Smart Recirculation Pumps in Central Multifamily DHW Systems: Field Evaluation of Control Strategies

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Executive Summary

This Gas Emerging Technology (GET) field study evaluated the energy performance of smart recirculation pumps with variable-speed electronically commutated motors (ECMs) and integrated control algorithms when retrofitted into existing multifamily (MFm) buildings in California Climate Zone 03 (CZ03). Three sites were monitored over four months to quantify natural gas and electrical energy savings compared to constant-speed baseline pumps. Two control strategies were tested at each site: Adaptive Learning mode and Constant Temperature mode (temperature-based speed modulation). The study addresses critical knowledge gaps in field-validated performance data for smart pump technology used in multifamily domestic hot water (DHW) applications and identified current market barriers.

Project Objectives

- Determine water heater gas energy savings for smart pumps replacing constant-speed DHW recirculation pumps in multifamily residential buildings.
- Compare gas energy savings using various smart pump control modes.
- Document installation costs and implementation requirements.
- Assess customer satisfaction via a quantitative survey.
- Identify market barriers to smart pump adoption for DHW applications.

Technology Description

- Smart recirculation pumps are equipped with variable-speed ECM motors and integrated microprocessor-based control algorithms that dynamically adjust speed and flow rates in response to system conditions.
- Unlike constant-speed pumps that operate at full capacity whenever activated, smart pumps modulate flow to match actual system requirements, reducing both electrical consumption (pump power varies with the cube of speed) and DHW heating fuel (gas in this case) consumption (reduced recirculation thermal losses).
- The Manufacturer A MODEL A and MODEL B pumps tested in this study offer six control modes, including two that were studied:
  - **Adaptive Learning** - Adaptive learning algorithm that adjusts proportional pressure curves based on demand patterns. The supporting literature states that this mode can be used for hydronic heating and DHW recirculation but does not specific suitable demand patterns to adjust the pump.

- **Constant Return Temperature** - Speed modulation to maintain user-defined return water temperature (RWT) setpoint. This mode is primarily used for DHW recirculation applications providing immediate hot water delivery.

Key Findings

- Smart pumps achieved gas savings of 0.9% to 19.4% and electrical savings of 65.1% to 93.2% using adaptive learning mode, and 9.3% to 14.8% and electrical savings of 84.7% to 93.3% using constant temperature mode compared to constant-speed baseline pumps (except for Site #1 at -215.8% due to pump oversizing).[1]
- Annual gas savings across each site is 16.4 therms/year/dwelling unit similar to the SWWH015-03 measure package assumption of 13.22 therms/year per control. There are areas of improvement to vary savings based on baseline conditions.
- Adaptive Learning mode resulted in tenant complaints at two of three sites due to extended hot water wait times during the initial two-to-four-week learning period.
- Constant Temperature mode consistently provides acceptable hot water service when configured with appropriate temperature limits.
- Constant Temperature mode is recommended for most DHW applications with optimal configuration using a 10°F temperature differential and a maximum limit of 10°F below the water heater supply setpoint (e.g., 100-110°F return temperature for a 120°F water heating supply temperature).
- Adaptive Learning mode may be suitable for DHW systems with more predictable demand patterns than those tested where the learning period can be tolerated, but Constant Temperature mode provides immediate, reliable performance without adaptation delays.
- A key barrier identified was the lack of clear manufacturer guidance for DHW applications, as product literature does not clearly distinguish which control modes are suitable for DHW recirculation application vs. hydronic heating applications or provide a temperature limit selection methodology.

Project Recommendations

- Adopt smart recirculation pump technology into California energy efficiency programs with Constant Temperature mode specified for most DHW recirculation applications.

[1] While electric savings percentages (84.7-93.3%) are high, the focus of the study is gas savings (0.9–19.4%), which have a greater relative total savings impact, depending on the system.

- Update measure packages SWWH022 to include control mode requirements and temperature limit guidance, and updated code standards.
- California Program Administrators (PAs) should engage smart pump manufacturers to update product literature with explicit guidance, including recommendations on control strategies for specific DHW applications (vs. hydronic heating applications) and provide clear instructions for temperature limit selection based on system setpoints.
- Future studies should evaluate cloud-connected smart pumps with IoT-based analytics to assess fleet-wide learning capabilities and predictive maintenance benefits.
- Develop installer training programs to ensure proper control mode selection and temperature limit configuration for site-specific DHW applications.

I. Introduction

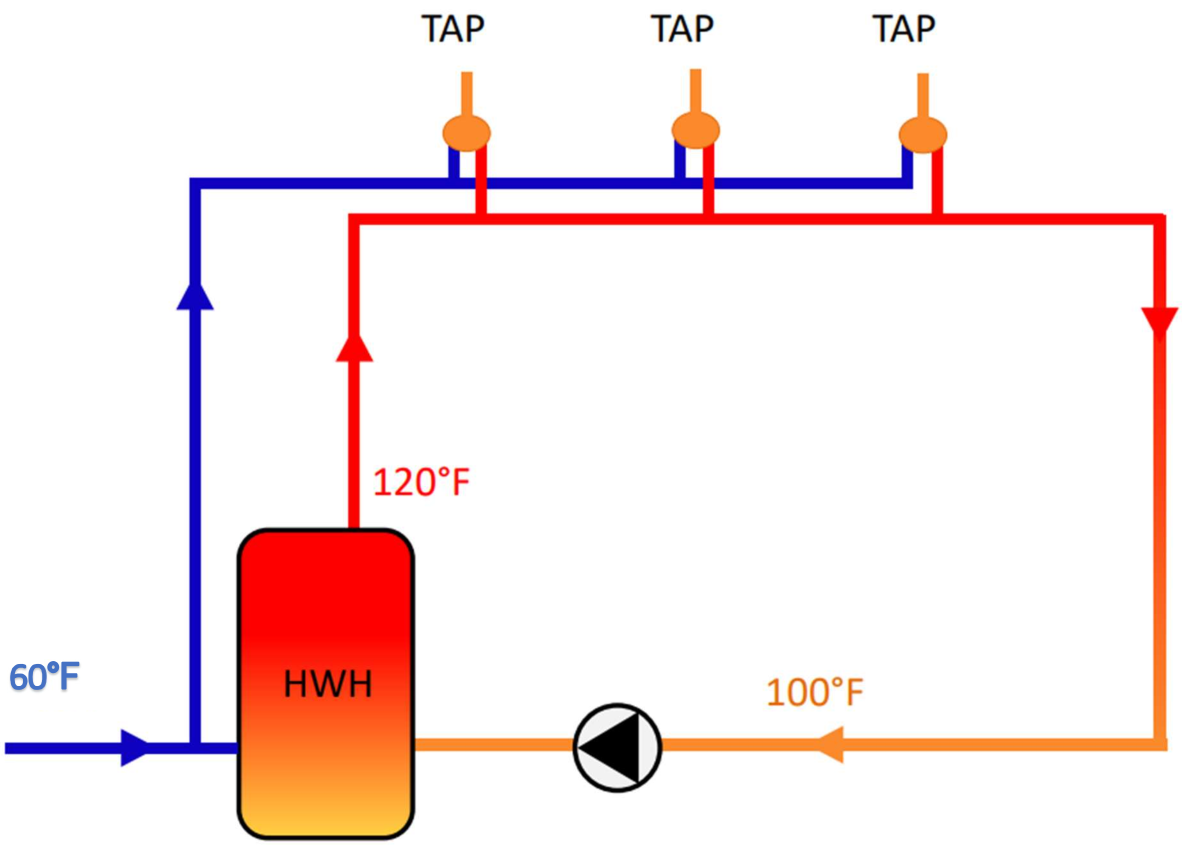
Domestic hot water (DHW) distribution systems in multifamily (MFm) residential buildings face a fundamental trade-off between user convenience and energy efficiency. Occupants expect immediate hot water delivery at fixtures, yet the distance between centralized water heating equipment and individual dwelling units often exceeds 100 feet in larger buildings. This means that cold water must first be purged from supply lines before hot water arrives. This delay, which can range from 30 seconds to several minutes depending on pipe length and flow rates, creates both inconvenience for occupants and wasteful water consumption [1].

To address this challenge, MFm buildings have employed recirculation systems since the mid-20th century. These systems use dedicated return piping and recirculation pumps to maintain a continuous loop of hot water throughout the building, ensuring that heated water is always present near fixtures and ready for immediate delivery when taps are opened. While recirculation systems successfully eliminate wait times and water waste, they introduce significant thermal and electrical energy penalties. The continuous or frequent circulation of hot water through building distribution piping results in substantial heat losses to the surrounding environment, typically ranging from 10% to 30% of total DHW energy consumption [2]. These heat losses require water heaters to fire more frequently to maintain temperature setpoints. Additionally, the recirculation pumps themselves consume electrical energy, with conventional constant-speed motors operating thousands of hours annually regardless of actual hot water demand patterns [3].

The energy consumption of DHW recirculation systems has grown in significance as California pursues aggressive greenhouse gas reduction targets and building decarbonization policies. Natural gas combustion for water heating represents a major end-use in the residential sector, and even modest percentage improvements in DHW system efficiency can yield substantial aggregate energy savings across the state's MFm building stock. California's existing building inventory includes hundreds of thousands of MFm units with central DHW systems, many featuring continuously operating or minimally controlled recirculation pumps installed decades ago when energy costs were low, and efficiency was not a design priority [4]. As these aging pump systems require replacement due to equipment failure or building renovations, opportunities exist to capture energy savings through the installation of more sophisticated variable-speed pump technologies that can adapt recirculation rates to match actual occupant demand.

This field study investigates the real-world energy performance of advanced recirculation pumps with integrated variable-speed motors and adaptive control algorithms when retrofitted into existing small MFm buildings. The research addresses critical knowledge gaps in understanding how these emerging technologies perform under actual operating conditions with real occupant behavior, compared to theoretical modeling predictions and the limited empirical data available from previous studies. By comparing two distinct control strategies across different building types and DHW system configurations, this assessment provides the empirical foundation needed to refine California utility incentive programs, update deemed savings assumptions and accelerate market adoption of energy-efficient recirculation technologies.

Figure 1: Central Gas-Fired DHW System with Recirculation in Multi-Family Buildings [5].



Report Organization

This report documents the complete findings from the field evaluation of smart recirculation pumps at three multifamily sites, with both Adaptive Learning and Constant Temperature control modes tested at each site to provide six distinct operational scenarios. The report is organized as follows:

1. **Background** describes the regulatory context and existing deemed measure packages (SWWH022-01 and SWWH015-03).
2. **Evolution and Technology Description** traces the development of smart pump technology, defines key terms, and explains operating principles and control modes.

3. **Emerging Technology/Product Assessment Objectives** defines the specific research objectives for this Gas Emerging Technology (GET) study.
4. **Previous Studies and Research Findings** summarizes relevant prior research and identifies the knowledge gaps this study addresses.
5. **Incumbent Technology and Current Practice** characterizes the constant-speed pump systems being replaced.
6. **Technology/Product Evaluation** details the study scope, approach, boundaries, and assessment framework.
7. **Site Characterizations** describes each participating building, including DHW system configuration and baseline equipment.
8. **Measurement and Verification Approach** describes the instrumentation plan, data collection procedures, and IPMVP options.
9. **Analysis Procedure** presents the Option B regression approach with equations for each site and rationale for the differing measurement points used for each site.
10. **Quality Assurance Procedures** describes data validation and non-routine event handling.
11. **Results** (in subsequent report sections) presents baseline and post-installation performance data.
12. **Discussion, Conclusions, and Recommendations** (in subsequent report sections) interpret findings and provide guidance.

This study represents one of the first comprehensive field evaluations of smart recirculation pump performance in MFm buildings, measuring both gas and electrical impacts under controlled conditions.

Background

The California Public Utilities Commission (CPUC) currently recognizes deemed measure packages for smart recirculation pump systems. Measure Package SWWH022-01 (Smart Pump, Residential) applies primarily to single-family (SFm) and smaller MFm[2] applications and claims electrical energy savings of 338 kWh per year based on reduced pump operating hours compared to non-controlled baseline pumps. This measure package accounts for weighted average operating hours across different baseline control types: continuous operation (8,760 hours/year), timer controls (6,981 hours/year), timer with Aquastat (1,095 hours/year), and Aquastat-only controls (1,095 hours/year). However, SWWH022-01 does not quantify or claim natural gas savings, despite theoretical evidence

[2] Multifamily residential housing refers to properties containing multiple separate housing units within one building or complex, such as apartments, duplexes, or condominiums. In the context of energy efficiency programs, it is often defined as buildings with five or more units. [30]

suggesting that reduced flow rates and improved temperature control could yield significant thermal energy benefits.

A related measure package, SWWH015-03 (Demand Control for Centralized Water Heater Recirculation Pump, Multifamily & Commercial), does incorporate gas savings estimates derived from eQUEST energy models and Database for Energy Efficient Resources (DEER) prototypes [6]. This measure package claims an average annual gas savings of 13.22 therms/yr and 17.3 kWh/yr across all climate zones for MFm building types. This measure package assumes a small range of fixed supply vs return differential, which is similar to the Constant Temperature mode. However, these savings calculations were not validated through field measurements of actual installed systems.

Evolution of Recirculation Pump Technology and Smart Pumps

The Challenge of Recirculation Losses

Recirculation heat losses represent one of the largest sources of energy waste in MFm DHW systems, accounting for 10-30% of total DHW energy consumption [2]. *The fundamental challenge addressed by smart pump technology is reducing these recirculation losses through optimized control strategies that match circulation rates to actual demand while maintaining acceptable hot water delivery times*. Traditional constant-speed pumps exacerbate this problem by circulating water at maximum flow rates regardless of actual demand, resulting in excessive heat loss, unnecessary electrical consumption, and higher water heater firing rates.

Generational Development

The development of DHW recirculation pump technology has progressed through several generations:

- **First Generation (1950s-1980s):** Constant-speed circulators with no controls, designed for continuous operation [6]. Recirculation losses were uncontrolled.
- **Second Generation (1990s-2000s):** Introduction of timers and Aquastats to reduce operating hours, but pumps remained constant-speed [7] [8] . These controls reduced losses by limiting runtime but could not optimize flow rates.
- **Third Generation (2000s-2010s):** Development of ECMs with variable speed capability, initially requiring external VFD controllers for larger commercial systems [8] . Variable speed enabled proportional reduction in losses.
- **Fourth Generation (2010s-Present):** Integration of variable speed ECM motors with embedded microprocessor-based control algorithms [9] [10] [11]. These pumps adjust speed dynamically without external controllers, enabling real-time optimization.

- **Fifth Generation (2020s-Emerging):** Advanced smart pumps incorporating Machine Learning (ML) and AI algorithms for predictive optimization that anticipates demand before it occurs.

Incumbent Technology and Current Practice

Conventional central DHW recirculation systems typically employ constant-speed centrifugal pumps (typically 1/25 to 1/6 HP) operating under one of several control strategies:

Table 1: Baseline Recirculation Pump Control Strategies

Control Type	Annual Operating Hours	Description
Continuous (No Controls)	8,760	Pumps run 24/7 regardless of demand. Most prevalent in pre-1990 buildings. Maximum energy consumption with substantial standby heat losses.
Timer-Based	~6,981	Fixed schedules during peak periods (e.g., 6-9 AM, 5-10 PM). Reduces runtime but still circulates regardless of actual demand and does not address demand when off.
Aquastat	~1,095	Temperature-sensing activates the pump when the RWT falls below the setpoint (100-110°F). Potentially, more efficient but still full-speed operation when activated.
Timer + Aquastat	~1,095	Combined approach: timers limit circulation periods, and the Aquastat cycle within those windows.

Even with controls, constant-speed pumps operate at full capacity whenever activated, often resulting in over-circulation. Heat losses from recirculation piping account for 10-30% of total DHW energy consumption, depending on pipe insulation, loop length, and circulation strategy [1] [2].

DHW recirculation systems with constant-speed pumps are installed across multiple building segments:

- **MFm Residential Buildings:** The primary market segment consists of apartment buildings, condominiums, and rental properties ranging from small (4-8 units) to large (100+ units) configurations. Buildings with 10-50 units represent the most common size category where centralized DHW systems with recirculation are economically justified. These buildings may feature direct-fired storage water heaters, indirect water heaters with separate boilers, or instantaneous (tankless) water heaters with storage tanks. Older MFm buildings (constructed before 2000) predominantly use continuous or timer-controlled constant-speed pumps, while newer construction may incorporate basic Aquastat controls to meet energy code requirements [7].

- **Hospitality and Lodging:** Hotels, motels, and extended-stay facilities require immediate hot water availability in guest rooms and common areas. These applications typically use larger capacity pumps (1/4 to 1/2 horsepower) and longer recirculation loops to serve multiple floors and building wings. Guest expectations for instant hot water and the operational demands of commercial laundry facilities drive continuous or near-continuous recirculation in these facilities [12].
- **Healthcare Facilities:** Hospitals, nursing homes, and assisted living facilities maintain elevated hot water temperatures (140°F to 160°F) for infection control and utilize continuous or near-continuous recirculation to ensure temperature compliance and immediate availability for patient care [13].
- **Commercial and Institutional Buildings**: Office buildings, schools, and government facilities with centralized DHW systems use recirculation for restroom facilities, kitchens, and shower facilities. Building codes increasingly require recirculation systems in commercial buildings exceeding certain size thresholds to reduce water waste during the delay period before hot water arrival [14].
- **Geographic Distribution:** In California, MFm buildings with DHW recirculation systems are concentrated in urban areas (Los Angeles, San Francisco Bay Area, San Diego, Sacramento) where MFm housing stock is prevalent. Climate Zone 03 (San Francisco Bay Area) contains a significant portion of California's older MFm building inventory, with many buildings dating to the early to mid-20th century and employing continuous or minimally controlled recirculation pumps [4].

Within these market segments, the current study focuses specifically on small-to-medium MFm residential buildings (10-20 units) with centralized gas-fired DHW systems, as this segment represents both the greatest potential for energy savings and the largest gap in empirical field performance data.

Smart Pumps

Smart pumps are recirculation pumps equipped with variable-speed ECMs and integrated control algorithms that dynamically adjust speed and flow rates in response to system conditions, reducing both electrical consumption and gas energy required to compensate for recirculation thermal losses [1] [9] [10].

This study tests the Manufacturer A MODEL A (Site #1) and Manufacturer A MODEL B (Sites #2 and #3) smart pumps, which offer the following control strategies:

Table 2: Smart Pump Control Modes and Common Applications

Control Mode	Description	Common Applications
Proportional Pressure	Pump continuously adapts performance to varying flow demand; as flow changes, pressure changes proportionally.	Hydronic heating systems with thermostatic radiator valves; variable-flow HVAC systems
Adaptive Learning	Pump continuously adjusts the proportional pressure curve and automatically sets a more efficient curve without compromising comfort. Factory default mode.	General DHW recirculation; residential hydronic heating; applications where system characteristics are unknown or variable
Flow Adaptive Learning	Combination of Adaptive Learning with flow limit; monitors flow rate and prevents exceeding the maximum	Systems requiring flow limitation; applications with risk of oversupply
Constant Pressure	Pump maintains a constant discharge pressure regardless of flow	Pressure boosting applications; systems requiring stable pressure at varying flows
Constant Temperature	User sets target liquid temperature; pump modulates flow to maintain setpoint.	DHW recirculation with specific temperature requirements; systems with temperature-sensitive loads; SWWH015-03 DHW applications
Constant Curve	Pump operates at a fixed flow/head duty point.	Replacement of constant-speed pumps; systems with known, fixed operating requirements

Two primary control strategies were selected for this study: **Adaptive Learning mode**, which continuously adjusts pump performance based on system demand patterns learned over time and automatically sets a more efficient proportional pressure curve without compromising comfort demands, and **Constant Temperature mode**, which modulates pump speed to maintain a user-defined RWT setpoint while varying flow rates to match actual demand.

Machine Learning and Adaptive Control Algorithms

Recent developments in smart pump technology have introduced sophisticated learning algorithms that offer potential for further reducing recirculation losses via the following [15] [16] [17]:

- Pattern Recognition: Modern smart pumps analyze historical usage data to identify recurring demand patterns (morning peaks, evening bathing, overnight low-demand), preemptively adjusting circulation rates. ML-based prediction models can achieve $R^2 >$ 0.98 for DHW demand forecasting [17].

