Grocery Store Thermal Energy Storage Retrofit Study

DR16SDGE0002 Report

Prepared for:

Emerging Technologies Program
San Diego Gas & Electric
Southern California Edison

September 2021

Prepared by:
Tsosie Reyhner, PE
kW Engineering
https://www.kw-engineering.com/

Acknowledgements

San Diego Gas & Electric Emerging Technologies (ET) and Southern California Edison Emerging Technologies groups are responsible for this project. It was developed as part of SDG&E's Emerging Technologies Program under internal project number DR16SDGE0002. kW Engineering conducted this technology evaluation with overall guidance and management from Kate Zeng, Christopher Roman, Dominique Michaud, Jeff Barnes, and Rafik Sarhadian. For more information on this project, contact Kate Zeng via email at kzeng@SDG&E.com.

EXECUTIVE SUMMARY

The goal of this Emerging Technologies study is to determine the load shifting potential of salt-water ice thermal energy storage systems installed as a retrofit on an existing grocery store refrigeration system.

TECHNOLOGY DESCRIPTION

This report presents findings from the field test of a new refrigeration ice storage system at a 46,000 square foot grocery store. At this store, the ice storage system was installed as a retrofit on the existing medium temperature refrigeration system, which accounts for approximately 20% of the store's annual electric energy consumption. The store's medium temperature refrigeration system serves a combination of walk-in coolers, reach-in and coffin refrigerated cases, and a low temperature compressor rack sub-cooler.

The thermal energy storage (TES) system was sized to completely offset the store's medium temperature compressor rack loads during the utility's On-Peak hours and charge the system during the early morning Super Off-Peak hours. However, unlike traditional load-shifting TES systems, this TES control system uses the whole-building meter demand as a trigger for charge/discharge optimization of the system. The TES control system modulates the output of the stored refrigeration energy from the ice storage tanks in order to reduce or increase the power consumed by the refrigeration compressors, which decreases or increases, respectively, the power provided to the store by the utility grid. In order to minimize the store's total energy costs, the TES control system monitors the grocery store's whole building load, as measured at the utility service meter, in order to optimize the TES discharge rate in a manner which reduces the utility demand charges while minimizing ice generation and storage losses.

The TES system directly shifts refrigeration loads on the store's medium temperature refrigeration system, by tying directly into the store's medium temperature refrigerant discharge and suction headers. Therefore, as originally designed, the maximum load shifting capacity is limited to the compressor load on the medium temperature compressor rack at any particular time, minus the power consumed by the TES unit itself (including refrigerant pumps, water loop pumps, and control hardware).

During the installation of the TES system, the system was modified by replacing the existing low-temperature sub-cooler with a unit with a larger capacity. Theoretically, this could allow the TES system to offset additional compressor loads on the low temperature refrigeration system, allowing the system to offset additional load.

PROJECT FINDINGS

This Emerging Technology reports describes the data collection and analysis done to evaluate the peak demand reduction and energy impacts associated with a salt-water ice thermal energy storage (TES) system installed as a retrofit on a grocery store refrigeration system. As part of the project, a Normalized Metered Energy Consumption (NMEC) analysis was performed on the grocery store TES installation in SDG&E's service territory.

The NMEC analysis consisted of analyzing whole-building power consumption through the utility interval meter for a period of 12 months prior to the retrofit and 9 months after the retrofit. Additionally, the walk-in cooler temperatures and the TES system

amp draw were measured to confirm consistency in operations of the refrigeration system, and once installed, to monitor the status of the TES system.

This data was used, along with weather data from local weather stations, to develop a regression model of the baseline building operation and the building operation after the TES system was installed. These models estimate the annual whole-building energy consumption before and after the project implementation to estimate the demand savings and efficiency losses associated with the TES system. Uncertainty analyses were run on both models to ensure that the models provided reasonable estimates of the refrigeration system operation and to determine the validity of the resulting demand impacts and energy cost savings.

The following table summarizes the demand savings and energy use and cost impacts associated with the TES operating at the grocery store in this study. Project cost effectiveness of the technology is reflected in the simple payback.

TABLE 1. SUMMARY OF NORMALIZED DEMAND REDUCTION AND ENERGY COST IMPACT

	Annualized Building Energy Consumption (kWh/yr)	12-Month Average Billed On-Peak Demand (kW)	12-Month Average Billed Non-Coincident Demand (kW)	Maximum On-Peak Demand Savings (June kW)	Utility Bill Impact on SDG&E AL-TOU CCP Tariff ($)	Simple Payback Without Incentive (Years)
Baseline	1,604,145	226.5	246.4	250.1	-	-
Post TES Installation	1,636,658	210.1	223.4	225.9	-	-
Project Impact	+32,513	-16.4	-23.0	-24.3	-$8,944	25.3

PROJECT RECOMMENDATIONS

At the singular site analyzed in this project, demand savings were achieved that can be directly correlated to the thermal energy storage system. However, the demand savings potential for this technology is limited by maximum load on the store's medium temperature refrigeration during peak hours, and the project site has a relatively small refrigeration system. Therefore, the limitations of this technology prevent making any conclusive statements regarding the load shifting potential of this system across other grocery stores, climate zones, and refrigeration system types.

Since this system demonstrated the potential for load shifting in a technology proof-of-concept test, it has the potential to be a successful measure through statewide customized incentive programs. However, continued development of the technology will be required to improve the load shifting efficiency in order to make it competitive with other energy storage systems currently in the marketplace, including battery storage systems.

Insufficient data has been gathered to generate any conclusions that could be extrapolated to thermal energy storage systems installed at other locations. Further testing across a wider range of grocery store refrigeration systems and climate zones would be required to determine if the demand savings could be predicted reliably without conducting the same level of M&V as was conducted in this study.

ABBREVIATIONS AND ACRONYMS

ASHRAE	American Society of Heating Refrigeration and Air Conditioning Engineers
BTU	British Thermal Units
CV(RMSE)	Coefficient of Variation of the Root Mean Squared Error
DR	Demand Response
DX	Direct Expansion
EMS	Energy management systems
ET	Emerging Technologies
hp	Horsepower
HVAC	Heating, ventilation, and air conditioning
IPMVP	International Performance Measurement and Verification Protocol
kW	Kilowatt
kWh	Kilowatt-hour
M&V	Measurement and Verification
NMBE	Net Mean Bias Error
NMEC	Normalized Metered Energy Consumption
NRE	Non-Routine Event
nRMSE	Normalized Root Mean Squared Error
PLS	Permanent Load Shifting
SDG&E	San Diego Gas & Electric
SGIP	Self-Generation Incentive Program
SOC	State of Charge
TES	Thermal Energy Storage
TA&TI	Technology Assistance and Technology Initiatives

TTOW	Temperature and Time of Week

CONTENTS

EXECUTIVE SUMMARY ____ **III**

ABBREVIATIONS AND ACRONYMS ____ **V**

INTRODUCTION ____ **1**

BACKGROUND ____ **2**

Test Site Description 2

Emerging Technology/Product 3

ASSESSMENT OBJECTIVES ____ **7**

TECHNICAL APPROACH/TEST METHODOLOGY ____ **8**

Initial M&V Methodology 8

Alternate M&V Methodology 9

Local Weather Data 12

Test Plan 13

RESULTS ____ **16**

Avoided Cost Calculations 16

Normalized Test Results 19

Project Financials 25

CONCLUSIONS ____ **26**

APPENDICES ____ **27**

Appendix A: Detailed Avoided Cost Calculations 27

Appendix B: Goodness of Fit Metrics 29

Appendix C: Data and Calculation Files 31

FIGURES

Figure 1. Medium Temperature Refrigeration System 3
Figure 2. TES Ice Generation and Storage System, in charging mode 4
Figure 3. TES Ice Generation and Storage System, in discharge mode 5
Figure 4. Retrofit Isolation M&V Approach 8
Figure 5. Whole Building M&V Approach 9
Figure 6. Walk-In Cooler Independent Temperature Sensors – October 12, 2017 11
Figure 7. Walk-In Cooler Independent Temperature Sensors – February 10, 2018 11
Figure 8. Baseline Modeled and Predicted 15-minute Demand.................... 16
Figure 9. Post-Installation Metered and Predicted Demand – July 2019 Billing Cycle... 21
Figure 10. Post-Installation Metered and Predicted Demand – August 2019 Billing Cycle... 21

TABLES

Table 1. Summary of Normalized Demand Reduction and Energy Cost Impact... iv
Table 2. Thermal Energy Storage System Proposed Project Attributes...........1
Table 3. Existing Building Characteristics..2
Table 4. NMEC (Single-site) M&V Analysis Details..................................... 10
Table 5. Weather Station Comparison 13er
Table 6. Baseline Model Accuracy Metrics 17
Table 7. 9-Month Post-Installation Avoided Costs 18
Table 8. Baseline Annualized Energy Consumption 19
Table 9. Post-Installation Model Accuracy Metrics.................................... 22
Table 10. Post-Installation Annualized Energy Consumption....................... 22
Table 11. 12-Month Post-Installation Normalized Annual Costs 24
Table 12. Project Financial Analysis 25
Table 13. 9-Month Post-Installation Avoided Costs Detailed Calculation....... 28

INTRODUCTION

Grocery stores are well suited for deploying energy storage systems, when viewed from a high-level energy market perspective. The grocery sector is one of the most energy-intensive building types among all commercial building types. The grocery sector, while consisting of approximately 3% of the commercial floor space in California, consumes almost 9% of the sector's electric energy[1]. In an average grocery store, the refrigeration systems consume over 50% of the store's total energy use. In other words, this grocery sector refrigeration equipment consumes close to 5% of the electric energy used in commercial buildings in California. This refrigeration load serves as large, consistent baseload which, in many stores, is concentrated in one or two large refrigeration compressor racks. Therefore, if a centralized energy storage system could be designed around these compressor racks, they have the potential to shift a significant portion of an individual store's electric demand to times when electricity is less expensive and the load on the grid is less critical.

This study consisted of a field test of a salt-water ice TES system. This system is unique in that it is designed to be a retrofit solution that can be installed on a grocery store's existing medium temperature refrigeration system. The system is designed to have the capacity to completely shut down the medium temperature compressors and condensers during peak hours. Table 2 provides an overview of the TES system attributes as detailed in the initial project proposal.

TABLE 2. THERMAL ENERGY STORAGE SYSTEM PROPOSED PROJECT ATTRIBUTES

Type	Salt-water ice storage
Maximum Peak Demand Reduction	75 kW, electrical equivalent
Maximum energy storage capacity	780 kWh, electrical equivalent
Total Installed Cost	$225,984
Total Estimated Annual Electricity Bill Savings	$20,414

[1] California Energy Commission. California Commercial End-Use Study. March 2006. Web. http://calmac.org/publications/CEC_CEUS_Executive_Summary_03012006.pdf

BACKGROUND

SDG&E's Emerging Technologies team conducted outreach to multiple grocery store chains to find a suitable host site. The project team, including the TES system vendor and measurement and verification (M&V) consultant performed on-site assessments of a total of five grocery stores. In 2015, the project team initially selected a 68,000 square foot grocery store located in Oceanside, CA as a host site for the field test of a vendor's TES system. However, after developing preliminary specifications for the system, the host site's owner pulled out of the project due to issues associated with real estate and the exterior space requirements for the energy storage tanks. In 2016, the project team performed site visits at three additional grocery stores. Based on these site visits, the project team selected the replacement test site location used in this analysis.

