## Field Testing and Modeling of Supermarket Refrigeration Systems as a Demand Response Resource

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#### ABSTRACT

Supermarkets offer a substantial demand response (DR) resource because of their high energy intensity and use patterns; however, refrigeration as the largest load has been challenging to access. Previous work has analyzed supermarket DR using heating, ventilating, and air conditioning; lighting; and anti-sweat heaters. This project evaluated and quantified the DR potential inherent in supermarket refrigeration systems in the Bonneville Power Administration service territory. DR events were carried out and results measured in an operational 45,590-ft<sup>2</sup> supermarket located in Hillsboro, Oregon. Key results from the project include the rate of temperature increase in freezer reach-in cases and walk-ins when refrigeration is suspended, the load shed amount for DR tests, and the development of calibrated models to quantify available DR resources. Simulations showed that demand savings of 15 to 20 kilowatts (kW) are available for 1.5 hours for a typical store without precooling and for about 2.5 hours with precooling using only the low-temperature, non-ice cream cases. This represents an aggregated potential of 20 megawatts within BPA's service territory. Inability to shed loads for medium-temperature (MT) products because of the tighter temperature requirements is a significant barrier to realizing larger DR for supermarkets. Store owners are reluctant to allow MT case set point changes, and laboratory tests of MT case DR strategies are needed so that owners become comfortable testing, and implementing, MT case DR. The next-largest barrier is the lack of proper controls in most supermarket displays over ancillary equipment, such as anti-sweat heaters, lights, and fans.

### Background

Demand response (DR) efforts can help utilities manage capacity additions to the electricity grid. Most buildings-related DR programs are planned around residential air-conditioning units, commercial lighting, and set point changes to heating, ventilating, and air-conditioning (HVAC) systems. These programs work well, but utilities are interested in additional DR resources. Beginning with its Fifth Power Plan (NPCC 2005), the Northwest Power and Conservation Council (NPCC) began to estimate the potential size of DR reserves in the Pacific Northwest and formulate strategies to encourage their creation. In its Sixth Power Plan (NPCC 2010), NPCC identified a need for additional pilot research programs to provide the precise and essential information needed to acquire cost-effective DR resources to help balance the supply and demand of electricity on the grid.

Supermarkets offer a substantial DR resource because of their high energy intensity and use patterns. In the 2009 Northwest Energy Efficiency Alliance Commercial Building Stock Assessment (The Cadmus Group, Inc. 2009), the "Grocery" category represented about 100 million ft<sup>2</sup> or roughly 3% of total commercial floor area, but had the second-highest electricity

energy use intensity of all building types—more than 40 kWh/ft<sup>2</sup>/year—due to extended operating hours and continuously operating commercial refrigeration systems. Electricity use was high all year but peaked in the summer. Total 2007 electricity use by the sector was 4,142,000 megawatt-hours (MWh) or 11% of total commercial building energy consumption in the Pacific Northwest. Averaged evenly over the year, this is about 470 megawatts (MW).

Supermarket refrigeration has several advantages over other commercial building end uses when considering DR. First, the equipment and controls necessary to execute DR strategies are common in refrigeration systems. Modern refrigeration controllers are also enabled to communicate over the Internet. These facts reduce the first cost of implementing DR in supermarkets because additional equipment is not required. Refrigerated display cases also have built-in thermal capacitance due to the large mass of cooled or frozen product. Therefore, product temperature will rise slowly when refrigeration is temporarily suspended, lagging behind the rise in air temperature and extending the length of time refrigeration can be paused.

Of course, there are limitations to how much cooling can be increased or reduced before product quality is affected. For this study, an upper limit of 15°F was placed on low-temperature (LT) cases and walk-ins, and a limit of -5°F was placed on ice cream cases and walk-ins. System capacity limits prevented case and walk-in temperatures from dropping below -12°F. Except for the beer case, medium-temperature (MT) cases were off limits for set point changes.

Unlike store lighting or HVAC, service need not be curtailed when DR is activated. Ideally, DR in refrigeration systems will be invisible to customers. This study investigates the amount of load shed that can be accomplished while keeping products within temperature boundaries recommended by supermarket owners.