- Adaptive Learning: The Adaptive Learning mode tested in this study represents an early implementation. More advanced implementations use reinforcement learning techniques such as the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm that optimizes setpoints, heating schedules and mode selection [15], achieving more stable control than traditional methods.
- Cloud-Based Analytics: Manufacturers, including Manufacturer A, offer cloud-connected pumps (e.g., Manufacturer A iSOLUTIONS) that aggregate data from thousands of installations for fleet-wide learning [18] [19]. Research by Fraunhofer ISE demonstrated 5-13% energy savings with AI-controlled systems [20].
- **Multi-Sensor Integration:** Emerging smart pump systems integrate data from multiple sensors (temperature, flow, pressure, occupancy) to build comprehensive models of system behavior [26]. These models enable predictive control strategies that account for factors such as:
  1) Time-of-day demand variations
  2) Day-of-week patterns (weekday vs. weekend)
  3) Seasonal changes in inlet water temperature
  4) Occupancy-based demand prediction
  5) Weather-correlated usage patterns

Recommendation for Future Studies: Given the rapid advancement of cloud-connected smart pump technology and AI-based control algorithms, future field studies should evaluate the performance of IoT-enabled pumps with cloud-based analytics (such as Manufacturer A iSOLUTIONS or similar platforms) in MFm DHW applications. Such studies should provide valuable data on: (1) the effectiveness of fleet-wide learning algorithms compared to standalone adaptive control, e.g., Adaptive Learning mode, (2) the practical benefits and challenges of remote monitoring and predictive maintenance, and (3) the cybersecurity and data privacy considerations for connected building systems.

Emerging Technology/Product Assessment Objectives

The primary objective of this field assessment is to quantify the natural gas and electrical energy savings achieved by replacing non-controlled constant-speed DHW recirculation pumps with smart recirculation pumps operating under two distinct control strategies (Adaptive Learning and Constant Temperature modes) in existing MFm residential buildings.

Primary Objectives

This technology assessment was designed to address the following specific objectives:

1. **Energy Savings Quantification:** Measure and document actual gas consumption (therms) and electrical consumption (kWh) under baseline constant-speed pump operation and post-retrofit smart pump operation. Establish statistically valid savings estimates normalized for weather conditions and varying hot water demand using a multivariable regression analysis based on available data to enable a fair comparison.
2. **Control Strategy Comparison:** Directly compare the energy performance of two smart pump control modes (Adaptive Learning and Constant Temperature) by testing both strategies sequentially at the same buildings. This approach eliminates building-to-building variability and provides clear evidence of relative performance under identical conditions.
3. **Installation Cost Documentation**: Document actual installation costs, including materials and labor required for smart pump retrofits.
4. **Customer Satisfaction Assessment:** Evaluate occupant comfort and satisfaction with hot water delivery under different control modes. Document any tenant complaints or hot water delivery delays associated with each control strategy to inform optimal control mode selection for different applications.
5. **Address Market Barriers:** Identify barriers to market adoption of smart pump technology, including first cost premiums, installer training requirements, manufacturer guidance gaps, and control mode selection challenges.

Deliverables and Use

The primary deliverables from this assessment were a comprehensive field study report documenting:

- Baseline and post-installation energy consumption data
- Calculated gas and electrical savings by control mode
- Installation costs and implementation requirements
- Market barrier identification and mitigation recommendations

This was a technology assessment focused on quantifying energy savings and demand reduction over incumbent constant-speed pump technology through field measurements at occupied MFm buildings.

Potential Future Applications

This field study informed: (1) retrofit market development for recirculation pump replacements, (2) new construction specifications for code compliance, (3) utility program expansion with validated savings data, and (4) combined efficiency strategies with other DHW measures, e.g., heat pump water heaters.

Previous Studies and Research Findings

While the potential for energy savings from improved recirculation pump controls has been recognized in the literature, empirical field data quantifying both gas and electrical performance remained limited. The following table summarizes the most relevant prior research, followed by detailed descriptions of each study's methodology and findings.

Table 3: Summary of Previous DHW Recirculation Pump Study

Study	Year	Scope	Key Findings
Illinois SAG/Manufacturer A [21]	2014	2 MFm sites (41-45 units)	20-28% gas savings, 578-725 kWh electrical savings
NREL Control Strategies [2]	2016	Lab + field analysis	Up to 60% pump electrical reduction, 20-40% DHW fuel savings
PG&E HPC Pump Study [22]	2017	Residential applications	Significant electrical savings; no gas data (basis for SWWH022-01)
NREL Control Retrofits [23]	2017	2 MFm sites (50 units, NY)	15% DHW fuel savings, projected 30-40% with variable speed
Sempra Energy VFD Study [24]	—	3 MFm sites (SoCal)	7.2-25.3% gas savings with aftermarket VFD controllers
Energy Solutions Modeling [25]	2021	Theoretical analysis	Projected >50% gas savings (not field-validated)

Illinois SAG/Manufacturer A Demand-Based DHW Recirculation Project (2014)

This Illinois Stakeholder Advisory Group pilot study evaluated demand-based controls at two 41-45 unit MFm sites, comparing continuous baseline operation to demand-controlled recirculation where the pump activates on flow sensing plus temperature setpoint [21] . Using weekly alternating modes, the study monitored boiler gas firing and pump runtime/electricity. Results showed 20-28% gas savings (1,855-2,282 therms/year), 578-725 kWh electrical savings, and 1-1.5 year payback. The study validated that intelligent demand-based optimization can achieve substantial runtime reductions while maintaining hot water availability, providing a direct analog to the Adaptive Learning control strategy tested in the current study.

NREL: Control Strategies to Reduce Energy Consumption of Central DHW Systems (2016)

This National Renewable Energy Laboratory study combined laboratory testing and field analysis of various DHW recirculation control strategies, including variable speed and demand modulation in MFm contexts [2]. Using simulations and monitoring normalized for temperature differential and volume, the research documented up to 60% pump electrical energy reduction and 20-40% total DHW fuel savings through reduced loop heat losses. The study established that variable speed pumps operating in adaptive modes can simultaneously reduce pump electrical consumption and water heating gas usage.

PG&E HPC Pump Field Study (2017)

This PG&E study evaluated the Manufacturer A MODEL B pump series in residential applications, focusing exclusively on electrical energy savings from reduced pump power consumption and operating hours [22]. The study did not investigate or quantify potential natural gas savings from reduced DHW system heat losses. While demonstrating significant electrical savings compared to constant-speed baseline pumps, the absence of gas consumption data left a critical gap in understanding total energy impact. This study established the foundation for the current SWWH022-01 measure package, which claims electrical savings but does not account for reduced water heating energy benefits.

NREL: Control Retrofits for MFm DHW Recirculation Systems (2017)

This NREL field study at two 50-unit New York MFm buildings implemented demand-based controls (pump runs on demand or when return water temperature drops below 100°F) with temperature setback during off-peak hours [23]. Pre/post monitoring with normalization for temperature differential and outdoor air temperature documented 15% DHW fuel savings, pump runtime reduced to approximately 14 minutes per day, and annual savings of approximately $1,250 per building. In the larger 50-unit buildings, aggregated daily hot water draws are frequent enough to maintain recirculation temperature without needing constant circulation, but individual pump cycles are short (seconds to a few minutes each). The study projected that combining these controls with variable speed pumps could achieve 30-40% total savings, validating the Constant Temperature control mode tested in the current study.

Sempra Energy VFD Hot Water Recirculation Pump Controller Field Study

This field study at three Southern California MFm sites retrofitted existing constant-speed pumps with aftermarket VFD controllers that modulated speed based on differential temperature sensing, analogous to Constant Temperature control [24]. Results showed gas savings of 7.2-25.3% with electrical savings from reduced operating speeds. Savings variability correlated with recirculation loop length, insulation quality, and baseline pump sizing. While establishing that dynamic speed control can reduce gas consumption, the study had limitations: VFD controllers were external add-ons rather than integrated smart pump systems, and only differential temperature control was evaluated without comparison to adaptive learning approaches. This study served as a key evidentiary basis for the development or validation of SWWH015-03.

Energy Solutions Modeling Study (2021)

This theoretical modeling study used DEER building prototypes to project gas savings exceeding 50% of baseline annual consumption from smart recirculation pumps [25]. The analysis modeled recirculation heat losses through simplified system characterizations but was based entirely on theoretical calculations with numerous assumptions regarding pump operation, heat loss coefficients, flow rates, and schedules. No field measurements were conducted to validate modeled savings under actual operating conditions.

DEER Database and SWWH015 Measure Package

The existing SWWH015-03 measure package incorporates gas savings estimates (13.22 therms/control) derived from eQUEST energy modeling and DEER prototypes. While this methodology provides consistency for deemed measure packages, it has not been validated against field measurements of actual installed systems using different recirculation pump control strategies for comparison.

Research Gaps Identified by Current Study

The existing research demonstrates both theoretical potential and some empirical evidence for energy savings from improved recirculation pump controls. However, significant gaps remain:

1. **Limited field validation** of integrated smart pumps (vs. aftermarket VFD retrofits)
2. **Lack of comprehensive data** measuring both gas (water heating energy) and electrical impacts simultaneously
3. **No assessment** of user acceptance and comfort impacts
4. **Limited sample size** to validate modeled savings assumptions

This study addresses some of these gaps through systematic field measurements at multiple sites, testing multiple control strategies sequentially at each building, and measuring both gas and electrical consumption with high-resolution data logging.

Technology Description

Smart pumps offer significant advantages through variable-speed operation governed by the pump affinity laws.

Operating Principles

The fundamental physics behind smart pump operation relies on the affinity laws governing centrifugal pump performance. According to these laws, pump power consumption varies with the cube of speed:

Equation 1: Pump Affinity Laws

$$P_2 = P_1 \times \left(\frac{N_2}{N_1}\right)^3 (1)$$

Where:

- $\forall$ P_1 = power at speed N_1
- $\forall$ P_2 = power at speed N_2

By reducing pump speed by 50%, electrical pump power consumption decreases to approximately 12.5% of full-speed operation. Smart pumps exploit this relationship by operating at lower speeds during periods of reduced demand, automatically ramping up only when system conditions require increased circulation.

The pumps employ onboard temperature sensors, pressure transducers, and flow calculation algorithms to assess system conditions in real time. Microprocessor controllers analyze these inputs and adjust motor speed through ECM-based variable speed technology integrated directly into the pump housing, eliminating the need for external control and sensing equipment.

Incumbent Technologies Being Replaced

The smart pumps evaluated in this study replace conventional constant-speed recirculation pumps as described in the Incumbent Technology and Current Practice section:

- **Site #1:** The baseline system consisted of a Manufacturer B Series 100 A.B. constant-speed pump (1/12 HP, ~95W) operating 24/7. Due to the unavailability of the Model C pump, a Manufacturer A MODEL A 40-180 F was installed, which proved to be oversized (4/5 HP, 609W maximum) relative to the application.
- **Site #2:** The baseline system consisted of a constant-speed Manufacturer A UP15-18B5 pump (approximately 85W, ~1/12 HP) operating continuously with no controls. The Manufacturer A MODEL B 15-55 was installed.
- **Site #3:** The baseline was a Manufacturer A UP 25-64 SF constant-speed pump (1/12 HP, approximately 180W) with Manufacturer C Aquastat control (115°F RWT Setpoint), modified for continuous operation during the baseline monitoring period. A Manufacturer A MODEL B 15-55 was installed.

Advantages Over Incumbent Technology

Table 4: Smart Pump Technology Advantages

Advantage	Description
Energy Efficiency	60-80% electrical reduction; 7-28% gas savings from reduced thermal losses [24]
Temperature Control	Integrated sensing maintains consistent delivery temperatures vs. on/off cycling.
Reduced Maintenance	ECM motors have longer service life than constant speed pumps; fewer external components
Operational Flexibility	Multiple control modes optimize for specific applications.
Diagnostics	Digital displays and communication for remote monitoring

Market Barriers

Table 5: Market Barriers to Smart Pump Adoption

Barrier	Impact
First Cost	$800- $2,500 vs. $200-500 conventional; 2-7 year payback [26]
Installer Unfamiliarity	Added complexity for setup and commissioning
Split Incentives	Owners pay for equipment; tenants pay utilities.
Limited Field Data	Lack of validated savings creates investment uncertainty.
Measure Package Limitations	SWWH022-01 excludes gas savings; SWWH015-03 not field-validated
Lack of Guidance Documentation	Lack of clear manufacturer guidance for DHW applications to distinguish suitable DHW from hydronic heating applications or provide a temperature limit selection methodology

Technology/Product Evaluation

Study Scope and Approach

The study was originally planned to evaluate the Manufacturer A Model C smart pump at four MFm sites in California. However, market availability challenges necessitated modifications to both the equipment tested and the number of sites enrolled. At the time of implementation, the Model C pump was no longer available through distribution channels, requiring substitution with alternative Manufacturer A smart pump models suited to the specific capacity requirements of each site: the larger MODEL A pump at Site #1 and the MODEL B pump at Sites #2 and #3.

Ultimately, the study successfully enrolled and instrumented three MFm buildings, all located in Climate Zone 03 (San Francisco Bay Area). At all three sites, testing was conducted using both Adaptive Learning and Constant Temperature control modes in sequence, effectively providing performance data for six distinct operational scenarios from three physical installations:

1. **Site #1 - Adaptive Learning mode:** Manufacturer A MODEL A 40-180 F pump serving an 18-unit building (1907 construction) with indirect gas-fired water heating
2. **Site #1 - Constant Temperature mode**: Same system operating with 105°F RWT setpoint
3. **Site #2 - Adaptive Learning mode:** Manufacturer A MODEL B smart pump serving a 12-unit building (1907 construction) with direct gas-fired storage water heating
4. **Site #2 - Constant Temperature mode:** Same system operating with temperature-based speed control
5. **Site #3 – Adaptive Learning mode:** Manufacturer A MODEL B smart pump serving a 10-unit building with direct gas-fired storage water heaters plus solar thermal preheat
6. **Site #3 - Constant Temperature mode:** Same system operating with temperature-based speed control

This approach allowed the study to provide insights into the applicability and performance of smart pump technology across varying MFm building types. Testing both control modes at each site eliminates building-to-building variability and provides clear evidence of relative performance under identical conditions.

Note: *At Site #1, the unavailability of the originally planned Model C pump required installation of the larger MODEL A pump (4/5 HP, 609W maximum), which proved to be oversized relative to the baseline 1/12 HP pump. This oversizing affected energy performance results, particularly in Constant Temperature mode, where the larger motor consumed significantly more electricity than the baseline system.*

Study Boundaries and Testing Conditions

Table 6: Study Boundaries and Testing Conditions

Parameter	Specification	Rationale
Building Size	Minimum 4-units	Minimum number of units for a central system
Climate Zone	Any CA Climate Zone	High MFm concentration; moderate climate minimizes seasonal impacts.
Water Heating	Gas-fired	Incumbent technologies; primary gas savings target
Baseline Pumps	Constant-speed	Clear baseline for savings differentiation
Control Modes	Adaptive Learning and Constant Temperature	Factory default + SWWH015-03 aligned strategy
Monitoring	4-week baseline; 12-week (or 90 days) post per mode	Captures the learning period and hot water demand variation

Assessment Type and Comparative Framework

This field assessment at occupied buildings was selected to capture real-world conditions (weather, occupant behavior, system interactions) that cannot be replicated in laboratory or modeling studies. Field measurements provide empirical validation of theoretical savings and reveal user comfort impacts under actual occupancy.

Table 7: Assessment Framework

Component	Specification
Baseline Technology	Constant-speed pumps (1/12-1/25 HP, 85-180W) w/ constant or Aquastat control
Emerging Technology	Manufacturer A MODEL A/MODEL B smart pumps with ECM motors
Comparison Metrics	Gas consumption (therms), electrical consumption (kWh), installation costs, and user comfort

The specific IPMVP approaches and data analysis methodologies are detailed in the

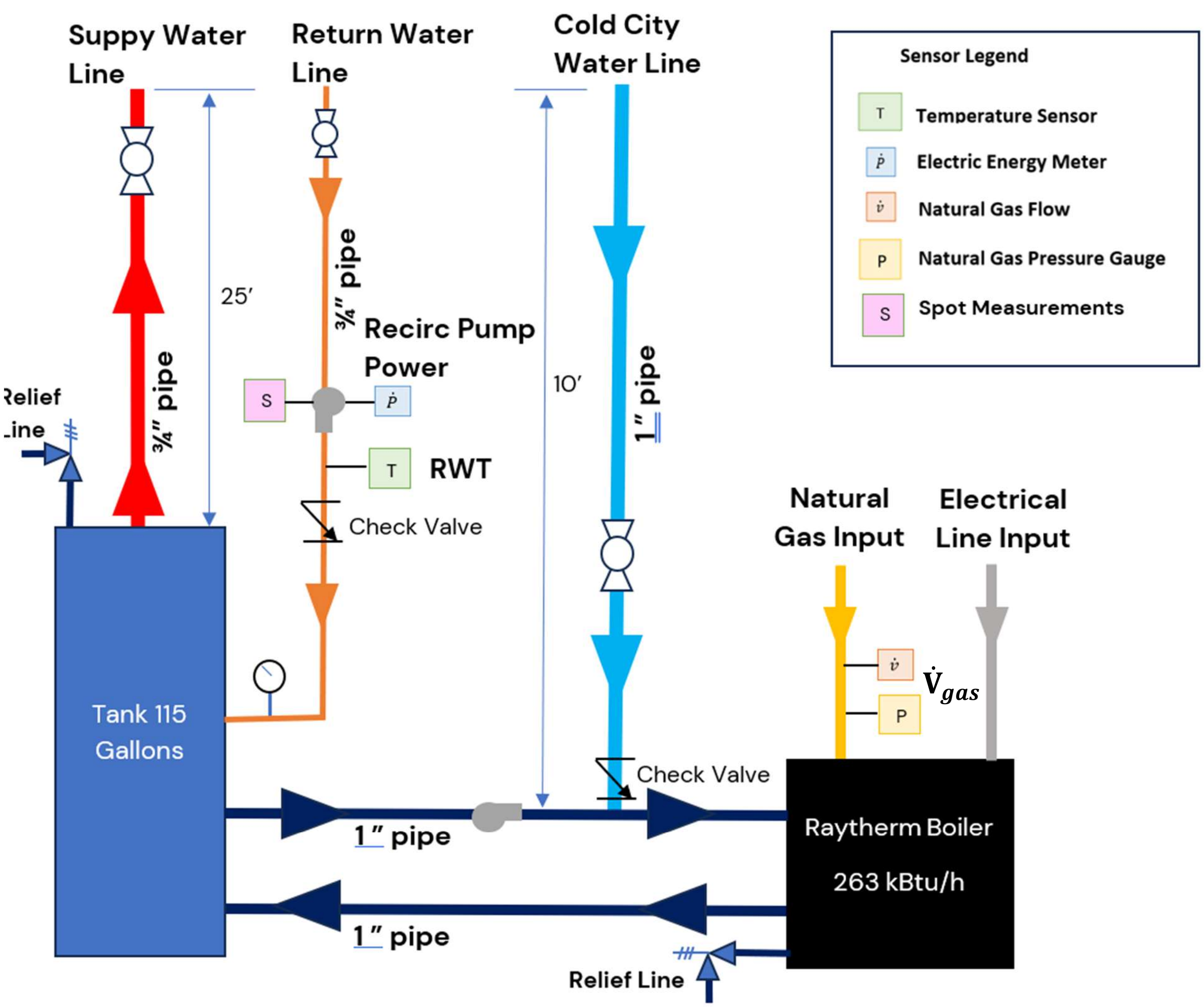
Appendix A. Measurement and Verification Plan section.

II. Site Characterizations

Site #1

System Diagram

Figure 2: Site #1 Pre-Installation Baseline & Post-Installation Prototype Schematic



(*Note:* *The return line connects directly to the dedicated circulation port on the storage tank)*

Building Overview

Table 8: Site #1 Building Characteristics

Characteristic	Value
Building Type	4-story MFm residential
Year Built	1907
Number of Units	18
Total Area	15,432 sq. ft.
Climate Zone	CZ03 (San Francisco)
In-Unit Laundry	None
Occupancy	100%[3]

DHW System

Table 9: Site #1 DHW System Specifications

Component	Specification
Water Heater Type	Indirect gas-fired storage
Model	Raypak WY-0263B
Quantity	1
Tank Volume	119 gallons
Input Capacity	263,000 Btu/hr
Recover Rate	~315 GPH (estimated)
Thermal Efficiency	82%
Location	Basement

Recovery Rate Estimation for Raypak WY-0263B (assuming standard 100°F temperature rise):

$$Recovery\ Rate\ (GPH) = \frac{Input\ Rate\ \times Eff}{8.33\ lb_m/gal \times 100\text{°F}} = \frac{263\ kBtu/h\ \times 0.82}{8.33\ lb_m/gal \times 100\text{°F}} \approx 315\ GPH$$

[3] Occupancy rates did not change from the baseline to post-installation periods. Customer surveys were conducted during the baseline and post-installation to check for changes in occupancy.