TEST SITE DESCRIPTION

OVERVIEW

A grocery store in the Southern California interior valley region (California Climate Zone 10) was selected by SDG&E for the study. The study called for selecting a site owned and operated by a single entity to simplify the authorization and permitting of the TES System. Thus, the site is owned and operated by the grocery store chain's parent corporation. The following describes the test site information for the building included in this study.

TEST SITE – NEIGHBORHOOD GROCERY STORE, ESCONDIDO, CA

After considering multiple factors, including store size, available space for the system, and the accessibility of the refrigeration rack, in the fall of 2016 the project team selected the final test site. This site consists of a 46,000 square foot grocery store located in Escondido, CA. The refrigeration system at the host site consists of two refrigeration racks: a low-temperature rack and a medium-temperature rack.

TABLE 3. EXISTING BUILDING CHARACTERISTICS

Building Type	Grocery Store
Hours of Operation	Monday-Sunday 7 AM – 11 PM
Store Area	46,000 Square Feet
System Vintage	2001
Refrigeration Systems	MTB (Medium Temperature System B): 3 refrigeration loops Loop 1B (340.4 BTU): 25 reach-in coolers, 3 coffin island coolers Loop 2B (291.7 BTU): 3 walk-in coolers (2 evap. each), 13 reach-in coolers Loop 3B (37.6 BTU): LTA Subcooler Condenser (1246.5 BTU): rooftop, 10 VSD fans, 50/50 split LTA (Low Temperature System A): 1 refrigeration loop Loop 1A (134.4 BTU): walk-in freezer (2 evap.), 24 reach-in coolers Condenser (278 BTU): rooftop, 4 VSD fans, 50/50 split

EMERGING TECHNOLOGY/PRODUCT

The installed TES system connects to the medium temperature refrigeration rack, shown in Figure 1, with connections to the TES system shown on the lower right. This rack is equipped with four semi-hermetic compressors, shown in yellow. Heat is rejected to the building's exterior with a roof-mounted 50/50 split condenser, equipped with variable speed condenser fans. The site's medium temperature loads are served by three refrigeration circuits. Two of the circuits, loops 1B and 2B, serve the store's 3 walk-in coolers, 38 reach-in cases, and 3 coffin cases. The third refrigeration circuit, the LTA Subcooler, serves a sub-cooler on the low-temperature rack, which is the only interconnection between the two systems. The refrigerant suction and liquid headers were originally designed and equipped with stub-out provisions for a fourth refrigeration circuit, for future expansion. These stub-outs are utilized for the new TES system.

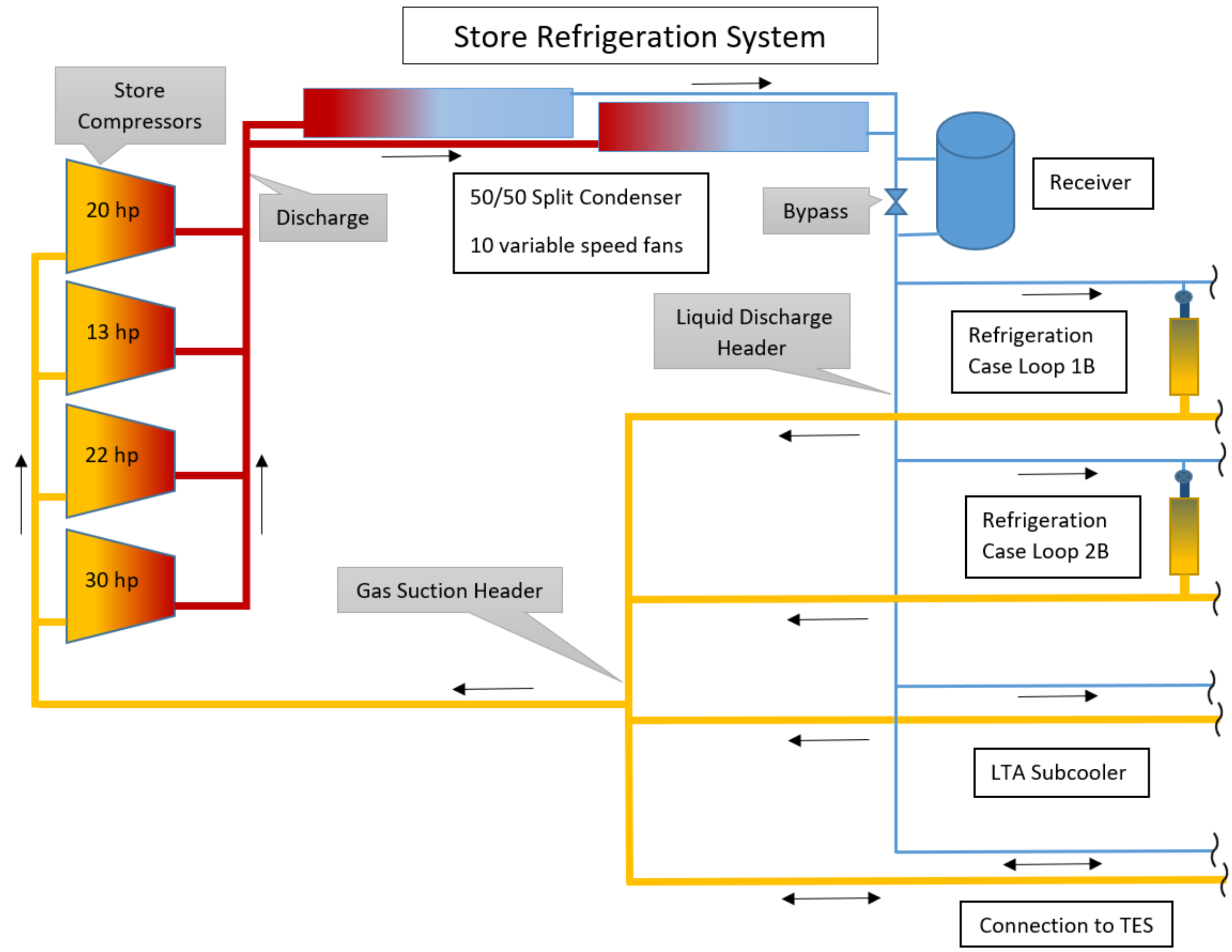

FIGURE 1. MEDIUM TEMPERATURE REFRIGERATION SYSTEM

The TES, shown in Figure 2, connects to the refrigeration header in the same manner as the three existing refrigeration circuits. During the ice generation charging phase, liquid refrigerant comes in from the store's liquid header (as shown by the arrow on the lower left in Figure 2) though an expansion valve to saltwater ice freezing temperatures (25-30°F). The TES system utilizes the suction pressure of three additional compressors to draw liquid refrigerant through the expansion valve and into a water/glycol heat exchanger. In the heat exchanger, the refrigerant absorbs heat from a low-temperature glycol mixture that is then pumped through the TES storage tanks to freeze the saltwater solution in the storage tanks. After the liquid refrigerant is evaporated in the heat exchanger, the TES compressors compress the refrigerant gas to a pressure high enough to push the evaporated refrigerant back into the store's refrigeration rack, where the refrigerant, mixed with the evaporated refrigerant from the other low-temperature refrigeration circuits, is further compressed to the pressures necessary to reject the heat out through the rooftop compressors.

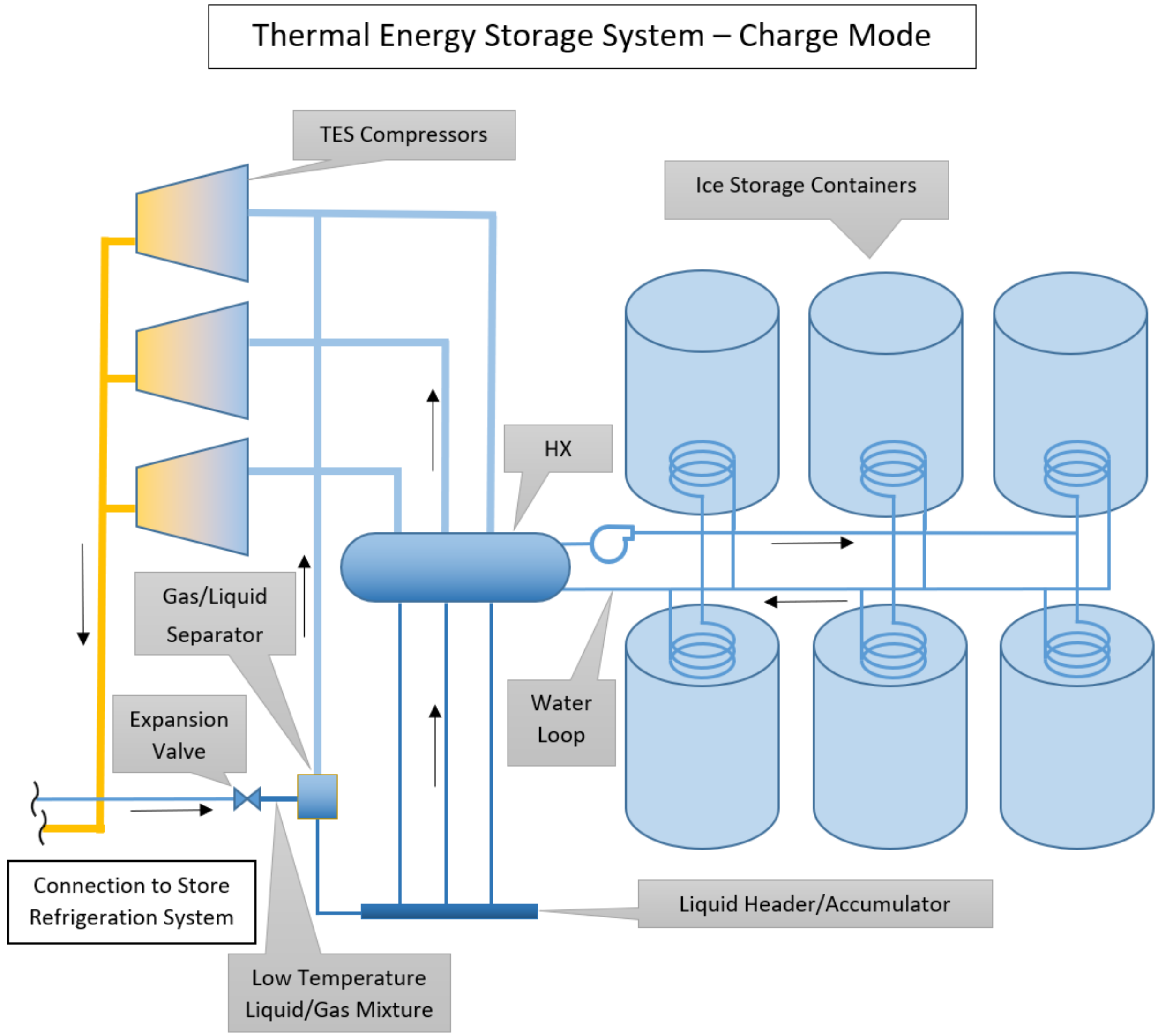

FIGURE 2. TES ICE GENERATION AND STORAGE SYSTEM, IN CHARGING MODE

During the discharge mode, shown in Figure 3, the refrigerant flow through the TES system is reversed. In this mode the evaporated refrigerant from the three other circuits is pulled into the TES system. In the water/glycol heat exchanger, glycol cooled by the thermal energy storage tanks condenses the evaporated refrigerant from the store's refrigerant loops back into liquid refrigerant. A liquid refrigerant pump circulates this liquid refrigerant back into the store's liquid heater, where it is distributed to the store's refrigeration loads, partially or fully offsetting the load on the store's medium temperature compressors and condenser.