Relevant, previous DR work includes pilot projects and deployment efforts in supermarkets and in refrigerated facilities. The California Energy Commission reported 7.5 MW of peak demand shed from 300 Albertsons supermarkets (equivalent to 6% load shed) using sales floor lighting and anti-condensate heaters (CEC 2005). Previous supermarket DR work appears to have excluded the compressors. To our knowledge, this project with the BPA is the first publicly documented DR pilot project in supermarkets that involves the refrigeration systems.

## **Project Overview**

This project was concerned with quantifying the DR potential inherent in supermarket refrigeration systems in an operating store. Ancillary aims of the project were to identify practical barriers to implementation of DR programs in supermarkets through real-world tests and to determine which high-level control strategies were most appropriate for achieving certain DR objectives through modeling and field testing. The scope of this project does not include detailed control strategy development for DR or development of a strategy for regional implementation of DR in supermarkets.

Specifically, five objectives were pursued in this study:

- Conduct pilot tests to understand stakeholder concerns and barriers to implementing DR.
- In the course of these tests, evaluate strategies that can provide 3- to 4-hour capacity reserves (identified as a key DR resource by BPA).
- Conduct additional experiments in an operating supermarket for the purpose of developing reliable models to quantify DR potential.
- Use these models to estimate the aggregated supermarket DR resource available to BPA.
- Recommend future research and other work to maximize DR potential in supermarkets.

### **Store Description**

The tests for this study were conducted at a 45,591-ft<sup>2</sup> full service supermarket located in Hillsboro, Oregon, that operates from 8 a.m. to 10 p.m., Monday through Friday. Based on two years of utility bills, the monthly peak demand varies between 350 kW and 450 kW.

The refrigeration system for this store has two compressor racks for two suction groups; rack A for -20°F and +13°F and rack B for a +18°F suction group. Rack B represents 65% of total refrigeration capacity. All MT cases were off limits for set point changes because these products have a narrow temperature range between freezing on the low end and spoilage at the high end. Ice cream consistency is sensitive to temperature changes. Therefore, only some of the LT cases were included in this study. The LT refrigeration cases and those eligible for DR testing (about 36%) are listed in Table 1.

Refrigeration	DR	Capacity	Suction	Defrost schedule	Case set
circuit	eligible	(Btu/h)	temp		point
	-		(°F)		(°F)
Seafood	Yes	10,000	-25	4/day 2:30, 8:30, 14:30, 20:30	0
Grocery	Yes	24,000	-25	4/day 3:00, 9:00, 15:00, 21:00	-8
Meat	Yes	9,000	-25	4/day 3:30, 9:30, 15:30, 21:30	0
Meat	Yes	8,960	-20	1/day 4:00	0
Food/ice cream	No	15,840	-16	1/day 5:00	8
Ice cream	No	10,560	-16	1/day 5:30	8
Frozen food	Yes	14,520	-16	1/day 0:00	0
Frozen food	Yes	11,880	-16	2/day 0:00, 12:00	0
Seafood	Yes	10,560	-16	1/day 1:00	0
Bakery	No	15,000	-25	4/day 3:00, 9:00, 15:00, 21:00	0
Prep. food	Yes	14,000	-25	3/day 3:30, 11:30, 19:30	-12
Roll prod	No	23,820	+21	6/day 4:30, 8:30, 12:30, etc.	+32
Seafood	No	17,500	+20	3/day 5:00, 13:00, 21:00	+39
Meat	No	17,500	+20	3/day 5:30, 13:30, 21:30	+30
Poultry #1	No	15,500	+20	4/day 0:00, 6:00, 12:00, 18:00	+36
Bakery	No	14,500	+20	2/day 00:30, 12:30	+35
Prep. foods	No	26,000	+20	3/day 1:00, 9:00, 17:00	+34
Poultry #2	No	9,400	+20	4/day 1:30, 7:30, 13:30, 19:30	+32

Table 1. Rack-A low temperature refrigeration cases

The refrigeration system in the test store uses a floating suction control strategy in which the suction pressure (refrigerant pressure entering the compressors) set point is raised under low load conditions. The floating suction control strategy saves energy by reducing the temperature "lift" that must be delivered by the refrigeration system to move heat from a cold side (the evaporator) to a warm side (the condenser). This control strategy works by shifting the saturated suction pressure set point higher when the critical cases are below a specified threshold and lower when the critical cases, and the suction pressure floated between 17 and 27 psig, corresponding to a range of  $-7^{\circ}$ F to  $+5^{\circ}$ F.

