Stephanie A. Cuello
SENIOR COUNSEL

April 29, 2022

VIA ELECTRONIC FILING

Adam J. Teitzman, Commission Clerk
Florida Public Service Commission
2540 Shumard Oak Boulevard
Tallahassee, Florida 32399-0850

Re: *Duke Energy Florida, LLC's Demand Side Management Annual Report for Calendar Year 2021*; Undocketed

Dear Mr. Teitzman:

Please find enclosed for electronic filing Duke Energy Florida, LLC's Revised Response to Staff's First Data Request (Nos. 1-15). The Response is being revised to include Attachments A and B, that were inadvertently omitted from the original response submitted on April 27, 2022.

Thank you for your assistance in this matter and if you have any questions, please feel free to contact me at (850) 521-1425.

Sincerely,

s/ Stephanie A. Cuello

Stephanie A. Cuello

SAC/mw
Enclosure

Cc: Michael Barrett, Division of Economics

Duke Energy Florida, LLC's Response to
Staff's First Data Request (1-15)
Regarding the 2021 DSM Annual Report

1. Please describe how Duke Energy Florida, LLC (DEF or Company) monitors federal energy efficiency standards and Florida Building Code requirements. Address in your response how the Company modifies existing programs to reflect changes, when necessary.

Response:
DEF's approach for monitoring any new federal energy efficiency standards and Florida Building Code requirements involves both internal and external resources. DEF stays informed about new federal energy efficiency standards and Florida Building Code requirements through participation in trade associations, industry groups, and building associations. DEF also stays informed about new technologies through monitoring activity in the other Duke jurisdictions, meetings with peer utilities and review of regulatory filings.

DEF also researches and evaluates new DSM technologies as they become available in the marketplace to identify potential program opportunities. This is a rigorous process that involves further analysis of both customer and company costs and benefits, projected participation levels, analysis of cost effectiveness test results, discussion of operational considerations, and customer rate.

2. Please answer the following regarding DEF's conservation research and development (CRD) initiatives that evaluate emerging DSM opportunities:

A. Identify and describe any new CRD initiatives that were launched in 2021.

Response:
Through this program, DEF launched a project for a study to evaluate the demand response capability of internet-connected residential batteries. Residential batteries potentially offer the ability to provide power reduction for demand response while eliminating any discomfort to the customer (as compared to residential appliance demand response). Certain battery manufacturers have developed technologies that allow for the collection of capacity and charge data, communication protocols for external aggregator software providers, and the ability to dispatch stored energy to serve the needs of the customer or the grid. This project will focus on the capabilities of a particular aggregator to collect data from multiple battery manufacturers, the feasibility of utilizing aggregation technology for dispatching demand response event commands, and the net impact of these events on shaping demand. Such an aggregation system enables existing units that are already installed by residential customers in Duke Energy territory to be used in this study. The results of this study could be used to develop a cost-effective demand response program in the future.

B. Provide updates on the status of all on-going CRD initiatives that began before 2021, and if applicable, attach interim and/or final reports on work completed in 2021.

Response:

- Continued a project with the University of Central Florida (UCF) to document the value of long-duration customer-side energy storage systems. This project is using the technology at UCF's Microgrid Control lab to directly test a long-duration energy storage system. Use cases to be investigated include study of battery performance during charging and discharging, documenting the effects of cycling on battery performance (battery degradation, efficiency, etc.), optimal operation of a battery energy storage system in a distribution system with high penetration of solar energy, control of behind-the-meter distributed energy resources to provide services including peak capacity management, DR (consuming or generating), frequency regulation, ramping capability and voltage management.
- Continued a pilot to develop software, firmware, and applications for a Smart Home Gateway to evaluate the potential for a future home energy management program and its ability to enhance the Company's future energy efficiency and DR programs. The Smart Home Gateway currently includes processing and communications capabilities to perform on-site operations including receiving energy data from the customer's AMI meter, communications using four radios and on-site processing. Capabilities are under development and testing that include enabling appliance demand response using CTA-2045 (EcoPort) local control and enabling local control of Energy Management Circuit Breakers (EMCBs) for monitoring and demand response. These technologies will allow automatic control of devices according to the customer's preference, and enabling open-source, utility demand response. The Smart Home Gateway can also potentially be used to engage customer awareness of how energy is being used in the home.
- Continued a project with the University of South Florida (USF) to leverage customer-sited solar PV and energy storage at the USF 5th Avenue Garage Microgrid. The system provides load smoothing, islanding, and demand response. A publicly available dashboard that shows live data, project specific facts and the capability of downloading data for further study is available for the site at https://dashboards.epri.com/duke-usfsp-parking. Additional testing is planned to utilize a new demand response interface to the energy storage system. Results of this research may be used for design of a potential cost-effective DR program. USF continued research on microgrid operation.
- Continued the Electric Power Research Institute (EPRI) Solar DPV project for data collection to document customer solar resources with a focus on larger PV arrays with and without energy storage. This project also provides the data stream for the dashboard mentioned above.
- Continued participation in an EPRI project to study the potential of using customer demand response to compensate for variable loads and intermittent renewable generation resources.
- Continued the Energy Management Circuit Breaker (EMCB) Project. This project

continued to explore the potential for developing a program for customer circuit breakers that includes communication, metering, and remote operation for potential applications including EE, DR, and integration of distributed energy resources. The prototype EMCB hardware and software in the field pilot program have been replaced with commercial versions, and operational data is being collected from appliances in 9 customer homes. The prototype EMCB-EV (a self-contained electric vehicle charger) will be replaced with a commercial version of this device. We will test the effectiveness of this product and consider potential program opportunities for implementation. This data will be used to document the operation of these breakers and assess the cost-effectiveness for potential EE and DR programs.

- Completed a project to do field evaluation with EPRI and the Grid Modernization Lab Consortium (GMLC) of a utility-integrated DSM solution using open standards and open source platforms. A consortium of National Labs, the Grid Modernization Lab Consortium, has developed both the software and hardware, all based on open-source technologies, to leverage DSM of residential loads to provide grid resiliency using a Home Energy Management System (HEMS). In 2021, DEF tested the cloud-based HEMS in 7 customer homes. This project leveraged the homes and equipment installations from our CTA-2045 Projects. The final report for this project will be available publicly in June 2022.
- Completed a project with EPRI to assess the DR opportunities for new and existing variable capacity heat pump systems for potential future load-management programs. DEF used manufacturer cloud communications to control existing, variable-capacity heat pumps at volunteer participants' homes. DR events were executed, and data showed promising results. This pilot confirmed the viability of cloud communications to provide triggering and impacts of DR events on variable-capacity heat pumps. The participant customers reported very little impact on comfort during the demand response events. Please see Attachment A, the Final Report for this project.
- Continued a project that will provide knowledge in methods to utilize customer Wi-Fi infrastructure to develop a dedicated, durable, and secure utility communication channel to connected devices. The project will also provide knowledge on the effectiveness of Wi-Fi-signal-strength-improvement technology. This technology could lead to lower costs and improved cost-effectiveness for existing and future DR and EE programs.
- Completed a project to gather robust data about residential customers that drive electric vehicles (EV). The project will determine what type of hardware customers use to charge their vehicle, where they charge (at home, work, or public charging station, in/out of DEF service territory, etc.) and how much power and energy are consumed by EV charging. In 2020 and 2021, the project assessed the effectiveness of incentives to shift on-peak EV charging to off-peak times. The incentives to charge off-peak and incentives to avoid charging on-peak were both shown to be very effective at changing charging behavior. Please see Attachment B, the Final Report for this project.
- Completed a pilot to determine the viability of using precision temperature measurement and analysis to determine issues with customer HVAC systems, duct work, or building envelope that could resolve high bill complaints. Precision temperature measurements were made at several points within the participant's homes.

Analysis of the temperature data and rate of change of the temperature provided conclusions on what could be causing a customer's high energy usage. These conclusions did not fully explain the temperature issues in the participant's home. We decided not to move forward with this technology at this time.

- Partnered with EPRI and other research organizations to evaluate EE, energy storage, and alternative energy / innovative technologies.

3. Please answer the following regarding DEF's Low Income Programs:

A. Describe the conservation efforts DEF used in 2021 to ensure low-income customers are aware of, and have access to, conservation programs. Address in your response whether any of these efforts were changed or modified in 2021, compared to prior years.

Response:
DEF uses a variety of marketing channels to promote its conservation programs to all customers including low-income customers. These channels include bill inserts, emails, direct mail, social media, and promotional information on its website.

Specific to the low-income programs, DEF works with local governments and non-profit agencies to educate them about benefits available to low-income customers. DEF meets with these organizations and shares information about what is offered through the programs and what DEF can do to assist them in getting incentives through these programs. COVID-19 continued to have an impact on activities in 2021 as both DEF and the low-income agencies suspended direct install of measures in customers' homes due to concerns about customer safety. The agencies have resumed activities and submitted applications for rebates through the Weatherization Program. DEF also resumed in-home installs through its Neighborhood Program.

B. Identify DEF's partnerships with government and non-profit agencies in 2021 designed to help identify low-income neighborhoods and educate customers on conservation opportunities.

Response:
- Pinellas County Urban League
- Mid-Florida Community Services
- Capitol Area Community Action Agency
- Central Florida Community Action Agency
- Orange County Community Development
- Osceola County Council on Aging
- Meals on Wheels
- Lake County Community Action Agency
- Tampa Hillsborough Action Plan
- Seminole County Government

4. On Page 2 of the Report, DEF provides Variance Explanations for 2021. Please answer the following:

A. Specifically describe how the "continued impacts of COVID-19" resulted in lower participation in 2021 compared to 2020 in the Neighborhood Energy Saver Program.

Response:
Impacts from COVID-19 impaired our ability to implement the normal field operations of the Neighborhood Energy Saver Program (NES). We were not able to deploy our teams into homes to installed measures in the program

B. Explain how the Neighborhood Energy Saver Program is uniquely vulnerable to these impacts compared to other residential programs by the Company.

Response:
NES is uniquely vulnerable to impacts by COVID-19 because it requires our team to have direct contact with customers, when they are in their homes installing measures. Without the ability to perform this "hands on" task, it was impossible to perform the job.

C. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
DEF increased staffing by re-establishing enough work crews to achieve our goals. We are working on simultaneous projects to increase participation. In addition, we continue to identify and work projects close to each other so that teams can minimize travel and stay in one area for extended times.

D. DEF provides information reflecting that the Utility Cost per Installation of the Neighborhood Energy Saver program was $552 in 2021. A comparative review of the same information from the 2020 Report (Page 5) reflects that the same cost was $1207, and a similar comparison shows the cost was $189 in 2019. Please explain the variance in final costs for this program between the three periods (from 2019 to 2020 to 2021). Discuss in your response how DEF monitors fluctuating costs in this program.

Response:
The increase in costs is driven by the impact of COVID-19 and production to achieve goals.

Duke Energy has an existing contract with our vendor of which all associated costs are fixed. However, DEF actively communicates regarding cost of installed measures in the customers home and makes proper adjustments in the annual budget to accommodate market fluctuations and costs. In addition, the NES Program Manager monitors the budget monthly to ensure costs do not exceed projected monthly budget.

5. Page 4 of the Report addresses the Residential Incentive program. Please explain whether this program is available to customers that rent, or do not own their residence. Address in your response why the Total Number of Customers Eligible (presented in Column "c") is equal to the Total Number of Customers (presented in Column "b").

Response:
The Residential Incentive program is available to customers that rent, or do not own their residence. The total eligible numbers are correct and the same as the total number of customers.

6. According to Page 6 of the report, the actual number of program participants in the Low Income Weatherization Assistance program was lower than the number the Company projected for this program.

A. Identify the specific reasons why this program did not achieve the projected participation levels for 2021.

Response:
The primary reason this program did not achieve the projected participation levels was because the weatherization agencies suspended direct install of measures in homes due to COVID-19.

B. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
Participation in this program is dependent on the weatherization agencies. DEF reimburses the weatherization agencies for measures they install. Some weatherization agencies are currently back in the field and actively engaging with customers.

7. According to Page 7 of the report, the actual number of program participants in the Residential Load Management program was lower than the number the Company projected for this program.

A. Identify the specific reasons why this program did not achieve the projected participation levels for 2021.

Response:
Program inventory was negatively impacted by supply chain disruptions resulting from the COVID-19 pandemic.

B. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
The Company will continue to investigate and implement new supply chain channels to aid the program through supply chain disruptions resulting from the COVID-19 pandemic.

8. According to Page 8 of the report, the actual number of program participants in the Business Energy Check program was lower than the number the Company projected for this program.

A. Identify the specific reasons why this program did not achieve the projected participation levels for 2021.

Response:
DEF believes that participation in this Program was impacted by COVID-19 due to managed restrictions of on-site visits by DEF and their customers. It is important to note however, that although the reported participation for the Business Energy Check Program was less than projected, the demand and energy savings from the commercial programs overall well-exceeded the projected savings included in the Program Plan.

B. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
DEF will continue to monitor CDC requirements to adjust our requirements to increase audit participation. DEF has increased marketing and adjusted marketing plans to meet 2020-2024 Program Plan, which includes a variety of emails, targeted publications, offered energy forums and continued site visits, phone assisted audits and online offerings.

9. According to Page 9 of the report, the actual number of program participants in the Better Business program was lower than the number the Company projected for this program.

A. Identify the specific reasons why this program did not achieve the projected participation levels for 2021.

Response:
DEF believes that participation in this Program was impacted by COVID-19 due to managed restrictions of on-site visits by DEF and their customers. It is important to note however, that although the reported participation for the Better Business Program was less than projected, the demand and energy savings from the commercial programs overall well-exceeded the projected savings included in the Program Plan. Because there is a wide diversity in both the types of commercial customers and the demand and energy requirements of those customers, the types of measures incentivized are often a larger driver of program achievements and cost-effectiveness than the actual number of participants.

B. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
DEF will continue to monitor CDC COVID-19 Restrictions to adjust our requirements in order to increase program participation. DEF has adjusted and increased marketing plans to meet 2020-2024 Program Plan, which includes a variety of emails, targeted publications, offered energy forums focusing on our program measures and will continue onsite audits, phone assisted audits and online offerings.

10. According to Page 11 of the report, the actual number of program participants in the Florida Custom Incentive program was lower than the number the Company projected for this program.

A. Identify the specific reasons why this program did not achieve the projected participation levels for 2021.

Response:
DEF believes that participation in this Program was impacted by COVID-19 due to managed restrictions of on-site visits by DEF and their customers. It is important to note however, that although the reported participation for the Custom Incentive Program was less than projected, the demand and energy savings from the commercial programs overall well-exceeded the projected savings included in the Program Plan. Custom Incentive Program is dependent upon various nonprescriptive measure offerings, which are analyzed under the RIM process, to meet goal projections. Updates under DEF's latest filing plan has changed the number and type of measures that will pass under the RIM analysis for the Custom Incentive Program.

B. What, if any, program modifications is the Company considering or researching to ensure that this program will be able to more closely achieve projected participation levels? Please explain.

Response:
DEF will continue to monitor CDC COVID-19 Restrictions to adjust our requirements to increase program participation. DEF has adjusted and increased marketing plans to meet 2020-2024 Program Plan, which includes a variety of emails, targeted publications, offered energy forums focusing on our programs and will continue onsite audits, phone assisted audits and online offerings.

11. In 2020, the Company implemented the use of several technology tools or adjusted practices which allowed it to continue to offer DSM program(s) or services while still adhering to public health recommendations. Were all such tools and practices continued in 2021? Please describe any changes, additional use of technology tools, or adjusted practices made in 2021 beyond those that were launched in 2020.

Response:
DEF continued the use of several technology tools and practices in 2021 to offer DSM programs and services. Due to continued COVID challenges DEF relied heavily on its online presence and tools to advise customers of offerings, similar to 2020.

12. Please respond to the following questions regarding residential and commercial/industrial DSM programs for which DEF suspended on-site visits in 2021.

A. Discuss how DEF communicated with or responded to customers about suspended programs.

Response:
DEF placed a banner on its website informing customers of suspended programs or measures and worked with trade allies to bring awareness to suspended programs. Customers with existing appointments were contacted to convert to online or phone assisted audits or were informed they could reschedule appointments.

B. Discuss how, or if, DEF changed any aspect of its communication with customers to draw a distinction between suspended and non-suspended programs.

Response:
DEF utilized and increased online communication channels to inform customers of the distinction between suspended and non-suspended programs through its website, social media presence and emails to customers.

C. Describe any educational and/or promotional resources that were developed by DEF during 2021 to encourage participation in non-suspended programs.

Response:
DEF relied heavily on online communications channels through its website, emails to customers and social media to promote online audits and advise of opportunities for savings available in non-suspended programs. DEF also used newsletters and bill inserts to encourage customers to complete audits and shared information about opportunities for savings through non-suspended programs.

D. For each program that suspended on-site visits, please fill in the data to complete the following table (or provide a response in an electronic file with formulas intact and the cells unlocked):

[Program Name_______] Wait List and Participation Details			
Period	Program Offered or Suspended (mark "O" or "S")	Number of Program Participants	Number of Wait-Listed Participants
January 2021			
February 2021			
March 2021			
April 2021			
May 2021			
June 2021			
July 2021			
August 2021			
September 2021			
October 2021			
November 2021			
December 2021			
January 2022			
February 2022			
March 2022 (if available)			

Response:
Home Energy Check, Residential Incentive and Residential Load Management programs resumed on March 1, 2021. There were no wait listed participants as the programs were suspended and rescheduling of appointments and audits were required. Low Income Weatherization Assistance program resumed on March 2, 2021. There were no wait listed participants as the program was suspended and field work only resumed on that date. Neighborhood Energy Saver program resumed on May 17, 2021. There were no wait listed participants the program was suspended and rescheduling of in-home installations were required.

13. In 2021, what was the Company's System Average Line Loss percentage?

Response:

RESIDENTIAL/COMMERCIAL INDUSTRIAL LOSS FACTOR

Residential	23,037,266	54.89%	6.39%
Commercial Industrial	18,931,092	45.11%	4.59%
Total	41,968,358	100.00%	5.58%

14. In 2021, did supply chain disruptions impair the Company's ability to offer conservation programs? If so, provide a detailed response that identifies the program(s), the specific challenge(s), and the responsive actions taken.

Response:
The supply chain disruptions impaired the Company's ability to meet conservation program goals not the ability to offer the programs. Long lead times and chip shortages were some of the factors to the supply chain disruptions. DEF worked with their vendors and suppliers to ensure the supply issue would improve and would not cause future delays. DEF also communicated challenges to partners and agencies to ensure awareness of the industry wide issue.

15. Pursuant to Rule 25.17.0021(5)(k), Florida Administrative Code, DEF's Report shall contain, at a minimum, "a justification for variances larger than 15% for the annual goals established by the Commission."

A. Please state the justification in 2021 for the variance larger than 15% for DEF's Residential Winter Demand Reduction (MW) goal.

Response:
DEF has and will continue to promote energy efficiency and demand response measures to provide Winter Demand Reduction (MW) savings. DEF achieved the highest cost-effective results possible with the unprecedented challenges that it continued to face in 2021. The goal value set in 2015 and was based on a significant taper in potential achievements that the company expected at the time.

B. Please state the justification in 2021 for the variance larger than 15% for DEF's Residential Summer Demand Reduction (MW) goal.

Response:
DEF has and will continue to promote energy efficiency and demand response measures to provide Summer Demand Reduction (MW) savings. DEF achieved the highest cost-effective results possible with the unprecedented challenges it continued to face in 2021. The goal value was set in 2015 and was based on a significant taper in potential achievements that the company expected at the time.

Demand Response with a Soft Touch, Delivered by Variable Capacity Heat Pumps

3002023420

Demand Response with a Soft Touch, Delivered by Variable Capacity Heat Pumps

3002023420

Technical Update, March 2022

EPRI Project Manager

A. Mammoli

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THE ELECTRIC POWER RESEARCH INSTITUTE (EPRI) PREPARED THIS REPORT.