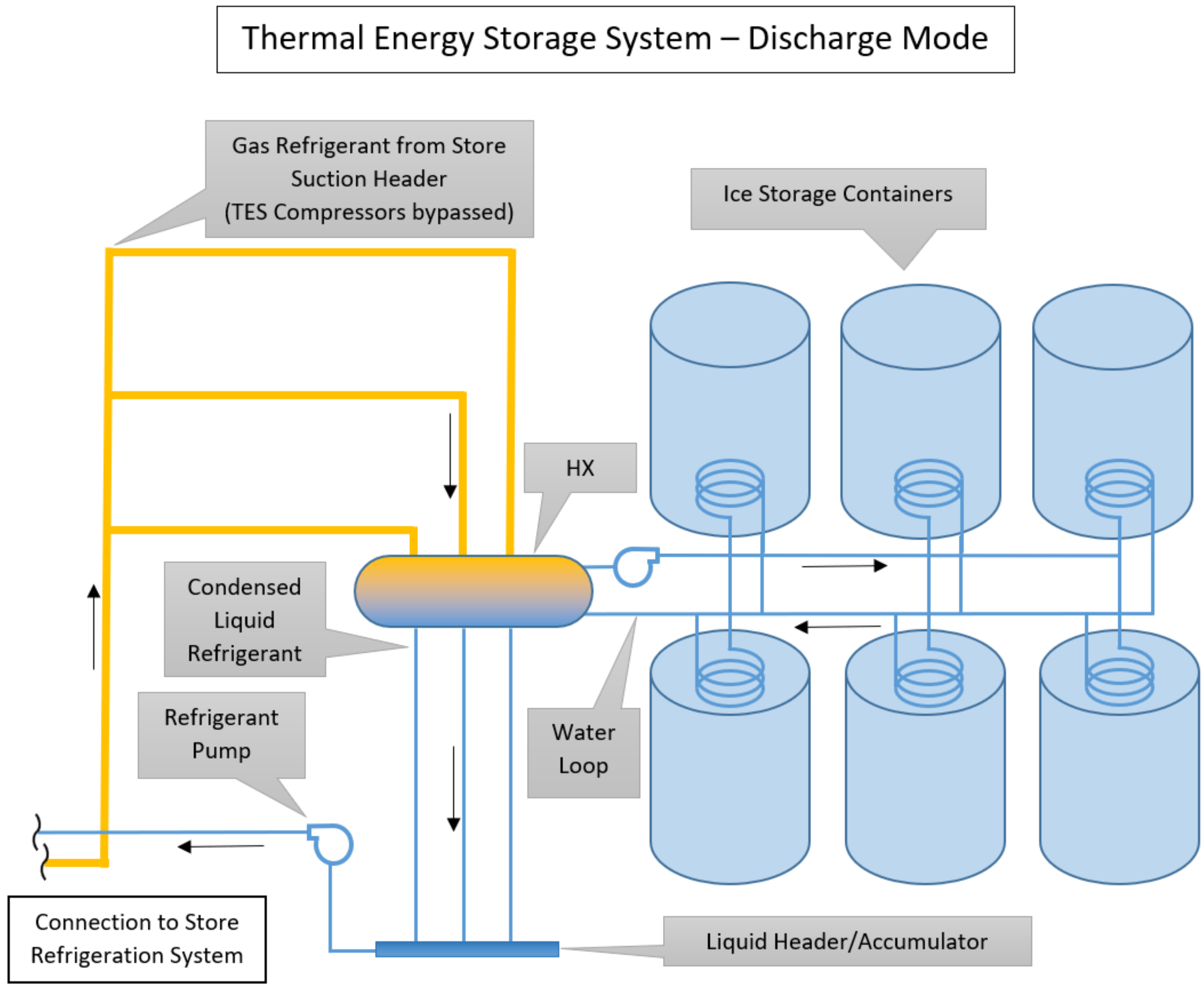

FIGURE 3. TES ICE GENERATION AND STORAGE SYSTEM, IN DISCHARGE MODE

The new TES system has a specified capacity of 780 kWh, with a maximum peak demand reduction capacity of 75 kW. This system's capacity was designed to supply any instantaneous load on the medium temperature refrigeration system with stored thermal energy, enabling the store to turn off the medium temperature compressors and condensers during the utility's peak hours.[2] Once the TES system was installed, the store's control system viewed the TES as simply a new fourth circuit. The store's refrigeration system responds to the net demand on the refrigeration headers as it had before the installation of the TES. Specifically, the store's existing refrigeration controller simply sees a reduction of *net* refrigeration load during times when the TES system is discharging, and stage off compressors accordingly. Conversely,

[2] SDG&E's demand charges consist of two components, the Non-Coincident demand, which is the maximum average demand over a 15-minute interval during each bill month, and the On-Peak demand, which is the maximum average demand over a 15-minute period during the On-Peak hours. Since December 2017, SDG&E's On-Peak hours consisted of: 4 PM – 9 PM Mon-Sun. The On-Peak hours remain the same 12 months of the year, however, the On-Peak demand charges are significantly higher during the five Summer months consisting of June to October. https://www.sdge.com/rates-and-regulations

during times when the TES system is charging, the TES system sees an increase in *net* refrigeration load, relative to the baseline, and stage on compressors accordingly.

Specifically, when the TES system is in charging mode (Figure 2) the TES system stores energy from the store's refrigeration system by serving as an additional load on the store's compressors via a fourth refrigeration loop, pulling liquid refrigerant from the discharge header of the compressor rack to make ice in the storage tanks, and discharging vapor refrigerant back into the suction header, by the same manner as the other refrigeration loops serving the walk-ins, reach-in, and coffin coolers. The store's refrigeration controls are unaware of the second compression cycle required by the TES system to bring the refrigerant to the lower evaporator temperature required to make ice and only see a net additional load on the refrigeration headers.

When the system is in discharge mode (Figure 3) the TES system reverses the flow of refrigerant into the headers, pushing liquid refrigerant into the discharge header, where it feeds the other refrigerant loops, and pulling vapor refrigerant from the suction header. Since the compressor rack sees less net load from the header when the TES is in discharge mode, the store's system will stage off compressors and lower the speed of and/or turn off the condenser fans.

ASSESSMENT OBJECTIVES

The primary objective of this technology assessment is to quantify the load shifting benefits that could result from installing the TES system on the medium temperature refrigeration system at the test site.

The main objectives of the project were as follows:

DEMAND REDUCTION OBJECTIVES

- Determine if the TES reliably reduces monthly On-Peak and/or Off-Peak demands, compared to the predicted baseline model, over the study period. Quantify the avoided costs under the effective tariff in place at the time of the study.
- Develop a model of the post-installation TES performance, and use the model to estimate the annual cost savings, using normalized climate data and the most recent tariff in place at the time the study is completed.
- Determine if the system maintained existing product storage conditions, consistent with the baseline period, over the course of the monitored post-installation period.

TES EFFICIENCY ASSESSMENT

- Determine the energy penalty associated with the additional energy required to charge the TES system during Super Off-Peak hours, over the study period. Quantify the additional energy costs associated with these losses under the effective tariff in place at the time of the study.
- Develop a model of the post-installation TES losses, and use the model to estimate the annual cost penalty, using normalized climate data, using the most recent tariff in place at the time the study is completed.

To achieve these project objectives, long-term modeling of the baseline and post-implementation refrigeration systems was conducted at the test site. The following sections provide detail on the testing approach.

TECHNICAL APPROACH/TEST METHODOLOGY

The following describes the field-testing and data analysis conducted to quantify the peak demand reduction potential of the TES system.

INITIAL M&V METHODOLOGY

To assess the thermal energy storage potential for this field test the researchers initially proposed analyzing the TES system using International Performance Measurement and Verification Protocol (IPMVP) "Option B: Retrofit Isolation." According to IPMVP, this analysis method is most appropriate for projects where the affected systems are clearly defined, and the energy savings are too small to be detected using whole building data[3]. In this case, the scale of the demand reductions and energy impacts were unknown, so the retrofit isolation approach was selected as the most appropriate data collection approach.

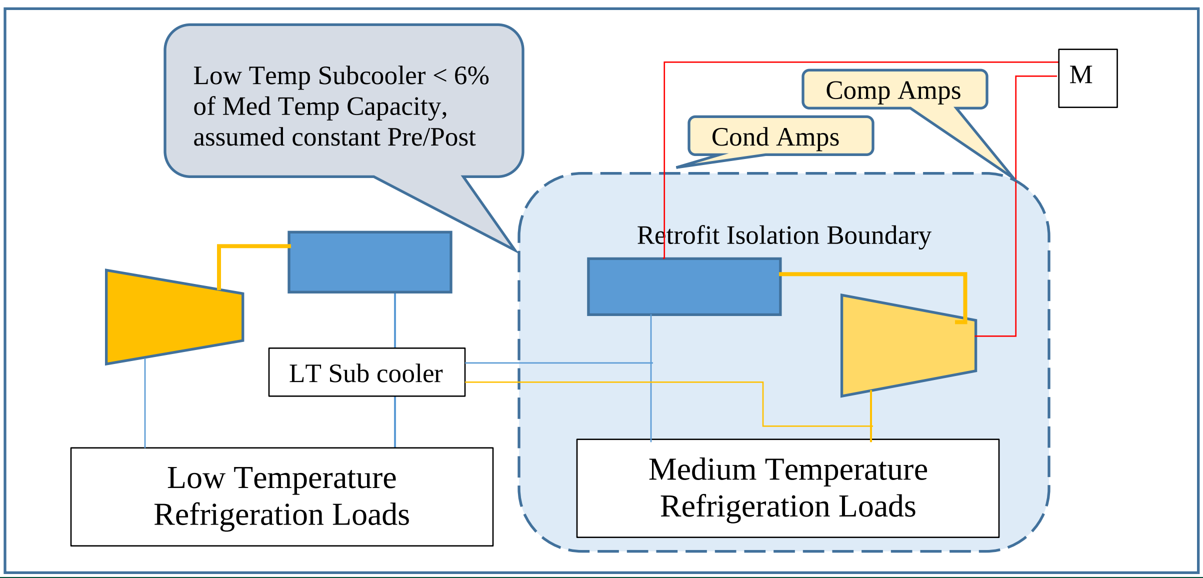

FIGURE 4. RETROFIT ISOLATION M&V APPROACH

As shown in Figure 4, this approach assumes that only the store's medium temperature refrigeration system is within the retrofit boundary, with the condenser and compressor motor currents serving as the primary analysis variables. By measuring the condenser and compressor current, as a proxy for the electric energy transferred into the system, the charge and discharge cycles in the TES system can be observed. Notably, this approach neglects the energy transfer into the system via the low temperature subcooler. Initially, this energy transfer into the retrofit boundary was not measured, due to the significant expenses associated with accurately measuring the refrigerant mass flow, and vapor and liquid conditions at the retrofit isolation boundary. The low temperature subcooler accounts for less than

[3] US Department of Energy, International Performance Measurement & Verification Protocol – Concepts and Options for Determining Energy and Water Savings, Volume 1. March 2002. Web. http://www.nrel.gov/docs/fy02osti/31505.pdf

6% of the total design capacity of the refrigeration system and, during design, the project was not expected to modify the controls for the low temperature subcooler. Therefore, a simplifying assumption was made that this load would remain constant in the baseline and performance periods, and the mass flow rate of this energy transfer through the retrofit boundary was not measured.