Electronic evaporator pressure regulators (EEPRs) were installed on the test circuits to enhance the controllability and allow each case evaporator to be changed using a digital signal rather than manual adjustment. This allowed precise and quick modulation of set points during testing. It also allowed many tests to be run remotely and on short notice by avoiding the need for a refrigeration technician to be present in the compressor room throughout the entire test.

Product simulators were installed to emulate product temperatures. The product simulators have a thermistor enclosed in a stainless-steel housing using epoxy. The associated thermal mass allowed the product simulators to respond to case air temperature changes in a manner similar to real products. Controllers specially equipped to allow control based on simulator temperature were also installed on cases of interest.

### **Testing Methodology**

An initial set of tests were performed to understand the warming rate of product and case air during a DR event. Several tests were run in which the refrigerant flow was shut off with the results shown in Figure 1. The rate of product simulator temperature rise in a reach-in frozen food case when refrigeration was turned off, based on an average of three product simulators, was found to be 0.16°F/min or 9.6°F/h. The rate of product simulator temperature rise in the meat walk-in freezer when refrigeration was turned off was 0.04°F/min, or 2.4°F/h. Note that the precision of the product simulators was 1°F, causing the illusion of a stepped progression of temperature in time.



Figure 1. Reach-in and walk-in freezer product simulator temperature rise with time

These numbers set a fundamental time constant for DR events and provide a rough estimate for how long cooling can be suspended. For example, the operation of the compressor rack is typically controlled based on the temperature in critical cases—generally reach-in freezer cases containing ice cream. Ice cream cannot exceed -5°F without risking change in consistency, and the product is typically kept at -8°F, so the amount of time the system can be "turned off" is only on the order of 20 minutes. This duration can be extended to about 45 minutes if the product is precooled to -12°F. The main focus of this report is evaluating strategies using existing equipment and controls that can provide 3- to 4-hour capacity reserves, which were identified as a key DR resource requirement by BPA.

Three control approaches were considered in this project—using existing control points, using product simulators, and precooling. Without adding equipment or making significant control algorithm changes, there were two control strategies that the team could use to modify the power consumption of the LT refrigeration system. These were the suction pressure set point of the whole compressor rack and the evaporator discharge air temperature (DAT) set points for the individual noncritical (i.e., not containing ice cream) reach-in and walk-in refrigeration

circuits. The saturated suction pressure set point could only be made  $4^{\circ}F$  colder ( $-8^{\circ}F$  to  $-12^{\circ}F$ ), reflecting the capacity of the system, and  $3^{\circ}F$  warmer (from  $-8^{\circ}F$  to  $-5^{\circ}F$ ) due to concerns about melting the ice cream in the critical reach-in case. The evaporator DAT set points for other cases were more flexible and could be varied from  $-12^{\circ}F$  to  $+15^{\circ}F$ . For all product types, it is critical to understand the supermarket owner's concerns in terms of food safety, food integrity, and store operation, so that DR does not result in adverse outcomes.

Product simulators were first installed in reach-in and walk-in cases as a risk mitigation strategy. The product simulators have a thermal mass that mimics a frozen product and a central thermistor that sends data to the refrigeration controller for viewing and trending. Controls based on the product simulators reduce the risk of exposing frozen products to unacceptably high temperatures. In addition they present a DR strategy alternative to the DAT set point because they warm up slower than the air temperature thus allowing the refrigeration compressors to be turned off for longer periods.