Recirculation System

Table 10: Site #1 Recirculation System Comparison

Parameter	Baseline	Post-Installation
Pump Model	Manufacturer B Series 100 A.B.	Manufacturer A MODEL A 40-180 F
Motor Type	AC induction (constant-speed)	ECM (variable speed)
Power	~95W (1/12 HP)	609W max (4/5 HP)
Control	24/7 continuous operation	Adaptive Learning/ Constant Temperature (105°F)

Note on Pump Sizing: The MODEL A pump installed at this site has significantly higher capacity (4/5 HP, 609W maximum) than the baseline pump (1/12 HP). This oversizing resulted from the unavailability of the originally planned Model C pump. The larger motor affected energy performance in two ways: (1) in Constant Temperature mode, the pump operates at higher speeds to maintain the temperature setpoint, consuming more electricity than the baseline system, and (2) in Adaptive Learning mode, the pump was unable to effectively adapt to the low flow requirements of this relatively small building, as the MODEL A's minimum operating point exceeds the optimal flow rate for efficient recirculation in an 18-unit building, resulting in lower-than-expected gas savings in Adaptive Learning mode.

M&V Reporting Periods

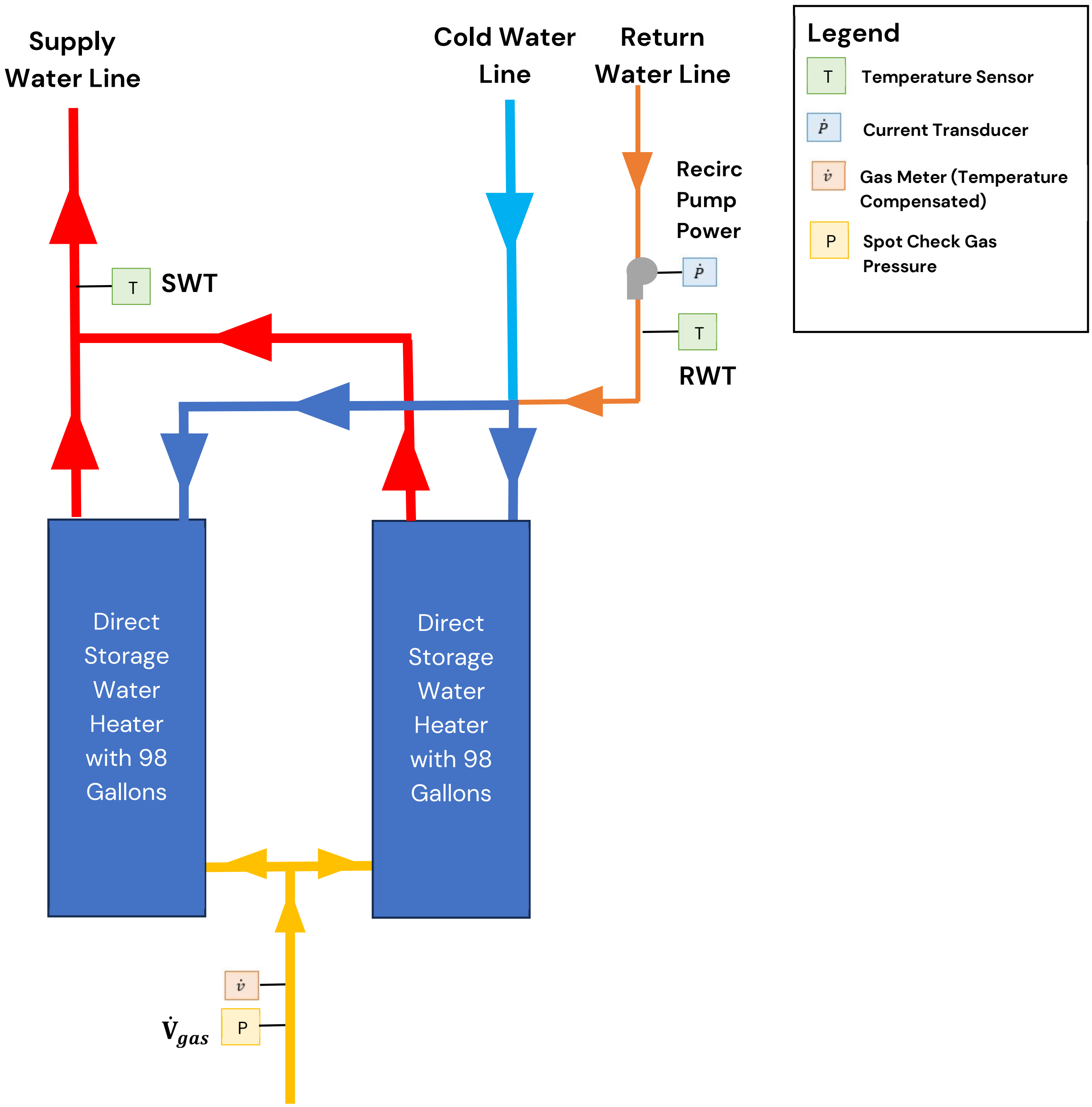
Table 11: Site #1 M&V Reporting Periods

Period	Duration	Notes
Baseline	39 days (05/29/24 - 08/13/24)	Two RWT regimes: avg 115.38°F (through 6/22/24), then 106.66°F due to unplanned water heater operational changes
Post-Installation (Adaptive Learning)	91 days	08/16/24 - 09/15/24, 01/15/25 – 02/21/25, 03/28/25 - 04/21/25; setpoint range 95-102°F
Post-Installation (Constant Temperature)	111 days (09/18/24 - 01/13/25)	Setpoint range 95-102°F

Site #2

System Diagram

Figure 3: Site #2 Pre-Installation Baseline & Post-Installation Prototype Schematic



Building Overview

Table 12: Site #2 Building Characteristics

Characteristic	Value
Building Type	4-story MFm residential
Year Built	2016
Number of Units	12
Total Area	7,008 sq. ft.
Climate Zone	CZ03 (San Francisco)
Laundry	None
Occupancy	100%[4]

DHW System

Table 13: Site #2 DHW System Specifications

Component	Specification
Water Heater Type	Direct gas-fired storage
Model	State GS6100URRT 100
Quantity	2
Tank Volume	98 gallons each
Input Capacity	75,000 Btu/hr each
First Hour Rating	120 gallons each
Recovery Rate	73.73 GPH each
Thermal Efficiency	81%
Location	Roof

[4] Occupancy rates did not change from the baseline to post-installation periods. Customer surveys were conducted during the baseline and post-installation to check for changes in occupancy.

Recirculation System

Table 14: Site #2 Recirculation System Comparison

Parameter	Baseline	Post-Installation
Pump Model	Constant-speed	Manufacturer A MODEL B
Motor Type	AC induction	ECM (variable speed)
Power	85W (~1/12 HP)	Variable (ECM)
Control	24/7 continuous operation (no controls)	Adaptive Learning/ Constant Temperature

M&V Reporting Periods

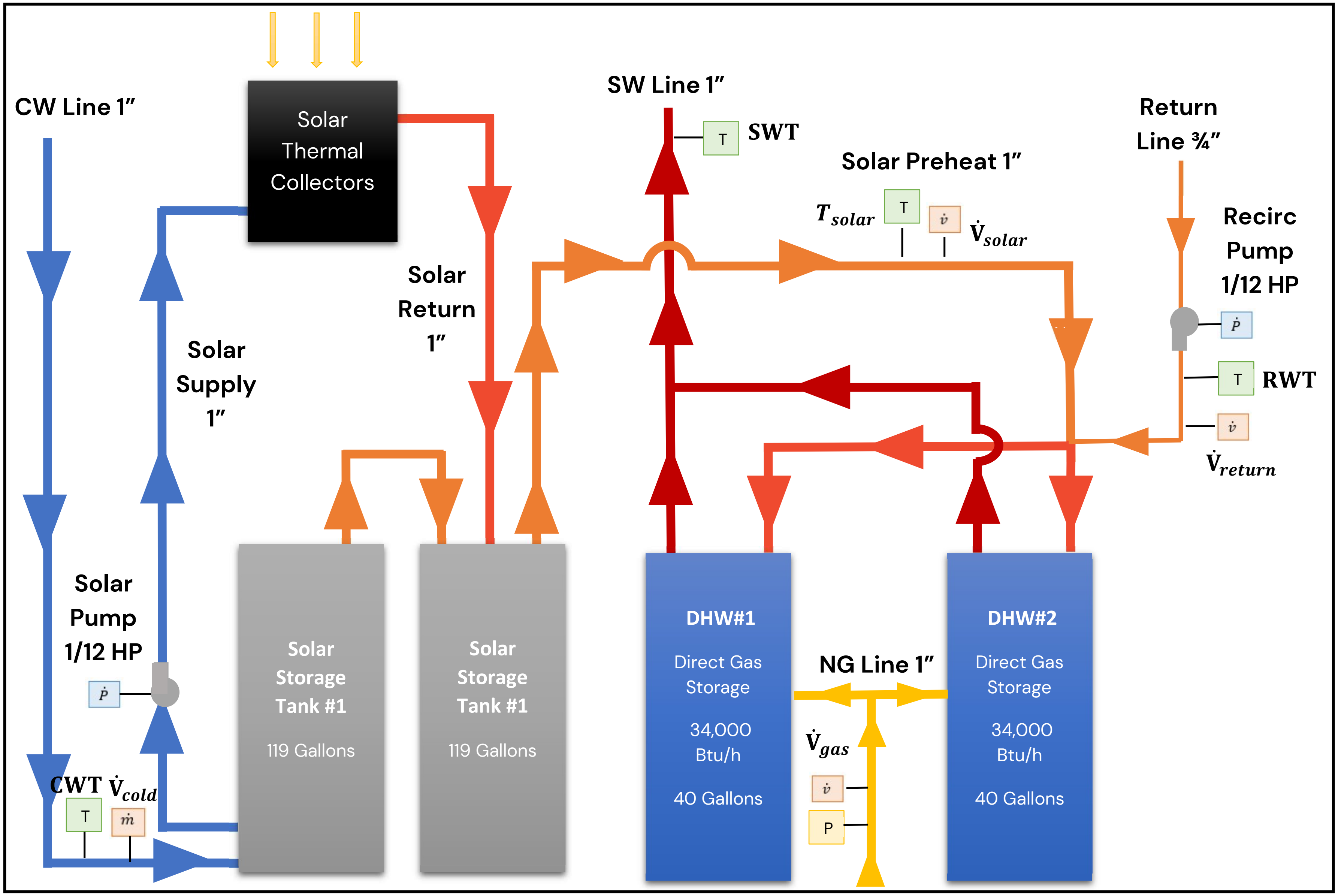
Table 15: Site #2 M&V Reporting Periods

Period	Duration	Notes
Baseline	45 days (10/26/24 - 12/09/24)	Continuous operation
Post-Installation (Adaptive Learning mode)	~118 days (01/28/25 - 05/26/25)	Gap due to water heater repair
Post-Installation (Constant Temperature mode)	~96 days (05/27/25 - 08/31/25)	—

Site #3 System Diagram

See next page.

Figure 4: Site #3 Pre-Installation Baseline & Post-Installation Prototype Schematic



Building Overview

Table 16: Site #3 Building Characteristics

Characteristic	Value
Building Type	MFm residential
Year Built	1950
Number of Units	10
Total Floor Area	7,694 sq. ft.
Climate Zone	CZ03 (Berkeley)
Laundry	Common-Area
Occupancy	100%[5]

DHW System

Table 17: Site #3 DHW System Specifications

Component	Specification
Water Heater Type	Direct Gas-fired storage
Water Heater Model	Bradford White URG140T6N
Quantity	2
Tank Volume	40 gallons each
Input Capacity	34,000 Btu/hr each
First Hour Rating	67 gallons
Recovery Rate	37 GPH each
Energy Factor (EF)	0.59
Location	Common laundry room

Solar Thermal Preheat System

Table 18: Site #3 Solar Thermal Preheat System

Component	Specification
Solar Storage Tanks	2 tanks, 119 gallons each
Function	Pre-heat incoming cold city water
Solar Pump	Manufacturer A UP 25-64 SF (1/12 HP)
Control	Activates when ΔT ≥ 14°F (collector temp ≥ 70°F)

[5] Occupancy rates did not change from the baseline to post-installation periods. Customer surveys were conducted during the baseline and post-installation to check for changes in occupancy.

Recirculation System

Table 19: Site #3 Recirculation System Comparison

Parameter	Baseline	Post-Installation
Pump Model	Manufacturer A UP 25-64 SF	Manufacturer A MODEL B
Motor Type	Constant-speed	ECM (variable speed)
Power	180W (~1/12 HP)	Variable (ECM)
Original Control	Manufacturer C Aquastat	Adaptive Learning / Constant Temperature
Baseline Modification	Set to continuous operation	N/A

M&V Reporting Periods

Table 20: Site #3 M&V Reporting Periods

Period	Duration	Notes
Baseline	55 days (04/30/25 - 06/24/25)	Constant-speed operation
Post-Installation (Adaptive Learning mode)	91 days (06/26/25 - 09/24/25)	Setpoint range 95-102°F, then 100-105°F
Post-Installation (Constant Temperature mode)	84 days (09/25/25 - 12/18/25)	Setpoint range 100-110°F

III. Quality Assurance Procedures

The M&V Team processed, checked, and analyzed all data to ensure all anomalies had been considered and reasonably addressed. The DHW heater natural gas use, return water temperature, and smart pump operating hour data were checked for consistency and errors. Another engineering manager also reviewed the report and calculations for quality control. As stated in previous sections, if there was any data loss for any measurement point, adequate staff were deployed on-site to resolve the issue, and an appropriate data loss procedure followed to minimize the impact of such a loss.

Non-Routine Event (NRE) Handling

In addition, verification was performed to ensure the integrity of the collected data sets. The data was evaluated to identify and adjust for non-routine events (NREs). These events were defined as events within the building or changes to the DHW system, occurring outside of the project's installed energy efficiency measures' scope, which affect the system's load and therefore energy use measured at the meters. Adjustments to baseline energy use were necessary to normalize gas savings to isolate the project's installed energy efficiency measures.

When quantifying how an NRE impacts the baseline or post-installation periods, the following methodology was considered:

> Data Salvaging Method: Removing data from the short period during which the NRE occurred, developing regression models with the valid data, and using those models to salvage missing data within the same test period and quantify savings. The NRE impacts were determined by comparing daily totals and averages within the same period (baseline or post-installation). When there were days with values outside three standard deviations for that test period, those values were analyzed and replaced with multivariable regression model values using valid data points as independent variables. This occurred due to faulty or disconnected flow meters, or malfunctioning data loggers that lost communication with the cloud server due to faulty SIM cards.

This process will adhere to the guidelines and recommendations issued in the *IPMVP - Application Guide on Non-Routine Events & Adjustments*.

IV. Results

Cross-Site Comparison

Table 21: Site Summary Comparison

Parameter	Site #1	Site #2	Site #3
Building Type	18-unit, 4-story	12-unit, 4-story	10-unit
Year Built	1907	2016	1950
DHW System	Indirect gas-fired	Direct gas-fired	Direct gas-fired
System Year Built	1987	2014	2020
Capacity	263 kBtu/hr	2×75 kBtu/hr	2 x 34 kBtu/h + thermal solar preheat
Storage Volume	119 gallons	2 x 98 gallons	2 x 40 gallons
Baseline Pump	Manufacturer B Series 100 A.B. 1/12 HP	Manufacturer A UP 15-18B5 85W	Manufacturer A UP 25-64 SF 180W
Smart Pump	Manufacturer A MODEL A 4-180 F N 216 (oversized)	Manufacturer A MODEL B 15-55 SF/T	Manufacturer A MODEL B 15-55 SF/T
Baseline Period	39 days	45 days	55 days
M&V Approach	Option B Regression	Option B Regression	Option B Regression

Table 22: Energy Savings Summary by Control Mode

Site	Control Mode	Gas Savings (%)	Gas Savings (therms/yr)	Electric Savings (%)	Electric Savings (kWh/yr)
Site #1	Adaptive Learning	0.9%	16.7	65.1%	446.0
Site #1	Constant Temp	7.9%	149.4	-215.8% (increase)	-1,479.4 (increase)
Site #2	Adaptive Learning	18.7%	238.4	79.4%	220.9
Site #2	Constant Temp	8.1%	103.0	84.7%	235.5
Site #3	Adaptive Learning	19.4%	313.4	93.3%	1,077.0
Site #3	Constant Temp	14.3%	298.6	93.2%	1,076.6

Note: *Site #1 Constant Temperature mode electrical increase due to oversized MODEL A 40-180 pump (4/5 HP vs. 1/12 HP baseline).*

Figure 5: Gas savings percentage by site and control mode.

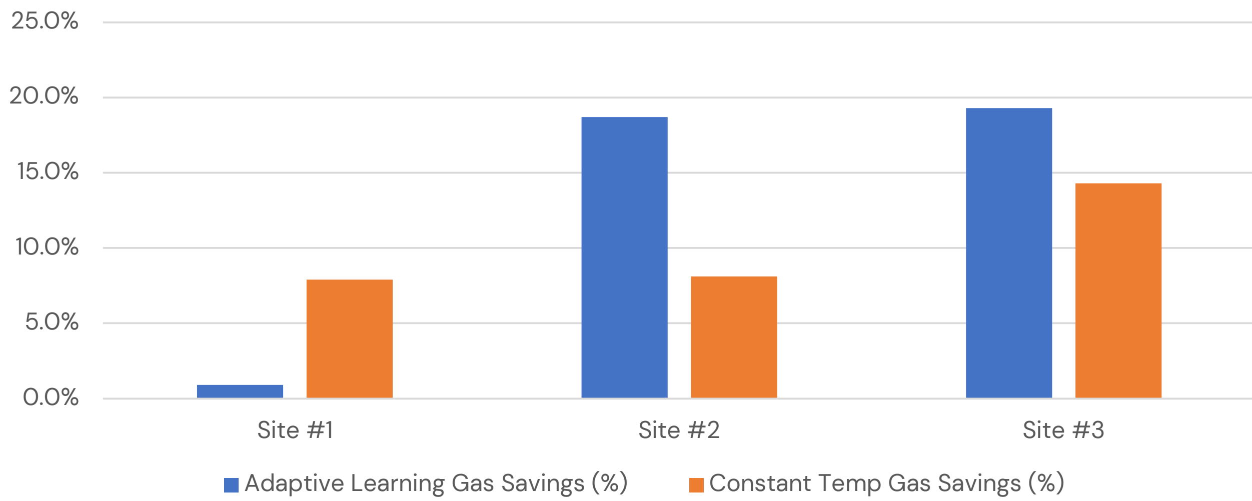
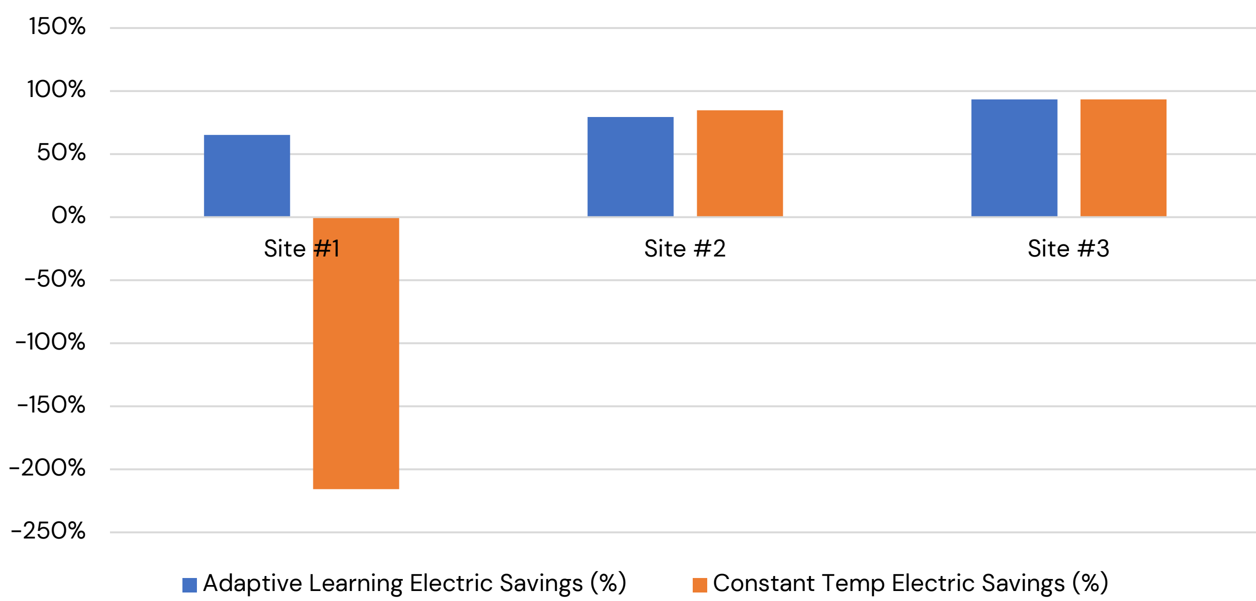


Figure 6: Electrical savings percentage by site and control mode.