After the TES system was installed and being commissioned, the TES vendor modified the design of the system by replacing the existing low temperature subcooler with a larger heat exchanger to increase the demand reduction capacity. In this revised design, the new low temperature subcooler has a significantly larger capacity compared to the baseline refrigeration system, and allows the TES system to partially curtail the compressor and condenser loads on the low temperature refrigeration system, in addition to curtailing the medium temperature refrigeration loads. An unfortunate side effect of this design modification was that the previously proposed M&V approach would no longer accurately measure the full impacts of the TES system.

ALTERNATE M&V METHODOLOGY

As an alternative to the retrofit isolation IPMVP Option B M&V approach, an alternate M&V approach was proposed to capture the project's savings without the need to install additional monitoring equipment and repeat the baseline data collection. The characteristics of the total refrigeration loads (medium and low temperature systems) at this store, and the larger, revised scope of the TES project are conducive to an IPMVP Option C: Whole Building analysis approach. First, with the updated design, the TES system is designed to curtail peak demands on both the low and medium temperature refrigeration system. By expanding the scope of the analysis to include both refrigeration systems, the loads analyzed comprise approximately half of the facility's electrical demand. With a larger curtailment capacity, the savings are expected to exceed the minimum thresholds required for the Option C approach.

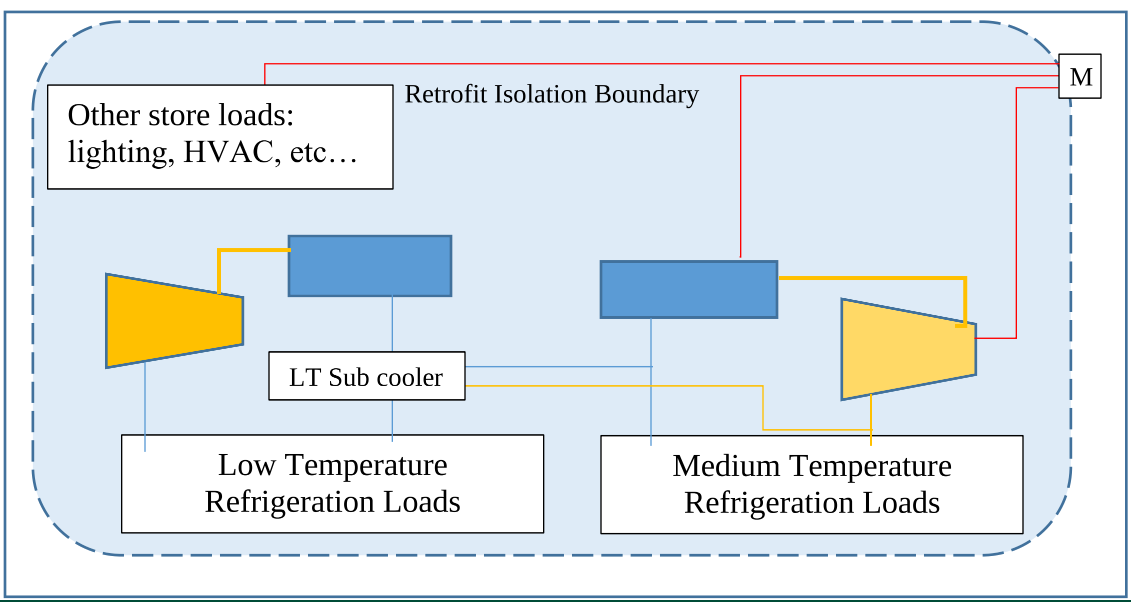

FIGURE 5. WHOLE BUILDING M&V APPROACH

The primary cost-savings driver for this project is the reduction in On-Peak demand[4] and Non-Coincident demand charges. Therefore, the NMEC analysis was performed at a 15-minute interval to mirror the interval periods used by the store's electric utility. The baseline and post-installation change-point regressions are annualized and summarized by month to accurately estimate the cost impacts of the measures.

TABLE 4. NMEC (SINGLE-SITE) M&V ANALYSIS DETAILS

Mathematical Model Form	LBNL-4944E, Time and independent variable, 6 equal seg.
Analysis Interval	15-minute average demand
Independent Variable	SDG&E Weather Station: San Pasqual dry bulb temperature
Dependent Variable	SDG&E Whole Building Revenue Meter
Baseline Analysis Period	April 3, 2017 – April 1, 2018 (12 months)
Post-Installation Analysis Period	June 3, 2019 – March 2, 2020 (9 months)
Normalization Data Set	CZ2018 Weather – Gillespie Field

BASELINE MODEL ACCURACY METRICS

The acceptance criteria for the baseline models' accuracy metrics[5] are:

1. CV(RMSE) – Less than 25%
2. NMBE – Less than 0.005%
3. Savings Uncertainty – Less than 50% at a 90% confidence level, for 10% savings at a minimum

Appendix B provides details on the formulations of these metrics.

BASELINE DATA COLLECTION

To establish the baseline energy consumption, 12 billing months of interval data was collected from the site. Data collection began on April 3, 2017, the first day of the May 2017 billing cycle, and the baseline monitoring period ended April 1, 2018, the last day of the April 2018 billing cycle, the last full billing cycle prior to when the TES installation began. This data was compiled with local weather data from the same period (discussed below) to establish a correlation between whole-building power consumption and ambient weather conditions.

Though over a full year of data was collected, not all of the data was used in the analysis. The following meter data was excluded from the regression analysis, as refrigeration load was affected by non-routine events:

- October 12, 2017 1:00-3:30 AM PDT – The building electricity meter shows signs of an unexpected power loss on the morning on October 12, 2017 from approximately 1:00 AM to 2:15 AM. Reviews of independent temperature logger data from the

[4] For the revised M&V analysis, the On-Peak demand definition is based on the new SDG&E TOU periods, which took effect in December 2017: 5 Summer months (6/1-10/31) @ 4-9 PM M-Su + 7 Winter (11/1-5/31) @ 4-9 PM M-Su

[5] Rulebook for Programs and Projects Based on Normalized Metered Energy Consumption, version 2.0, January 7, 2020. Available at: https://www.cpuc.ca.gov/General.aspx?id=6442456320

walk-in coolers indicates that there was a loss of refrigeration beginning at approximately 1:00 AM. The refrigeration system appears to have recovered from the outage by approximately 3:30 AM.

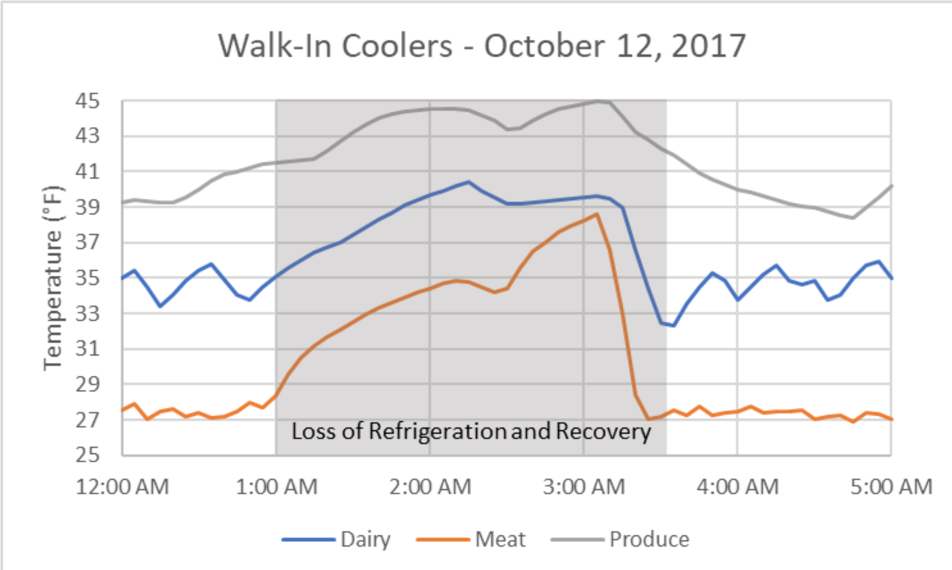

FIGURE 6. WALK-IN COOLER INDEPENDENT TEMPERATURE SENSORS – OCTOBER 12, 2017

- February 10, 2018 11:00 AM-1:00 PM PST - The building electricity meter shows signs of an unexpected power loss mid-day on February 10, 2018 from approximately 11:15 AM to 12:15 PM. Reviews of independent temperature logger data from the walk-in coolers indicates that there was a loss of refrigeration beginning at approximately 11:00 AM. The refrigeration system appears to have recovered from the outage by approximately 1:00 PM.

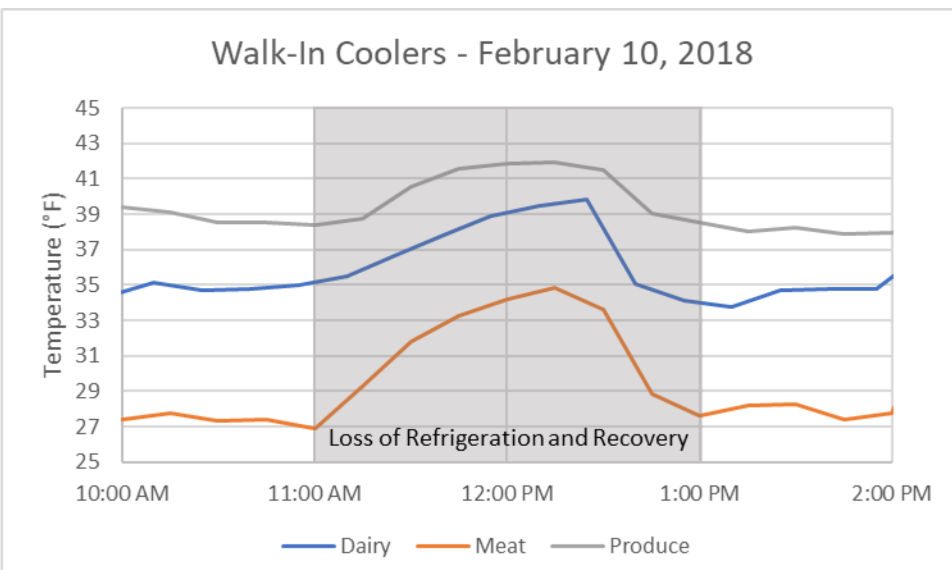

FIGURE 7. WALK-IN COOLER INDEPENDENT TEMPERATURE SENSORS – FEBRUARY 10, 2018

Reporting Period Model Accuracy Metrics

The acceptance criteria for the reporting period model accuracy metrics are as follows:

1. CV(RMSE) – Less than 25%
2. NMBE – Less than 0.005%

Post-Installation Data Collection

After the installation and commissioning of the TES System during the second half of 2018 and first half of 2019, an additional set of utility interval data was collected to confirm the post-installation TES load shift. Nine months of utility interval data for post-installation analysis was collected from June 3, 2019, the first day of the July 2019 billing cycle through March 2, 2020, the last day of the March 2020 billing cycle.