There are two challenges to be aware of when using a product simulator temperature as a control strategy. First, the set point should be set conservatively to avoid product temperature overshoot as there is a delay in cooling the product when cooling is restored to the case. Second, control should be returned back to the evaporator DAT at the conclusion of the DR event to avoid the compressors running at a high power for an extended period trying to bring the product simulator temperature down. Under DAT control, the air temperature control signal will drop quickly, allowing the system to return to its original operation (and power consumption) sooner.

Precooling was investigated as a way to extend the DR events and was achieved by dropping the discharge air set point for the critical cases and noncritical reach-ins and walk-ins to -12°F for several hours. This was done operationally by dropping the set point for the critical cases and opening the EEPR valves on the noncritical cases and walk-ins. This approach can also be used to provide a demand-add event, consuming additional power to balance a variable renewable resource such as wind.

### **Modeling Methodology**

Pilot tests offer many opportunities for identifying real-world issues that may arise during DR events, including a better understanding of the potential load shedding available in supermarkets, and insight into the effectiveness of specific strategies. However, due to the time and cost constraints associated with field testing, a much broader understanding of DR potential as well a more exhaustive investigation of candidate control strategies can be gained by using accurate and reliable models. Two modeling efforts were pursued for this project. The first was with existing whole building energy simulation software, in this case EnergyPlus (DOE 2015a). For the second effort, new models were generated from measured data that allowed for simulation of refrigerated case dynamics.

#### Whole Building Energy Model

The analysis of DR resources began with a calibrated EnergyPlus model of a similar store. This energy model was used to explore the maximum potential DR by turning off all cases and walk-ins on one LT rack and select cases/walk-ins on the MT rack. The LT cases and walk-ins that were disabled included the ice cream cases, two bakery dessert cases, the blast chiller, and the bakery and kitchen freezer. The MT cases that were disabled included produce/floral cases/coolers and cases with nondairy drinks (soda, beer, etc.). This analysis estimated that it was

possible to shed 60 kW for the duration of a 4-hour DR event. However, the effect of this event on product temperature was not known because it is not modeled within EnergyPlus. The product simulator tests on the LT cases provide some insight into the warming rate on the MT cases without cooling. The initial warming rate for doored MT cases would probably be between the high and low rates and probably near the high end of 9.6°F/hr for open cases.

This approach was a good place to start and provided an upper bound on the DR resource available. However, it is limited because the EnergyPlus refrigeration model is a load-based steady-state calculation, meaning that EnergyPlus captures the energy flows in and out of the refrigeration equipment and does not model the case temperatures. The refrigerated cases and all of the products are assumed to be maintained at a constant operating temperature. Therefore, typical control strategies that might be used to deliver DR cannot be realistically modeled and the impact on food temperatures cannot be evaluated directly in EnergyPlus.

#### **Gray-Box Energy Model**

New energy models for refrigerated display cases and walk-ins were developed to explicitly model product temperatures and allow control based on these temperatures. For the display case modeling efforts, the team followed the approach of O'Connell et al. (2014). This approach is particularly well-suited for modeling problems in which the transient variation of model variables is of interest, and in which a simplified approach must be taken to reduce the computation time required for model execution.

For the purposes of this project, models were developed to capture important DR information while allowing for many model runs through a simplified model structure and efficient solution algorithm. A semiempirical correlation between saturated suction temperature (SST), saturated condensing temperature, cooling load delivered, and power input to the compressors is assumed. The correlation is semiempirical in that it outputs the necessary input power as a function of actual load on the system and Carnot coefficient of performance (COP) (the theoretical relationship between input power and cooling load delivered). Hasse et al. (1996) showed that using the Carnot COP multiplied by a modification factor that aggregates all the inefficiencies in the system provides acceptable predictions of necessary power at the range of operating conditions expected to be seen in this study. The model employed is:

$$Q_{cooling} = \alpha * P_{input} * COP_{Carnot} = \alpha * P_{input} * [SST/(SCT-SST)]$$

Where:

 $\dot{Q}_{cooling}$  is the rate of energy removal from the system [kW]  $P_{input}$  is the electrical power input into the compressors [kW]  $COP_{Carnot}$  is the theoretical maximum efficiency (Carnot efficiency) SST is the saturated suction temperature [K] SCT is the saturated condensing temperature [K]  $\alpha$  is the empirical modification factor.