This is an EPRI Technical Update report. A Technical Update report is intended as an informal report of continuing research, a meeting, or a topical study. It is not a final EPRI technical report.

NOTE

For further information about EPRI, call the EPRI Customer Assistance Center at 800.313.3774 or e-mail askepri@epri.com.

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ACKNOWLEDGMENTS

The Electric Power Research Institute (EPRI) prepared this report.

Principal Investigator
A. Mammoli

This report describes research sponsored by EPRI. EPRI would like to acknowledge Duke Energy for the direction and strategic guidance on this project:

G. Gurlaskie

This publication is a corporate document that should be cited in the literature in the following manner:

Demand Response with a Soft Touch, Delivered by Variable Capacity Heat Pumps. EPRI, Palo Alto, CA: 2022. 3002023420.

ABSTRACT

Heat pumps and air conditioners are a class of appliances that utilities traditionally turn to for managing residential demand during times of grid stress, including summer and winter peaks. First-generation residential demand response (DR) programs utilized one-way communicating switches that would cycle air conditioners / heat pumps with prior agreement of the customer. Second-generation programs utilized two-way communication with smart thermostats, usually by re-setting the temperature setpoint. In both cases, some level of user discomfort could result. This has been a problem historically because DR events often coincide with extreme temperatures events, when the AC unit or heat pump is needed the most. Repetitive DR events could lead to many customers deciding to override the DR event or opting out of their participation in the program altogether. Recent advances in power electronics are making variable speed heat pumps more cost-effective, leading to their increasing market penetration. Moreover, these heat pumps are controlled by sophisticated management systems that can report operating data to the manufacturer and potentially to the utility back office or to an aggregator. We will show promising results from a pilot project, in which a utility company is collaborating with an independent research organization and with a technology provider, to demonstrate that the ability to control compressor speed can be leveraged to provide high levels of demand response, while at the same time maintaining good comfort levels. In addition, data available from the heat pump control systems allow the utility or aggregator to target demand response events more effectively.

Keywords
Heat pumps
Demand response
Air conditioning
Variable capacity

Deliverable Number: 3002023420

Product Type: Technical Update

Product Title: Demand Response with a Soft Touch, Delivered by Variable Capacity Heat Pumps

PRIMARY AUDIENCE: Utility program managers who wish to understand the demand response potential of widespread adoption of variable capacity heat pumps

SECONDARY AUDIENCE: Stakeholders, including energy efficiency and decarbonization advocates; State and Federal regulators wishing to understand the potential of heat pump technology as flexible grid resources

KEY RESEARCH QUESTION

Recent advances in power electronics are making variable speed heat pumps more cost-effective, leading to their increasing market penetration. Moreover, these heat pumps are controlled by sophisticated management systems that can report operating data to the manufacturer and potentially to the utility back office or to an aggregator. This project evaluates the potential of demand response with variable capacity heat pumps using information available from onboard instrumentation and demonstrates variable capacity heat pumps' ability to reduce HVAC load and maintain occupant comfort.

RESEARCH OVERVIEW

In this pilot project, a fleet of variable capacity heat pumps are deployed in central Florida homes. The systems are monitored with the manufacturer's onboard instrumentation and EPRI's independent sensors. Several DR events were scheduled using the manufacturer's diagnostic portal. The study examines the instrumentation data before, during, and after such DR events, and is compared against a baseline without DR events under similar operating conditions. Additionally, compressor speed and outdoor temperature data were correlated to power consumption of the system, providing a potential method to assess the DR potential of variable capacity heat pumps in real time.

KEY FINDINGS

- Variable capacity heat pumps were able to provide high levels of demand response, while at the same time maintaining good comfort levels.
- The complex control systems required for variable capacity heat pumps also provide sufficient information for utilities or aggregators to identify the potential for demand response and target events effectively.
- Compared against single speed systems, variable capacity systems can maintain comfort with higher indoor thermostat setpoint and provide more precise control over indoor relative humidity.

WHY THIS MATTERS

This research provides quantitative and qualitative information on the behavior of variable capacity heat pumps during DR events. The results provide program implementors a simple method to assess the potential of load reduction in real time from a fleet of heat pumps using information from onboard sensors.

HOW TO APPLY RESULTS

The results from this project can be used as reference when considering utility Energy Efficiency and Demand Response programs. The findings show the potential of leverage variable capacity heat pumps to reduce HVAC loads without compromising occupant comfort. This potential may be verified in larger scale studies and deployments of variable capacity equipment.

EPRI CONTACTS: Andrea Mammoli, Principal Project Manager, amammoli@epri.com and Aaron Tam, Engineer / Scientist II, atam@epri.com

PROGRAM: Customer Technologies (P170)

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1
INTRODUCTION

The total electricity consumption for U.S. households in 2015 was 1267 billion kWh. The two largest single electric loads, air conditioning and space heating, were responsible for 214 billion kWh and 187 billion kWh respectively. For the South Atlantic region of the U.S., where this study takes place, the 2015 total household electricity consumption was 316 billion kWh, of which 70 billion kWh (22% of the total) were for air conditioning and 47 billion kWh (15% of the total) were for heating (U.S. Energy Information Administration, 2017). The share of peak electricity demand for cooling services in areas with similar warm and humid climate is well over 50% (Waite, et al., 2017). For heating, the picture is less clear because electricity is not the primary fuel in most locations. However, electrification of residential heating services resulting from decarbonization efforts, and increased climate variability leading to increasingly frequent extreme cold events in lower latitudes (Cohen, et al., 2019) mean that the severity of peak winter loads may increase in the next few decades. Because cooling and heating are the largest single loads for the residential sector, these have long been the target of Demand Response (DR) programs designed to reduce generation, transmission and distribution capacity requirements in a service area by curtailing demand during a small fraction of time when grid stress is highest (Mathieu, Dyson, Callaway, & Rosenfeld, 2012). First-generation DR efforts reduced demand effectively by cycling off air conditioner (AC) units via switches controlled by pagers, FM data radio and other one-way broadcast technologies, but left homeowners with little control on their comfort (Sullivan, Bode, Kellow, Woehleke, & Eto, 2013). Second-generation DR programs took advantage of the introduction of web-enabled smart thermostats and allowed customers to opt-out if they so desired, for example if comfort levels were compromised excessively. Some smart thermostat DR programs reduced overall load indirectly by altering thermostat setpoints, while still allowing for user opt-out (Siano, 2014). Both first- and second-generation DR programs were modeled on the assumption that AC and heat pump compressors are either on or off. Recent advances in power electronics are making it possible to run the compressor, and the associated blower fans, at speeds anywhere between 25% to over 100% of nominal full speed. This has significant advantages from several points of view. For instance, continuously adjustable capacity means that the control system can maintain temperatures very close to the setpoint. Comfort is also enhanced as a consequence of fewer periods of transient operation, resulting in better temperature and humidity control (Rice & Fischer, 1985).

In a DR setting, instead of completely turning off the heat pump or AC unit by direct control or temperature setpoint reset, it is now possible to simply reduce the capacity of the system, while still maintaining partial air flow and humidity control. By operating the heat pump or AC unit at reduced capacity, the system coefficient of performance (COP) improves considerably, so that the percent reduction in service is smaller than the percent reduction in electricity consumption. As a result, we hypothesize that the magnitude of the perceived reduction in individual customer comfort is smaller than the corresponding reduction of electric load associated with heat pump or AC operation in the service area affected. To test this hypothesis, we formed a team consisting of researchers from a utility company operating in the Southeastern U.S. (Duke Energy), from an independent research organization (Electric Power Research Institute), and from a heat pump manufacturer (Trane), to implement a pilot program involving Duke Energy customers who own a variable capacity heat pump produced by Trane. The pilot project was set up with the long-term view of implementing a scaled-up program that could include various incentives, such as rebates on the purchase of advanced heat pump equipment, compensation for participation in a DR program, or other incentives. In the pilot program, a relatively small number of customers agreed to having monitoring equipment installed at their premises, and to accepting demand response events initiated during certain weather events, such as high ambient temperatures during the cooling season or low ambient temperatures during the heating season. The goal of this study was to estimate the load reduction resulting from a DR event and its associated effect on customer comfort, as a function of weather conditions.

The paper is organized as follows: in section 2, we discuss the experimental setup and methodology. In section 3, we present and analyze the experimental results. In section 4, we discuss the implications of the results.

2
METHODOLOGY

The demand response capabilities of the variable speed heat pumps are tested at 20 different demonstration sites in Florida (referred to as Site 1-20), all of which are residential buildings (Figure 2-1). 11 of the units are enrolled in the DR program starting in summer 2019, and the remaining units are added in late 2020. The heat pumps range from two to five tons of refrigeration capacity. Some sites have multiple units serving separate zones within the house. All heat pump units have on-board instrumentation that relays the system status to a communicating controller, which in turn sends and receives information to and from the manufacturer's diagnostics portal. The portal dashboard shows a list of all thermostats that are registered and their current status, sourced from a database that continuously records data from the unit controllers. Disconnected thermostats, and thermostats that are not yet enrolled can be identified on the dashboard. For each connected thermostat, the portal can show current readings from the onboard instrumentations. This includes the measured outdoor and indoor temperature and relative humidity, cooling and heating setpoint, static pressure, indoor blower air flow rate, and compressor speed. The information is stored in the manufacturer database and can be retrieved for further analysis. Control and sensor data are sent to the portal when data point values change by a minimum threshold, to minimize bandwidth and storage requirements.

Demand Response signals can be sent manually from the diagnostics portal to select units, with durations up to four hours in increments of 15 minutes. Three of the sites (4, 5, and 11) were also instrumented with independent (EPRI) monitoring units which transferred data to a central database through a cell modem, at a regular interval of 1 minute. also instrumented with independent (EPRI) monitoring units which transferred data to a central database through a cell modem, at a regular interval of 1 minute.

Figure 2-1
Location of test houses in central Florida, shown by the markers (left) and aerial view of the Central Florida neighborhood where one of the test houses is located, typical of the entire set (right).

The DR control and monitoring setup is shown schematically in Figure 2-2. The role of the independent instrumentation serves the dual purpose of verifying manufacturer instrumentation data, and to augment the data with information that is not available from the manufacturer portal, including the power consumption. The strategy of the study was to send DR signals during certain weather events (e.g. particularly warm cooling days or particularly cold heating days), and to record the response of the system. The data captured by the manufacturer instrumentation and by the EPRI instrumentation before, during and after DR events is summarized in Table 2-1.

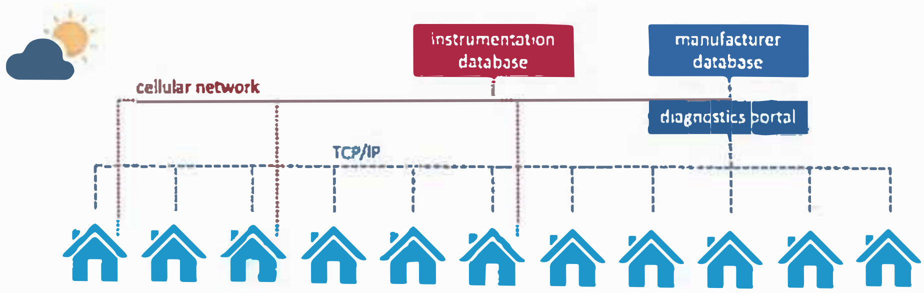


Figure 2-2
DR control and monitoring setup, showing manufacturer communications (via TCP/IP) and independent monitoring (via cell modem).

Table 2-1
Data captured by system onboard controller, sent to the manufacturer database, and by the EPRI independent instrumentation, sent to the EPRI database

	Manufacturer Monitoring	Unit	EPRI Monitoring	Unit
Indoor space	Temperature RH setpoint	°F % °F	Temperature RH	°C %
Air handler	Air flow Liquid temperature Gas temperature superheat	% °F °F °F	Power Supply temperature Return temperature	 kW °C °C
Outdoor unit	Temperature RH Compressor speed	°F % %	Temperature RH Power	°C % kW

3
RESULTS

DR in a laboratory

A cooling-mode DR event was triggered on August 6, 2019 at 4:08PM, and lasted until 4:23PM, for a variable capacity unit in the EPRI thermal chambers in Knoxville, TN. The system response, monitored from the manufacturer portal, is shown in Figure 3-1. In this experiment, the capacity of the equipment that maintains chamber temperatures is very large and is able to maintain essentially steady temperatures independently of the operation of the heat pump being tested. The "outdoor" chamber temperature was maintained at 80°F, while the indoor temperature was maintained at 70°F. For this test, the indoor setpoint for the heat pump was set to 60°F, but the thermostat was located outside of the thermal chamber, in an environment where the temperature was maintained at around 72°F. The heat pump is constantly attempting to reduce the space temperature without the ability to do so, since the thermostat is located in a different space from the one controlled, ensuring the compressor operates at maximum speed prior to the DR event. During the DR event, the compressor speed, shown by the blue band at the bottom of the graph, goes from maximum level to approximately one third capacity. Correspondingly, the air flow at the indoor air handler also decreases. We found that the compressor speed was roughly proportional to indoor air handler flow. Despite the drastic reduction in compressor speed, the refrigerant conditions in the indoor unit (functioning as an evaporator for this test) did not change appreciably. After the end of the DR event, the compressor speed slowly returned to its original state, while the airflow reached levels higher than the original. This experiment confirmed that triggering a DR event when the compressor is running at peak results in a substantial reduction in load.

Figure 3-1
Operational status of a variable capacity heat pump from the manufacturer diagnostics portal. Note the 15-minute DR event triggered at 4:08PM.

Understanding the DR Potential of a Fleet of Variable Capacity Heat Pumps

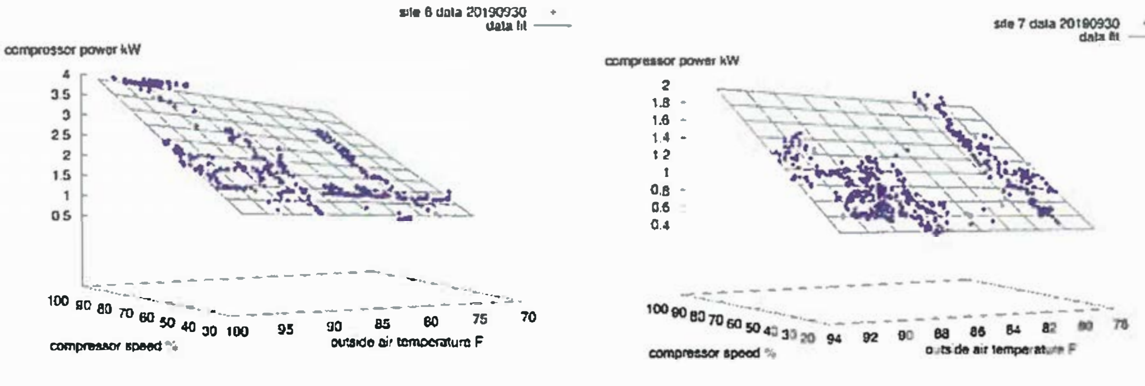
Existing DR programs rely on large numbers of end use devices to respond to a signal, in such a way that the collective response is close to the expected magnitude. The response of an individual end-use device depends on whether the device is active and on whether it is able to respond under its operating conditions. Statistics on these parameters are increasingly being collected by smart thermostats, however they still do not provide a complete picture. For example, the on/off state of a device does not provide information on the change in power consumption following a state switch. On the other hand, for variable capacity heat pumps like the ones considered in this project, while direct measurements of power consumption are not available, it should be possible to estimate power consumption at any given time based on known compressor speed and other sensor measurements.

The mechanical work done by the compressor in a variable capacity heat pump can be assumed to depend on the flow rate of the refrigerant, and on the compression ratio between the condenser and the evaporator. We consider the case of cooling mode operation. Under the assumption that evaporator conditions are approximately constant (because indoor setpoints are generally stable), it may be assumed that flow rate is directly proportional to compressor speed. The compression ratio is a nonlinear function of the outdoor temperature, which can be approximated as a power law. Thus, the electric power consumption P of the compressor can be expressed as

$$P = AS(B + T)^C \quad \textbf{Equation 3-1}$$

where A, B and C are constants, S is the compressor speed and T is temperature. Data from two sites, 6 and 7, where EPRI monitoring was installed, were collected. A five-ton cooling capacity unit is installed at site 6, while a three-ton unit is installed at site 7. A least-squares fit of Equation 3-1 to the data produces $A = 0.000118425$, $B = 0.000999942$ and $C = 1.26082$ for the five-ton unit and $A = 0.0000681833$, $B = 0.000999956$ and $C = 1.25951$. The ratio of the constants A for the three-ton and the five-ton units is 0.575, close to the expected 0.6 ratio of the machine nominal ratings. The constants B and C are virtually the same, giving us good confidence that the heuristic model of Equation 3-1 describes the same thermophysical mechanisms in the refrigeration cycle accurately.

The lab experiment is not completely representative of actual field conditions in its present configuration, as it does not accurately model the varying thermal load and the thermal response of a house and cannot account for customer behavior or comfort perceptions. We therefore set up an ongoing field-testing schedule, and here we report a summary of the results of the experiments to date. Using the manufacturer diagnostics portal, we triggered a number of field DR events between July 2019 and December of 2020. A typical cooling season response, in terms of state of the conditioned space, system power draw and outdoor conditions, is shown in Figure 3-2 for site 4, where a 3-ton unit is installed. The DR event was triggered at 5:48PM and lasted 30 minutes. Prior to the DR event, the system had just gone from unoccupied set point, at 79°F, to occupied set point at 77°F. As a result, the heat pump was working at high capacity to quickly reduce the space temperature, at a rate of approximately 0.3°F/min according to the onboard sensor readings. When the DR event was triggered, the heat pump began working at reduced capacity and space temperature began to rise at a rate of approximately 0.02°F/min according to the onboard sensor readings. Relative humidity remained essentially constant, between 49% and 50% according to the onboard sensors. It is interesting to note that the EPRI temperature sensor readings differed from the onboard readings both in magnitude and rate of change. The difference in magnitude can simply be attributed by a calibration bias. The difference in rate of change is likely due to the fact that the sensor is located inside an enclosure that does not promote air flow and therefore responds more slowly to temperature changes. Regardless, the 30-minute DR event results in a temperature change of 0.6°F, unlikely to cause occupant discomfort or even be noticed changes. Regardless, the 30-minute DR event results in a temperature change of 0.6°F, unlikely to cause occupant discomfort or even be noticed.



(a) (b)

Figure 3-2
Relationship between compressor power (EPRI measurement), compressor speed and outside air temperature (manufacturer sensor data), for a five-ton unit (a) and a three-ton unit (b).

Upon triggering of the DR event, the power consumption of the outdoor unit (the compressor and fan ensemble) decreased from the original 1.3 kW to approximately 0.5 kW, while the power consumption of the indoor unit went from 0.15 kW to 0.02 kW. The power consumption of both outdoor and indoor units remained essentially constant throughout the DR event. After the DR event, the power consumption of the outdoor unit ramped up approximately linearly to just under 2 kW (corresponding to full capacity, assuming a coefficient of performance of 5, as indicated by the manufacturer) over the span of an hour, while the indoor unit also ramped linearly to 0.35 kW during the same period. We also note that the outdoor temperature was decreasing at a rate of approximately 0.03°F/min during the DR event and also during the prior and subsequent one-hour periods.

It is also interesting to observe the collective effect of a DR event, with the understanding that the sample is limited and that we cannot determine statistically significant DR capacity indicators based on this. A test requesting all test sites (11 total at the time) to participate in a DR event was conducted on June 28th, 2020. The compressor speed of the connected variable capacity heat pumps starting 30 minutes before a 30-minute DR event and ending 30 minutes after the DR event is shown in Figure 3-3(a). Compressor speed is a good indicator of the total DR potential, since the compressor consumes the majority of power in a heat pump. We observe that, collectively, this DR event produces good demand reduction from the units. All the units resumed normal operation after the event, with most ramping up capacity to provide additional cooling to the space to return to setpoint.

