Market Potential for Saving Energy and Carbon Emissions with Load Shifting Measures

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Definition of Terms and Acronyms

ASHP - Air source heat pump

CIP – Conservation Improvement Program

EV – Electric vehicles

IOU – Investor owned utility

IRP – Integrated Resource Plan

ISO – Independent system operator

MISO – Midcontinent Independent System Operator

PCM – Phase change materials

RTO – Regional transmission organization

TRM – Technical reference manual

Executive Summary

Background

As lighting and other basic efficiency measures reach saturation, utility energy efficiency programs need to fill the gap with more complex and often costlier measures. At the same time, due to changing load shapes and generation mix, utilities are increasingly interested in measures that shift the *time* of energy use in addition to reducing overall energy use. As renewable generation increases, increasing both the daily and yearly variation of emissions and avoided cost profiles, the ability to shift the *time* of energy use becomes increasingly important.

This area of work is especially valuable in Minnesota where the electricity supply mix is changing rapidly. Currently, Minnesota generates about 22 percent of its electricity production from renewable energy resources (EIA 2018a). This percent is likely to increase substantially over the next 10 to 15 years as the state retires its large baseload coal generation; an estimated 50 percent of the statewide electricity production will come from wind and solar by 2035. If, as anticipated, wind and solar become the dominant generation resources in the region (Clean Power Research 2018), variable production and ever-increasing differentials in prices will be the new standard throughout a typical day in Minnesota.

This changing landscape provides a clear value stream for measures that shift the time of energy use, which is the main focus of this study. However, one major barrier to some load shifting measures is when they lead to an increase in overall energy use, which conflicts with energy efficiency policy and creates a potential incentive to build load. To date, Minnesota's Conservation Improvement Programs (CIPs) allow for load shifting measures that save energy (Minnesota Statutes 2019). The Minnesota Department of Commerce (Commerce) oversees CIP, which is administered by utilities in the state. The program requires utilities in the state meet 1.5 percent energy savings each year, which utilities accomplish by promoting energy efficiency technologies through rebates, marketing, and technical assistance.

Given that state policy is designed to correct the disincentive of decreased sales, technologies that shift load while *increasing* energy use (e.g. thermal ice storage) are not eligible under Minnesota's statewide energy efficiency resource standard. Utilities in the state offer separate incentives for measures that save energy and measures that may shift load, such as demand response programs. Furthermore, load shapes used in efficiency portfolio planning or cost-effectiveness calculations neither focus on load shifting as a primary consideration nor take into consideration future economic scenarios.

This research, funded through the Commerce's Conservation Applied Research and Development program, quantifies the Minnesota-specific economic, energy, and emissions impacts of measures that shift load with or without saving energy. The goal of the research is to identify how these measures may fit within the state's energy efficiency program. The project team, composed of Slipstream, Minnesota Center for Energy and Environment, and Rakon Energy, modeled multiple measures in a variety of future planning scenarios that include higher penetrations of renewable generation.

Model Development

To quantify the emissions, cost, and energy impacts from load shifting measures, the project team developed hourly annual models of energy, costs, and emissions for both present day and the future. Figure 1 provides a simplified illustration of the key steps in the model development.

Figure 1. Model development process

To start, the project team chose 14 measures that represent both the residential and commercial sectors and have various impacts on energy reduction and load shifting. The project team also categorized each of the measures based on the type of load shift, which are defined as follows:

- A measure categorized as a **regularly-occurring shift** can shift energy use each day from one period of the day to a different period of the day.
- An **event-based measure** only shifts load on a select number of days, typically when demand is high, and utilities are near capacity.
- **Energy efficiency** measures serve as a comparison for measures that are currently in Minnesota's CIP and have no load shifting.

The first two categories are similar to the "shift" and "shed" taxonomy introduced by Berkeley Lab (Potter and Cappers 2017), but the key distinction is the frequency with which the demand change occurs – either consistently across the year, or for a handful of events throughout the year.

Table 1 provides a summary of the measures and their baseline conditions.

Table 1. Summary description of measures in this study

Type of shift	Measure	Description	Baseline
Regularly-occurring	Phase change materials (PCM) for space conditioning (*commercial*)	PCM are melted and frozen at temperatures near the setpoint to shift load in conditioned places.	Space conditioning (variable air volume – no PCM)
Regularly-occurring	PCM for refrigeration (*commercial*)	In refrigerated areas, PCM are frozen during non-peak hours and melted to cool goods during peak hours.	Typical commercial refrigeration load shape
Regularly-occurring	Active ice thermal storage (*commercial*)	Cool thermal storage attached to a chilled water system; chillers make ice or chilled water at off-peak times for use during peak-times.	Space conditioning (variable air volume)
Regularly-occurring	Electric vehicles (EVs) with charging controls (*residential*)	A managed controlled charging program that sets charging time, 9 pm - 5 am.	Level 2 uncontrolled charging

Type of shift	Measure	Description	Baseline
Regularly-occurring	Strategic energy management with demand focus (*industrial*)	Programming common efficiency measures' controls, based on worker shifts to shift load.	Typical industrial load
Regularly-occurring	Refrigeration load control *(commercial)*	Refrigeration system operators use the setpoints in refrigerated spaces to shift the time at which compressors run, without impacting food quality.	Typical commercial refrigeration load shape
Event-based	Smart thermostats with demand response (*residential)*	Smart thermostat with demand response functionality, to run air conditioning less when loads are peaking, or utility prices are high.	SEER 12 AC with current mix of programmable + smart thermostat
Event-based	Air source heat pumps (ASHP) with demand response control (*residential)*	ASHPs with controls that allow utilities to remotely adjust heating or cooling load. Includes pre-cooling or pre-heating and a recovery period after the event.	Electric resistance heat + SEER 12 AC
Event-based	Envelope measures combined with ASHP (*residential*)	Deep envelope retrofits combined with the ASHP measure to show the impact of having a well-insulated home.	Baseline space conditioning + median SF in Minnesota
Event-based	Heat pump water heater (HPWH) with controls (*residential*)	Use of HPWH for efficiency and pre-heat during off peak times to shift usage.	Electric resistance with no controls
Event-based	Networked lighting controls with demand response (*commercial*)	A lighting retrofit with controls that are digitally networked for additional energy savings during peak times.	Typical commercial LED lighting
Event-based	Critical peak pricing to drive behavior change (*residential*)	Advanced notice of higher prices for certain hours of days when demand is expected to be high.	Typical residential load shape from Minnesota TRM
Energy efficiency	Plug load controls (commercial)	Commercial plug load controls turn off computing equipment and peripherals, saving energy.	Typical office settings
Energy efficiency	Lighting efficiency and controls (commercial)	A typical LED retrofit along with daylighting, task tuning, and occupancy controls.	Typical commercial fluorescent bulbs

The cost and emissions data in the model represent present day and future day scenarios as well as different geographic territories. The geographic territories include the state, the Xcel Energy Minnesota utility territory, and the Midcontinent Independent System Operator (MISO) territory.

The **avoided cost data** included avoided energy costs and avoided capacity costs. Avoided energy costs represent the cost saved by saving energy while the avoided capacity cost represents the cost saved by deferring or delaying the need for a new power plant, new transmission lines or local distribution to be added to the grid.

The **avoided emissions data** represents the amount of avoided carbon emissions per unit of electricity. These values are hourly in nature. The present-day scenarios included both marginal and average emissions. Average emissions consider the entire mix of generation on the grid at a point in time while marginal emissions consider only the generation that a change in energy use at a given time will likely impact.

The project team optimized each load shape to save energy when prices were high and use energy when prices were low. Additionally, the project team developed a sensitivity case to test how shifting energy based on emissions changed the results. This involved shifting energy from times when emissions are high to times when emissions are low. The price scenario is the baseline case as it is similar to how utilities often promote demand reduction during the high demand or high price times of the day.

Lastly, to present an apples-to-apples comparison between different measures, the project team assumed that each measure achieved peak savings of 500 kW at some point in the year. This approach controls for the variability in the per unit demand impact across measures. For example, one home on critical peak pricing saves less than 1 kW at its peak hour but a commercial building with PCM for cooling saves 25 kW at its peak hour. By using 500 kW peak savings, the number of participants differ across measures, but the potential for total demand reduction is held constant allowing for comparison across results.

Results

The results compare annual energy costs, annual emissions, and annual capacity cost of each measure's load shapes to baseline load shapes. This section first presents the costs savings and emissions impacts for the cost optimization model and then details the results from the carbon sensitivity analysis. More detailed results can be found in the full report.

Cost Optimization Results

Energy Cost, Emissions, and Capacity

One of the overarching findings is that energy efficiency measures, due to their often-daily effects on energy consumption, continue to offer significant overall energy cost savings, even when optimizing for load shifting potential. For measures that have both an energy efficiency component as well as a load-shifting effect, the portion of the energy costs or emissions savings attributed to energy efficiency eclipses the load shifting effect.

Table 2 summarizes the overall results of the study, including the total energy savings per measure and the 2018 percent cost and percent average emission savings over the measure baseline. The majority of measures percent cost savings stay constant across time and percent emission savings are similar to percent cost savings for most measures. The full report outlines future changes in costs and emissions.

Table 2. Study results - energy savings, 2018 percent cost savings and percent emission savings

Measure	Measure type	Energy Savings (MWh)	Percent Cost Savings over Baseline	Percent Emissions Savings over Baseline
PCM for space conditioning	Shift	496	9%	9%
PCM for refrigeration	Shift	862	16%	14%
Active ice thermal storage	Shift	-102	-2%	-16%
EVs with charging controls	Shift	0	25%	8%
Industrial strategic energy management	Shift	-74	2%	0%
Refrigeration load control	Shift	-108	0%	0%
Smart thermostats with demand response	Event-based	76	17%	20%
ASHPs with demand response	Event-based	1,721	54%	56%
Envelope measures combined with ASHP	Event-based	1,529	74%	75%
HPWH with controls	Event-based	1,311	55%	53%
Networked lighting controls with demand response	Event-based	38	34%	19%
Critical peak pricing to drive behavior change	Event-based	37	11%	9%
Lighting efficiency + controls	Efficiency	1,662	63%	63%
Plug loads	Efficiency	2,207	55%	57%

Figures 2 and 3 show the percent cost savings for regularly-occurring shift measures and event-based measures, respectively. Figure 2 shows the percent cost savings for regularly-occurring shifts. The values above the bar show the annual energy savings for each measure in the study. As a reminder, the number of participants is determined from the model's assumption that each measure hits 500 kW savings in at least one hour of a year. The shift measures shown in Figure 2 show a wide range of percent savings over baseline. Additionally, the results show that measures that are energy neutral or have small energy penalties can still save money. EVs save the most energy costs as the entire load can be shifted from high price times to low price times while other measures can only shift some energy use due to performance constraints.

Figure 2. Shift measures: percent cost savings over baseline and annual energy savings (2018 prices)

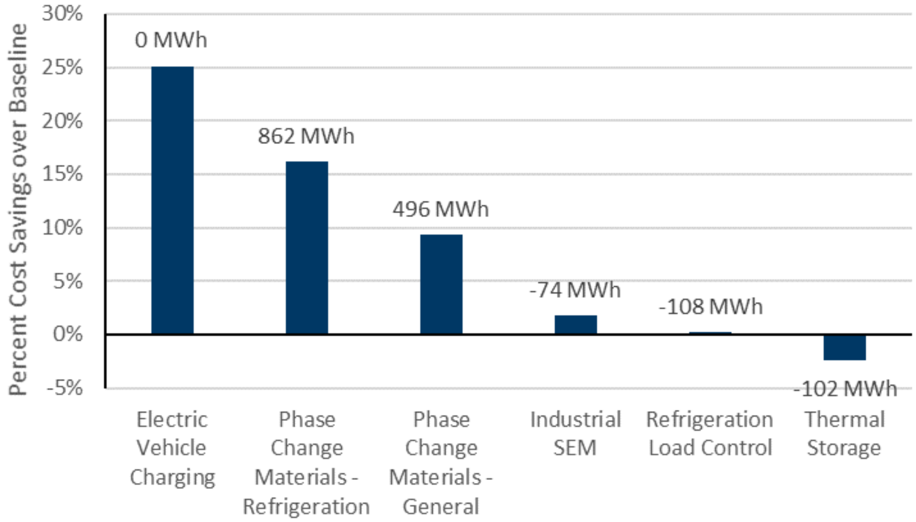
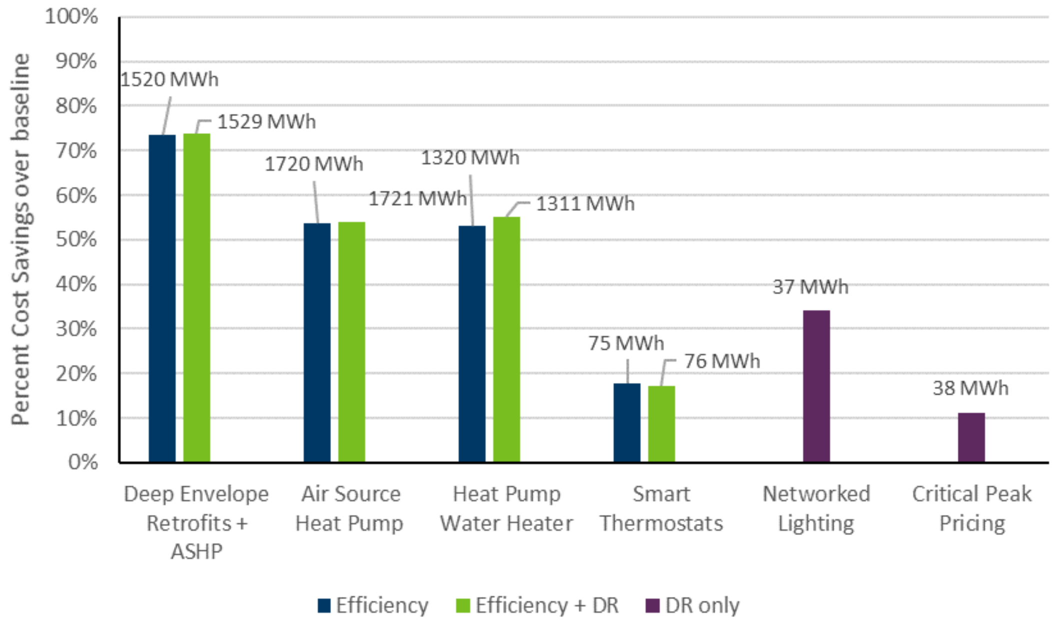


Figure 3 illustrates the percent cost savings for event-based demand response measures. Efficiency only represents the percent cost savings without any demand response events called. Efficiency and demand response represent the percent cost savings from the efficiency portion of the measure as well as the demand response portion of the measure. Demand response only represents two measures that do not have efficiency savings and only save on the called event days.

The comparison of efficiency to efficiency plus demand response illustrates that the relative energy and cost savings impact of adding demand response to an efficiency measure is insignificant. However, the measures that are demand response only, networked lighting controls and critical peak pricing, have small but significant percent savings over the baseline. There are a couple of potential reasons for this difference. Each of the four efficiency plus demand response measures have an increase in energy use before and after the event hours, decreasing the energy savings from events while the two demand-response only measures do not. For this reason, the demand response only measures save significantly more energy during the events, which translates directly into more significant cost savings over the baseline.

Figure 3. Event-based measures: cost savings over baseline and annual energy savings (2018 prices)



Finally, this research found that capacity costs can have a significant impact on the total cost savings of a measure, especially for shifting and event-based measures. Capacity costs range from 20 to 100 percent of total cost savings.

Cost-Effectiveness

The project team calculated financial impact and cost-effectiveness ratios using the Societal Cost Test. The costs include the installation cost as well as the program administration costs for the utility. The benefits include the avoided energy costs, the avoided capacity costs, and the monetized benefit of emission savings. Table 3 illustrates the cost-effectiveness results for each measure. The cost-effectiveness ratios vary measure by measure with most measures resulting in a cost-effectiveness ratio between 1 and 2.

A few measures have more extreme values. ASHPs are significantly more cost-effective than most measures, due to energy efficiency savings across the entire year compared to the baseline of electric resistance heat. On the other extreme, active ice thermal storage and refrigeration load control have a large energy penalty which does not outweigh any system costs. This is not to say that these two measures do not have a benefit to customers, but those values would need to be calculated using specific customer rates. Lastly, the smart thermostat measure shows a cost-effectiveness ratio slightly below 1. This is largely due to this study's model structure where the peak energy saving days, when temperature is high, do not coincide with the top demand days. This leads to low capacity savings in 2018 compared to other years. If the model was adjusted to use 2019 capacity cost savings, the smart thermostat measures would result in a cost-effectiveness of between 1.2 and 1.6, illustrating the sensitivity of weather in this study's model.

Table 3. Cost-effectiveness results - total annual cost range, total annual benefits, and benefit cost ratio range

Measure	Total Annual Costs (Installation + Administration)	Benefits (Avoided costs + emissions)	Benefit cost ratio range
PCM for space conditioning	$21,680 - $43,140	$27,725	0.6– 1.3
PCM for refrigeration	$33,135 - $44,685	$55,230	1.2 – 1.7
Active ice thermal storage	$13,540 -$17,415	$600	0.0 – 0.0
Refrigeration load control	$124,835 - $168,865	$2,665	0.0 – 0.0
EVs with charging controls	$10,200 - $24,015	$23,250	1.0 – 2.3
Industrial strategic energy management	$14,450 - $19,455	$34,365	1.8 – 2.4
Smart thermostats with demand response	$7,730 - $10,200	$3,805	0.4 – 0.5
ASHPs with demand response control	$14,325 - $24,765	$79,810	3.2 – 5.6
Envelope measures combined with ASHP	$40,635 - $74,155	$75,060	1.0 – 1.9
HPWH with controls	$41,285 - $61,445	$69,550	1.1 – 1.7
Networked lighting controls with demand response	$14,325 - $20,680	$29,330	1.4 - 2.1
Critical peak pricing to drive behavior change	$3,170 - $10,625	$8,285	0.8 – 2.6
Lighting efficiency + controls	$47,925 - $74,765	$89,270	1.2 – 1.9
Plug loads	$41,890 - $101,085	$108,045	1.1 – 2.6

Carbon Emission Sensitivity

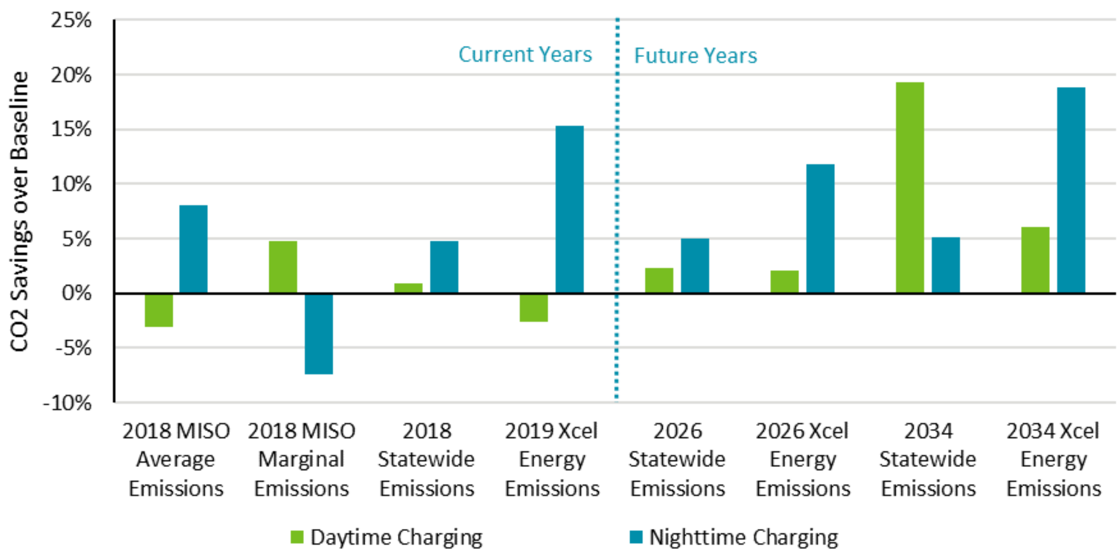
The carbon emissions sensitivity analysis shifted energy use energy use away from time periods of higher carbon emissions and towards times of lower carbon emissions. While price and emissions are fairly correlated in the 2018 market, there is a changing emissions dynamic as the grid mix changes in the future. Additionally, results will help inform the impact of choosing one grid region over another to evaluate emissions savings.

The project team conducted this load shifting analysis for three load shapes: ASHPs with and without enabled demand response, EV charging, and commercial PCM for refrigeration. These three measures were selected to represent a variety of load shifting options: an energy efficiency measure with demand response, a load shift with no energy savings and a load shift with energy savings, respectively.

Of the three measures, EV charging shows the highest degree of variation based on emissions footprint. Since shifting EV charging times does not save energy, all of the carbon savings comes from time-of-day emissions variations. Figure 4 shows the percent change over baseline for charging at different times of day, either with daytime charging or nighttime charging. The eight different emission scenarios represent a mix of present and future day as well as geographic territories.

Nighttime charging provides higher emissions benefits than daytime charging with two exceptions: 1) the current (2018) MISO marginal emissions and 2) the 2034 statewide emissions profile. This is for two very different reasons. In 2018, a large portion of MISO's nighttime marginal emissions were from must-run coal plants. In 2034, it is a result of high solar penetration during the day. And finally, these results also demonstrate that emissions patterns may vary utility-by-utility. In 2034, the statewide emissions forecast favors daytime charging, whereas Xcel Energy Minnesota shows higher carbon savings when load is shifted to nighttime charging.

Figure 4. EV carbon emission savings over baseline across 8 emissions optimization scenarios



Key Takeaways

Load shifting measures can have a positive impact on both emissions and energy savings. Although the forecasts for both prices and emissions are uncertain, the results show that these impacts can persist into the future. The following takeaways summarize the main conclusions from this study:

Energy efficiency dominates both cost and emission savings opportunities. The measures with the highest cost and emissions savings in the study are those that have year-round energy savings (such as lighting or ASHPs). These are followed by measures that can permanently shift energy use throughout the entire year (such as EVs).

Measures that increase energy use can save energy costs through shifting time of consumption. Two measures that increase overall energy use, industrial strategic energy management and refrigeration load control, still display costs savings by using energy during less expensive times of the day. Thermal storage is an example of a measure that increases energy use but does not save energy costs when using 2018 energy costs.

Absolute carbon savings can as much as double depending on which grid region is used to analyze emissions. Similarly, the carbon savings as a percent over baseline can vary for measures that purely shift the time of energy use, such as EVs, making the choice of grid region crucial for these measures. However, for measures with significant energy savings, the carbon savings as a percent of baseline stays relatively constant across grid regions.

For load shifting measures that save energy, there is not significant change in *average* emissions savings when optimizing based on prices versus average emissions in the current Minnesota grid. For the measures in the study, shifting the load based on price also has an emissions benefit. There is limited advantage to managing load based on carbon signals. However, for those measures that do not save any energy, shifting energy use to nighttime hours, when prices are low, will increase *marginal* emissions.

Capacity costs can have a significant impact on cost savings for pure demand response and shifting measures. For demand response measures, such as networked lighting control and critical peak pricing, capacity cost savings can account for over 90 percent of total cost savings. There are two main reasons for this: (1) the measures have relatively low annual energy savings and (2) the times when these measures shave energy coincides well with the system peak, resulting in high kW savings. As such, the inclusion of these capacity savings has a significant impact on the cost-effectiveness of the measures. This is also true for regularly-occurring shifts that have little to no energy savings.

Load shifting and demand response measures are cost-effective. Most of this study's measures had a cost-effectiveness ratio between 1 and 2. The only exceptions are active ice thermal storage and refrigeration load control, which both have large energy penalties.

Recommendations

Based on the results and key conclusions, the project team developed a set of recommendations to be considered as outcomes of this study:

Continue to pursue load shifting measures that can save energy in CIP portfolios. Emerging technologies, such as PCM for refrigeration and PCM for space conditioning, are primarily load shifting measures but generate electricity savings across the year. Like demand response programs that save energy, these measures bring customer and system benefits that should be pursued when cost-effective.

Integrate cost-effective load shifting measures into CIP portfolios when they can be bundled to create energy saving opportunities. Results of this study show that the cost and emissions benefits of saving energy still outweigh the benefits of shifting electricity use, under multiple scenarios. While recognizing that current statute limits the ability to include load shifting measures under CIP, the results also show that there is ample opportunity to have an impact on carbon and energy cost savings through measures that shift load.

Consider the long-term avoided costs of renewables integration. This study included limited cost forecasts and does not account for costs of renewable energy integration that load shifting could help to mitigate. These costs include the balancing needed during ramp-up or ramp-down events, or generation shortfalls during times of high demand and low renewable production. While these future costs are uncertain, they may offer additional cost savings for load shifting measures.

Explore additional measures that may offer similar load shifting benefits. There are additional measures that have promising potential for emission and energy reduction through load shifting which were not included in this study. For example, energy management information systems and retro commissioning both take established methods of reducing energy and adjust them to also shift load and energy. Other examples of load shifting measures to explore further include irrigation load control and residential solar and storage.

Apply a utility-specific grid region to calculate emissions benefits where available. This would allow a utility to capture the benefits of the renewable energy dynamics specific to that utility's portfolio. Using emissions rates from utility integrated resource plans (IRPs) would also allow emissions rates to be vetted through the stakeholder process. Given the uncertainty of future year emissions, the project team recommends that forecasted emissions benefits be evaluated after the fact, similar to energy efficiency achievements, to bring additional transparency to the changing dynamics of carbon emissions.