Hasse et al. (1996) used a modification factor of 0.4 and justified this assumption for SST values from -30°C to -10°C. Data collected by the National Renewable Energy Laboratory show that a modification factor of 0.38 is appropriate for an operating store. This model does not account for changes in the thermal mass, which may introduce inaccuracies for large changes in product stocked in the cases. The model proved to be accurate for this study, however.

Tests were conducted on a reach-in LT case and a walk-in freezer for calibrating and validating the gray-box models. Multiple product simulators were placed in the cases to capture the full range of temperature variations in the cases. In order to get a range of performance, the systems were excited with a pseudo-random binary signal that oscillated between a high of  $+15^{\circ}$ F and a low of 0°F over two days.

#### **Statistical Analysis of Measured Data**

Energy-saving or power-modifying actions require a baseline against which the savings are determined. There are many approaches to constructing a statistical customer baseline load (CBL). One standard approach, "10 of 10 method," accounts for time of week and averages the 10 preceding days of data. For example, if 2 p.m. is included in a DR period, data from the previous 10 weekdays are averaged to provide the baseline. This is the approach used by the California Independent System Operator (Goldberg and Agnew 2013).

Accounting for the impact of outdoor air temperature and outdoor dew point variations on power consumption can increase the baseline accuracy for HVAC and refrigeration systems. These factors can be accounted for using a multiple linear regression statistical model of the CBL based on time of week and meteorological variables and by evaluating uncertainty in the CBL and therefore in the modeled DR. Many buildings will have, at best, only 15-minute interval data from the main electrical meter. The estimated DR will have to contend with the statistical noise inherent in this signal. Isolating the building system or piece of equipment in question using strategically placed electrical submeters will reduce statistical noise.

To establish the baseline CBL, the team used a method previously devised for a separate BPA-funded project. In that project, Heaney, Doebber, and Hirsch (2015) determined that a regression model including factors for diurnal variations and weekly variations, outdoor air temperature, and outdoor air dew point provided an estimate for baseline power during a DR event that meets or exceeds the accuracy of a 10-day rolling average.

## **Demand Response Testing**

Several trials were conducted to test DR methods. These methods included various combinations of local and global control summarized in Table 2. The tests were done at various outdoor air temperatures, which affects the amount of load present and thus the amount of load shed available. It should be noted that some strategies are more suitable for a "day-ahead" DR bid, when the client has the option to do precooling, and some strategies are more likely to be implemented when the client has little notice before a DR event. Types of control tested include:

- Precool the cases before the simulated DR event.
- Change the DAT set point for noncritical cases.
- Change the DAT set point for the critical case.
- Control the compressor based on product simulator temperature rather than DAT.

Test	Date	Precool	Change	Change	DAT or
			critical case	noncritical	product
			DAT set	case DAT	simulator (PS)
			point	set point	control
1	9/23/14	No	Yes	No	DAT
2	11/10/14	No	Yes	No	PS
3	7/14/15	No	Yes	No	DAT
4	7/20/15	No	Yes	Yes	DAT
5	7/22/15	Yes	Yes	Yes	DAT
6	7/24/15	Yes	Yes	No	DAT
7	7/28/15	No	No	Yes	DAT
8	7/30/15	Yes	Yes	Yes	DAT
9	7/31/15	Yes	No	No	DAT