The indoor temperature and thermostat setpoint are two parameters that are essential in understanding the variable capacity heat pump response to DR events. Figure 3-3(c) shows the difference between indoor temperature and thermostat setpoint. The deviation is calculated by subtracting the setpoint from indoor temperature, so a deviation of -1°F means the indoor temperature is 1°F below the thermostat setpoint. The units had the same thermostat setpoint before, during, and after the event except for site 5 and 11b. The setpoint for site 5 changes from 80°F to 74°F then to 77°F during the event, where it remains for the remainder of the test. This manual setpoint adjustment may be caused by the indoor temperature increase during the event. For site 11b, the setpoint adjustment was likely due to a scheduled change. Most of the units did not see a significant increase in deviation from setpoint during the DR event, demonstrating the variable capacity heat pumps' ability to maintain good comfort levels even when operating at a reduced capacity, partially due to the increased COP.

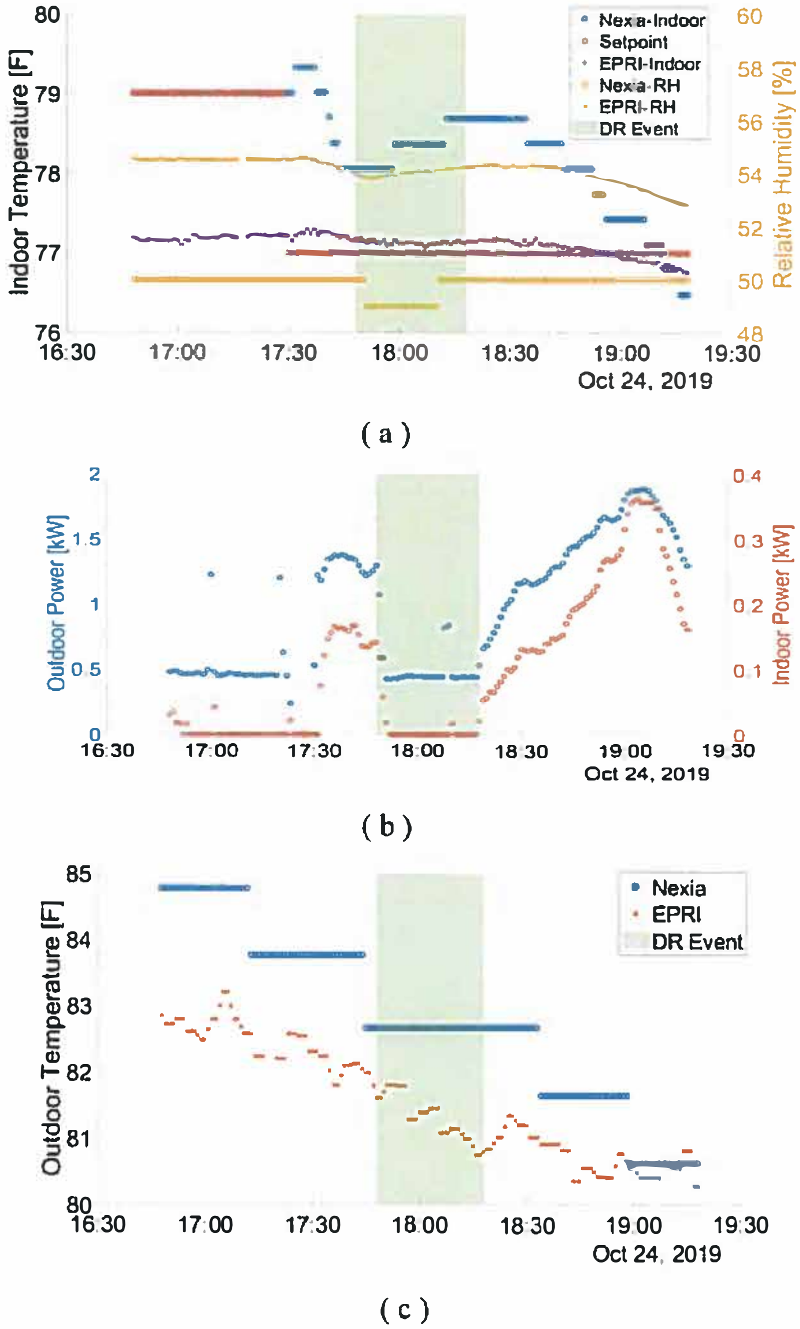


Figure 3-3
DR event in the field on October 24, 2019 at 5:48PM, showing indoor temperature, setpoint and relative humidity (a), outdoor and indoor unit power consumption (b) and outdoor temperature (c). Note the change in setpoint prior to the DR event, resulting in high compressor speed. Green shading indicates a DR event.

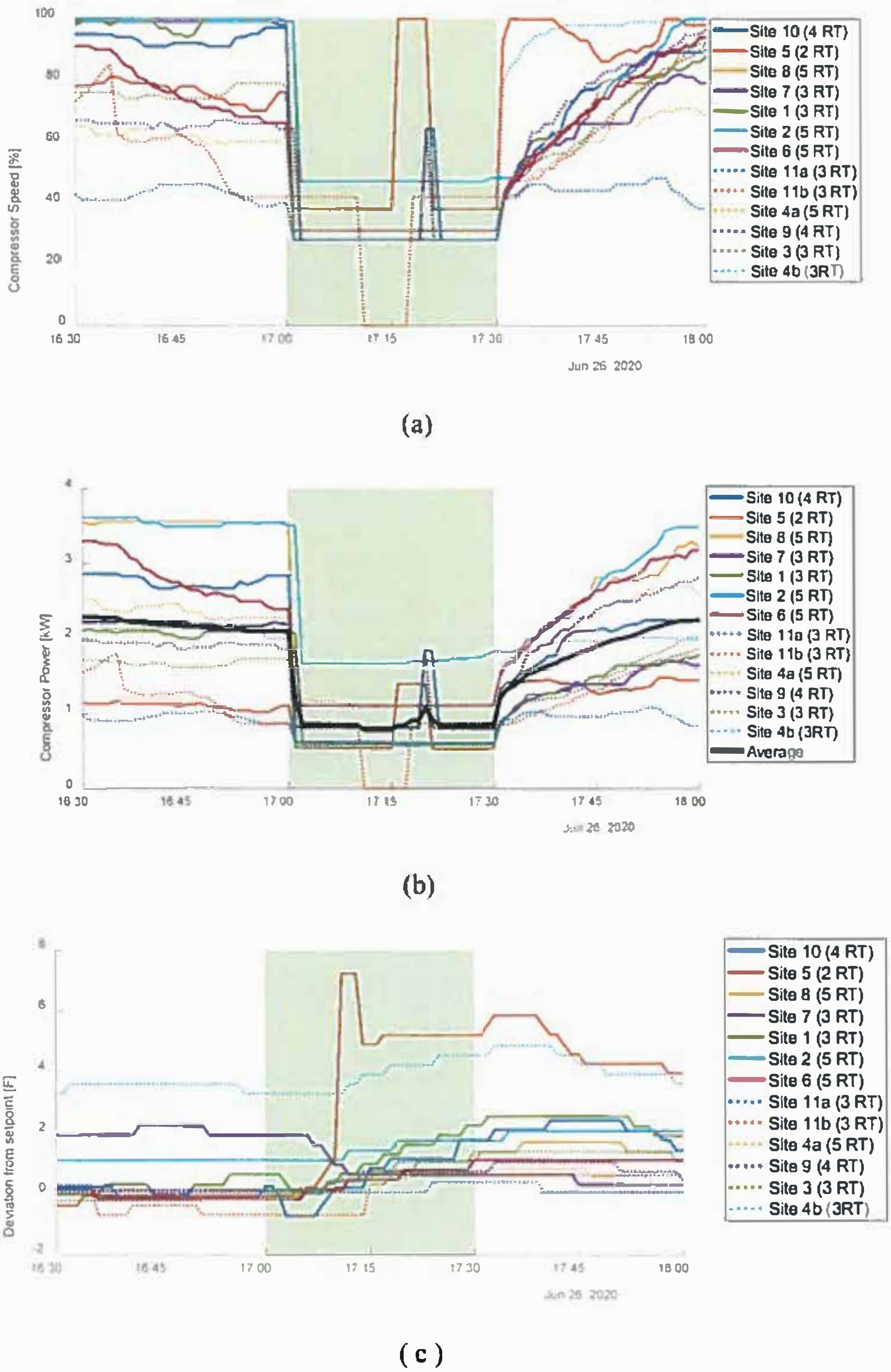
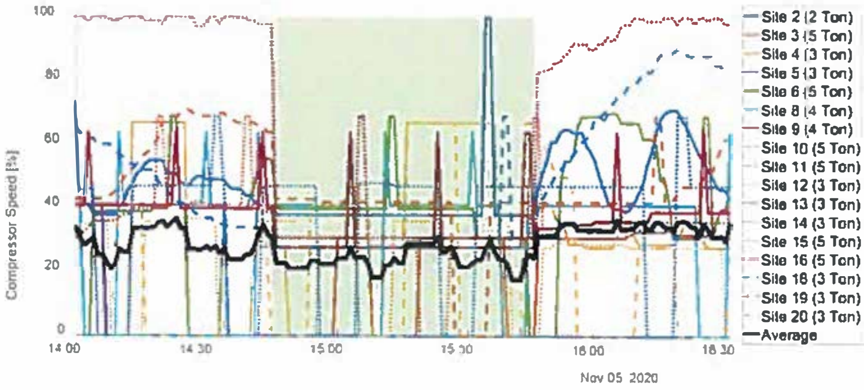
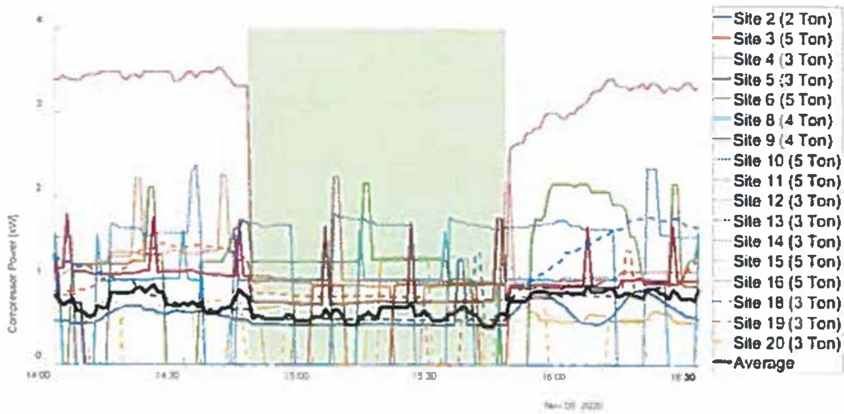


Figure 3-4
Collective DR response of all test units on September 30, 2019, showing compressor speed (a), compressor power (b) and space temperature deviation from setpoint (c). Each heat pump is denoted by an ID number, while the DR period is shaded in green.

A 1-hour DR event on November 5, 2020, is shown in Figure 3-5, with data from all except 3 enrolled units. The DR event started at 2:45PM and the results are presented in the same fashion as the previous example. Figure 3-5(a) shows that only 1 unit (site 16) was operating at its maximum compressor speed prior to the event, and several units are operating above 50% capacity. All of those units saw a reduction in compressor speed at the start of the event, and several units saw spikes in compressor speed during the course of the event. This is likely due to manufacturer's control algorithm that requires high compressor speed for oil return cycles. A closer inspection at the deviation from setpoint in Figure 3-5(c) shows the spikes in compressor speed during the DR event is unlikely to be caused by customer discomfort, since all but 1 site (site 16) were at or below setpoint during the entirety of the DR event as well as 1 hour before and after the event. The unit at site 16 was operating at 100% capacity before the event and ramped up towards 100% shortly after the event ended. The deviation at this site during the DR event increased from 2.5F to 4.9F and decreased to 3.8F 1 hour after the event. It should be noted that this site has a setpoint temperature of 70F, while the other sites range between 74F and 81F, which may also contribute to the higher deviation. The overall results actually show much lower deviations from setpoint for most of the units when compared to the 30min event, it could be due to factors such as setpoint and outdoor temperature, internal and solar gain, as well as the higher compressor speed observed during the event. Future studies should consider factors that cause nonuniform compressor speed adjustment during the DR event, as the phenomenon is not well understood from this study. However, this may be difficult without full understanding and knowledge of the proprietary controls.



(a)



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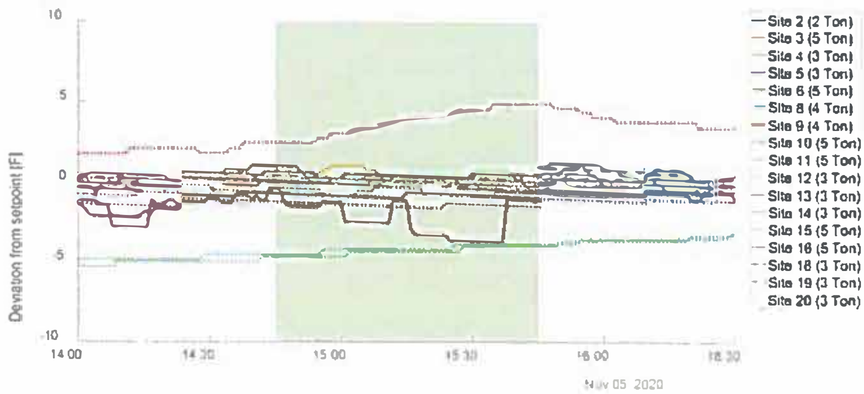
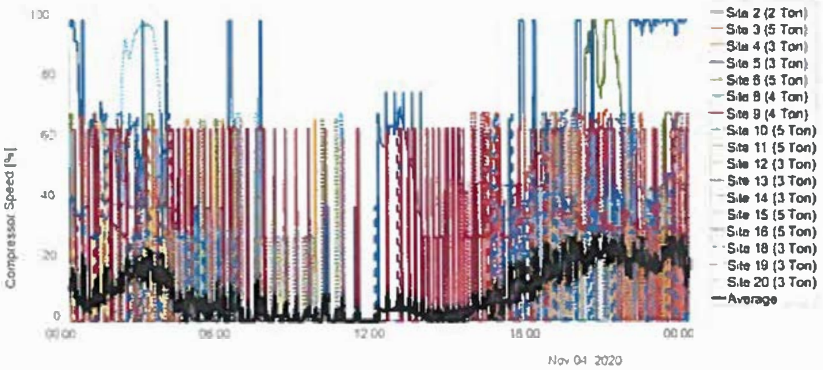


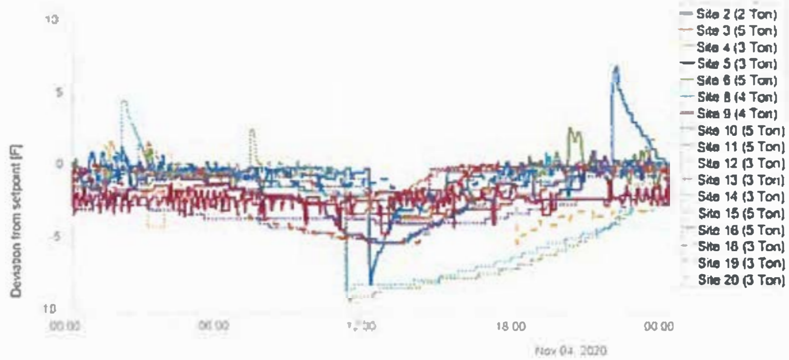
(c)

Figure 3-5
Collective DR response of all test units on November 5, 2020, showing compressor speed (a), compressor power (b) and space temperature deviation from setpoint (c). Each heat pump is denoted by an ID number, while the DR period is shaded in green.

Figure 3-6 shows the compressor speed and deviation from setpoint for all responsive units on a typical day without DR events in November. Due to the mild temperatures experienced on this day, the average compressor speed is quite low throughout the day, with a small spike after midnight and another starting around 6PM. We see several units cycle to 64% and 67% (similar to the hour-long DR event), likely due to oil return cycles at default settings by the manufacturer. It is also interesting to see the deviation from setpoint of the units, where large spikes can be observed around noon for 3 units, and a large spike in the evening for 1 unit. This provides information on the occupant habits at the host sites, where some of the units are set to a much higher setpoint during the day (likely coincident with lower building occupancy) and reduced at night. The majority of the units maintained a deviation less that 3F consistently, demonstrating again the variable capacity units' ability to provide high customer comfort.



(a)



(b)

Figure 3-6
Collective data of all test units on a typical baseline day with no DR event, showing compressor speed (a) and deviation from setpoint (b). Each heat pump is denoted by a site number and rated capacity.

The practical consequence of this result is that it is possible to estimate the power consumption of a variable capacity heat pump very accurately based on the machine rating, the outside air temperature, and the compressor speed, all of which are known by the manufacturer and available in real time, and historically on their database, for thousands of installed units at high temporal resolution, and potentially spatial resolution. An example of the data that would be used to produce such correlations is shown in Figure 3-7, which contains the compressor speed data for all sites (20 total) from November 3 to 5, 2020. The outdoor temperature during this period span from 54F up to 98F, and therefore includes both heating and cooling mode operation of the heat pumps. Inspection of the figure reveals that compressor speed is indeed proportional to outside temperature, with data clustered around lines whose slope is determined by the combination of the thermal losses of the structure and the capacity of the unit. Other factors influencing compressor speed may be disturbances in temperature due to indoor air flows, solar gains, humidity and cycling of the compressor at low speed. The data also reveals whether the unit is sized appropriately for the structure it is installed in.

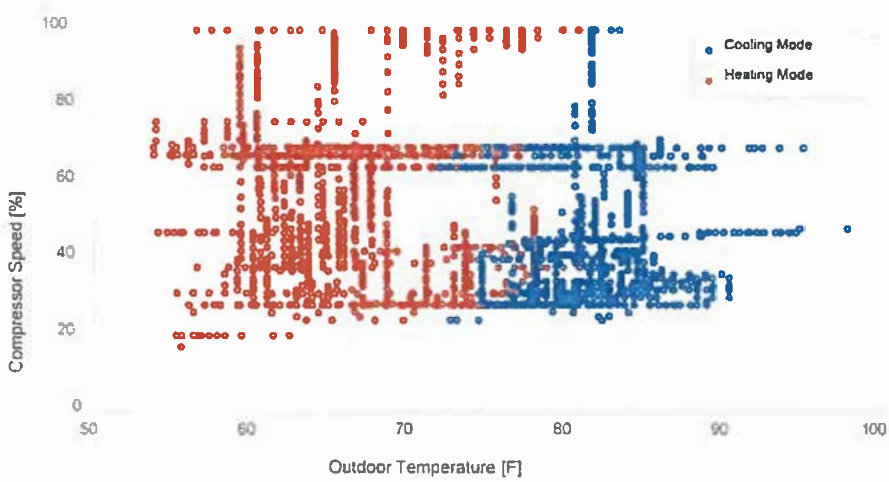


Figure 3-7
Compressor speed as a function of outside temperature for a three-day period (November 3 to 5, 2020). Colors represent heating and cooling mode of individual units.

Moreover, the thermal characteristics of each house where a variable capacity heat pump is installed can be calculated by analyzing the space temperature response to a step change such as a scheduled setpoint change or a DR event. These data can therefore provide real-time status of DR availability, as well as the capacity to forecast this for time horizons commensurate with weather forecasting.

Comfort Benefits of Variable Capacity Heat Pumps

The benefits to customer comfort can be best illustrated by comparing houses with variable capacity heat pumps to those with single speed systems. While customer behavior such as thermostat setpoints and occupancy will vary from home to home, these effects can be normalized to an extent by including a large sample of homes. The data from variable capacity heat pumps under study here is compared to a dataset of single speed systems totaling 148 homes, with the observation period spanning the month of April 2016. Similar to the variable capacity systems, the single speed systems were installed in various locations in central Florida. Key parameters such as thermostat setpoint, indoor/outdoor temperature and indoor relative humidity were monitored. Figure 3-8 shows the comparison of indoor conditions between single (blue) and variable speed systems over a range of outdoor temperatures, the variable speed data is separated into two groups, one for 2020 over several months (red), and one for 2021 April (yellow) to match the typical climate for that month. It should be noted the variable capacity data did not include any DR events for a more direct and fair comparison against the single speed baseline. Since the systems were observed during different time periods, the range of outdoor temperatures were slightly different. The comparison only includes data when the system is operating and in cooling mode.