As in the baseline case, the billing data was analyzed to determine if there were any changes to the store's operation or issues with the refrigeration system's operation that should not be considered in the post-implementation analysis. The following modifications were made:

- In early 2020, the COVID-19 Pandemic resulted in significant changes to the operation of the store and disrupted normal, seasonal variations in the retail grocery store. The pandemic resulted in changes to store hours, variations in occupancy, and changes in the refrigeration load associated with the changes to the normal product sales and restocking practices. The extent of these changes was so extreme that this study was truncated with only nine-months of post-installation data collected.

The Results section of this report provides details of the data collected during both the baseline and post-installation monitoring periods.

Local Weather Data

Outdoor air temperature and humidity data in 15-minute increments was pulled from a local SDG&E owned weather station (in this case nearby 'San Pasqual' weather station). This data was collected for the entire baseline and post-implementation monitoring period. The data was used to develop the regression model of baseline and post-implementation energy consumption, discussed in the Test Plan below.

Normalized weather data was not available for the SDG&E San Pasqual weather station. Therefore, to conduct the normalized weather analysis, normalized weather data from a different station was used. A weather station with normalized CZ2018 weather data[6] that most closely matched the project site's location, elevation, and climate zone[7], which is located in CCZ10 at an elevation of 673 feet above sea level was selected.

[6] Huang, Joe. 'Update of California Weather Files for Use in Utility Energy Efficiency Programs and Building Energy Standard Compliance Calculations.' Pacific Gas and Electric Company. March 2020. Web. http://calmac.org/weather.asp

[7] California Energy Commission. 'Climate Zone tool, maps, and information supporting the California Energy Code.' California Energy Commission. March 2021. Webhttps://www.energy.ca.gov/programs-and-topics/programs/building-energy-efficiency-standards/climate-zone-tool-maps-and

CZ2018 data, compiled by White Box Technologies for utility analysis, provides hourly average weather data for a normalized meteorological year for over a hundred weather stations throughout California. The closest station to the test site is Ramona Airport. However, this weather station was not used due to it being located at a significantly higher elevation, 1,391 feet, compared to the test site. The next four closest stations were ruled out as they were located in the coastal marine CCZ07, as opposed to the test site, which is located in the inland interior valleys, with significantly less marine influence. Therefore, the Gillespie Field weather station, located in El Cajon, was selected for normalization, as this site has more similar elevation and is in the same climate zone as the test site.

Table 5 shows a list of the weather stations considered for use in the analysis. The San Pasqual SDG&E weather station was used for developing the baseline and post-installation regressions and the San Diego Gillespie CZ2018 weather station was used for normalization.

TABLE 5. WEATHER STATION COMPARISON

Station Name	Latitude (N)	Longitude (W)	Distance (miles)	Elevation (feet)	CCZ	CZ2018 Normalized
San Pasqual (SDG&E owned)	33.3	117.35	4.2	255	10	No
Camp-Pendleton-MCAS	33.3	117.35	20.1	75	07	Yes
Carlsbad-Mcclellan	33.128	117.279	12.3	328	07	Yes
Imperial-Beach-Ream-Field	32.567	117.117	39.0	23	07	Yes
Oceanside-Muni-AP	33.219	117.349	17.5	26	07	Yes
Ramona	33.033	116.917	11.0	1391	10	Yes
San-Diego-Brown-Fld-Muni-AP	32.572	116.979	38.9	515	07	Yes
San-Diego-Gillespie	32.826	116.973	21.8	387	10	Yes
San-Diego-IAP	32.735	117.169	28.0	26	07	Yes
San-Diego-Miramar-MCAS	32.867	117.15	18.9	479	07	Yes
San-Diego-Montgomery	32.816	117.139	22.2	420	07	Yes
San-Diego-N-Island-NAS	32.7	117.2	30.8	23	07	Yes

TEST PLAN

The above collected data was used to test two aspects of the TES system's performance – the demand reduction potential and the associated impact on annual energy consumption. The test plan uses a regression analysis of whole-building interval data and outdoor air temperature to test the TES load shift on the store's refrigeration system. Further details on each test plan are provided below.

ANNUAL ENERGY SAVINGS TEST PLAN

To test the annual energy savings, a statistical regression model was applied to the electrical whole-building meter data for the store. This regression approach was applied to both the baseline and post-installation data. The statistical models were developed using the approach presented in LBNL-4944E, an April 2011 article from Lawrence Berkeley

National Laboratory entitled 'Quantifying Changes in Building Electricity Use, with Application to Demand Response'[8].

Each regression model was developed using the following steps:

1) Collect 15-minute utility interval data from the whole-building utility meter.
2) Collect 15-minute outdoor air temperature and humidity data from SDG&E, collected at San Pasqual weather station in Escondido, California.
3) Use a single occupancy schedule for the site, as the refrigeration systems operate year-round, 24-hours a day.
4) Collect CZ2018 Normalized weather data for the location, Gillespie Field, to annualize the energy savings.
5) Identify any periods of time during the data collection period that major changes to systems or operation occurred. Remove this data from the analysis to provide a like-for-like comparison between the baseline and post-installation operating conditions. See the Utility Data Collection section, above, for specific data that was removed from this site's regression analysis. The final data used in the analysis is as follows:
    a. Baseline data from 4/3/2017 to 4/2/2018 (34,922 15-minute data points)
    b. Post-installation data from 6/3/2019 to 3/2/2020 (26,304 15-minute data points)
6) Generate, using the data above, a baseline statistical model for the baseline data. Compare this model to the actual power data for the utility meter over the post-installation period. Use the comparison of the baseline model and the actual meter data to calculate the impact of the TES on the billed On-Peak demand, Non-Coincident demand, and energy use for each TOU period. Combine this data with the SDG&E TOU tariff in place for each billing month during the post-installation period to calculate the avoided energy costs for the site over the post-installation study period.
7) Generate, in addition to the baseline model, a second statistical model for the post-installation data. Apply both models to the normalized CZ2018 weather data in order to calculate the predicted impacts of the TES on each month's demand and energy use in a normalized year. Combine this data with the most current SDG&E TOU tariff available at the time of this report publication to calculate the expected avoided energy costs for an entire typical year. These cost savings were then used to estimate a payback period for the TES system.
8) Conduct statistical analyses per ASHRAE Guideline 14[9] standards to determine the level of uncertainty in the models and in the overall savings claims. This analysis determines how well the model fits the actual data, and thus how

[8] Mathieu, Johanna; Price, Phillip; Kiliccote, Sila; Piette, Mary Ann. 'LBNL-4944E: Quantifying Changes in Building Electricity Use, with Application to Demand Response.' Lawrence Berkeley National Laboratory. April 2011. Web: http://eande.lbl.gov/sites/all/files/LBNL-4944E.pdf

[9] American Society of Heating, Refrigerating and Air Conditioning Engineers, *Guideline 14-2014 -- Measurement of Energy, Demand, and Water Savings* (2014) https://www.techstreet.com/ashrae/products/1888937

reliably it can predict building power consumption. The lower the uncertainty in the model, the greater the accuracy of the energy savings predictions.

The Results section of this report, below, provides the verified energy savings and identifies uncertainty of the energy models.

RESULTS

The following sections provide the results of all testing done to assess the demand reduction savings and energy use cost associated with the TES installation at the test site.

AVOIDED COST CALCULATIONS

As discussed in the Test Plan above, the researchers created a baseline regression model of the grocery store's load profile. This regression model predicts 15-minute demand of the store, prior to the installation of the TES system, based on time of day and outdoor air temperature. The following summarizes the results of the baseline regression calculations and avoided energy costs calculated using this model for the post-installation performance period.

BASELINE REGRESSION RESULTS

The baseline monitored data shows a clear correlation between whole-building load and two variables – outdoor air temperature and each 15-minute time period of the week. Therefore, a multi-variant regression model was developed to predict the whole building power use based on these two variables. The regression model predicts the power for every 15-minute period of the year based on outdoor air temperature and the time of the week.

BASELINE REGRESSION MODEL ACCURACY METRICS

This regression model was tested against goodness of fit metrics. The following graph shows a comparison of the regression model and the measured data during a portion of the baseline monitoring period.

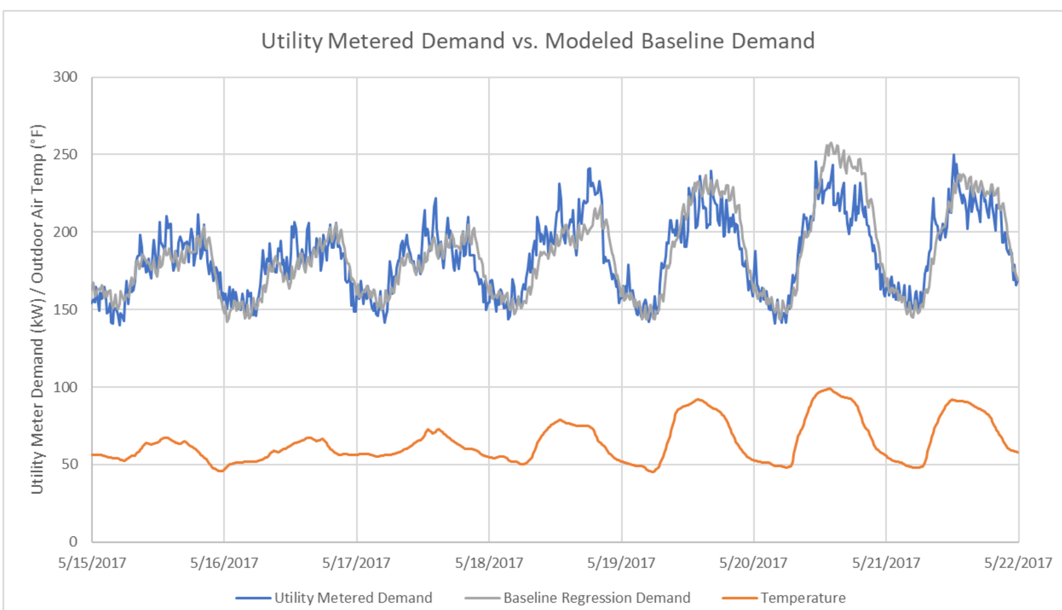

FIGURE 8. BASELINE MODELED AND PREDICTED 15-MINUTE DEMAND

As is evident from the graph, the regression model appears to follow the whole-building utility meter. However, visual evaluation of the model accuracy is not sufficient. The statistical metrics used to determine how well the model correlates to the real-world data include an R-Squared analysis, a Coefficient of Variation of the Root Mean Squared Error CV(RMSE), and the Net Determination Bias Error calculation. As shown in Table 6, the baseline model met the metrics detailed in Appendix B.