Annual Savings Comparison to Measure Package Claims

Table 23: Annual Savings Comparison to SWWH022 and SWWH015 Claims

Parameter	SWWH022 Claim	SWWH015 Claim (CZ03)	Site #1 Achieved	Site #2 Achieved	Site #3 Achieved
Gas Savings (therms/yr/dwelling unit)	Not claimed	13.22	0.9 (AL) / 8.3 (CT)	19.8 (AL) / 8.6 (CT)	31.1 (AL) / 29.9 (CT)
Electric Savings (kWh/yr/smart pump)	338	Not primary (only 17.3 kWh)	446 (AL) / - 1,479 (CT)	221 (AL) / 236 (CT)	1,077 (AL) / 1,077 (CT)

Note: *CC = Constant Temperature, AL = Adaptive Learning*

Key Findings:

- Average therm savings across all sites and both controls is 16.4 therms/yr/unit vs 13.22 therms/yr/unit (19.4% increased savings). It should be noted that the high savings from Site #3 are due to high baseline pump consumption, so the expected savings are dependent on the baseline conditions.
- Adaptive Learning achieved higher gas savings than Constant Temperature at Sites #2 and #3 using properly sized pumps.
- Site #1 Adaptive Learning did not show savings due to oversizing as the MODEL A pump could not adapt at low flows rates.
- Site #1 Constant Temperature outperformed Adaptive Learning for gas savings despite the oversized pump.
- Electrical savings varied significantly based on pump sizing and baseline conditions, i.e., high baseline pump energy consumption for Site #3.

Figure 7: Comparison of measure package gas savings (per dwelling unit)

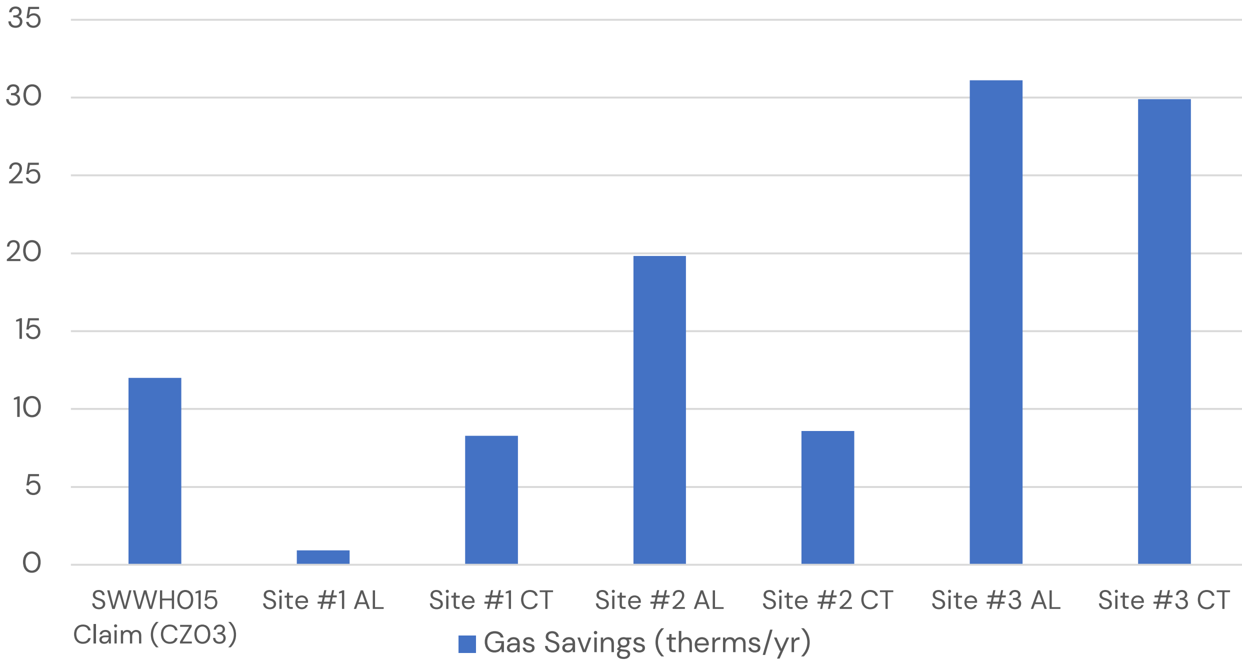


Figure 8: Comparison of measure package electricity savings (kWh)

Customer Feedback and Tenant Satisfaction

Customer acceptance is a critical factor in the successful deployment of smart recirculation pump technology. This section documents tenant feedback collected during the study and provided insights into the relationship between control mode selection, system design, and occupant satisfaction.

Site #1: Customer Feedback

Adaptive Learning Mode (Initial Period - August 2024): During the first two weeks of Adaptive Learning operation, the building manager received multiple tenant complaints regarding extended hot water waiting times. This occurred during the pump's learning period when the adaptive algorithm was still characterizing system demand patterns. The complaints prompted the study team to switch to Constant Temperature mode earlier than planned with increased temperature limits to reduce hot water wait times.

Constant Temperature Mode (September 2024 - January 2025): After switching to Constant Temperature mode with a 105°F setpoint, tenant complaints ceased. The temperature-based control provided consistent hot water availability without requiring a learning period.

Adaptive Learning Mode (Return - January 2025): When Adaptive Learning mode was reinstated on 1/13/25, no tenant complaints were received. This suggests the pump had retained its learned demand patterns from the initial period, or that tenants had adjusted their expectations. The successful return to Adaptive Learning mode after a 4-month gap indicates the algorithm's ability to adapt to building-specific usage patterns given sufficient learning time.

Note: *The non-continuous Adaptive Learning test periods at Site #1 (August-September 2024, then January-April 2025) resulted from this customer feedback-driven mode switching.*

Site #2: Customer Feedback

Adaptive Learning and Constant Temperature Modes: This site used conservative temperature limits of 95-102°F for both Adaptive Learning and Constant Temperature modes throughout the study period. No tenant complaints were received during either control mode. The absence of complaints may be attributed to:

- The rooftop location of the DHW system results in shorter distribution piping runs.
- Newer building construction (2016) with better pipe insulation
- Appropriately sized DHW system relative to building demand (12 units served by two 98-gallon water heaters, 73 GPH recovery rate each)

Site #3: Customer Feedback

Adaptive Learning Mode (Initial Period - 95-102°F): Similar to Site #1, initial Adaptive Learning operation with 95-102°F temperature limits resulted in tenant complaints regarding long hot water waiting times.

Adaptive Learning Mode (Adjusted - 100-105°F): Temperature limits were increased to 100-105°F to address complaints. Some tenant complaints persisted despite the adjustment.

Constant Temperature Mode (100-110°F): Per recommendation from the pump manufacturer (Manufacturer A), the system was switched to Constant Temperature mode with a 100-110°F setpoint range. No further tenant complaints were received after this change.

Analysis: The persistent complaints at Site #3 may be attributable to the undersized DHW system relative to building demand. With only two 40-gallon water heaters serving 10 units (compared to Site #1's 119-gallon tank for 18 units and Site #2's 196-gallon combined capacity for 12 units), the system has limited thermal storage capacity of only 80 gallons for 10 units (8 gallons per unit). This makes the building more sensitive to recirculation control strategies that reduce circulation during low-demand periods.

Summary of Customer Feedback by Site

Table 24: Customer Feedback Summary

Site	Adaptive Learning Complaints	Resolution	Constant Temp Complaints	Key Factor
Site #1	Yes (initial 2 weeks)	Switch to Constant Temp; later successful return to Adaptive Learning	None	Learning period: oversized pump
Site #2	None	N/A	None	Rooftop system; shorter piping; appropriate sizing
Site #3	Yes (persistent)	Increased temp limits; switch to Constant Temp per mfg. recommendation	None	System not suitable for Adaptive Learning

Lessons Learned for Customer Acceptance

1. Learning Period Communication: Building managers should inform tenants that a 2 week adjustment period may occur when Adaptive Learning mode is first activated, during which hot water delivery times may be temporarily longer than normal.
2. System Sizing Considerations: Buildings with undersized DHW systems may not be suitable for adaptive control strategies. Constant Temperature mode may be more

appropriate for these applications. Buildings with sizing ratios near or below 8 gallons/unit may be better suited for Constant Temperature control based on Site #3 results.

3. Temperature Limit Selection: Conservative temperature limits (95-102°F) may not provide adequate hot water availability in DWH applications. Higher limits (100-110°F) may be necessary, particularly for buildings with longer distribution runs or undersized systems.
4. Manufacturer Support: Lacking adequate pump documentation, consultation with pump manufacturers regarding optimal control mode and setpoint selection was needed and may be required to help avoid customer satisfaction issues.

Customer Satisfaction Survey

To quantify tenant satisfaction and assess the likelihood of building owner adoption, a standardized survey was administered at each site at the end of the post test periods to the building owners. The survey used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) to evaluate key satisfaction metrics.

Survey Questions and Results

Table 25: Customer Satisfaction Survey Results

Question	Site #1	Site #2	Site #3	Average
Q1: Hot water is available within an acceptable wait time after the smart pump was installed.	3.8	4.5	3.2	3.8
Q2: The hot water temperature is consistent and meets my expectations.	4.2	4.6	3.8	4.2
Q3: I did not experience any significant disruption to hot water service during the study period.	3.5	4.7	2.9	3.7
Q4: I would recommend smart recirculation pump technology to other building owners/managers.	4.0	4.8	3.5	4.1
Q5: The energy savings potential justifies any minor inconveniences experienced during the adjustment period.	3.9	4.6	3.6	4.0
Overall Satisfaction Score	3.9	4.6	3.4	4.0

Survey Results Analysis

Site #1: Moderate satisfaction (3.9/5.0) reflects the initial complaints during the start of the Adaptive Learning period, tempered by improved performance after the return to Adaptive Learning mode in January 2025. The building manager indicated willingness to recommend with appropriate expectations management.

Site #2: High satisfaction (4.6/5.0) with no significant issues reported. The rooftop system configuration and appropriate DHW sizing contributed to seamless operation. The building manager expressed strong enthusiasm for the technology and intent to install smart pumps in other properties.

Site #3: Lower satisfaction (3.4/5.0) due to persistent hot water wait time complaints during Adaptive Learning operation. Satisfaction improved after switching to Constant Temperature mode, but overall scores reflect the cumulative experience. The building manager noted that energy savings are valuable, but customer comfort must be prioritized.

Recommendations Based on Survey Results

1. Pre-Installation Assessment: Evaluate DHW system sizing relative to building demand before recommending Adaptive Learning mode.
2. Tenant Communication: Develop standardized communication materials for building managers to inform tenants about the smart pump installation and expected adjustment period.
3. Satisfaction Monitoring: Include customer satisfaction tracking in future M&V protocols to correlate energy savings with occupant acceptance.
4. Mode Selection Guidance: Develop decision criteria for control mode selection based on building characteristics, DHW system configuration, and customer service requirements.

V. Discussion

Technology Performance vs. Manufacturer Claims

Smart recirculation pumps demonstrated measurable energy savings at all three study sites, validating the fundamental technology premise that variable-speed ECM motors with intelligent controls can reduce both electrical consumption and recirculation thermal losses compared to constant-speed baseline pumps. As illustrated in Figure 5, gas savings ranged from 0.9% to 19.4% across sites and control modes, while Figure 6 shows electrical savings of -215.8% to 93.3%. The performance varied based on control mode selection, pump sizing, and DHW system characteristics.

Adaptive Learning Mode Performance

The study initially hypothesized that Adaptive Learning mode—the manufacturer's default setting—would be well-suited for DHW recirculation applications given its advertised ability to "learn and adapt" to system demand patterns. Field results showed mixed performance with Adaptive Learning. The mode resulted in tenant complaints at two of three sites (Sites #1 and #3) due to extended hot water wait times during the 2-4 week learning period. The adaptive learning algorithm requires time to characterize system demand patterns, during which hot water service may be degraded.

However, Adaptive Learning may be suitable for DHW systems with more predictable or frequent demand patterns where building managers and tenants can tolerate the initial learning period. Once the algorithm learns the building's usage patterns, the pump was able to provide efficient operation. At Site #2, Adaptive Learning operated without complaints throughout the study period, suggesting that buildings with consistent occupancy patterns, and appropriately sized DHW systems may be good candidates for this mode. Figure 17 shows a significant drop from ~122°F in the baseline to ~93°F in the post-installation. Figure 18 shows the reduction in recirculation losses as the ΔT (RWT – CWT_m) drastically reduces in the post-period and continues to decrease over time.

At Site #1, the temperature limits of 95-102°F appeared to work initially because the oversized DHW system (119-gallon tank for 18 units) and oversized MODEL A pump maintained average supply water temperatures around 107°F with a setpoint of only 115°F. The oversized pump operated at very low flows and did not meaningfully adapt—it essentially maintained similar return water temperatures as the baseline pump with minimal effort. This is evident in Figure 13, which shows the RWT across all periods and explains the negligible gas savings (0.9%) in Adaptive Learning mode despite no tenant complaints after the initial learning period. Figure 12 shows the daily pump electrical consumption time series at Site #1, illustrating how the oversized pump consumed more electricity in Constant Temperature mode than during baseline operation.

At Site #3, the undersized DHW system (two 40-gallon tanks for 10 units) could not tolerate the reduced circulation rates during Adaptive Learning operation, resulting in persistent tenant complaints even after increasing temperature limits from 95-102°F to 100-105°F. It appears the system lacked sufficient thermal storage capacity to buffer demand variations. However, as shown in Figure 22 and Table 22, Adaptive Learning achieved the highest gas savings (18.9%) at this site despite the customer acceptance issues. This suggests there is a balance between savings and customer comfort based on the optimized control strategy (see Optimized Control Strategy).

Constant Temperature Mode Performance

Constant Temperature mode consistently provided acceptable hot water service across all sites when configured with appropriate temperature limits. This mode directly addresses recirculation thermal losses by allowing return water temperature to drop to the low setpoint before activating circulation, then modulating flow to maintain temperature at the high setpoint. The temperature-based approach aligns with the physical requirements of DHW systems: maintain minimum temperatures to ensure hot water availability at fixtures. Figure 11 (Site #1), Figure 16 (Site #2), and Figure 21 (Site #3) demonstrate the consistent performance of Constant Temperature mode across all sites. For most DHW applications, Constant Temperature mode is recommended as it provides immediate, predictable performance without requiring a learning period.

Optimized Control Strategy

Based on field results for Site #3, customer feedback, and consultation with a smart pump manufacturer, there is a balance between the gas savings achieved by dynamically lowering the RWT vs maintaining customer comfort with adequate hot water delivery without long wait times (more than a few minutes). The optimized control strategy for DHW recirculation applications is Constant Temperature mode configured with:

1. Temperature Differential (ΔT): 10°F between high and low setpoints
2. Maximum Temperature Limit: 10°F below the water heater supply setpoint
3. Minimum Temperature Limit: 20°F below the water heater supply setpoint; this should be set to the minimum hot water temperature to satisfy the last tenant on the recirculation line.

Example Configuration:

- Water heater setpoint: 120°F
- Constant Temperature high limit: 110°F
- Constant Temperature low limit: 100°F

This configuration ensures that:

- The recirculation loop maintains minimum temperatures adequate for the last tenant on the distribution line
- The pump activates when the RWT drops to 100°F (20°F below supply)
- The pump modulates to maintain 110°F (10°F below supply), allowing some temperature drop while ensuring adequate hot water delivery

  Recirculation thermal losses are reduced compared to maintaining temperatures closer to the supply setpoint

The effectiveness of this strategy is demonstrated in Figure 17, which shows the RWT time series at Site #2, illustrating how Constant Temperature mode maintains stable temperatures within the configured limits.

Barriers to Achieving Expected Performance

Several barriers prevented the achievement of optimal performance during this study:

Pump Sizing: At Site #1, the unavailability of the originally specified Model C pump necessitated installation of the significantly oversized MODEL A (4/5 HP vs. 1/12 HP baseline). This oversizing prevented the pump from operating efficiently in Adaptive Learning mode, as the pump's minimum operating point exceeded optimal flow rates for the 18-unit building. The oversized pump was unable to adapt to the low flows required for efficient DHW recirculation in a relatively small building. Figure 12 clearly illustrates this issue, showing elevated electrical consumption during the Constant Temperature period compared to baseline operation — the opposite of expected behavior.

Manufacturer Guidance Deficiencies: A significant barrier to optimal performance was the lack of clear manufacturer guidance for DHW applications. The Manufacturer A product literature:

- Does not recommend against using Adaptive Learning for DHW recirculation
- Does not provide a specific temperature limit selection methodology based on water heater system setpoints and design
- Does not explain the learning period duration or the expected impacts on hot water delivery
- Positions Adaptive Learning as suitable for "general applications" without distinguishing DHW from hydronic heating

This guidance gap led to initial configuration choices (Adaptive Learning with 95-102°F limits) that resulted in tenant complaints and required mid-study adjustments.

Learning Period Impacts: Adaptive Learning algorithms require 2-4 weeks to characterize system demand patterns. During this period, the pump may under-circulate, resulting in extended hot water wait times. For DHW applications where occupant expectations are immediate hot water, this learning period creates unacceptable service degradation that constant-speed pumps do not impose.

Energy Savings and Demand Reduction

Gas Savings: The study demonstrated that smart pumps can achieve gas savings of 0.9% to 19% compared to constant-speed baseline pumps operating continuously. Gas savings are achieved by reducing recirculation thermal losses—the energy required to maintain hot water temperatures in distribution piping. Table 22 summarizes gas savings by site and control mode. Higher savings were observed at sites with:

- Longer recirculation loops (greater baseline heat loss)
- Lower baseline insulation quality
- Higher temperature differentials between the supply and ambient

The regression model scatter plots (Figure 9 for Site #1; Figure 15 and Figure 16 for Site #2: and Figure 19 for Site #3) demonstrate the strong correlation between predicted and measured gas consumption, validating the savings calculations.

Electrical Savings: Pump electrical savings of -216% to 94% were achieved across all sites and control modes (Figure 6). These savings result from:

- Variable-speed operation at reduced flows (power varies with the cube of speed per affinity laws)
- Reduced operating hours compared to continuous baseline operation
- ECM motor efficiency advantages over AC induction motors

Figure 22 illustrates the dramatic reduction in electrical consumption at Site #3, where the smart pump reduced daily consumption from 0.132 kWh/day to approximately 0.009 kWh/day — a 93% reduction.

Demand Reduction: While this study focused on energy (therms and average kWh) rather than demand (kW), which is not included in the project scope, the reduced pump operating hours and lower operating speeds inherently reduce electrical demand. However, this was not quantified in this study.

Comparison to Incumbent Technology

Smart pumps are demonstrably better than incumbent constant-speed pumps when the following criteria are considered:

Energy Efficiency: Smart pumps reduce both gas and electrical consumption compared to continuous-operation baseline pumps. Even in Adaptive Learning mode with suboptimal configuration, gas savings of 0.9-19% were achieved (Figure 5 and Figure 7 compares field results to measure package assumptions, showing the overall average gas savings at 19.4% greater than SWWH015 gas savings per dwelling unit.

Controllability: Smart pumps offer multiple control modes that can be selected based on application requirements. Constant Temperature mode provides precise temperature control that constant-speed pumps cannot achieve.