Give additional scrutiny to measures that shift load to nighttime hours absent any energy savings benefits, in the near term. Depending on the baseline assumptions, these measures may increase marginal emissions given the prevalence of fossil generation on the margin in the Minnesota region. The dynamics of marginal emissions are changing and may vary with a utility-specific emissions footprint; hence this will require examination on a case-by-case basis.

Consider future rate designs that incentivize customers to shift energy when system is near capacity. This analysis did not explicitly explore the impact of rate design; however, research strongly suggests that deliberate rate design directly influences customers to shift or shed energy use. In the future, rate design could reflect carbon and incentivize shifts of energy away from high carbon times.

For future demand side management potential studies in the state, expand consideration of measure benefits to include cost savings and carbon benefits associated with load shifting. Researchers should include the time-varying benefits that a measure would generate. These time-varying benefits can have a significant influence on cost-effectiveness, sometimes even making the difference between whether a measure is cost-effective or not.

Conduct future research on both load shapes and impacts of load shifting measures on both costs and emissions. Additional field research and monitoring efforts are needed to generate accurate and geographic-specific load shapes, especially on innovative grid-interactive technologies and utility-scale battery storage, both of which are rapidly commercializing in the market.

Similarly, further research on marginal emissions in the current grid and in future grid scenarios is needed. By shifting load, each of these measures impact the generating plant on the margin and a better understanding of which plant, and fuel, is being impacted will more accurately demonstrate the carbon benefits of these measures and the overall benefits of shifting on the system.

Further research on capacity costs and distribution avoided costs can also help increase the certainty of the impact on total cost savings. Lastly, this report was limited in the future price data available. Additional research on how prices will adjust to more renewables on the grid is needed in order to understand the cost implications of these measures in the future.

Introduction

Background

As lighting and other basic efficiency measures reach saturation, utility energy efficiency programs need to fill the gap with more complex and often costlier measures. At the same time, due to changing load shapes and generation mix, utilities are increasingly interested in measures that shift the *time* of energy use in addition to reducing overall energy use.

As renewable generation increases, increasing both the daily and yearly variation of emissions and avoided cost profiles, the ability to shift the *time* of energy use is becoming increasingly important. This area of work is especially valuable in Minnesota where the electricity supply mix is changing rapidly. Currently, Minnesota generates about 20 percent of its electricity production from non-hydroelectric renewable energy resources, and hydroelectricity adds an additional 1.6 percent (EIA 2018a).

This percent is likely to increase substantially over the next 10 to 15 years as the state's large baseload coal generation continues to be retired. Xcel Energy Minnesota, which delivers 45 percent of Minnesota's electricity sales (EIA 2018b), has plans to retire all coal-fired generation facilities by 2030, replacing the large majority with utility-scale wind and solar power (Northern States Power Company 2019). Great River Energy, the state's largest generation and transmission cooperative, also recently announced closure of their 1.1 GW Coal Creek power plant in 2022, one of the last remaining large coal facilities serving Minnesota (GRE 2020). Using numbers from Minnesota's three electric investor-owned utilities' (IOUs) most recently submitted, but not yet approved, integrated resource plans (IRPs), the project team estimates that 50 percent of the statewide electricity production will come from wind and solar by 2035.

Additionally, Midcontinent Independent System Operators' (MISO) Transmission Expansion Plan process continues to show a need for peaking power plant resources, as well as energy efficiency and storage, in the short term (MISO 2018). If, as anticipated, wind and solar become the dominant generation resources in the region (Clean Power Research 2018), variable production and ever-increasing differentials in marginal prices will be the new standard throughout a typical day in Minnesota.

This changing landscape provides a clear value stream for measures that can shift the time of energy use, which is the focus of this study. However, one major barrier with promoting measures that shift load is the potential increase of overall energy use, which conflicts with energy efficiency policy and creates an incentive to build load. To date, Minnesota's Conservation Improvement Programs (CIPs) allow for load shifting measures, but only those that save energy also (Minnesota Statutes, 2019). Given that state policy is designed to correct the disincentive of decreased sales, CIPs that shift load while *increasing* energy use (e.g. thermal ice storage) are not eligible under Minnesota's energy efficiency resource standard. Therefore, utilities in the state offer separate incentives for measures that save energy and measures that may shift load, such as demand response programs.

Furthermore, the load shapes that are used in technical reference manuals (TRMs), cost-effectiveness calculations, and efficiency portfolio planning have not been updated and were not initially developed with load shifting as a primary consideration. And the energy efficiency planning conducted by some utilities does not typically consider a broad spectrum of future economic and emissions scenarios, and how the load shifting aspects of some measures could benefit the utilities – and their ratepayers – in those scenarios.

Taken together, Minnesota's current energy efficiency framework overlooks the overlap between energy efficiency and load shifting, and stakeholders in Minnesota lack the geographically specific information needed to assess the system value of load shifting to weigh these tradeoffs. Many electric utilities in the state have growing interest in activities that shift the timing of energy use in addition to, or instead of, reducing overall energy use. There are opportunities within Minnesota's framework to design future programs that take advantage of load shifting as well as energy savings opportunities.

This research, funded through the Minnesota Department of Commerce's Conservation Applied Research and Development program, addresses these barriers by quantifying the Minnesota-specific economic, energy, and emissions impacts of measures that shift load with or without saving energy. The goal of the research is to identify how these measures may fit within Minnesota's energy efficiency programs.

Review of Similar Research

In recent years, several other studies have examined the importance of the time-varying value of energy efficiency as well as the benefits from demand flexibility. The primary focus of most of these studies was the monetary value of demand flexibility or load shifting, with less emphasis on the emissions impact.

Most notably, two studies by Lawrence Berkeley National Lab (Mims et al., 2017; Mims et al., 2018) quantified the time-based value of energy savings for five traditional energy efficiency measures. These studies' goals were to demonstrate how the time of energy use directly impacts the value of energy savings. One of those studies was specific to Michigan and the other study covered four geographic areas: the Northwest region, Georgia, Massachusetts and California. The results show that time-varying value differs both across measures and across regions, depending on grid system characteristics and time of use for the measures. These two studies provided a base methodology for the avoided cost portion of the model used in this project.

Several studies have examined this topic specifically for the grid system in California. In 2016, Energy and Environmental Economics completed a time-dependent valuation to be used in the cost-effectiveness calculations for the California Title 24 building standards (E3 2016). The goal of this evaluation was to provide values that better reflect the potential energy cost savings from efficiency upgrades. A second California-specific article evaluated the savings profile of energy-efficient air conditioners in Southern California to demonstrate the value of using time-varying energy costs in efficiency evaluations (Boomhower 2017). The paper uses prices from wholesale energy and forward capacity markets in order to quantify the value of the energy savings from the program. It finds that the program is 48 percent more valuable if time of energy use is considered when compared to an evaluation that ignores timing. Both articles show the benefit of using time-varying cost values, highlighting the importance of considering measures that take advantage of variation in energy prices by strategically shifting load across the day.

Lawrence Berkeley National Lab completed a two-phase evaluation on how to enhance the role of demand response in the California grid. The evaluation estimated the cost-effectiveness of various demand response curves and how they could help meet the needs of the changing grid (Alstone et al. 2017; Gerke 2020). This evaluation ultimately conclude that the scale of demand flexibility potential depends on policy, market design, and technology research and development.

Lastly, a study by the Rocky Mountain Institute evaluated how demand flexibility can increase the benefits of renewable energy in the future (Goldenberg and Dyson, 2018). The authors created a simulation of a future Texas grid and shifted the load of eight common end-uses to times of high renewable availability to demonstrate the value of load shifting for renewables. The study found that highly flexible demand could reduce curtailment of renewable resources by 40 percent while also lowering the magnitude of multi-hour ramps by 56 percent. These findings emphasize the importance of considering load shifts that respond to emissions as well as to prices.

Methodology

Advisory Committee

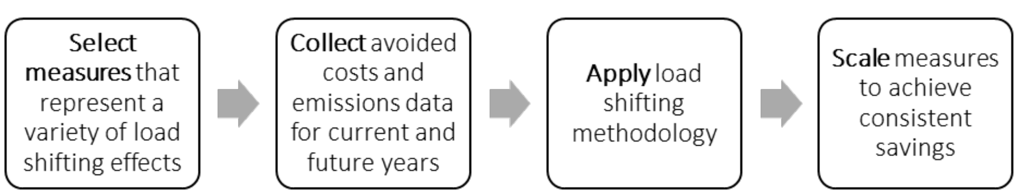
An advisory committee comprised primarily of utilities in the state that would directly benefit from the research, as well as other research organizations, was formed to provide feedback to the project team. This committee was present at the project kick-off meeting where the project team outlined the research approach and received feedback and suggestions for modifications. The advisory committee continued to play a role in providing feedback throughout the research. This included one-on-one phone calls with several of the committee members to gain more insight on data sources as well as a large group meeting to present preliminary results and receive feedback. The advisory committee included the following individuals:

- Jeremy Petersen, Principal Technical Consultant, Demand-Side Management and Renewable Strategy and Planning, Xcel Energy Minnesota
- Erin Buchannan, Technical CIP/DSM Regulatory Consultant, Xcel Energy Minnesota
- Jeff Haase, Leader, Member Technology & Innovation, GRE
- Matt Prorock, Senior Policy Manager, Great Plains Institute
- Brandon Heath, Former Advisor in Regulatory and Economic Studies, MISO
- Michelle Rosier, Distributed Energy Resources Specialist, Economic Analysis Unit, Minnesota Public Utility Commission
- Allen Gleckner, Director, Energy Markets, Fresh Energy
- Andrew Twite, Senior Policy Associate, Fresh Energy
- Beth Soholt, Executive Director, Clean Grid Alliance
- Lisa Beckner, Customer Business Analyst, Minnesota Power
- Theresa Drexler, Senior Market Planning Specialist, Ottertail Power

Model Development

To quantify the emissions, cost, and energy impact from load shifting measures, the project team developed hourly annual models (i.e., 8760 models) of energy, costs, and emissions for both present day and the future. Figure 5 provides a simplified schematic that represents the key steps in the development of the model. Methods and assumptions made for each element of the model are described below.

Figure 5. Methods summary: key steps in the development of the model



Measure Selection

The measure selection process began with a review of existing literature of similar research and a review of known measures that have load shifting potential. The project team identified a mix of residential and commercial measures as well as measures with various impacts on energy reduction and load shifting.

Each of the measures were then categorized based on the type of load shift, which are defined as follows:

- A measure categorized as a **regularly-occurring shift** can shift energy use each day from one period of the day to a different period of the day. These measures may include an energy efficiency component, may be energy neutral, or may use more energy than the baseline measure.
- An **event-based measure** only shifts load on a select number of days, typically when demand is high, and utilities are near capacity. These measures are also sometimes referred to as shed measures, as they decrease energy use for a select number of hours rather than shifting the use to a different time. The load shape combines the traditional energy efficiency installation with demand response for four of these measures. The other two measures are purely demand response measures.
- The two **energy efficiency measures** with no load-shifting potential were included to represent measures currently in Minnesota's efficiency programs and do not shift load.

The first two categories are similar to the "shift" and "shed" taxonomy introduced by Lawrence Berkeley National Lab (Potter and Cappers 2017), but the key distinction is the frequency with which the demand change occurs – either consistently across the year, or for a handful of events that happened as a results of an event signal. While certain measures in this research could possibly fall under the "shift" and "shed" categories of Potter and Cappers, the project team felt that event-based shifts and regularly occurring shift naming convention more accurately captured this distinction. For example, refrigeration PCM is a shift measure that happens every day, whereas smart thermostats with pre-cooling and pre-heating are shift measures that happen only when events are called.

For each measure, the project team developed both an hourly baseline and measure load shape. The data points for developing the load shapes come from a mixture of empirical data from technology field tests conducted by the project teams' organizations as well as secondary sources and research. Table 4 provides the type of shift, a short description, and the baseline for each measure in this study. A full description of the measures and assumptions made for each measure can be found in Appendix B: Load Shape Assumptions.

Table 4. Summary description of measures included in this study

Type of shift	Measure	Description	Baseline
Regularly-occurring shift	Phase change materials (PCM) for space conditioning (*commercial*)	PCM are melted and frozen at temperatures near the setpoint to shift load in conditioned places.	Space conditioning (variable air volume – no PCM)
Regularly-occurring shift	PCM for refrigeration (*commercial*)	In refrigerated areas, PCM are frozen during non-peak hours and melted to cool goods during peak hours.	Typical commercial refrigeration load shape
Regularly-occurring shift	Active ice thermal storage (*commercial*)	Cool thermal storage attached to a chilled water system; chillers make ice or chilled water at off-peak times for use during peak-times.	Space conditioning (variable air volume)
Regularly-occurring shift	Electric vehicles (EVs) with charging controls (*residential*)	A managed controlled charging program that sets charging time: 9 pm to 5 am.	Level 2 uncontrolled charging
Regularly-occurring shift	Strategic energy management with demand focus (SEM) (*industrial*)	Programming common efficiency measures' controls, based on worker shifts to shift load.	Typical industrial load
Regularly-occurring shift	Refrigeration load control *(commercial)*	Refrigeration system operators use the setpoints in refrigerated spaces to shift the time at which compressors run, without impacting food quality.	Typical commercial refrigeration load shape
Event-based	Smart thermostats with demand response (*residential)*	Smart thermostat with demand response functionality, to run air conditioning less when loads are peaking, or utility prices are high.	SEER 12 AC with current mix of programmable + smart thermostat
Event-based	Air source heat pumps (ASHPs) with demand response control (*residential)*	ASHPs with controls that allow utilities to remotely adjust heating or cooling load. Includes pre-cooling or pre-heating prior to the event and a recovery period after the event.	Electric resistance heat + SEER 12 AC
Event-based	Envelope measures combined with ASHP (*residential*)	Deep envelope retrofits combined with the ASHP measure to show the impact of having a well-insulated home.	Baseline space conditioning + median SF in Minnesota
Event-based	Heat pump water heaters (HPWH) with controls (*residential*)	Use of more efficient HPWH and pre-heat during off peak times to shift usage.	Electric resistance with no controls
Event-based	Networked lighting controls with demand response (*commercial*)	A lighting retrofit with controls that are digitally networked for additional energy savings during peak times.	Typical commercial LED lighting
Event-based	Critical peak pricing to drive behavior change (*residential*)	Advanced notice of higher prices for certain hours of days when demand is expected to be high.	Typical residential load shape from Minnesota TRM
Energy efficiency	Plug load controls (commercial)	Commercial plug load controls turn off computing equipment and peripherals, saving energy.	Typical office settings

Type of shift	Measure	Description	Baseline
Energy efficiency	Lighting efficiency and controls (commercial)	A typical LED retrofit along with daylighting, task tuning, and occupancy controls.	Typical commercial fluorescent bulbs

Avoided Cost and Emissions Data Collection

The availability of avoided cost and emissions data varies by grid region and timeframe of analysis. Avoided costs in this study include energy costs, capacity costs, and transmission and distribution costs.

Table 5. Summary of hourly emissions and cost data sources by timeframe provides an overview of the hourly data available for avoided costs and emissions. The cost data consisted of wholesale prices from either the MISO's market data or Xcel Energy Minnesota's proprietary forecast.

The project team similarly utilized emissions data from MISO's publicly available market data and from Xcel Energy Minnesota's forecast. The team also forecasted hourly average statewide emissions rates based on EPA hourly emission data and the known future resource mix of the state's utilities.

Table 5. Summary of hourly emissions and cost data sources by timeframe

Grid Region	Timeframe	Costs	Emissions
Utility	Current Year	Xcel Energy Minnesota's filed IRP	Xcel Energy Minnesota's filed IRP
Utility	Forecast	Xcel Energy Minnesota's filed IRP	Xcel Energy Minnesota's filed IRP
State	Current Year	Not applicable	EPA Hourly Emissions Data (EIA 2018)
State	Forecast	Not applicable	EPA Hourly Emissions Data (EIA 2018) + Known Retirements
ISO	Current Year	MISO Market Data	MISO fuel mix + marginal plant data
ISO	Forecast	No available data	No available data

Avoided generation and transmission and distribution capacity costs represent the cost saved by deferring or delaying the need for a new power plant, new transmission lines or local distribution to be added to the grid. Avoided generation capacity data was gathered from Xcel Energy Minnesota's proprietary forecasts. As a sensitivity analysis, the project team also used MISO's one-year cost of new entry (MISO 2020). The cost of new entry is derived from MISO's planning resource auction and represents a more near-term scenario compared to the capacity cost included in the utilities' planning process.

The project team applied the average of the three IOU's values from their CIP Triennial Plan (Minnesota Commerce 2019) for avoided transmission and distribution costs. For a more in-depth discussion of the methods used to collect all these costs, refer to Appendix A: Emissions and Cost Data Collection.

The annual emissions and cost data focused on three reference years: 2018, 2026, and 2034. Minnesota utilities currently forecast out 15 years in the IRP documents submitted to the state, making year 2034 a natural long-term scenario. The year 2026 serves as the mid-point between 2018 and 2034. Additionally, as these years fall before and after the 2030 decommissioning of large coal plants serving Minnesota, it is possible to analyze the impact of little to no coal in the market and how increased renewable energy capacity changes the impact of load shifting measures.

Figure 6 shows capacity forecasts by fuel for the statewide scenarios. These capacity values include any Minnesota generation facility that reports data to the Energy Information Administration. However, the project team did not model retirement dates for municipal utilities and cooperatives, so the generation from those plants remains constant across the years.

Table 6 illustrates these differences across all grid regions, showing the percent renewable capacity in the present-day, mid-term, and long-term.

Figure 6. Forecasted Capacity for the Statewide Emissions Scenario

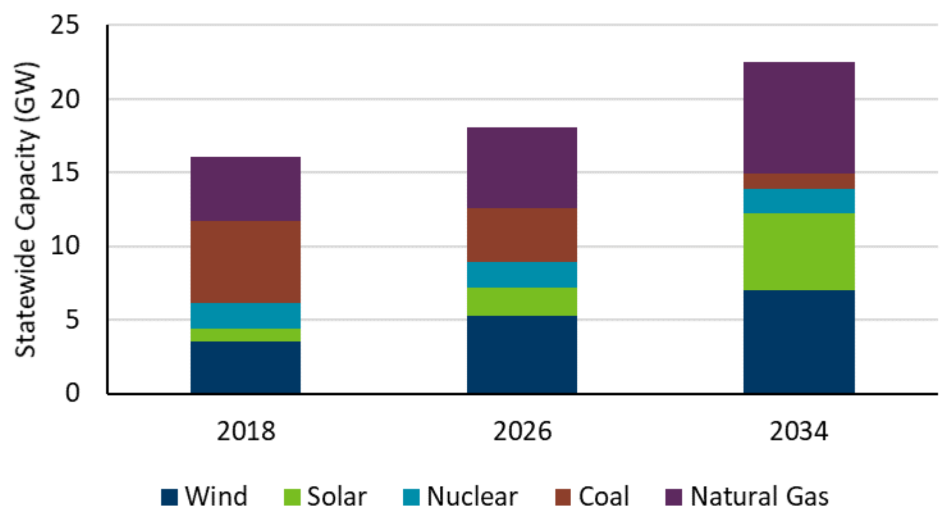


Table 6. Percent renewable energy capacity by grid region and year

Grid Region	Present day (2018/2019)	Mid-term (2026)	Long-term (2034)
Xcel Energy Minnesota	25% renewable	45% renewable	59% renewable
State[a]	27% renewable	40% renewable	54% renewable
MISO	13% renewable	*N/A*	*N/A*

a) Note that these renewable capacity projections do not include renewable additions announced in May 2020.

Applying Load Shifting Methodology

Using the data collected for each load shape, the project team optimized each of the measures to shift energy during peak times of the day. Table 7 summarizes the method used to shift energy use for each type of measure. Each of the fourteen measures was optimized around price and a sensitivity case was applied to three measures to test against emission scenarios. The price scenario was used as the baseline as it is similar to how utilities often promote demand reduction during the high demand or high price times of the day.

Table 7. Load Shifting Methodology Overview

Scenario	Regularly-occurring shift	Event-based shift	Energy efficiency
Price	Avoid energy use during the middle of the day	Shed energy during high price hours of top days	Shed energy all day
Sensitivity	Avoid energy use during middle of night	Shed energy during high emissions hours of top days	Shed energy all day

For regularly-occurring shifts, the measure load profiles were shifted away from the middle of the day in response to higher prices during that time. For each event-based load shape, the project team assumed a set number of called events within each year and used wholesale energy price data to determine which days should have an event, and which hours of the day were most important to shed energy use. Typically, utilities would use proprietary data to determine when to call events; however, without access to that data, the project team used wholesale energy prices as a proxy.

The project team also developed a sensitivity analysis for three of the measures: EVs, PCM for refrigeration, and ASHPs plus demand response. These three measures were selected as they represent a variety of load shifting options: a load shift with no energy savings, a load shift with energy savings, and an energy efficiency measure with demand response, respectively. Emissions intensity, like price, changes throughout the day and year based on the prevalence of renewable generation as well as overall load. For example, 2018 MISO average emissions are typically lower in the middle of the night while marginal emissions and the 2034 statewide forecasted emissions are typically lower in the middle of the day.

In this emissions optimization analysis, the two shifting measures, EVs and PCM for refrigeration, had a daytime charging scenario in addition to night-time charging to compare emissions implications. The daytime shift avoids energy use overnight and uses energy from 9 am to 4 pm. For ASHPs, the project team dispatched demand response events similar to the methods for price optimization, again targeting the top twenty days of the year and the top hours in each of those days based on emissions factors.

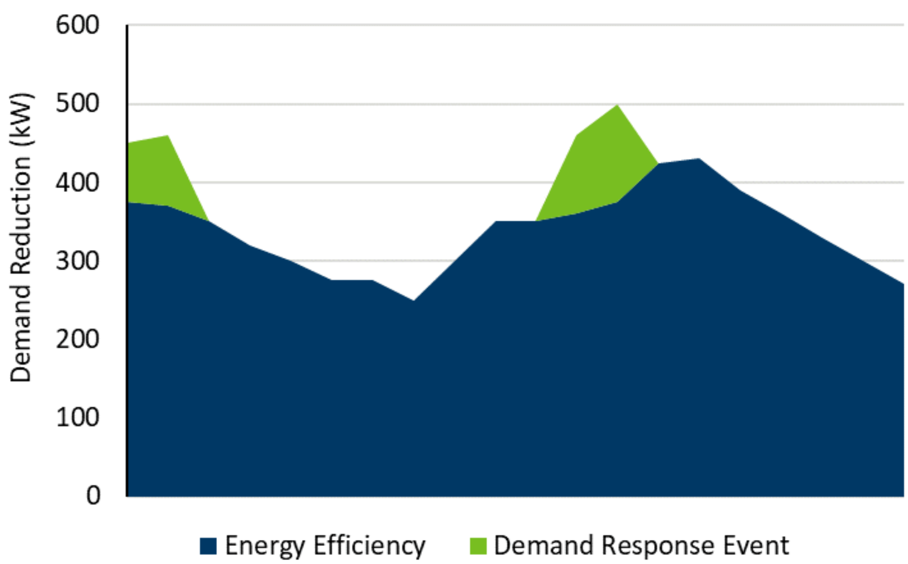
Scaling Measures to Achieve a Consistent Demand Reduction

Lastly, to present an apples-to-apples comparison between measures with significantly different per-participant savings, the project team scaled each load shape so that the measure achieved a maximum savings of 500 kW during at least one hour throughout the year.[1] This method controls for the variability in the per unit demand impact across measures. For example, one home on critical peak pricing saves less than 1 kW at its peak hour but a commercial building with PCM for cooling saves 25 kW at its peak hour.

Thus, measures with a higher kW savings value per participant, such as lighting efficiency and controls, require fewer participants to hit the 500 kW; other measures, such as residential smart thermostats, require a significantly higher number. The assumed levels of participation are detailed in Appendix B: Load Shape Assumptions.

When a measure reduced customer peak demand through both efficiency and demand response, it was scaled against their combined savings. Figure 7 demonstrates such a hypothetical measure, with the total savings scaled to the combined value of 500 kW. Note that this scaling happens at the *customer* peak, not at the coincident *system* peak.

Figure 7. Hypothetical measure savings scaled to 500 kW



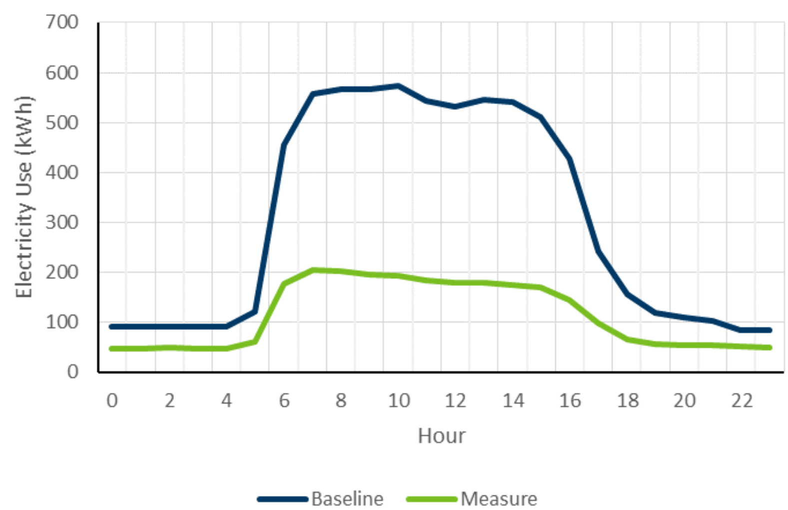
This approach makes results more easily comparable, though it also has implications for measures whose savings are highly weather dependent, such as ASHPs. As these measures are dispatched in this study's model to meet price or emissions conditions for a given scenario, those triggers may or may not fall on a peak weather day. This therefore changes the number of participants needed to hit 500 kW. For demand response measures, there is a chance that peak energy use will occur on non-event days. The implications of this will be discussed further in the results section.