Figure 3-8(a) shows the thermostat setpoint of the homes. The single speed systems ranged from 65F to 75F while the variable speed system ranged from 70F up to 82F. Interestingly, the setpoint for variable speed systems remained in that range even when the outdoor temperature increased over 90F. The higher setpoints for the variable capacity system are likely a consequence of their ability to precisely control indoor temperature and relative humidity, the latter of which plays a significant role in perceived comfort in humid climates experienced in Florida. This can be seen in Figure 3-8(b), which compares the indoor relative humidity of the homes. The variable speed units are able to maintain the relative humidity between 40%-60% and the relative humidity covered a large range from 35%-90% for the single speed systems. It should be noted that outdoor relative humidity was not monitored and would have an effect on the indoor conditions, but the variations should be minor since the systems are located in similar climates. Figure 3-9 shows the comparisons of the same data in whisker plot format, and it more clearly shows the higher thermostat setpoint and indoor temperature for the variable speed systems. Figure 3-9(b) in particularly, highlights the wide range of relative humidity for the single speed systems, while the variable speed systems maintain much tighter control on indoor relative humidity.

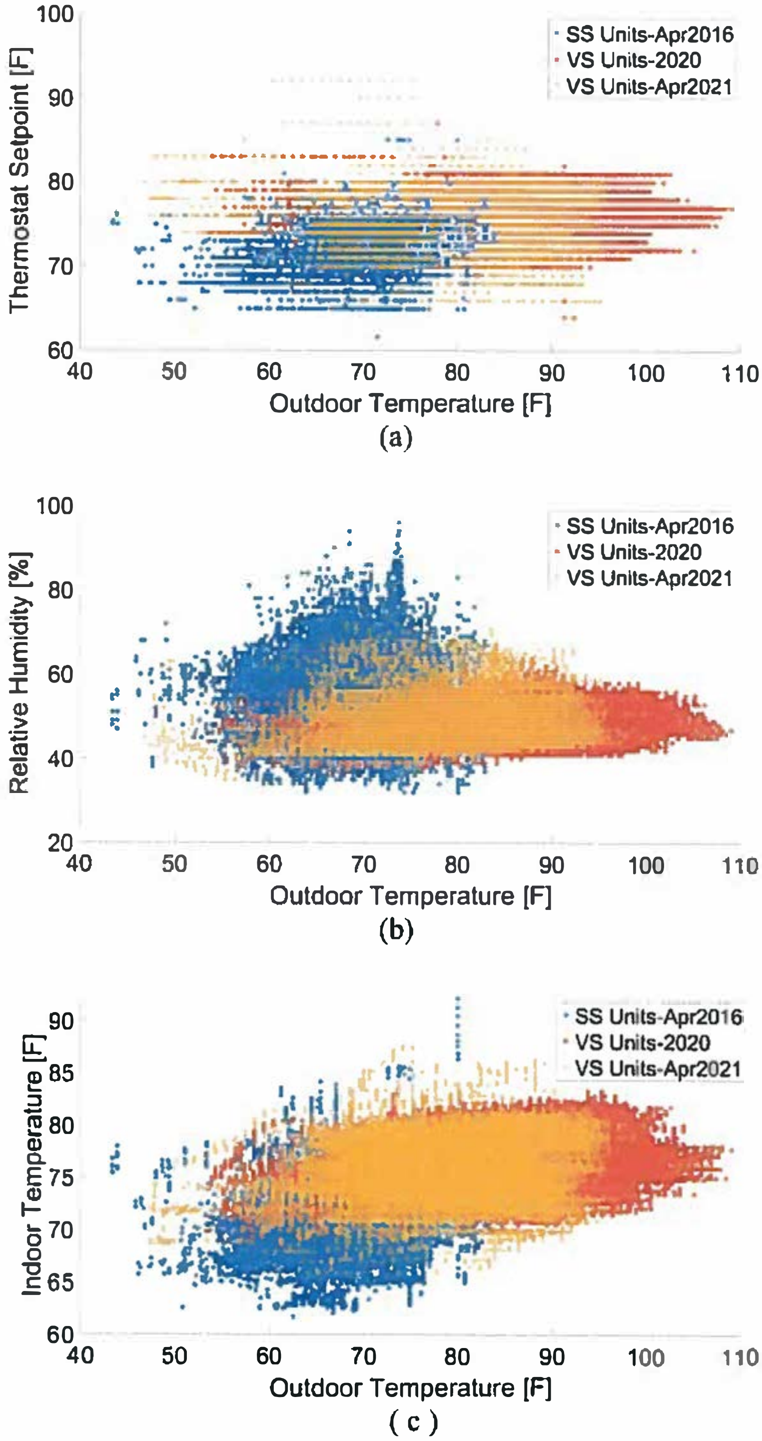


Figure 3-8
Collective data of all test units compared against a fleet of single speed heat pumps, showing thermostat setpoint (a), indoor relative humidity (b), and indoor temperature (c) for a range of outdoor temperatures. Variable capacity data is separated into data from 2020 over several months and April 2021.

These comparisons against single speed systems exemplifies the benefits of variable capacity systems in terms of occupant comfort. The reduction in thermostat setpoints translates to a reduction of thermal load of the homes under similar outdoor temperature, internal and solar gains. This can also reduce the temperature lift required to condition the homes, resulting in more efficient operation from the heat pumps. If deployed on a large enough scale, fleets of variable capacity systems may reduce the overall grid demand caused by residential HVAC systems, particularly during extreme weather conditions. When coupled with their potential to shed load during DR events, variable capacity systems are flexible grid resources that also maintain comfortable indoor conditions for customers. The enhanced comfort for customers also reduces the likelihood of customers opting out of DR events or exiting DR programs entirely.

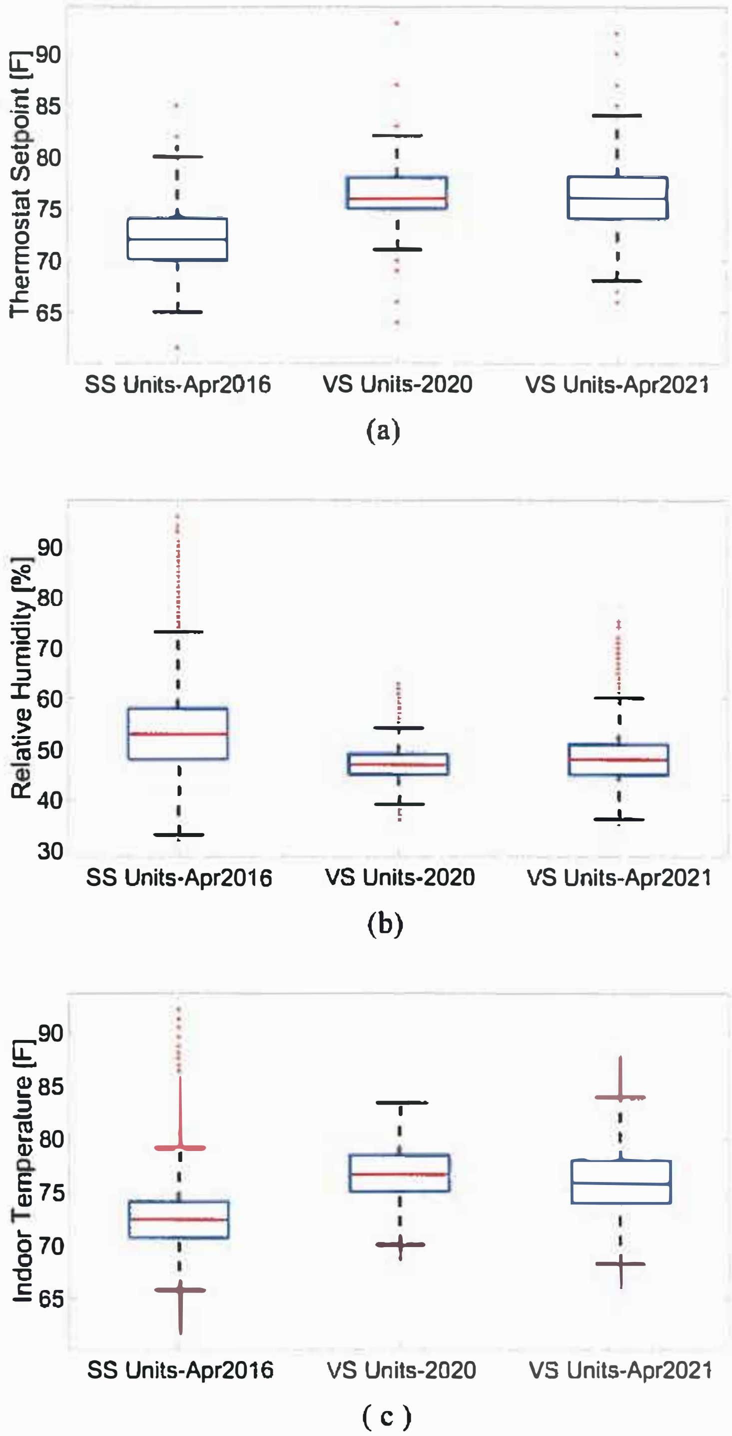


Figure 3-9
Collective data of all test units compared against a fleet of single speed heat pumps, showing thermostat setpoint (a), indoor relative humidity (b), and indoor temperature (c) for a range of outdoor temperatures. Variable capacity data is separated into data from 2020 over several months and April 2021.

4
DISCUSSION AND CONCLUSION

Although the number of participants in this study was limited, this study provides strong evidence that variable capacity systems offer more flexibility than corresponding single-speed units for demand response and for its closely related concept, load flexibility. Demand response has traditionally been associated with a utility's need to reduce load during times of grid stress, while load flexibility is an evolution of DR associated with the evolving need to match demand to variable renewable generation. For traditional DR, the need to reduce demand usually coincides with severe weather conditions (very hot or very cold). In this case, a well-designed system may very well be working at or near maximum capacity, but DR with variable capacity equipment merely reduces its capacity instead of cycling the system off like conventional equipment, so the impact on comfort (and perception thereof) is more limited. The well-known fact that a variable capacity system at part load is more efficient than at full load also contributes to mitigating the reduction in thermal comfort in comparison to a single speed system at the same average load reduction. The ability of fleet of heat pumps to provide a flexible load also depends on the season. In hot summer conditions, there is more capacity to reduce load rather than to increase it, and this is a good match for traditional DR programs where the need is usually for a system load reduction. In shoulder seasons, on the other hand, when systems are at part load, variable capacity heat pumps offer opportunities for load flexibility, for example to compensate for intermittent PV generation on the grid. Here too, the ability to vary load continuously means better load flexibility than with conventional systems, where cycling units on and off is limited by the compressor deadtime between start and stop. It should also be noted that variable capacity units offer better control of humidity than units that cycle, because they can vary the ratio of compressor speed and fan speed to control moisture.

Because variable capacity units depend on more sophisticated controls, the information available is far more than with conventional units, even those where smart thermostats have been installed. As a consequence, it is increasingly possible to characterize the thermal response of a house to changes in capacity. This can be done in a variety of ways - passively, by observing the temperature response as a function of setpoint changes or capacity reductions during a DR event, or actively, by perturbing the capacity by a small amount, imperceptible to the user, and observing the resulting temperature change. Knowledge of the thermal response of a house can be helpful to target DR levels to individual homes. For example, houses with slow response (good insulation, high thermal mass) may be able to support longer DR times than ones with faster response and may thus be targeted differently. The availability of information on the state of a structure and on its thermal response may also be useful in estimating the overall DR capacity / flexibility of a service region, for real-time response and for forecasting purposes.

Finally, the nature of modern variable HVAC controls is difficult to access by traditional utility DR implementations. Enrolling and controlling these sophisticated devices can now be done remotely in contactless way with no need for additional hardware installed by the utility or the customer. This makes future DR programs with variable capacity equipment potentially cheaper to setup and administer. Customers also benefit from transparency and cost effectiveness of the program, which could lead to higher utility cost savings.

5
REFERENCES

Cohen, J., Zhang, X., Francis, J., Jung, T., Kwok, R., Overland, J., . . . Feldstein, S. (2019). Divergent consensuses on Arctic amplification influence on midlatitude severe winter weather. *Nature Climate Change*, 1-10.

Mathieu, J., Dyson, M., Callaway, D., & Rosenfeld, A. (2012). Using residential electric loads for fast demand response: The potential resource and revenues, the costs, and policy recommendations. *ACEEE Summer Study on Energy Efficiency in Buildings* (pp. 189-203). Monterey, CA, USA: ACEEE.

Rice, C. K., & Fischer, S. K. (1985). A Comparative Analysis of Single-and Continuously-Variable-Capacity Heat Pump Concepts. *Proc. of the DOE/ORNL Heat Pump Conference*, (pp. 57-65). Washington, D.C., USA.

Siano, P. (2014). Demand response and smart grids—A survey. *Renewable and sustainable energy reviews, 30*, 461-478.

Sullivan, M., Bode, J., Kellow, B., Woehleke, S., & Eto, J. (2013). Using residential AC load control in grid operations: PG&E's ancillary service pilot. *IEEE Transactions on Smart Grid,, 4*(2), 1162-1170.

U.S. Energy Information Administration. (2017). *2015 Residential Energy Consumption Survey.* Retrieved from https://www.eia.gov/consumption/residential/index.php

Waite, M., Cohen, E., Torbey, H., Piccirilli, M., Tian, Y., & Modi, V. (2017). Global trends in urban electricity demands for cooling and heating. *Energy, 127*, 786-802.

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Duke Energy Charge FL

Final Report

Delivered On	Prepared By	Prepared For
October 18, 2021	Geotab Energy	Duke Energy Florida

Table of Contents

Executive Summary

The Duke Energy Charge FL program was designed to monitor driving and charging data from 200 residential electric vehicle (EV) customers in the Duke Energy Florida service territory using the SmartCharge Rewards™ Platform. This report analyzes data collected from October 1, 2018 to September 30, 2021. The first year of the program was used to establish a baseline of data for comparison. The second year had the introduction of off-peak charging incentives and had the participants split into two groups, a Control Group and a Treatment Group. The Treatment Group received the behavioral charging rewards, while the Control Group was used as a point of comparison. The third year had the participants remaining in their respective groups, but replaced the off-peak charging incentives with on-peak avoidance charging incentives.

Long-Range Battery Electric Vehicles (LR BEVs) tend to drive the most electric miles compared to other powertrain types, and on average consume the most electricity (11.34 kWh per calendar day). LR BEVs also tend to have the highest charging power levels, especially when utilizing publicly available DC Fast Charging stations. Short-Range Battery Electric Vehicles (SR BEVs) consume slightly more electricity on average than Plug-in Hybrid Electric Vehicles (PHEVs), which have gasoline engines as an additional power source. On average, 69.29% of PHEV miles driven were electric, and PHEVs drove more total miles than SR BEVs. When comparing the starting state-of-charge (SOC) of trips across the powertrain types, the majority of SR BEV and LR BEV drivers started their trips with an SOC of 95-100%, while many PHEV drivers started their trips with an SOC of 0-5%, meaning that they relied on their engine as often as they did their vehicle's high voltage battery.

An analysis was conducted to compare the load curves for the three EV powertrains, it showed that EV charging occurs mostly in the late evening and into the early morning hours, with load curves similar across the three vehicle segments. Weekend charging was slightly higher in the afternoon than on weekdays, but most other times are higher on weekdays. The load shape of EV charging across seasons illustrated that the seasons that often require more vehicle cabin conditioning (summer and fall) have a higher load associated with them.

When analyzing the load curves for the Control and Treatment Groups in Years 2 and 3, it was noticed that the Treatment Group participants responded to the incentives being offered by generally adapting their charging habits to match the off-peak periods. This highlighted the effectiveness of the incentives on participant charging behavior and the utility's ability to control customer load.

The substation impacts of EV charging were fairly minimal as, at this level, the load is aggregated across many EVs resulting in smooth load profiles with low power demands. At the transformer level, the load curves are more volatile with notably higher power demands. Depending on the number of EVs per transformer and their battery capacity, this may suggest that EV load needs to be controlled to avoid any negative impact on distribution assets.

When participants were surveyed on their experience within the Duke Energy Charge FL program, the response was very positive overall. A majority of participants were satisfied with the program and appreciated the value that it provided them. The biggest motivator that would influence a change in participant charging behavior would be monetary incentives, while competition with other EV drivers proved to not be an ineffective motivator. The SmartCharge Rewards™ platform, including the C2 devices and portal, were ultimately very favourable with the participants.

Overall, the Duke Energy Charge FL program was successful in meeting the objectives of the project. A baseline was established for EV charging in the Duke Energy Florida service area, and participants who have received incentives to modify their charging behavior have demonstrated a willingness to charge their EVs at times specified by Duke Energy. Both surveys that were sent to participants provided some promising feedback, and showed that participants were overall very satisfied with how the program was conducted and the data that they got out of it.

Introduction

The Duke Energy Charge FL program was a three year residential electric vehicle (EV) load management program that was provided by Duke Energy Florida, in collaboration with Geotab Energy. The program launched on October 1, 2018 and was designed to monitor driving and charging data from 200 residential EV customers in the Duke Energy Florida service territory using the SmartCharge Rewards™ Platform. The objectives of the program were as follows:

- Establish a baseline load profile of EV charging from residential EV customers in the Florida service territory;
- Demonstrate how to manage EV load growth in a scalable and cost-effective model for Duke Energy and its ratepayers;
- Evaluate the willingness and ability for EV customers to charge during off-peak periods through various strategies;
- Evaluate the impact of the SmartCharge Rewards™ mechanism on stimulating grid-friendly EV charging behaviors; and
- Evaluate the customer's interest in collecting EV charging and driving feedback.

The focus of this report is to provide a summary of the overall findings of the program, including all data collected from **October 1, 2018 to September 30, 2021**. There is a Baseline Report that was written and shared with Duke Energy Florida in January 2020 that focused entirely on the first full year of the program which can be used as an additional reference to this report.

The SmartCharge Rewards™ Platform

The program was created using the SmartCharge Rewards™ Platform. This platform leverages connected vehicle hardware and software to implement programs for EV initiatives. This allows utilities, like Duke Energy, to easily implement new ways to engage their customers while incentivizing off-peak charging and stimulating load growth during desirable times for the electrical grid. All participants in the Duke Energy Charge FL program received a C2 connected car device, which can be seen in Figure 1. This device is installed by inserting the device into the vehicle's on-board diagnostic port (OBD) or using a similar process for vehicles that are not equipped with the standard diagnostics port (i.e. Tesla vehicles).

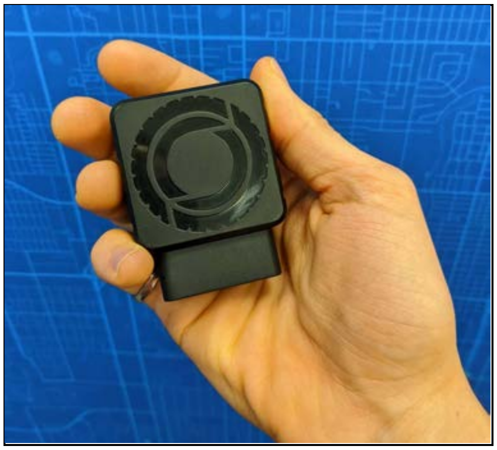

Figure 1: C2 Connected Car Device

The C2 device transmits data from the vehicle to the SmartCharge Rewards™ cloud-based platform. Relevant data is presented to participants through a user-friendly web-portal, which provides participants with insights into their charging behavior by displaying a dashboard of their EV's electricity usage and other general vehicle performance metrics.