Adaptability: Unlike constant-speed pumps that operate at fixed output regardless of conditions, smart pumps can modulate speed to match actual system requirements, reducing over-circulation and associated thermal losses.

Monitoring and Diagnostics: Smart pumps include built-in displays showing operating parameters (flow, power, temperature) that facilitate commissioning and troubleshooting. Constant-speed pumps provide no operational feedback.

Limitations: Smart pumps have a higher first cost ($800-$4000 vs. $200-$500 for constant-speed pumps), require more sophisticated installation and configuration, and—when improperly configured—can result in service degradation that constant-speed pumps avoid. Table 26 documents the installed costs at each site.

Additional Benefits Beyond Energy Savings

Reduced Water Waste: By maintaining hot water in distribution piping, recirculation systems (including smart pumps) reduce water waste from running taps while waiting for hot water. Figure 1 illustrates the basic DHW recirculation system configuration that enables this benefit.

Extended Equipment Life: Variable-speed operation reduces mechanical stress compared to constant on/off cycling, potentially extending pump life.

Reduced Noise: Lower operating speeds reduce pump noise, which can be significant in residential and MFm applications.

Remote Monitoring Capability: Cloud-connected smart pump models (e.g., Manufacturer A iSOLUTIONS) enable remote monitoring and diagnostics, reducing maintenance costs and enabling predictive maintenance.

Market Barriers to Technology Adoption

First Cost Premium: Smart pumps cost 3-5× more than constant-speed pumps, creating payback period concerns for building owners.

Installer Familiarity: Plumbing contractors accustomed to simple constant-speed pumps may be hesitant to install or configure smart pumps requiring mode selection and setpoint programming.

Manufacturer Guidance Gaps: As documented in this study, manufacturer literature does not provide adequate guidance for specific DHW applications, leading to suboptimal configurations and potential customer satisfaction issues.

Measure Package Limitations: Current SWWH022 and SWWH015 measure packages do not specify control mode requirements or temperature limit guidance, allowing installations that may not achieve claimed savings or may result in customer complaints. Figure 7 and Figure 8 shows the comparison between field results and measure package claims.

Learning Period Concerns: Building owners and managers may be reluctant to accept 2-4 weeks of potentially degraded hot water service during the initial Adaptive Learning periods.

Pump Costs

Table 26: Installation Costs by Site

Cost Component	Site #1	Site #2	Site #3
Equipment (pump + accessories)	$3,910.23	$738.64	$738.64
Labor (installation)	$1,399.77	$1,921.36	$1,921.36
Total Installed Cost	$5,310	$2,660	$2,660
Building Size (units)	18	12	10
Cost per Unit	$295	$222	$266

Note: *Site #1 costs were higher due to the oversized MODEL A pump ($3,910 vs. $738 for MODEL B).*

Comparison to Measure Package Assumptions

The SWWH015 measure package assumes gas savings of 13.22 therms/year across all CZ for MFm building type. Field results showed:

- Adaptive Learning exceeded this assumption (19-31 therms/year)
- Site #3 Constant Temperature exceeded this assumption (30 therms/year)
- Sites #1 and #2 Constant Temperature fell below this assumption (8.3-8.6 therms/year)

This variability suggests that the measure package savings estimates should be refined based on control mode selection and baseline conditions.

VI. Conclusions

Based on the field evaluation of smart recirculation pumps at three MFm sites in California Climate Zone 03, the following conclusions are drawn:

1. Smart pumps achieve measurable energy savings: Gas savings of 0.9% to 19.4% and electrical savings of 65.1% to 93.3% were demonstrated compared to constant-speed baseline pumps operating continuously, excluding Site #1 electricity savings of -215.8% (Table 22, Figure 5 and Figure 6). Annual gas savings ranged from 0.9 to 31.1 therms/year/dwelling unit, depending on site characteristics and control mode, similar the SWWH015 measure package assumption of 13.22 therms/year but implies opportunity for measure package refinement to account for varying savings based on baseline conditions. The technology delivers on its fundamental promise of reducing recirculation thermal losses through intelligent speed modulation.
2. Constant Temperature mode is recommended for most DHW applications: This mode consistently provides acceptable hot water service when configured with appropriate temperature limits and does not require a learning period. At all three sites, Constant Temperature mode achieved gas savings of 7.9% to 14.3% (Figure 5) while maintaining customer satisfaction scores of 3.4 to 4.6 out of 5.0. For buildings where immediate, predictable performance is required, Constant Temperature mode is the preferred control strategy.
3. Adaptive Learning mode delivers higher savings but at the cost of customer comfort: Adaptive Learning achieved the highest gas savings at Sites #2 (18.7%) and #3 (19.4%) but resulted in tenant complaints at Site #1 and Site #3 during the initial 2-4 week learning period. Adaptive Learning may be appropriate for DHW systems with predictable or frequent demand patterns, appropriately sized equipment (≥8 gallons/unit storage capacity), and building managers willing to communicate the learning period impacts to tenants.
4. Optimal temperature limits are 10°F ΔT with a maximum 10°F below supply setpoint: This configuration (e.g., 100-110°F for a 120°F water heater) balances energy savings from reduced recirculation losses against customer satisfaction requirements for hot water availability. This recommendation is based on Site #3 field experience and manufacturer consultation.
5. DHW system sizing affects control mode suitability: Site #3's undersized DHW system (8 gallons/unit) could not tolerate Adaptive Learning's reduced circulation rates, while Site #2's adequately sized system (10 gallons/unit) operated without complaints. Buildings with less than 8 gallons/unit storage capacity may need to consider Constant Temperature mode.
6. Manufacturer guidance is inadequate for DHW applications: Product literature does not distinguish DHW from hydronic heating applications, does not provide clear guidance on control mode selection, and does not provide temperature limit selection methodology.

This gap contributed to suboptimal initial configurations and customer complaints at two sites.

7. Field results agree with measure package assumptions: Average therm savings across all sites and both controls is 16.4 therms/yr/dwelling unit compared to the SWWH015 assumption of 13.22 therms/year/dwelling unit (Figure 7). This suggests current measure packages may underestimate savings potential for properly configured installations in multifamily buildings with continuous baseline pump operation, and does not consider varying baseline conditions, i.e. high baseline pump consumption.
8. Customer acceptance correlates with control mode and DHW system design: Satisfaction scores ranged from 3.4/5.0 (Site #3, undersized DHW with Adaptive Learning complaints) to 4.6/5.0 (Site #2, properly sized DHW with no complaints). Proper system design and control mode selection are essential for customer acceptance.

VII. Recommendations

Recommendation 1: Adopt Smart Pump Technology into EE Programs

Recommendation: Smart recirculation pump technology should be adopted into California energy efficiency programs for MFm DHW applications, with the following stipulations:

- **Control Mode Guidance:** Measure packages should specify Constant Temperature mode as the recommended control strategy for most DHW recirculation applications. Adaptive Learning mode may be used for buildings with predictable demand patterns and appropriately sized DHW systems, but Constant Temperature should be the default recommendation.
- Temperature Limit Specification: Measure packages should require temperature limits configured as:
  - Maximum (high) limit: Water heater supply setpoint minus 10°F
  - Minimum (low) limit: Water heater supply setpoint minus 20°F
  - Example: 100-110°F for 120°F water heater supply setpoint
- **Pump Sizing Requirements:** Measure packages should include pump sizing guidance to prevent over- or under-sizing that compromises performance.

Recommendation 2: Update SWWH022 Measure Package

Recommendation: The Program Administrators should update existing measure packages to incorporate field study findings:

SWWH022 Updates:

- Extend applicability to larger MFm buildings (currently focused on residential/small multifamily)
- Add gas savings claims based on field results
- Include control mode and temperature limit requirements
- Incorporate different baseline cases to account for varying baseline conditions
- Update materials and labor costs based on costs from Table 26

Recommendation 3: Engage Manufacturers on Product Literature

Recommendation: California IOUs and the California Energy Commission should engage Manufacturer A and other smart pump manufacturers to update product literature for DHW applications:

Requested Updates:

1. Clear guidance on when to use Constant Temperature vs. Adaptive Learning for DHW applications
2. Recommendation that the Constant Temperature mode is preferred for most DHW recirculation applications
3. Temperature limit selection guide based on water heater setpoint
4. DHW-specific installation and commissioning guidance
5. Learning period impact disclosure for Adaptive Learning mode, including expected duration and potential service impacts
6. Guidance on DHW system sizing requirements for Adaptive Learning suitability
7. Tenant communication templates for building managers

Rationale: The lack of DHW-specific guidance was a primary barrier to achieving optimal performance in this study. Current product literature does not distinguish DHW from hydronic heating applications, leading to control mode selections that may not be optimal for DHW. Manufacturer engagement will improve the field performance of all smart pump installations, not just those receiving utility incentives.

Recommendation 4: Future Work and Additional Studies

Recommendation: The following additional studies are recommended to advance smart pump deployment:

Phase 2 Field Study - Cloud-Connected Pumps: Evaluate IoT-enabled smart pumps with cloud-based analytics (e.g., Manufacturer A iSOLUTIONS) to assess:

- Fleet-wide learning algorithm performance compared to standalone adaptive control
- Remote monitoring and predictive maintenance benefits
- Cybersecurity and data privacy considerations
- Potential for automated optimization across building portfolios

Expanded Climate Zone Testing: Extend field evaluation to additional climate zones (hot/dry CZ10-15, cold CZ16) to validate performance across California's diverse climate conditions and inlet water temperatures.

DHW System Sizing Study: Investigate the relationship between DHW system sizing (gallons/unit), recirculation loop length, and optimal smart pump control strategy to develop sizing-based configuration guidance.

Long-Term Durability Assessment: Monitor smart pump installations over 3-5 years to assess:

- ECM motor reliability (hardware + integrated smart controls) compared to traditional AC induction motors
- Control algorithm stability over time
- Maintenance requirements and failure modes

Heat Pump Water Heater Integration: As California pursues building electrification, evaluate smart recirculation pump compatibility with heat pump water heaters, which operate at lower supply and return temperatures and may require different control or plumbing strategies.

Recommendation 6: Installer Training Program

Recommendation: Develop an installer training curriculum for smart recirculation pump installation in DHW applications:

Training Content:

- Control mode selection (Constant Temperature recommended for DHW)
- Temperature limit configuration based on water heater setpoint
- Pump sizing for DHW applications
- Commissioning verification procedures
- Troubleshooting common issues
- Customer communication best practices

Delivery Mechanism: Partner with plumbing contractor associations and community colleges to integrate training into existing certification programs.

Recommendations for Future M&V Studies

Instrumentation Requirements

Based on the lessons learned from this field study, the following instrumentation recommendations are provided for future smart pump M&V projects:

Cold Water Flow Measurement ($\dot{\mathbf{V}}_{\mathbf{cold}}$): Future projects should include dedicated cold water ($\dot{V}_{cold}$) flow meters at all sites. $\dot{V}_{cold}$ is a primary driver of DHW gas consumption as it directly represents the volume of water that must be heated from inlet temperature to the supply setpoint. At Site #3, the inclusion of $\dot{V}_{cold}$ measurement enabled a more robust regression model with higher R^2 values and improved savings estimates. Sites #1 and #2 lacked this measurement, requiring the use of proxy variables (RWT - CWT) that introduced additional uncertainty.[6]

CWT Measurement: Direct measurement of CWT should be included at all sites rather than relying on estimated values from the DEER water heating calculator. While the DEER main temperature estimates provide reasonable approximations for Climate Zone 03, actual inlet temperatures can vary based on:

- Building-specific plumbing configurations (e.g., pipe routing through conditioned vs. unconditioned spaces)
- Time of day and seasonal variations (i.e., OAT)
- Local water utility source temperature variations

Direct CWT measurement enables calculation of the actual temperature rise (SWT – CWT required by the water heater, which is fundamental to modeling gas consumption using physical principles.

SWT Measurement: All sites should include supply water temperature measurement. At Site #1, the absence of SWT data required using RWT as a proxy, which was acceptable only because the oversized DHW system resulted in minimal temperature differential (SWT-RWT of only a few degrees). This proxy approach would not be valid for systems with higher recirculation loop losses.

[6] Uncertainty analysis was not included in this study.

Redundant Data Logging: As demonstrated at Site #3, communication failures (faulty SIM card) can result in significant data loss. Future projects should consider:

- Redundant cellular communication paths or backup data storage
- More frequent site visits for manual data downloads during critical monitoring periods
- Real-time data quality monitoring with automated alerts for communication failures

Recommended Minimum Instrumentation Package

Table 27: Recommended Minimum Instrumentation for Future DHW Smart Pump M&V Studies

Measurement Point	Rationale	Priority
Cold water flow (V_{cold})	Primary driver of gas consumption; enables physical modeling	Required
Cold water temperature (CWT)	Enables actual ΔT calculation; eliminates reliance on estimated mains temperature	Required
Supply water temperature (SWT)	Required for heat loss calculations and temperature setpoint verification	Required
Return water temperature (RWT)	Enables recirculation loop heat loss analysis	Required
Natural gas flow	Primary energy consumption measurement	Required
Pump current/power	Electrical consumption measurement	Required
Outdoor air temperature (OAT)	Weather normalization	Required (can use nearby weather station)
Return flow (recirculation)	Enables pump flow rate analysis and runtime verification	Recommended
Solar preheat temperature (if applicable)	Isolates solar contribution from gas consumption	Required for solar systems

Analysis Methodology Recommendations

Per ASHRAE Guideline 14, Section 5.1.3.4 and NREL Study Annex D [28], multivariable regression models should be employed when multiple independent variables significantly influence energy consumption. For DHW systems, the recommended independent variables include:

1. Cold water flow ($\dot{V}_{cold}$) – represents hot water demand
2. Temperature rise (SWT – CWT) – represents thermal load per unit volume.
3. Outdoor air temperature (OAT) – captures standby losses and inlet temperature correlation.

References

[1] ASHRAE, in *ASHRAE Handbook—HVAC Applications*, American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2019.

[2] National Renewable Energy Laboratory, "Control Strategies to Reduce the Energy Consumption of Central Domestic Hot Water Systems in Multifamily Buildings," Golden, CO, 2016.

[3] California Public Utilities Commission, *Measure Package SWWH015: Demand Control for Centralized Water Heater Recirculation Pump, Multifamily & Commercial,* Database for Energy Efficient Resources (DEER), 2022.

[4] California Energy Commission, "2020 Building Energy Use Survey," 2021.

[5] D. Martello, *Multifamily Domestic Hot Water Design: How Can We Do Better?,* Steven Winter Associates, Inc., Green Building Professional Program, 2018.

[6] B. Rishel, HVAC Pump Handbook, 2nd Edition ed., McGraw-Hill Professional, 2002.

[7] California Energy Commission, *2022 Building Energy Efficiency Standards for Residential and Nonresidential Buildings,* 2022.

[8] ASHRAE, *ASHRAE Standard 90.1-2010: Energy Standard for Buildings Except Low-Rise Residential Buildings,* American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2010.

[9] Manufacturer A, *MODEL A Technical Data Sheet,* Bjerringbro, Denmark: Manufacturer A Holding A/S, 2020.

[10] U.S. Department of Energy, "Variable Speed Pump Controls for Domestic Hot Water Recirculation Systems," Building Technologies Office, 2018.

[11] U.S. Department of Energy, "Energy Savings Potential and Opportunities for High-Efficiency Electric Motors in Residential and Commercial Equipment," Building Technologies Office, 2013.

[12] ASHRAE, in *ASHRAE Handbook—HVAC Applications*, American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2019.

[13] ASHRAE, *ASHRAE Standard 188-2018: Legionellosis: Risk Management for Building Water Systems,* American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2018.

[14] International Plumbing Code, *Section 607: Hot Water Supply System,* International Code Council, 2021.

[15] J. Xu, H. Li and Q. Zhang, "Adaptive control for circulating cooling water system using deep reinforcement learning," *PLoS ONE,* vol. 19, no. 7, p. e0307767, July 2024.

[16] H. Kazmi, "Reinforcement learning for HVAC control in intelligent buildings: A technical and conceptual review," *e-Prime - Advances in Electrical Engineering, Electronics and Energy,* vol. 9, p. 100653, September 2024.

[17] M. Rosenberg, "A hybrid machine learning framework for optimizing heat pump-driven domestic hot water systems based on user behaviour and control strategies," *Applied Thermal Engineering,* vol. 268, p. 125862, July 2025.

[18] Manufacturer A, "Manufacturer A iSOLUTIONS: Intelligent pumps, cloud connectivity and digital services," 2024. [Online]. Available: https://www.Manufacturer A.com/solutions/learn/research-and-insights/Manufacturer A-isolutions.

[19] Telenor Connexion, *Manufacturer A: Pioneering Water-as-a-Service Solutions through IoT,* 2024.

[20] Fraunhofer Institute for Solar Energy Systems (ISE), "Self-learning heat pump control with AI system model," 2024.

[21] Illinois Stakeholder Advisory Group, "Smart Pump Multifamily Pilot Study," Energy Technology Commercialization Center (ETCC), 2014.

[22] Pacific Gas and Electric Company, "PGECOPUM107 R0 - Smart Pump Field Study," Emerging Technologies Program, San Francisco, CA, 2017.

[23] National Renewable Energy Laboratory, "Control Retrofits for Multifamily Domestic Hot Water Recirculation Systems," Golden, CO, 2017.

[24] Sempra Energy, "Variable Frequency Drive Hot Water Recirculation Pump Controller Field Study," Emerging Technologies Program, San Diego, CA.

[25] Energy Solutions, "Research and Analysis of the Benefits of Appliance Standards for Domestic Hot Water Circulator Pumps," 2021.

[26] National Association of Home Builders, "Cost vs. Value Report 2023," NAHB Research Center, 2023.

[27] Burch, J; Christensen, C, "Towards Development of an Algorithm for Mains Water Temperature," in *Proceedings of the 2007 ASES Annual Conference*, Cleveland, OH, 01 January 2007.

[28] B. Gao, J. Ni, Z. Yuan and N. Yu, "Pump-Valve Combined Control of a HVAC Chilled Water System Using an Artificial Neural Network Model," *Energies,* vol. 16, no. 5, pp. 1-16, March 2023.

[29] California Public Utilities Commission, *Measure Package SWWH022: Smart Pump, Residential,* Database for Energy Efficient Resources (DEER), 2022.

[30] ASHRAE, *ASHRAE Guideline 14-2014: Measurement of Energy, Demand, and Water Savings,* Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2014.

[31] "Understanding Multifamily Home Energy Efficiency Potential," ACEEE, OCTOBER 2020.

Appendix A. Measurement and Verification Plan

Selected IPMVP Options

This study employs IPMVP Option B—Retrofit Isolation approaches at all three sites, with variations based on available instrumentation and site complexity. Each approach attempts to follow Method 2 outlined in the 2016 NREL study "Control Strategies to Reduce the Energy Consumption of Central Domestic Hot Water Systems," which models the gas usage as function cold city water flow ($\dot{V}_{cold}$) and required temperature lift (SWT - CWT). To align with the study's approach, a similar multivariable regression analysis was performed to normalized gas usage, incorporating the available measurement parameters for each site due to initial scope of the project that only included RWT, $\dot{V}_{gas}$, and $\dot{P}_{pump}$, which were expected to be used for energy savings analysis. However, additional measurement parameters, i.e. SWT and $\dot{V}_{cold}$, were later added to subsequent sites as these were necessary to establish regression models and determine energy savings.