[1] This approach uses a method similar to the one used in Mims et al. (2018), which scaled each measure to reach 1,000 kWh of savings.

Examples of Load Shapes

Figure 8 through Figure 10 provide examples of load shapes for each of the three measure types: energy efficiency only, regularly-occurring shift, and event-based measures. The figures show the hourly average of the baseline electricity usage compared to the hourly average of the measure electricity usage. Figure 8 and Figure 9 represent the average across the full year while Figure 10 represents one day when an event is called. The lighting efficiency measure reduces energy over the entire day as a typical energy efficiency measure would. The EV measure shifts energy use to non-peak times, either defined as 10 pm to 5 am for nighttime charging or 9 am to 4 pm for daytime charging. Lastly, the ASHP example (shown here for the cooling season) shows an overall reduction due to energy efficiency with an additional reduction in demand for the peak hours within a day. Each load shape in this study is described detail in Appendix B: Load Shape Assumptions.

Figure 8. Energy efficiency load shape example: commercial lighting hourly average electricity use before and after LED retrofit



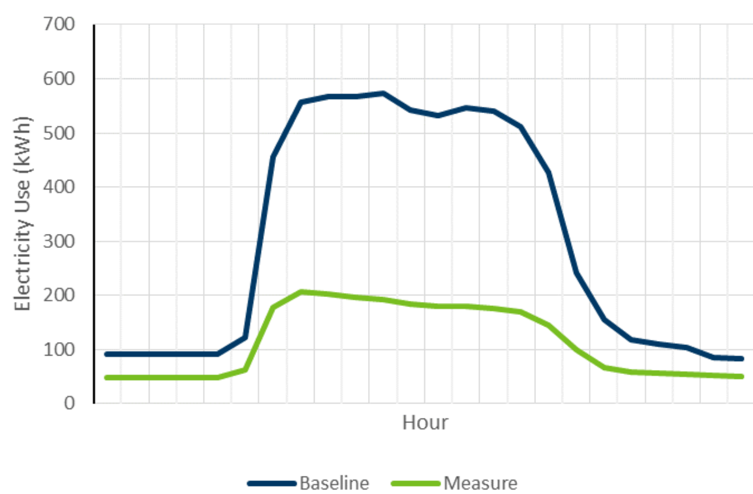


Figure 9. Regularly-occurring shift measure example: EV-controlled charging hourly average electricity use and uncontrolled baseline

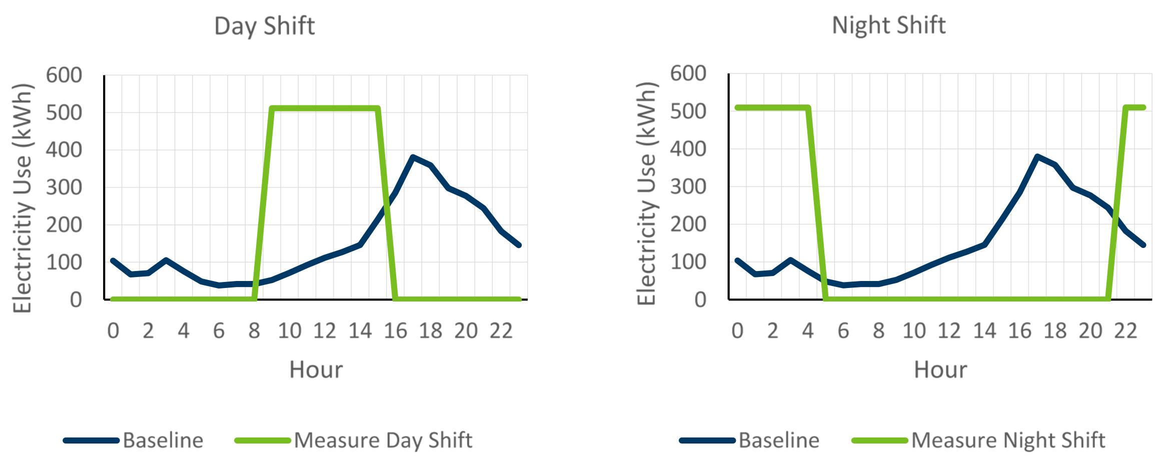
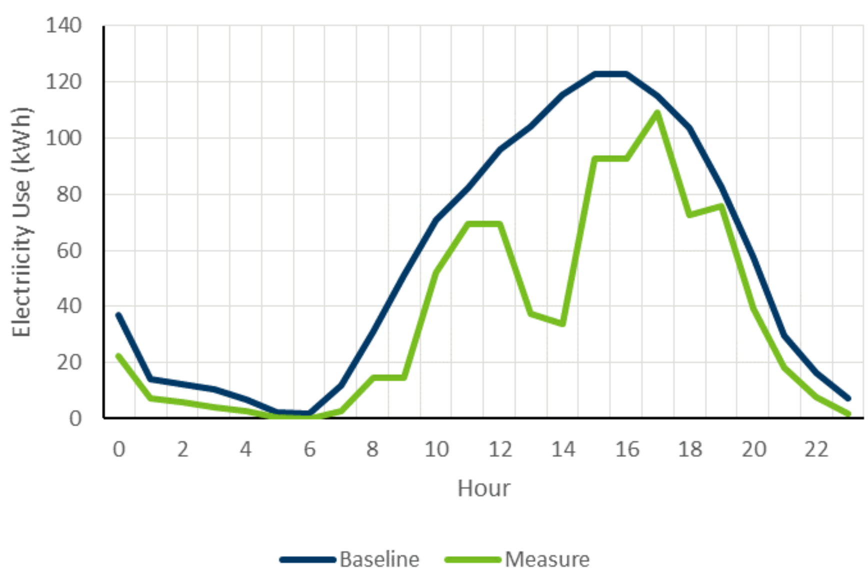


Figure 10. Event-based example: ASHP with demand response hourly average electricity usage compared to SEER 12 AC baseline



Analysis

To analyze the results, the project team combined the data gathered during the data collection phase to estimate annual energy costs, annual emissions, and annual capacity costs for both the measure and baseline load shapes. Using those values as well as collected data on program costs and installation costs, the project team also then calculated cost-effectiveness ratios for each of the measures.

To estimate the annual value for energy costs and emissions, the hourly baseline and measure load shapes were multiplied by the annual cost and emissions data from each data source. Summing hourly values across the year generated annual point values for the baseline and measure load shapes. The difference in these two values represented the absolute savings from the measure as well.

Capacity cost savings were calculated using the average kW savings during peak hours, determined by top wholesale prices, and multiplied by the dollar per kW-year value for both generation capacity and transmission and distribution capacity. For additional details on these calculations, see Appendix C: Calculation Methodology.

Results

The results of the study's modelling are presented below in two sections. The first section details the costs savings and emissions impacts, both now and in the future, for the optimization based on energy costs. Similar results are then explained for the carbon emissions sensitivity analysis.

One of the overarching findings is that energy efficiency measures, due to their often-daily effects on energy consumption, continue to offer significant overall energy savings, even when optimizing for load shifting potential. For those measures that have both an energy efficiency component as well as a load-shifting effect, the portion of the energy costs or emissions savings attributed to energy efficiency eclipses the load shifting effect. For this reason, the results are split out by measure category which allows for easier comparison of impacts.

Cost Optimization Results

Present Day Energy Cost Results

Key Takeaway

Efficiency measures lead to the highest percent cost savings of all measure types. However, shift measures can save money even if they are energy-neutral or have an energy penalty.

The percent cost savings varies significantly across measures. Figures 12, 14, and 16 illustrate these patterns by showing the percent savings over baseline, using 2018 MISO prices, for each of the load shapes included in the study. MISO 2018 prices were, on average, higher than both 2017 and 2019 average prices. However, both 2017 and 2019 had mild summers with fewer hot degree days over the typical peak months, suggesting that 2018 is still a good representation for the market.

The results below are presented with a graphic showing percent savings over baseline. The values on the top of each bar represent each measures' annual energy savings. As described above, energy savings were calculated by multiplying the savings from one measure by the number of participants needed to hit 500 kW during at least one hour throughout the year. For the number of participants assumed per measure, see Appendix B: Load Shape Assumptions.

Regularly-occuring shift measures

The shift measures in Figure 12 show a wide range of percent cost savings over baseline. The values on the top of each bar represent the energy savings across the entire year.

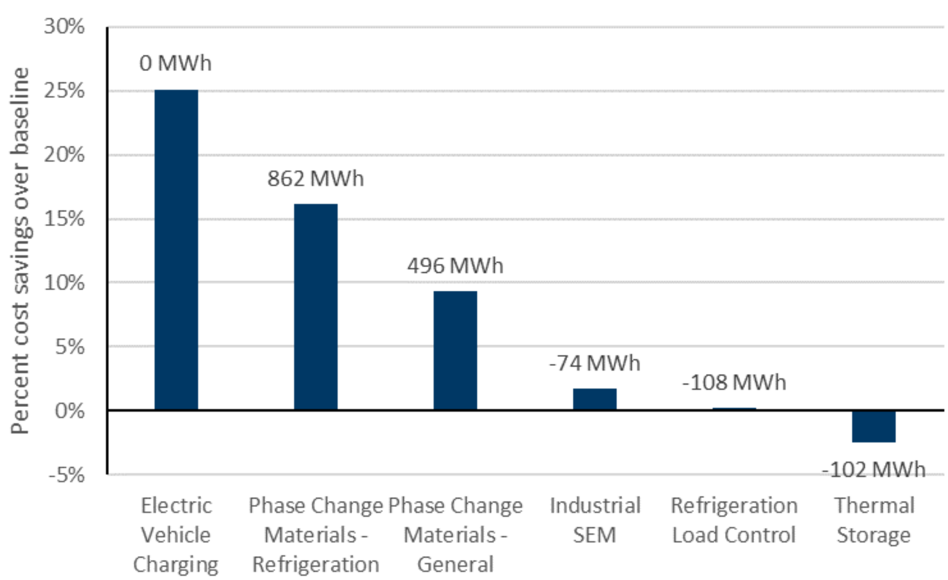
While not saving any energy compared to the baseline measure, EVs have the highest percent cost savings as the entire load can be shifted from high price times to low price times. The other measures can shift energy from one time to another, but still must use some energy during high price times to maintain performance requirements. This allows EVs to save more money compared to its baseline than the shift measures that have an energy savings component, such as both the PCM measures. Industrial strategic energy management and refrigeration load control have small positive cost savings despite an increase in energy use across the year. These examples demonstrate the value of shifting load to times when prices are low.

Figure 11: Picture of example PCM

Retrieved from: https://designbuilder.co.uk/helpv6.0/#Phase_Change.htm

Lastly, although thermal storage shows an energy cost penalty, costing more when shifting compared to the baseline, there are individual days where the measure results in cost savings. This occurs when the price differential between the peak and off-peak hours is particularly large. However, the price differences averaged over a year are not large enough in the MISO market to overcome the inherent energy penalty from the measure. This does not mean that there is no potential benefit to customers, as the use of specific customer rates could potentially lead to cost savings.

Figure 12. Regularly-occurring shift measures: percent cost savings over baseline and annual energy savings (2018 MISO real-time prices)



Event-based measures

Figure 14 shows the six event-based measures' percent cost savings over baseline. The percent cost savings for event-based measures varies based on whether the measure includes an efficiency component. For measures with efficiency and demand response, the figure shows the efficiency-only cost savings (navy) in comparison to the efficiency *plus* demand response cost savings (green). For the other two demand-response only measures, the figure illustrates just the one savings value (purple). The values on the top of each bar represent the energy savings across the entire year.

Figure 13: Photo of a smart thermostat

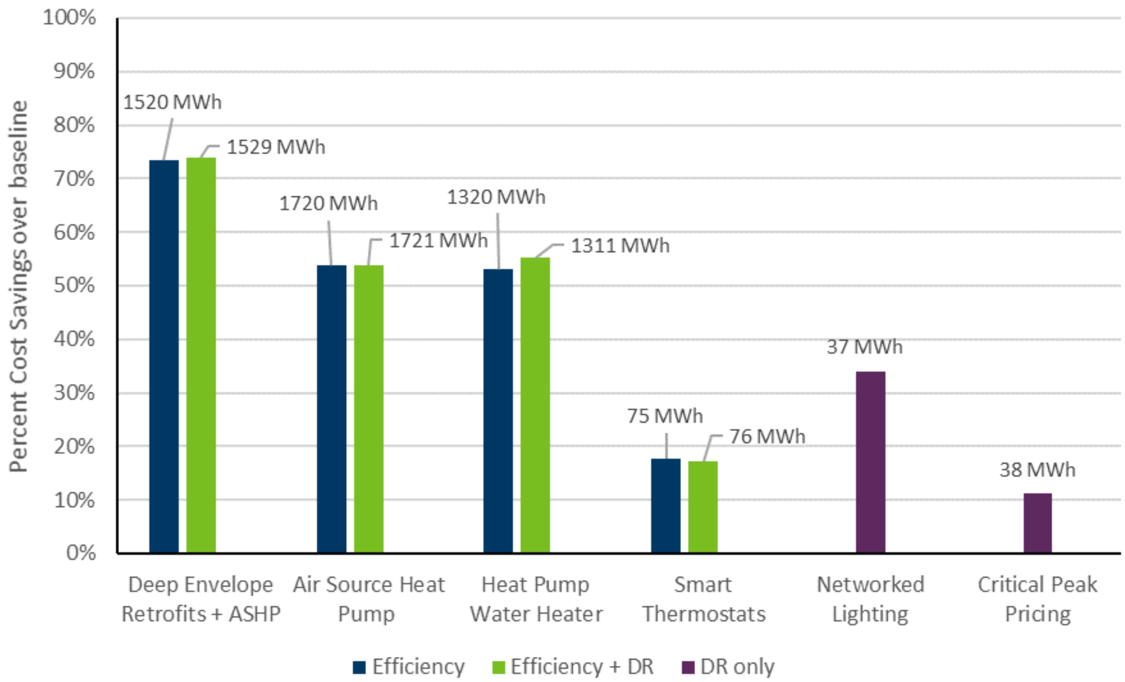
Photo by Dan LeFebvre (Unsplash)

The comparison of efficiency to efficiency plus demand response illustrates that the relative impact of adding demand response to an efficiency measure is insignificant. However, the measures that are demand-response only, networked lighting controls and critical peak pricing, have moderate but significant percent savings over the baseline.

There are a couple of potential reasons why critical peak pricing and networked lighting controls generate significant savings from demand response events while the energy efficiency plus demand response measures do not. The four efficiency plus demand response measures have an increase in energy use before and after the event hours, decreasing the energy savings from events, while the two demand-response only measures do not. For this reason, the demand response only measures save significantly more energy during the events, which translates directly into more significant cost savings compared to the demand response plus energy efficiency measures.

Networked lighting and critical peak pricing are both compared to baseline energy use on the days when demand response is called. Networked lighting achieves more savings over baseline compared to critical peak pricing because commercial lighting energy use can be significantly reduced during the middle of the day when natural light is available. In contrast, critical peak pricing results in behavioral-based changes to reduce energy across the entire home, so savings may be more dispersed and lower compared to commercial lighting.

Figure 14. Event-based measures: cost savings over baseline and annual energy savings (2018 MISO real-time prices)



Energy efficiency measures

Figure 16 illustrates the percent cost savings over baseline for the two energy efficiency reference cases included in the study. The figure illustrates a high percent cost savings for both measures, achieving about 60 percent cost savings compared to the baseline. The values on the top of each bar represent the energy savings across the entire year. Plug loads save more energy but comparatively less cost savings over baseline as the measure targets energy consumption at non-peak times while commercial lighting efficiency saves energy during peak times.

Figure 15: Photo of plug load controls

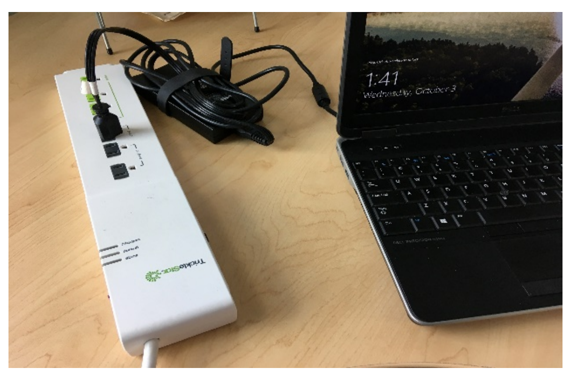
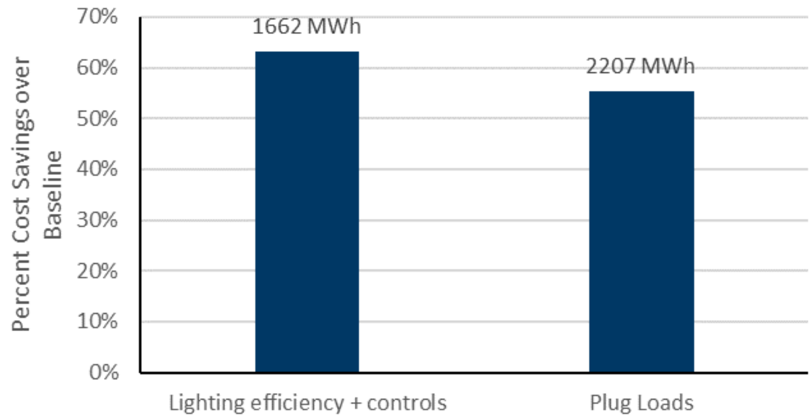


Photo courtesy of Slipstream

Figure 16. Energy efficiency measures: cost savings over baseline and annual energy savings (2018 MISO prices)



Future Year Energy Cost Results

Key Takeaway

Percent cost savings do not change significantly in future scenarios for measures with energy savings. Shift measures see a decrease in cost savings over time, which is related to the projected increase in renewable generation and the associated change in price patterns.

This section presents energy cost results for the two future year scenarios: 2026 and 2034. These results represent just one possible future scenario utilizing data from one utility in the state, Xcel Energy Minnesota. How renewables will impact market prices in the future is still uncertain, so these results serve as just one example of the potential impact of these measures. To model future impacts, the event-based measures are called when prices are highest based on future price data from Xcel Energy Minnesota. For shift measures, however, the project team did not optimize the time of shift based on future cost profiles, but rather applied the same time of shift as the current-day model. This was done as an analysis of future price data suggests that the future energy price profile only changes significantly in the spring of 2034.

Table 8 lists the percent cost savings over baseline for the current day Xcel Energy Minnesota price scenario and the change in percent cost savings from current day to 2034. The results illustrate that most measures have stable percent cost savings across time. This reflects the fact that the energy cost savings attributed to energy efficiency obscure the load shifting effect.

However, for measures with neutral energy use compared to the baseline or for those with an energy penalty, the results reflect the impact of load shifting more clearly. This is most noticeable for EV charging, which shows a decline in percent cost savings across each scenario. This change is related to the projected increase in renewable generation in future years, which results in the highest prices occurring less often in the middle of the day. It is likely that the electricity markets would adjust to the lower prices by adding load during that time, even though the limitations of the model do not allow us to demonstrate this effect. To understand the implication of not shifting the load to a different timeframe, the project team conducted a sensitivity analysis that changed the shift profile for EVs to use more energy during the day for April and May of 2034 when daytime prices drop below zero. The adjusted profile results in 38 percent cost savings in 2034, which would result in a 3 percent increase in cost savings in 2034 compared to 14 percent decrease that is shown in the table below.

The results show that refrigeration load control has higher percent savings in 2034 compared to 2019. Refrigeration load control shifts energy differently than the other shift measures, reducing use from 4 pm to 10 pm rather than from 9 am to 4 pm (this shift is based on the empirical data used for this load shape). This load shape aligns with future energy price profiles by using more energy when renewables are on the grid and prices are low in the middle of the day. The measure saves energy in the early evening when prices spike as neither wind nor solar are on the grid. This measure profile likely explains the increase in percent cost savings over time and represents how other measures could be shifted to optimize price savings in the future.

Lastly, event-based measures are dynamically based on price for each scenario, which results in stable cost savings across time as well.

Table 8. Current day percent cost savings and trend over time (Xcel Energy Minnesota prices)

Measure	Measure type	Current Day Percent Cost Savings over Baseline (2019)	Change in Percent Costs Savings in 2034 Compared to Current Day
PCM for space conditioning	Shift	9%	Stable
PCM for refrigeration	Shift	18%	3% decrease
Active ice thermal storage	Shift	2%	4% decrease
EVs with charging controls	Shift	35%	14% decrease
Industrial strategic energy management	Shift	3%	2% decrease
Refrigeration load control	Shift	1%	2% increase
HPWH with controls	Event-based	54%	Stable
Smart thermostats with demand response	Event-based	25%	Stable
ASHP with demand response	Event-based	55%	Stable
Envelope measures combined with ASHP	Event-based	75%	Stable
Networked lighting controls with demand response	Event-based	25%	3% increase
Critical peak pricing to drive behavior change	Event-based	11%	Stable
Lighting efficiency + controls	Energy efficiency	63%	Stable
Plug loads	Energy efficiency	55%	Stable

Carbon Emissions Implications

Key Takeaway

Energy savings have the largest impact on 2018 average emissions savings. However, measures that are energy neutral and shift load still save carbon.

Table 9 illustrates the carbon savings over baseline for average emissions when load shapes are optimized on 2018 MISO real-time prices. The table also lists the annual electricity savings for reference. Most measures save emissions when compared to the baseline. The only exceptions are the measures with an energy penalty, which either have a negligible impact on emissions or cause an increase in average emissions compared to the baseline. The measures that save more energy generally have higher percent emission savings. However, similar to price, the timing of energy savings impacts the results. For example, lighting efficiency has higher percent savings than plug loads even though plug loads save more energy. The main reason for this is that lighting efficiency saves energy during the peak of the day while plug loads save more energy in the evening. Similarly, EVs generate emission savings without saving any energy.

A more in-depth discussion of emission results, including future results, is discussed in the carbon emissions sensitivity analysis section below.

Table 9. Annual energy savings and percent emissions savings over baseline, 2018 MISO average emissions

Measure	Measure type	Energy Savings (MWh)	Average Emissions Savings over Baseline
PCM for space conditioning	Shift	496	9%
PCM for refrigeration	Shift	862	14%
Active ice thermal storage	Shift	-102	-16%
EVs with charging controls	Shift	0	8%
Industrial strategic energy management	Shift	-74	0%
Refrigeration load control	Shift	-108	0%
Smart thermostats with demand response	Event-based	76	20%
ASHPs with demand response	Event-based	1,721	56%
Envelope measures combined with ASHP	Event-based	1,529	75%
HPWH with controls	Event-based	1,311	53%
Networked lighting controls with demand response	Event-based	38	19%
Critical peak pricing to drive behavior change	Event-based	37	9%
Lighting efficiency + controls	Efficiency	1,662	63%
Plug loads	Efficiency	2,207	57%

Capacity Cost Implications

Key Takeaway

Capacity costs make up a significant portion of total cost savings for shifting and event-based measures, especially in comparison to energy efficiency measures.

Capacity costs can have a significant impact on the total cost savings of a measure, especially for shifting and event-based measures. Table 10 shows the percent of total cost savings that capacity savings contribute for a baseline and sensitivity case. Both scenarios use an average of the three IOU's CIP-filed transmission and distribution costs. However, they differ in source for generation capacity cost: the baseline uses Xcel Energy Minnesota's proprietary capacity cost forecasts while the sensitivity uses the cost of new entry from MISO's resource auction. The remaining percent of costs is made up of energy cost savings.

The table indicates several important results regarding the impact of capacity costs. First, the impacts of capacity costs vary based on type of load shifting measure. For energy efficiency measures, capacity costs generally make up a much smaller percentage of the total cost savings. This is seen in pure efficiency measures, like plug loads, as well as in measures with high efficiency components, such as ASHP plus demand response. On the other extreme, purely shift or shed measures see a large percentage of total cost savings coming from capacity costs. This is seen for measures like EVs as well as networked lighting controls and critical peak pricing. The most extreme case is ice thermal storage, which has an energy cost penalty across the modeled year but still generates significant capacity savings.

Additionally, the use of capacity cost matters as the two values result in significantly different savings for generation capacity. The CIP cost leads to capacity costs representing anywhere from 20 to 100 percent of total cost savings while the cost of new entry leads to significantly lower values ranging from only 4 to 53 percent. The large variation in these costs are primarily a result of the difference in how they are calculated. The CIP filing cost is a long-term value that represents how much it would cost a utility to have to build a new combined cycle natural gas turbine. In contrast, the MISO cost of new entry value is a short-term value that takes into consideration how likely the need for new capacity is. As the region is currently long on capacity (in other words, there is enough generation in the near-future to meet demand), this value is extremely low.