Participant Enrollment and Vehicle Breakdown

Participants in the Duke Energy Charge FL program were recruited using various marketing campaigns designed by Duke Energy. The participants were directed to a registration page hosted by Geotab Energy which included an outline of the program goals, the application process and answers to common questions. Participants applied to the program by entering their email address and completing an application form with their personal information, which included their address and EV make, model and year. Participants also had to confirm that they were a customer of Duke Energy Florida. If the information in the application form met the required criteria, the participant was accepted into the program.

Once accepted, participants were shipped a C2 device and instructions to install the device. These instructions also included details for participants to set up their SmartCharge Rewards™ account in the SmartCharge Regards™ portal and activate their device. These steps were all necessary for active participation in the program. By setting up an account, participants had the ability to view the data being collected from their device. Activating the device facilitated the flow of data from the participant's device into the participant's SmartCharge Rewards™ account.

Throughout this report, vehicles are classified by vehicle powertrain:

- **Long-Range Battery Electric Vehicles (LR BEVs)**: Any fully electric vehicle that has a battery capacity greater than 50 kWh.
- **Short-Range Battery Electric Vehicles (SR BEVs)**: Any fully electric vehicle that has a battery capacity less than 50 kWh.
- **Plug-in Hybrid Electric Vehicles (PHEVs)**: Any vehicle with both a conventional engine and a high voltage battery as its primary powertrains.

Table 1 describes the program's vehicle breakdown by vehicle powertrain and vehicle make and model. A total of 242 vehicles have reported data since the launch of the program (including those that had withdrawn throughout the course of the program).

Table 1: Breakdown of Vehicles in the Duke Energy Charge FL Program by Powertrain and Vehicle Model

Powertrain	Vehicle Make & Model	Count of Vehicles	Total Count
LR BEV	Chevrolet Bolt EV	28	104
	Tesla Model 3	45	
	Tesla Model S	20	
	Tesla Model X	10	
	Tesla Model Y	1	

SR BEV	BMW i3	14	61
	Chevrolet Spark EV	2	
	Fiat 500e	2	
	Hyundai Ioniq Electric	1	
	Mitsubishi i-MiEV	2	
	Nissan Leaf	39	
	Smart fortwo	1	
PHEV	BMW i3 REX	1	77
	Chevrolet Volt	50	
	Chrysler Pacifica Hybrid	7	
	Ford C-Max Energi	4	
	Ford Fusion Energi	6	
	Kia Niro Plug-in Hybrid	1	
	Mitsubishi Outlander	1	
	Toyota Prius Plug-in/Prime	7	

Program Design

Year 1 - Baseline Period

The program baseline period took place between **October 1, 2018 to December 31, 2019**. This was extended by three months from the original September 30, 2019 end date to accommodate for the length of the enrollment period, ensuring an adequate amount of data was collected for baseline analysis. The initial enrollment campaign was moderately successful, however, a newsletter sent out by Duke Energy Florida in December 2018 brought in a substantial number of applications (went from 167 to 822 applications in two days), which allowed for the program capacity of 200 participants to be reached. Any participants that applied after registration ended were added to an internal waitlist.

During this period, participants were incentivized to apply and stay in the program through a $25 incentive after six months of participation (provided in March 2019 as an Amazon gift code) and another $25 incentive after one year of participation (provided in September 2019 using PayPal and integrated within the SmartCharge Rewards™ portal).

Year 2 - Off-Peak Charging Incentives

After the completion of the baseline period, all participants were separated into two equal and distinct groups with similar vehicle powertrain compositions (vehicle breakdowns can be found in Tables i and ii in Appendix I). These groups were the Control Group and the Treatment Group, with each group having their own rewards structures:

- **Control Group**: Participants earned a $25 incentive per vehicle at the end of Year 2 - no behavioral incentives were offered for this group.
- **Treatment Group**: Participants earned $0.05/kWh in off-peak charging incentives to a maximum of $10 per vehicle each month.

The inclusion of a customer-controlled charging load management solution allowed Duke Energy to assess how successful this method of load control may be for the effective management of EV load. The introduction of the Treatment Group allowed the participant to modify their charging behavior in order to maximize financial rewards. The off-peak time-of-use (TOU) hours for this period were as follows:

- 10 am - 6 pm EST & 10 pm - 6 am EST, Monday to Friday; and
- All-day on weekends and major US holidays.

Year 2 of the program took place between **January 1, 2020 to October 31, 2020**. It was initially intended to be 9 months long (with the other three months of that year being added to the baseline period). October 2020 was also included in this period as Geotab Energy and Duke Energy were actively discussing a revised structure for Year 3 of the program (as described in the following section) during this month and had not adjusted the incentive structure.

Year 3 - On-Peak Avoidance Incentives

As Year 3 of the program was approaching, a number of participants were withdrawn from the program due to inactivity (EV charging data was no longer being provided by the participant). Approximately 90% of the participants that were withdrawn from the program due to inactivity were a part of a group that did not provide regular incentives (namely the control group and the initial baseline group). The lack of incentives was thought to be a reason why participants were disengaging from the program, so the idea of introducing a monthly participation incentive for the Control Group was discussed and agreed upon. Additionally, the goal for Year 3 was to study how on-peak avoidance incentives would influence EV charging for participants in the Treatment Group, but the initial agreement only had these incentives offered in the summer of 2021 (June to September). Upon further discussion, this was modified to offer these incentives to the Treatment Group participants the entirety of Year 3.

Given that there was some unused funds remaining from the original program budget, Duke Energy requested that additional participants be recruited in order to use the remaining budget and collect additional data within the final year of the program. As a result, 45 additional vehicles were accepted into the program from the waitlist generated at the start of the program.

Year 3 of the program took place between **November 1, 2020 to September 30, 2021**, with the end of this period coinciding with the end of the program as a whole. The rewards structure for this period included:

- **Control Group**: Participants earned a $5 in monthly participation incentive per vehicle each month - no behavioral incentives were offered for this group.
- **Treatment Group**: Participants earned $15 per vehicle each month for avoiding charging during Duke Energy Florida's on-peak TOU hours (i.e. on-peak avoidance incentives).

The on-peak TOU hours for this period were as follows:

- 6 pm - 9 pm EST, Monday to Friday, Year Round; and
- 5 am - 10 am EST, Monday to Friday, December 1, 2020 to February 28, 2021 only.

Aggregate Driving Metrics

Driving and charging statistics were classified by vehicle segment and were analyzed in two ways, by 'calendar day' and by 'driving day'. Calendar day driving represents the total distance driven by a vehicle divided by the total number of days the device has been installed and logging data. Driving day distance represents the total distance driven by a vehicle divided by the number of days the vehicle has logged at least one trip. These metrics are summarized in Table 2.

Table 2: Summary Driving Metrics From All Trips Since Program Launch (October 2018 - September 2021)

Vehicle Type	Average Miles per Calendar Day	Average Miles per Driving Day	Average Electric Miles per Calendar Day	Average Electric Miles per Driving Day	Percent Electric Miles per Driving Day
PHEV	25.61	34.45	17.57	23.87	69.29%
SR BEV	23.25	29.87	23.25	29.87	100%
LR BEV	31.76	40.75	31.76	40.75	100%
Overall	**27.66**	**36.00**	**25.10**	**32.64**	**90.67%**

PHEVs show different values for the electric distances and total distances as these vehicles are able to drive both electrically and using gasoline in a combustion engine. All distances driven by the SR BEV and LR BEV vehicle segments are electric distances. On average, 69.29% of PHEV miles are electric and both PHEVs and LR BEVs cover more overall miles than SR BEVs. However, LR BEVs and SR BEVs cover more electric miles than PHEVs.

The average daily calendar and driving day distances are broken down by vehicle make and model in Table iii in Appendix II. Smart ForTwo participants have the lowest daily driving distances, while Tesla Model X and Model Y participants drive the furthest, with the sole Model Y participant reporting the highest driving distances. When comparing the electric distances travelled, Tesla Model X participants and the Model Y participant cover the most electric miles of all vehicles in this program.

Starting State-of-Charge

A vehicle's state-of-charge (SOC) refers to the percentage of usable battery energy available. The vehicle's trip starting SOC can be useful to determine how much charge is needed by EV drivers to begin a trip. An analysis of the trip starting SOC for PHEVs and BEVs can be seen in Figure 2 and 3 respectively. Approximately 17% of PHEVs start trips with an almost completely empty battery (SOC of 0-5%) while less than 1% of trips in BEVs start with this SOC. This difference can be attributed to PHEVs having gasoline as an alternative fuel source and still being able to travel when there is no usable battery energy available. The distribution of BEV starting SOC shows the majority of trips starting with an SOC of 95-100%. Figure 3 shows an interesting dip in BEVs starting with an SOC of 90-95%, which could be a result of battery-conscious participants setting their chargers to stop charging below the 90% range to prevent battery degradation, or participants simply leaving their vehicles plugged in until they reach 100%.

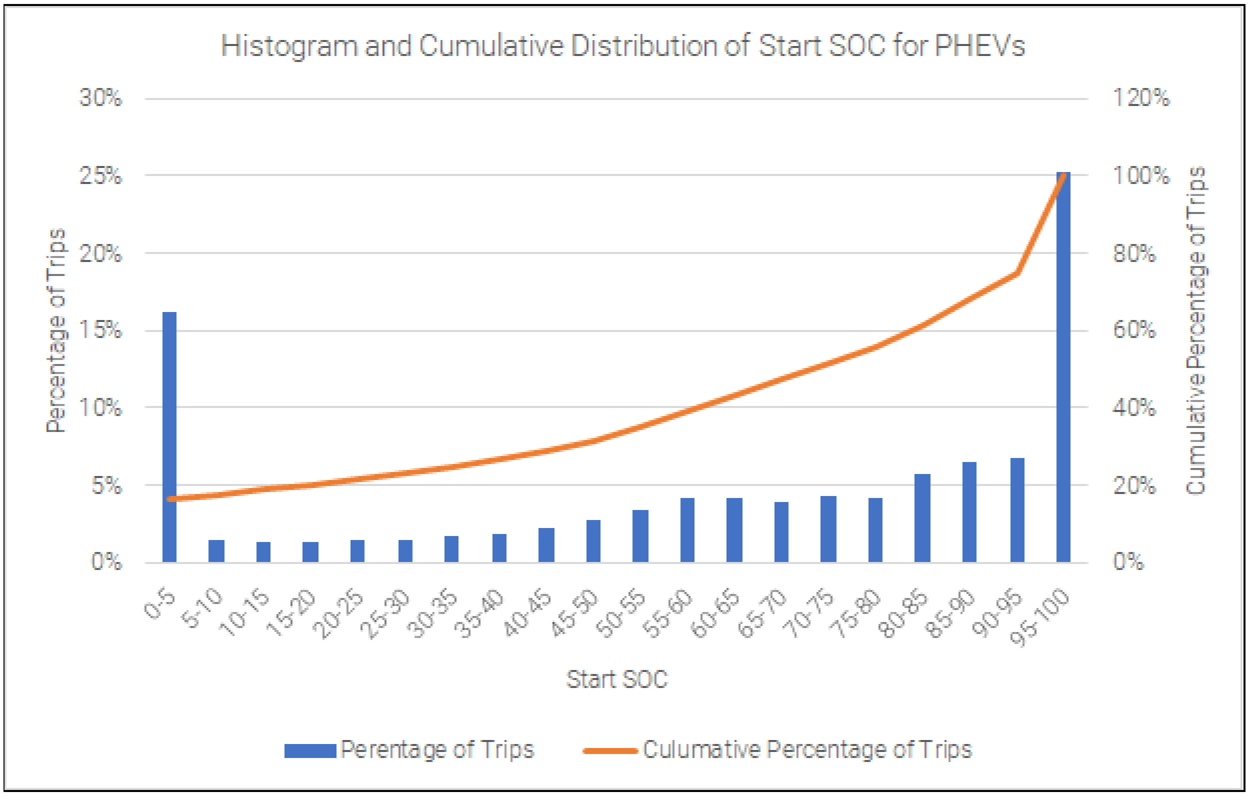

Figure 2: Histogram and Cumulative Distribution for the Battery SOC for all PHEV Trips

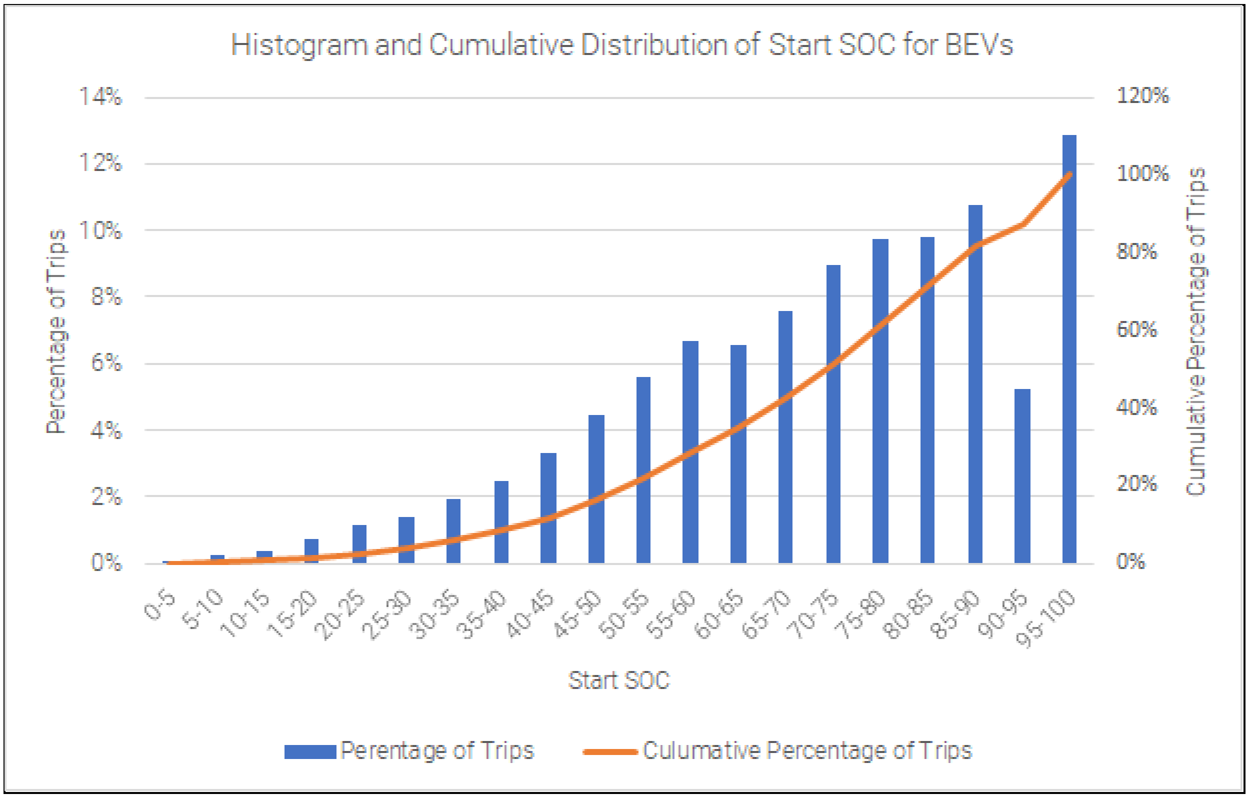

Figure 3: Histogram and Cumulative Distribution for the Battery SOC for All BEV Trips

Carbon Emissions Offset

Across the 242 vehicles reporting data throughout the program, the total electric distance driven was 4.63 million miles. Using the corresponding charging data set, the vehicle efficiency of all vehicles within this program was calculated at 0.24 kWh/mile.

Using this efficiency factor, a carbon offset was calculated using the following assumptions to convert the electric miles to a carbon emissions offset:

- The average fuel economy of a new conventional vehicle in the United States is 25.7 mpg [1]
- Tailpipe fuel emissions are 19.59 lb CO_2/gal [2]
- 6.01 lb CO_2/gal are emitted in the production of gasoline [3]
- 1.29 lb CO_2/kWh are emitted in the production of electricity in Florida (provided by Duke Energy)

The total carbon offset by the electric vehicle miles travelled by program participants from October 1, 2018 until September 30, 2021 is 1587 US tons of carbon dioxide (CO_2).

Aggregate Charging Metrics

When and how electric vehicles are charged can be sporadic and unpredictable, especially as the vehicles travel on longer trips and utilize public charging stations. To understand charging energy metrics, the data was analyzed in two ways, by 'calendar day' and by 'charging day'. Calendar day charging represents the total kWh charged by a vehicle divided by the total number of days the connected car device has been installed and logging data. Charging day statistics represent the total kWh charged by a vehicle divided by the number of days on which the vehicle had any charging events. These metrics were summarized and can be seen in Table 3.

Table 3: Summary Charging Metrics From All Charging Sessions Since Program Launch

Vehicle Type	Total Energy [kWh]	Average Energy per Calendar Day [kWh]	Average Energy per Charging Day [kWh]	Max Charging Power [kW]	Average Charging Power [kW]
PHEV	233,134.89	6.01	11.39	11.48	2.21
SR BEV	244,395.07	6.63	14.85	50.04	3.46
LR BEV	639,943.56	11.34	26.38	249.87	8.80
Overall	**1,117,473.52**	**8.48**	**18.77**	**249.873**	**5.35**

The highest rate of charging for any PHEV in the program is 11.48 kW, which corresponds to Level 2 charging. This data shows that both SR BEVs and LR BEVs are making use of some DC Fast Charging because their maximum charging power exceeds the AC charging capabilities of the vehicles by using a Level 1 or Level 2 charger. Maximum charging rates are not typical every day. The average charging powers are much lower with on-board AC charging systems usually designed for < 7 kW for most vehicles.

In general, vehicles with larger batteries and longer electric ranges are covering more miles and therefore charge more per calendar and charging day. The total electricity consumption for all participating vehicles in this study is shown in Figure 4. This box and whisker plot shows the distribution of charging energy for all EVs in each vehicle segment along with the average charging energy represented by the blue dot. In general, LR BEVs generally utilize more charging energy, followed by SR BEVs and PHEVs. The range of charging energy is more wide-ranging for BEVs due to the use of Direct Current (DC) Fast Charging.

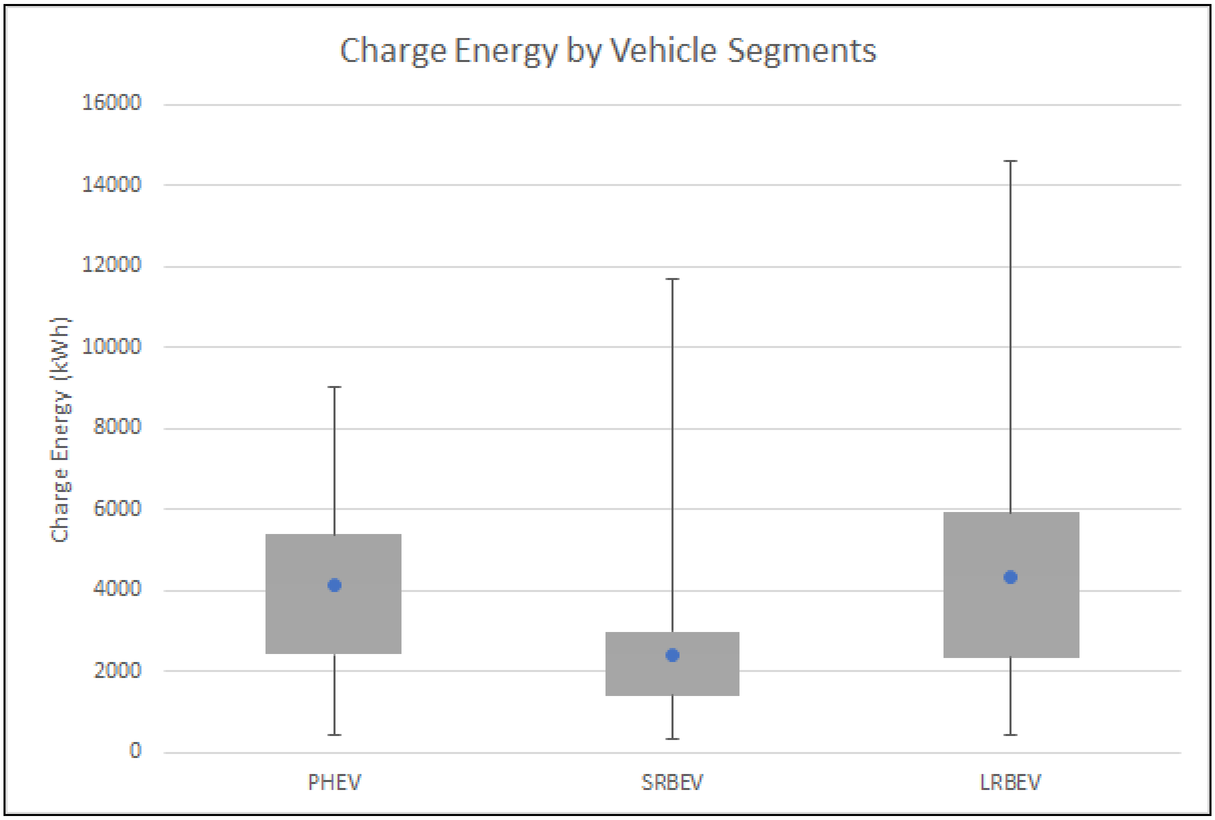

Figure 4: Box and Whisker Plot Showing the Total Charge Energy per Powertrain

Charging by Location

The location charging occured at can be classified as home charging, private non-residential charging, or public charging. Homes were assumed to be the location where the participant did most of their overnight charging. Public charging was determined based on a list of known public charging stations. The remainder of charging locations are considered private non-residential which could include locations such as workplaces.

