EM&V Report for the Duke Energy 2020/2021 EnergyWise Business Program

Prepared for:

Duke Energy Progress, Duke Energy Carolinas

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Executive Summary

Guidehouse Inc. (Guidehouse) conducted an impact evaluation to estimate demand response (DR) impacts from events occurring in the 2020/2021 season, using participant and non-participant advanced metering infrastructure (AMI) interval data. Guidehouse also performed a separate evaluation in 2020 to estimate energy impacts contributed by participants that received the thermostat between January 2018 and February 2019, using monthly energy consumption data, included in Appendix B

The EnergyWise® Business ("EnergyWise Business") program in the Duke Energy Progress (DEP) and Duke Energy Carolinas (DEC) territories, provides small and medium business customers that consume an average of at least 1,000 kWh per month and have one or more central air conditioning or heat pump units at their facility, with an opportunity to earn bill credits by allowing DEP and DEC to periodically cycle their HVAC equipment during conservation periods (i.e. curtailment or DR events).

In the summer, participating devices may be controlled by DEP and DEC from May through September for up to four hours per event. Events occur on non-holiday weekdays, and in 2021 occurred between 4pm and 7pm. During the curtailment events, the HVAC compressors are typically cycled in 30-minute intervals for the duration of the event. Participants may opt out of up to two events per season. Additional opt-outs may result in the forfeiture of the annual bill credit. Participants who have electric heat pumps with electric resistance auxiliary heat strips can also participate in the winter DR season for an additional $25 bill credit. For the winter 2020/2021 season, events occurred in the morning from 6:30am to 8:30am, around the peak demand hour of 7-8am.

Participants may elect to have curtailment dispatched via thermostat or switch. Participants equipped with the thermostat (the majority) can access the EnergyWise Business portal using a smartphone, tablet, or computer. The portal allows users to monitor and modify their facility HVAC runtimes, change the temperature setpoints, and program customized cooling and heating schedules. The purpose of the portal is to facilitate the adoption of energy efficiency behaviors by participants, specifically the practice of adjusting HVAC setpoints to reduce space heating and cooling energy consumption. The portal includes tips to help participants optimize energy use, including tutorials and preset features for energy efficiency, away times, and vacations.

Over the course of the 2020/2021 DR season, the program had more than 9,000 participants (accounts), in four distinct groups, defined by season (winter or summer) and combinations of selected control strategy (30%, 50%, or 75% cycling) and control device type (thermostat or switch). DEP and DEC called ten DR events, five in winter and five in summer. On average, there were 528 participants (accounts) in winter events and 8,927 in summer events.

Table 1 and Table 2 show average per participant impacts for each of the ten events, by energy provider, for the winter and summer seasons respectively. These estimated impacts correspond to actually-observed curtailment events – the "ex-post" impacts. In addition to showing per participant impacts, the table also lists event temperatures, relative precision, and total number of participating accounts.

Table 1. Average Per Participant Demand Response Event Impacts, Winter

Event Date	Energy Provider	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Participants (Accounts)
1/11/2021	DEC	33.7	0.88	26.4%	445
1/29/2021	DEC	24.8	1.10	26.4%	448
2/2/2021	DEC	32.7	0.88	26.4%	448
2/4/2021	DEC	25.8	1.07	26.4%	449
3/8/2021	DEC	31.4	0.96	26.4%	463
Average	**DEC**	**29.7**	**0.98**	**26.4%**	**451**
1/11/2021	DEP	33.7	0.88	26.4%	77
1/29/2021	DEP	24.8	1.10	26.4%	77
2/2/2021	DEP	32.7	0.88	26.4%	77
2/4/2021	DEP	25.8	1.07	26.4%	77
3/8/2021	DEP	31.4	0.96	26.4%	77
Average	**DEP**	**29.7**	**0.98**	**26.4%**	**77**

Source: Guidehouse analysis. Values subject to rounding.

Table 2. Average Per Participant Demand Response Event Impacts, Summer

Event Date	Energy Provider	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Participants (Accounts)
5/26/2021	DEC	87.6	1.03	4.9%	6,937
7/28/2021	DEC	89.1	1.10	4.7%	6,281
7/30/2021	DEC	91.4	1.16	4.7%	6,258
8/12/2021	DEC	86.7	1.06	4.7%	6,155
8/24/2021	DEC	91.3	1.18	4.7%	6,137
Average	**DEC**	**89.2**	**1.11**	**4.7%**	**6,354**
5/26/2021	DEP	87.6	1.11	4.4%	2,970
7/28/2021	DEP	89.1	1.21	4.3%	2,520
7/30/2021	DEP	91.4	1.27	4.3%	2,502
8/12/2021	DEP	86.7	1.17	4.3%	2,444
8/24/2021	DEP	91.3	1.30	4.3%	2,432
Average	**DEP**	**89.2**	**1.21**	**4.3%**	**2,574**

Source: Guidehouse analysis. Values subject to rounding.

The estimated total program impacts for each energy provider and event season are shown in Table 3. Average total event impacts are calculated by multiplying the per-participant impacts by the average number of participants across all events, per energy provider and season. Since

Guidehouse used a pooled regression model with DEC and DEP consumption data, impacts are identical by cycling strategy and device type. Therefore, impacts for the winter season are identical for the two energy providers because only one participant group exists in winter (thermostat, complete curtailment). For summer events, results differ by energy provider as a result of differing distributions of customers among cycling strategies and device types. The number of participants in each event varies due to new enrollments, withdrawals, and opt-outs.

Table 3. Aggregate Demand Response Event Impacts by Energy Provider

Event Season	Energy Provider	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Avg # Participants	Total Program Impact (MW)
Winter	DEC	29.7	0.98	26.4%	451	0.4
	DEP	29.7	0.98	26.4%	77	0.1
Summer	DEC	89.2	1.11	4.7%	6,354	7.0
	DEP	89.2	1.21	4.3%	2,574	3.1

Source: Guidehouse analysis. Values subject to rounding.

The estimated per device program impacts by technology type, cycling strategy, and event season (winter/summer) are shown in Table 4. Estimated impacts are identical for the two energy providers because this analysis uses a regression model applied to pooled DEC and DEP consumption data.

Table 4. Average Per Device Demand Response Event Impacts by Technology Type and Cycling Strategy

Event Season	Energy Provider	Technology Type	Cycling Strategy	Impact Per Device (kW)	Relative Precision +/-% (90% Confidence)	Avg # Devices
Winter	DEC	Thermostat	-	0.59	26%	1.66
	DEP	Thermostat	-	0.59	26%	1.66
Summer	DEC	Thermostat	30%	0.49	7%	1.74
			50%	0.92	7%	1.77
			75%	1.06	8%	2.29
		Switch	30%	0.34	45%	1.61
			50%	0.55	31%	1.99
			75%	0.35	96%	2.05
	DEP	Thermostat	30%	0.49	7%	1.74
			50%	0.92	7%	1.77
			75%	1.06	8%	2.29
		Switch	30%	0.34	45%	1.61
			50%	0.55	31%	1.99
			75%	0.35	96%	2.05

Source: Guidehouse analysis. Values subject to rounding.

This report also includes projections of the program's demand response capability under a variety of different temperatures, assuming no change in the composition of the program participants (e.g., no change in the proportion that subscribe to 30% cycling, that use switches, etc.)

Evaluation Methods

Guidehouse's evaluation approach for this report focuses on demand impacts.

Demand Response Impact Evaluation Approach

Guidehouse estimated demand reduction and snapback impacts using a lagged dependent variable regression analysis applied to interval consumption, weather (dry-bulb temperatures), and program tracking data. To maximize the number of participants in each group of device type and cycling strategy, Guidehouse analyzed DEP and DEC customers together.

Guidehouse used a matched comparison group (MCG) to estimate savings. In this approach, non-event days with similar temperatures to the event days are selected. Consumption data on non-event days are used for selecting a comparison group of non-participants that are similar to participants. The underlying assumption is that consumption of similar non-participants informs the baseline demand of participants on event days.

Guidehouse calculated program impacts by multiplying estimated per participant impacts by the average number of participants across all events in a season. Impacts per device were calculated by dividing the per participant results by the average number of devices at each participant site. Similarly, impacts per energy provider were calculated by multiplying estimated per participant impacts by the average number of participants per energy provider across events.

Based upon the regression estimated relationships between DR impacts and outdoor temperature from which the above impacts were developed, Guidehouse estimated an ex-ante forecast of event impacts. Ex-ante estimates are Guidehouse's projection of how much DR the program could offer under a range of different possible temperatures at different cycling levels, for the different technologies and event day types. This forecast of capability provides an estimate of a given DR program's value as a system resource and how much of a demand reduction the program may be counted on to deliver in future system peak conditions.

Findings and Recommendations

The principal EM&V findings and recommendations regarding the estimated demand impacts are as follows:

- **On average, the program delivered approximately 0.5 MW of load curtailment during winter events, and approximately 10.1 MW of load curtailment during summer events.** For DEC, this amounts to 0.4 MW of estimated load curtailment in winter and 7 MW of estimated load curtailment from in summer. Estimated load curtailment for DEP is approximately 0.1 MW in winter and 3.1 MW in summer. The program-level impacts for each event vary depending on the number of participants, the temperature, and other factors.

- **On average, the program delivered nearly 1 kW of demand response per participant during winter events, and over 1.1 kW of demand response per participant during summer events.** For DEC, this amounts to 0.6 kW of demand response per device in both winter and summer. Estimated curtailment per device for DEP is approximately 0.6 kW per device in winter and 0.7 kW per device in summer.

- The results of the ex-post evaluation informed the development of ex-ante forecast of program capability across a range of temperatures at different cycling levels, which can be used for calculating benefits for cost-effectiveness tests. For summer events at an assumed temperature of 95°F, ex-ante impacts are estimated to be 0.8 kW per thermostat device and 0.5 kW per switch device. During winter events at an assumed temperature of 20°F, thermostats are estimated to deliver 0.7 kW of curtailment per device.

- **Thermostats deliver greater relative impacts for events in both seasons compared to load control switches. While no switch impacts were measured for winter events, thermostat impacts are materially higher than switch impacts during summer events.** On average across cycling strategies, thermostats delivered demand reductions during summer events of 13% of total facility baseline load, and switches 8%. During winter events, thermostats deliver demand reductions of approximately 14% of total facility baseline load. According to Duke program staff, this may be because participants with switches tend to have smaller HVAC equipment.

- **Participants that have selected the 75% cycling strategy deliver the highest per participant impacts for summer events.** During summer events, 75% cycling strategy participants deliver an average impact equivalent to 27% of their estimated facility baseline demand. In contrast, 30% and 50% cycling strategy participants delivered an average impact of approximately 9% and 19% of their baseline demand, respectively.

Based on the impact findings above, Guidehouse recommends that Duke Energy consider the following recommendations:

- **Consider using future process evaluations to better understand differences in businesses that enroll in each cycling strategy.** Consistent with expectations, Guidehouse estimated significantly greater savings for participants enrolled in the 75% cycling strategy during demand response events than for the 30% and 50% cycling strategies. Because of the high impact being delivered, Duke Energy may want to further explore characteristics of this group of participants to better target similar businesses in the future, through participant surveys or interviews.

- **Continuing to evaluate the program on an annual basis, particularly if enrollment changes in any material way.** The total number of enrolled participants is over 9,000, and the energy use at commercial facilities is generally more heterogeneous than at residential facilities. This means that the average participant (and aggregate program) impacts and capability could change materially as a result of relatively modest changes in the absolute number of participants enrolled, or if the distribution of participants across cycling strategies shifts. Duke Energy should carefully consider this when using the capability estimates provided above for any planning exercises.

1. Introduction

The EnergyWise® Business ("EnergyWise Business") program in the Duke Energy Progress (DEP) and Duke Energy Carolinas (DEC) territories, provides small and medium business customers that consume an average of at least 1,000 kWh per month and have one or more central air conditioning or heat pump units at their facility, with an opportunity to earn bill credits by allowing DEP and DEC to periodically cycle their HVAC equipment during conservation periods (i.e. curtailment or demand response events).

Upon enrollment, eligible participants select to receive either: (1) a "smart" Wi-Fi communicating thermostat[1] capable of remote set-point adjustment, (2) or a switch device, to allow DEP and DEC to cycle the participant's HVAC during DR events. The switch device may be either Wi-Fi connected or cellular. Participants may select one of three options for participating:

- 30% Cycling - Participants receive an annual bill credit of $50 per device controlled for the summer season.
- 50% Cycling - Participants receive an annual bill credit of $85 per device controlled for the summer season.
- 75% Cycling - Participants receive an annual bill credit of $135 per device controlled for the summer season.

In the summer, participating devices may be controlled by DEP and DEC from May through September, for up to four hours per event. Events occur on non-holiday weekdays and in 2022, occurred between 4pm and 7pm. During the curtailment events, the HVAC compressors are cycled in 30-minute intervals for the duration of the event. Participants may opt out of up to two events per season. Additional opt-outs may result in the forfeiture of the annual bill credit. Participants with electric heat pumps or electric resistance heating can also participate in the winter DR season for an additional $25 bill credit. For the winter season, events occurred in the morning from 6:30am to 8:30am, around the peak demand hour of 7 to 8am.

Participants with the thermostat can access the EnergyWise Business portal using a smartphone, tablet, or computer. The portal allows users to monitor and modify their facility HVAC runtimes, change the temperature setpoints, and program customized cooling and heating schedules. The purpose of the portal is to facilitate the adoption of energy efficiency behaviors by participants, specifically the practice of adjusting HVAC setpoints to reduce space heating and cooling energy consumption. The portal includes tips to help participants optimize energy use, including tutorials and preset features for energy efficiency, away times, and vacations.

1.1 Objectives of the Evaluation

The key objectives for the impact analysis of this evaluation, as identified in Guidehouse Inc.'s (Guidehouse) evaluation plan, include:

- **Demand Response Impacts:** estimate the demand response impacts for events called by the program during 2020/2021 DR season and provide estimates of curtailment capability

[1] Note that this is not an "adaptive" thermostat.

for a range of temperatures (with emphasis on impacts coincident with DEC/DEP seasonal system peaks).