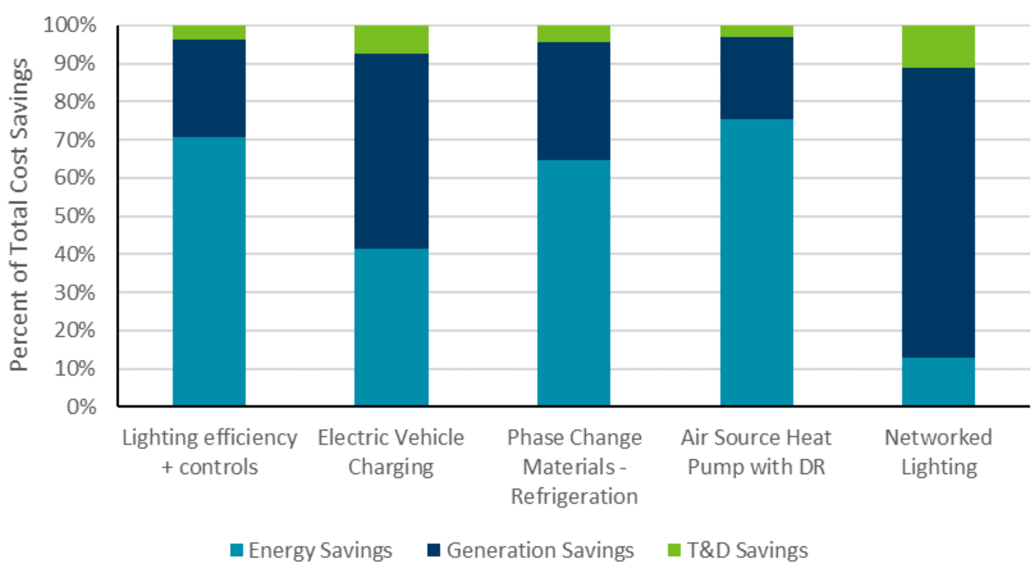
Table 10. Cost of new entry vs. Xcel Energy Minnesota CIP generation capacity cost - percent of total cost savings

Measure	Measure type	Capacity Cost Percent of Total Costs Savings – Xcel CIP Filing	Capacity Cost Percent of Total Costs Savings – Cost of New Entry
PCM for space conditioning	Shift	31%	6%
PCM for refrigeration	Shift	35%	7%
Active ice thermal storage	Shift	122%	-

Measure	Measure type	Capacity Cost Percent of Total Costs Savings – Xcel CIP Filing	Capacity Cost Percent of Total Costs Savings – Cost of New Entry
EVs with charging controls	Shift	59%	18%
Industrial strategic energy management	Shift	63%	21%
Refrigeration load control	Shift	87%	50%
Smart thermostats with demand response	Event-based	19%	4%
ASHPs with demand response	Event-based	24%	5%
Envelope measures combined with ASHP	Event-based	28%	6%
HPWH with controls	Event-based	29%	6%
Networked lighting controls with demand response	Event-based	87%	51%
Critical peak pricing to drive behavior change	Event-based	72%	28%
Lighting efficiency + controls	Efficiency	29%	6%
Plug loads	Efficiency	27%	5%

To illustrate this, Figure 17 shows the percent total cost savings for a select number of measures. The graph illustrates the proportion of CIP capacity cost values against the total costs savings. The capacity cost values are proportionally large for EV charging as it does not save energy and for networked lighting controls as it saves an insignificant amount of energy during the year but effectively sheds during peak times. It also illustrates how much of the capacity savings come from generation compared to distribution and transmission.

Figure 17. Avoided costs' contribution to total percent savings, applied with CIP capacity cost



Cost-Effectiveness Results

Key Takeaway

Most measures have a cost-effectiveness ratio between 1 and 2. Those that do not are measures with significant energy penalties.

The overall financial impact of these measures can be compared by calculating cost-effectiveness ratios for each of them. This section summarizes the benefits, costs, and overall cost-effectiveness ratio for each of the load shapes. The cost-effectiveness ratio is calculated using the Societal Cost Test. The costs include the installation cost as well as the program administration costs for the utility. The benefits include the avoided energy costs, the avoided capacity costs, and the monetized benefit of emission savings. The assumptions applied in these calculations can be found in *Appendix D: Cost-Effectiveness Assumptions.*

Table 11 summarizes these results with annual values for both benefits and costs. It presents a range for the costs and a resulting range for the cost-effectiveness ratio. The project team utilized a cost range to represent the uncertainty in the installation cost numbers as many measures are emerging technology and costs naturally vary project to project. It is important to note that these numbers represent 2018 benefits and costs and could change based on system conditions or program characteristics.

The cost-effectiveness ratios vary measure by measure – with most measures having a cost-effectiveness ratio between 1 and 2. A few measures have more extreme values. The cost-effectiveness ratio for ASHPs are significantly higher than most measures based on the high energy savings across the entire year due to energy efficiency savings compared to the baseline of electric resistance heat. On the other extreme, active ice thermal storage and refrigeration load control have too large of an energy penalty to lead to significant enough benefits to outweigh any potential cost range; this is not to say that the measures do not have a benefit to customers, but those values would need to be calculated using specific customer rates.

Lastly, the smart thermostat measure shows a cost-effectiveness ratio slightly below 1. This is largely due to this study's model structure where the peak energy saving days when temperatures are high do not coincide with the top demand days. This leads to low capacity savings in 2018 compared to other years. If the model was adjusted to use 2019 capacity cost savings, the smart thermostat measures would result in a cost-effectiveness of between 1.2 and 1.6, illustrating the sensitivity of weather in this study's model.

Table 11. Societal cost-effectiveness test

Measure	Total Annual Costs (Installation + Administration)	Benefits (Avoided costs + emissions)	Benefit cost ratio (low to high range)
PCM for space conditioning	$21,680 - $43,140	$27,725	0.6– 1.3
PCM for refrigeration	$33,135 - $44,685	$55,230	1.2 – 1.7
Active ice thermal storage	$13,540 -$17,415	$600	0.0 – 0.0
Refrigeration load control	$124,835 - $168,865	$2,665	0.0 – 0.0
EVs with charging controls	$10,200 - $24,015	$23,250	1.0 – 2.3
Industrial strategic energy management	$14,450 - $19,455	$34,365	1.8 – 2.4
Smart thermostats with demand response	$7,730 - $10,200	$3,805	0.4 – 0.5
ASHPs with demand response control	$14,325 - $24,765	$79,810	3.2 – 5.6
Envelope measures combined with ASHP	$40,635 - $74,155	$75,060	2.0 – 1.9
HPWH with controls	$41,285 - $61,445	$69,550	1.1 – 1.7
Networked lighting controls with demand response	$14,325 - $20,680	$29,330	1.4 - 2.1
Critical peak pricing to drive behavior change	$3,170 - $10,625	$8,285	0.8 – 2.6
Lighting efficiency + controls	$47,925 - $74,765	$89,270	1.2 – 1.9
Plug loads	$41,890 - $101,085	$108,045	1.1 – 2.6

Carbon Emissions Sensitivity Analysis

To better understand carbon implications of load shifting measures, emissions optimization scenarios shift load away from time periods of higher carbon emissions, and towards times of lower carbon emissions, rather than responding to price signals. While price and emissions are fairly correlated in the 2018 MISO market, this analysis allowed for the examination of the changing emissions dynamics of future years as the grid mix changes. Results will help inform the effect of choosing one grid region over another to evaluate emissions savings.

Overview of Emissions by Scenario

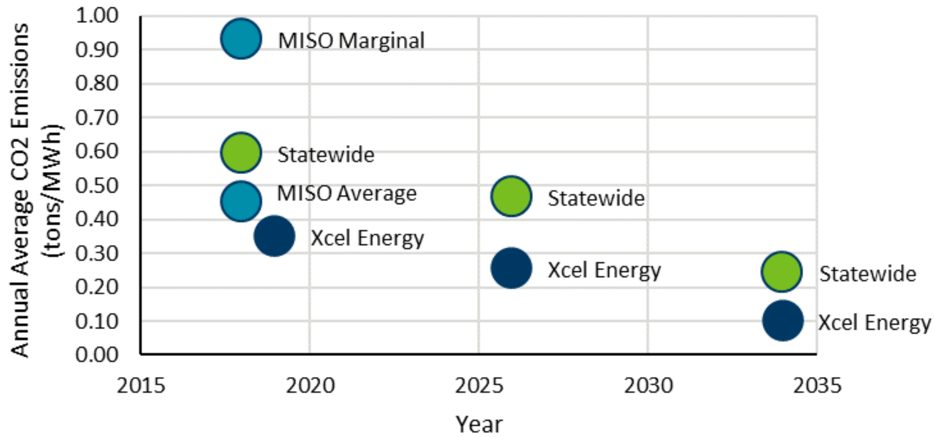
Key Takeaway

While average emission factors decrease in future years, the hour by hour variability increases.

The analysis compared results across eight different emissions scenarios, which vary by year and by geographic footprint. All scenarios except for one represent the average emissions rate for a given hour.

Figure 19 shows how these emissions vary across scenarios. Not surprisingly, average emissions track downwards over time, forecasted to be less than half of what they are today by the year 2034. Statewide emissions, based on in-state power plants serving Minnesota utilities, are higher than either MISO or the Xcel Energy Minnesota. However, these statewide numbers do not include recent announcements for early retirement of coal facilities.

Figure 18. Annual CO2 emission factors by geographic footprint and year

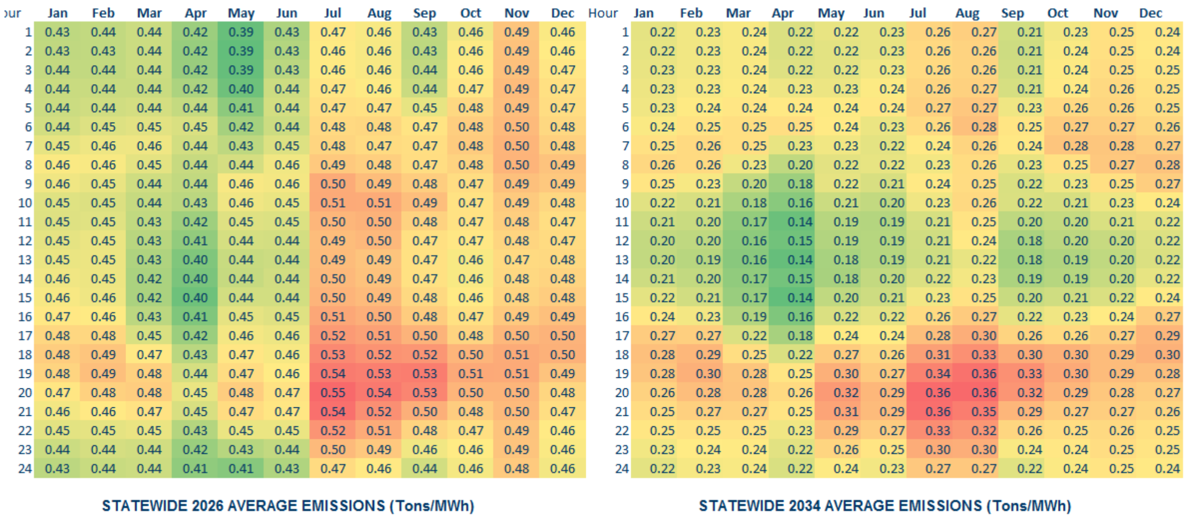


The absolute difference between these emissions datasets is significant and illuminates trends worth discussing. First, as anticipated, average emissions in Minnesota will decrease 60 to 70 percent between now and 2034, depending on which forecast one uses, because of the number of coal plant retirements and the fact that coal is a baseload fuel, running for a high number of hours throughout the year.

The second trend is how much higher MISO marginal emissions are than the other datasets; those emissions are twice as high as MISO average emissions. In today's market, where MISO reports capacity reserves, coal is often the fuel on the margin, especially during low load hours. This difference is also amplified by the use of average and marginal heat rates to determine emissions factors for fossil generation. As more coal plants retire, this marginal value will decrease. Finally, it is worth noting that in all years Xcel Energy Minnesota's emissions factors are lower than the statewide average, which is a result of its specific fuel mix.

While average emissions are a key indicator, this project is additionally concerned with *when* the periods of high and low emissions occur, i.e. how variable they are over the year and throughout the day. Renewable electricity growth will increase the variability of emissions factors, especially in future years. Figure 20 shows a heatmap for two future statewide emissions scenarios: 2026 and 2034. By 2026, the increasing amounts of wind on the system will drive average emissions down (in green) during periods of high wind and low load, primarily during the middle of the night and springtime. Higher emissions (in red) occur during summer days and evenings, when load is high and the wind resource is low, and fossil generation is filling in supply gaps. By 2034, the increasing presence of solar PV creates the lowest emissions periods during the middle of the day, with highest emissions in the evening hours of 6 pm to 9 pm, when load is still high but solar production is down. Note that the color scales are relative to that year – a "high" carbon value in 2034 is lower than the low values on 2026.

Figure 19. Heatmap of forecasted average statewide carbon emissions on 2026 (left) and 2034 (right)



our	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.43	0.44	0.44	0.42	0.39	0.43	0.47	0.46	0.43	0.46	0.49	0.46
2	0.43	0.43	0.44	0.42	0.39	0.43	0.46	0.46	0.43	0.46	0.49	0.46
3	0.44	0.44	0.44	0.42	0.39	0.43	0.46	0.46	0.44	0.46	0.49	0.47
4	0.44	0.44	0.44	0.42	0.40	0.44	0.47	0.46	0.44	0.47	0.49	0.47
5	0.44	0.44	0.44	0.44	0.41	0.44	0.47	0.47	0.45	0.48	0.49	0.47
6	0.44	0.45	0.45	0.45	0.42	0.44	0.48	0.48	0.47	0.48	0.50	0.48
7	0.45	0.46	0.46	0.44	0.43	0.45	0.48	0.47	0.47	0.48	0.50	0.48
8	0.46	0.46	0.45	0.44	0.44	0.46	0.49	0.48	0.47	0.48	0.50	0.49
9	0.46	0.45	0.44	0.44	0.46	0.46	0.50	0.49	0.48	0.47	0.49	0.49
10	0.45	0.45	0.44	0.43	0.46	0.45	0.51	0.51	0.49	0.47	0.49	0.48
11	0.45	0.45	0.43	0.42	0.45	0.45	0.50	0.50	0.48	0.47	0.48	0.47
12	0.45	0.45	0.43	0.41	0.44	0.44	0.49	0.50	0.47	0.47	0.48	0.47
13	0.45	0.45	0.43	0.40	0.44	0.44	0.49	0.49	0.47	0.46	0.47	0.48
14	0.46	0.45	0.42	0.40	0.44	0.44	0.50	0.49	0.47	0.46	0.48	0.48
15	0.46	0.46	0.42	0.40	0.44	0.44	0.50	0.49	0.48	0.46	0.48	0.48
16	0.47	0.46	0.43	0.41	0.45	0.45	0.51	0.50	0.48	0.47	0.49	0.49
17	0.48	0.48	0.45	0.42	0.46	0.46	0.52	0.51	0.50	0.48	0.50	0.50
18	0.48	0.49	0.47	0.43	0.47	0.46	0.53	0.52	0.52	0.50	0.51	0.50
19	0.48	0.49	0.48	0.44	0.47	0.46	0.54	0.53	0.53	0.51	0.51	0.49
20	0.47	0.48	0.48	0.45	0.48	0.47	0.55	0.54	0.53	0.50	0.50	0.48
21	0.46	0.46	0.47	0.45	0.47	0.47	0.54	0.52	0.50	0.48	0.50	0.47
22	0.45	0.45	0.45	0.43	0.45	0.45	0.52	0.51	0.48	0.47	0.49	0.46
23	0.44	0.44	0.44	0.42	0.43	0.44	0.50	0.49	0.46	0.46	0.49	0.46
24	0.43	0.44	0.44	0.41	0.41	0.43	0.47	0.46	0.44	0.46	0.48	0.46

STATEWIDE 2026 AVERAGE EMISSIONS (Tons/MWh)

Hour	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.22	0.23	0.24	0.22	0.22	0.23	0.26	0.27	0.21	0.23	0.25	0.24
2	0.22	0.23	0.24	0.22	0.22	0.23	0.26	0.26	0.21	0.24	0.25	0.24
3	0.23	0.23	0.24	0.22	0.22	0.23	0.26	0.26	0.21	0.24	0.25	0.25
4	0.23	0.23	0.24	0.23	0.23	0.24	0.26	0.27	0.21	0.24	0.26	0.25
5	0.23	0.24	0.24	0.24	0.24	0.24	0.27	0.27	0.23	0.26	0.26	0.25
6	0.24	0.25	0.25	0.25	0.24	0.23	0.26	0.28	0.25	0.27	0.27	0.26
7	0.25	0.26	0.25	0.23	0.23	0.22	0.24	0.26	0.24	0.28	0.28	0.27
8	0.26	0.26	0.23	0.20	0.22	0.22	0.23	0.26	0.23	0.25	0.27	0.28
9	0.25	0.23	0.20	0.18	0.22	0.21	0.24	0.25	0.22	0.23	0.25	0.27
10	0.22	0.21	0.18	0.16	0.21	0.20	0.23	0.26	0.22	0.21	0.23	0.24
11	0.21	0.20	0.17	0.14	0.19	0.19	0.21	0.25	0.20	0.20	0.21	0.22
12	0.20	0.20	0.16	0.15	0.19	0.19	0.21	0.24	0.18	0.20	0.20	0.22
13	0.20	0.19	0.16	0.14	0.18	0.19	0.21	0.22	0.18	0.19	0.20	0.22
14	0.21	0.20	0.17	0.15	0.18	0.20	0.22	0.23	0.19	0.19	0.20	0.22
15	0.22	0.21	0.17	0.14	0.20	0.21	0.23	0.25	0.20	0.21	0.22	0.24
16	0.24	0.23	0.19	0.16	0.22	0.22	0.26	0.27	0.22	0.23	0.24	0.27
17	0.27	0.27	0.22	0.18	0.24	0.24	0.28	0.30	0.26	0.26	0.27	0.29
18	0.28	0.29	0.25	0.22	0.27	0.26	0.31	0.33	0.30	0.30	0.29	0.30
19	0.28	0.30	0.28	0.25	0.30	0.27	0.34	0.36	0.33	0.30	0.29	0.28
20	0.26	0.28	0.28	0.26	0.32	0.29	0.36	0.36	0.32	0.29	0.28	0.27
21	0.25	0.27	0.27	0.25	0.31	0.29	0.36	0.35	0.29	0.27	0.27	0.26
22	0.25	0.25	0.25	0.23	0.29	0.27	0.33	0.32	0.26	0.25	0.26	0.25
23	0.23	0.24	0.24	0.22	0.26	0.25	0.30	0.30	0.24	0.24	0.25	0.25
24	0.22	0.23	0.24	0.22	0.24	0.23	0.27	0.27	0.22	0.24	0.25	0.24

STATEWIDE 2034 AVERAGE EMISSIONS (Tons/MWh)

Table 12 summarizes this variability for each of the eight emissions scenarios. The largest range occurs within MISO marginal emissions, and the smallest range occurs within 2034 emissions for Xcel Energy Minnesota. While average emissions decrease in future years, the hour by hour variability increases, as measured by the coefficient of variation. This variability is important in forecasting the future emissions benefits of various load shifting strategies.

Table 12. Minimum, maximum, and coefficient of variation for 8 emission scenarios

Scenario	Minimum Hourly Emissions (tons/MWh)	Average Hourly Emissions (tons/MWh)	Maximum Hourly Emissions (tons/MWh)	Coefficient of Variation (%)
MISO Average 2018	0.15	0.45	0.64	23%
MISO Marginal 2018	0.00	0.93	1.25	26%
Statewide 2018	0.32	0.59	0.81	14%
Xcel Energy Minnesota 2019	0.10	0.35	0.64	26%
Statewide 2026	0.18	0.46	0.66	19%
Xcel Energy Minnesota 2026	0.02	0.26	0.59	42%
Statewide 2034	0.03	0.24	0.45	41%
Xcel Energy Minnesota 2034	0.01	0.10	0.32	67%

Emissions Implications of Three Load Shifting Measures

Key Takeaway

Energy savings have the largest impact on emissions savings. However, when measures are energy-neutral, time-of-use has a significant influence on emissions savings.

The project team conducted a load shifting analysis to optimize based on carbon emissions for a subset of three load shapes: ASHPs with and without enabled demand response, EV charging, and commercial PCM for refrigeration. These three measures were selected as they represent a variety of load shifting options: an energy efficiency measure with demand response, a load shift with no energy savings, and a load shift with energy savings, respectively. As described above, the heat pump demand response is called only in response to specific events, with a limit of 20 events per year. The EV and PCM permanently shift load to different times of day each day of the year. These are listed below along with a reminder of the baseline to which they are compared, and the number of participants required to achieve a 500-kW demand reduction.

Table 13. Measures, baseline description and estimated number of participants in emissions optimization

Measure	Baseline	Number of Participants for 500 kW Demand Reduction
ASHPs with demand response – 20 events per year	Electric resistance heat + SEER 12 AC	127 single-family residential homes
EV charging	Level 2 uncontrolled charging	307 passenger vehicles
PCM for Refrigeration	Typical Commercial Refrigeration	2 Large Commercial Properties

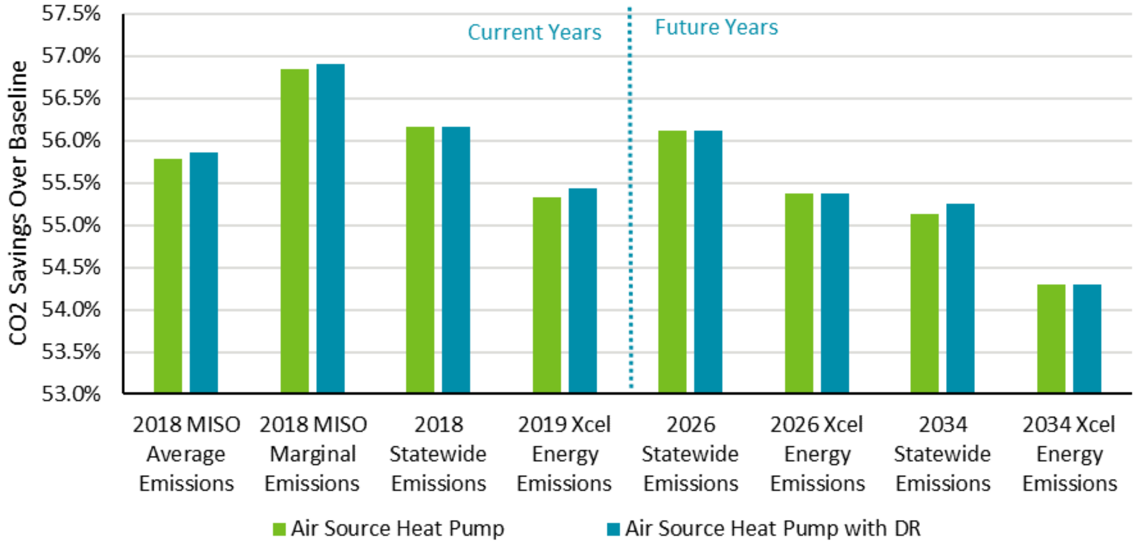
Heat pump emissions results

The heat pump measure has the highest emissions savings over baseline, which is a result of the energy savings from switching from electric resistance heating. However, the incremental emissions savings from deploying demand response is negligible (on the order of 0.1 percent). This is largely because demand response events happen only 20 times per year, and the length of time available to shift these thermal loads in a typical Minnesota home is only two to three hours, which does not provide significant emissions changes.

Figure 20: Photo of an ASHP

Photo courtesy of CEE

Figure 21. ASHP carbon emission savings over baseline across 8 emissions optimization scenarios



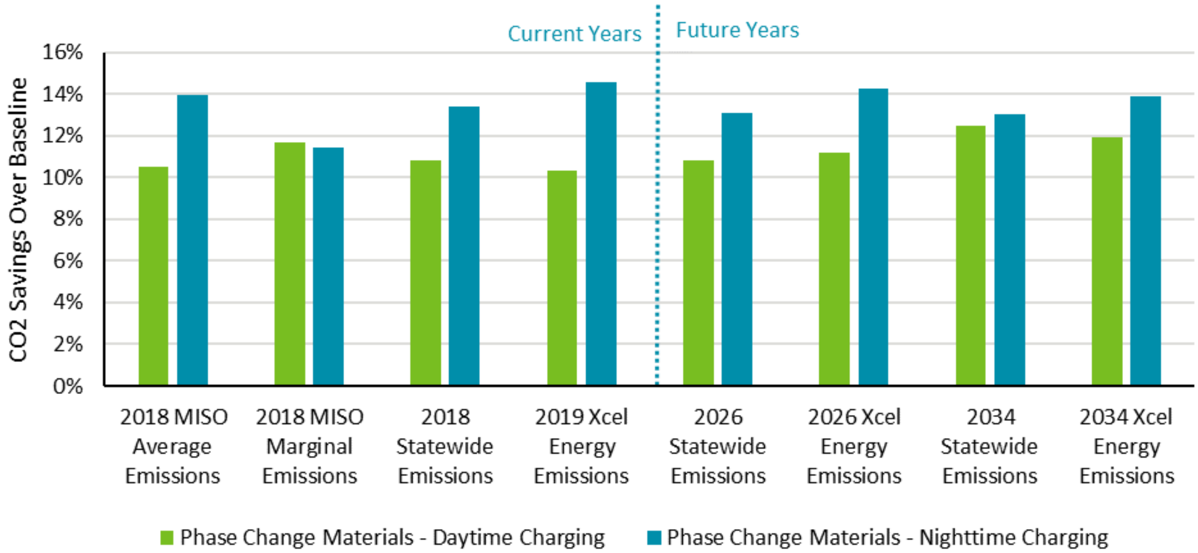
Phase change materials for refrigeration emissions results

PCM for refrigeration will lower emissions by 10 to 14 percent over typical commercial refrigeration. Like heat pumps, the majority of the emissions savings are from energy saved rather than time of day effects. Other than the case of MISO marginal emissions, a nighttime charging regime is more beneficial than daytime charging on the order of 1 to 2 percent, even in future years of high solar penetration. Also, note that the PCM for refrigeration measure has one of the highest overall baseline emissions footprints, and therefore offers the highest absolute carbon savings from shifting measures.