TABLE 6. BASELINE MODEL ACCURACY METRICS

MODEL DESIGNATION	NUMBER OF DATA POINTS	R-SQUARED ERROR	CV(RMSE)	NMBE
Baseline	34,922	82.12%	7.07%	-0.0004%

9-MONTH POST-INSTALLATION AVOIDED COSTS

After confirming the baseline model is accurate according to the goodness of fit criteria, the baseline model was combined with the actual billed demand and energy under the SDG&E AL-TOU CCP Tariff[10] to calculate the avoided costs shown in Table 7. As shown in the table, the avoided cost calculation results in On-Peak demand savings up to 46.8 kW, a 17% reduction, and Non-Coincident demand savings up to 51.3 kW, a 19% reduction, resulting in demand charge reductions totaling $14,641 over the 9-month post-installation period. Energy losses associated with the TES system totaled 23,118 kWh, resulting in additional energy costs of $1,836 over the same period. The net result is that the TES system saved $12,805 in SDG&E electricity costs over the nine billing periods.

The avoided cost savings estimates show that in two of the bill months, the February and March 2020 cycles, the TES system achieved a net energy *savings*. Typically, thermal energy storage systems result in an increase in net energy use, due to losses in the ice generation and storage processes. This is likely due to an overestimate of the baseline load in the regression model in these months. However, some efficiency gains are possible due to the refrigeration system's ability to operate more efficiently at night, when cool temperatures allow the system to operate at lower condensing temperatures.

[10] The grocery store is currently utilizing SDG&E's Critical Peak Pricing (CCP) energy tariff, which is the default for commercial customers who do not opt-out of the tariff. This tariff provides lower energy costs during most of the year, while incurring a higher, CCP adder during a limited number of CCP pricing events, as determined by the utility. The overall impact of the CCP tariff would be difficult to quantify over a post-installation study period of less than a year. The scope of the M&V plan did not expect the TES system to respond to CCP events, and therefore did not attempt to quantify or annualize cost savings or penalties associated with CCP events. The marginal energy costs used in the cost savings calculations include the lower energy costs associated with the CCP tariff.

TABLE 7. 9-MONTH POST-INSTALLATION AVOIDED COSTS

AL-TOU CCP Secondary Service Rate Simulation - IPMVP Option C NMEC M&V Avoided Cost - Summary by Bill Month

Primary	Billing Period				Demand Impact (kW)			Energy Impact (kWh)				Total
Tariff Date	Season	Month	End Date	Days	On-Peak	Non-Coin	Subtotal	On-Peak	Off-Peak	Super Off	Subtotal	
2/1/2020	Winter	Mar-20	3/2/2020	32	-38.9	-46.7	-$1,889.63	-3,436	-2,513	2,716	-$439.50	-$2,329.13
1/1/2020	Winter	Feb-20	1/30/2020	30	-12.0	-22.4	-$778.33	-1,695	-1,056	1,122	-$197.27	-$975.60
6/1/2019	Winter	Jan-20	12/31/2019	30	-18.8	-14.7	-$678.07	-1,403	1,492	2,813	$274.23	-$403.84
6/1/2019	Winter	Dec-19	12/1/2019	32	-41.0	-48.9	-$1,898.37	-2,452	336	6,581	$384.93	-$1,513.44
6/1/2019	Summer	Nov-19	10/30/2019	30	-40.1	-43.8	-$2,168.22	-2,445	1,540	6,212	$456.23	-$1,711.99
6/1/2019	Summer	Oct-19	9/30/2019	32	-40.7	-37.0	-$2,022.15	-1,972	2,914	4,841	$552.24	-$1,469.91
6/1/2019	Summer	Sep-19	8/29/2019	29	-23.2	-14.5	-$993.13	-1,646	2,358	4,164	$464.26	-$528.87
6/1/2019	Summer	Aug-19	7/31/2019	30	-32.4	-32.2	-$1,677.28	-2,344	1,658	4,340	$298.93	-$1,378.35
6/1/2019	Summer	Jul-19	7/1/2019	29	-46.8	-51.3	-$2,536.01	-2,029	1,362	1,660	$41.79	-$2,494.21
	9-month Total			274			-$14,641.19				$1,835.85	-$12,805.34

NORMALIZED TEST RESULTS

As discussed in the Test Plan above, two regression models of the TES demand impacts were generated – one baseline model and one post-installation model. The post-installation regression model predicts the 15-minute demand of the grocery store after the installation of the TES system, based on time of day and outdoor air temperature. Both models are used to estimate the normalized annual load of the grocery store, with and without the TES. The following summarizes the results of the post-installation regression calculations and the expected annual cost savings resulting from the TES system operating over a normalized year.

ANNUALIZED BASELINE ENERGY CONSUMPTION

The regression model used actual weather and utility meter power consumption data collected during the monitoring interval. During the 12 billing month (364 days) baseline monitoring period, the total building energy consumption was 1,592,965 kWh.

To estimate the baseline energy consumption for a typical year, which may have different weather patterns than April 2017 to April 2018 when the baseline data was collected, CZ2018 weather data was input into the regression model. This data was linearly interpolated to provide weather data for each 15-minute period of the normalized year. The resulting calculated energy consumption for a typical meteorological year is as follows.

TABLE 8. BASELINE ANNUALIZED ENERGY CONSUMPTION

MODEL DESIGNATION	ANNUAL ENERGY CONSUMPTION (KWH/YR)	MAXIMUM PEAK (KW)
Baseline	1,604,145	280.36

NORMALIZED POST-INSTALLATION RESULTS

Similar to the baseline period, the post-installation whole-building power consumption data and outdoor air temperature data were used to develop a post-installation regression model. However, unlike the baseline regression model where the building load showed a strong correlation to outdoor air temperature, in the post-installation timeframe the TES system was actively curtailing the building load during many of the On-Peak and Off-Peak hours, primarily during warmer periods, and adding to the building load during charge cycles that occurred primarily in the cooler late night and early morning hours. As a result, the post installation regression was more heavily impacted by the time of week regression independent variable.

After developing a regression based on two independent variables—the outdoor air temperature and the time of week (TTOW)—the comparisons of the post-installation meter data and predicted load showed that there was still a rather large error caused by seeming random variations in building load, which was orders of magnitude larger than the baseline regression errors. Time-series graphs of several of the billing months were compared to see if other factors could be identified to account for the variations in the post-installation regression error, which could be attributed to other factors.

Figure 9 and Figure 10 below, show times series charts for two months in the post-installation performance period, the July 2019 and August 2019 billing cycles. In these charts the utility metered load is shown in blue, the post-installation regression prediction in yellow, and the baseline regression prediction in grey. When the TES is typically in discharge mode the baseline regression load will be higher than the post-installation regression. Conversely, when the TES is in charge mode, the baseline regression load will be lower than the post-installation regression. The detailed load analysis shows the TES system typically charges from approximately 9:30 PM to 6:30 AM.

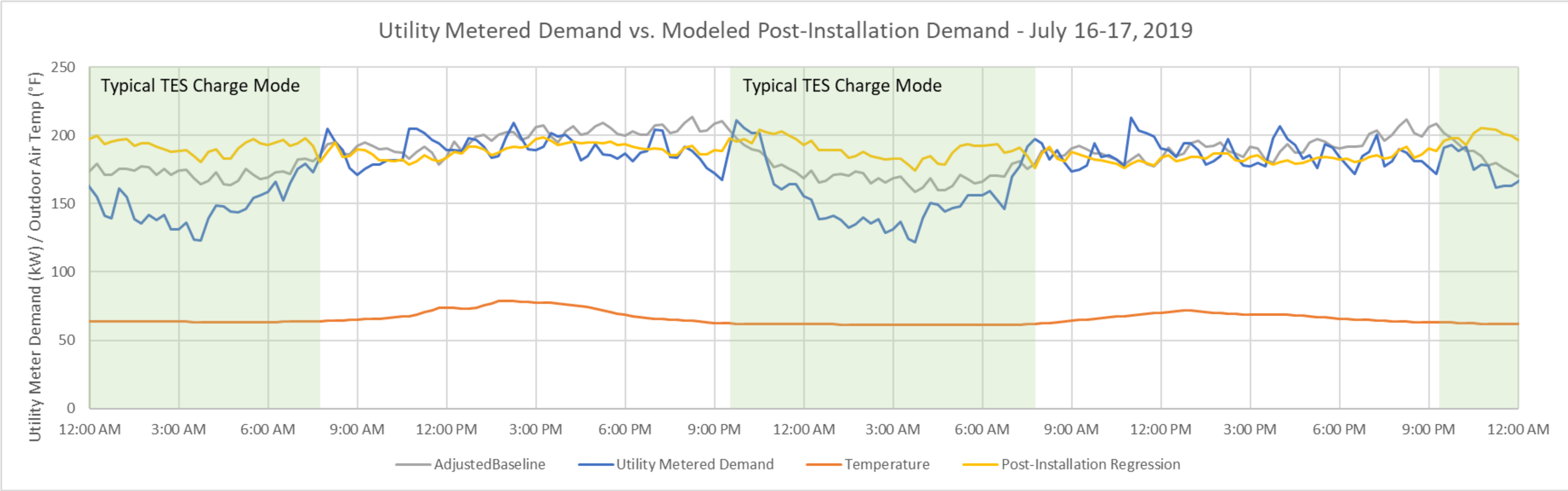

Figure 9. Post-Installation Metered and Predicted Demand – July 2019 Billing Cycle