- **Energy Efficiency Impacts:** estimate the annual energy efficiency impacts for participants who have a thermostat and enrolled in the program between January 2018 and February 2019 (included in this report as Appendix B).

1.2 Reported Program Participation

1.2.1 Demand Response Enrollment

Enrollment for the demand response program extended from 2016 into 2021, as participants are eligible to enroll at any time, upon installation of a thermostat or switch device. Over 9,000 accounts participated in at least one event in the 2020/2021 season. Of these, close to 550 accounts also opted into the winter event season. Most participants enrolled in the 30% cycling strategy with the smart thermostat control technology. All winter participants and 94% of summer participants have the smart thermostat. The distribution of the average number of participants included in the analysis by energy provider, technology type, and cycling strategy is summarized in Table 1-1.

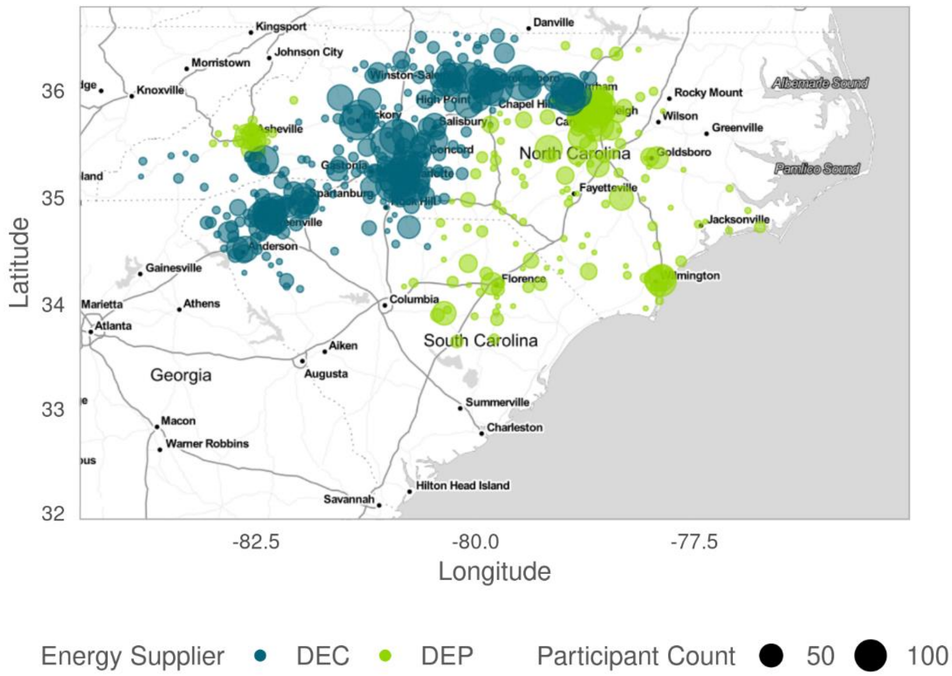
Table 1-1. Distribution of Participants by Cycling Strategy and Technology

Event Season	Energy Provider	Device Type	Cycling Strategy	Participants (Accounts)
Winter	DEC	Thermostat	-	463
	DEP	Thermostat	-	77
Summer	DEC	Thermostat	30% Cycling	5,232
		Thermostat	50% Cycling	928
		Thermostat	75% Cycling	601
	DEP	Thermostat	30% Cycling	248
		Thermostat	50% Cycling	92
		Thermostat	75% Cycling	72
	DEC	Switch	30% Cycling	1,898
		Switch	50% Cycling	653
		Switch	75% Cycling	280
	DEP	Switch	30% Cycling	130
		Switch	50% Cycling	40
		Switch	75% Cycling	27

Source: Guidehouse analysis of Duke Energy data

Figure 1-1 shows the geographic distribution of participants. Most installations occurred around cities including Charlotte and Raleigh, although participation was achieved throughout the service territories.

Figure 1-1. Geographic Distribution of Participants



Source: Guidehouse Analysis of Duke Energy data

2. Evaluation Methods

2.1 Demand Response Impact Methodology

Guidehouse estimated demand reduction and snapback impacts using a lagged dependent variable regression analysis applied to interval consumption, weather (dry-bulb temperatures), and program tracking data. To maximize the amount of participants in each group of device type and cycling strategy, Guidehouse analyzed DEP and DEC customers together.

Guidehouse used a matched comparison group (MCG) to estimate savings. In this approach, non-event days with similar temperatures to the event days are selected. Consumption data on non-event days are used for selecting a comparison group of non-participants that are similar to participants. The underlying assumption is that consumption of similar non-participants informs the baseline demand of participants on event days.

Guidehouse estimated both ex-post and ex-ante impacts. Ex-post impacts are the average impacts of observed (historical) events. Ex-ante impacts are projections of the program's capability at a range of different temperatures. This forecast of capability provides the truest estimate of a given DR program's value as a system resource because it provides DEC and DEP staff with an understanding of how much of a demand reduction the program may be counted on to deliver in future system peak conditions.

2.1.1 Participant, Event, and Weather Data

For the demand response evaluation, Guidehouse used the following data provided by Duke Energy:

- AMI consumption (kWh) data in 30 minute intervals, for DEC and DEP participants and non-participants
- A list of participants, including enrollment dates, technology, cycling strategy, and changes over the season
- Event reports for all 2020/2021 events, including cycling strategy, and event times
- Opt-out reports for each event, indicating which customers did not participate in each event
- Program disenrollment data for all participants

In total, Duke Energy called ten events, including five events in winter and five events in summer. Listed in Table 2-1, all events were on weekdays and included the hour coincident with the seasonal system peaks for the DEP and DEC territories (7 – 8 AM in winter, 4 – 5 PM in summer).

Table 2-1. 2020/2021 Events and Average Temperatures

Event Date	Season	Start	End	Average Event Temperature (°F)
1/11/2021	Winter	6:30 AM	8:30 AM	33.7
1/29/2021	Winter	6:30 AM	8:30 AM	24.8
2/2/2021	Winter	6:30 AM	8:30 AM	32.7
2/4/2021	Winter	6:30 AM	8:30 AM	25.8
3/8/2021	Winter	6:30 AM	8:30 AM	31.4
5/26/2021	Summer	4:30 PM	6:30 PM	87.6
7/28/2021	Summer	4:00 PM	6:00 PM	89.1
7/30/2021	Summer	4:00 PM	6:00 PM	91.4
8/12/2021	Summer	4:00 PM	6:00 PM	86.7
8/24/2021	Summer	4:00 PM	6:00 PM	91.3

Source: NOAA

Guidehouse collected hourly dry-bulb temperature data for the period of November 2020 through September 2021 from eight weather stations across the Carolinas and developed a weighted average hourly time series for the analysis based on the number of participants closest to each station, per season. This time series was then used in subsequent matching and modeling to estimate demand response event impacts. The stations and corresponding weights are listed in Table 2-2.

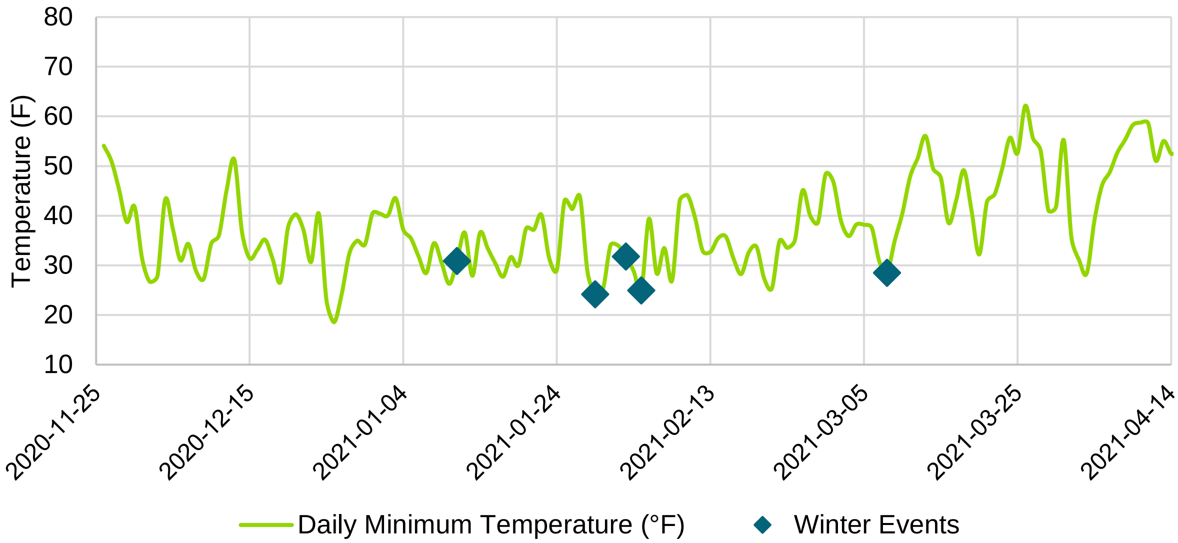
Table 2-2. Weather Stations and Weighting Used for Demand Response Analysis

Weather Station	Weight (Winter Events)	Weight (Summer Events)
Charlotte Douglas International Airport	32%	25%
Raleigh-Durham International Airport	7%	22%
Piedmont Triad International Airport	26%	17%
Spartanburg Downtown Memorial Airport	15%	15%
Hickory Regional Airport	11%	6%
Asheville Regional Airport	3%	6%
Fayetteville Regional Airport	2%	5%
Wilmington International Airport	2%	4%

Source: Guidehouse analysis of Duke Energy data and NOAA data

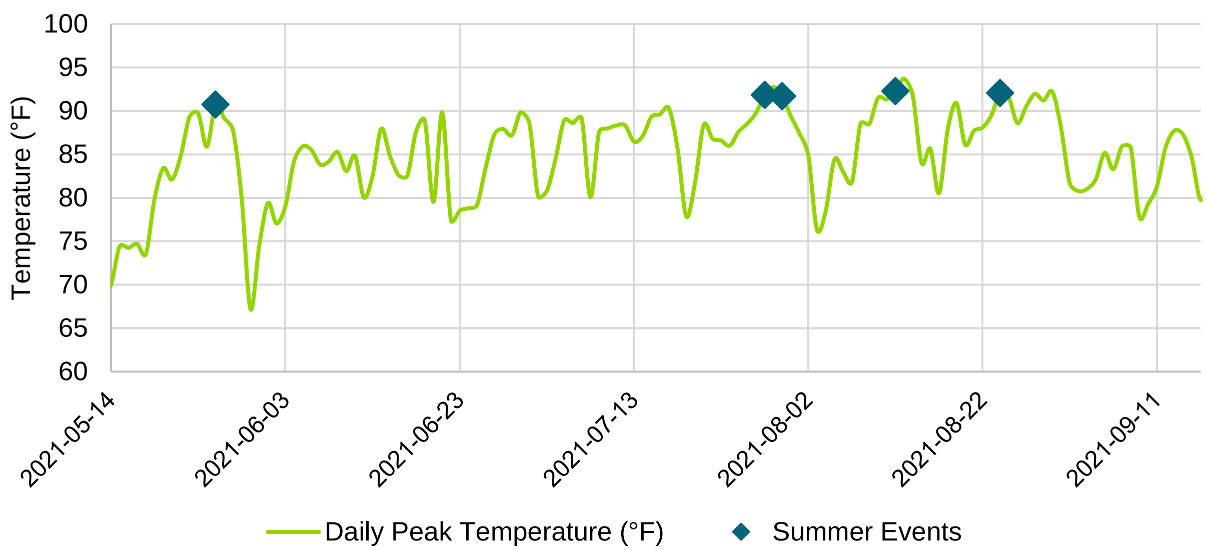
For winter events, daily minimum temperatures were similar for all event days, between 24°F and 32°F. Daily peak temperatures for summer event days ranged from 90°F to 93°F. As illustrated in Figure 2-1 and Figure 2-2, events took place on days with some of the most extreme temperatures of the season.

Figure 2-1. Daily Minimum Temperatures for the 2021 Winter Demand Response Season



Source: Guidehouse analysis and NOAA data

Figure 2-2. Daily Peak Temperatures for the 2021 Summer Demand Response Season



Source: Guidehouse analysis and NOAA data

For DR Impacts, Guidehouse used a single model combining both DEP and DEC participants. This method was used to maximize the number of participants – and therefore confidence and precision of estimates – for certain groups with few participants (e.g. those with a switch in the 75% cycling strategy). Table 2-3 lists the number of participants who participated in at least one event for each event type, technology, and cycling strategy. Most participants were in the thermostat, 30% cycling group. A small number of participants switched cycling strategies or withdrew from the program, and participants may have opted-out of as many as two events during the season without penalty. The most opt-outs occurred on August 12, specifically 123 out of 8,193 thermostat participants and 1 out of 583 switch participants.

Table 2-3. Participants by Event Season, Technology, and Cycling Strategy

Season	Technology	Cycling Strategy	Participants* (Accounts)
Winter	Thermostat	-	540
Summer	Switch	30%	378
		50%	132
		75%	99
	Thermostat	30%	7,130
		50%	1,581
		75%	881

Source: Guidehouse analysis of Duke Energy data

* The number of participants that participated in at least one event for a given event type, technology, and cycling strategy. Participation varies between events due to different enrollment dates, opt-outs, drop-outs, deactivations, or changes in cycling strategy and/or technology. Forty-seven participants had a mix of both thermostats and switches and were excluded from the analysis as impacts could not be distinguished between the different technologies.

