers are dominated by isolated events such as heat pump defrost cycles, dryer activation, and oven use. Another appropriate metric would be the dP/dt values for profiles that are averaged over each season. Unfortunately, the averaged data from the NZERTF are dominated by pre-scheduled appliance activation at the same times each day, so the average profile incorporates many of the peaks that are seen in daily results. Average profiles in more typical residences, however, will be smoother due to the diversity in times when those large pieces of equipment are activated.

Table 5. Power change metrics (dP/dt) and times for typical days in each season.

| | | Spring | Summer | Fall | Winter |
|-------------|-----------------------|--------|--------|-------|--------|
| Consumption | Max dP/dt , [W/min] | 332 | 223 | 252 | 376 |
| | Time of Max dP/dt | 06:14 | 18:02 | 06:07 | 00:15 |
| | Min dP/dt , [W/min] | -483 | -256 | -201 | -444 |
| | Time of Min dP/dt | 06:29 | 18:22 | 06:25 | 06:47 |
| Net Import | Max dP/dt , [W/min] | 332 | 540 | 272 | 376 |
| | Time of Max dP/dt | 06:14 | 13:10 | 12:07 | 00:15 |
| | Min dP/dt , [W/min] | -483 | -571 | -268 | -444 |
| | Time of Min dP/dt | 06:29 | 13:03 | 10:01 | 06:47 |

Discussion and Conclusions

Metrics have been discussed that aim to characterize the power performance of net-zero homes in hopes of shedding light on how they would integrate into an electric grid or incorporate local battery storage. Table 6 summarizes some of the most basic metrics and provides their values for the home studied in this manuscript during the winter and summer meteorological seasons. While a single home will not necessarily have a great impact on the electric grid,

metrics such as these could help in developing bottom-up models of the projected impact of groups of net-zero and near-zero energy homes on the distribution system and could guide efforts to incorporate demand response or energy storage to stabilize the grid. Furthermore, identification of the key contributors to peak loads as described in this paper through averaging the power inputs from end uses during peak power measurements and ranking those factors through univariate selection approaches will help identify equipment that could be controlled in load shedding algorithms. Other metrics not listed in this table are less intuitive, but can provide valuable information. An example of one such metric presented was the auto-correlation with a lag of one, which can provide an estimate of the “bumpiness” of the power profile that could impact power quality.

Information provided for this net-zero house are provided only as an example; collection of similar metrics for homes across a broad level of energy efficiency will help to better understand requirements to supply power to net-zero and near-zero energy homes and remove a potential barrier for their integration into the power system.

Table 6. Key Metrics for Power Performance of a Home and Sample Values from the NZERTF.

| Metric | Value for NZERTF (Winter // Summer) |
|--|--|
| Peak Overall Power Use | 11.2 kW // 10.3 kW |
| Peak Power Export to Grid | 9.6 kW // 9.5 kW |
| Time of Peak Power Use for Most Typical Day (By Season) | 06:39 // 18:09 |
| Time of Peak Power Export to Grid for Most Typical Day (By Season) | n.a. // 13:08 |
| Peak Absolute Time Rates of Change of Power for Most Typical Day | 444 W•min ⁻¹ // 256 W•min ⁻¹ |
| Time of Peak Absolute Rate of Power Change for Most Typical Day | 06:47 // 18:22 |
| Key Contributors to Peak Power | Heat Pump, Dryer, HPWH // Oven, Dryer, AC |

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