Table 2. Site and control parameters for each demand response test

The results for each of these DR tests are shown in Table 3. The load shed range in column 3 represents the predicted range within a 95% confidence limit. Tests 1 and 2 were terminated after 1 hour and 30 minutes and 1 hour and 15 minutes when the critical case (ice cream) air temperature reached  $-5^{\circ}$ F. The highest average load shed was 9.0 kW from test 2; however, this was also the shortest test and had the lowest outdoor air temperature of 60.8°F. The second highest average load shed was 8.4 kW in test 4 over a 4-hour event with an average outdoor air temperature of 92°F. Test 8, shown in Figure 2, used a combination of the best practices from the previous tests over a 6-hour event with an average outdoor air temperature of 105.8°F (which is very high for this area). The entire LT system including critical and noncritical cases and walk-ins were precooled to  $-12^{\circ}$ F from 11 a.m. to 2 p.m. The team changed the float control of critical case (and thus the rack) from  $-8^{\circ}$ F to  $-5^{\circ}$ F, and changed the set points of the noncritical cases from 0°F to  $+15^{\circ}$ F. The system maintained a drop in demand of more than 10 kW for most of the first three hours. However, the amount of load shed dropped around 5 p.m., possibly due to increased customer traffic after the workday. This apparent drop in load shed could also be a failure of the baseline prediction to capture the increase in the load.

Table 3. Demand response results for each evaluation test

Test	DR test	Load shed	Ave.	OA temp.	Average	Average	Average
	time	range 95%	load	range	OA temp.	baseline	precool
		CL	shed	(°F)	(°F)	load (kW)	power add
		(kW)	(kW)				(kW)
1	0830-1000	-0.4-8.0	3.8	60.8-63.7	62.3	26.2	N/A
2	1315-1430	4.7–13.2	9.0	59.7-61.7	60.8	28.9	N/A
3	1200-1600	-1.3-8.3	3.5	87.4–92.3	90.2	38.9	N/A
4	1230-1630	3.2–13.6	8.4	90.0–94.3	92.2	40.6	N/A
5	1315-1715	-1.9–9.2	3.6	71.4–75.2	73.8	32.6	7.7
6	1330-1730	-3.3–7.6	2.1	84.9–91.4	88.0	39.2	3.5
7	1300-1700	-3.1–6.8	1.9	87.1–92.1	89.3	38.3	N/A
8	1400-2000	2.5-11.9	7.2	95.5-111.9	105.8	47.2	4.6
9	1430-1830	-7.3-3.1	-2.1	104.4-108.5	106.1	46.7	5.7



Figure 2. Power for demand response test #8 on July 30, 2015

#### **Demand Response Modeling**

Multiple model structures using the gray-box approach were tested for their ability to predict the validation data accurately and provide the information needed for DR calculations. The models were first developed with the training data then validated with additional data for case temperature and power predictions. The best models matched the reach-in and walk-in case temperatures very well with root mean squared errors of 0.40°F and 0.57°F respectively over a 24-hour period. The model was then used to predict the electrical power for the LT cases for the conditions during DR test 4. The comparison of the modeled and measured results is shown in Figure 3, with the modeled power generated knowing only outdoor conditions and set points. The model matched the peak demand shed during the DR event and the rebound power draw after the event very well, and it is conservative on the average power shed during the DR event. The model predicts performance well despite not including changes in the amount of product stocked in the cases. Large changes in product will impact performance.



Figure 3. Comparison of modeled and "measured" electrical power during a demand response event

The calibrated and validated models were then used to estimate performance beyond the field tests. The model was used to predict DR availability in locations within BPA's service territory on critical days with the assumption that equipment suitable for this type of operation is included in the store (e.g., variable capacity compressors, properly organized suction groups).

The team assumed for all simulations that the amount of refrigeration capacity of each type of case was equal to that of the U.S. Department of Energy supermarket reference building (DOE 2015b), and that all LT cases (excluding ice cream) could be manipulated during a DR event. This was equivalent to changing approximately twice the capacity of cases as was done in the store tests. Simulations were conducted for major population centers representing geographic and climatic variation within BPA's service area: Seattle, Washington; Portland, Oregon; Spokane, Washington; and Boise, Idaho. For DR simulations, the hottest day of 2014 was selected for each location (this varied by site) and compiled into a weather file used for the simulations. The team also ran a load-add simulation for each location with weather conditions from April 21, to quantify the amount of additional demand that could be added. The model inputs are listed below for each case and the results are shown in Table 4.