Guidehouse reviewed the data to ensure its completeness, identifying any gaps or potential outlier data, and addressing any issues accordingly. After review of the AMI data provided by Duke Energy, Guidehouse found that interval data was not available for all customers on all days. Table 2-4 lists the number of participants that were found to be missing some data (e.g. one or more days in the season) for each technology, cycling strategy, and event type. Generally, these participants were missing data for one event, and so were still included in Guidehouse's analysis for all other events. Across all groups, 707 customers lacked AMI data throughout the entire period of analysis; however, around 80% of these 707 accounts deactivated after the first event, so are only missing data for a single day of analysis.

Table 2-4. Participants with Some Missing ~~Some~~ Interval Data

Event Season	Technology	Cycling Strategy	Participant Accounts with Missing Usage Data	% of Accounts
Winter	Thermostat	-	10	2%
Summer	Thermostat	30%	709	10%
		50%	64	4%
		75%	37	4%
	Switch	30%	37	10%
		50%	11	8%
		75%	15	15%

Source: Guidehouse analysis of Duke Energy data

The vast majority of missing data is attributed to a lack of AMI data. Participants also may have been missing data on specific event days and/or the corresponding matched non-event day. Missing data could occur for different reasons, for example: a participant may not have an AMI meter installed (i.e., missing data for the entire season); or if database or meter read errors occurred for some days. Customers that were missing data were not included when estimating average per participant impacts; however, Guidehouse included these participants when scaling per participants impacts by total participation in each event to calculate aggregate per participant impacts. This method assumes that those participants with AMI data (the majority) are representative of those without.

2.1.2 Selecting a Matched Control Group

Selecting an appropriate matched control group for participants in the program involves two steps: (1) selecting matched non-event days; and (2) selecting a non-participant match for each participant based on a comparison of participant and non-participant demand patterns on the matched non-event days.

Guidehouse first selected a matched non-event day for each event day. This process involves finding the non-holiday, non-event weekday in the DR season that most closely matches the 24 hour temperature profile of each event day. Guidehouse calculated the Euclidean distance in temperature for all 24 hours between each event day and all potential non-event day candidates. Guidehouse then selected the top three non-event days associated with the lowest values. Matches are selected with replacement, meaning that a given non-event day could be matched to multiple event days. Under the circumstance that a customer is missing data for the best match for a given event day, the next best match day was used.

Table 2-5 lists the top matched non-event date selected for each 2021 event date. Figure 2-3 shows an example for the event occurring on August 24, 2021, which was matched to August 30, 2021. The similarity in weather profile across all 24 hours suggests that the demand of participants would be similar between both days in absence of a DR event. Therefore, the selected non-event day serves two purposes: (1) serving as a predictor of demand on event days; and (2) providing an “event-like” non-event day with which to select appropriate non-participants that are most like participants.

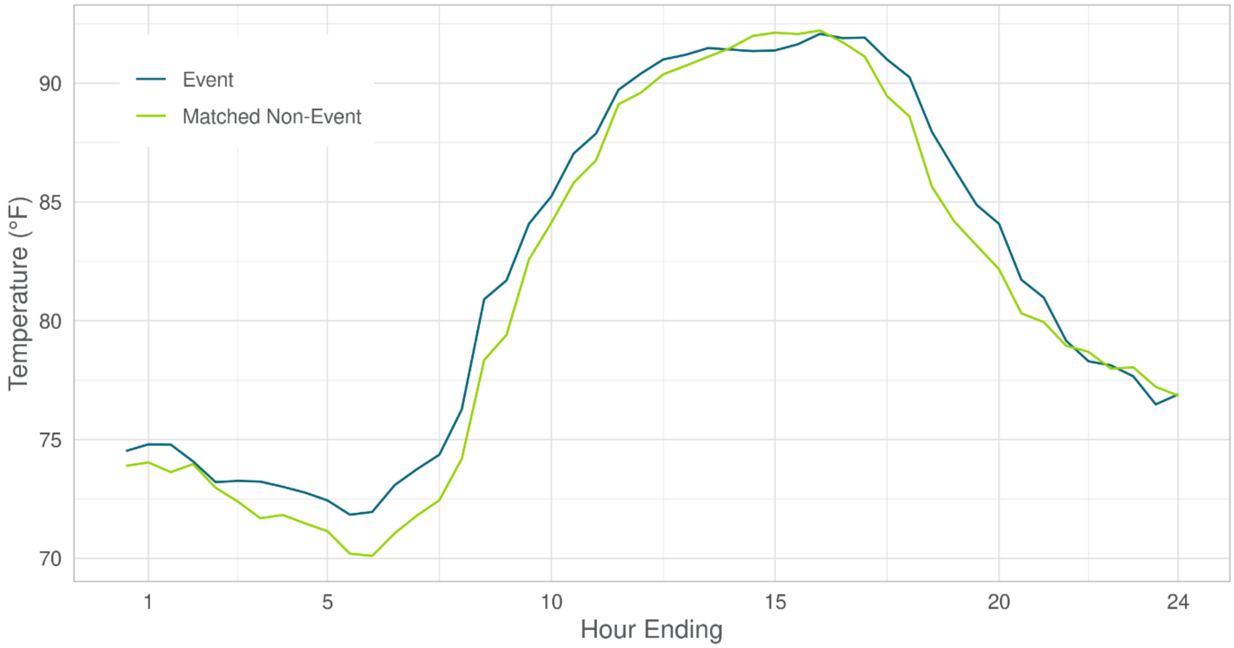
Table 2-5. Top Matched Non-Event Date for Each 2021 Demand Response Event Date

Event Season	Event Date	Top Matched Non-Event Date
Winter	1/11/2021	12/15/2020
	1/29/2021	12/8/2020
	2/2/2021	1/28/2021
	2/4/2021	2/8/2021
	3/8/2021	2/23/2021
Summer	5/26/2021	5/27/2021*
	7/28/2021	8/30/2021
	7/30/2021	7/29/2021
	8/12/2021	8/10/2021
	8/24/2021	8/30/2021

Source: Guidehouse analysis and NOAA data

* For the event on May 26, 2021, match days were limited to other days in May to ensure a more representative match was selected. Although the most similar weather to this event day occurred in later months, behavioral changes occur in usage patterns from early to late summer. As a result, selecting another day in May more accurately controls for unobserved factors that may impact demand.

Figure 2-3. Hourly Temperatures for Event (2021-08-24) and Matched Non-Event (2021-08-30)



Source: Guidehouse analysis of Duke Energy data

After identifying matched non-event dates, Guidehouse identified a non-participant match for each program participant. Selecting a match for a given participant means finding the non-participant whose usage across all selected non-event days is most like the participants usage. For each participant, the process includes the following steps:

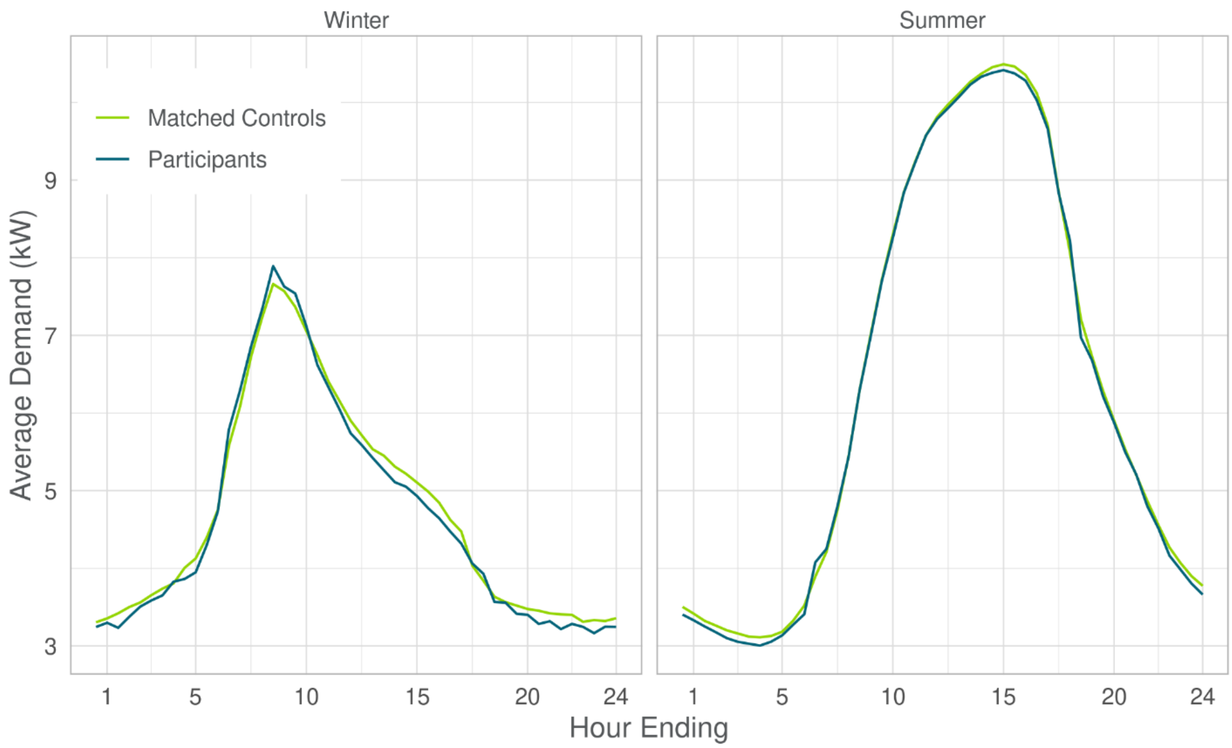
1. Calculate the average 24-hour usage profile across all matched non-event days.
2. Calculate the average 24-hour usage profile for each non-participant across all matched non-event days.
3. Calculate the Euclidean distance[2] between the participant usage profile and each non-participant usage profile.
4. Select the non-participant associated with the lowest value (i.e., the one whose profile is most similar to the participant being matched).

Matches are selected with replacement, meaning that a non-participant may be matched to multiple participants.

[2] Euclidean distance is calculated by taking the square root of the sum of squared differences between the two vectors (participant and non-participant demand over 24 hours).

Figure 2-4 shows a comparison in average usage profiles between all participants and their selected matches for all winter and summer selected non-event days. Overall, the matches and participants showed similar usage profiles in both event seasons. For example, for summer events, the participants and matches have very similar profiles over all hours. The matching process does not (and is not expected to) deliver an exact match between participant and control group demand on non-event days – some deviations between average participant and control demand patterns are inevitable. For example, for winter events, participants show consistent, slightly lower usage between hours ending 10 and 18.

Figure 2-4. Average Demand for Participants and Matched Controls by Event Season



Source: Guidehouse analysis of Duke Energy data

The process of matching is not expected to produce perfect controls, but instead to find the closest non-participants possible. Small businesses tend to exhibit heterogenous usage patterns, meaning that very few customers will have an exact match among the non-participant population. To account for any remaining differences between participants and their matched controls, Guidehouse employed a lagged dependent variable model in the regression analysis described in Section 2.1.3. This method relies on the assumption that any differences between participants and matched controls on non-event days is consistent with the differences that would be expected on event days, precisely the reason why the most weather-similar non-event days are selected for matching.

2.1.3 Estimating Ex-Post and Ex-Ante DR Impacts

Guidehouse estimated 7 sets of ex-post impacts: one set for winter and one set for each summer event combination of technology (thermostat and switch); and cycling strategy (30%, 50%, and 75%). Guidehouse aggregated these granular impacts to present impacts by event season, by technology, and by cycling strategy[3]. To maximize the sample size, Guidehouse used a pooled regression model combining both DEC and DEP data. As a result, at the per participant level by technology and cycling strategy, impacts are identical for the two energy providers. To estimate impacts, Guidehouse used a lagged dependent variable model, that estimates customer load on a per participant basis as a function of the event hours, snapback in post-event hours, lagged non-event day usage, temperature, humidity, and hourly fixed effects. Only event day data is included in the regression model, although matched non-event day data informs the baseline through the lagged usage variable.

Lagged non-event day usage refers to including directly in the regression equation usage for each customer (participants and non-participants) and event day from the corresponding matched non-event day. For example, for a given customer in half-hour-ending 13 on the first event day, then this variable would take the value of that same customer's consumption in half-hour-ending 13 of the corresponding non-event day used for matching purposes.

Guidehouse used six different temperature variables in the current analysis, dependent upon the event season impacts being estimated. For winter events, the following weather variables were used:

- Heating degree hours, base 65°F (HDH65) – accounts for the contemporaneous temperature during each interval (i.e. half hour) of an event;

- 3-hour exponential moving average of HDH65 – accounts for short-term temperature history and mitigates the effect of rapid temperature variations, such as storms;

- 72-hour cold buildup term – accounts for long-term temperature history, and incorporates the effect of consistently low temperatures, such as a cold spell, that increase heating demand.

For summer events, the following weather variables were used:

- Cooling degree hours, base 65°F (CDH65) – accounts for the contemporaneous temperature during each interval (i.e. half hour) of an event;

- 3-hour exponential moving average of CDH65 – accounts for short-term temperature history and mitigates the effect of rapid temperature variations, such as storms;

- 72-hour heat buildup term – accounts for long-term temperature history, and incorporates the effect of consistently high temperatures, such as a heat wave, that increase cooling demand.

Formal model specifications with additional input variable detail may be found in Appendix A.

All estimates of uncertainty presented in this report are derived from standard errors that have been clustered at the individual participant level. Since the current analysis includes estimating impacts relative to baseline usage on matched non-event days, the DR impacts can be considered as incremental relative to any demand savings realized through consistent shifts in

[3] Cycling strategy is not relevant for winter analysis, as all customers are controlled in the same way.

participant behavior (e.g., changes in programmed setpoints) associated with the installation of the technology.

For winter events, Guidehouse estimated ex-ante impacts for the temperature range of 20°F to 40°F based on the range of observed minimum temperatures on event days which were between 24°F and 32°F. For summer events, Guidehouse estimated ex-ante impacts for the temperature range of 85°F to 95°F based on the range of observed peak temperatures on event days which were between 90°F and 93°F. The ex-ante estimates leverage this temperature range and the impact parameter estimates from the ex-post impact regression analysis for hour ending 8 and hour ending 17, for winter and summer events, respectively. Finally, the ex-ante estimate for a given temperature X assumes that temperature has remained constant for at least the previous 3 hours. This assumption is a construction of the regression model that uses the 3-hour exponential moving average of CDH65 or HDH65 which mitigates sudden changes in temperature.