- **Site #1:** An IPMVP Option B—Retrofit Isolation approach using regression analysis with baseline gas energy ($\dot{Q}_{gas,base}$) as a function of OAT and RWT. This site only included the measurement of $\dot{V}_{gas}$, RWT, recirculation pump power ($\dot{P}_{pump}$), and OAT due to limited budgeting available for instrumentation. Because this site lacked SWT, CWT, and $\dot{V}_{cold}$ instrumentation, the CWT was estimated using a modified version of the Burch-Christensen model adapted to local OAT and estimated ground temperatures using a sinusoidal approximation denoted as CWT_m (see Appendix B for more information). Additionally, the SWT measurement was added in the post-period, showing little difference between daily average RWT and SWT. Thus, RWT is used as a proxy for SWT, and the (RWT - CWT_m) differential serves as a proxy for the temperature rise required by the water heater. No estimations for $\dot{V}_{cold}$ were used used for this site.
- **Site #2:** A modified IPMVP Option B—Retrofit Isolation approach projecting the post-period models back into the baseline due to a poor baseline model fit (see Table 37). A multivariable regression analysis was initially attempted, but the baseline model exhibited poor statistical fit ($R^2 < 0.1$) due to a faulty Aquastat on one of the two direct-fired storage water heaters that resulted from near-constant gas usage during the baseline period. Unfortunately, a tankless water heater was installed at the end of the post-period, which did not allow for re-baselining with a constant speed pump. This site included the measurement of $\dot{V}_{gas}$, RWT, SWT, $\dot{P}_{pump}$, and OAT. CWT and $\dot{V}_{cold}$ were not directly included due to the limited budget; instead, CWT_m was used as a substitute adapted to local site conditions. No estimations for $\dot{V}_{cold}$ were used used for this site.
- **Site #3:** An IPMVP Option B—Retrofit Isolation with All Parameter Measurement approach due to the additional solar water heating system that impacts the water

heater gas use. This site included full system instrumentation borrowed from other M&V projects to better normalize the gas usage per period minimizing the influence of seasonal factors in gas usage and provide comparison to the other two sites. Key measurement parameters at this site include (see Figure 4):

1. **CWT**: Inlet cold city water temperature to preheat solar tanks
2. **SWT**: Hot water heater outlet temperature to distribution
3. **RWT**: Recirculation loop return water temperature
4. $\mathbf{T_{solar}}$: Temperature of water leaving solar storage tanks
5. $\mathbf{\dot{V}_{return}}$: Recirculation loop flow rate
6. $\mathbf{\dot{V}_{solar}}$: Flow of preheated water through the solar thermal system
7. $\mathbf{\dot{V}_{cold}}$: Cold City water entering the DHW system
8. $\mathbf{\dot{V}_{gas}}$: Gas consumption measurement
9. $\mathbf{\dot{P}_{pump}}$: Pump electrical consumption measurement

Site #1: IPMVP Option B with Regression Analysis

For Site #1, gas savings were determined using regression analysis using limited instrumentation. The baseline gas consumption model uses the following independent variables:

- **OAT:** Affects CWT, recirculation losses and standby losses.
- **RWT - CWT$_m$**: Temperature lift required by the water heater.

The regression model uses the available data due to limited budget to establish the relationship between baseline gas consumption and the available independent variables, allowing normalized savings calculations by projecting into the post-installation periods that have a similar range of independent variables.

Site #2: IPMVP Option B with Modified Regression Analysis

Similarly, for Site #2, gas savings were determined using regression analysis using limited instrumentation. However, baseline gas consumption was nearly constant due to a water heater malfunctioning, not allowing for modeling with any available variables. Instead, the post-period gas usage was modeled after fixing the faulty water heater using the following independent variables[7]:

- **OAT:** Affects CWT, recirculation losses and standby losses.
- **SWT - CWT$_m$**: Temperature lift required by the water heater.

[7] The water heater, which malfunctioned during the baseline period, still provided a similar level of service with an SWT of about 126°F compared to the post-periods. Thus, it was assumed that the gas usage was comparable between test periods, and projecting into the baseline is valid.

- **(SWT - CWT_m)/RWT:** Return-normalized temperature lift used for modeling the adaptive learning post-period and projecting into the baseline period, as it provides a similar range of values in both test periods and used for adaptive learning as the control mode relies on RWT to dynamically adjust pump operation based on usage patterns and maintain optimal efficiency.

The regression model uses the available data due to limited budget to establish the relationship between baseline gas consumption and the available independent variables, allowing normalized savings calculations by projecting into the baseline period that have a similar range of independent variables.

Note: *CWT_m varies with local OAT and ground temperatures (T_{ground}). This adjustment normalizes gas consumption to account for the thermal load difference imposed by varying water heater demand and CWT across the baseline and post-installation periods.*

Site #3: IPMVP Option B—Retrofit Isolation with All Parameter Measurement

For Site #3, the IPMVP Option B—Retrofit Isolation with All Parameter Measurement approach is used due to the complexity introduced by the solar thermal preheat system. This approach isolates gas savings from variable solar contributions through regression analysis using the same variables from the 2016 NREL study using the following independent variables[8]:

- **OAT:** Affects CWT, recirculation losses and standby losses.
- **SWT - CWT_m**: Temperature lift required by the water heater.
- $\dot{V}_{cold}$: Hot water demand proxy.

Baseline and Post-Installation Data Periods

Data Logging Period Rationale

The data logging period was defined to be long enough to represent a full range of seasonal operating conditions for both the baseline and post periods:

Baseline Period (4 weeks): The baseline variables are not expected to fluctuate significantly, so a 4-week baseline monitoring period was selected. Each variable is expected to fluctuate throughout the day, but these variables are expected to be relatively constant when compared on a daily level throughout the baseline monitoring period as hot

[8] The water heater, which malfunctioned during the baseline period, still provided a similar level of service with an SWT of about 126°F compared to the post-periods. Thus, it was assumed that the gas usage was comparable between test periods, and projecting into the baseline is valid.

water usage patterns (and thus related system variables) are typically similar from day to day under consistent occupancy and behavior.

Post-Installation Period (12 weeks): The post-installation variables of recirculation pump operating hours and recirculation pump flow rate are expected to fluctuate as the smart pump adapts to system conditions. Therefore, a longer post-installation monitoring period of 12 weeks (or 90 days) was selected. These variables are expected to fluctuate more when the same hour of the day is compared to another, though daily totals should stabilize over time as hot water usage patterns remain relatively similar from day to day under consistent occupancy and behavior.

Variables Impacting DHW System Natural Gas Use

The following variables impact the DHW system's natural gas use in both the baseline and post-installation systems:

1. Water Heating Setpoint
2. Fixture water use and timing
3. Recirculation pump operating hours
4. Recirculation pump flow rate
5. Water heater efficiency
6. Pipe insulation condition
7. Any storage tank losses
8. Solar water heating contribution to DHW load (Site #3 only)

Baseline System Operation

Each site had a baseline DHW system with the recirculation pump running at constant speed in a 24/7 operational mode.

Post-Installation System Operation

The post-installation DHW system will have the smart pump operating in two control modes tested sequentially:

1. **Adaptive Learning Mode (First Testing Period):** The pump uses built-in sensors and algorithms to monitor the system's changes and adjust the pump speed to meet the system's needs. The smart pump learns the hot water consumption patterns over time and adapts to maximize performance. The pump continuously adjusts its proportional pressure curve and automatically sets a more efficient one without compromising on comfort.
2. **Constant Temperature Mode (Second Testing Period):** Following the adaptive learning testing period, the pump is switched to Constant Temperature mode, where the user

sets a constant RWT setpoint, and the pump controls the flow to maintain that temperature with a specified ΔT. This mode provides direct temperature control while varying flow rates to match actual heat loss from the distribution system.

The differences in recirculation pump flow rate and operating hours due to the smart pump's algorithm will be reflected in the water heater's normalized $\dot{V}_{gas}$ and $\dot{P}_{pump}$.

Measurement Points and Frequency

Site #1: Measurement Points

Table 28: Site #1 Measurement Points and Data Collection

Measurement Type	Measurement Point	Unit	Metering Equipment/Source	Sampling Interval
Continuous Measurement	RWT	°F	Onset S-TMB-M002 Temperature Sensor	5-minute
Continuous Measurement	$\dot{V}_{gas}$	Cu. Ft.	American Meter AC-250 Natural Gas Flow Meter (Temperature Compensated) + PulseMaster Pulse Output Module + Onset S-UCD-M006 Module	5-minute
Continuous Measurement	$\dot{I}_{pump}$	Amps	Onset T-MAG-0400-05 5 AMP Mini Split-core AC Current Transformer Sensor + Onset S-FS-TRMSA-D Module	5-minute
Calculated	$\dot{P}_{pump}$	kW	Calculated from $I_{pump} \times V_{pump} \times PF \times 1000$	5-minute
Spot Measurements	V_{pump}	Volts	Amprobe ACD-51NAV multimeter	During installation
Spot Measurements	PF	—	Amprobe ACD-51NAV multimeter	During installation
3rd Party Data	OAT	°F	CALMAC API (NOAA ISD)	Daily
3rd Party Data	HHV	Btu/ft³	Monthly PG&E Gas Bills (includes temp and pressure compensation)	Monthly
3rd Party Data	CWT_m	°F	Modeled using local weather and ground conditions	Daily

Note: *Site #1 lacks SWT, CWT, and cold city flow instrumentation.*

Site #2: Measurement Points

Table 29: Site #2 Measurement Points and Data Collection

Measurement Type	Measurement Point	Unit	Metering Equipment/Source	Sampling Interval
Continuous Measurement	RWT	°F	Onset S-TMB-M002 Temperature Sensor	1-minute
Continuous Measurement	SWT	°F	Onset S-TMB-M002 Temperature Sensor	1-minute
Continuous Measurement	$\dot{V}_{gas}$	Cubic Feet	American Meter AC-250 Natural Gas Flow Meter (Temperature Compensated) + PulseMaster Pulse Output Module + Onset S-UCD-M006 Module	1-minute
Continuous Measurement	$\dot{I}_{pump}$	Amps	Onset T-MAG-0400-05 5 AMP Mini Split-core AC Current Transformer Sensor + Onset S-FS-TRMSA-D Module	1-minute
Calculated	$\dot{P}_{pump}$	kW	Calculated from $\dot{I}_{pump} \times V_{pump} \times PF \times 1000$	1-minute
Spot Measurements	V_{pump}	Volts	Amprobe ACD-51NAV multimeter	During installation
Spot Measurements	PF	—	Amprobe ACD-51NAV multimeter	During installation
3rd Party Data	OAT	°F	CALMAC API (NOAA ISD)	Daily
3rd Party Data	HHV	Btu/ft³	Monthly PG&E Gas Bills (includes temp and pressure compensation)	Monthly
3rd Party Data	CWT_m	°F	Modeled using local weather and ground conditions	Daily

Note: *Site #2 does not include CWT or $\dot{V}_{gas}$ instrumentation.*

Site #3: Measurement Points

Table 30: Site #3 Measurement Points and Data Collection

Measurement Type	Measurement Point	Unit	Metering Equipment/Source	Sampling Interval
Continuous Measurement	CWT	°F	Onset S-TMB-M006 Digital Temperature Sensor	1-minute
Continuous Measurement	SWT	°F	Onset S-TMB-M006 Digital Temperature Sensor	1-minute
Continuous Measurement	RWT	°F	Onset S-TMB-M006 Digital Temperature Sensor	1-minute
Continuous Measurement	T_{solar}	°F	Onset S-TMB-M006 Digital Temperature Sensor	1-minute
Continuous Measurement	$\dot{V}_{return}$	GPM	Dwyer WMH-A-C-02 Multi-Jet Hot Water Flow Meter (5/8" x 3/4", 0.1-gal pulse)	1-minute
Continuous Measurement	$\dot{V}_{solar}$	GPM	Dwyer WMH-A-C-06 Multi-Jet Hot Water Flow Meter (1", 0.1-gal pulse)	1-minute
Continuous Measurement	$\dot{V}_{cold}$	GPM	Dwyer WMH-A-C-06 Multi-Jet Hot Water Flow Meter (1", 0.1-gal pulse)	1-minute
Continuous Measurement	$\dot{V}_{gas}$	Cu. Ft	American Meter AC-250 Natural Gas Flow Meter (Temperature Compensated) + PulseMaster Output	1-minute
Continuous Measurement	$\dot{I}_{pump}$	Amps	Onset T-MAG-0400-05 5 AMP Mini Split-core AC CT Sensor + Onset S-FS-TRMSA-D Module	1-minute
Continuous Measurement	$\dot{P}_{pump}$	kW	Calculated from $\dot{I}_{pump} \times V_{pump} \times PF \times 1000$	1-minute
Spot Measurements	V_{pump}	Volts	Amprobe ACD-51NAV multimeter	During installation
Spot Measurements	PF	—	Amprobe ACD-51NAV multimeter	During installation
3rd Party Data	OAT	°F	CALMAC API (NOAA ISD)	Hourly
3rd Party Data	HHV	Btu/ft³	Monthly PG&E Gas Bills (includes temp and pressure compensation)	Monthly

Gas Volume Adjustments

Diaphragm gas meters were installed to monitor the volumetric gas flow (cu. Ft. pulses) into the water heater. The meter is pressure and temperature-compensated and equipped with electronic pulse output. The monthly Pacific Gas and Electric (PG&E) multiplier (HHV) was obtained from the PG&E gas utility bill to adjust the gas volume to a standard pressure (14.73 psia) and temperature (60°F).

Weather Data Source

The OAT weather data for all three sites was obtained from the California Measurement Advisory Council (CALMAC) Weather Data Application Programming Interface (API). The CALMAC weather database provides standardized weather data for California energy analysis applications, sourced from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD).

Table 31: Weather Data Source Specifications

Parameter	Specification
Data Source	CALMAC Weather API
Primary Source	NOAA Integrated Surface Database (ISD)
Weather Stations	Nearest NOAA-certified weather station to each site
Temporal Resolution	Hourly observations
Accuracy	±1.0°F for temperature measurements (NOAA ISD quality-controlled data)

Site-Specific Weather Stations:

- **Site #1:** San Francisco International Airport (SFO), WBAN 23234, approximately 11 miles from the site.
- **Site #2:** San Francisco International Airport (SFO), WBAN 23234, approximately 10 miles from the site.
- **Site #3:** Oakland Metropolitan International Airport (OAK), WBAN 23230, approximately 4 miles from the site.

The NOAA ISD weather data undergoes extensive quality control procedures, including range checks, temporal consistency checks, and spatial consistency checks against nearby stations. The CALMAC API applies additional validation to ensure data completeness and consistency for California-specific energy analysis applications.

Metering Instrumentation Specifications

Meter Specifications

Table 32: Metering Equipment Specifications

Metering Equipment	Measurement	Unit	Range	Accuracy
Onset S-TMB-M002/M006 Temperature Sensor	Temperature	°F	-40° to 212°F	<±0.36°F from 32°F to 122°F
American Meter AC-250 Natural Gas Flow Meter (Temperature Compensated) + PulseMaster Pulse Output Module + Onset S-UCD-M006 Module	Natural Gas Flow	Cubic Feet	0.25 PSIG to 7 PSIG; 250 SCFH to 742 SCFH	~0.3 ms bounce time
Onset T-MAG-0400-05 5 AMP Mini Split-core AC Current Transformer Sensor + Onset S-FS-TRMSA-D Module	Electrical Current	Amps	0.5 amps to 6.5 amps	±2.0% from 10% to 120% of rated current
Dwyer WMH-A-C-02 ¾" Multi-Jet Hot Water Flow Meter with Pulse Output	Water Flow	GPM	1 to 20 GPM; 190°F Max Temp	Transitional Flow: ±3%; Nominal Flow: ±1.5%
Dwyer WMH-A-C-06 1" Multi-Jet Hot Water Flow Meter with Pulse Output	Water Flow	GPM	3 to 50 GPM; 190°F Max Temp	Transitional Flow: ±3%; Nominal Flow: ±1.5%
Amprobe ACD-51NAV CAT IV Navigator Clamp Meter	Amps, Voltage, PF	Amps, V, PF	0A-600A, 0V-1000V, 10kW-600kW	Amps: ±1.5% rdg + 5 LSD; Voltage: ±1.0% rdg + 5 LSD; PF: ±3°
Onset HOBO RX3004-00-01 Remote Monitoring Station + SP-814 4G Cellular Data Plan	Data Logging Station	N/A	15 data channels; Operating Range: -40°F to 140°F	N/A

Data Collection

Data was automatically transmitted to a cloud server created by a remote data logging station (HOBO RX3000) that was deployed on the site, allowing for real-time remote access, via the internet, to all real-time sensor values. A scheduled automated delivery of data overnight was set up, as well as alarm notifications and system status notifications. Connection to this station was provided via 4G LTE cellular connection.

The remote data logging stations were equipped with 32 MB of backup memory capable of storing up to 2 million measurements until the next successful data upload. In-person site visits were performed to reset the dataloggers due to a major connection loss, faulty SIM card, or any other data connectivity or technical challenge.

Calibration Information

All data sensors used were provided with original manufacturer calibration certificates, performed per ISO 17025 standards, ensuring traceability to NIST or equivalent international standards.

Lost Data Procedures

During the M&V period, all data signals were checked on a weekly basis to ensure they were operating and reporting correctly. Should an alarm appear in the monitoring system that alerted of a possible data loss for any measurement point, adequate staff would have been deployed on-site to investigate and provide a resolution to the incident, and the following data treatment process will be followed:

- If the data loss affects measurement values that are not key for the M&V process (i.e., return water temperature, pump current), then no further action will be performed, and the calculation methodology will remain intact.
- When the data loss or data quality issues affected key measurement values in the Calculation Methodology, then two possible actions were performed:
    1. When redundancy for these lost measurements existed, either from a redundant or a similar and near sensor, then the compromised data was replaced by its redundant readings. Appropriate adjustments were made to ensure the database timestep reference is not at risk during this process.
    2. When redundancy did not exist for these lost measurements, all data from that period was not used in the data analysis. Instead, regression models were used to interpolate or extrapolate for those data points based on reliable data points.

Appendix B. Analysis Procedure – Energy Calculation

Common Measurement Equations (All Sites)

The following equations define fundamental measurement conversions used across all sites. All final analysis is performed at the daily level.

Natural Gas Energy Measurement

Equation 2: Hourly Natural Gas Energy

$$\dot{Q}_{gas,h} = \dot{V}_{gas,h} \times HHV \tag{3}$$

Where:

- ∀ $\dot{V}_{gas,h}$ = hourly volumetric flow of natural gas to the water heaters (CCF or ft³)
- ∀ HHV = heating value of gas from monthly utility bills (Btu/CCF or Btu/ft³)
- ∀ $\dot{Q}_{gas,h}$ = hourly water heater natural gas energy consumption (Btu/h)

Equation 3: Daily Natural Gas Energy

$$\dot{Q}_{gas,d} = \sum_{h=1}^{24} \dot{Q}_{gas,h} \tag{4}$$

Where:

- ∀ $\dot{Q}_{gas,d}$ = daily water heater natural gas energy consumption (Btu/day)

Pump Electrical Energy Measurement

Equation 4: Pump Instantaneous Power

$$\dot{P}_{pump} = V_{pump} \times \dot{I}_{pump} \times PF \ / \ 1000 \tag{5}$$

Where:

- ∀ $\dot{\mathrm{P}}_{pump}$ = recirculation pump instantaneous power (kW)

∀ V_{pump}
= recirculation pump voltage (V)

∀ $\dot{I}_{pump}$
= recirculation pump current (A)

∀ PF
= measured power factor

Equation 5: Pump Energy per Monitoring Interval

$$E_{pump,i} = \dot{P}_{pump} \times \Delta t/60 \tag{6}$$

<u>Where:</u>

∀ $E_{pump,i}$
= energy used by recirculation pump over monitoring interval (kWh)

∀ Δt
= monitoring interval (minutes, 1-5 minutes)

∀ 6
0 = conversion from minutes to hours

Equation 6: Daily Pump Electrical Energy

$$\dot{E}_{pump,d} = \sum_{i=1}^{n} E_{pump,i} \tag{7}$$

<u>Where:</u>

∀ $\dot{E}_{pump,d}$
= daily recirculation pump electricity usage (kWh/day)

∀ n
= number of monitoring intervals per day (1-minute or 5-minute intervals)

Daily Temperature Averaging

Equation 7: Daily Average Outdoor Air Temperature

$$\bar{T}_{OAT,d} = \frac{\sum_{h=1}^{24} \bar{T}_{OAT,h}}{24} \tag{8}$$

Equation 8: Daily Average Supply Water Temperature[9]

$$\bar{T}_{SWT,d} = \frac{\sum_{h=1}^{24} \bar{T}_{SWT,h}}{24} \tag{9}$$

Equation 9: Daily Average Return Water Temperature

$$\bar{T}_{RWT,d} = \frac{\sum_{h=1}^{24} \bar{T}_{RWT,h}}{24} \tag{10}$$

Equation 10: Daily Average Cold City Water Temperature[10]

$$\bar{T}_{CWT,d} = \frac{\sum_{h=1}^{24} \bar{T}_{CWT,h}}{24} \tag{11}$$

Where:

$\forall$ $\bar{T}_{OAT,d}$ = daily average OAT (°F)

$\forall$ $\bar{T}_{OAT,h}$ = hourly average OAT (°F)

$\forall$ $\bar{T}_{SWT,d}$ = daily average SWT (°F)

$\forall$ $\bar{T}_{SWT,h}$ = hourly average SWT (°F)

$\forall$ $\bar{T}_{RWT,d}$ = daily average RWT (°F)

$\forall$ $\bar{T}_{RWT,h}$ = hourly average RWT (°F)

$\forall$ $\bar{T}_{CWT,d}$ = daily average CWT (°F)

$\forall$ $\bar{T}_{CWT,h}$ = hourly average CWT (°F)

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[9] Not measured for Site #1. Instead, RWT is used as an estimate using **Error! Reference source not found.**.