As seen in Figures 5 and 6, a majority of all participant charging takes place at home for all powertrains. The highest number of charge events (63 - 76%) and the largest charging energy consumption (54 - 71%) occurred at home. These numbers are higher than the ones reported in the Baseline Report, possibly due to the declaration of the COVID-19 pandemic causing people to work from home more often.

PHEVs are the least likely to charge away from their homes, only utilizing public charging infrastructure for 1.65% of charge events. DC Fast Charging (i.e. Public L3) utilization appears only in the SR BEVs (1.05%) and LR BEVs (2.89%) because most PHEVs are not equipped with DCFC capabilities. While DCFC makes up only a small amount of charge events, it covers 14.86% of charging energy for LR BEVs, as these vehicles generally have faster charging rates allowing for significantly more charging energy per session.

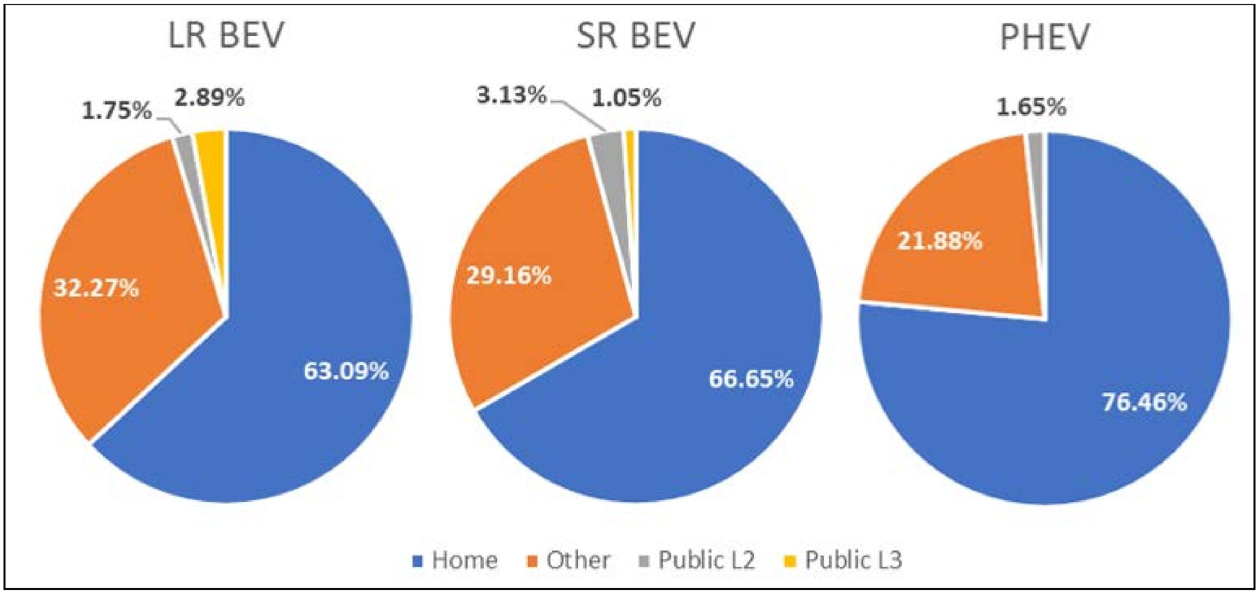

Figure 5: Charging Locations Shown by the Number of Unique Charge Events for Each Powertrain

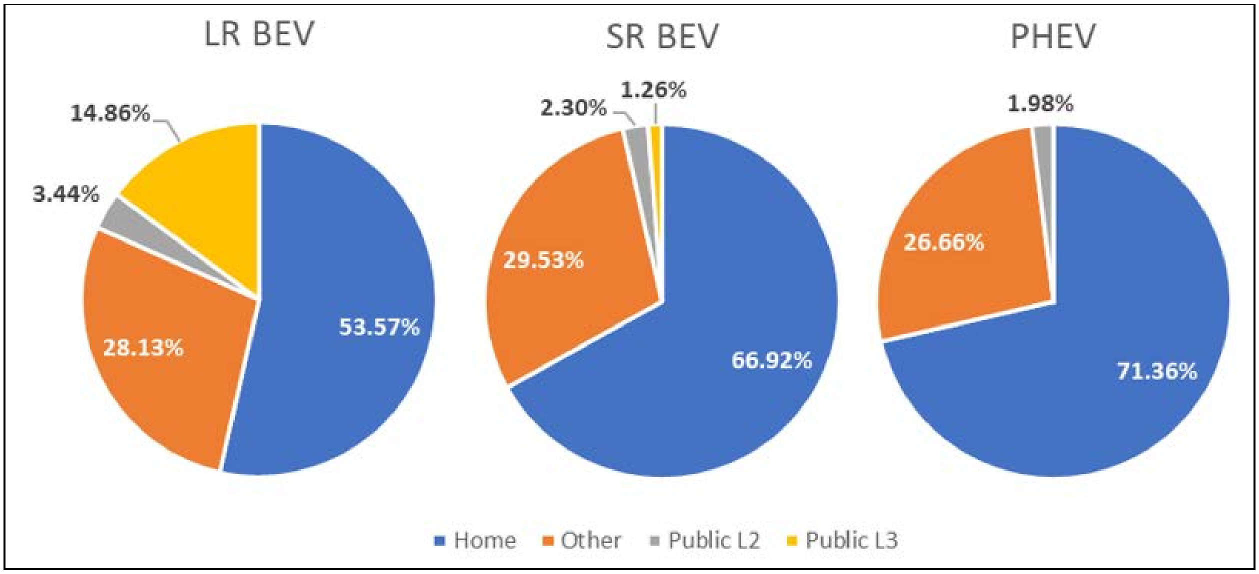

Figure 6: Charging Locations Shown by the Number of Unique Charge Events for Each Powertrain

The charge sessions and charge energy for Charge FL vehicles within the Duke Energy Florida service territory were analyzed, the results of which are illustrated in Figures 7 and 8. The majority of charging energy and charge sessions occurred within the service territory at 96% and 95% respectively. This indicates that participants in the program are most likely to do charging within their utility's service territory.

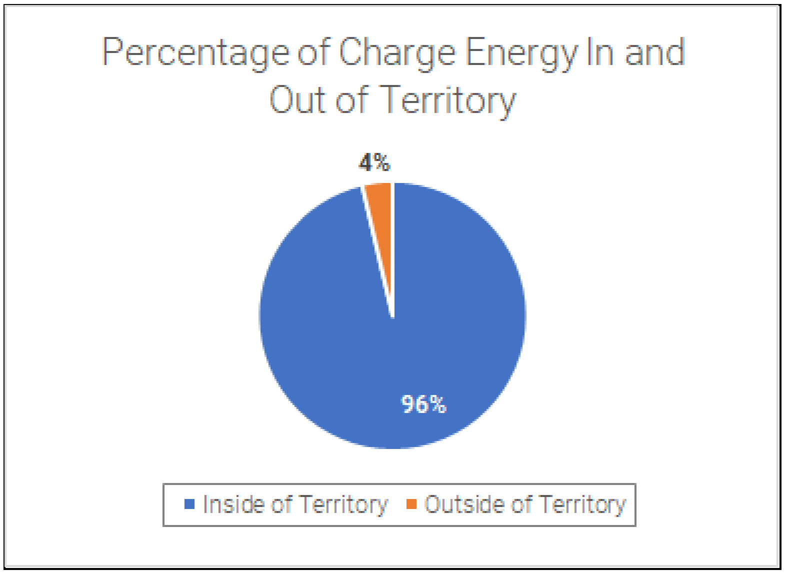

Figure 7: Percentage of Charge Energy In and Out of the Duke Energy Florida Service Territory

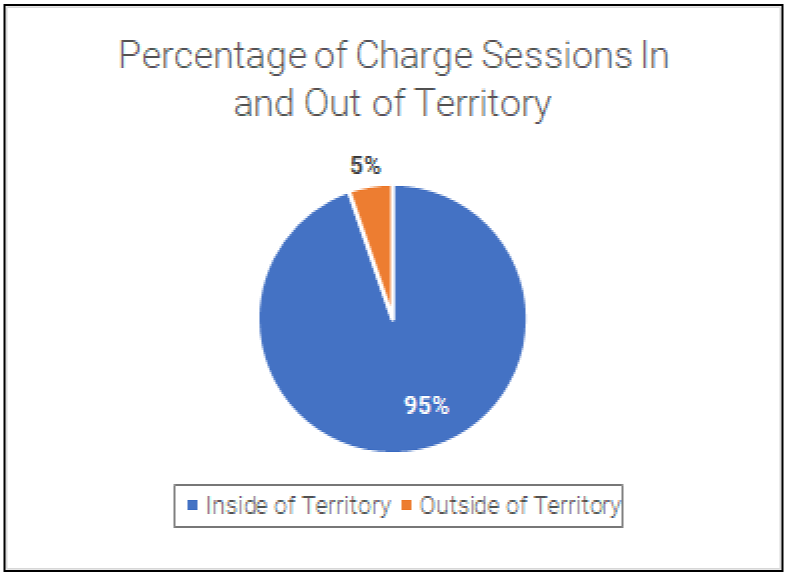

Figure 8: Percentage of Charge Sessions Occurring In and Out of the Duke Energy Florida Service Territory

Aggregate Charging Load Impacts

Understanding the load impacts from electric vehicles are complicated by the nature of charging events and the differences in charging speeds (kW) possible. This is especially true for SR BEVs and LR BEVs that can use public DC Fast Chargers capable of providing 20-250 kW of power over short periods of time (<30 minutes). The analysis in this section includes data from all program participants across both the Control and Treatment Groups.

Impact of Vehicle Powertrain

Load curves are used in this report to provide a graphical representation of the power demand over time. This allows the complexity of EV owner charging behaviors, along with the wide variety of EV makes, models and model years with varying battery sizes, to be compared together. In Figure 9, an average daily load curve across the program is presented and shows the average power draw over time of a representative vehicle from each powertrain type. Given that the smallest comparable sample size between the three powertrains is 61 (SR BEVs), the same sample size of 61 was used in this analysis for all powertrains.

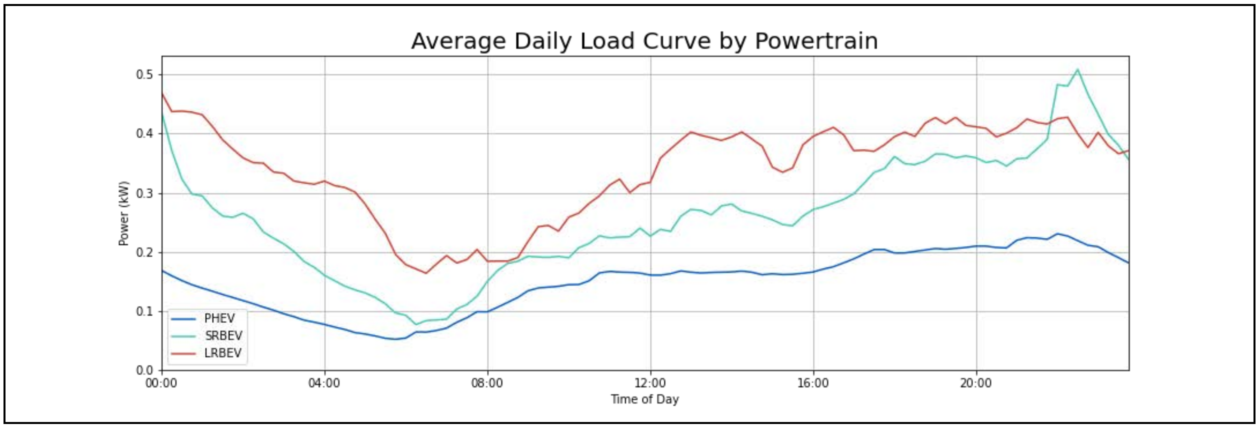

Figure 9: Average Daily Load Curve by Powertrain

As can be seen in Figure 9, all representative vehicles do most of their charging overnight, with daytime and evening charging occuring. The average power level for LR BEVs is higher than both the SR BEV and PHEV, which may be expected given the larger battery capacity in these vehicles. Charging is lowest in the early morning, around 6 am. This may correspond with the beginning of the work day when participants are utilizing their vehicles and no longer charging. This may also correspond with the end of a pre-programmed charging schedule that some participants may have set while charging overnight.

Some EVs charge every day while others charge as needed when the battery becomes depleted. Given this diversity, average load shapes, which include 0 kW when charging is not occuring, the average load curve tends to show much smaller power levels (kW) than any individual charging event.

Temporal Analysis

Figure 10 shows the average weekday and weekend load shapes for all the vehicles in this program. Although the figures are similar with peaks in the evening and after midnight, there is somewhat more variability in the late morning/early afternoon. It can be seen that afternoon charging is typically higher on weekends, but most other times are higher on weekdays. This could be due to participants being more likely to charge midday on weekends when they're not working, or connecting their vehicles either when arriving at work in the morning or when they get home in the evening on workdays.

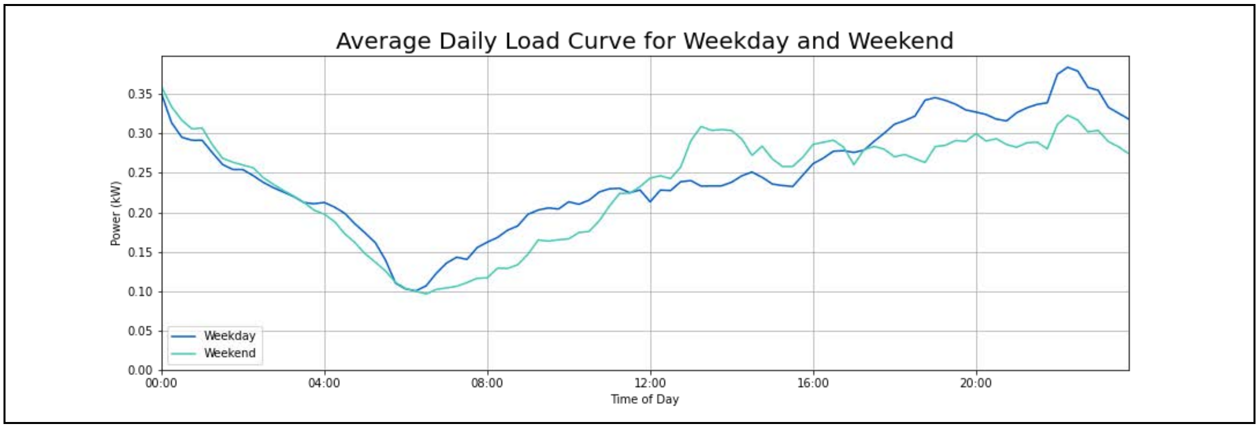

Figure 10: Average Daily Load Curve for Weekdays and Weekends

The effects of seasonal variation in EV charging were analyzed by comparing the load curve for all vehicles across the four months in 2020. Figure 11 illustrates that seasons that often require more vehicle cabin conditioning (i.e. vehicle cooling), summer and fall in Florida, have a higher load associated with them. It can also be seen that all graphs peak at around 10 pm, which corresponds with the off-peak TOU period which began in January 2020 for Year 2 (January to October 2020) and Year 3 (November 2020 to September 2021) of the program.

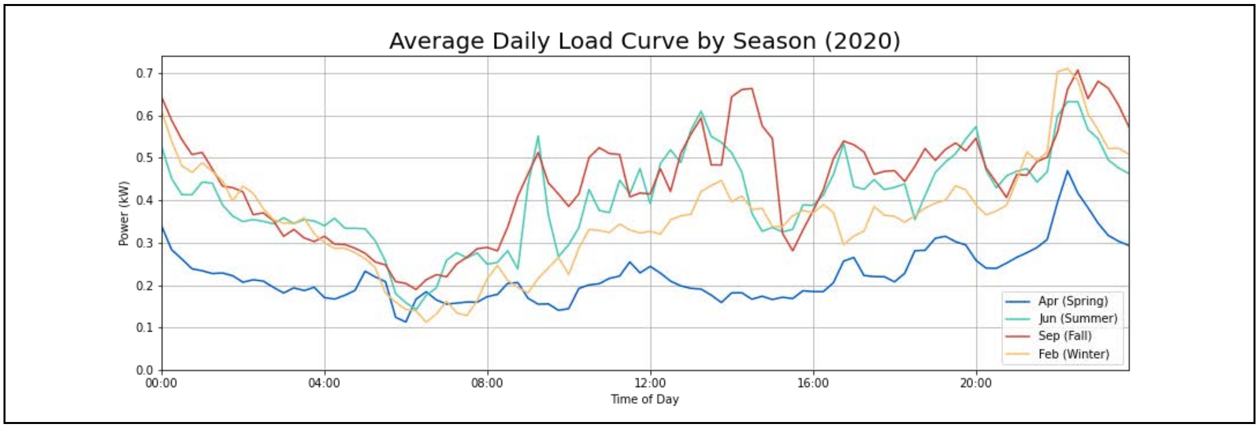

Figure 11: Average Daily Load Curves by Season for 2020

Control and Treatment Group Comparison

Program participants were split into two separate groups starting in Year 2 of the program (Control and Treatment Groups). An analysis was conducted to observe the impacts that the introduction of behavioral rewards and a TOU period had on overall load demands. Figures 12 and 13 highlight the trends during Year 2, comparing load curves pre-COVID-19 pandemic (January to March 2020) and during the pandemic (April to October 2020). The shaded areas represent the off-peak periods in Year 2 (10 pm - 6 am, and 10 am - 6 pm).

As both figures illustrate, there is a peak for the Treatment Group at the start of the evening off-peak period (10 pm), and a dip at the end of that off-peak period (6 am). The second off-peak period of 10 am to 6 pm did not play a significant role in changing the load, possibly due to participants being at work and unlikely to charge. The load curve for the Control Group is overall flatter and less volatile than the Treatment Group. This is expected given there was no communication or incentives given to direct charging to specific times. Additionally, comparing the pre-pandemic load curves with the load curves captured during the pandemic highlight that charging demand was overall more volatile, which is the result of less overall charging and more sporadic charging times.