Ex-ante estimates will be highly sensitive to the range of event temperatures and the characteristics of participant, so should be considered prudently. The range of event day temperatures for this evaluation was relatively narrow, particularly for summer events. There were also several technology and cycling strategy groups (e.g. switches in all cycling groups) where the number of enrolled participants was small with fewer than 150 participants. These small sample sizes mean that there is higher uncertainty in these impact estimates. Finally, impacts could be altered by future enrollment. A considerable portion of participants were medium-size customers with peak demand greater than 30 kW. Since most customers have peak demand around 10 kW, these larger customers can influence results. Enrollment of additional large customers could also generate different impacts.

3. Impact Findings

This chapter provides a detailed summary of the impact findings, and is divided into five sections:

- **Demand Response Events – Ex Post Impacts.** This section provides the estimated impacts of A/C curtailment during the ten demand response events observed in 2020/2021.

- **Forecast Curtailment Capability – Ex-Ante Impacts.** This section provides the estimated DR capability of load curtailment across a variety of different temperatures.

- **Net to Gross.** This section describes the assumptions informing the net-to-gross ratio applied in this evaluation.

3.1 Demand Response Events – Ex Post Impacts

The ex-post impacts are the estimated impacts for the actual events that were called during the 2020/2021 winter and summer DR seasons. This section is divided into 2 sub-sections.

1. **Winter Event Impacts.** Provides a summary of the estimated impacts for winter events.

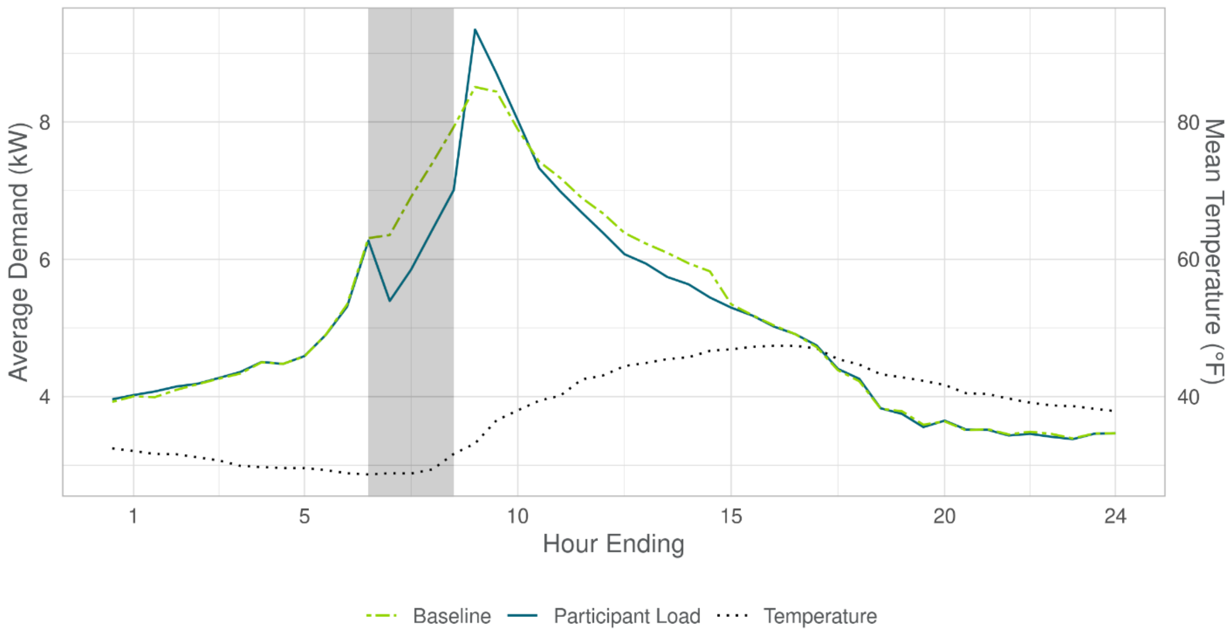
2. **Summer Event Impacts.** Provides a summary of the estimated impacts for summer events overall, as well by the two types of control technology (thermostat and switch) and three cycling strategies (30%, 50%, and 75%)

3.1.1 Winter Event Impacts

During the 2020/2021 winter DR season, five events were called. Because all participants enrolled with the same load control technology (thermostat) and same cycling strategy (i.e. complete curtailment of auxiliary electric resistance heat), impacts do not require summarization by technology type or cycling strategy.

Figure 3-1 illustrates the average hourly load and average participant in winter. In this figure, average observed demand is represented by the dark blue solid line. The dashed green line represents the regression-estimated baseline. A clear reduction in load occurs during event hours, as represented by the light gray shading.

Figure 3-1. Event Day Load Profiles – Winter



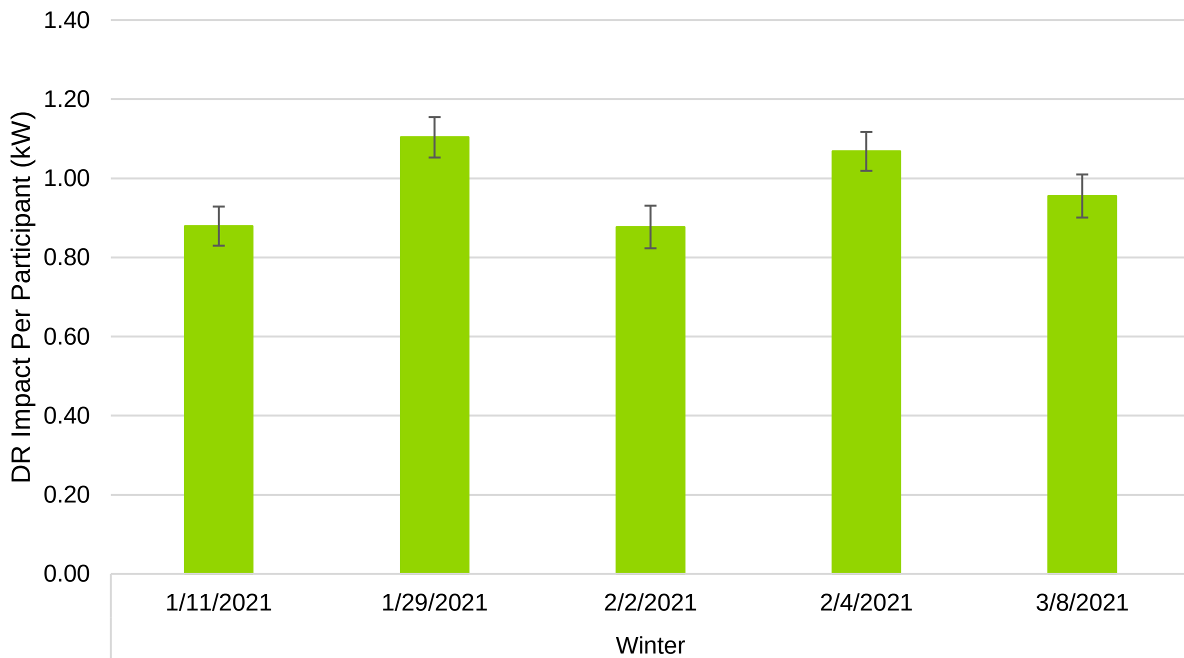
Source: Guidehouse analysis of Duke Energy data

In addition to the depth and shape of the DR impact, the snapback is noteworthy. "Snapback" is the term typically applied in demand response evaluation to the increase in loads observed in the period immediately following a curtailment event.

As visible in Figure 3-1, observable snapback occurs following winter events. In electric heat pump or electric resistance heating curtailment programs, this effect is driven by the indoor temperature falling below the thermostat setpoint during the event, leading to increased heating demand when the event is over.

Figure 3-2 shows the average DR impact per participant by event. In addition to showing the average impact per participant on each date, this plot shows the 90% confidence interval, represented by the whiskers straddling to top of each column.

Figure 3-2. Average Impact Per Participant Per Event - Winter



Source: Guidehouse analysis of Duke Energy data

Per participant and aggregate impacts are presented in Table 3-1 and Table 3-2. These impacts are identical for the two energy providers for winter events, because there is only one technology and control strategy, and the regression model includes both energy providers, described in Section 2.1.3. In addition to the per-participant impacts and the aggregate program impact for each event, these tables also show relative precision, as well as the average impact across events. Total program impacts reflect the larger number of DEC participants than DEP participants, who deliver average load curtailment of 0.4 MW and 0.1 MW per event, respectively.

Table 3-1. Impact by Event – Per Participant and in Aggregate, DEC

Event Date	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Participants (Accounts)	Total Program Impact (MW)
1/11/2021	33.7	0.88	26.4%	445	0.39
1/29/2021	24.8	1.10	26.4%	448	0.49
2/2/2021	32.7	0.88	26.4%	448	0.39
2/4/2021	25.8	1.07	26.4%	449	0.48
3/8/2021	31.4	0.96	26.4%	463	0.44
Average	**29.7**	**0.98**	**26.4%**	**451**	**0.44**

Source: Guidehouse analysis of Duke Energy data

Table 3-2. Impact by Event – Per Participant and in Aggregate, DEP

Event Date	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Participants (Accounts)	Total Program Impact (MW)
1/11/2021	33.7	0.88	26.4%	77	0.07
1/29/2021	24.8	1.10	26.4%	77	0.08
2/2/2021	32.7	0.88	26.4%	77	0.07
2/4/2021	25.8	1.07	26.4%	77	0.08
3/8/2021	31.4	0.96	26.4%	77	0.07
Average	**29.7**	**0.98**	**26.4%**	**77**	**0.08**

Source: Guidehouse analysis of Duke Energy data

Impacts are also presented on a per device basis in Table 3-3, below. Per device impacts are computed as estimated impact divided by the average number of devices per participant. The average number of devices, in this case thermostats, per participant was 1.66. The maximum number of devices observed for any participant in the winter season was 23.

Table 3-3. Impact by Energy Provider Per Device

Event Season	Energy Provider	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)*	Impact Per Device (kW)	Avg. # Devices
Winter	DEC	0.98	26%	0.59	1.66
	DEP	0.98	26%	0.59	1.66

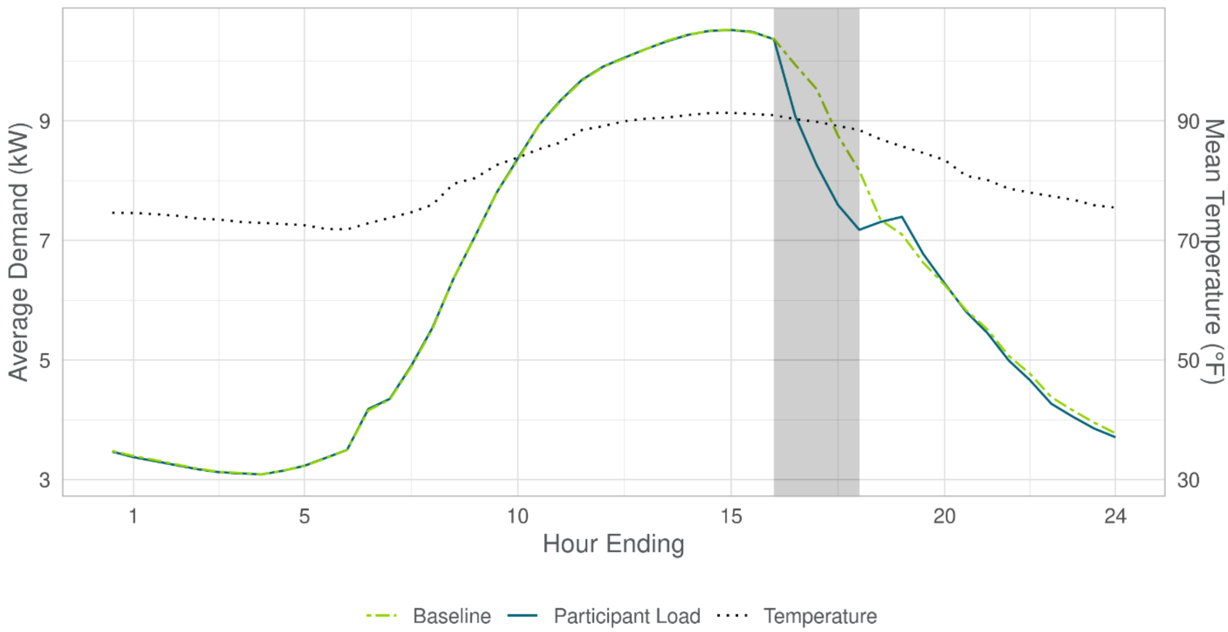
Source: Guidehouse Analysis of Duke Energy data
** Relative precision applies to impact per participant.*

3.1.2 Summer Event Impacts

Guidehouse estimated summer event impacts for each combination of device type (thermostat or switch) and cycling strategy (30%, 50%, or 75%), using a pooled regression model including both DEP and DEC participants. The results are therefore identical across energy providers at the participant, device type and cycling strategy level.

Figure 3-3 illustrates the average hourly load and average participant in summer. In this figure, average observed demand is represented by the dark blue solid line. The dashed green line represents the regression-estimated baseline. A clear reduction in load occurs during event hours, as represented by the light gray shading.