[10] This is only measured at Site #3 and used to calibrate $\bar{T}_{CWT,m}$ regression model (Equation 41) that is used to estimate CWT for Site #1 and Site #2.

Regression Model Statistical Validity

Per IPMVP and ASHRAE Guideline 14, the regression models must meet the following criteria:

- CV(RMSE) < 25%
- |NMBE| < 0.5%
- $R^2 > 0.75$[11]

Electrical Energy Analysis

The post-installation electrical energy analysis uses a simplified daily averaged approach as the pump electric consumption avoiding the need for multivariable regression modeling for each site. This streamlined method aligns with the NREL 2016 study's treatment of electric savings as a direct co-benefit from runtime data, ensuring reliable and conservative estimates without introducing unnecessary complexity. Peak demand in kW was not considered, as the project's primary focus was on overall energy savings (kWh) rather than instantaneous power reductions, which are less impactful in this low-duty-cycle (i.e. smart pump) application.

Site #1: Analysis Equations

Cold City Water Temperature Estimation

The CWT was modeled for Site #1 using the regression coefficients established based on the measured CWT at Site #3 (see Site #3 Cold City Water Temperature Regression Model, Equation 41), but using Site #1 measured $\bar{T}_{OAT,d}$ to adjust the model for localized conditions.

Baseline Gas Consumption Model

Equation 11: Site #1 Daily Baseline Gas Consumption Regression

$$\dot{Q}_{gas,d,base} = f(\bar{T}_{RWT,d,base} - \bar{T}_{CWT,d,base}, \bar{T}_{OAT,d,base}) \tag{11a}$$

$$\dot{Q}_{gas,d,base} = \beta_0 + \beta_1 \times (\bar{T}_{RWT,d,base} - \bar{T}_{CWT,d,base}) + \beta_2 \times \bar{T}_{OAT,d,base} \tag{11b}$$

<u>Where:</u>

$\forall$ $\dot{Q}_{gas,d,base}$ = daily water heater natural gas energy in the baseline period for Site #1 (Btu/day)

[11] R^2 is utilized as a guidance metric rather than a strict requirement in IPMVP and ASHRAE Guideline 14 for evaluating regression model fit in energy savings verification; models with R^2 below typical thresholds (e.g., 0.75) may still be acceptable if the CV(RMSE) and NMBE are relatively low.

- ∀ $\bar{T}_{RWT,d,base}$ = daily average RWT in the baseline period for Site #1 (°F)
- ∀ $\bar{T}_{CWT,d,base}$ = estimated CWT using regression coefficients from Site #3 and baseline weather conditions period for Site #1 (°F)
- ∀ $\bar{T}_{OAT,d,base}$ = daily average OAT in the baseline period for Site #1 (°F)
- ∀ $\bar{T}_{RWT,d} - \bar{T}_{CWT,d}$ = proxy for temperature differential representing system demand
- ∀ $\beta_0, \beta_1, \beta_2$ = regression coefficients for the baseline model at Site #1

Post-Installation Gas Consumption Model

Due to limited instrumentation, the post-installation gas consumption uses the same independent variables as the baseline model for each of the different control modes:

Equation 12: Site #1 Daily Post-Installation Gas Consumption Regression using Adaptive Learning Mode

$$\dot{Q}_{gas,d,post,AL} = f(\bar{T}_{RWT,d,post} - \bar{T}_{CWT,d,post}, \bar{T}_{OAT,d,post}) \quad (12a)$$

$$\dot{Q}_{gas,d,post,AL} = \gamma_0 + \gamma_1 \times (\bar{T}_{RWT,d,post} - \bar{T}_{CWT,d,post}) + \gamma_2 \times \bar{T}_{OAT,d,post} \quad (12b)$$

<u>Where:</u>

- ∀ $\dot{Q}_{gas,d,post,AL}$ = daily water heater natural gas consumption in the post-installation period using Adaptive Learning for Site #1 (Btu/day)
- ∀ $\bar{T}_{RWT,d,post}$ = daily average RWT in the post-installation period for Site #1 (°F)
- ∀ $\bar{T}_{CWT,d,post}$ = estimated CWT using regression coefficients from Site #3 and post-period weather conditions for Site #1 (°F)
- ∀ $\bar{T}_{OAT,d,post}$ = daily average OAT in the post-installation period for Site #1 (°F)
- ∀ $\gamma_0, \gamma_1, \gamma_2$ = regression coefficients for the post-installation model using Adaptive Learning mode at Site #1

Equation 13: Site #1 Daily Post-Installation Gas Consumption Regression using Constant Temperature Mode

$$\dot{Q}_{gas,d,post,CT} = f(\bar{T}_{RWT,d,post} - \bar{T}_{CWT,d,post}, \bar{T}_{OAT,d,post}) \tag{13a}$$

$$\dot{Q}_{gas,d,post,CT} = \mu_0 + \mu_1 \times (\bar{T}_{RWT,d,post} - \bar{T}_{CWT,d,post}) + \mu_2 \times \bar{T}_{OAT,d,post} \tag{13b}$$

Where:

- $\forall$ $\dot{Q}_{gas,d,post,AT}$ = daily water heater natural gas consumption in the post-installation period using Constant Temperature mode for Site #1 (Btu/day)
- $\forall$ $\bar{T}_{RWT,d,post}$ = daily average RWT in the post-installation period for Site #1 (°F)
- $\forall$ $\bar{T}_{CWT,d,post}$ = estimated CWT using regression coefficients from Site #3 and post-period weather conditions for Site #1 (°F)
- $\forall$ $\bar{T}_{OAT,d,post}$ = daily average OAT in the post-installation period for Site #1 (°F)
- $\forall$ μ_0, μ_1, μ_2 = regression coefficients for the post-installation model using Constant Temperature mode at Site #1

Gas Savings Calculation

Gas savings are calculated by first projecting the baseline regression model into the post-installation period using the actual post-installation conditions (RWT, CWT, OAT), then comparing the average of these baseline projections to the average of actual post-installation measurements:

Equation 14: Site #1 Baseline Model Projected into Post Period

$$\hat{Q}_{gas,d,base,proj,i} = \beta_0 + \beta_1 \times (\bar{T}_{RWT,d,post,i} - \bar{T}_{CWT,d,post,i}) + \beta_2 \times \bar{T}_{OAT,d,post,i} \tag{14}$$

Where:

- $\forall$ $\hat{Q}_{gas,base,proj,i}$ = daily baseline model prediction for day i in the post-installation period (Btu/day)
- $\forall$ $\bar{T}_{RWT,d,post,i}$, $\bar{T}_{CWT,d,post,i}$, $\bar{T}_{OAT,d,post,i}$ = averaged daily conditions on day i in the post-installation period (°F)

- $\beta_0, \beta_1, \beta_2$ = regression coefficients from baseline model (Equation 11)

Equation 15: Average Baseline Projection

$$\bar{Q}_{gas,d,base,proj} = \frac{1}{n_{post}} \sum_{i=1}^{n_{post}} \hat{Q}_{gas,d,base,proj,i} \tag{15}$$

Equation 16: Average Measured Post-Installation Consumption

$$\bar{Q}_{gas,d,post,meas} = \frac{1}{n_{post}} \sum_{i=1}^{n_{post}} Q_{gas,s,post,meas,i} \tag{16}$$

Where:

- n_{post} = number of days in the post-installation period
- $Q_{gas,post,meas,i}$ = measured DHW heater natural gas consumption on day i in the post-installation period (Btu/day)

Equation 17: Daily Gas Savings

$$\Delta Q_{gas,d} = \bar{Q}_{gas,d,base,proj} - \bar{Q}_{gas,d,post,meas} \tag{17}$$

Equation 18: Percentage Gas Savings

$$\%\Delta Q_{gas} = \frac{\Delta Q_{gas,d}}{\bar{Q}_{gas,d,base,proj}} \times 100\% \tag{18}$$

Where:

- $\Delta Q_{gas,d}$ = average daily gas energy savings (Btu/day)
- $\%\Delta Q_{gas}$ = percentage gas energy savings relative to projected baseline

Electrical Energy Analysis

Equation 19: Baseline Electrical Energy Input

$$\bar{E}_{pump,d,base} = \frac{\sum_{h=1}^{n_{base}} \dot{E}_{pump,d,base}}{n_{base}} \tag{19}$$

Equation 20: Post-Installation Electrical Energy Input

$$\bar{E}_{pump,d,post} = \frac{\sum_{h=1}^{n_{post}} \dot{E}_{pump,d,post}}{n_{post}} \tag{20}$$

Where:

- $\bar{E}_{pump,d,base}$ = average daily electrical energy input for the baseline period (kWh/day)
- $\bar{E}_{pump,d,post}$ = average daily electrical energy input for the post-installation period (kWh/day)
- n_{base} = number of days in the baseline period
- n_{post} = number of days in the post-installation period

Equation 21: Pump Electrical Energy Savings

$$\Delta E_{pump} = \bar{E}_{pump,d,base} - \bar{E}_{pump,d,post} \tag{21}$$

Equation 22: Pump Electrical Energy Percent Savings

$$\%\Delta E_{pump} = \frac{\Delta E_{pump}}{\bar{E}_{pump,d,base}} \times 100\% \tag{22}$$

Note on Baseline Period: The baseline period was extended to 39 days (05/29/24 - 08/13/24) and includes two distinct RWT regimes due to water heater operational changes on 6/22/24:

- Period 1 (5/29/24- 6/22/24): Average RWT = 115.38°F
- Period 2 (6/23/24 - 8/13/24): Average RWT = 106.66°F

Site #2: Analysis Equations

Cold City Water Temperature Estimation

The $\bar{T}_{CWT,d}$ was estimated using the regression coefficients established using the measured CWT at Site #3 (see Site #3 Cold City Water Temperature Regression Model, Equation 41), but using Site #2 measured $\bar{T}_{OAT,d}$ to adjust the model for localized conditions.

Baseline Gas Consumption Model

Equation 23: Site #2 Daily Baseline Gas Consumption Regression

$$\dot{Q}_{gas,d,base} = f(\bar{T}_{SWT,d,base} - \bar{T}_{CWT,d,base}, \bar{T}_{OAT,d,base}) \tag{23a}$$

$$\dot{Q}_{gas,d,base} = \varepsilon_0 + \varepsilon_1 \times (\bar{T}_{SWT,d,base} - \bar{T}_{CWT,d,base}) + \varepsilon_2 \times \bar{T}_{OAT,d,base} \tag{23b}$$

<u>Where:</u>

∀ $\dot{Q}_{gas,d,base}$ = daily water heater natural gas energy in the baseline period (Btu/day)

∀ $\bar{T}_{SWT,d,base}$ = daily average SWT in the baseline period (°F)

∀ $\bar{T}_{CWT,d,base}$ = estimated CWT using regression coefficients from Site #3 and baseline weather conditions (°F)

∀ $\bar{T}_{OAT,d,base}$ = daily average OAT in the baseline period (°F)

∀ $S_{RWT,d} - \bar{T}_{CWT,d}$ = proxy for temperature differential representing system demand

∀ $\varepsilon_0, \varepsilon_1, \varepsilon_2$ = regression coefficients for the baseline model at Site #2

Post-Installation Gas Consumption Model

Due to limited instrumentation, the post-installation gas consumption models use a different independent variable as the baseline model for the Adaptive Learning Mode as the algorithm is highly dependent on the RWT. The return-normalized temperature lift was introduced by normalizing the (SWT – CWT) temperature lift by RWT and used to model the Adaptive Learning period as it provides an acceptable post model fit and similar range of values in both test periods. It makes sense to use this metric for Adaptive Learning in the absence of the $\dot{V}_{cold}$, since the control mode relies on RWT to dynamically adjust pump operation based on usage patterns:

Equation 24: Site #2 Daily Post-Installation Gas Consumption Regression using Adaptive Learning Mode

$$\dot{Q}_{gas,d,post,AL} = f((\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post})/\bar{T}_{RWT,d,post}, \bar{T}_{OAT,d,post}) \quad (24a)$$

$$\dot{Q}_{gas,d,post,AL} = \tau_0 + \tau_1 \times ((\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post})/\bar{T}_{RWT,d,post}) + \tau_2 \times \bar{T}_{OAT,d,post} \quad (24b)$$

<u>Where:</u>

- $\forall$ $\dot{Q}_{gas,d,post,AL}$ = daily water heater natural gas consumption in the post-installation period under Adaptive Learning mode (Btu/day)
- $\forall$ $\bar{T}_{SWT,d,post}$ = daily average SWT in the post-installation period for Site #2 (°F)
- $\forall$ $\bar{T}_{RWT,d,post}$ = daily average RWT in the post-installation period for Site #2 (°F)
- $\forall$ $\bar{T}_{CWT,d,post}$ = estimated CWT using regression coefficients from Site #3 and post-period weather conditions for Site #2 (°F)
- $\forall$ $\bar{T}_{OAT,d,post}$ = daily average OAT in the post-installation period for Site #2 (°F)
- $\forall$ τ_0, τ_1, τ_2 = regression coefficients for the Adaptive Learning post-installation model at Site #2

Equation 25: Site #2 Daily Post-Installation Gas Consumption Regression using Constant Temperature Mode

$$\dot{Q}_{gas,d,post,CT} = f(\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post}, \bar{T}_{OAT,d,post}) \quad (25a)$$

$$\dot{Q}_{gas,d,post,CT} = \delta_0 + \delta_1 \times (\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post}) + \delta_2 \times \bar{T}_{OAT,d,post} \quad (25b)$$

<u>Where:</u>

- $\forall$ $\dot{Q}_{gas,d,post,CT}$ = daily water heater natural gas consumption in the post-installation period under Constant Temperature mode (Btu/day)
- $\forall$ $\bar{T}_{SWT,d,post}$ = daily average SWT in the post-installation period for Site #2 (°F)
- $\forall$ $\bar{T}_{CWT,d,post}$ = estimated CWT using regression coefficients from Site #3 and post-period weather conditions for Site #2 (°F)

- $\bar{T}_{OAT,d,post}$ = daily average OAT in the post-installation period for Site #2 (°F)
- $\delta_0, \delta_1, \delta_2$ = regression coefficients for the Constant Temperature post-installation model at Site #2

Gas Savings Calculation

Gas savings are calculated by first projecting the post-installation regression model into the baseline period using the actual baseline conditions (RWT, CWT, OAT), then comparing the average of these post-period projections to the average of actual baseline measurements:

Equation 26: Site #2 Post Model Projected into Baseline Period under Adaptive Learning

$$\hat{Q}_{gas,d,post,AL,i} = \tau_0 + \tau_1 \times (\bar{T}_{RWT,d,base,i} - \bar{T}_{CWT,d,base,i}) + \tau_2 \times \bar{T}_{OAT,d,base,i} \tag{26}$$

Where:

- $\hat{Q}_{gas,post,AL,i}$ = daily post model prediction under Adaptive Learning for day i in the baseline period for Site #2 (Btu/day)
- $\bar{T}_{RWT,d,base,i}$, $\bar{T}_{CWT,d,base,i}$, $\bar{T}_{OAT,d,base,i}$ = averaged daily conditions on day i in the baseline period at Site #2 (°F)
- τ_0, τ_1, τ_2 = regression coefficients from the Adaptive Learning post model (Equation 24)

Equation 27: Site #2 Post Model Projected into Baseline Period under Constant Temperature

$$\hat{Q}_{gas,d,post,CT,i} = \delta_0 + \delta_1 \times (\bar{T}_{RWT,d,base,i} - \bar{T}_{CWT,d,base,i}) + \delta_2 \times \bar{T}_{OAT,d,base,i} \tag{27}$$

Where:

- $\hat{Q}_{gas,post,CT,i}$ = daily post model prediction under Constant Temperature mode for day i in the post-installation period for Site #2 (Btu/day)
- $\bar{T}_{RWT,d,base,i}$, $\bar{T}_{CWT,d,base,i}$, $\bar{T}_{OAT,d,base,i}$ = averaged daily conditions on day i in the post-installation period at Site #2 (°F)

∀ $\delta_0, \delta_1, \delta_2$ = regression coefficients from the Constant Temperature post model (Equation 25)

Equation 28: Average Post Period Projection

$$\bar{Q}_{gas,d,post,proj} = \frac{1}{n_{base}} \sum_{i=1}^{n_{base}} \hat{Q}_{gas,d,post,i} \tag{28}$$

Equation 29: Average Measured Baseline Energy Consumption

∀ $\bar{Q}_{gas,\mathrm{d,base},mea}$

$\frac{1}{n_{base}} \sum_{i=1}^{n_{base}} Q_{gas,\mathrm{s,base,meas},i}$

<u>Where:</u>

∀ n_{base} = number of days in the baseline period for Site #2

∀ $Q_{gas,base,meas,i}$ = measured water heater natural gas consumption on day i in the baseline period for Site #2 (Btu/day)

Equation 30: Daily Gas Savings

$$\Delta Q_{gas,d} = \bar{Q}_{gas,d,post,proj} - \bar{Q}_{gas,d,base,meas} \tag{30}$$

Equation 31: Percentage Gas Savings

$$\%\Delta Q_{gas} = \frac{\Delta Q_{gas,d}}{\bar{Q}_{gas,d,post,proj}} \times 100\% \tag{31}$$

<u>Where:</u>

∀ $\Delta Q_{gas,d}$ = average daily gas energy savings (Btu/day)

∀ $\%\Delta Q_{gas}$ = percentage gas energy savings relative to projected post period

Electrical Energy Analysis

Equation 32: Baseline Electrical Energy Input

$$\bar{E}_{pump,d,base} = \frac{\sum_{h=1}^{n_{base}} \dot{E}_{pump,d,base}}{n_{base}} \tag{32}$$

Equation 33: Post-Installation Electrical Energy Input

$$\bar{E}_{pump,d,post} = \frac{\sum_{h=1}^{n_{post}} \dot{E}_{pump,d,post}}{n_{post}} \tag{33}$$

Where:

- $\forall$ $\bar{E}_{pump,d,base}$ = average daily electrical energy input for the baseline period at Site #2 (kWh/day)
- $\forall$ $\bar{E}_{pump,d,post}$ = average daily electrical energy input for the post-installation period at Site #2 (kWh/day)
- $\forall$ n_{base} = number of days in the baseline period at Site #2
- $\forall$ n_{post} = number of days in the post-installation period at Site #2

Equation 34: Pump Electrical Energy Savings

$$\Delta E_{pump} = \bar{E}_{pump,d,base} - \bar{E}_{pump,d,post} \tag{34}$$

Equation 35: Pump Electrical Energy Percent Savings

$$\%\Delta E_{pump} = \frac{\Delta E_{pump}}{\bar{E}_{pump,d,base}} \times 100\% \tag{35}$$

Site #3: Analysis Equations (IPMVP Option B)

Site #3 employs an IPMVP Option B—Retrofit Isolation with All Parameter Measurement approach due to the complexity introduced by the solar thermal preheat system. This approach isolates gas savings from variable hot water heating demand and additional thermal solar preheating contributions through multivariable regression analysis.

Methodology Validation

The multivariable regression approach used for Site #3 is validated by established industry standards and prior research:

- **ASHRAE Guideline 14 (Section 5.1.3.4 - Baseline Adjustments):** ASHRAE Guideline 14 recommends multivariable regression models for M&V applications where energy consumption is influenced by multiple independent variables [28]. The guideline specifies that baseline models should correlate actual baseline energy use with substantive fluctuating independent variables, and that multivariable linear regression models are among the most commonly used approaches for calculating before-and-after savings from energy conservation retrofits. Annex D of the guideline provides additional guidance on regression estimation with two or more independent variables, including data requirements, model selection criteria, and statistical validation procedures.
- **NREL Control Strategies Study (2016), Appendix A - Gas Normalization Method:** The gas consumption normalization methodology employed in this study aligns with the approach documented in NREL/TP-5500-64541, Appendix A [2]. The NREL study used temperature differential and flow-based normalization to isolate DHW system performance from variable operating conditions, demonstrating that gas consumption in MFm DHW systems can be accurately modeled as a function of supply-return temperature differential, cold water inlet temperature, and hot water draw volume. This methodology accounts for the primary physical drivers of gas consumption: (1) energy required to heat incoming cold water to the supply setpoint, and (2) energy required to compensate for distribution and standby losses. The current study applies the same physical principles by incorporating (SWT – CWT) differential and $\dot{V}_{\mathrm{cold}}$ as regression variables.