Figure 22. Photo example of PCM for refrigeration

Photo courtesy of Slipstream

Figure 23. PCM for refrigeration carbon emission savings over baseline across 8 emissions optimization scenarios



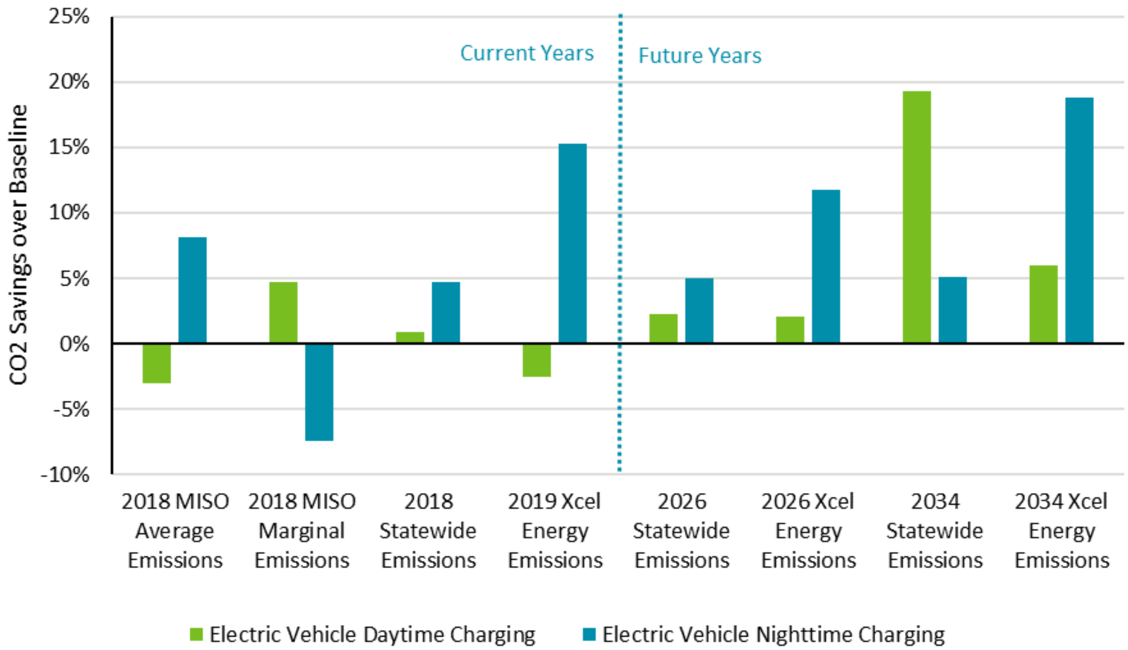
Electric vehicle charging emissions results

Of the three measures, EV charging shows the highest degree of variation based on emissions footprint. Since shifting EV charging times does not save energy, all of the carbon savings comes from time-of-day emissions variations. Figure 26 shows the percent change over baseline for charging at different times of day. Nighttime charging provides higher emissions benefits than daytime charging with two exceptions: the current (2018) MISO marginal emissions, and the 2034 statewide emissions profile. This is for two very different reasons. In 2018, a large portion of MISO's nighttime marginal emissions are from must-run coal plants. In 2034, it is a result of high solar penetration during the day. And finally, these results also demonstrate that emissions patterns may vary utility-by-utility. In 2034, the statewide emissions forecast favors daytime charging, whereas Xcel Energy Minnesota shows higher carbon savings when load is shifted to nighttime charging.

Figure 24. Photo of an EV charger

Photo by Waldemar Brandt (Unsplash)

Figure 25. EV carbon emission savings over baseline across 8 emissions optimization scenarios



Overall, optimizing load shifting around emissions provides very different results for these three measures. The baseline measure is a critical point of comparison. Overall carbon savings are higher if there are energy efficiency savings over the baseline. And, using EV results as an example, the baseline "uncontrolled" charging profile peaks in the late afternoon, which is a volatile time for carbon emissions and leads to more variation in results than the relatively flat refrigeration baseline. Overall, load shifting to daytime energy use has emissions benefits in the future years, as more solar comes online, especially if energy use can be avoided during the early evening hours (as with EVs).

Emissions Versus Price Optimization

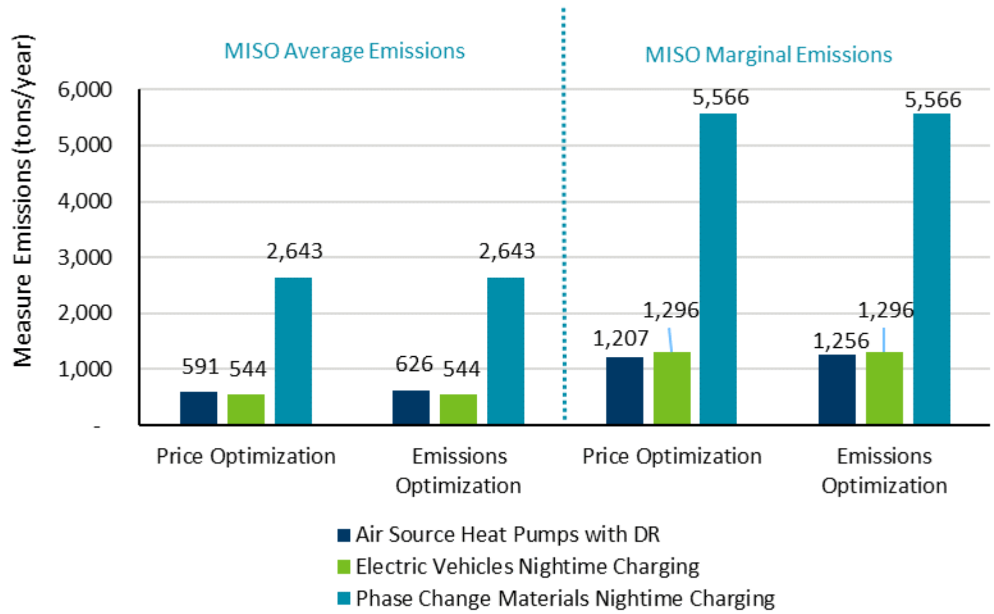
Key Takeaway

Optimizing on average emissions does not lead to different results than optimizing on price. Optimizing on marginal emissions leads to a cost penalty.

The project team compared the emissions savings of dispatching these demand side measures in response to price signals (e.g. times of high or low prices) versus dispatching in response to emissions signals (e.g. times of high or low emissions). The results are limited to current day MISO emissions and prices, which offer correlated price and emissions datasets.

Figure 27 compares MISO average and marginal emissions for both the price and emissions optimization scenarios. As expected, the results for EVs and PCM do not change, since these represent permanent shifts and therefore are not "dispatched" according to signals. PCM have the highest energy use, and therefore the highest emissions footprint, with marginal emissions more than double average emissions. The ASHP, however, actually increases both energy and emissions when optimized against emissions. While this is counterintuitive, the results shed light on the 500-kW scaling and its effect on results, discussed below.

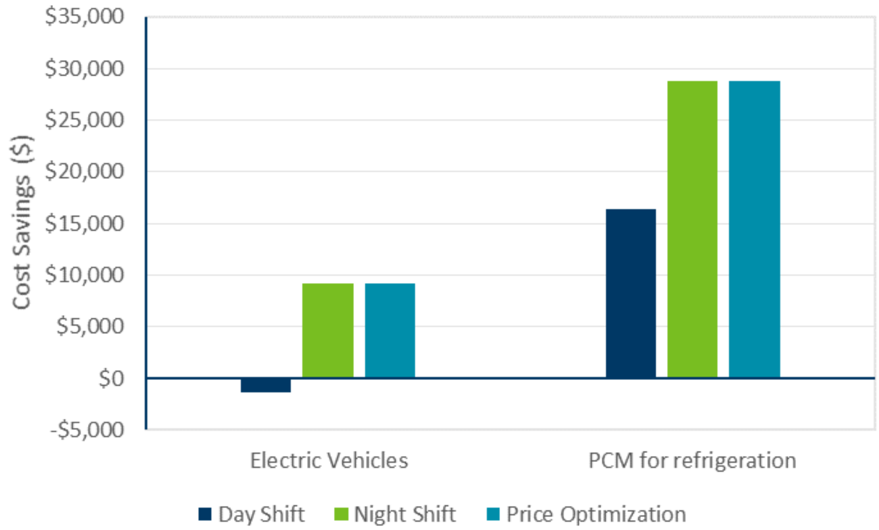
Figure 26. Comparison of measure emissions across price and emissions optimization – 2018 MISO average and marginal



In the case of ASHPs, dispatching the demand response event in response to high emissions actually increases the number of participants required to hit the 500 kW savings from 120 to 127, and that scaling effect is what increases overall measure emissions. This implies that high price days are more likely to be peak weather days, where the heat pump demand reduction is providing high savings. The peak emissions days, in contrast, are less directly correlated with hot weather, which means the demand savings per participant will be lower.

Although the differences between measure emissions for nighttime charging are not significant across price and emissions optimization, there are significant results when comparing optimizing for marginal emissions to optimizing for average emissions or price. As Figures 23 and 25 show, the daytime charging coincides with when marginal emissions are low, and thus, is the optimal shift to save the most marginal emissions. However, this shift will have negative impacts on both average emissions and cost. Figure 28 illustrates this for energy cost savings, showing lower cost savings for the day shift for PCM for refrigeration and a cost penalty for EVs from the day shift.

Figure 27. 2018 cost savings - comparison of day shift, night shift, price optimization



This issue needs more research to fully understand the effects of weather, prices, and carbon intensity beyond the single test year. However, some guiding principles still emerge which indicate the most important factors for measuring carbon reductions are:

- The difference in emissions between a load measure and its baseline
- The emissions grid used to measure the emissions footprint

These issues are discussed further in the key takeaways, below.

Conclusions and Recommendations

Key Takeaways

Load shifting measures can have a positive impact on both emissions, energy, and energy cost savings. Although the forecasts for both prices and emissions are uncertain, this study's results show that these impacts can persist into the future. The following takeaways summarize the main conclusions from this study:

Energy efficiency dominates both cost and emission savings opportunities. The measures with the highest cost and emissions savings in the study are those that have year-round energy savings (such as lighting or ASHPs). These are followed by measures that can permanently shift energy use throughout the entire year (such as EVs).

Measures that increase energy use can save energy costs through shifting time of consumption. Two measures that increase overall energy use, industrial strategic energy management and refrigeration load control, still display costs savings by using energy during less expensive times of the day. Thermal storage is an example of a measure that increases energy use but does not save energy costs when using 2018 MISO real-time energy costs.

Absolute carbon savings can as much as double depending on which grid region is used to analyze emissions. Similarly, the carbon savings as a percent over baseline can vary for measures that purely shift the time of energy use, such as EVs, making the choice of grid region crucial for these measures. However, for measures with significant energy savings, the carbon savings as a percent of baseline stays relatively constant across grid regions.

For load shifting measures that save energy, there is not significant change in *average* emissions savings when optimizing based on prices versus average emissions in the current Minnesota grid. For the measures in the study, shifting the load based on price also has an emissions benefit. There is limited advantage to managing load based on carbon signals. However, for those measures that do not save any energy shifting energy use to nighttime hours, when prices are low, will increase *marginal* emissions.

The timing of shifts will likely change in the future to respond to changes in price profiles. Several shift measures experienced a decline in cost savings from 2019 to 2034. This suggests that increased energy use during the middle of the day may be the optimal strategy in the future to take advantage of times when more renewables are on the grid and prices are low. This will also allow these measures to take advantage of variable renewables and help avoid curtailment of those resources. These prices may be affected by future advancements in utility scale battery storage.

Capacity costs can have a significant impact on cost savings for pure demand response and shifting measures. For demand response measures, such as networked lighting control and critical peak pricing, capacity cost savings can account for over 90 percent of total cost savings. There are two main reasons for this: (1) the measures have relatively low annual energy savings and (2) the times when these measures shave energy coincides well with the system peak, resulting in high kW savings. As such, the inclusion of these capacity savings has a significant impact on the cost-effectiveness of the measures. This is also true for regularly-occurring shifts that have little to no energy savings.

Load shifting and demand response measures are cost effective. Most of the measures included in this study had a cost-effectiveness ratio between 1 and 2. The only exceptions are active ice thermal storage and refrigeration load control, which both have large energy penalties.

Recommendations

Based on the results and key conclusions, the project team developed a set of recommendations to be considered as outcomes of this study:

Continue to pursue load shifting measures that can save energy in CIP portfolios. Emerging technologies such as PCM for refrigeration and PCM for space conditioning are primarily load shifting measures but generate electricity savings across the year. Like demand response programs that save energy, these measures bring customer and system benefits that should be pursued when cost-effective.

Integrate cost-effective load shifting measures into CIP portfolios when they can be bundled to create energy saving opportunities. Results of this study show that the cost and emissions benefits of saving energy still outweigh the benefits of shifting electricity use, under multiple scenarios. While recognizing that current statue limits the ability to include load shifting measures under CIP, the results also show that there is ample opportunity to have an impact on carbon and energy cost savings through measures that shift load.

Consider the long-term avoided costs of renewables integration. This study offered limited cost-forecasting and does not account for costs of renewable energy integration that load shifting could help to mitigate. These costs include the balancing needed during ramp-up or ramp-down events, or generation shortfalls during times of high demand and low renewable production. While these future costs are uncertain, they may offer additional cost savings for load shifting measures.

Explore additional measures that that may offer similar load shifting benefits. There are additional measures that have promising potential for emission and energy reduction through load shifting which were not included in this study. For example, energy management information systems and retro commissioning both take established methods of reducing energy and adjust them to also shift load and energy. Energy management information systems are software-based technologies that are layered on top of building automation. These systems provide guidance for building operators to improve performance, and several offer shift or shed options. Similarly, retro-commissioning programs primarily aim to make low-cost adjustments to HVAC and lighting controls to save energy. However, with tailored recommendations, these same programs could impact load shape and shift as well. Other examples of additional load shifting measures to explore further include irrigation load control and residential solar and storage.

Apply a utility-specific grid region to calculate emissions benefits where available. This would allow a utility to capture the benefits of the renewable energy dynamics specific to that utility's portfolio. Using emissions rates from utility IRPs would additionally allow emissions rates to be vetted through the stakeholder process. Given the uncertainty of future year emissions, the project team recommends that forecasted emissions benefits be evaluated after the fact, similar to energy efficiency achievements, to bring additional transparency to the changing dynamics of carbon emissions.

Give additional scrutiny to measures that shift load to nighttime hours absent any energy savings benefits, in the near term. Depending on the baseline assumptions, these measures may increase marginal emissions given the prevalence of fossil generation on the margin in the MISO north region. The dynamics of marginal emissions are changing and may vary with a utility-specific emissions footprint; hence this will require examination on a case-by-case basis.

Consider future rate designs that incentivize customers to shift energy when system is near capacity. This analysis did not explicitly explore the impact of rate design; however vast research exists that shows that deliberate rate design directly influences customers to shift or shed energy use. Empirical data collected for this study supports that, with load shapes showing that customers do shift energy use under certain rate structures. For example, customers under critical peak pricing shed energy use during the hours of the called event. Additionally, the empirical dataset for active ice thermal storage showed that the facility optimized around the rate structure – shedding energy during peak times and using more energy during off-peak times. Rate design is one key mechanism utilities can use to generate benefits from load shifting. And in the future, rate design could reflect carbon and incentivize shifts of energy away from high carbon times.

For future demand side management potential studies in the state, expand consideration of measure benefits to include cost savings and carbon benefits associated with load shifting. Researchers should include the time-varying benefits that a measure would generate. These time-varying benefits can have a significant influence on cost-effectiveness, sometimes even making the difference between whether a measure is cost-effective or not. Additional research may be leveraged through the potential study process to fill in the data gaps, which is explained more in the next recommendation.

Conduct future research on both load shapes and impacts of load shifting measures on both costs and emissions. Additional field research and monitoring efforts are needed to generate accurate and geographic-specific load shapes. The project team recommends exploring innovative grid-interactive technologies and utility scale batter storage, both of which are rapidly commercializing in the market. As an example, measures in this study that lacked Midwest empirical data included active ice thermal storage, refrigeration load control, and EV charging. Furthermore, multiple additional measures were based on a small subset of buildings, meaning that they could also benefit from additional fieldwork. This work is vital to further the understanding on how these measures can help utilities manage load, keep energy costs low for both utilities and consumers, and reduce carbon emissions.

In addition to developing better load shapes, it is imperative to study the potential adoption rates of these measures in order to fully understand the potential impact on the market. In future Minnesota potential studies, load shifting impacts from different measures should be considered.

Additionally, further research on marginal emissions in the current grid and in future grid scenarios is needed. By shifting load, each of these measures impact the generating plant on the margin and a better understanding of which plant, and fuel, is being impacted will more accurately demonstrate the carbon benefits of these measures. Finally, more advanced modeling into how the measures impact the plant on the margin can further the understanding of the total benefits and impacts on the system.

Further research on capacity costs can also help increase the certainty of the impact on total cost savings. There are several sources of uncertainty in this study's calculation of avoided capacity costs, including the coincidence factor of emerging technologies for local grids and the assumed avoided cost values for capacity. The two values applied for generation capacity avoided costs used in this study's model, had a significant impact on the overall cost-effectiveness of each measure. Furthermore, distribution avoided cost is geographically-specific even within the state of Minnesota or within utility territories. More research on these items will help further the understanding of the benefits of these measures to the grid.

Lastly, this report was limited in the future price data available. Additional research on how prices will adjust to more renewables on the grid is needed in order to understand the cost implications of these measures in the future.

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Appendix A: Emissions and Cost Data Collection

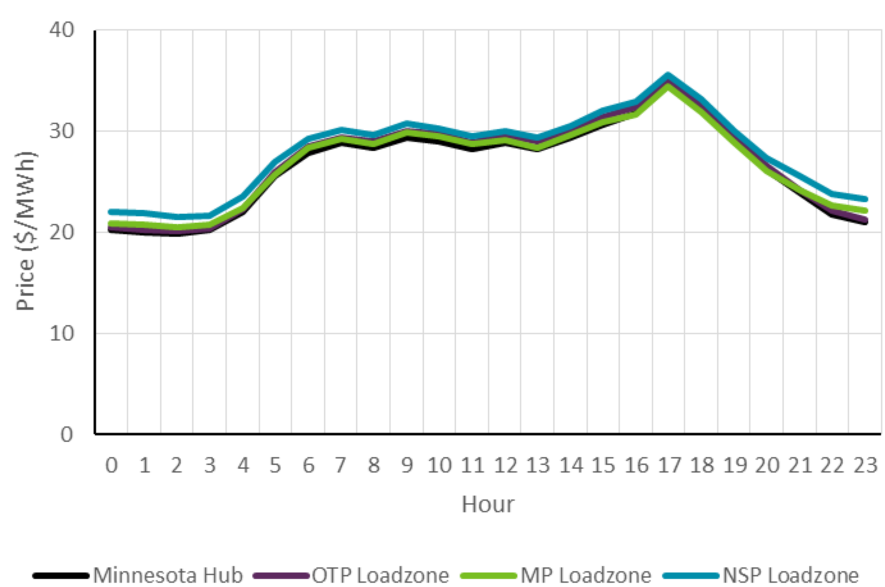
This appendix provides additional detail on the data collection process for cost and emissions data. It covers avoided energy cost, avoided capacity cost, and avoided emissions data in depth.

Avoided Energy Cost

The primary source for present-day energy costs is MISO's publicly available market data. MISO provides day-ahead and real-time wholesale market prices (MISO n.d.). Since real-time prices represent the most up-to-date market conditions, the project team chose to use real-time prices only in the analysis. The project team compared day-ahead and real-time prices to understand the implications of this decision and found that the two were highly correlated.

The decision was also made to apply energy price data from Minnesota Hub data to represent ISO-level energy costs as it encompasses MISO price nodes in all of Minnesota as well as parts of Iowa, Wisconsin, and the Dakotas. In making this decision, the project team compared this Minnesota Hub data to load zones that correspond closely to Minnesota IOU territories (i.e. NSP corresponds with Xcel, MP with Minnesota Power, and OTP with Otter Tail Power). While these load zones would correspond more directly to the conditions seen in the territory of each utility, they also are highly correlated with the Minnesota Hub prices, justifying the decision to only reporting impacts for the Minnesota Hub. Figure 29 illustrates this, showing that the average hourly price profiles for the load zones and Minnesota Hub follow the same pattern over time.

Figure 28. Hourly average prices: Minnesota Hub versus utility load zones



Xcel Energy Minnesota's forecasted marginal energy cost serves as a second source of present-day prices and the only source for future energy prices. For the current year analysis, these prices are not compared to the MISO present day prices as they come from a forecast model. Instead, they are used as a base for comparison against the future energy prices.

While ideally the data would include multiple utilities for forecasted energy prices, using only one utility forecast still represents statewide effects since there is good correlation between current-day statewide and utility prices. However, future prices in markets with higher percentages of renewables on the grid are highly uncertain. Therefore, the focus is primarily on the variation in cost savings across years compared to the baseline over time rather than the differences in absolute savings over time.

Avoided Generation, T&D Capacity Cost

As a number of these measures shift load from peak periods, avoided generation, transmission, and distribution capacity cost is an important consideration. In fact, for certain load shifting measures, capacity costs can be a determining factor for whether a measure makes economic sense to implement.

Avoided distribution, and transmission capacity costs represent the cost saved by deferring or delaying the need for new transmission lines or local distribution to be added to the grid. Distribution and transmission costs are difficult to estimate as they are predictions with no easy proxy. The values are typically impacted by local factors, making it difficult to use estimates from other studies or regions. However, each IOU in Minnesota must calculate these values for use in its CIP Triennial Plans. As the most recent yearly estimates ($/kw-year) were publicly available for all three IOUs, they were used as the estimate (Minnesota Commerce 2019).

Avoided generation capacity is the monetary value saved from deferring the built of a new power plant. There are generally two methods used to calculate capacity costs. The first method is to use Xcel Energy Minnesota’s calculated cost. This cost generally represented the expected cost to build a new combined cycle gas power plant and are used by utilities in their planning process CIP Triennial Plan. As most utilities regard these costs as trade secret, the project team was again limited by the availability of data and only able to collect this cost for Xcel Energy Minnesota.

A second source of generation capacity cost data comes from the MISO planning resource auction, a voluntary capacity market. The cost of new entry (CONE) is determined in the auction, which represents the current annual capital cost of constructing a power plant. When the MISO market has an oversupply of capacity, this value is typically low in value. Additionally, this cost typically represents a more near-term scenario compared to the capacity cost included in the utilities’ planning process. The current cost of new entry in the load zone that includes Minnesota is $1.83 per kW-year, which is substantially smaller than Xcel Energy Minnesota ’s calculated capacity cost (MISO 2020).

Avoided Emissions Data

The project team created annual 8760 simulations of hourly emissions rates for both the current generation mix and for Minnesota’s future generation mix where renewable energy and natural gas are forecasted to replace coal generation. The forecasts projected hourly emissions rates 15 years into the future, to 2034. One project goal is to determine how results might vary depending on which grid region is assumed for the emissions footprint. The project team examined three distinct grid regions, each of which would make a reasonable assumption but carries distinct pros and cons:

- **Utility specific region:** In a vertically integrated state (like Minnesota), this is the most direct way to evaluate how demand-side measures will change which type of generation gets built and operated. However, this method requires utility specific data, which is often proprietary.
- **Statewide Region:** This region (i.e. the Minnesota footprint) aligns with state specific policies, goals, and carbon tracking. However, given that there is no single statewide utility, it does not align with a natural planning or operational footprint. A statewide emissions footprint can also average out what might be large carbon variations across utilities.
- **ISO Region:** This reflects real time short-term dispatch decisions and is the closest to what would likely be the emissions outcome were these measures dispatched today. However, in a vertically integrated state, this loses the value of utility specific planning and has low forecast certainty.

The utility-specific dataset is from Xcel Energy Minnesota's present-day modeled hourly emissions factors. For future scenarios the project team used proprietary outputs from Xcel Energy Minnesota's IRP. This dataset offers granularity of a specific utility and results are from robust IRP dispatch model forecasts. The dataset contains hourly, but not marginal emissions factors.