Figure 3-3. Event Day Load Profiles – Summer



Source: Guidehouse analysis of Duke Energy data

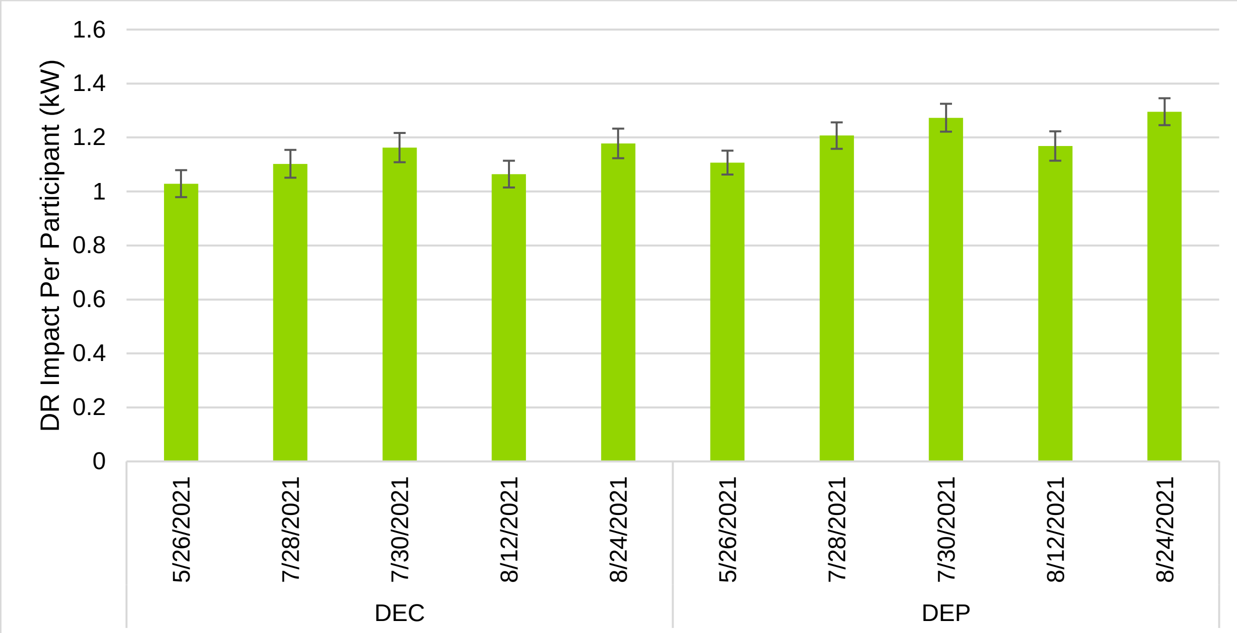
In addition to the depth and shape of the DR impact, the snapback, or lack thereof is noteworthy here. In air-conditioning curtailment programs, this effect is driven by the increased indoor temperature rising above the thermostat setpoint requiring the compressor to run more than it usually would when the event is over.

As may be seen in the plot above, almost no snapback occurs following summer events. This is a commonly observed phenomenon in A/C direct load control programs for small and medium businesses[4] and is typically because curtailment events tend to end as most businesses start to close for the day. In addition, summer event temperatures were relatively low compared to past evaluation years, which may have prevented indoor temperature from rising as far above the thermostat or switch setpoint during events as it would have given higher outdoor temperatures.

Figure 3-4, below, plots the average DR impact per participant by event and energy supplier. In addition to showing the average impact per participant on each date, this plot shows the 90% confidence interval, represented by the whiskers straddling to top of each column. Impacts differ slightly for the two energy providers, due to differing distributions of participants across cycling strategies and device types.

[4] See for example
Navigant, prepared for Southern California Edison, *2014 Load Impact Evaluation of Southern California Edison's Residential and Commercial Summer Discount Plan (SDP) Programs*, March 2015

Figure 3-4. Average Impact Per Participant Per Event - Summer



Source: Guidehouse analysis of Duke Energy data

The impacts presented above are also presented below in tabular form in Table 3-4 and Table 3-5. In addition to the per-participant impacts and relative precision, these tables show the aggregate program impact for each event, as well as the average impact across events. On average, impacts per participant are slightly lower for DEC than DEP, which is attributed to the higher proportion of participants at lower cycling levels (30% cycling and 50% cycling). Total program impacts however, are more than twice as high on average for DEC than DEP, due to higher enrollment numbers for DEC.

Table 3-4. Impact by Event – Per Participant and in Aggregate, DEC

Event Date	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Participants (Accounts)	Total Program Impact (MW)
5/26/2021	87.6	1.03	4.9%	6,937	7.14
7/28/2021	89.1	1.10	4.7%	6,281	6.93
7/30/2021	91.4	1.16	4.7%	6,258	7.28
8/12/2021	86.7	1.06	4.7%	6,155	6.55
8/24/2021	91.3	1.18	4.7%	6,137	7.23
Average	**89.2**	**1.11**	**4.7%**	**6,354**	**7.03**

Source: Guidehouse analysis of Duke Energy data

Table 3-5. Impact by Event – Per Participant and in Aggregate, DEP

Event Date	Avg. Event Temperature (°F)	Impact Per Participant (kW)	Relative Precision +/- % (90% Confidence)	Participants (Accounts)	Total Program Impact (MW)
5/26/2021	87.6	1.11	4.4%	2,970	3.29
7/28/2021	89.1	1.21	4.3%	2,520	3.04
7/30/2021	91.4	1.27	4.3%	2,502	3.19
8/12/2021	86.7	1.17	4.3%	2,444	2.86
8/24/2021	91.3	1.30	4.3%	2,432	3.15
Average	**89.2**	**1.21**	**4.3%**	**2,574**	**3.11**

Source: Guidehouse analysis of Duke Energy data

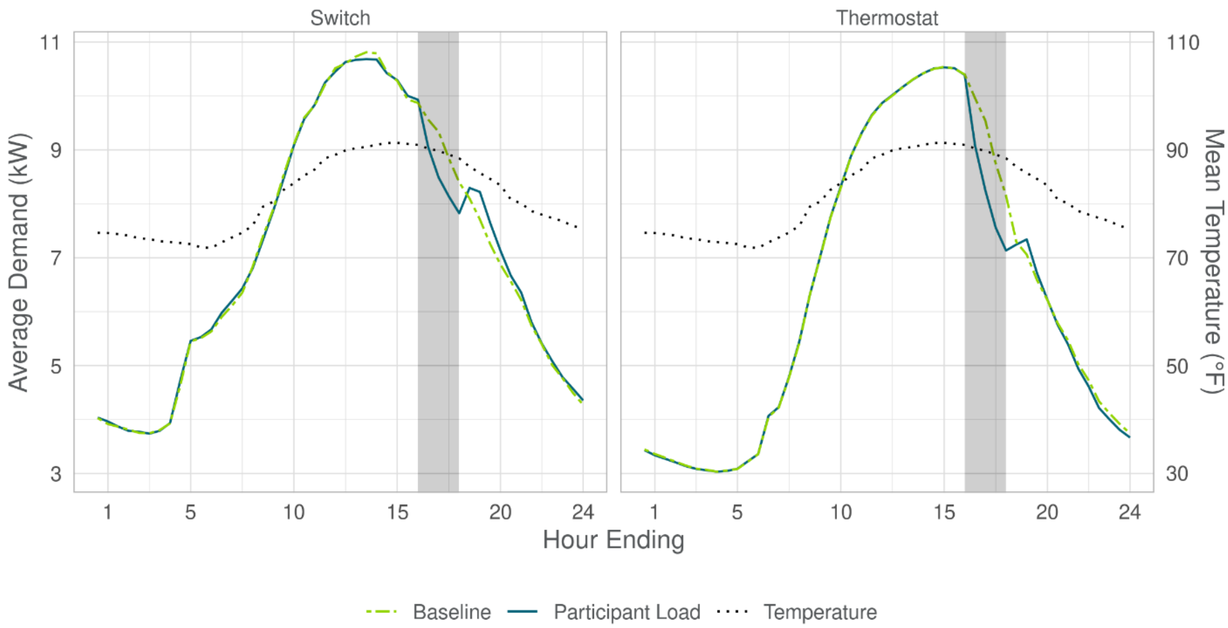
3.1.2.1 Ex-Post Impacts by Technology Type

Participants enrolling in the EnergyWise for Business program for the summer season may select one of two control technologies: a load switch or a smart thermostat. Only customers with a password-protected wireless network may select the thermostat. Overall, far more participants are controlled by thermostat than by switch. As shown in Section 1.2.1, almost 95% of participants in the estimation data set are controlled by thermostat, rather than load switch.

This difference in sample sizes is evident when comparing average load plots of participants, split by device type, during summer events, as shown in Figure 3-5. Specifically, the average demand of the thermostat group is relatively smooth compared with the switch group, reflecting the difference in number of participants (over 8,000 participants have thermostats vs approximately 600 have switches).

Businesses with load switches tend to have a load profile that extends slightly later into the evening than those with thermostats. This is a possible reason why snapback is more apparent for businesses equipped with switches than it is for businesses equipped with thermostats. Even so, snapback for both technologies is relatively low in magnitude.

Figure 3-5. Event Day Load Profiles – Summer Events by Technology Type



Source: Guidehouse analysis of Duke Energy data

The smaller size of the switch sample compared to the thermostat sample for summer events is equally evident in the relative precision of the estimated impacts by technology type as shown in Table 3-6. In addition to presenting the average impact per participant, this table shows the average temperature per event type, the average number of participants that did not opt out of the event, and the aggregate program impact. Differences in per participant impacts across the two energy providers are attributed to the proportion of participants in each cycling strategy group per device type, per energy provider.

Table 3-6. Impact by Technology Type – Per Participant and in Aggregate

Energy Provider	Technology Type	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Avg. Participants (Accounts)	Total Program Impact (MW)
DEC	Thermostat	1.13	5%	5,958	6.75
	Switch	0.71	29%	396	0.28
DEP	Thermostat	1.25	4%	2,383	2.98
	Switch	0.69	29%	190	0.13

Source: Guidehouse analysis of Duke Energy data

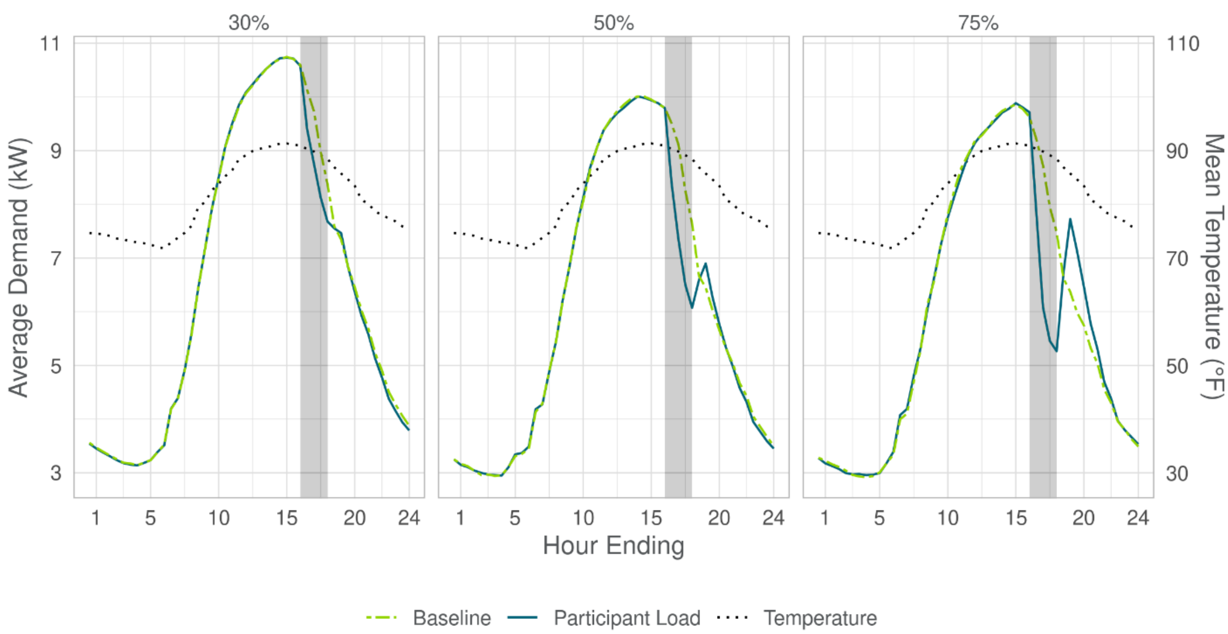
The standard error of an estimated impact – the statistic which delivers the relative precision, or confidence interval, around an impact – is a direct function of the number of observations available. The fewer the observations, the less certain the estimated impact and the wider the confidence interval.

Average impact per switch is lower than that of thermostats for summer events. There is a statistically significant difference between the switch and thermostat impacts for summer events (the confidence interval of the switch impact does not overlap with that of the thermostat). Moreover, the average DR impact of switches during summer events is an 8% reduction of the total facility estimated baseline, whereas the average impact of the thermostats is a 13% reduction. On average, participants enrolled with a switch device have lower baseline demand than participants enrolled with thermostats. This may result in reduced potential for demand savings, particularly if indoor temperatures did not rise far above the switch setpoint during some events. Feedback from Duke program staff indicates that participants with switches tend to have smaller HVAC units.

3.1.2.2 Ex-Post Impacts by Cycling Strategy

Impacts by cycling strategy show that the more aggressive the cycling strategy, the greater the impact. For summer events, differences in impacts do not appear to be linear in cycling strategy: the estimated impact from 75% cycling participants is more than 2.5 times the estimated impact from 30% cycling participants (see Table 3-7, below). This differential in impacts is also not related to baseline demand – in fact, as is evident from Figure 3-6 below, the participants that select the 75% cycling strategy (plot on far right) have, on average, the *lowest* daily peak demand of the three groups.