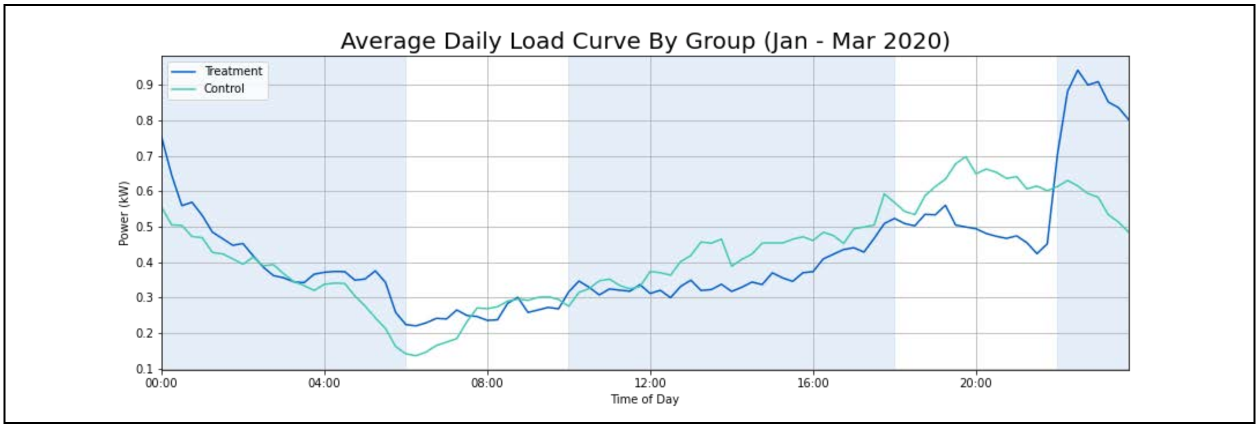

Figure 12: Average Daily Load Curves by Group (Jan - Mar 2020)

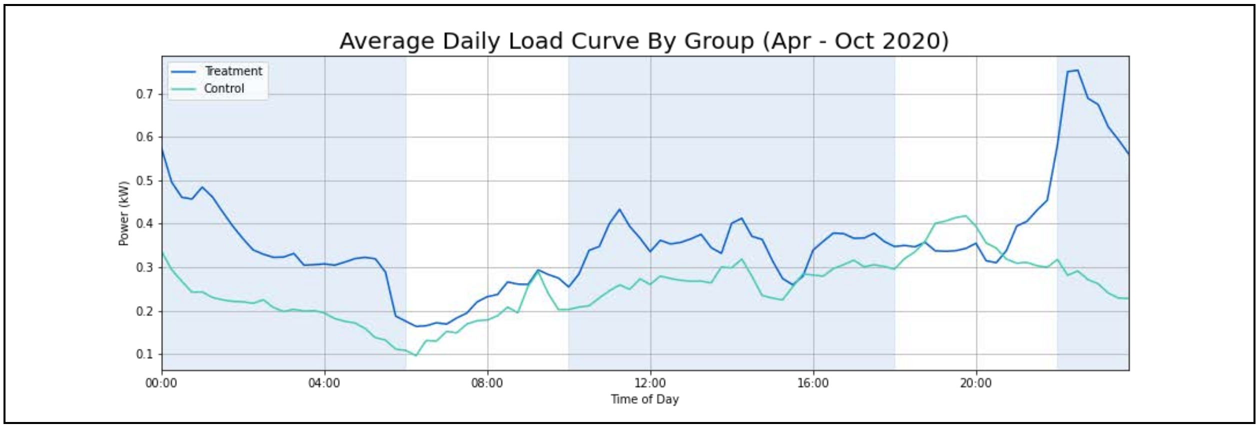

Figure 13: Average Daily Load Curves by Group (Apr - Oct 2020)

Figure 14 shows the average load curve for Year 3 of the program, in which an on-peak avoidance TOU period was introduced. The shaded areas represent the on-peak periods in Year 3 (6 - 9 pm year-round, 5 -

10 am December 2020 to February 2021). The Treatment Group shows a reduction in overall charging during the evening on-peak period when compared to the Control Group. This indicates that the on-peak incentive is effective in reducing charging demand during specific times. The morning on-peak period does not show a similar reduction in charging demand. This may be reflective of the limited exposure to the on-peak period, as it was in effect for only three months (December 2020 to February 2021).

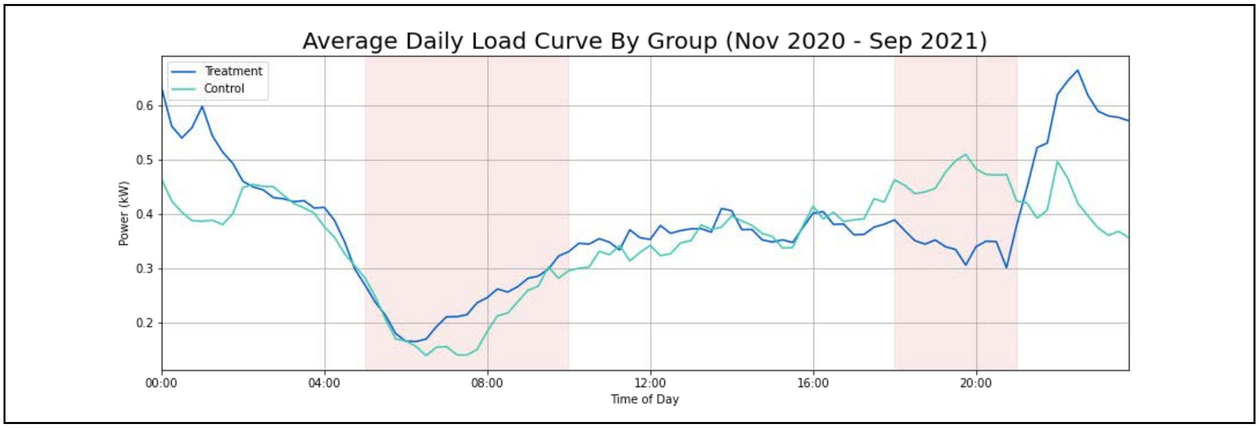

Figure 14: Average Daily Load Curves by Group (Nov 2020 - Sep 2021)

Substation and Transformer Impacts

The charging data from the program vehicles was used to generate load curves which can show the impact of distinguishing between various system levels. This includes the substation and distribution transformer levels.

When considering the impact of EVs for long term energy planning, it is useful to look at the substation level examining a large range of time and for all vehicles. The substation line (blue) in Figure 15 averages all vehicles in the program over a single day. In this graph, the day was selected randomly and the charging behavior of individuals is averaged over all program participants. The result is demand ranging from 0.2 kW to 1.4 kW throughout the day.

It is also important to understand the impact of EV charging on the distribution transformer infrastructure to power a section of a city on a given day. The transformer curve (green) includes the charging from four randomly selected vehicles (1 PHEV, 2 SR BEV and 1 LR BEV) as a model for a single neighborhood transformer. This load is more volatile, with some incidents of no charging and some incidents over 3.3 kW per vehicle. This represents an approximate potential peak load of 13.2 kW if all four vehicles charge simultaneously.

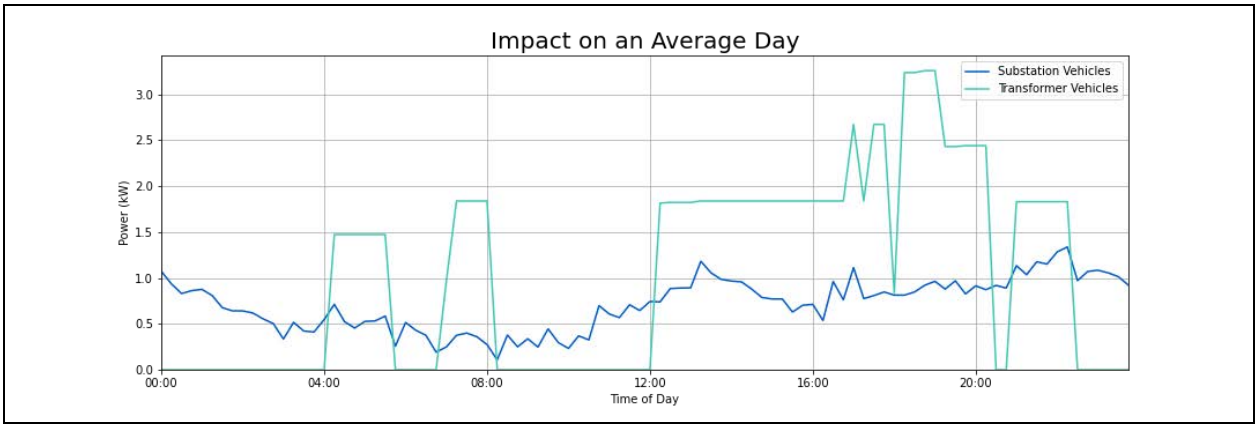

Figure 15: Average Charging Load at the Substation and Transformer Infrastructure Levels

The load curve for a day with high demand has been provided in Figure 16. In this case, the impact of coincidence load at the transformer level is higher with a potential peak load of 17.6 kW if all four randomly selected electric vehicles were charging at the same time.

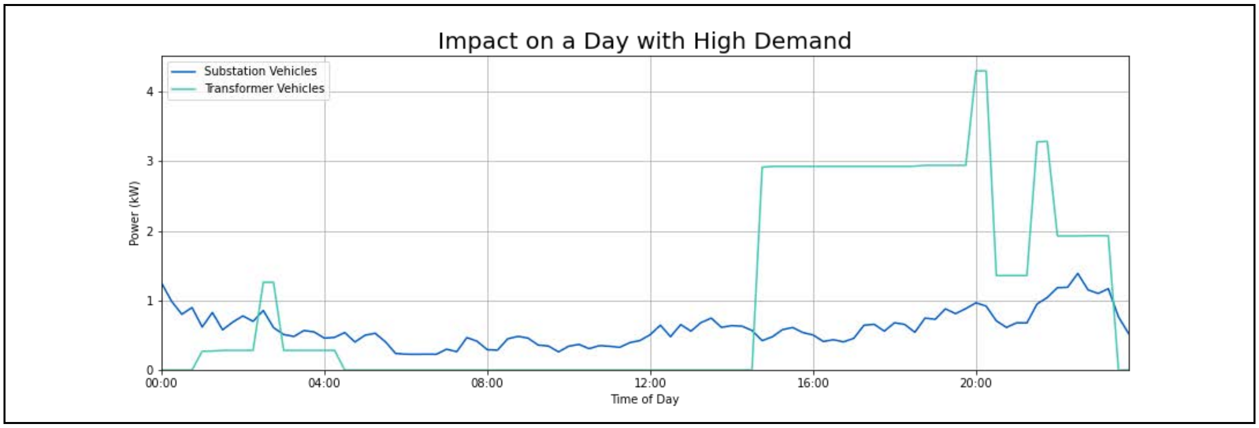

Figure 16: Average Charging Load at the Substation and Transformer Infrastructure Level on a Day of High Demand

In order to model what a substation and transformer load curve may look like in the future, a load curve of four LR BEVs has been included in Figure 17. The larger battery size of LR BEVs allows these vehicles to travel much farther on a single charge, and requires more charging energy when the battery is depleted. The coincident load for four LR BEVs is approximately 24 kW and suggests that EV load will need to be shaped to avoid negative impacts on distribution assets.

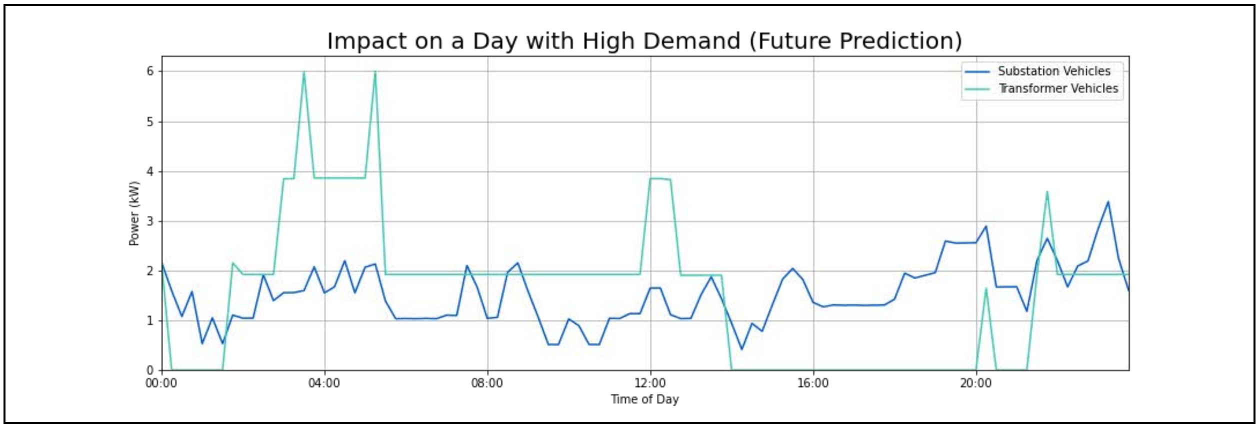

Figure 17: Average Charging Load at the Substation and Transformer Infrastructure Level with Only LR BEVs

Participant Experience

On April 13, 2021, a survey was conducted by Geotab Energy which was delivered to the Duke Energy Charge FL program participants via email. This voluntary survey was made available for a 10 day period. In total, 84 out of a total 169 participants completed the survey, resulting in a response rate of 49.70%. The objective of the survey was to enhance the program research data by collecting qualitative data. This section will highlight the results of the survey, particularly regarding feedback on the overall program satisfaction, demographics, EV charging habits, and the SmartCharge Rewards™ platform. Survey results specific to the baseline period were analyzed in the Baseline Report (January 2020).

Program Satisfaction

When participants were asked about their satisfaction with the Duke Energy Charge FL program, the results were overall very positive. As Figure 18 shows, 75% of participants stated that they were somewhat or completely satisfied with the program.

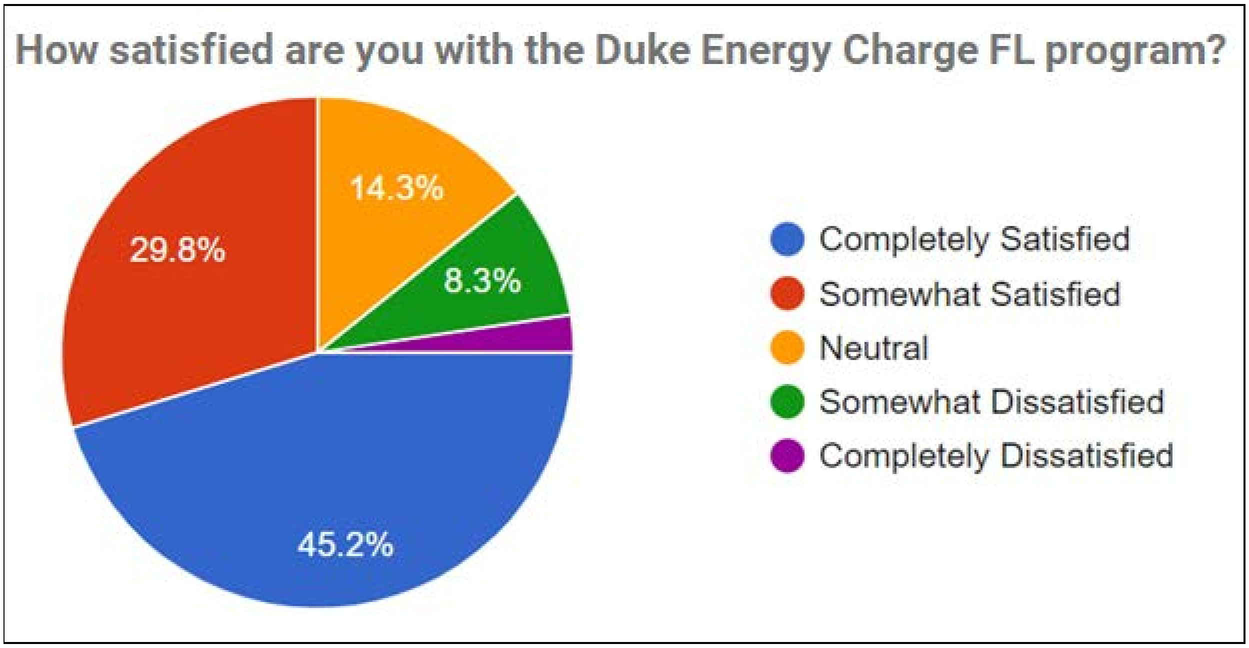

Figure 18: Participant Responses Regarding Their Satisfaction with the Duke Energy Charge FL Program

Figure 19 below highlights the benefits and values that the SmartCharge Rewards™ platform intends to offer to its participants. Overall, the majority of participants (between 64% and 85%) agree or strongly agree with the statements regarding the value being provided to them by the SmartCharge Rewards™ platform, specifically the points regarding the rewards they can earn by participating, and their ability to track their charging habits and energy consumption.

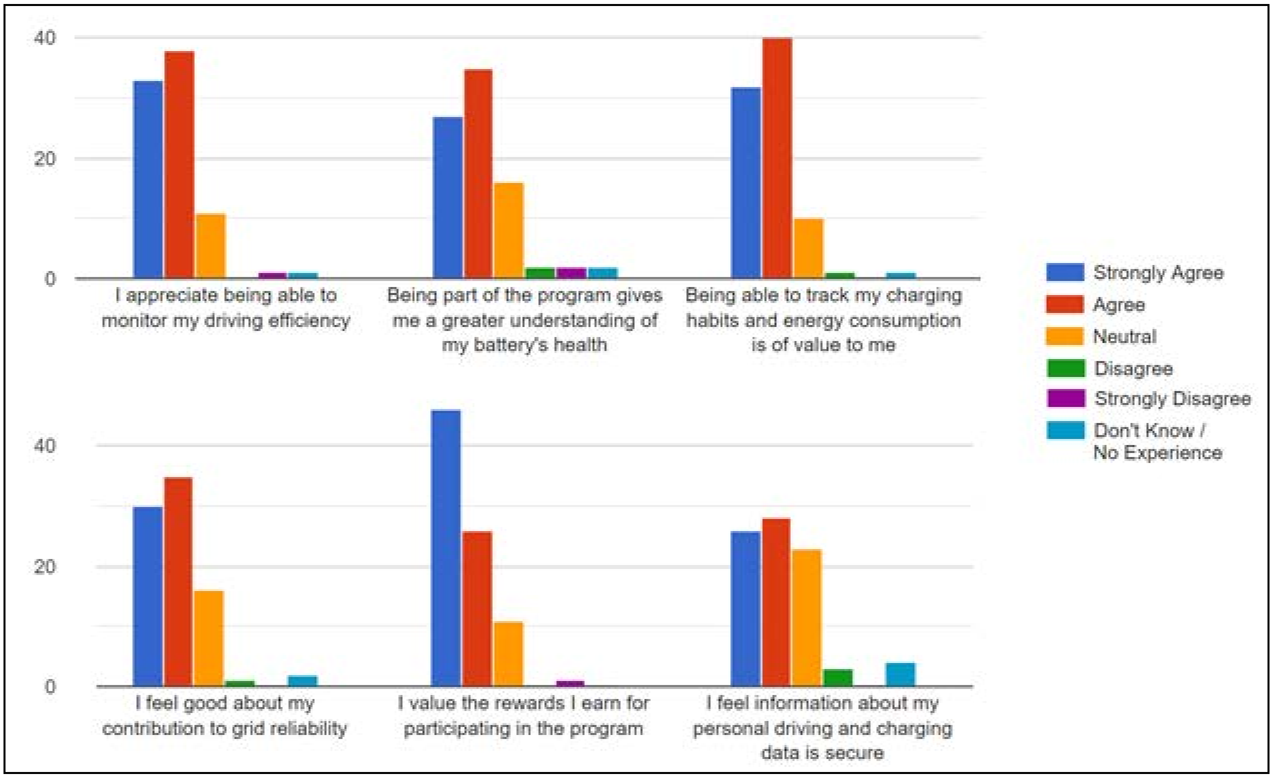

Figure 19: Participant Responses Regarding the Values Provided by the Duke Energy Charge FL Program

Program Demographics

Through the survey, participant demographics regarding the gender, age, annual income, level of education and type of home for each participant were collected. The majority of participants were male (94%) with 93% of participants aged 35 or older. Few participants had a household annual income of less than $80,000 (29%). A majority of participants had a Bachelor's or Master's degree (52%). As Figure 20 illustrates, 87% of participants who responded to the survey lived in a single family home that they owned.