For the state of Minnesota, the project team used EPA plant-level data which contains hourly generation data by plant. This source provides a more granular estimate of average emissions but also does not allow for the calculation of marginal emissions. For future scenarios, the project team modeled hourly average emissions rates based on the future resource mix in existing approved IRPs. The method therefore accounts for any planned fossil retirements and additions of renewable energy, but preserves the status quo if no decision has been made for a specific resource, e.g. Minnesota's two nuclear plants.[2] The hourly dispatch of this future mix replicates hourly patterns seen in historic data, in both the EPA and MISO data sets. That is, in every hour, renewable resources are taken if available, nuclear plants and a percentage of coal (if it still exists) are must-run, and natural gas plants will fill in any supply gaps. These methods are similar to those used by the EPA in their emission forecasting model, Avoided Emissions and Generation Tool (AVERT), though calculated for Minnesota only (EPA n.d.).

For the ISO-level dataset, the project team used publicly available fuel mix data from MISO (MISO n.d.). This dataset provides both the marginal fuel at a 5-minute increment and total generation by fuel type at a 1-hour increment for each of the three MISO subregions. The project team then assigned heat rates specific to Minnesota power plants for any fossil generation to determine fuel input and carbon emissions. The average heat rates were used calculate average emissions, and it was assumed the plant with the highest heat rate made up the marginal fuel. As MISO covers a large geographic area, the data used covers MISO North only, which covers Minnesota, Wisconsin, Iowa and parts of the Dakotas.

[2] Due to timing of this research, the statewide forecast also does not include the 2022 planned retirement of Coal Creek Station (a 1.2 GW coal plant that serves Minnesota customers), announced by Great River Energy on May 7, 2020.

However, MISO determines the marginal plant at each interval across its entire footprint, so data from the Central and South region was relied on—if the marginal plant was located there—to create a full dataset. The ISO is therefore the only grid region where the project team estimates both a marginal emissions factor per hour as well as an average emissions factor per hour.

The emissions forecasts focused on three reference years: 2018, 2026, and 2034. The project team selected 2018 as the base year as it represents a more typical meteorological year compared to 2019. In 2019, the number of summer days with temperatures above 90 degrees Fahrenheit was significantly lower than past years and the cooling degree days also dropped. However, the utility-forecast data the project team had access to only started in 2019. To preserve a year with more peak temperature days, the project team used 2018 for all statewide and MISO scenarios and 2019 for utility level data.

Minnesota utilities currently forecast out 15 years in IRPs submitted to the state, making year 2034 a natural long-term scenario. The year 2026 serves as the mid-point between 2018 and 2034. Additionally, as these years fall before and after the 2030 decommissioning of large coal plants serving Minnesota, the project team was able to analyze the impact of little to no coal in the market and how increased renewable energy capacity changes the impact of load shifting measures. Figure 30 shows capacity forecasts by fuel for the statewide scenarios. Table 14 illustrates these differences across all grid regions, showing the percent renewable capacity in the present-day, mid-term, and long-term.

Figure 29. Forecasted Capacity for the Statewide Emissions Scenario

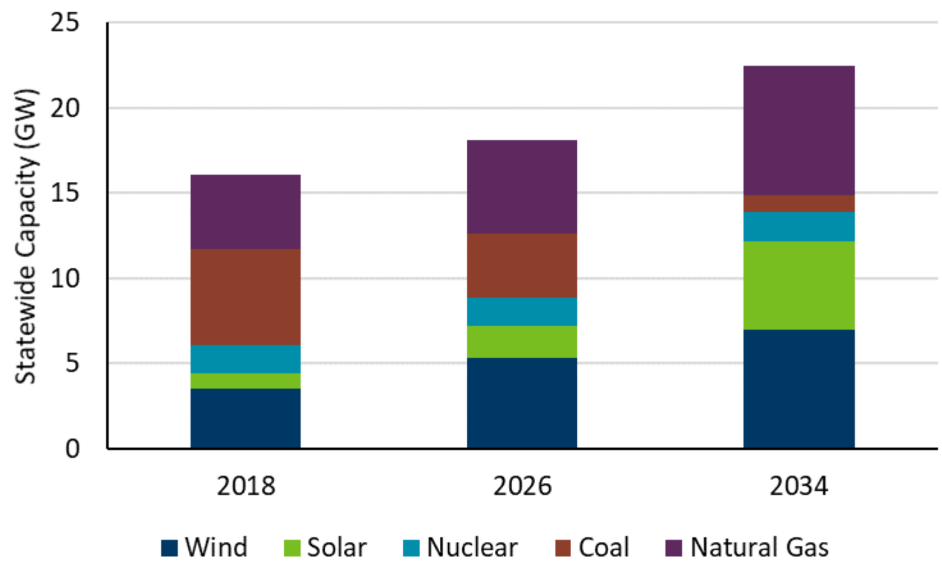


Table 14. Percent renewable energy capacity by grid region and year

Grid Region	Present day (2018/2019)	Mid-term (2026)	Long-term (2034)
Xcel Energy Minnesota	25% renewable	45% renewable	59% renewable
State[a]	27% renewable	40% renewable	54% renewable
MISO	13% renewable	*N/A*	*N/A*

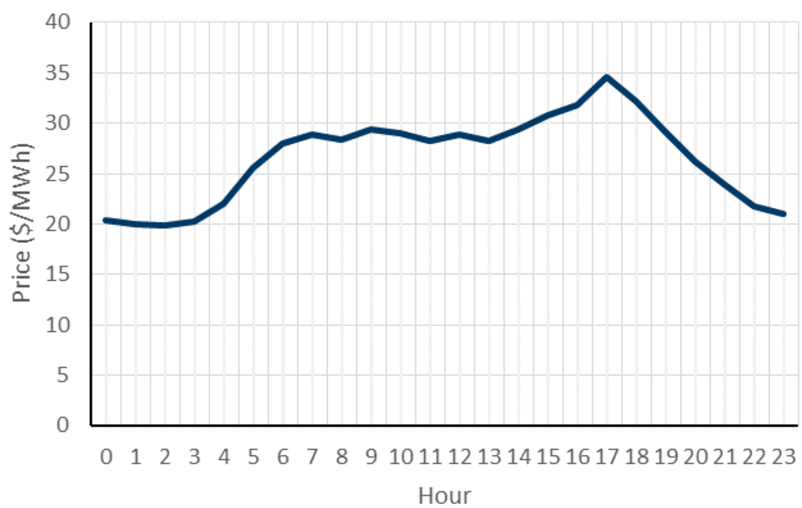
a) Note that these renewable capacity projections do not include renewable additions announced in May 2020.

Appendix B: Load Shape Assumptions

Methodology Overview

The project team optimized each load shape on price, which serves as a good proxy for times of high demand. This is similar to how utilities currently promote demand reduction during the high demand or high price times of the day. To develop the assumptions of when shifts should be applied in the model, the project team examined wholesale MISO prices and identified, on average, when prices were high. Figure 31 shows that Minnesota Hub real-time prices are highest, on average, from around 5 am to 9 pm.

Figure 30. Hourly average real-time prices - Minnesota Hub



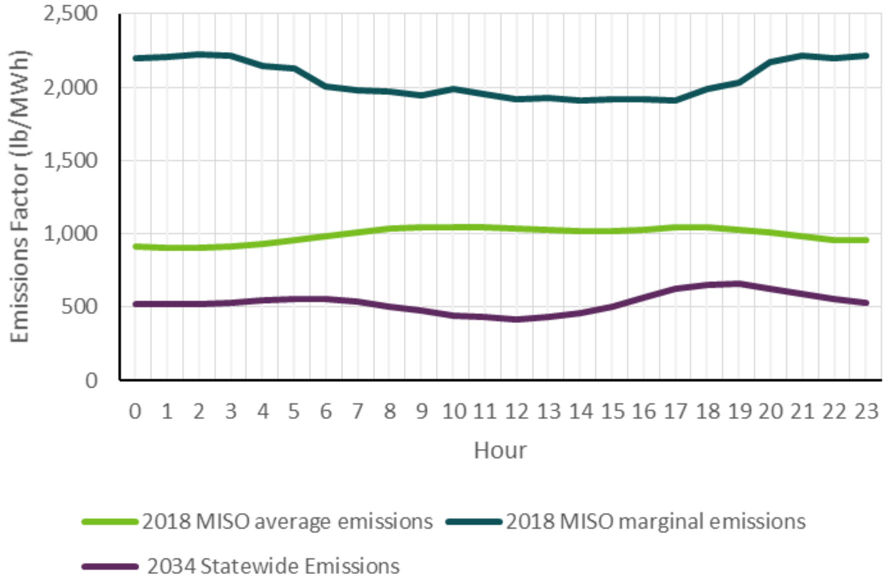
The approach for modifying the load shape pattern was different for each category of load shift. For regularly occurring shifts, the load shapes with empirical data from the Midwest followed the pattern of shifting energy away from the middle of the day. For modeled shapes or for shapes from other regions, the project team adjusted the timing of the shift to match this pattern and avoid energy use during the middle of the day. The shift occurred daily and followed the same pattern each day, shifting use away from the 9 am to 4 pm time period.

Each technology has varying technical limitations which constrains the ability to modulate the length of shift in the model, so not all measures decrease energy use for this entire time period. For example, active ice storage only shifts energy for six hours in the afternoon, from about noon to 6 pm. As it acts as a substitute for active cooling, the technology is limited in the energy reduction it can achieve, with the load shifting away from the top price hours of the day to maximize the potential cost savings. As another example, refrigeration load control follows shift pattern that reflects the empirical data collected from California where the time-of-use rate's highest price is early evening rather than middle of the day. The rate structure results in energy being shifted from about 4 pm to 10 pm rather than the 9 am to 4 pm shift of the other regularly occurring shift measures in the model and serves a sensitivity case to demonstrate the effects of future price patterns when more renewables are on the grid. As future prices are highly uncertain, the project team did not try to optimize differently based on the forecasted prices and instead maintained the same pattern across time.

For each event-based load shape, the project team assumed a set number of called events within each year. The project team used wholesale energy price data to determine when events occurred as there was limited information on how utilities determine when to call events and the available data did not always link the event to an exact date. The project team used the twenty days with the top wholesale hourly prices in a year as the days when events were called. This method also allowed for use of future price data to ensure events were called on days when prices were high. On the day of the event, the project team then used wholesale price data for that day as well as assumptions on technology or user acceptance restraints to model the exact pattern of the events. This method was modified slightly for HPWH with controls because it has a unique ability to be modulated through direct control on a regular basis without impacting comfort. As such, for this measure, include shifts that occur *every day* of the year based on the wholesale price profile of that day. The modeled load shape avoided energy use during the top five hours of the day when performance constraints allowed and tried to use energy during the bottom five price hours of the day to pre-cool water for future use. Due to differences in temperature or time of day when prices were high, each event had slight variations in its shed pattern.

The project team also developed a sensitivity analysis that instead optimized around emissions rather than prices for three of the measures that represent the variety of load shifting options of the larger list of fourteen measures: EVs, PCM for refrigeration, and ASHPs plus demand response. Emissions intensity, like price, changes throughout the day and year based on the prevalence of renewable generation as well as overall load. For comparison, Figure 32 shows the hourly averages across the year for 2018 MISO marginal and average emissions as well as the 2034 statewide emissions. The 2018 MISO average emissions are typically lower in the middle of the night while marginal emissions and the 2034 statewide forecasted emissions are typically lower in the middle of the day.

Figure 31. Emissions Factors Hourly Profiles



For the two shifting measures, EVs and PCM for refrigeration, the project team constructed a daytime charging scenario in addition to night-time charging to run against the emissions scenarios. This night-time shift was the same as the price optimization case, while the daytime shift avoids energy use overnight and uses energy from 9 am to 4 pm. For ASHPs, the project team dispatched demand response events similar to the methods for price optimization, again targeting the top twenty days of the year and the top hours in each of those days based on emissions factors.

Shift measures

For the shift measures, the project team deployed a number of methods to develop 8760 load shapes, including the use of models and the use of empirical data from other sources. Table 15 provides the high-level information on the modeling efforts and each measure subsection provides additional detail. The size column lists the size of the building for commercial measures and the size of the equipment for residential measures.

Table 15. Shift measures load shape development

Measure	Number of Participants	Baseline	Size	Data source
PCM for space conditioning (*commercial*)	20	Space conditioning (variable air volume – no PCM)	17,890 square foot building	Model

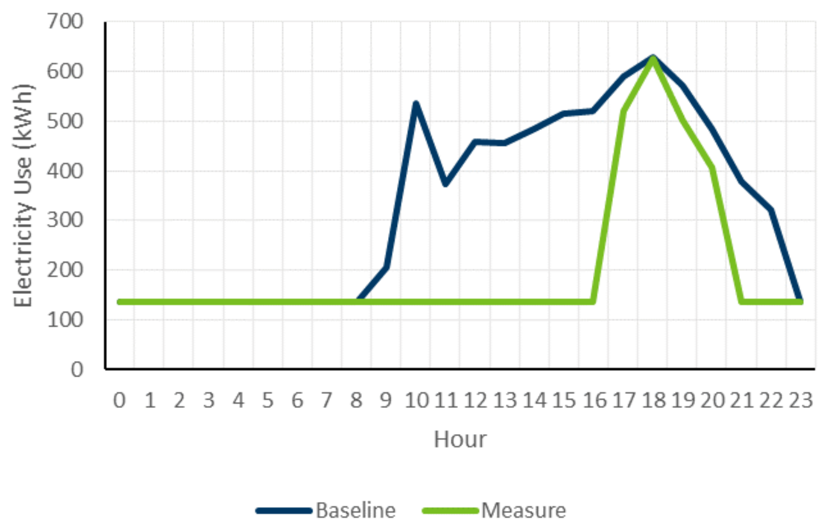
Measure	Number of Participants	Baseline	Size	Data source
PCM for refrigeration (*commercial*)	2	Refrigeration	100,000 square foot building	Field study empirical data (1 building)
Active ice thermal storage (*commercial*)	230	Space conditioning (VAV)	11,900 square foot building	Field study empirical data (1 building) with modeling
EVs with charging controls (*residential*)	307	Level 2 uncontrolled charging	6.6 kW charger	Model
Strategic energy management with demand focus (*industrial*)	25	Traditional industrial load	*N/A*	Model
Refrigeration load control	8	Refrigeration	500,000 square foot building	Field study empirical data (1 building)

Phase change materials for space conditioning

PCM for space conditioning function by storing and releasing thermal energy. The PCM material is "tuned" to change phases (freeze or melt) at the desired room temperature. When the indoor air is above this temperature, the PCM absorbs excess heat by melting – below this temperature, the PCM freezes and releases stored heat back to the space. These properties result in spaces with PCM having a passive thermal buffer, improving thermal comfort and reducing the amount of times that HVAC systems must cycle. HVAC controls can also be tuned to use this property to pre-cool or pre-heat spaces or shift peak demand.

Data for this measure was derived from a previous study conducted by Slipstream for Minnesota CARD (Becky et al. 2020). This study used a reference EnergyPlus model based on the DOE commercial prototype model (DOE 2018) for a medium office. For the present study, the only change applied to the model from that study was to update the location and weather file to St. Cloud, Minnesota (to be consistent with other weather-dependent measures). The model includes only the ambient, temperature-buffering effects of PCM.

Figure 32. PCM for space conditioning baseline and measure electricity use – one day



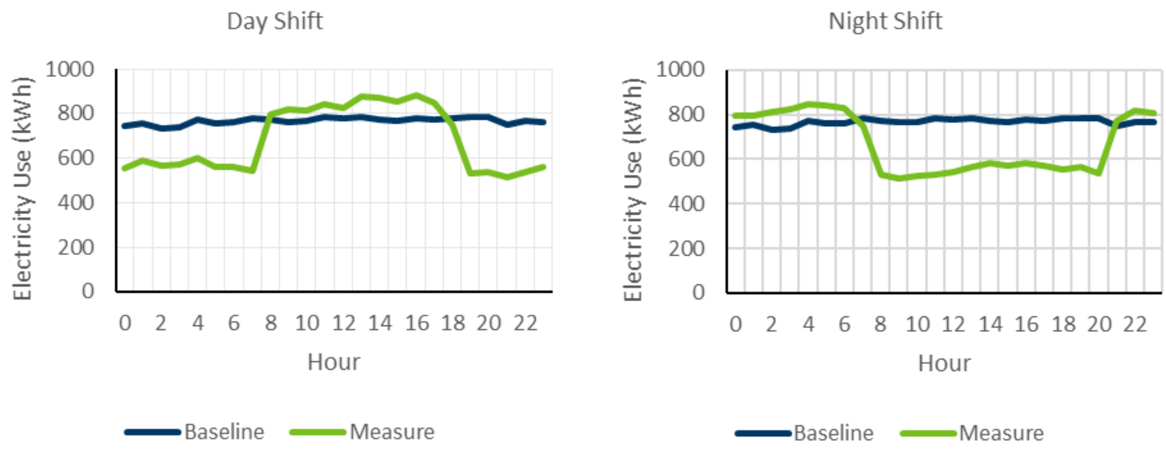
Phase change materials for refrigeration

PCM can also be used for thermal storage in refrigeration. During non-peak hours in refrigerated areas, such as refrigerated warehouses or supermarket walk-ins, the tuned PCM is frozen at a temperature slightly below the typical space setpoint. When load needs to be shed or shifted the setpoint is raised slightly, and the PCM melts to cool the refrigerated goods while the refrigeration system remains off.

The data for this measure came from metering of a building that was shifting refrigeration energy use by utilizing the installation of PCM. The data collected represented one week in the month of August. Using refrigeration efficiency curves and temperature data, the project team extrapolated the empirical data into a full year of data.

While the measured data came from a building utilizing PCM for cost savings, the project team used the data to develop a sensitivity for carbon emissions. This was done by using the electric load, refrigeration performance curves, and ambient temperature data to infer a cooling load for each hour. This cooling load was then shifted to minimize marginal emissions, and a new electric load was calculated for each hour.

Figure 33. PCM for refrigeration day shift and night shift electricity use compared to baseline



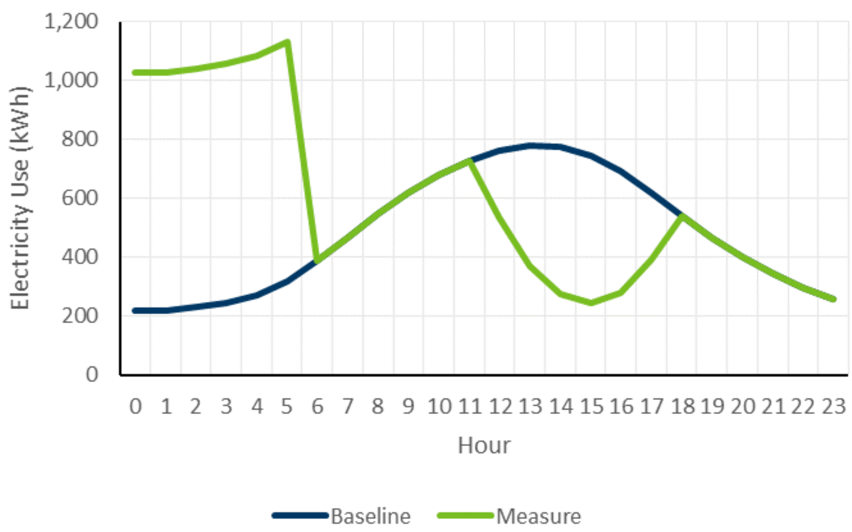
Active ice thermal storage

Ice thermal storage attaches to a chilled water system, to allow chillers to stay off during peak times. Chillers make ice or chilled water at night to prepare for the next day.

Using results from a LBNL study, the project team developed a load shape for a peak and non-peak day for May through September (Luo et al. 2017). The original study provided data on cooling load and electricity consumption for a system with three chillers and an ice tank serving a shopping mall in China. Data was provided for three different typical days covering minimum, average, and maximum cooling demand. This data was combined with ambient temperature data for the period of the study to determine response of the system to changes in ambient temperature. This characteristic performance was then applied to known cooling load profiles in Minnesota from the TRM to develop an ice thermal storage load profile for characteristic day types in cooling season.

Using wholesale Minnesota hub prices, the project team adjusted the shape to save energy around the hours where prices were highest the most often. This translated to savings occurring between 12 and 4 pm, with the peak reduction occurring at 3 pm. Using those load shapes, the project team applied the peak weekday shape for the two hottest non-holiday weekdays in each month, the non-peak weekday shape on every other weekday, and the weekend shape for weekend days. To find the hottest weekdays in a month, the project team used 2018 St. Cloud weather data.

Figure 34. Active ice thermal storage measure and baseline electricity use

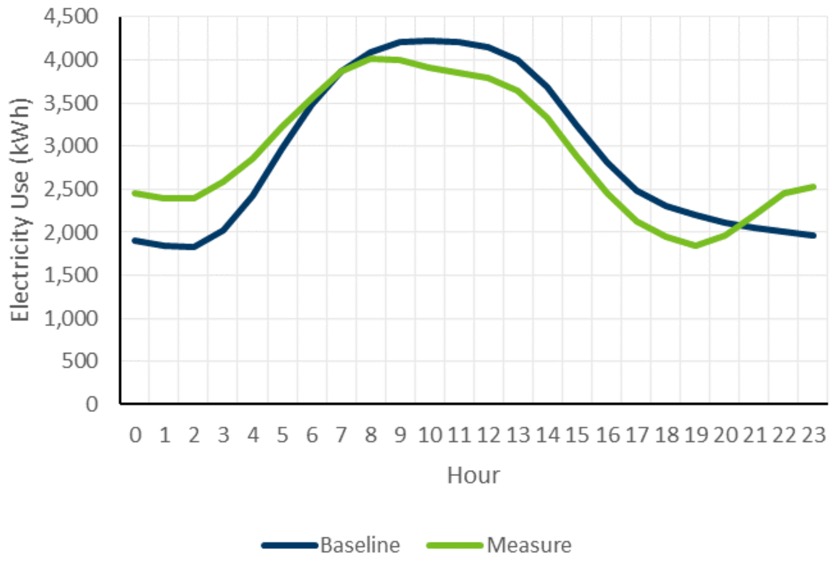


Strategic energy management

Strategic energy management includes programming common efficiency measures' controls, based on worker shifts, to shift cooling load each day. The uncontrolled load profile was informed through engineering experience with small industrial customer. These loads vary by weekend and weekday and with temperature. Peak loads are typically 3 to 4 times baseload and are about 25 percent higher in summer than winter. More energy is consumed during summer months to account for increased cooling to counteract heat generated from industrial equipment. The average small industrial customer was assumed to use 1,023,000 kWh/yr.

For the controlled energy profile, 20 kW of load per industrial customer was shifted away from peak periods. These periods were weekdays from 10 pm to 5 am.

Figure 35. Industrial strategic energy management measure and baseline electricity use



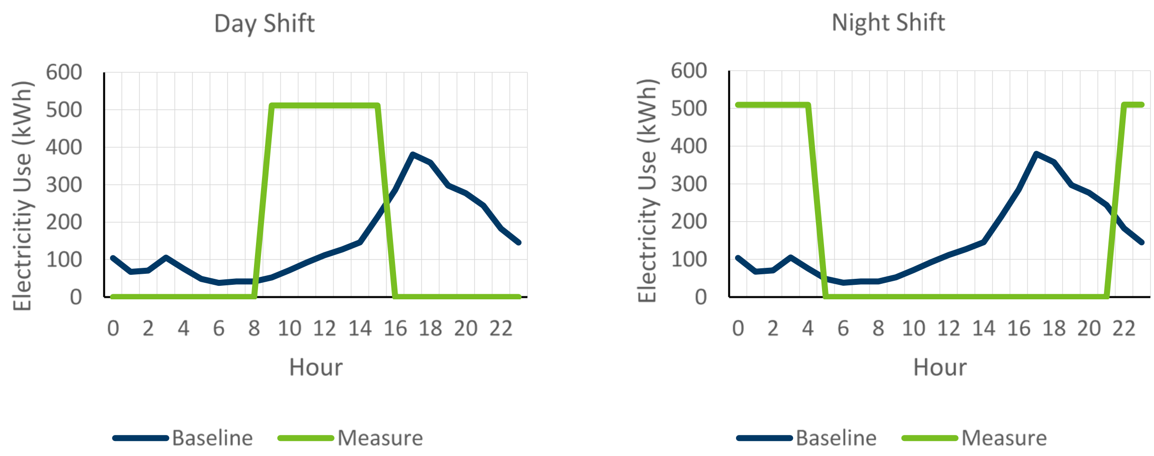
Electric Vehicles with charging controls

EVs with charging controls is a managed charging program run by utilities. Managed charging offers utilities the most control over EVs and will likely be the most practical method for utilities in the future (Muratori 2018). As the utility will control the load, the shape can be managed in terms of ramp rate and duration.

The uncontrolled charging load profile was sourced from an electric utility based in the Western US (Farley et al. 2019). Battery EV load shapes were utilized to represent a population of vehicles that regularly commutes to work. These consisted of both a weekend and weekday load shape. The shape was adjusted to account for average EV efficiency, EV supply equipment (charger) efficiency, average daily mileage on weekends and weekdays, and temperature impacts on EV efficiency for each calendar day of the year. The weather data used was a 2018 St. Cloud weather file.

The controlled charging profile set parameters around charging start and stop time, either defined as weekdays from 10 pm to 5 am for the night shift or as 9 am to 4 pm for the day shift. The day shift assumes there is no constraint on workplace charging availability. The charging model utilizes static commute times (8:00 am and 4:00 pm). The requirement for the commute is to reach 90 percent of battery capacity before the vehicle leaves the charger. Given variation between weekday and weekend driving as well as temperature impacts on efficiency, the magnitude of controlled load varies over the course of a year.