Figure 3-6. Event Day Load Profiles – Summer Events by Cycling Strategy



Source: Guidehouse analysis of Duke Energy data

There are a variety of possible explanations for why the impact is relatively larger for the most aggressive cycling strategy. The smaller baseline load overall suggests this group contains smaller businesses where A/C is likely a much higher proportion of their overall load, so aggressive curtailment leads a larger relative impact. It may seem counterintuitive that a business for which A/C is so important would select the most aggressive curtailment strategy. One possibility is that these are small businesses looking for opportunities to reduce costs and so are attracted by the larger incentive offered for the more aggressive cycling strategy, but that are using relatively inefficient cooling equipment. Entrepreneurs with smaller businesses may not realize the potential bill savings achievable through improved A/C efficiency or may lack the access to capital to make the required replacement investment. In either case, Guidehouse would recommend that Duke Energy consider targeting these participants with marketing for other program opportunities.

These impacts (along with the count of the average number of participants that did not opt out, and the overall system impact, in MW) are shown in tabular format in Table 3-7 below. The estimated impacts for summer events are much more precise than those in the winter season, primarily due to a larger sample size and larger magnitude impacts. The estimated impacts for the 75% cycling strategy participants are only incrementally less precise than for the 30% and 50% participants in the summer season, despite being the smallest of the three groups. This suggests a greater consistency in impacts for these customers and implicitly suggests that a much higher proportion of these customers' loads is A/C (compared to the 30% and 50% cycling participants). Per participant impacts are nearly identical for the two energy suppliers, due to similar proportions of participants using each device type.

Table 3-7. Impact by Cycling Strategy – Per Participant and in Aggregate

Energy Provider	Cycling Strategy	Impact Per Participant (kW)	Relative Precision +/-% (90% Confidence)	Avg. Participants (Accounts)	Total Program Impact (MW)
DEC	30%	0.84	7%	4,690	3.95
	50%	1.59	7%	1,004	1.60
	75%	2.24	8%	660	1.48
DEP	30%	0.83	7%	1,591	1.33
	50%	1.61	7%	679	1.09
	75%	2.27	8%	303	0.69

Source: Guidehouse analysis of Duke Energy data

3.1.2.3 Ex-Post Impacts by Technology Type and Cycling Strategy – Per Device

Most participants in the 2020/2021 demand response season had 2 load control devices, but the number of devices per participant ranged from 1 to 40. Estimated impacts from switches are lower, consistent with results per participant. This is evident in Table 3-8, which presents estimated impact per device for each event season, technology type, and cycling strategy. The average number of devices per participant in each group is also included. By construction of the regression model, estimated impacts are the same for both energy providers.

Table 3-8. Impact by Energy Provider, Cycling Strategy, and Technology Type

Energy Provider	Device Type	Cycling Strategy	Impact Per Participant (kW)	Relative Precision +/- % (90% Confidence)*	Impact Per Device (kW)	Avg. Devices
DEC	Thermostat	30%	0.86	7%	0.49	1.74
		50%	1.64	7%	0.92	1.77
		75%	2.43	8%	1.06	2.29
	Switch	30%	0.55	45%	0.34	1.61
		50%	1.10	31%	0.55	1.99
		75%	0.72	96%	0.35	2.05
DEP	Thermostat	30%	0.86	7%	0.49	1.74
		50%	1.64	7%	0.92	1.77
		75%	2.43	8%	1.06	2.29
	Switch	30%	0.55	45%	0.34	1.61
		50%	1.10	31%	0.55	1.99
		75%	0.72	96%	0.35	2.05

Source: Guidehouse Analysis of Duke Energy data
** Relative precision applies to impact per participant.*

Interestingly, for participants with thermostats during summer events, estimated impacts per device increase as cycling strategy increases, despite that the average number of devices for participants with a higher cycling strategy is also greater. One potential explanation is that participants with a greater number of devices have a larger baseline load and can therefore deliver a deeper impact. While this may be true for some participants, baseline load for the 75% cycling strategy group is, on average, the lowest of the three cycling strategies, which suggests that businesses selecting into this cycling strategy may be of a smaller size. Because of the high impact being delivered, Duke Energy may want to further explore characteristics of this group of participants to better target similar businesses in the future.

Compared with a previous evaluation (2017) of the EnergyWise Business program, the current estimated per device impacts are lower on average by 35%. This result may be due to several reasons:

- The maximum temperature during 2021 events was on average 5°F cooler than during 2017 events; therefore, baseline demand on event days would be expected to be lower, contributing to lower demand impacts. Section 3.2.2 describes this phenomenon, showing the ex-ante relationship between outdoor temperature and estimated impacts. As temperatures become more extreme, estimated event impacts increase.

- The program has added many new participants, changing the composition of participants involved. These new participants may have different patterns of usage, leading to different baseline demand and different event impacts.

- Since the onset of the COVID-19 pandemic in 2020, many businesses have experienced changes in capacity and operations, with corresponding changes in energy usage patterns (e.g., lower demand for HVAC consumption associated with fewer operating hours). Consequently, baseline demand and associated curtailment would be expected to be lower. Guidehouse has recently observed similar results in evaluations of demand response programs in other jurisdictions, where the small and medium business sector exhibited substantially reduced demand as a result of the pandemic.

- The previous evaluation used a different set of methods, primarily estimating a percentage reduction in run time using device telemetry data, and subsequently estimating a reduction in energy based on assumed equipment sizes and full load demand. Assumptions around the conversion of runtime to energy impacts add uncertainty to estimated impacts. Whole-premise AMI consumption data was available for businesses in the current study, so Guidehouse did not have to make any such assumptions.

3.2 Forecast Curtailment Capability – Ex-Ante Impacts

This section provides the estimated EnergyWise for Business DR capability, or ex-ante impacts. These estimates are Guidehouse's projection of how much DR the program could offer under a range of different possible temperatures at different cycling levels, for the different technologies and event day types. This estimate of capability is based on the regression-estimated relationships between DR impacts and outdoor temperature from which the ex-post impacts were also developed.

It is this forecast of capability that provides the truest estimate of a given DR program's value as a system resource because it provides DEC and DEP staff with an understanding of how much of a demand reduction the program may be counted on to deliver in future system peak conditions. This is also why it is the forecast DR capability that should be used to calculate the benefits for any cost-benefit ratio test (e.g., total resource cost test, or TRC).

Forecast program capability per participant is projected by applying a series of temperature values to the estimated model parameters. Guidehouse's projected capability assumes that the temperature at which the capability is estimated lasts the entire length of the event and is the same as the temperature in the 3 hours leading up to the event. This assumption is required due to the manner in which impacts are estimated. Because buildings have thermal mass, a sudden swing in outdoor temperature does not immediately provoke a concomitant swing in cooling load—it takes time for the building's indoor temperature to rise above the setpoint temperature because of that outdoor temperature swing. This is reflected in Guidehouse's estimation approach (see Appendix A for more details), where impacts are modeled as a function of a 3-hour exponential moving average of cooling or heating degree quarter-hours (outdoor temperature), dependent on event season. Therefore, projecting capability requires an assumption of what the temperature is in the 3 hours leading up to the event.

This section is divided into two sub-sections:

1. **Ex-Ante Impacts for Winter Events.**
2. **Ex-Ante Impacts for Summer Events.**

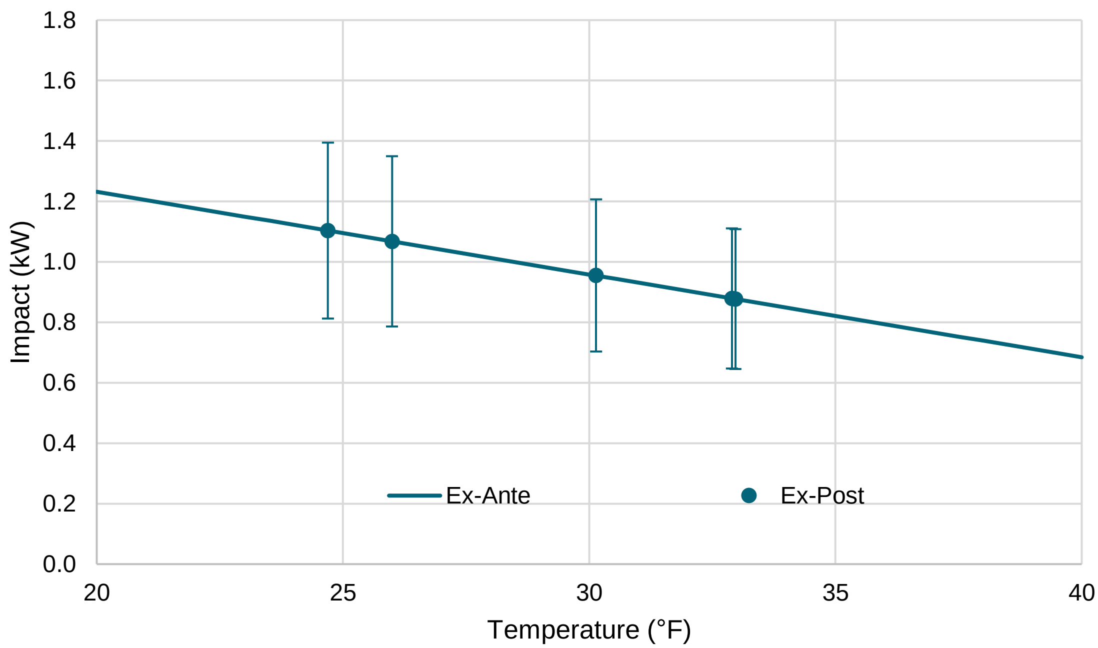
Ex-ante impacts are presented graphically in each of these sub-sections. Numerical values underlying these charts may be found in the Excel Appendix provided separately. Specific tab references for finding these values are provided in the sub-sections below.

Guidehouse would note that the observant event temperatures cover a relatively narrow band, especially for summer events. A high proportion of the range of ex-ante values occur outside of the temperature range inside which events were observed in 2021. Caution should therefore be used in working with impacts estimated outside the range of observed temperatures in the winter and summer of 2021 used to estimate the model parameters.

3.2.1 Ex-Ante Impacts for Winter Events

Ex-ante impacts for winter events were estimated using temperatures from 20°F to 40°F. Temperatures below this range are unusual and occurred on only one day throughout the event season. Total estimated impact ranges from 360 kW to 650 kW and increases steadily as temperatures become more extreme (decrease). Per participant, estimated impacts range from roughly 0.7 kW to over 1.2 kW. This is illustrated in Figure 3-7 which shows the per participant curtailment capability per event. This plot shows the ex-ante relationship between outdoor temperature and estimated impacts for winter events (blue line). Ex-post impacts (and the corresponding average event temperature) are identified by blue dots. The whiskers surrounding the ex-post impacts represent the 90% confidence interval. Since Guidehouse employed a pooled regression model, impacts are identical across energy providers by device type and cycling strategy. In the winter, there is only one device type and cycling strategy, so estimated ex-post and ex-ante impacts are identical for the two energy providers.

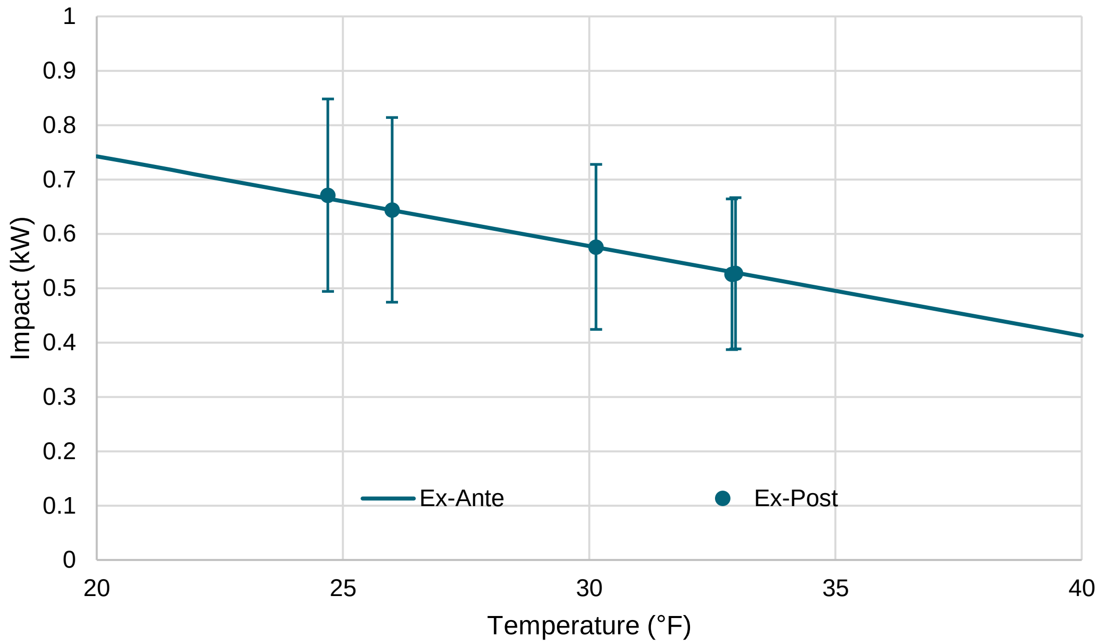
Figure 3-7. Ex-Ante Impacts, Winter Events – Per Participant



Source: Guidehouse analysis of Duke Energy data

Figure 3-8 shows ex-ante impacts on a per device basis. Per device, estimated impacts range from approximately 0.4 kW to 0.75 kW. Ex-post impacts (and the corresponding average event temperature) are identified by blue dots. The whiskers surrounding the ex-post impacts represent the 90% confidence interval.