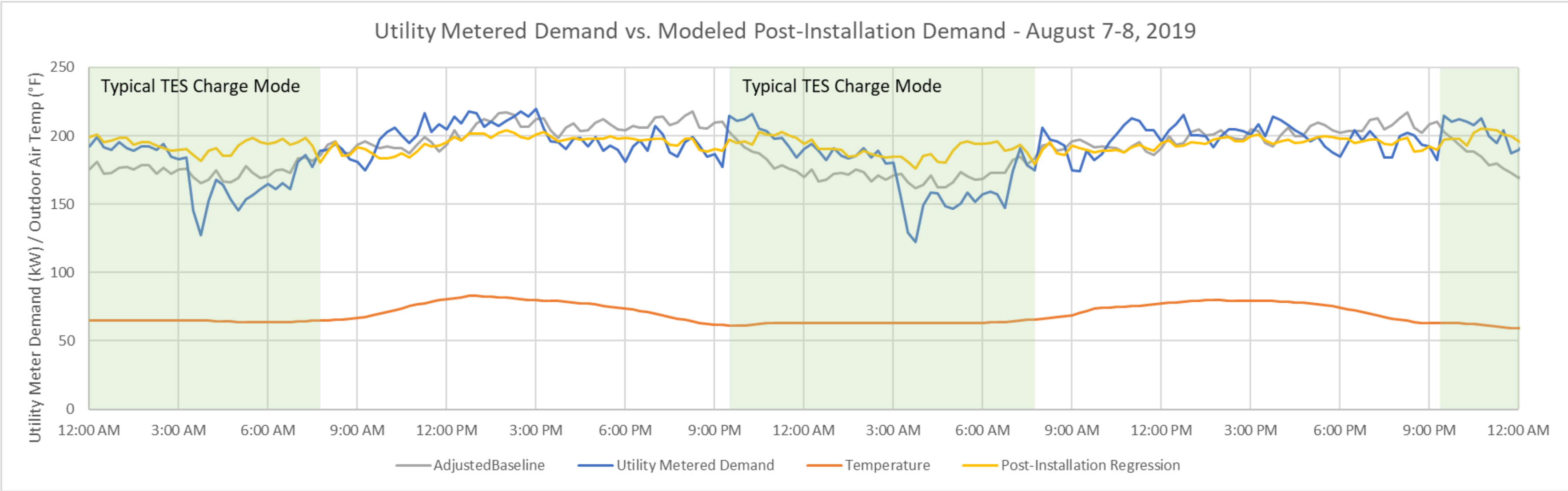

Figure 10. Post-Installation Metered and Predicted Demand – August 2019 Billing Cycle

In these two figures, the building meter shows drops in building load for a portion of the early morning periods, when the TES is typically charging, on several days in the middle of the July billing cycle and in the beginning of the August billing cycle. These periods, when the metered building load is significantly lower than the post-installation regression predicted load, correspond to nighttime hours when the TES system was idle. Since these idle events occur sporadically—some weeks have multiple days when the TES is idle at night, and in other weeks the TES is in charge mode every night of the week—the overall impact of these idle periods is an increased error in the regression model. This increases the uncertainty of the overall model, which is quantified in the following section.

Post-Installation Regression Model Accuracy Metrics

The post-installation whole-building power data shows a weaker correlation to outdoor air temperature than the baseline. This is expected because the TES is actively curtailing the whole-building power demand during On-Peak and Off-Peak TOU hours when temperatures are higher than average, and the system is consuming more energy while charging the TES during Super Off-Peak hours, when temperature are lower than average. This discrepancy is evident in the R-squared error for the post-installation model, when compared to the baseline model.

However, the charge and discharge schedule of the TES is relatively constant over the course of the post-installation period, so the 15-minute time-of-week regression variable accounts for much of the discrepancy in the temperature variable caused by the TES. As a result, the post-installation TTOW regression still meets the accuracy metrics. These include an R-Squared analysis and a Coefficient of Variation of the Root Mean Squared Error CV(RMSE) calculation. As shown in Table 9, the baseline model met the accuracy metrics.

Table 9. Post-Installation Model Accuracy Metrics

Model Designation	Number of Data Points	R-squared Error	CV(RMSE)	NMBE	Uncertainty for 10% Savings[11]
Post-Installation	26,304	58.21%	7.85%	0.0000%	3.6%

Annualized Post-Installation Energy Consumption

Like the baseline model, the post-installation regression model was generated using actual weather data and whole-building power consumption data. During the 9-month post-installation monitoring period, the total energy consumption was 1,215,802 kWh, and the maximum peak demand was 244.8 kW.

The same CZ2018 weather data used to normalize the baseline was applied to the post-installation model in order to calculate energy consumption for a typical meteorological year, as seen below.

Table 10. Post-Installation Annualized Energy Consumption

[11] The uncertainty of the model is estimated using methods consistent with ASHRAE Guideline 14-2014. However, the savings uncertainty is underestimated due to serial autocorrelation in the regression inputs. The serial autocorrelation is inherent in models using hourly and higher frequency interval data as regression inputs.

Model Designation	Annual energy Consumption (kWh/yr)	Maximum Peak (kW)
Post-Installation	1,636,658	233.2

Normalized Annual Energy Cost Impacts

To determine the normalized annual energy cost savings, the normalized annual baseline modelled demand and energy was combined with the normalized post-installation modelled demand and energy. The annual cost impacts shown in Table 11 were calculated using the SDG&E AL-TOU CCP Tariff effective April 1, 2020. As shown in the table, the two models show the TES system reduces On-Peak demand up to 24.3 kW and Non-Coincident demand up to 49.3 kW, resulting in demand charge reductions totaling $11,342 over the 12-month normalized year. Energy losses associated with the TES system totaled 32,513 kWh, resulting in additional energy costs of $2,398 over the same period. The net result is that the TES system saved $8,944 in SDG&E electricity costs over the normalized year.

The normalized energy cost savings are less than the avoided cost savings for the post-installation performance period, despite the post-installation period consisting of only nine months. The reasons for this discrepancy are likely due to a combination of factors. First, warmer weather conditions specific to the post-installation performance period compared to the normalized weather data would favor larger demand savings. Second, since the post-installation period consists of only nine-months and the baseline regression is based on an entire year, the seasonal variations that would be averaged out if a full year of post-installation data was included, might appear as larger avoided costs in the truncated post-installation performance period.

Finally, in general, regression models tend to average out extremes in the demand profiles. As a consequence, the normalized results, which compare two regressions, may provide a more accurate look at On-Peak and Non-Coincident maximum demand reductions. Conversely, in the avoided cost results, the post-installation monthly peak demands are based on the actual peak demands, the extreme events that actually occurred during the post-installation analysis period, while the baseline regression-modeled peak demands are based on a time-averaged demand. The resulting demand savings are therefore the difference between a single actual extreme peak kW reading, minus an average baseline demand, which is an average of several observations during the baseline period. As a result, the calculated demand savings may be overstated in the avoided cost calculations.

TABLE 11. 12-MONTH POST-INSTALLATION NORMALIZED ANNUAL COSTS

AL-TOU Secondary Service Rate Simulation - IPMVP Option C NMEC M&V Normalized Cost

Tariff Date	Billing Period				Demand Impact (kW)			Load Shift				Total
	Season	Month	End Date	Days	On-Peak	Non-Coin	Subtotal	On-Peak	Off-Peak	Super Off	Subtotal	
4/1/2020	Winter	Dec-21	12/31/2021	31	-12.7	-4.9	-$362.28	-1,976	1,371	4,275	$295.32	-$66.96
4/1/2020	Winter	Nov-21	11/30/2021	30	-13.1	-20.5	-$754.69	-1,970	1,032	3,944	$232.55	-$522.14
4/1/2020	Summer	Oct-21	10/31/2021	31	-15.0	-49.3	-$1,641.50	-1,729	590	3,016	$103.88	-$1,537.62
4/1/2020	Summer	Sep-21	9/30/2021	30	-12.7	-37.3	-$1,279.98	-1,524	385	2,832	$91.79	-$1,188.19
4/1/2020	Summer	Aug-21	8/31/2021	31	-20.2	-30.8	-$1,339.14	-1,611	704	3,268	$153.91	-$1,185.23
4/1/2020	Summer	Jul-21	7/31/2021	31	-11.5	-19.8	-$818.23	-1,622	773	3,252	$158.74	-$659.49
4/1/2020	Summer	Jun-21	6/30/2021	30	-24.3	-28.6	-$1,402.92	-1,706	715	3,003	$119.59	-$1,283.33
4/1/2020	Winter	May-21	5/31/2021	31	-17.7	-16.3	-$738.89	-1,705	949	3,341	$200.48	-$538.41
4/1/2020	Winter	Apr-21	4/30/2021	30	-14.2	-25.1	-$888.15	-1,645	1,512	2,922	$226.86	-$661.29
4/1/2020	Winter	Mar-21	3/31/2021	31	-12.4	-16.2	-$633.92	-1,806	1,661	3,373	$263.76	-$370.16
4/1/2020	Winter	Feb-21	2/28/2021	28	-20.7	-9.7	-$634.09	-1,818	1,217	3,884	$262.91	-$371.18
4/1/2020	Winter	Jan-21	1/31/2021	31	-22.1	-17.3	-$847.88	-2,038	1,364	4,280	$288.11	-$559.77
	12-month Total			365			-$11,341.68				$2,397.89	-$8,943.78

AL-TOU CCP Marginal Costs

Tariff Date	Season	Demand			Energy		
		On-Peak	Non-Coin		On-Peak	Off-Peak	Super Off
4/1/2020	Summer	$28.92	$24.48		$0.1305	$0.1112	$0.0875
4/1/2020	Winter	$19.23	$24.48		$0.1122	$0.1010	$0.0886

PROJECT FINANCIALS

Based on the verified energy savings and costs supplied by the TES provider, the cost-effectiveness of the TES system was estimated using the cost savings for the normalized year. For the purposes of this report, the cost-effectiveness is defined by the simple payback. The following table summarizes the costs to the customer and the simple payback based on the calculated energy savings. As shown in Table 12, the TES system cost, provided by the TES vendor in the site-specific proposal on December 6, 2016 is $225,984.

Based on the costs listed above, and the expected normalized demand savings, the project's simple payback is over 25 years. Note that, although there were design changes to the system during the project, no additional costs were incurred by the ET program, or the grocery store chain, so the project cost used in the payback calculations is the same. Table 12 below provides an overview of the project financials.

TABLE 12. PROJECT FINANCIAL ANALYSIS

MODEL DESIGNATION	PROJECT COST	ELECTRIC COST SAVINGS	SIMPLE PAYBACK (WITHOUT INCENTIVES)
Proposal Estimate	$225,984	$20,414	11.1 years
Normalized M&V Estimate	$225,984	$8,944	25.3 years

Shortly after the conclusion of this study, the TES provider that installed the system for this field test ceased operations. There are currently no other comparable saltwater ice TES systems serving the grocery sector on the market. Given these circumstances, it is not possible to reliably estimate a simple payback for this technology that may apply to other sites.

If estimating costs and calculating paybacks for similar technologies in the future, it is important to note several factors that impacted both the cost and timeline for installing this TES system:

The process for obtaining construction permits from the city for the project lasted over six months, several months longer than estimated. Some of the delays can be attributed to site-specific issues, such as research on existing utility easements for the proposed installation location.

The commissioning process lasted several months longer than estimated. During much of this time, the TES provider had staff onsite.

The cost and timeline increased due to the scope change that included replacing the existing low temperature subcooler with a larger heat exchanger to increase the demand reduction capacity. This cost was not passed on to the host site or the sponsoring ET programs.

The 2020 COVID-19 Pandemic affected the projects performance period and led to the researcher's decision to truncate the M&V performance period to less than a full year. As a result of this shortened M&V period, there is an increased uncertainty surrounding the estimated project savings.