Figure 36. EV day and night charging compared to baseline electricity use



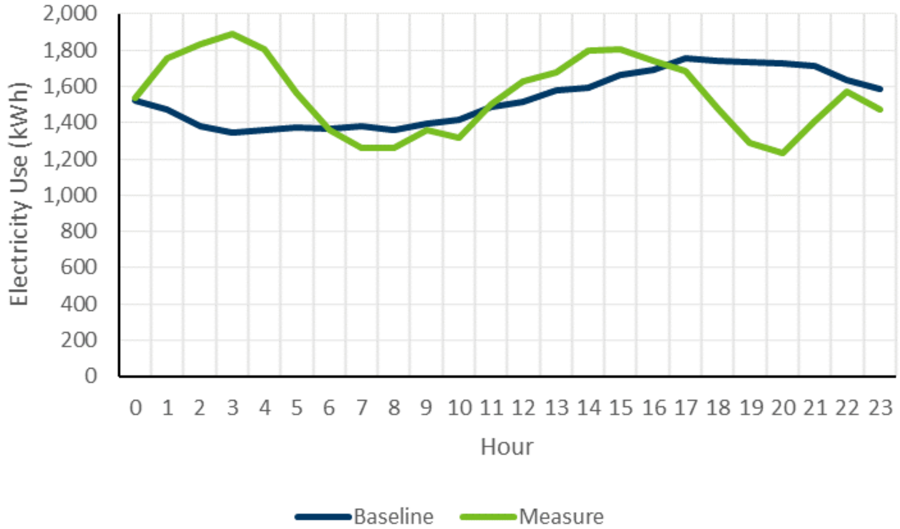
Refrigeration load control

Cold storage facilities with freezer rooms are able to store thermal energy by super-cooling rooms below the typical setpoint temperature of -1 °F. This allows the refrigeration system to precool at night when lower ambient temperatures allow for higher efficiencies, to reduce runtime during higher-priced TOU periods, or to manage demand.

Data for this measure was provided by an operator of a cold storage facility in California. The facility has roughly 500,000 square feet of freezer rooms with cooling provided by two compressors. Hourly demand, temperature setpoint (a proxy for the control algorithm), and measured temperature data for a period of over two years was provided. The facility uses a control algorithm to manage compressor runtime based on electric rates, ambient temperature, and demand charges. The data was analyzed to determine typical performance for a single day in three seasons – peak, off-peak, and mid-peak. The data also included time periods during which the algorithm was not active, which was used to develop a baseline. Due to several changes at the facility (including electric rates, control algorithm, and infrastructure), data for the off-peak season was not as consistent as the peak and mid-peak seasons. Given that less savings would be expected during the off-peak season, the measure was not applied for this period.

The measure shift pattern reflects the empirical data collected from California where the time-of-use rate's highest price is early evening rather than middle of the day. The rate structure results in energy being shifted from about 4 pm to 10 pm rather than the 9 am to 4 pm shift of the other regularly occurring shift measures in the analysis.

Figure 37. Refrigeration load control measure and baseline electricity use



Event-based measures

For the event-based measures, the project team used a mixture of models as well as empirical data combined with modeled baseline shapes. Table 16 provides the high-level information on the modeling efforts and each measure subsection provides additional detail. For the first several measures, the development process included an efficiency 8760 load shape as well as a load shape that includes the efficiency savings and the demand response events.

Table 16. Event-based measure load shape development

Measure	Number of Participants	Baseline	Size	Seasons when events called	Data source
Smart thermostats with demand response	548	SEER 12 AC with current mix of programmable + smart thermostat	2,000 Btu/°F	Summer only	Model
ASHPs with demand response control (*residential)*	120	Electric resistance heat + SEER 12 AC	2,000 Btu/°F	Summer or winter	Model

Measure	Number of Participants	Baseline	Size	Seasons when events called	Data source
Envelope measures combined with ASHP (*residential*)	80	Baseline space conditioning + median SF in Minnesota	2,000 Btu/°F	Summer or winter	Model
HPWH with controls (*residential*)	754 DR; 1270 EE	Electric resistance with no controls	Electric resistance with no controls	60-gallon tank	Model
Networked lighting controls with demand response (*commercial*)	146	LED lighting	11,900 square foot building	All seasons	Empirical data modeled against Minnesota TRM shapes
Critical peak pricing to drive behavior change (*residential*)	2,486	Typical consumer behavior	*N/A*	Summer only	Empirical field data (~600 homes)

Smart thermostats with demand response

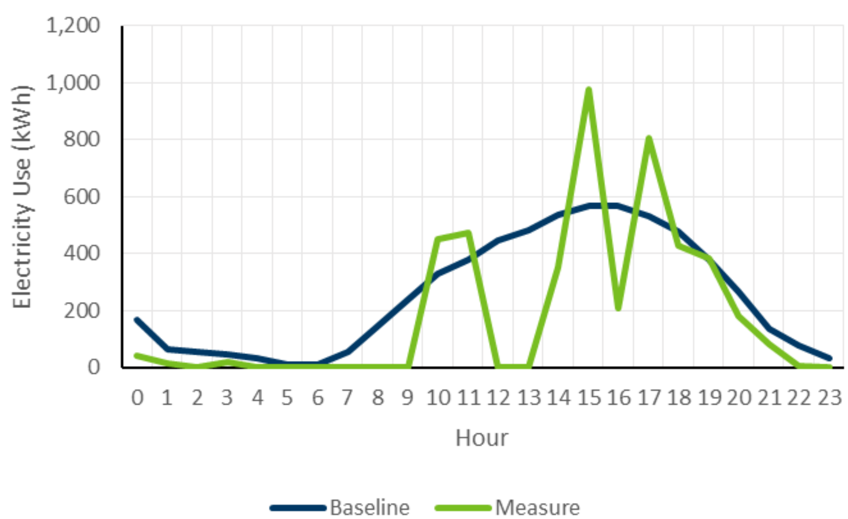
The existing install base of thermostats (a mix of programmable and non-programmable thermostats) is replaced with smart thermostats. During cooling season (June – September). These thermostats can be operated to respond to high price periods through demand response calls that pre-cool where possible and coast through high price periods.

Load profiles representing hourly residential HVAC loads aggregated across a population of single-family buildings were developed using a first-order energy balance model subject to a representative set of building parameters, HVAC equipment models, and measured occupancy schedules with thermostat setpoints. The energy balance model uses Minnesota specific data, such as average heating load of Minnesota customer and temperature and humidity data. The temperature data came from 2018 St. Cloud weather data. Occupancy schedules and thermostat settings were obtained from the Residential Energy Consumption Survey (RECS2015) and Ecobee Donate your Data Public Smart Thermostat

(ECOBEE2019) datasets. RECS2015 survey responses include thermostat setpoints for occupied, away, and nighttime periods for heating and cooling equipment for both standard and programmable thermostats. Thermostats are paired with a representative SEER 12 central AC system estimated to use 970 kWh/yr for cooling.

Representative setpoints for the smart thermostat measure are the average hourly set points from the Ecobee Smart Thermostat dataset. The baseline thermostat schedule is the weighted average of RECS2015 thermostat setpoints. The key assumption is that the smart thermostat occupancy schedules comparable, on average, to those of the population with standard and programmable thermostats. The setpoint data were further averaged into monthly average 24-hour schedules for weekdays and weekends, yielding 24 daily profiles. The standard setpoint schedules were used as baselines for each residential HVAC measure. The smart thermostat schedules were used only for the smart thermostat measure.

Figure 38. Smart thermostats baseline and measure electricity use – demand response day

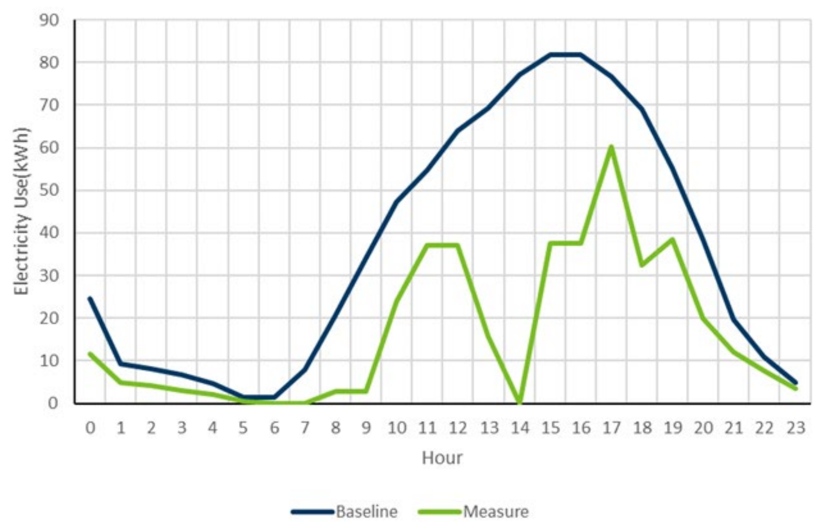


Air source heat pumps with demand response

ASHPs with demand response is an efficiency with demand response measure. The measure has efficiency savings across the entire year and twenty demand response events called across the year based on price data. The baseline electric resistance heating and SEER 13 cooling load is 25,300 kWh/yr. Baseline systems are displaced by ASHP systems with SEER 16 cooling and an average heating COP of 1.9 based on measurements on Minnesota systems.

The measure uses the same HVAC model developed for the smart thermostat measure without the smart thermostat setpoint schedule. For the events each day, the model attempts to save energy during the top five price hours in a day subject to thermal comfort constraints. For events of 2 hours or less, the setpoints are adjusted such that the systems will coast through event periods. For events of 3 to 5 hours, the systems will precondition for 1 to 2 hours (as necessary) to prepare for coasting through the high price periods. Similar logic is used to optimize around high emissions periods.

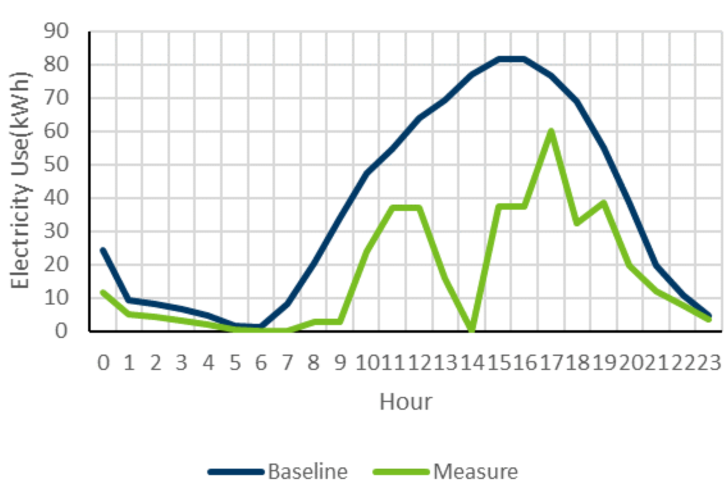
Figure 39. ASHP baseline and measure electricity use – demand response day



Envelope measures combined with ASHP

Envelope measures combined with ASHPs is a home with an ASHP that is also tightly insulated. The model assumes the homes to have undergone extensive retrofit work (e.g. exterior insulation resulting in 50% lower losses through the envelope, resulting in a 43% lower energy use than the baseline identified above. These low-load homes are also subject to the ASHP and demand response assumptions detailed above.

Figure 40. Envelope retrofits combined with ASHP baseline and measure electricity use – demand response day

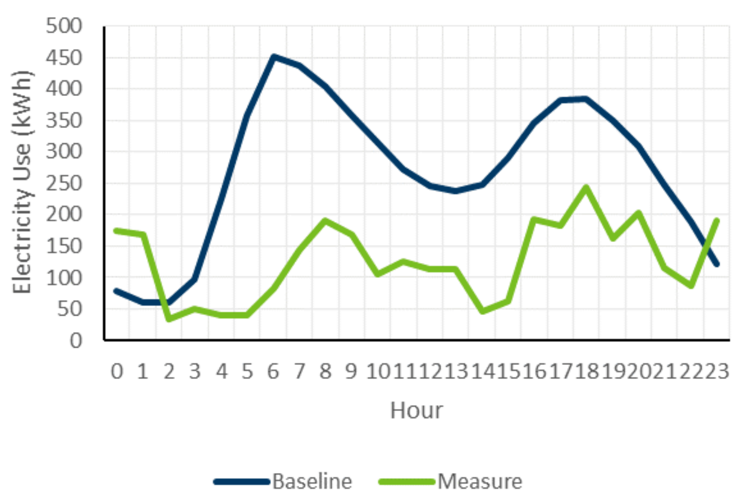


Heat pump water heater with controls

The HPWH measure has two components to it – the efficiency upgrade from an electric resistance water heater to a generic 60-gallon HPWH and the use of controls to shift load based on price signals. The measure was modeled using an energy balance model which included terms for domestic hot water draws, heat loss to the environment, and tank heating via equipment models for each type of water heater. The fleet average 24-hour residential domestic hot water draw profile was taken from Hendron and Burch 2007 with weekend use adjusted down 15% and weekday use adjusted up 6%. A HPWH performance map was generated using data from Shapiro and Puttagunta 2016 to account for changes in ambient temperature and mains water temperature. The baseline electrical resistance water heater was assumed to have constant efficiency of 98%. Mains water temperature was estimated from Burch and Cristensen 2007. Results were scaled to a representative single family residential domestic hot water load estimated at 3297 kWh/yr.

The use of demand response is operated daily to encourage use during low cost periods and discourage during high cost periods. The high and low-cost periods are defined as the five hours with the highest prices in a day and the five hours with the lowest prices in a day. These demand response calls are constrained by the physical limits of the tank and the requirement that all domestic hot water loads must be satisfied.

Figure 41. HPWH with controls measure and baseline electricity use – one representative day



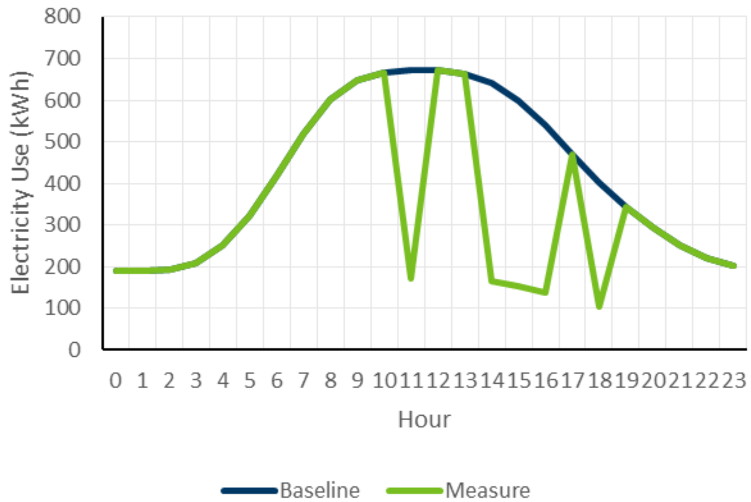
Networked lighting controls with demand response

Networked lighting controls with demand response is the use of controls to reduce lighting energy use at certain times of the day.

Using data from several different studies, the project team modeled a reduction in energy use for each hour of the day based on the amount of lighting power one can reduce in a fully occupied space without occupants noticing. The final value used was an average of six values from four studies (Lutron 2018;

Piette et al. 2005; Akashi 2004; CEC 2011). For the baseline, the project team use the lighting end use shape from the Minnesota TRM. Combining the expected reduction and the baseline, the project team estimated the measure load shape.

Figure 42. Networked lighting baseline and measure – demand response day



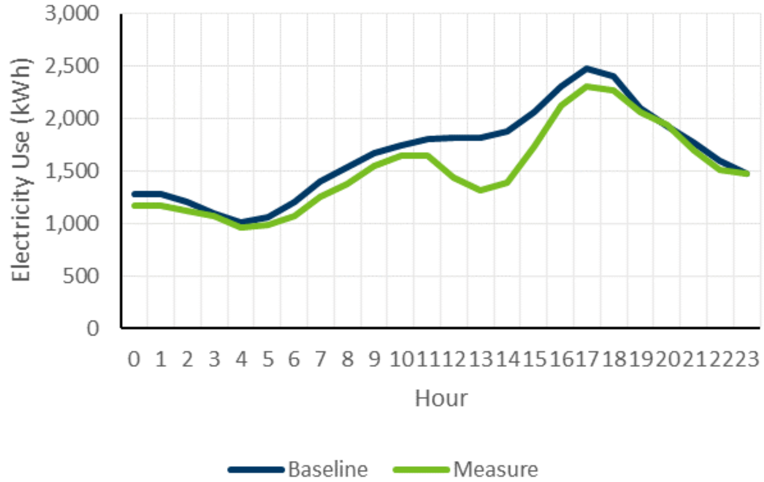
Critical peak pricing to drive behavior change

Critical peak pricing is the use of high electric rates on certain days to encourage enrolled participants to decrease their energy use. The days are typically called when utilities are expecting to be near capacity as demand is high.

The data for this measure comes from a field study conducted in the Minnesota Power territory in 2016. The field study data provided data on the expected electricity savings for each hour on a day when an event is called. The field study data suggested that participants lowered their electricity use across most hours of the day when an event was called, leading to more significant savings.

To estimate a baseline load shape, the project team utilized the summer residential load shape from the Minnesota TRM. Combining the expected savings with the baseline load shape, the project team was able to calculate a measure load shape as well.

Figure 43. Critical peak pricing baseline and measure electricity use



Energy efficiency measures

The two efficiency measures were developed using data from previous field studies conducted by the organizations. For each measure, the project team used the field study data to find an average weekday electricity use pattern as well as an average weekend electricity use pattern. The project team converted these numbers into electricity use per square foot and used the size of a typical commercial office building in Minnesota to determine the impact for one building. Table 17 summarizes the key characteristics of each load shape and the two subsections detail the assumptions made for each shape.

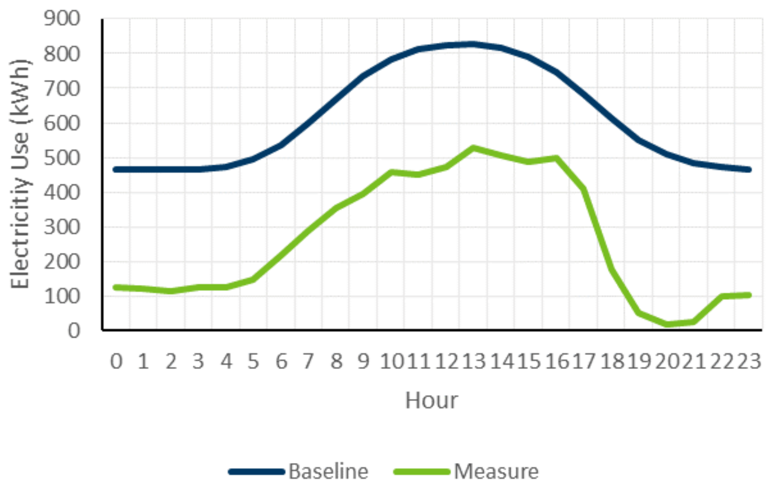
Table 17. Energy efficiency load shape assumptions

Measure	Number of Participants	Baseline	Size of Building	Data source
Plug loads	1,025	Typical office settings	10,000	Field study empirical data (8 buildings)
Lighting efficiency + controls	55	Fluorescent bulbs	11,900	Field study empirical data (3 buildings)

Plug Loads

Plug load controls use scheduling and occupancy sensing to turn off computing equipment and peripherals in cubicles and offices in office buildings to save energy. The measure is expected to have a similar impact across the entire year, but little to no impact on weekends. Based on this, the project team calculated an average weekday's saving profile using the field study data and applied it on each weekday in the year. The empirical data only provided a savings profile, so the project team used an office equipment load shapes from the Minnesota TRM to estimate the baseline load shape. The measure load shape is the difference between the baseline and savings shape.

Figure 44. Plug load baseline and measure electricity use

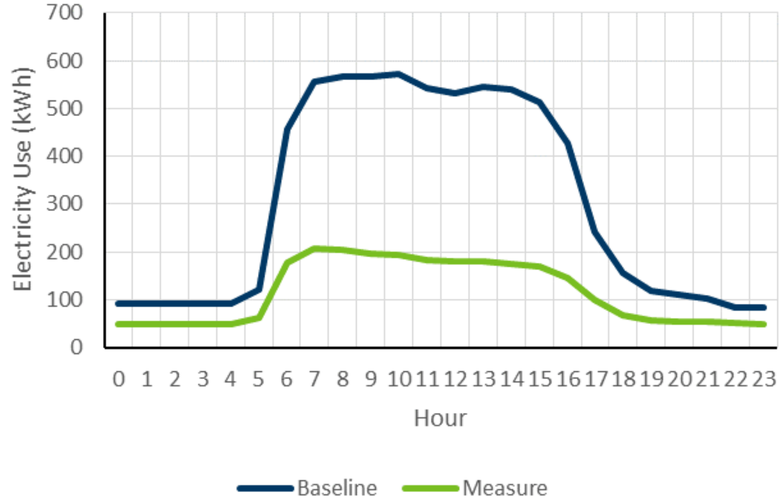


Lighting efficiency and controls

Lighting efficiency and controls include a LED retrofit upgrade as well as the installation of daylight, tuning, and occupancy controls. The LED retrofit includes full fixture replacements. The daylighting sensors were set to dim lights based on the amount of outdoor light and the occupancy sensors were set to turn off the light if no motion was detected for a set period of time.

The field study data covered a portion of the year for the pre-retrofit and post-retrofit periods. Using this data, the project team created typical weekday and weekend load shapes. This made the simplifying assumption that seasonality of light levels outside did not have a significant impact on the measure load shape.

Figure 45. Lighting efficiency and controls baseline and measure electricity use



Appendix C: Calculation Methodology

The analysis consisted of combining all the data gathered during the data collection phase to estimate annual energy costs, annual emissions, and annual capacity costs. Using those values as well as collected data on program costs and installation costs, the project team also then calculated cost-effectiveness ratios for each of the measures.

To estimate the annual value for energy costs and emissions, the hourly baseline and measure load shapes were multiplied by the number of participants calculated for each measure. The hourly baseline and measure load shapes were multiplied by the 8,760 cost and emissions data from each data source. Summing hourly values across the year generated annual point values for the baseline and measure load shapes. The difference in these two values represented the absolute savings from the measure as well.

Generation, transmission, and distribution capacity cost savings are directly related to a measure's ability to reduce demand during the system's peak hours. This is often referred to as coincident peak kW reductions. These deferred kWs are typically estimated by calculating a coincidence factor which represents how much of the total measure demand is in operation at the time of system peak (Stern, 2013). For this study, coincident factors were not readily available for most measures for two main reasons: (1) a number of measures are new technologies and not included in traditional utility programs and (2) research shows that coincident factors generally need to be region-specific to be accurate. In lieu of region-specific value for estimating a coincident-peak kW savings, the project team used the simplified approach described below.

The primary step in calculating capacity savings is estimating how often the measure is saving energy during a system's peak hours. Without access to demand data at the utility or ISO level, the project team instead assumed that peak hours coincided with the 80 maximum price hours across the entire year and applied the 8760 load shapes the project team developed to estimate the average power (kW) saved across these hours. This corresponded with the assumption about when events would be called by utilities, resulting in demand response capturing significant capacity benefits as expected. The major assumptions associated with this method are when the system peak hours occur and how many hours in a year are considered peak hours by the utility. To calculate a monetary value, the project team took this 80-hour average kW savings value multiplied by the dollar per kW-year value for both generation capacity and transmission and distribution capacity. The project team applied this method for both the emissions optimization and cost optimization.

Appendix D: Cost-Effectiveness Assumptions

The benefits side of the calculation consisted of applying each measures' calculated energy cost savings, capacity savings, and transmission and distribution savings. All of these were derived from the main analysis. For emissions savings, the project team used the calculated tons of emissions saved and multiplied it by the midpoint value for the social cost of carbon determined in a recent PUC decision for 2021-2023 Cost-Effectiveness Review (dockets G999/CIP-18-782, E99/CIP-18-783).

For the cost side, the project team relied on secondary research. As the focus of the research was the benefit side of the calculation, simplifying assumptions were made for program administration costs and installation costs. For installation costs, this included data primarily from the Minnesota Potential Study, Minnesota TRM, or from the empirical studies used for energy values. For program administration costs, the project team relied on data reported by utilities in their CIP filings. Table 18 and Table 19 provide more detailed information on the source for each measure.

As the benefit calculations were done for one year, all costs were annualized. The project team decided to annualize costs rather than calculate lifetime benefits as the project team expect cost savings and emission savings to change significantly over the lifetime of these measures as the grid changes. For that reason, the project team did not want to make the simplifying assumption that benefits continue as is into the future.

Program Administration Costs

The first component of costs included in a societal cost calculation is the program administration costs. These are the administration and advertising costs that a utility incurs to run and promote the program to customers. To estimate these costs, the project team used reported utility costs from 2018 Status Report and Associated Compliance Filings (Xcel Energy Minnesota 2019). As some measures included in the study are not traditional CIP measures, the default was costs for the residential segment and business segment overall. The project team used the cost, lifetime, and number of participants reported to convert each of these costs into an annualized per participant administration cost. Table 18 lists the program used for each measure as well as the associated annualized participant cost.