Figure 3-8. Ex-Ante Impacts, Winter Events – Per Device

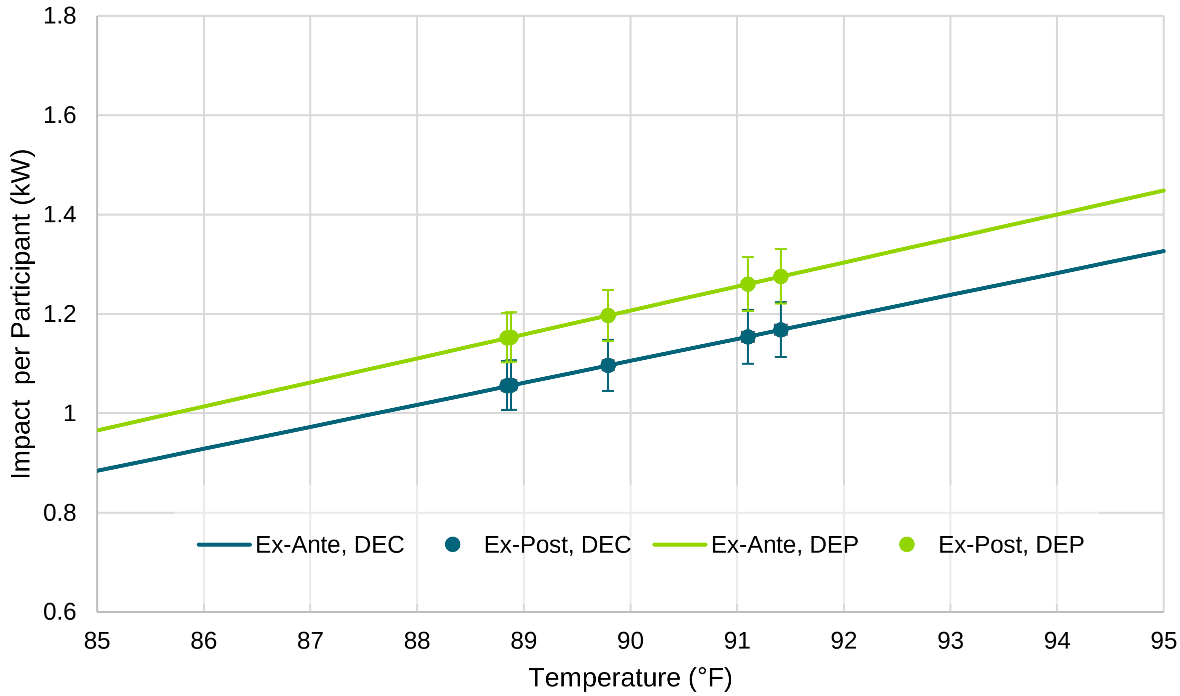


The kW values associated with ex-ante estimates above may be found in the Excel spreadsheet Appendix in the tab “03a Ex-Ante by Event Type”. As noted above, care should be taken when using ex-ante values that are outside the range of historically observed temperature values. If the true relationship between temperature and demand response impacts does not remain linear as temperatures increase or decrease, the ex-ante value may not accurately reflect the impact that could be expected at higher and lower temperatures than represented by actual events.

3.2.2 Ex-Ante Impacts for Summer Events

Ex-ante impacts for summer events were estimated using temperatures from 85°F to 95°F. Total estimated impact ranges from 8,000 kW to over 12,000 kW and increases as temperature rises. Per participant, estimated impacts range from approximately 0.9 kW to almost 1.5 kW. This can be seen in Figure 3-9 which shows the per participant curtailment capability per event. This plot shows the ex-ante relationship between outdoor temperature and estimated impacts for summer events for each energy provider (straight lines). Ex-post impacts (and the corresponding average event temperature) are identified by dots. The whiskers surrounding the ex-post impacts represent the 90% confidence interval. As noted in Section 3.1.2, estimated per participant impacts are slightly higher for DEP than DEC, due to a larger proportion of participants enrolled in the 50% and 75% cycling strategies.

Figure 3-9. Ex-Ante Impacts, Summer Events – Per Participant

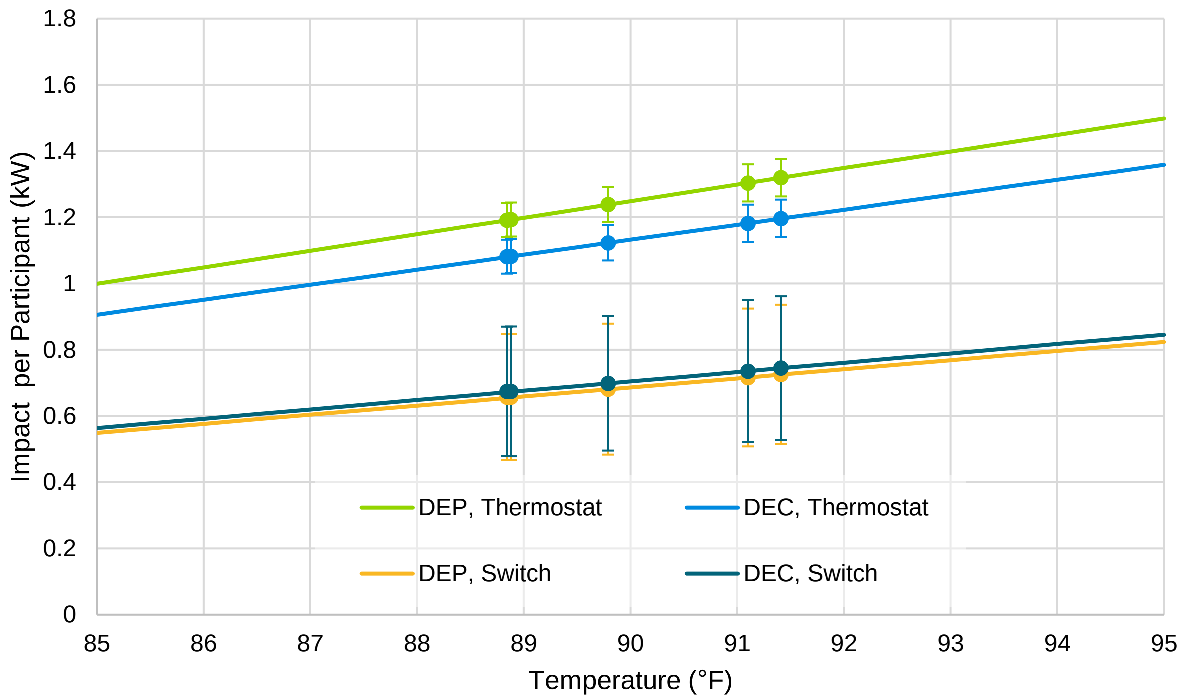


Source: Guidehouse analysis of Duke Energy data

3.2.2.1 Ex-Ante Impacts by Technology Type

As noted in Section 3.1.2.1, the point-estimate for the DR impact from thermostats is higher than that of switches and this difference is statistically significant (for summer events). This difference may reflect the fact that participants with switches tend to have smaller HVAC units, rather than an effect of the difference in device type itself. The difference in projected impacts is evident in Figure 3-10. In this plot, the actual (ex-post) impact/event temperature pairs for summer events are represented by the markers and the 90% confidence interval is captured by the whiskers. The bright green and light blue markers and lines identify the average impacts for thermostats for DEP and DEC, respectively. The orange and dark blue markers and lines identify the average impacts for switches for DEP and DEC, respectively.

Figure 3-10. Ex-Ante Impacts, Summer Events, by Technology Type – Per Participant



Source: Guidehouse analysis of Duke Energy data

The kW values associated with ex-ante estimates above may be found in the Excel spreadsheet Appendix in the tab “01b Ex-Ante by Device, Splr”.

As noted previously, actual events were only observed over a relatively narrow band of temperatures, and caution must be applied in extrapolating curtailment capability too far beyond that window. The true relationship at those unobserved temperatures may differ from that estimated in the band of temperatures observed. Additional caution should be used in applying the estimated results for switches. With fewer participants equipped with switches, the average (and aggregate) impacts of this group will be very sensitive to changes in the composition of that group over time. Additional enrollment or program withdrawals of even a small number of participants may meaningfully alter this average relationship.

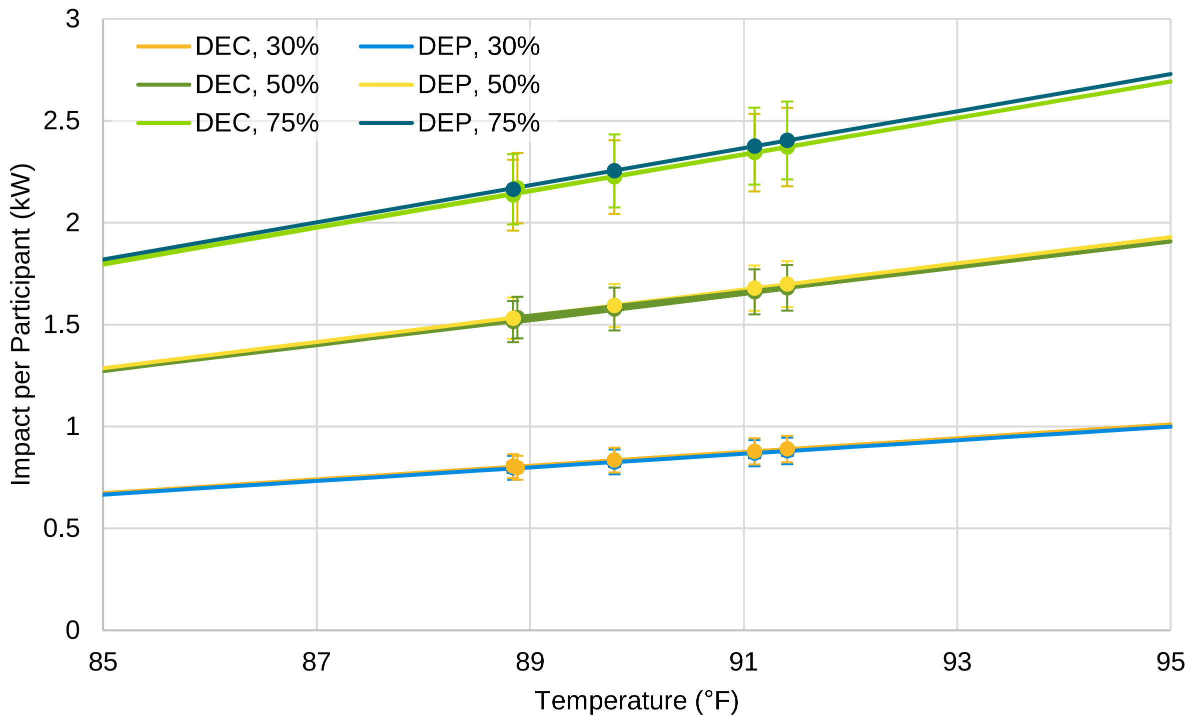
3.2.2.2 Ex-Ante Impacts by Cycling Strategy

The same patterns noted in the ex-post analysis are present in the ex-ante estimate of curtailment capability. Participants in the 75% cycling strategy deliver far more summer event DR per participant than either of the two other cycling strategies. These participants also deliver DR that is a far higher proportion of their baseline consumption compared to the other cycling strategies, indicating that DR impacts (either absolute or as a proportion of baseline) are not linear in the cycling strategy selected.

Current program incentives to some degree reflect this (the incentive for 75% cycling is $135, whereas the incentive for 30% cycling is only $50). Still, given the relationship apparent in, Figure 3-11, below, and the proportion of participants enrolled for the summer season, Duke Energy may consider whether it may be appropriate to further adjust the offered incentive to reflect the relative benefit delivered by each of the different cycling strategies.

In Figure 3-11, 75% cycling impacts are represented by the light green and dark blue line and markers, 50% cycling by the darker green and yellow line and markers, and 30% cycling by the light blue and orange line and markers.

Figure 3-11. Ex-Ante Impacts, Summer Events, by Cycling Strategy – Per Participant



Source: Guidehouse analysis of Duke Energy data

Due to similar proportions of participants per device type, per participant impacts by cycling strategy are nearly identical for the two energy providers. Duke Energy may wish to consider undertaking some additional cross-sectional analysis of the characteristics of the 75% cycling strategy participants to focus future recruitment efforts to capture higher value (higher DR potential) customers.

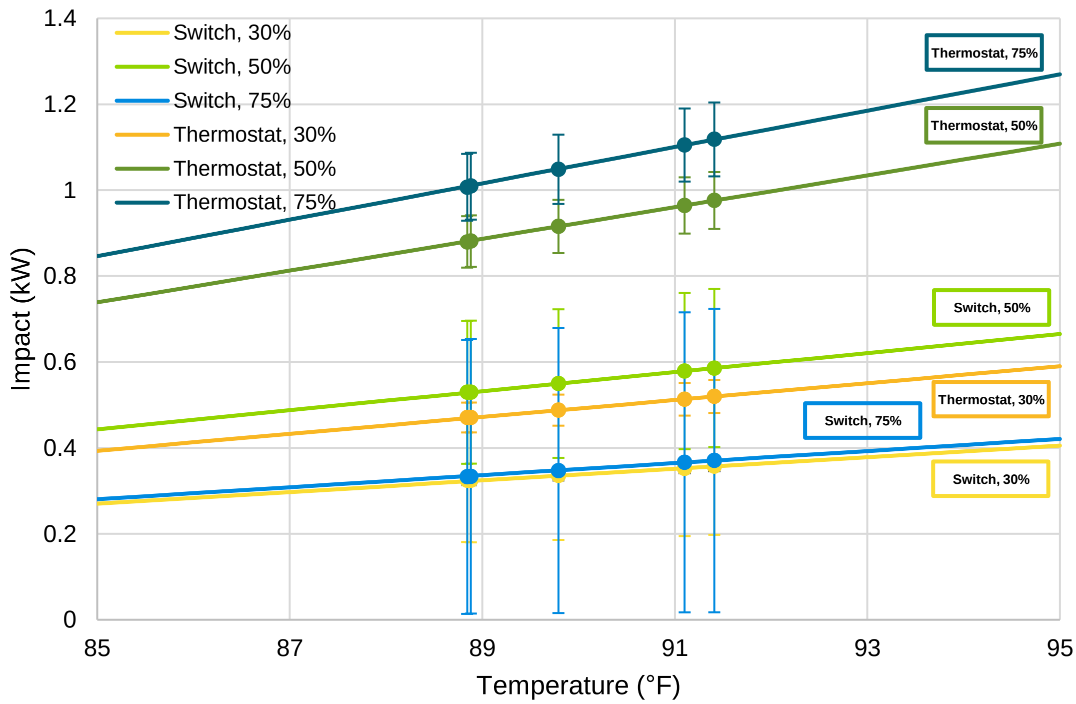
The kW values associated with ex-ante estimates above may be found in the Excel spreadsheet Appendix in the tab "02b Ex-Ante by Cyc, Splr". Note that care should be taken when using ex-ante values that are outside the range of historically observed temperature values.