Model inputs in response to a ten-minute notice:

- Raise set points for critical (ice cream) cases and walk-ins from -8°F to -5°F.
- Allow the SST to float up 3°F in response to the change in the critical case.
- Raise set points for noncritical LT cases and walk-ins from  $0^{\circ}$ F to  $+15^{\circ}$ F.
- Maintain set point changes for 90 minutes.

Model input in response to a day-ahead notice:

- Schedule a 4-hour precool with all LT case and walk-in set points at -12°F.
- Implement the set point modifications for the 10-minute notice for a period of 4 hours.

To simulate added load during periods of excess supply, set points for all LT cases and walk-ins were lowered to -12°F from 3 a.m. to 6 a.m.

Table 4. Modeled estimates of low-temperature demand response resource, rebound, and loadadd potential

		Precool		DR event		Rebound	
Location	Simulation	Additional	Time	Load shed	Time	Additional	Time
		load (kW)	(h)	(kW)	(h)	load (kW)	(h)
Seattle	10-minute	NA	NA	18.5	1.25	6.5	3
Spokane	10-minute	NA	NA	19.5	1.5	6.8	2.75
Portland	10-minute	NA	NA	15.0	1.5	5.3	2.75
Boise	10-minute	NA	NA	19.8	1.5	6.8	3
Seattle	Day-before	6.8	4	17.8	2.5	6.6	3.5
Spokane	Day-before	6.9	4	19.3	2.5	6.9	3.5
Portland	Day-before	5.5	4	15.0	3	5.5	4
Boise	Day-before	6.9	4	19.3	2.25	6.9	3.5
Seattle	Load-add	5.4	3	N/A	N/A	-12.0	0.75
Spokane	Load-add	5.2	3	N/A	N/A	-11.2	0.75
Portland	Load-add	5.5	3	N/A	N/A	-12.0	0.75
Boise	Load-add	5.2	3	N/A	N/A	-11.5	0.75

## Conclusions

This study provided an estimate of the amount of power that may be shed by manipulating typical LT refrigeration systems in supermarkets in the northwestern United States. Power shedding potential was evaluated through nine store DR field tests. Additional field tests were performed to inform the development and calibration of a set of gray-box refrigeration models that allow the field-test results to be applied to supermarkets across the Pacific Northwest. Optimal strategies for including supermarkets in a larger portfolio of grid resources will likely need to include not only refrigeration systems, but also HVAC, lighting, and energy storage systems, as well as detailed algorithms for increasing and decreasing overall electric demand. Significant opportunities exist for further supermarket refrigeration DR savings; although additional modeling and testing is required to fully explore these opportunities.

Specific lessons learned and recommendations:

- Install EEPRs on all circuits to be used in DR programs.
- For best results, raise the saturated suction pressure of rack(s) as well as the control set points of individual circuits.
- Precooling the product may increase the amount and time of power shed available.
- Enable floating suction control and possibly even steady-state case-level control to be switched between case air temperature and product simulators.
- Implement variable capacity compressors to maintain low and predictable power consumption during DR events.
- Assemble cases into suction groups that allow greater freedom. Moving the lowesttemperature circuits (ice cream) to a dedicated refrigerant loop provides permanent energy efficiency in the form of a higher SST for other LT cases and allows DR strategies to include a larger increase in SST on non-ice cream cases.
- Enable and test control of refrigeration lights, fans, and anti-condensate heaters to increase the available DR resource.
- Two possible approaches to include MT cases in DR are to precool a secondary working fluid or cycle the MT compressors and/or case controls across a collection of stores to manage the peak demand while maintaining product temperatures, similar to the way utilities control residential air-conditioning units.

This work is important to BPA because it provides quantifications for estimating potential demand response programs across the Pacific Northwest that include grocery refrigeration, a resource that can be centrally managed across a chain. This research, in combination with other research that provides similar quantifications for other grocery end uses (HVAC, case lighting, overhead lighting, etc.) provides a firm ground to estimate the total potential DR available at grocery stores. In addition, this research provides guidance for achieving refrigeration DR, accounting for obstacles, and identifying further research topics.

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