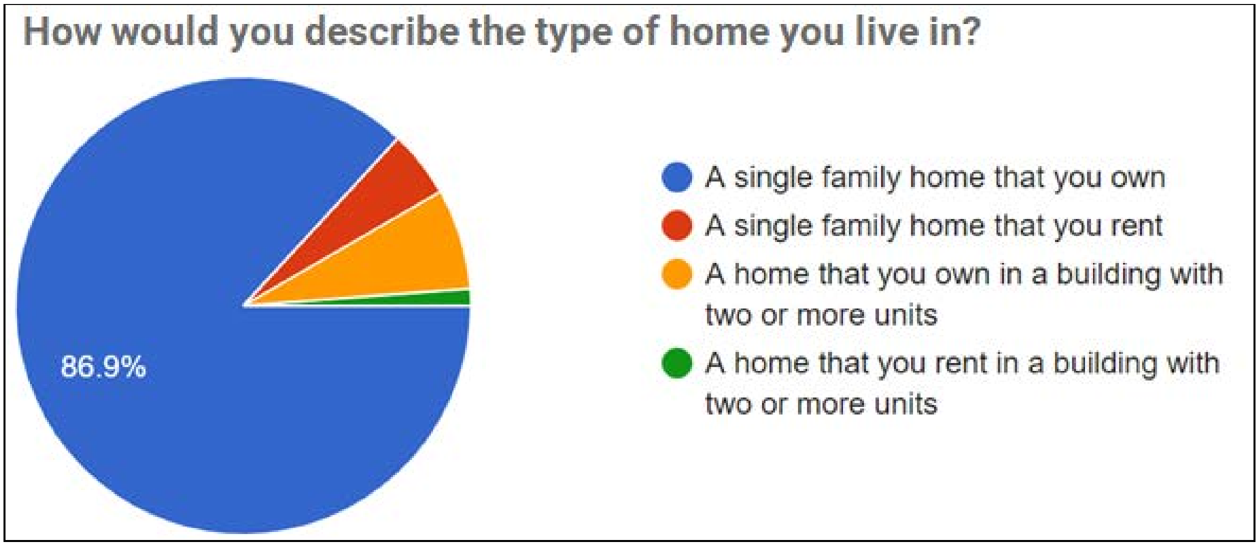

Figure 20: Participant Responses Regarding the Type of Home They Live In

Participant EV Usage and Charging Behaviors

Participants were asked questions specific to their EV charging behavior. This facilitated participant feedback regarding their charging location, charging level at home, motivation to change charging behavior and questions specific to smart charging. According to the survey, the majority of participants reported charging at home (95%) or using public charging stations (45.2%). This metric was specific to charging sessions and is not representative of the amount of energy drawn from these locations.

When charging at home, 60% of participants are using a Level 2 charging station that is not WiFi enabled, 21% are using a Level 1 charging, and 18% have a Level 2 smart charging station (WiFi enabled). When asked about smart charging behaviors, most participants are willing to participate in smart charging (69%) and allow the charging station to control EV charging based on personal preferences. A large percentage of responses were unsure (24%) if they would be willing to do so. This may indicate a lack of education in terms of smart charging and how it could affect their charging behavior. Of those willing to smart charge, most (59%) indicated that they would require a minimum SOC of 50% or greater to begin their day. Only 12% indicated they would be satisfied with a minimum SOC of less than 30%.

When reviewing participant motivations for changing charging behavior, participants expressed a high level of motivation to earn monthly incentives. Participants did not report competition with peers or one's self as a motivation to change charging behavior. The results of this survey question is shown in Table 4.

Table 4: Participant Motivations to Change Charging behavior

Answer	Absolutely	Yes	Maybe	No	Unsure
Willingness to work with Duke Energy to provide an EV-friendly grid	**45.24%**	27.38%	21.43%	0.00%	5.95%
Willingness to work with Duke Energy to build an EV-charging network	**42.86%**	26.19%	23.81%	1.19%	5.95%
Change to time of use rates from Duke Energy	**53.57%**	26.19%	14.29%	4.76%	1.19%
Monthly monetary incentives to charge my EV at certain times of day	**69.05%**	22.62%	5.95%	2.38%	0.00%
Monthly monetary incentives to avoid charging my EV at certain times of day	**63.10%**	21.42%	13.10%	2.38%	0.00%
Competition with myself or relative to others	13.10%	14.29%	27.38%	**38.10%**	7.14%
Reduction in environmental impacts	**36.90%**	33.33%	22.62%	5.95%	1.19%

Figure 21 shows that Charge FL participants predominantly drive EVs in order to save money on fuel and reduce greenhouse gases. The majority of participants (83.3%) use their EV to commute to and from work and/or for personal trips.

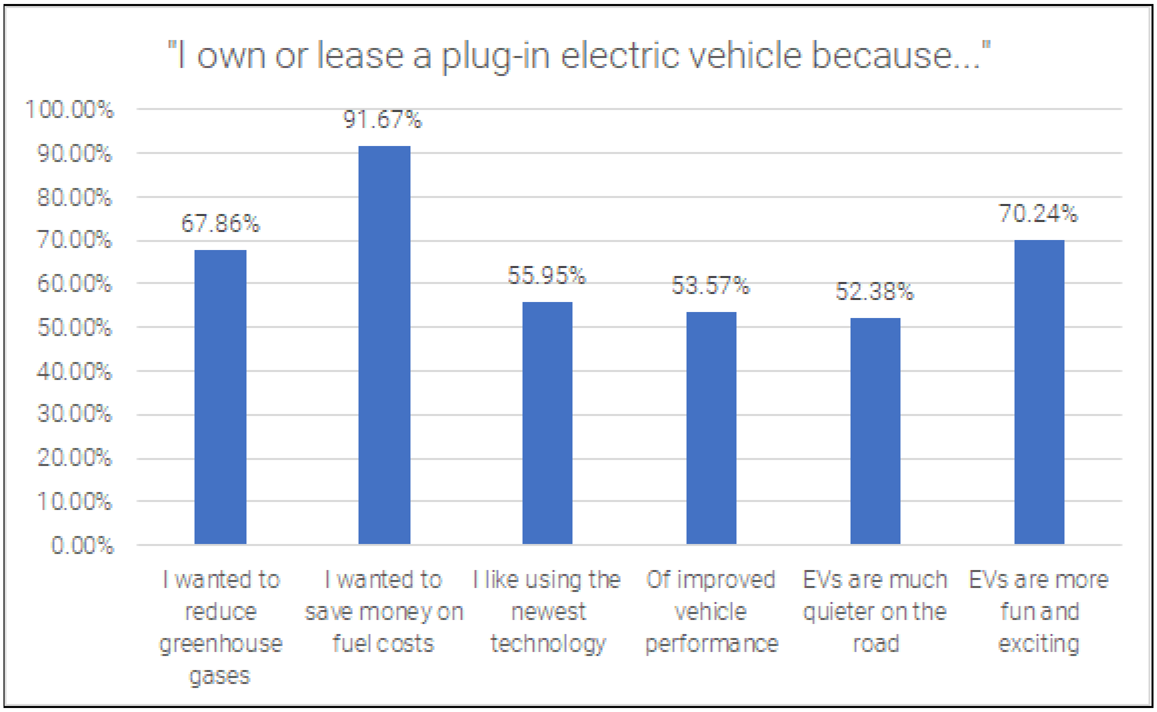

Figure 21: Participant Responses for the Reason They Drive an Electric Vehicle

Participant Thoughts on the SmartCharge Rewards™ Platform

Duke Energy Charge FL participants were asked several questions regarding their program experience, mainly focusing on their installation experience, program set up experience, and satisfaction with the SmartCharge Rewards™ portal. The overall participant experience with the C2 connected car device was very positive, with 83% to 96% of all participants either agreeing or strongly agreeing with the following statements:

- I received my device in a timely manner.
- The written installation instructions were clear and easy to understand.
- I was able to easily locate the OBDII port in my vehicle.
- I experienced no issues with installation.

When it comes to the SmartCharge Rewards™ Portal, the majority of participants (94%) stated that they were able to set up their accounts without any issues. As Figure 22 shows, almost 74% of participants were somewhat or completely satisfied with the SmartCharge Rewards™ Portal and the data that it offered to them.

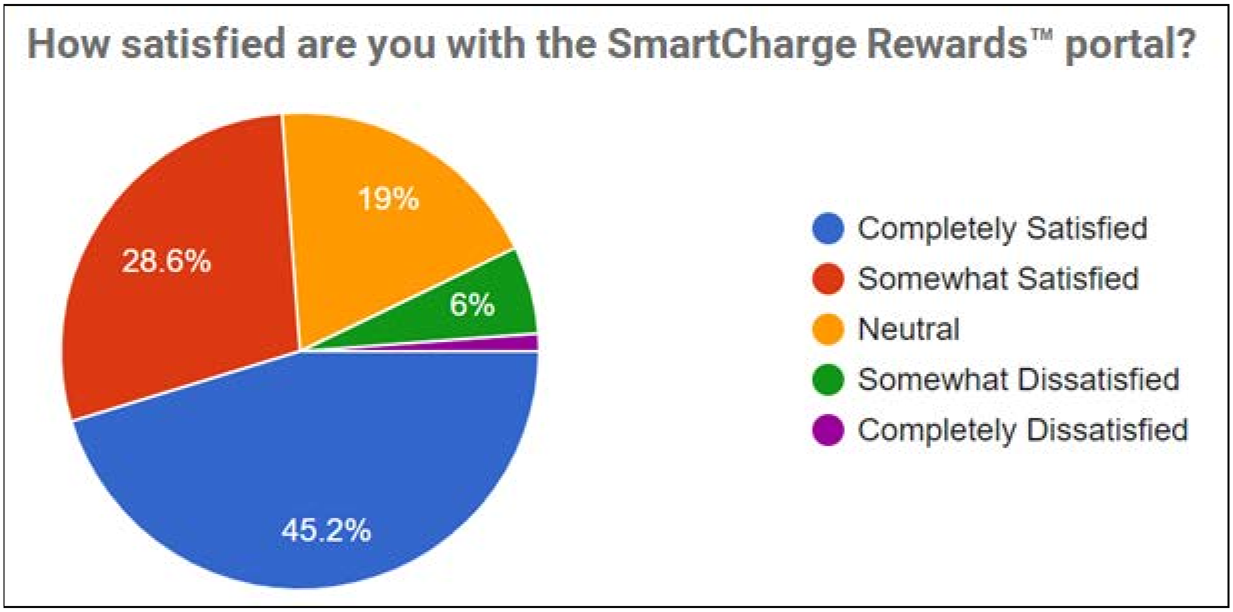

Figure 22: Participant Responses Regarding Their Satisfaction with the SmartCharge Rewards™ Portal

Conclusions

The Duke Energy Charge FL program was designed to monitor driving and charging data from 200 residential electric vehicle (EV) customers in the Duke Energy Florida service territory. Year 1 of the program established a baseline of data for comparison, while Year 2 and Year 3 evaluated the effectiveness of charging-based incentives influencing participant charging behaviors.

Through this analysis, aggregated driving and charging metrics have been determined which outline the differences in driving and charging behavior between different powertrain types. LR BEVs tend to drive the most electric miles compared to other powertrains and on average consume the most electricity (11.34 kWh per calendar day). LR BEVs also tend to the highest charging power levels, especially when utilizing publicly available DC Fast Charging stations. SR BEVs consume slightly more electricity on average than PHEVs, which have gasoline engines as an additional power source. On average, 69.29% of PHEV miles driven were electric, but PHEVs drove more total miles than SR BEVs.

EV charging occurs mostly in the late evening and into the early morning hours, with load curves similar across the three vehicle segments. Weekend charging was slightly higher in the afternoon than on weekdays, but most other times are higher on weekdays. The load shape of EV charging across seasons illustrated that the seasons that often require more vehicle cooling (summer and fall) have a higher load associated with them. When analyzing the load curves for the Control and Treatment Groups in Years 2 and 3 of the Charge FL program, it was noticed that the Treatment Group participants responded to the incentives being offered by overall adapting their charging habits to match the off-peak periods, whereas the control group did not exhibit this behavior. This highlighted the effectiveness of the incentives on participant charging behavior and the utility's ability to manage customer load.

The substation impacts of EV charging may be minimal. At this level, the load is aggregated across many EVs resulting in smooth aggregated load profiles with low power demands. At the transformer level, the load curves are more volatile with notably higher power demands (coincident peaks). Depending on the number of vehicles per transformer and the battery capacity of these vehicles, this may suggest that EV load be shaped to avoid any negative impact on distribution assets as demonstrated by a predictive load curve consisting of four LR BEVs.

When participants were surveyed on their experience within the Duke Energy Charge FL program, the overall response was positive. The majority of participants were satisfied with the program and appreciated the value that it provided them. The biggest motivator that would influence a change in participant charging behavior would be monetary incentives, while competition with other EV drivers proved to not be an ineffective motivator. The SmartCharge Rewards™ platform, including the C2 devices and portal, were ultimately very favourable with the participants.

Overall, the Charge FL program was effective at collecting EV charging and driving data from Duke Energy customers to help inform Duke Energy of the energy demands from their EV customers. Implementing EV charging incentives to encourage customers to charge at times beneficial to the grid has proven to be an effective strategy in managing EV load. Participants who have received incentives to modify their charging behavior have demonstrated a willingness to charge their EVs at times specified by Duke Energy. Both surveys that were sent to participants provided some promising feedback, and showed that participants were overall very satisfied with how the program was conducted and are open to both customer-controlled EV charging (incentives) or possibly utility-controlled charging (smart charging).

References

[1] "FOTW# 1177, March 15, 2021: Preliminary data show average fuel economy of new light-duty vehicles reached a record high of 25.7 mpg in 2020," | *Energy.gov*, 15-Mar-2021. [Online]. Available: https://www.energy.gov/eere/vehicles/articles/fotw-1177-march-15-2021-preliminary-data-show-average-fuel-economy-new-light. [Accessed: 13-Oct-2021].

[2] "Greenhouse Gas Emissions from a Typical Passenger Vehicle" | US EPA, [Online]. Available: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle. [Accessed: 13-Oct-2021].

[3] A. Hoekstra, "Producing gasoline and diesel emits more CO2 than we thought" | Innovation Origins, 16-Feb-2020, [Online]. Available: https://innovationorigins.com/en/producing-gasoline-and-diesel-emits-more-co2-than-we-thought/. [Accessed: 18-Oct-2021].

Appendix I - Vehicle Model Breakdown by Group

Table i: Breakdown of Vehicles in the Control Group

Powertrain	Vehicle Make & Model	Count of Vehicles	Total Count
LR BEV	Chevrolet Bolt EV	14	49
	Tesla Model 3	23	
	Tesla Model S	8	
	Tesla Model X	3	
	Tesla Model Y	1	
SR BEV	BMW i3	6	27
	Chevrolet Spark EV	1	
	Hyundai Ioniq Electric	1	
	Mitsubishi i-MiEV	1	
	Nissan Leaf	17	
	Smart fortwo	1	
PHEV	BMW i3 REX	1	36
	Chevrolet Volt	22	
	Chrysler Pacifica Hybrid	6	
	Ford C-Max Energi	2	
	Ford Fusion Energi	2	
	Mitsubishi Outlander	1	
	Toyota Prius Plug-in/Prime	2	

Table ii: Breakdown of Vehicles in the Treatment Group

Powertrain	Vehicle Make & Model	Count of Vehicles	Total Count
LR BEV	Chevrolet Bolt EV	11	45
	Tesla Model 3	19	
	Tesla Model S	9	
	Tesla Model X	6	
SR BEV	BMW i3	7	27
	Fiat 500e	2	
	Nissan Leaf	18	
PHEV	Chevrolet Volt	24	33
	Ford C-Max Energi	2	
	Ford Fusion Energi	4	
	Toyota Prius Plug-in/Prime	3	

Appendix II - Average Driving Metrics by Vehicle Make and Model

Table i contains aggregated driving metrics by vehicle make and model.

Table iii: Aggregated Driving Metrics by Vehicle Make and Model

Model Name	Average Miles per Calendar Day	Average Miles per Driving Day	Average Electric Miles per Calendar Day	Average Electric Miles per Driving Day
BMW i3	24.83	33.04	24.83	33.04
BMW i3 REX	11.33	23.38	10.80	22.30
Chevrolet Bolt EV	31.71	38.55	31.71	38.55
Chevrolet Spark EV	35.80	37.53	35.80	37.53
Chevrolet Volt	24.11	33.55	18.85	26.11
Chrysler Pacifica Hybrid	45.30	50.43	23.58	25.58
Fiat 500e	11.28	18.21	11.28	18.21
Ford C-Max Energi	20.25	28.21	11.61	16.56
Ford Fusion Energi	19.96	29.10	10.97	16.55
Hyundai Ioniq Electric	21.44	25.4	21.44	25.4
Kia Niro Plug-in Hybrid	8.32	20.57	5.41	13.39
Mitsubishi i-MiEV	6.95	10.46	6.95	10.46
Mitsubishi Outlander	32.84	41.60	15.36	19.46
Nissan Leaf	24.06	30.47	24.06	30.47
Smart fortwo	2.84	13.87	2.84	13.87
Tesla Model 3	30.60	39.72	30.60	39.72
Tesla Model S	25.89	36.49	25.89	36.49
Tesla Model X	43.04	54.40	43.04	54.40
Tesla Model Y	89.63	97.19	89.63	97.19
Toyota Prius Plug-in	22.24	28.64	7.35	8.90
Toyota Prius Prime	32.40	40.79	19.79	24.70

Glossary

Calendar Day - a full civil day from midnight to midnight.

Carbon Dioxide - a key component of greenhouse gas, leading to the greenhouse effect.

Carbon Offset - the reduction in emissions of carbon dioxide or other greenhouse gases made in order to compensate for emissions made by the production of electricity.

Charger Types - in today's market, three different charge types exist: Level 1 (L1), Level 2 (L2) and DCFC (Direct Current Fast Charger).

Charging Day - a day, midnight to midnight, in which the vehicle was driven.

Direct Current Fast Charging - there is no standard for DCFCs but they range in charge power from 20-350 kW and can deliver a charge of approximately 80% in 30 minutes.

Driving Day - a day, midnight to midnight, in which the vehicle was driven. This is used to calculate averages only for days that the individual vehicle drove some distance.

Level 1 Charging - a Level 1 (L1) charger is included with most EVs. It plugs into a traditional 110-120v household outlet and is capable of a charge power of 1.5kW. This can generally supply an EV with 5-10km of range per hour of charge.

Level 2 Charging - a Level 2 (L2) charger can be found in areas for public parking and also be installed at a residential location for personal use. They provide power at 220-240 V and up to 30 amps. On average, EVs can add 20-50 km of range per hour of charge.

Load Curves - a graph of electrical load over time. This is useful for utilities to determine how much electricity will need to be available at a given time for efficiency and reliability of power transmission.

Long-Range Battery Electric Vehicle (LR BEV) - a battery electric vehicle with a larger battery capacity, powered only by its high voltage battery.

Plug-in Hybrid Electric Vehicle (PHEV) - a vehicle which combines a conventional engine with an electric motor and rechargeable battery that allows the battery to be recharged from an outlet

Short-Range Battery Electric Vehicle (SR BEV) - a battery electric vehicle with a smaller battery capacity, powered only by its high voltage battery.

Smart Charging - the intelligent charging of EVs where charging can be shifted based on grid loads and in accordance with the vehicle owner's needs.

State of Charge (SOC) – the percentage of usable battery energy available.

Vehicle Efficiency - the ratio of distance travelled per unit of fuel consumed.