3.2.2.3 Ex-Ante Impacts by Technology Type and Cycling Strategy

Since this analysis implements a pooled regression model, estimated ex-post and ex-ante impacts for the two energy providers are identical at the technology type and cycling strategy level. Unlike the results in Sections 3.2.2.1 and 3.2.2.2, estimated impacts at this level are not dependent on the distribution of participants across technology types and cycling strategies.

Figure 3-12 illustrates estimated impacts per device for two technology types and three cycling strategies during summer events. Ex-post impacts are represented by the dots, with the surrounding whiskers representing the 90% confidence interval. The straight lines denote ex-ante impacts.

Figure 3-12. Ex-Ante Impacts for Summer Events, by Technology Type and Cycling Strategy – Per Device



Source: Guidehouse analysis of Duke Energy data

Consistent with patterns observed in the ex-post analysis, thermostats in the 75% cycling strategy group deliver the highest estimated impacts, ranging from approximately 1.95 kW to 2.9 kW per participant. Notably, these impacts are significantly larger than all other technology and cycling strategy groups (the 90% confidence intervals do not overlap). Moreover, estimated impacts from switch devices are lower than the estimated impacts for thermostats at the same cycling strategy. Even at the 75% cycling strategy level, estimated impacts from switches are not significantly different from the impacts delivered by the thermostat, 30% cycling group. Given these results, Duke Energy should continue to install thermostat devices as the default technology type, except in the case that incompatibility issues exist.

The kW values associated with ex-ante estimates above may be found in the Excel spreadsheet Appendix in the tab “04b Ex-Ante by Cyc, Dev per Dev”. Note that care should be taken when using ex-ante values that are outside the range of historically observed temperature values.

3.3 Net to Gross

Evaluations of demand-side management programs typically estimate both net and gross savings, and often present a net-to-gross (NTG) ratio based on the evaluated percentage of energy reductions that may be ascribed either to free ridership (which decreases the NTG ratio) or to program spillover (which increases the NTG ratio).

Free ridership is typically defined as the percentage of savings that would have occurred absent the presence of the program. Spillover is typically defined as incremental savings actions undertaken by a program's participants not directly incented by the program.

All savings presented in this report should be considered net.

3.3.1 Demand Response Impacts

In this analysis, demand reductions are estimated in contrast to an implied estimated baseline, the average level of behavior implied by the estimated parameter values of the regression used. Because this captures expected participant behavior absent an event, Guidehouse can state that the free ridership is 0. Absent the EnergyWise for Business program, none of the observed demand reductions would have taken place, as the events themselves would not have taken place. It is possible that there may have been some spillover resulting from the program (from participants becoming more aware of their sites' consumption profiles, for example). However, it is likely impossible to estimate such an effect in a sufficiently robust manner and the assessment of such impacts is beyond the scope of this report.

Since spillover cannot be robustly estimated and because free ridership must, by program design, be considered 0, Guidehouse considers the program to have a NTG ratio of 1.

4. Findings and Recommendations

The principal EM&V findings regarding the estimated demand impacts are as follows:

- **On average, the program delivered approximately 0.5 MW of load curtailment during winter events, and approximately 10.1 MW of load curtailment during summer events.** For DEC, this amounts to 0.4 MW of estimated load curtailment in winter and 7 MW of estimated load curtailment from in summer. Estimated load curtailment for DEP is approximately 0.1 MW in winter and 3.1 MW in summer, consistent with enrollment numbers. The program-level impacts for each event vary depending on the number of participants, the temperature, and other factors.

- **On average, the program delivered nearly 1 kW of demand response per participant during winter events, and over 1.1 kW of demand response per participant during summer events.** For DEC, this amounts to 0.6 kW of demand response per device in both winter and summer. Estimated curtailment per device for DEP is approximately 0.6 kW per device in winter and 0.7 kW per device in summer.

- The results of the ex-post evaluation informed the development of ex-ante forecast of program capability across a range of temperatures at different cycling levels, which can be used for calculating benefits for cost-effectiveness tests. For summer events at an assumed temperature of 95°F, ex-ante impacts are estimated to be 0.8 kW per thermostat device and 0.5 kW per switch device. During winter events at an assumed temperature of 20°F, thermostats are estimated to deliver 0.7 kW of curtailment per device.

- **Thermostats deliver greater relative impacts for events in both seasons compared to load control switches. While no switch impacts were measured for winter events, thermostat impacts are materially higher than switch impacts during summer events.** On average across cycling strategies, thermostats delivered demand reductions during summer events of 13% of total facility baseline load, and switches 8%. During winter events, thermostats deliver demand reductions of approximately 14% of total facility baseline load. According to Duke program staff, this may be because participants with switches tend to have smaller HVAC equipment.

- **Participants that have selected the 75% cycling strategy deliver the highest per participant impacts for summer events.** During summer events, 75% cycling strategy participants deliver an average impact equivalent to 27% of their estimated facility baseline demand. In contrast, 30% and 50% cycling strategy participants delivered an average impact of approximately 9% and 19% of their baseline demand, respectively.

Based on the impact findings above, Guidehouse recommends that Duke Energy consider the following recommendations:

- **Consider using future process evaluations to better understand differences in businesses that enroll in each cycling strategy.** Consistent with expectations, Guidehouse estimated significantly greater savings for participants enrolled in the 75% cycling strategy during demand response events than for the 30% and 50% cycling strategies. Because of the high impact being delivered, Duke Energy may want to further explore characteristics of this group of participants to better target similar businesses in the future, through participant surveys or interviews.

- **Continuing to evaluate the program on an annual basis, particularly if enrollment changes in any material way.** The total number of enrolled participants is over 9,000, and the energy use at commercial facilities is generally more heterogeneous than at residential facilities. This means that the average participant (and aggregate program) impacts and capability could change materially as a result of relatively modest changes in the absolute number of participants enrolled, or if the distribution of participants across cycling strategies shifts. Duke Energy should carefully consider this when using the capability estimates provided above for any planning exercises.

5. Summary Form

EnergyWise Business

2019-2021

Completed EMV Fact Sheet

Description of Program

EnergyWise Business is a commercial HVAC load control program that targets small and medium businesses. At the time of enrollment participants are provided either with a thermostat or a load switch, with most customers having a thermostat. Participants must have a password-protected wireless network in order to qualify for a thermostat.

Participants may elect to be controlled using one of three cycling strategies: 30%, 50%, or 75%. Incentive for participation increases commensurate with the increased aggressiveness of the cycling strategy selected.

Five events took place in each season, winter and summer. On average, there were over 500 participants in winter events and almost 9,000 participants in summer events. Most participants enrolled with the thermostat technology and 30% cycling strategy.

Date:	2022-03-11
Region:	DEC and DEP
Evaluation Period	EE: 2019 – 2020 DR: 2020 - 2021
DR Event Impact per Participant (kW)	
Average across cycling strategies and technology types.	Winter, DEC: 0.98 kW Winter, DEP: 0.98 kW Summer, DEC: 1.11 kW Summer, DEP: 1.21 kW
DR Event Impact per Device (kW)	
Average across cycling strategies and technology types.	Winter, DEC: 0.6 kW Winter, DEP: 0.6 kW Summer, DEC: 0.6 kW Summer, DEP: 0.7 kW
DR Event Program Impact (MW)	
Average across cycling strategies and technology types.	Winter, DEC: 0.4 MW Winter, DEP: 0.1 MW Summer, DEC: 7 MW Summer, DEP: 3.1 MW
Net-to-Gross Ratio	1

Impact Evaluation Methods

Guidehouse estimated DR impacts using a lagged dependent variable regression model that compares average participant demand on event days to that of a carefully selected control group. Control customers are selected by comparing the demand patterns of a large pool of non-participants to each participant and selecting the non-participant with the most similar non-event day demand patterns. The non-event days used for this comparison were selected based on a comparison of hourly temperature values, such that the non-event day used to select controls were subject to temperatures as similar as possible to those observed on event days.

Impacts were estimated separately by event season (winter and summer) using a pooled regression model with DEC and DEP data. Impacts were estimated as a function of the three-hour exponential moving average of heating degree hours in winter and cooling degree hours in summer. This allows Guidehouse to both estimate the impact of observed historical events (ex-post impacts) as well as project an estimate of program capability under a range of different temperatures (ex-ante impacts).

Impact Evaluation Details

- **On average, the program delivered approximately 0.5 MW of load curtailment during winter events, and approximately 10.1 MW of load curtailment during summer events.**

- **On average, the program delivered nearly 1 kW of demand response per participant during winter events, and over 1.1 kW of demand response per participant during summer events.** For DEC, this amounts to 0.6 kW of demand response per device in both winter and summer. Estimated curtailment per device for DEP is approximately 0.6 kW per device in winter and 0.7 kW per device in summer.

- **Thermostats deliver greater relative impacts for summer events compared to load control switches.** On average, thermostats delivered demand reductions during summer events of 13% of total facility baseline load, and switches 8%. During winter events, thermostats deliver demand reductions of approximately 14% of total facility baseline load.

- **Participants that have selected the 75% cycling strategy deliver the highest per participant impacts for summer events.** During summer events, 75% cycling strategy participants deliver an average impact equivalent to 27% of their estimated facility baseline demand. In contrast, 30% and 50% cycling strategy participants delivered an average impact of approximately 9% and 19% of their baseline demand, respectively.

Appendix A. Demand Response Regression Model Specification

This appendix provides additional technical details regarding the model specification used by Guidehouse to estimate impacts for each combination of event season (winter and summer); technology (thermostat and switch); and cycling strategy (30%, 50%, and 75%).

Equation A-1 shows the lagged dependent variable model regression equation. This model estimates customer load on a per participant basis as a function of the event hours, snapback in post-event hours, lagged non-event day usage, temperature, humidity, and hourly fixed effects. Only event day data is included in the regression model, although matched non-event day data informs the baseline through the lagged usage (prekW) variable.

This equation was estimated separately for each event season. Altogether two different estimation sets were used.

Equation A-1. Lagged Dependent Variable Regression Model

$$\begin{aligned} y_{i,d,t,es} &= \sum_{h=1}^{H=48} \beta_{1,h} hhour_{h,t} + \sum_{h=1}^{H=48} \beta_{2,h} hhour_{h,t} prekW_{i,t,e} \\ &+ \sum_{h=1}^{H=48} \beta_{3,h} hhour_{h,t} EMA3dh_t + \sum_{h=1}^{H=48} \beta_{4,h} hhour_{h,t} NBU_t \\ &+ \sum_{d}^{D} \sum_{k}^{K} \sum_{c=1}^{C} \gamma_{1,d,k,c} D_{i,d,t} K_{i,k,t} C_{i,c,t} EMA3dh_t + \sum_{d}^{D} \sum_{k}^{K} \sum_{s=1}^{S} \gamma_{2,e,s} D_{i,d,t} K_{i,k,t} SB_{i,s,t} \end{aligned}$$

Where:

i	=	Customer.
t	=	Half-hour ending.
$y_{i,t}$	=	Demand for customer i during half-hour-ending t.
$hhour_{h,t}$	=	A set of 48 dummy variables, each equal to one when t is the h-th half-hour of the day and zero otherwise. This is a time-wise fixed effect.
$prekW_{i,t,e}$	=	Customer i's half-hourly consumption in half-hour t of the matched non-event day for event day e. For example, if hour t is half-hour-ending 13 on the first event day, then this variable would take the value of that same customer's consumption in half-hour-ending 13 of the corresponding non-event day used for matching purposes.
$EMA3dh_t$	=	An exponential moving average of heating degree hours (base 65°F) for winter events and cooling degree hours (base 65°F) for summer events observed in the six-hour period leading up to, and including, hour t
NBU_t	=	is the normalized cold build up term (winter events) or heat buildup term (for summer events) during hour ending i. This variable captures the effect of heat or cold build up in previous hours on the current hours demand. This is a 72-hour

geometrically decaying average of heating degree half-hours in winter and cooling degree hours in summer. It is calculated in the following manner

$$CBU_t = \frac{\sum_1^{72}(0.96)^t *(HDH65_t\ halfhours\ prior)}{1{,}000} \text{ or } HBU_t = \frac{\sum_1^{72}(0.96)^t *(CDH65_t\ halfhours\ prior)}{1{,}000}$$

$D_{i,d,t}$ = A set of dummy variables that capture the technology of each customer (i.e., thermostat, switch, or no device). Since some customers may have changed devices mid-season, the variables capture a customer's device on the day containing hour t.

$K_{i,k,t}$ = A set of three dummy variables that capture the economic cycling strategy for each customer (i.e., 30%, 50%, 75%). These values also capture the corresponding Emergency cycling strategy for each customer on those event days. Since some customers may have changed cycling strategy mid-season, the variables capture a customer's cycling strategy on the day containing hour t.

$C_{i,c,t}$ = A set of C dummy variables, capturing the impacts of event curtailment. Each variable is equal to one when customer i is a DR participant and hour t is the c-th curtailment hour of the event, and zero otherwise.

$SB_{i,s,t}$ = A set of S dummy variable, capturing the impacts of snapback. Equivalent to the $C_{i,c,t}$ except that they apply to the hours following the event, rather than during the event. Guidehouse applied these variables to all hours following the end of the curtailment event up to midnight of the event day.

β, γ = Parameter estimates. These values are the estimated relationship between demand and the variable for which the beta represents.

Appendix B. Energy Efficiency Impact Evaluation Interim Report

DEP-DEC EnergyWise
Business EMV Interim