Table 18. Program administration cost values

Load Shape	Utility Program	Annualized Program Cost ($/participant)	Total Administration Cost
PCM for space conditioning	Business Segment Total	$11	$220
PCM for refrigeration	Commercial refrigeration	$205	$410

Load Shape	Utility Program	Annualized Program Cost ($/participant)	Total Administration Cost
Active ice thermal storage	Business Segment Total	$11	$2,560
Refrigeration load control	Business Segment Total	$11	$90
EVs with charging controls	Residential Demand Control	$28	$8,665
Industrial strategic energy management	Business Segment Total	$11	$280
Smart thermostats with demand response	Residential Heating	$1.4	$745
ASHPs with demand response control	Residential Heating	$1.4	$165
Envelope measures combined with ASHP	Insulation Rebate	$1.9	$155
HPWH with controls	Residential Segment Total	$1.3	$965
Networked lighting controls with demand response	Business Segment Total	$11	$1,625
Critical peak pricing to drive behavior change	Residential Segment Total	$1.3	$3,170
Lighting efficiency + controls	Lighting Efficiency	$60	$3,320
Plug loads	Business Segment Total	$11	$11,400

Installation Costs

To estimate installation cost ranges for these measures, the project team relied on a variety of sources. This included cost data from internal field study research, secondary sources on costs, and wholesaler interviews. If the research indicated a range of costs, the project team used that range directly. If the data pointed to one number, the project team added a 15 percent interval around the cost to reflect the uncertainty in using just one cost number.

Table 19. Installation cost assumptions

Load Shape	Lifetime	Cost	Description of Calculation	Source
PCM for space conditioning	25	$53,665	Used direct cost from literature for high value; multiplied this value by 50% for low value to represent that PCM is typically installed in about half the space	Alexander et al., 2020. Field Study of Phase Change Material (PCM)
PCM for space conditioning	25	$53,665	Used direct cost from literature for high value; multiplied this value by 50% for low value to represent that PCM is typically installed in about half the space	Alexander et al., 2020. Field Study of Phase Change Material (PCM)
PCM for refrigeration	20	$385,000	Applied +/- 15% to cost estimate from market research	Manufacturer (Viking Cold) cost estimate
Active ice thermal storage	20	$1,125	Applied +/- 15% to cost estimate from NREL cost estimate	Deru and Hayes. Spacing Conditioning Tech Team Webinar.
Refrigeration load control	25	$458,630	Applied +/- 15% to cost estimate from field study report	Woolf et al. (2019) Mira Loma Flywheeling – Technical Report
EVs with charging controls	10	$100	Range of $50 to $500 for making a charger ‘smart’ from RMI report	Nelder and Rogers (2019). Reducing EV Charging Infrastructure Costs
Industrial strategic energy management	15	$10,000	Applied +/- 15% to cost estimate from…	Small to medium-sized industrial energy efficiency program administrator
Smart thermostats with demand response	10	$150	Applied +/- 15% to cost estimate for Ecobee on retails sites and Xcel rebate store	https://www.xcelenergystore.com/
ASHPs with demand response	18	$2,645	Collected 153 system costs via wholesalers and used the 95% confidence interval of range	Wholesaler cost research

Load Shape	Lifetime	Cost	Description of Calculation	Source
Envelope measures combined with ASHP	25	$13,900	Applied +/- 30% to cost estimate from RSMeans to represent uncertainty on estimate	RSMeans
HPWH with controls	15	$1,000	Collected costs from retail sites and used the low and high end of the range	Market research (retail site review)
Networked lighting controls with demand response	15	$1,300	Used cost from Brattle NSP report on demand response for low value; used this multiplied by 1.5 for high value	Hledik et al. (2019) The Potential for Load Flexibility in Xcel's NSP Service Territory
Critical peak pricing to drive behavior change	1	$3	Used a proxy cost for the Minnesota Potential Study for high cost; assumed no installation cost for low value	Nelson et al. (2019) Minnesota Energy Efficiency Potential Study Appendix E
Lighting efficiency + controls	50	$52,750	Utilized cost estimates per square foot from two recent reports for low and high value	Osbourne et al. (2020) DOE Lites Program Findings; PNNL (2018) Evaluation of Advanced Lighting Control Systems
Plug loads	20	$1,175	Utilized low and high end of cost per workstation multiplied by average number of workstations in office building	Hackel et al. (2016) Impacts of Office Plug Load Reduction Strategies

Appendix E: Full Table of Results

Cost Optimization Results

Table 20. 2018 MISO results

Load Shape	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Baseline Marginal Emissions (tons)	Measure Marginal Emissions (tons)	Marginal Emissions Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Avg Hours per Shift)
ASHPs with demand response	3,037	1,316	1,721	$86,100	$39,749	$46,351	1,339	591	748	2,799	1,207	1,592	120	20	6
ASHP	3,037	1,317	1,720	$86,100	$39,874	$46,226	1,339	592	747	2,799	1,208	1,592	120	355	24
Critical Peak Pricing	399	363	37	$14,980	$13,310	$1,670	198	180	18	366	335	32	2,486	10	22
Envelope measures with ASHP demand response	2,024	496	1,529	$57,400	$15,034	$42,366	893	223	670	1,866	454	1,412	80	20	6
Envelope measures combined with ASHP	2,024	496	1,520	$57,400	$15,077	$42,146	893	223	666	1,866	455	1,403	80	355	24
EV Charging	1,303	1,302	1	$36,407	$27,258	$9,149	592	544	47	1,206	1,296	-90	307	365	17
HPWH with controls	2,486	1,175	1,311	$70,140	$31,431	$38,710	1,133	532	601	2,272	1,085	1,187	756	365	10
HPWH Efficiency	2,486	1,166	1,320	$70,140	$32,938	$37,202	1,133	531	601	2,272	1,066	1,206	756	365	24
Ice Thermal Storage	484	587	-102	$14,225	$14,576	-$350	244	283	-39	442	572	-130	230	153	6
Industrial SEM	25,581	25,656	-74	$713,311	$700,965	$12,346	11,793	11,751	42	23,313	23,566	-253	25	365	11
Lighting efficiency + controls	2,664	1,002	1,662	$78,533	$28,941	$49,592	1,245	465	780	2,358	897	1,462	55	365	24
Networked Lighting	618	580	38	$59,169	$55,490	$3,679	322	302	20	517	485	32	146	20	5
PCM - Refrigeration	6,723	5,861	862	$178,472	$149,662	$28,810	3,072	2,643	429	6,286	5,566	719	2	365	13
PCM - General	5,485	4,989	496	$161,575	$146,490	$15,085	2,559	2,327	232	4,941	4,502	440	20	365	16
Plug Loads	3,847	1,640	2,207	$109,500	$48,844	$60,656	1,772	767	1,006	3,473	1,444	2,029	1,025	260	24
Refrigeration Load Control	9,011	9,119	-108	$231,432	$230,972	$461	4,086	4,119	-33	8,464	8,588	-124	8	261	9
Smart Thermostats with demand response	376	300	76	$13,566	$11,243	$2,323	186	148	38	329	261	68	548	10	6
Smart Thermostats	376	301	75	$13,566	$11,156	$2,409	186	149	37	329	263	67	548	131	11

Table 21. 2019 Xcel Energy Minnesota Price and Emissions Results

Load Shape	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per Shift)
ASHPs with demand response	3,113	1,348	1,764	$70,909	$31,984	$38,925	1,066	475	591	123	20	6
ASHP	3,113	1,350	1,763	$70,909	$32,053	$38,856	1,066	476	590	123	355	24
Critical Peak Pricing	399	363	37	$12,202	$10,911	$1,291	162	147	15	2,486	10	22
Envelope measures combined with ASHP with demand response	1,999	489	1,510	$45,543	$11,603	$33,940	685	173	512	79	20	6
Envelope measures combined with ASHP	1,999	490	1,509	$45,543	$11,624	$33,919	685	173	512	79	355	24
EV Charging	1,303	1,302	1	$29,846	$19,351	$10,495	465	394	71	309	365	17
HPWH with controls	2,492	1,175	1,317	$57,959	$26,543	$31,416	890	414	476	756	365	11
HPWH Efficiency	2,492	1,169	1,323	$57,959	$27,243	$30,716	890	418	472	765	365	24
Ice Thermal Storage	484	587	-102	$11,957	$11,750	$207	185	210	-25	230	153	6
Industrial SEM	25,581	25,656	-74	$576,079	$561,533	$14,546	9,093	9,020	73	25	365	11
Lighting efficiency + controls	2,664	1,002	1,662	$65,648	$24,003	$41,645	969	361	608	55	365	24
Networked Lighting	655	614	41	$31,900	$29,914	$1,986	270	253	17	146	20	5
PCM - Refrigeration	6,721	5,860	861	$142,059	$116,693	$25,366	2,349	2,006	343	2	365	13
PCM - General	5,485	4,989	496	$131,758	$119,675	$12,083	1,988	1,810	178	20	365	16
Plug Loads	3,847	1,640	2,207	$89,790	$40,562	$49,228	1,371	593	778	1,025	260	24
Refrigeration Load Control	9,011	9,119	-108	$180,976	$179,020	$1,956	3,116	3,123	-8	8	261	9
Smart Thermostats with demand response	320	240	81	$8,230	$6,172	$2,057	127	96	31	583	10	4
Smart Thermostats	320	241	79	$8,230	$6,259	$1,970	127	96	31	583	101	13

Table 22. 2026 Xcel Energy Minnesota Price and Emissions Results

Load Shape	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per Shift)
ASHPs with demand response	3,340	1,448	1,893	$91,843	$40,875	$50,967	817	364	453	132	20	4
ASHP	3,340	1,449	1,892	$91,843	$40,942	$50,901	817	365	452	132	355	24
Critical Peak Pricing	399	363	37	$19,691	$17,635	$2,056	147	134	13	2,486	10	22
Envelope measures combined with ASHP with demand response	2,100	514	1,586	$57,750	$14,536	$43,214	514	130	384	81	20	4
Envelope measures combined with ASHP	2,100	514	1,586	$57,750	$14,554	$43,196	514	130	384	81	355	24
EV Charging	1,303	1,302	1	$37,976	$26,394	$11,582	339	299	40	307	365	17
HPWH with controls	2,492	1,178	1,315	$73,147	$33,253	$39,894	647	299	348	756	365	12
HPWH Efficiency	2,492	1,169	1,323	$73,147	$34,347	$38,800	647	303	344	756	365	24
Ice Thermal Storage	485	587	-103	$17,267	$17,377	-$110	149	176	-28	230	153	6
Industrial SEM	25,581	25,656	-74	$725,858	$711,172	$14,686	6,587	6,567	20	25	365	11
Lighting efficiency + controls	2,664	1,002	1,662	$82,313	$30,241	$52,072	699	262	437	55	365	24
Networked Lighting - DR	720	675	45	$45,931	$43,060	$2,871	261	245	16	146	20	5
PCM - Refrigeration	6,721	5,860	861	$187,449	$155,116	$32,333	1,745	1,496	248	2	365	13
PCM - General	5,491	4,996	495	$167,454	$152,038	$15,416	1,430	1,301	129	20	365	16
Plug Loads	3,847	1,640	2,207	$113,874	$51,045	$62,829	1,005	429	576	1,026	260	24
Refrigeration Load Control	9,011	9,119	-108	$246,884	$244,075	$2,808	2,246	2,252	-6	8	261	9
Smart Thermostats with demand response	320	239	81	$12,271	$9,192	$3,079	99	74	25	583	10	3
Smart Thermostats	320	241	79	$12,271	$9,343	$2,928	99	75	24	548	101	13

Table 23. 2034 Xcel Energy Minnesota Price and Emissions Results

Load Shape	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per Shift)
ASHPs with demand response	3,113	1,349	1,763	$103,996	$47,104	$56,893	305	139	166	123	20	5
ASHP	3,113	1,350	1,763	$103,996	$47,168	$56,828	305	139	166	123	355	24
Critical Peak Pricing	399	363	37	$24,643	$22,094	$2,549	79	72	7	2,486	10	22
Envelope measures combined with ASHP with DR	2,100	514	1,586	$70,176	$17,973	$52,203	206	53	153	83	20	5
Envelope measures combined with ASHP	2,100	514	1,586	$70,176	$17,988	$52,188	206	53	153	83	355	24
EV Charging	1,303	1,302	1	$45,248	$35,818	$9,429	133	108	25	307	365	17
HPWH with controls	2,491	1,175	1,317	$85,152	$39,033	$46,119	253	117	136	756	365	12
HPWH Efficiency	2,491	1,169	1,323	$85,152	$39,964	$45,188	253	119	134	756	365	24
Ice Thermal Storage	484	587	-102	$20,993	$21,375	-$382	60	72	-12	230	153	6
Industrial SEM	25,581	25,656	-74	$844,310	$836,706	$7,604	2,537	2,527	10	25	365	11
Lighting efficiency + controls	2,658	1,000	1,657	$94,931	$35,067	$59,864	264	99	164	55	365	24
Networked Lighting - DR	692	649	43	$54,175	$50,792	$3,383	126	118	8	146	20	5
PCM - Refrigeration	6,722	5,860	862	$218,763	$185,905	$32,859	663	571	93	2	365	13
PCM - General	5,486	4,989	496	$198,808	$181,573	$17,236	553	504	49	20	365	16
Plug Loads	3,832	1,634	2,198	$136,258	$59,401	$76,857	381	161	220	1,025	260	24
Refrigeration Load Control	9,011	9,119	-108	$270,168	$263,092	$7,076	852	845	7	8	260	9
Smart Thermostats with demand response	362	270	92	$16,787	$12,518	$4,269	45	34	11	659	10	4
Smart Thermostats	362	273	89	$16,787	$12,760	$4,026	45	34	11	659	101	13

Table 24. Capacity Cost Results

Load Shape	Year	kW Savings	Generation Savings – CIP Filing	Generation Savings – Cost of New Entry	Distribution Savings – CIP Filing
ASHPs with demand response	2018	228	$13,124	$416	$1,897
ASHPs with demand response	2019	254	$14,889		$2,573
ASHPs with demand response	2026	35	$2,343		$415
ASHPs with demand response	2034	97	$7,657		$1,395
ASHP	2018	220	$12,668	$401	$1,831
ASHP	2019	247	$14,456		$2,498
ASHP	2026	26	$1,735		$307
ASHP	2034	91	$7,188		$1,309
Critical Peak Pricing	2018	66	$3,790	$120	$548
Critical Peak Pricing	2019	107	$6,233		$1,077
Critical Peak Pricing	2026	188	$12,624		$2,236
Critical Peak Pricing	2034	179	$14,096		$2,567
Envelope measures combined with ASHP with demand response	2018	245	$14,133	$448	$2,043
Envelope measures combined with ASHP with demand response	2019	235	$13,777		$2,381
Envelope measures combined with ASHP with demand response	2026	34	$2,304		$408
Envelope measures combined with ASHP with demand response	2034	93	$7,293		$1,328
Envelope measures combined with ASHP	2018	243	$14,018	$444	$2,027
Envelope measures combined with ASHP	2019	233	$13,634		$2,356
Envelope measures combined with ASHP	2026	30	$1,990		$352
Envelope measures combined with ASHP	2034	90	$7,091		$1,291
EV Charging	2018	196	$11,309	$358	$1,635
EV Charging	2019	241	$14,099		$2,437
EV Charging	2026	179	$12,020		$2,129
EV Charging	2034	213	$16,765		$3,053
HPWH with controls	2018	243	$14,001	$443	$2,024
HPWH with controls	2019	234	$13,671		$2,363
HPWH with controls	2026	178	$11,932		$2,113
HPWH with controls	2034	196	$15,438		$2,812
HPWH Efficiency	2018	204	$11,757	$372	$1,700
HPWH Efficiency	2019	208	$12,156		$2,101
HPWH Efficiency	2026	149	$10,037		$1,777
HPWH Efficiency	2034	172	$13,550		$2,468
Ice Thermal Storage	2018	29	$1,668	$53	$241
Ice Thermal Storage	2019	93	$5,466		$945

Load Shape	Year	kW Savings	Generation Savings – CIP Filing	Generation Savings – Cost of New Entry	Distribution Savings – CIP Filing
Ice Thermal Storage	2026	213	$14,303		$2,533
Ice Thermal Storage	2034	182	$14,313		$2,607
Industrial SEM	2018	318	$18,332	$581	$2,650
Industrial SEM	2019	340	$19,866		$3,433
Industrial SEM	2026	225	$15,120		$2,678
Industrial SEM	2034	387	$30,510		$5,557
Lighting efficiency + controls	2018	310	$17,868	$566	$2,583
Lighting efficiency + controls	2019	304	$17,790		$3,074
Lighting efficiency + controls	2026	441	$29,637		$5,248
Lighting efficiency + controls	2034	393	$30,931		$5,633
Networked Lighting	2018	381	$21,980	$696	$3,178
Networked Lighting	2019	394	$23,044		$3,982
Networked Lighting	2026	453	$30,455		$5,393
Networked Lighting	2034	428	$33,700		$6,138
PCM - Refrigeration	2018	240	$13,844	$438	$2,001
PCM – Refrigeration	2019	280	$16,364		$2,828
PCM – Refrigeration	2026	436	$29,317		$5,192
PCM - Refrigeration	2034	278	$21,908		$3,990
PCM - General	2018	105	$6,047	$192	$874
PCM – General	2019	103	$6,022		$1,041
PCM – General	2026	164	$11,017		$1,951
PCM - General	2034	157	$12,350		$2,249
Plug Loads	2018	343	$19,737	$625	$2,853
Plug Loads	2019	357	$20,875		$3,607
Plug Loads	2026	298	$20,034		$3,548
Plug Loads	2034	309	$24,296		$4,425
Refrigeration Load Control	2018	46	$2,635	$83	$381
Refrigeration Load Control	2019	96	$5,618		$971
Refrigeration Load Control	2026	60	$4,056		$718
Refrigeration Load Control	2034	66	$5,235		$953
Smart Thermostats with demand response	2018	39	$477	$15	$69
Smart Thermostats with demand response	2019	131	$7,640		$1,320
Smart Thermostats with demand response	2026	93	$6,251		$1,107
Smart Thermostats with demand response	2034	105	$8,297		$1,511
Smart Thermostats	2018	13	$758	$24	$110
Smart Thermostats	2019	74	$4,313		$745
Smart Thermostats	2026	76	$5,124		$907
Smart Thermostats	2034	82	$6,423		$1,170

Emission Optimization Results

Table 25. Emissions Optimization Results

Load Shape	Scenario	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per shift)
EV Charging Day Shift	2018 MISO Average Emissions	1,303	1,303	0	$36,407	$37,743	-$1,336	592	610	-18	307	365	17
EV Charging Night Shift	2018 MISO Average Emissions	1,303	1,302	0	$36,407	$27,258	$9,149	592	544	47	307	365	17
EV Charging Day Shift	2018 MISO Marginal Emissions	1,303	1,303	0	$36,407	$37,743	-$1,336	1,206	1,149	57	307	365	17
EV Charging Night Shift	2018 MISO Marginal Emissions	1,303	1,302	0	$36,407	$27,258	$9,149	1,206	1,296	-90	307	365	17
EV Charging Day Shift	2018 Statewide Average Emissions	1,303	1,303	0	$36,407	$37,743	-$1,336	782	775	6	307	365	17
EV Charging Night Shift	2018 Statewide Average Emissions	1,303	1,302	0	$36,407	$27,258	$9,149	782	745	37	307	365	17
EV Charging Day Shift	2019 Xcel Emissions	1,317	1,317	0	$30,157	$33,577	-$3,419	470	482	-13	307	365	17
EV Charging Night Shift	2019 Xcel Emissions	1,317	1,316	0	$30,157	$19,547	$10,610	470	398	72	307	365	17
EV Charging Day Shift	2026 Statewide Average Emissions	1,303	1,303	0				615	601	14	307	365	17
EV Charging Night Shift	2026 Statewide Average Emissions	1,303	1,302	0				615	584	31	307	365	17
EV Charging Day Shift	2026 Xcel Emissions	1,303	1,303	0	$37,986	$41,166	-$3,180	340	333	7	307	365	17
EV Charging Night Shift	2026 Xcel Emissions	1,303	1,302	0	$37,986	$26,425	$11,561	340	300	40	307	365	17
EV Charging Day Shift	2034 Statewide Average Emissions	1,303	1,303	0				331	267	64	307	365	17
EV Charging Night Shift	2034 Statewide Average Emissions	1,303	1,302	0				331	314	17	307	365	17
EV Charging Day Shift	2034 Xcel Emissions	1,303	1,303	0	$44,414	$41,350	$3,064	133	125	8	307	365	17

Load Shape	Scenario	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per shift)
EV Charging Night Shift	2034 Xcel Emissions	1,303	1,301	0	$44,414	$35,835	$8,579	133	108	25	307	365	17
PCM - Refrigeration Day Shift	2018 MISO Average Emissions	6,723	5,990	733	$178,472	$162,058	$16,415	3,072	2,749	323	2	365	14
PCM - Refrigeration Night Shift	2018 MISO Average Emissions	6,723	5,861	862	$178,472	$149,662	$28,810	3,072	2,643	429	2	365	14
PCM - Refrigeration Day Shift	2018 MISO Marginal Emissions	6,723	5,990	733	$178,472	$162,058	$16,415	6,286	5,551	735	2	365	14
PCM - Refrigeration Night Shift	2018 MISO Marginal Emissions	6,723	5,861	862	$178,472	$149,662	$28,810	6,286	5,566	719	2	365	14
PCM - Refrigeration Day Shift	2018 Statewide Average Emissions	6,723	5,990	733	$178,472	$162,058	$16,415	3,981	3,549	432	2	365	14
PCM - Refrigeration Night Shift	2018 Statewide Average Emissions	6,723	5,861	862	$178,472	$149,662	$28,810	3,981	3,448	532	2	365	14
PCM - Refrigeration Day Shift	2019 Xcel Emissions	6,721	5,987	733	$142,059	$129,834	$12,225	2,349	2,107	241	2	365	14
PCM - Refrigeration Night Shift	2019 Xcel Emissions	6,721	5,860	861	$142,059	$116,693	$25,366	2,349	2,006	343	2	365	14
PCM - Refrigeration Day Shift	2026 Statewide Average Emissions	6,721	5,988	734				3,137	2,797	340	2	365	14
PCM - Refrigeration Night Shift	2026 Statewide Average Emissions	6,721	5,860	861				3,137	2,726	411	2	365	14
PCM - Refrigeration Day Shift	2026 Xcel Emissions	6,721	5,988	734	$187,449	$170,825	$16,624	1,745	1,550	195	2	365	14
PCM - Refrigeration Night Shift	2026 Xcel Emissions	6,721	5,860	861	$187,449	$155,116	$32,333	1,745	1,496	248	2	365	14
PCM - Refrigeration Day Shift	2034 Statewide Average Emissions	6,722	5,989	733				1,640	1,435	205	2	365	14
PCM - Refrigeration Night Shift	2034 Statewide Average Emissions	6,722	5,860	862				1,640	1,426	214	2	365	14
PCM - Refrigeration Day Shift	2034 Xcel Emissions	6,720	5,988	732	$218,763	$195,928	$22,835	663	584	79	2	365	14
PCM - Refrigeration Night Shift	2034 Xcel Emissions	6,720	5,858	862	$218,763	$185,905	$32,859	663	571	93	2	365	14
ASHP with demand response	2018 MISO Average Emissions	3,214	1,393	1,821	$91,114	$42,112	$49,002	1,418	626	792	127	20	4

Load Shape	Scenario	Baseline Energy (MWh)	Measure Energy (MWh)	Energy Savings (MWh)	Baseline Cost	Measure Cost	Cost Savings	Baseline Emissions (tons)	Measure Emissions (tons)	Emission Savings (tons)	Participants	Number of Days with Shift	Length of Shift in Day (Average Hours per shift)
ASHP with demand response	2018 MISO Marginal Emissions	3,163	1,370	1,794	$89,679	$41,448	$48,231	2,915	1,256	1,659	125	20	6
ASHP with demand response	2019 Xcel Emissions	3,087	1,338	1,749	$70,454	$31,798	$38,656	1,059	472	587	122	20	4
ASHP with demand response	2026 Statewide Average Emissions	3,062	1,327	1,735				1,431	628	803	121	20	4
ASHP with demand response	2026 Xcel Emissions	3,113	1,349	1,763	$85,695	$38,157	$47,538	762	340	422	123	20	3
ASHP with demand response	2034 Statewide Average Emissions	3,062	1,327	1,735				751	336	414	121	20	5
ASHP with demand response	2034 Xcel Emissions	3,087	1,339	1,748	$102,965	$46,690	$56,275	302	138	164	122	20	3
ASHP	2018 MISO Average Emissions	3,214	1,394	1,820	$91,114	$42,159	$48,955	1,418	627	791	127	356	24
ASHP	2018 MISO Marginal Emissions	3,163	1,372	1,791	$89,679	$41,495	$48,184	2,915	1,258	1,657	125	356	24
ASHP	2019 Xcel Emissions	3,087	1,339	1,748	$70,454	$31,824	$38,629	1,059	473	586	122	356	24
ASHP	2026 Statewide Average Emissions	3,062	1,328	1,734				1,431	628	802	121	356	24
ASHP	2026 Xcel Emissions	3,113	1,350	1,763	$85,695	$38,178	$47,517	762	340	422	123	356	24
ASHP	2034 Statewide Average Emissions	3,062	1,328	1,734				751	337	414	121	356	24
ASHP	2034 Xcel Emissions	3,087	1,339	1,748	$102,965	$46,702	$56,263	302	138	164	122	356	24

Appendix F: Appendix References

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