CONCLUSIONS

Based on the testing performed during this project, the following can be concluded:

- As shown in the Results and Discussion sections, there were verifiable electrical demand reductions during both the On-Peak and Non-Coincident Peak TOU periods for each of the post-installation billing months, which were a direct result of the TES system. However, the resulting normalized 12-month average On-Peak and Non-Coincident demand savings, 20.8 kW and 18.7 kW, respectively, are significantly less than the 75 kW maximum peak demand reduction capacity estimate provided by the TES vendor at the beginning of the project. It is difficult to make any broad conclusions based on this data, because the savings are expected to vary significantly based on climate zones, refrigeration equipment sizing, and existing energy management system capabilities. Specifically, this grocery store is smaller than a typical chain grocery store, and the refrigeration system is smaller than the TES system's design capacity. As a result, the same TES system may be able to curtail more load at a store with a larger refrigeration load.
- Based on comparison of payback period with other energy storage systems, such as chemical battery storage system, other energy storage system may provide a more favorable payback compared to the thermal energy storage system tested at this site.
- The demand reduction savings potential of this technology scales with the size of the refrigeration system it is installed on. Due to the relatively small size of the test site that this system was installed at, the savings potential was very likely limited by the existing medium temperature refrigeration load. Due to the large upfront fixed capital costs associated with this thermal energy storage system, and tendency of the benefits of this system to scale with store size, this technology, in its current form, is best suited for larger grocery stores. As a rule of thumb, this technology is best suited for stores with a floor area of at least 100,000 SF.

Over the course of this field study, the market for energy storage systems, in general has changed significantly. Since this TES project was proposed, the market for chemical battery storage has progressed rapidly. At the time that this study was published, market-ready chemical battery storage solutions offer more flexibility in sizing, a smaller footprint for equivalent capacity, and less maintenance as a more competitive cost than the field-tested saltwater storage TES. Due to the flexibility in sizing and relative design simplicity, the researchers conclude that chemical battery storage solutions now provide a better value proposition as a retrofit add-on solution for load-shifting and peak-shaving energy storage in grocery stores. Grocery store refrigeration systems that incorporate TES in the initial design, or incorporate TES as comprehensive redesign/replacement of the stores compressor systems, such as may occur at older store as part of high-GWP refrigerant replacement projects, may offer an improved value proposition.

APPENDICES

APPENDIX A: DETAILED AVOIDED COST CALCULATIONS

Table 7 in the report provides a simplified overview of the Avoided Cost Calculation results by billing period. However, due to changes in tariffs and seasons within several of the monthly billing periods, the detailed avoided costs include prorated demand charges and separate energy cost calculations for billing months that include days that fall under different seasons and/or different tariffs in effect. Table 11 provides additional details on the avoided cost calculations, including partial bill month demand and energy charges for bill months, as applicable.

TABLE 13. 9-MONTH POST-INSTALLATION AVOIDED COSTS DETAILED CALCULATION

AL-TOU CCP Secondary Service Rate Simulation - IPMVP Option C NMEC M&V Avoided Cost

Tariff Date	Billing Period				Demand Impact (kW)			Energy Impact (kWh)				Total
	Season	Month	End Date	Days	On-Peak	Non-Coin	Subtotal	On-Peak	Off-Peak	Super Off	Subtotal	
2/1/2020	Winter	Mar-20	3/2/2020	2	-38.9	-46.7	-$118.10	-155	7	59	-$12.71	-$2,329.13
2/1/2020	Winter	Mar-20	2/29/2020	29	-38.9	-46.7	-$1,712.49	-3,162	-2,367	2,568	-$405.88	
1/1/2020	Winter	Mar-20	1/31/2020	1	-38.9	-46.7	-$59.04	-119	-153	89	-$20.91	
1/1/2020	Winter	Feb-20	1/30/2020	29	-12.0	-22.4	-$778.33	-1,695	-1,056	1,122	-$197.27	-$975.60
1/1/2020	Winter	Jan-20	1/1/2020	1	-18.8	-14.7	-$23.24	2	67	6	$7.55	-$403.84
6/1/2019	Winter	Jan-20	12/31/2019	30	-18.8	-14.7	-$654.84	-1,406	1,426	2,807	$266.69	
6/1/2019	Winter	Dec-19	12/1/2019	31	-41.0	-48.9	-$1,825.90	-2,291	522	6,442	$416.28	-$1,513.44
6/1/2019	Summer	Dec-19	10/31/2019	1	-41.0	-48.9	-$72.47	-161	-186	139	-$31.35	
6/1/2019	Summer	Nov-19	10/30/2019	30	-40.1	-43.8	-$2,168.22	-2,445	1,540	6,212	$456.23	-$1,711.99
6/1/2019	Summer	Oct-19	9/30/2019	32	-40.7	-37.0	-$2,022.15	-1,972	2,914	4,841	$552.24	-$1,469.91
6/1/2019	Summer	Sep-19	8/29/2019	29	-23.2	-14.5	-$993.13	-1,646	2,358	4,164	$464.26	-$528.87
6/1/2019	Summer	Aug-19	7/31/2019	30	-32.4	-32.2	-$1,677.28	-2,344	1,658	4,340	$298.93	-$1,378.35
6/1/2019	Summer	Jul-19	7/1/2019	29	-46.8	-51.3	-$2,536.01	-2,029	1,362	1,660	$41.79	-$2,494.21
	9-month Total			274			-$14,641.19				$1,835.85	-$12,805.34

AL-TOU CCP Marginal Costs (Combined Delivery and Commodity Charges)

Tariff Date	Season	Demand			Energy		
		On-Peak	Non-Coin		On-Peak	Off-Peak	Super Off
2/1/2020	Winter	$19.22	$24.47		$0.1240	$0.1113	$0.0972
1/1/2020	Winter	$19.21	$24.47		$0.1120	$0.1008	$0.0883
6/1/2019	Winter	$17.07	$24.23		$0.1267	$0.1142	$0.1004
6/1/2019	Summer	$27.65	$24.23		$0.1414	$0.1203	$0.0992

APPENDIX B: GOODNESS OF FIT METRICS

Coefficient of Variation of the root mean squared error, CV(RMSE)

$$CV(RMSE) = \frac{\left(\frac{\sum_{i=1}^{n}\left(E_i - \hat{E}_i\right)^2}{(n-p)}\right)^{1/2}}{\bar{E}}$$

CV(RMSE) is a measure of how much random error there is between a model's predictions and the actual data. Generally, the goal is to minimize this error as much as possible.

Net Mean Bias Error (NMBE)

$$NMBE = \frac{\sum_{i=1}^{n}(E_i - \hat{E}_i)}{(n-p)\cdot\bar{E}}$$

NMBE is a measure of the difference between the model's predictions of training period total energy use and the actual energy use. This error should be very low.

Coefficient of Determination

$$R^2 = \left\{\frac{1}{n}\sum\frac{[(x_i-\bar{x})(E_i-\bar{E})]}{\sigma_x\cdot\sigma_E}\right\}^2$$

The coefficient of determination describes how well the independent variables explain the variations in the dependent (energy) variable. Higher R^2 means the independent variables have more explanatory power. This is an informative metric only, not a criterion, because while the energy use sometimes may not have high variation, an independent variable may adequately 'explain' the existing variation in the energy use, despite a low R^2.

Fractional Savings Uncertainty

ASHRAE Guideline 14-2014 provided the following 'fractional savings uncertainty' formulas as a means to estimate the uncertainty of the savings estimated with this modeling approach. The formulas also enable the estimation of how well the savings are known based only on the baseline model's goodness of fit, the number of points in the baseline and post-installation periods, the amount of savings, and the level of confidence at which the uncertainty is estimated. For daily or hourly models, they include a correction for autocorrelation. Using these formulas, the savings uncertainty is estimated, at 90% confidence, for a project that yields 10% savings, with a year of post-installation period monitoring, using a baseline model with its MSE or MSE' value and a year of baseline data. The goal is for the uncertainty to be low, but the minimum level of uncertainty cannot be greater than ± 50% at the 90% confidence level. Note the percentage refers to the amount of savings, not to the baseline energy use.

Additional research by LBNL showed that ASHRAE's formula underestimated uncertainty when used on hourly models, due to the high degree of autocorrelation in the data. This is why uncertainty in hourly models is not reported in the prescreen report.

Savings Uncertainty, models with autocorrelation (hourly or daily):

$$U = \frac{\Delta E_{save,m}}{E_{save,m}} = \frac{\alpha * t_{(1-\alpha)/2,n\prime-p}}{m * \overline{E_{base,n}} * F}\left[MSE'(1+2/n') * m\right]^{1/2}$$

$$MSE = \frac{1}{n'-p}\sum_{i}^{n}(Y_i - \hat{Y}_i)^2$$

Savings Uncertainty, models without autocorrelation (monthly):

$$U = \frac{\Delta E_{save,m}}{E_{save,m}} = \frac{\alpha * t_{(1-\alpha)/2,n-p}}{m * \overline{E_{base,n}} * F}[MSE(1 + 2/n) * m]^{1/2}$$

Energy Savings Required for Uncertainty @ 90% Confidence Interval (10%) = 0.1*E

Where:

E_i is the measured energy use in any time interval, in energy units (kWh or therms)

$\hat{E}_i$ is the model's predicted energy use in any time interval, in energy units

$\bar{E}$ is the average energy use over all the time intervals, in energy units

E is the total energy use over the training time period

$E_{save,m}$is the estimated energy savings over m time periods, in energy units

n is the number of data points in the training period

p is the number of parameters in the model

x_i is the value of the independent variable in any time interval

σ_x is the standard deviation of the distribution of dependent variable values

σ_E is the standard deviation of the distribution of energy use values

$\Delta E_{save,m}$is the absolute precision of the savings estimate over m time periods, in energy units

t is student's t-statistic for the specified confidence level and n-p degrees of freedom

a is an equation depending on the analysis time interval:

a = 1.26 for hourly interval data

a = -0.00024M^2 + 0.03535M + 1.00286 for daily interval data

a = -0.00022M^2 + 0.03306M + 0.94054 for monthly interval data

M is the number of months of reporting period data

n' is the number of data points in the model training period, corrected for autocorrelation

m is the number of data points in the proposed post-installation period

F is the expected savings, expressed as a fraction of training period energy use

Appendix C: Data and Calculation Files

The following data and calculation files were used to generate this report. All external data files will be made available upon request.

Whole-Building Interval Data

SDG&E revenue meter interval data was used to build the regression models as well as in the demand savings and TES energy efficiency calculations.

Weather Data

The historical weather data used to develop the baseline and post-installation regressions was provided by SDG&E. The San Pasqual Valley SDG&E weather station was used for in the analysis:

https://weather.sdgeweather.com/station/SPV

Normalized CZ2018 weather data for the Gillespie Field weather station, compiled by White Box Technologies for utility analysis was used to calculation the Normalized Post-Installation results:

http://calmac.org/weather.asp

Regression Model Calculation Files

The collected data was used to generate the regression model, and the model simulation files using the data analysis program, Universal Translator 3:

http://utonline.org

TOU Tariff Data

The SDG&E tariff data was used to calculate TOU marginal cost savings:

https://www.sdge.com/rates-and-regulations

Project Financials

Project cost data was based on the vendor proposal dated December 5, 2016.