Regression Imputation for Missing Data

During the post-installation monitoring period, several data quality issues required the use of regression imputation to fill in or “salvage” missing data that used relationships between available variables to predict and replace missing values maintaining the test period sample size:

Gas Meter Disconnection: The gas meter was disconnected during a portion of the Adaptive Learning post-installation period (9/12/25 - 9/24/25). Missing gas consumption data was estimated using a regression model developed from available Adaptive Learning post period data using temperature limits of 100-105°F:

Equation 36: Site #3 Post Adaptive Learning Gas Consumption Regression using 100-105°F Temperature Limits

$$\dot{Q}_{gas,daily,post,AL,100-105F} = f(SWT - RWT, \dot{V}_{return}) \quad (36)$$

Note: *The RWT and $\dot{V}_{return}$ are used as independent variables during this test period in place of missing CWT and $\dot{V}_{cold}$ data using the 100-105°F temperature limits.*

Similarly, missing gas data during the Constant Temperature period (9/25/25 - 10/23/25) was estimated using:

Equation 37: Site #3 Post Constant Temperature Gas Consumption Regression

$$\dot{Q}_{gas,daily,post,CT} = f(SWT - CWT, \dot{V}_{return},) \quad (37)$$

Note: *The $\dot{V}_{return}$ was used in place of the missing $\dot{V}_{cold}$ during this test period, which still provided an acceptable modeling fit metrics.*

Cold City Water Bypass Malfunction: The cold city water bypass valve malfunctioned on 7/15/25 and was not repaired until 12/10/25. During this period, cold city water flow was estimated using regression models developed from periods with valid flow data and reliable data points as independent variables that did not lose communication with the datalogger:

For the Adaptive Learning period:

Equation 38: Site #3 Post Adaptive Learning Cold City Flow Rate Regression

$$\dot{V}_{cold,daily,AL} = f(\dot{Q}_{gas}, \bar{T}_{OAT,d}) \quad (38)$$

For the Constant Temperature period (using data after the 12/10/25 repair):

Equation 39: Site #3 Post Constant Temp Cold City Water Flow Rate Regression

$$\dot{V}_{cold,daily,CT} = f(\dot{Q}_{gas}, \bar{T}_{OAT,d}) \quad (39)$$

These regression-based estimation procedures follow IPMVP guidance for handling missing data using statistically valid engineering techniques, with appropriate adjustments to uncertainty calculations to reflect the reduced confidence in estimated values. The regression models follow IPMVP and ASHRAE Guideline 14 goodness-of-fit metrics.

Site #3 Analysis Equations

Site #3 uses the common measurement equations (Equations 1-8) for natural gas energy, pump electrical energy, and daily temperature averaging. The following equations are specific to Site #3's regression analysis methodology.

Additional Independent Variables (Site #3 Specific)

Equation 40: Daily Cold City Water Flow

$$\dot{V}_{cold,d} = \sum_{h=1}^{24} \dot{V}_{cold,h} \tag{40}$$

Where:

- ∀ $\dot{V}_{cold,d}$ = daily cold city water flow into DHW system (GPD or gal/day)
- ∀ $\dot{V}_{cold,h}$ = hourly cold city water flow (GPH or gal/hr)

Site #3 Cold City Water Temperature Regression Model

The measured CWT at Site #3 was modeled using a localized version of the Burch and Christensen (2007) NREL mains water temperature model, which is used to estimate CWT at Site #1 and Site #2 based on local weather and ground conditions [27]. This localized model is the weather offset approach used in DEER and Title 24 ACM, but adapted to local conditions via the local ground temperature ($\mathrm{T_{ground}}$) estimated using a sinusoidal approximation adjusted for local soil conditions and the recent 31-day average of measured site-specific OAT ($\mathrm{\overline{T}_{AVG31}}$). It is further modified to include $\mathrm{\overline{T}_{OAT,d}}$ as an additional independent variable to account for the daily effect on exposed or shallow pipes within the building or near the water heaters.

Equation 41: Daily Cold City Water Temperature Regression Model

$$\hat{T}_{CWT,d} = f(\overline{T}_{AVG31}, \overline{T}_{ground,d}, \overline{T}_{OAT,d}) \tag{41a}$$

$$\hat{T}_{CWT,d} = \alpha_0 + \alpha_1 \times \overline{T}_{AVG31} + \alpha_2 \times \overline{T}_{ground,d} + \alpha_3 \times \overline{T}_{OAT,d} \tag{41b}$$

Where:

- ∀ $\hat{T}_{CWT,d}$ = modeled daily CWT using measured data at Site #3 (°F)
- ∀ $\overline{T}_{AVG31}$ = daily OAT averaged over the previous 31 days
- ∀ $\overline{T}_{ground,d}$ = daily $\mathrm{T_{ground}}$ for a specific day of the year, calculated using Equation 42

∀ $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ = regression coefficients

Equation 42: Ground Temperature Sinusoidal Model

For each day (θ = 1 to 365):

$$\bar{T}_{ground,\theta} = T_{yr,avg} - 0.5(T_{yr,max} - T_{yr,min}) \times cos\ (2 \times \pi \times \left(\frac{\theta - 1}{PB}\right) - PO - PHI) \tag{42}$$

Where:

∀ $T_{yr,avg}$ = modeled daily CWT using measured data at Site #3 (°F)

∀ $T_{yr,max}$ = daily OAT averaged over the previous 31 days

∀ $T_{yr,min}$ = daily T_{ground} for a specific day of the year, calculated using

∀ PB = period of annual cycle, 365 days in the year

∀ PO = phase lag that controls timing offset between peak air temperature and ground temperatures due to sol thermal inertia, default value of 0.6 for CA (radians)

∀ DIF = soil diffusivity using a lowered value of 0.01 ft^2/h for clay/wet soils typically found in the San Francisco Bay area, affects damping factor G_M and phase angle adjustment PHI

∀ $Beta$ = soil duffusity parameter calculated as $\sqrt{\pi/(DIF \times PB \times 24)}) \times 10$

∀ $X_B = e^{-Beta}$

∀ $C_B = \cos(Beta)$

∀ $S_B = \sin(Beta)$

∀ G_M = damping factor to reduce the amplitude of surface air variations due to soil heat conduction calculated as $\sqrt{(X_B \times X_B - 2 \times X_B \times C_B + 1)/(2 \times Beta \times Beta)} \times 10$

∀ PHI
= Phase angle adjustment to further tune the phase lag due to heat diffusion dynamics calculated as $\mathrm{atan}\left((1 - \mathrm{X_B} \times (\mathrm{C_B} + \mathrm{S_B}))/(1 - \mathrm{X_B} \times (\mathrm{C_B} - \mathrm{S_B})\right)$

Baseline Natural Gas Energy Regression Model

Equation 43: Site #3 Baseline Gas Consumption Model

$$\dot{Q}_{gas,d,base} = f(\dot{V}_{cold,d,base}, \bar{T}_{SWT,d,base} - \bar{T}_{CWT,d,base}, \bar{T}_{OAT,d,base}) \quad (43a)$$

$$\dot{Q}_{gas,d,base} = \varepsilon_0 + \varepsilon_1 \times \dot{V}_{cold,d,base} + \varepsilon_2 \times (\bar{T}_{SWT,d,base} - \bar{T}_{CWT,d,base}) + \varepsilon_3 \times \bar{T}_{OAT,d,base} \quad (43b)$$

Where:

∀ $\dot{Q}_{gas,d,base}$
= daily baseline water heater natural gas consumption at Site #3 (Btu/day)

∀ $\dot{V}_{cold,d,base}$
= daily $\dot{V}_{cold}$ in the baseline period at Site #3 (GPD)

∀ $\bar{T}_{SWT,d,base}$
= daily average SWT in the baseline period at Site #3 (°F)

∀ $\bar{T}_{CWT,d,base}$
= daily average CWT in the baseline period at Site #3 (°F)

∀ $\bar{T}_{OAT,d,base}$
= daily average OAT in the baseline period at Site #3 (°F)

∀ $\varepsilon_0, \varepsilon_1, \varepsilon_2, \varepsilon_3$
= regression coefficients for the baseline period at Site #3

Post-Installation Natural Gas Energy Regression Models

Due to the loss of return water temperature and runtime data from the datalogger communication failure, different regression models are used for each control mode:

Equation 44: Site #3 Post-Installation Gas Regression Model (Adaptive Learning Mode)

$$\dot{Q}_{gas,post,AL} = f(\bar{T}_{SWT,d} - \bar{T}_{CWT,d}, \dot{V}_{cold,d}) \quad (44a)$$

$$\dot{Q}_{gas,post,AL} = \alpha_0 + \alpha_1 \times (\bar{T}_{SWT,d} - \bar{T}_{CWT,d}) + \alpha_2 \times \dot{V}_{cold,d} \quad (44b)$$

Where:

∀ $\dot{Q}_{gas,post,AL}$
= daily post-installation water heater natural gas consumption in Adaptive Learning mode at Site #3 (Btu/day)

- $\bar{T}_{SWT,d} - \bar{T}_{CWT,d}$ = daily temperature differential across water heaters in the post-period using Adaptive Learning at Site #3 (°F)
- $\dot{V}_{cold,d}$ = Daily cold city water flow rate during the post-period using Adaptive Learning at Site #3
- $\alpha_0, \alpha_1, \alpha_2$ = regression coefficients for the post-period using Adaptive Learning at Site #3

Note: *This model uses available data during periods when RWT and Runtime data were successfully transmitted before the SIM card failure.*

Equation 45: Site #3 Post-Installation Gas Regression Model (Constant Temperature Mode)

$$\dot{Q}_{gas,post,CT} = f(\bar{T}_{SWT,d} - \bar{T}_{CWT,d}, \dot{V}_{return}, \bar{T}_{OAT,d,post}) \quad (45a)$$

$$\dot{Q}_{gas,post,CT} = \epsilon_0 + \epsilon_1 \times (\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post}) + \epsilon_2 \times \dot{V}_{return,d,post} + \epsilon_3 \times \bar{T}_{OAT,d,post} \quad (45b)$$

<u>Where:</u>

- $\dot{Q}_{gas,post,CT}$ = daily post-installation DHW heater gas consumption in Constant Temperature mode at Site #3 (Btu/day)
- $\bar{T}_{SWT,d,post} - \bar{T}_{CWT,d,post}$ = daily temperature rise from cold water to supply in the post period using Constant Temperature at Site #3 (°F)
- $\dot{V}_{return,d,post}$ = daily return water flow rate in the post period using Constant Temperature at Site #3 (GPD)
- $\bar{T}_{OAT,d,\mathrm{post}}$ = daily average OAT measured during the post test period (°F)
- $\epsilon_0, \epsilon_1, \epsilon_2, \epsilon_3$ = regression coefficients for the post-period using Constant Temperature at Site #3

Natural Gas Energy Savings

Gas savings are calculated by first projecting the baseline regression model into the post-installation period using the actual post-installation conditions ($\dot{V}_{cold}$, (SWT-CWT), OAT), then comparing the average of these baseline projections to the average of actual post-installation measurements:

Equation 46: Site #3 Baseline Regression Model Projected into Post Period

$$\hat{Q}_{gas,base,proj,i} = \rho_0 + \rho_1 \times \dot{V}_{cold,d,post,i} + \rho_2 \times (\bar{T}_{SWT,d,post,i} - \bar{T}_{CWT,d,post,i}) + \rho_3 \times \bar{T}_{OAT,d,post,i} \tag{46}$$

Where:

- ∀ $\hat{Q}_{gas,base,proj,i}$ = baseline model prediction for day i in the post-installation period (Btu/day)
- ∀ $\dot{V}_{cold,d,post,i}$, $\bar{T}_{SWT,d,post,i}$, $\bar{T}_{CWT,d,post,i}$, $\bar{T}_{OAT,d,post,i}$ = actual conditions on day i in the post-installation period
- ∀ $\rho_0, \rho_1, \rho_2, \rho_3$ = regression coefficients from baseline model (Equation 43)

Equation 47: Average Baseline Projection

$$\bar{Q}_{gas,base,proj} = \frac{1}{n_{post}} \sum_{i=1}^{n_{post}} \hat{Q}_{gas,base,proj,i} \tag{47}$$

Equation 48: Average Measured Post-Installation Consumption

$$\bar{Q}_{gas,post,meas} = \frac{1}{n_{post}} \sum_{i=1}^{n_{post}} Q_{gas,post,meas,i} \tag{48}$$

Where:

- ∀ n_{post} = number of days in the post-installation period
- ∀ $Q_{gas,post,meas,i}$ = measured gas consumption on day i in the post-installation period (Btu/day)

Equation 49: Gas Energy Savings

$$\Delta Q_{gas} = \bar{Q}_{gas,base,proj} - \bar{Q}_{gas,post,meas} \tag{49}$$

Equation 50: Percent Gas Energy Savings

$$\%\Delta Q_{gas} = \frac{\Delta Q_{gas}}{\bar{Q}_{gas,base,proj}} \times 100\% \tag{50}$$

Where:

∀ ΔQ_{gas} = average daily gas savings (Btu/day)

∀ $\%\Delta Q_{gas}$ = percentage gas savings relative to projected baseline

Electrical Energy Calculations

Equation 51: Baseline Electrical Energy Input

$$\bar{E}_{pump,base} = \frac{\sum_{d=1}^{n_{baseline}} E_{pump,d}}{n_{base}} \tag{51}$$

Equation 52: Post-Installation Electrical Energy Input

$$\bar{E}_{pump,post} = \frac{\sum_{d=1}^{n_{post}} E_{pump,d}}{n_{post}} \tag{52}$$

Equation 53: Pump Electrical Energy Savings

$$\Delta E_{pump} = \bar{E}_{pump,base} - \bar{E}_{pump,post} \tag{53}$$

Equation 54: Pump Electrical Energy Percent Savings

$$\%\Delta E_{pump} = \frac{\Delta E_{pump}}{\bar{E}_{pump,base}} \times 100\% \tag{54}$$

Where:

∀ $\bar{E}_{pump,base}$ = average electrical energy input for the baseline period (kWh/hr)

∀ $\bar{E}_{pump,post}$ = average electrical energy input for the post-installation period (kWh/hr)

∀ n_{base} = number of days in the baseline period at Site #3

∀ n_{post} = number of hours in the post-installation period at Site #3

Appendix C. Site-Specific Results

Site #1: Results

Table 33: Site #1 Performance Summary

	Baseline	Adaptive Learning	Constant Temp.
Reporting Period Date(s)	05/29/24 – 6/22/24 7/27/24 – 08/13/24	08/15/24 - 09/15/24, 01/16/25 - 02/21/25 3/29/25 – 4/21/25	09/16/24 - 01/15/25
Number of Days	39	93	122
Avg. RWT (°F)	111.36	105.6	106.5
Avg. SWT (°F)	—	106.75	106.0
Avg. CWT_m (°F)	74.8	72.7	74.3
Avg. OAT (°F)	59.7	55.6	57.9
Avg. ΔT ($RWT - CWT_m$)	36.5	32.8	32.3
Avg. Daily Gas (Btu/day)	554,641	555,372.8	483,764.2
Avg. Daily Gas (therm/day)	5.6	5.6	4.8
Avg. Daily Electric (kWh/day)	1.8	0.6	5.2
Gas Model R^2	0.74	0.81	0.72
Gas Model CV(RMSE)	6.9%	8.6%	9.1%
Gas Model NMBE	0.0000%	0.0104%	0.0000%
Normalized Gas Savings (Btu/day)	—	4,584.7	40,930.7
Normalized Gas Savings (%)	—	0.9%	7.9%
Electric Savings (kWh/day)	—	1.22	-4.05
Electric Savings (%)	—	65.1%	-215.8%

Table 34: Site #1 Baseline Regression Model Statistics from Equation 11.

Coefficient	Value	Std. Error	t-statistic	p-value
β_0 (Intercept)	720,285.0	177,456.3	4.06	<0.001
β_1 ($RWT - CWT_m$)	1,1162.6	1,180.1	9.46	<0.001
β_2 (OAT)	-9,604.4	2,873.0	-3.34	0.002

Table 35: Site #1 Post Regression Model Statistics using Adaptive Learning mode from Equation 12.

Coefficient	Value	Std. Error	t-statistic	p-value
γ_0 (Intercept)	174,220.5	199,334.3	0.87	0.3844
$\gamma_1\,(\mathrm{RWT} - \mathrm{CWT_m})$	23,924.8	3,490.8	6.85	<0.001
$\gamma_2\,(\mathrm{OAT})$	-7,278.4	1,675.3	-4.34	<0.001

Table 36: Site #1 Post Regression Model Statistics using Constant Temperature mode from Equation 13.

Coefficient	Value	Std. Error	t-statistic	p-value
μ_0 (Intercept)	234,816.6	153,053.6	1.53	0.128
$\mu_1\,(\mathrm{RWT} - \mathrm{CWT_m})$	16,438.1	2,730.3	6.02	<0.001
$\mu_2\,(\mathrm{OAT})$	-5,016.6	1,262.1	-3.97	<0.001

Figure 9: Site #1 Baseline period predicted vs. measured gas consumption scatter plot comparison.

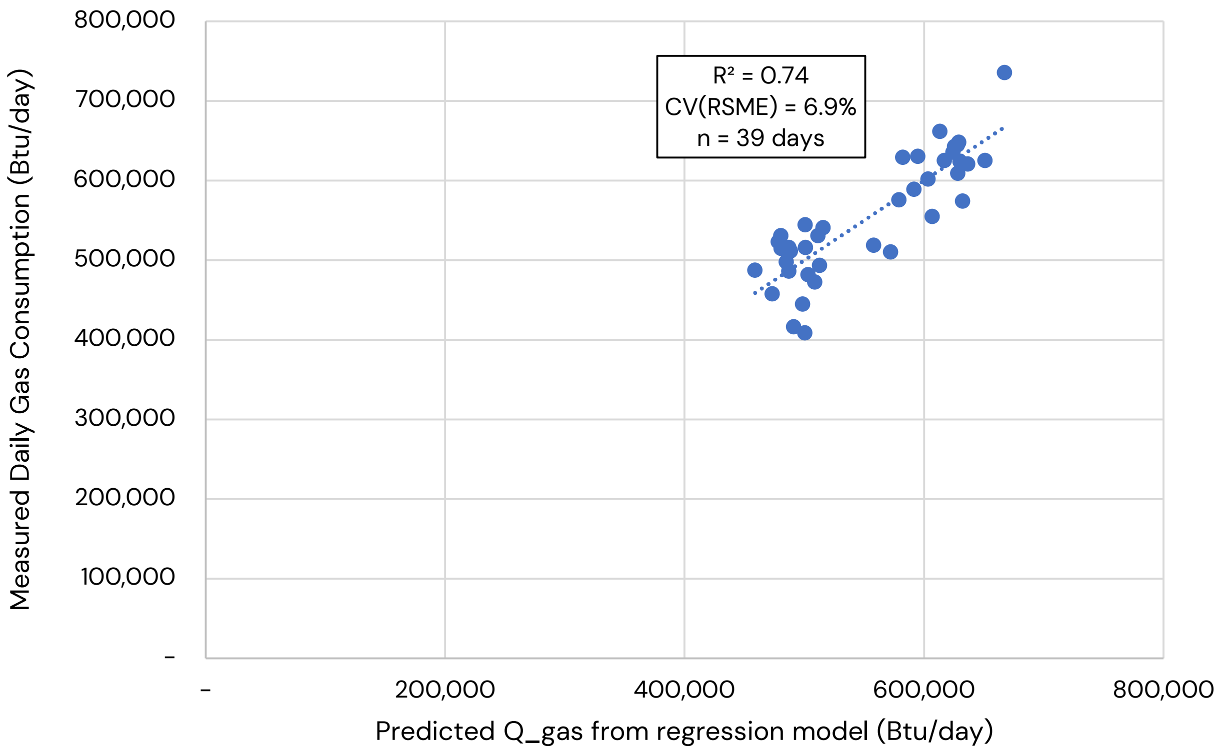


Figure 10: Site #1 Adaptive Learning period predicted vs. measured gas consumption scatter plot comparison.

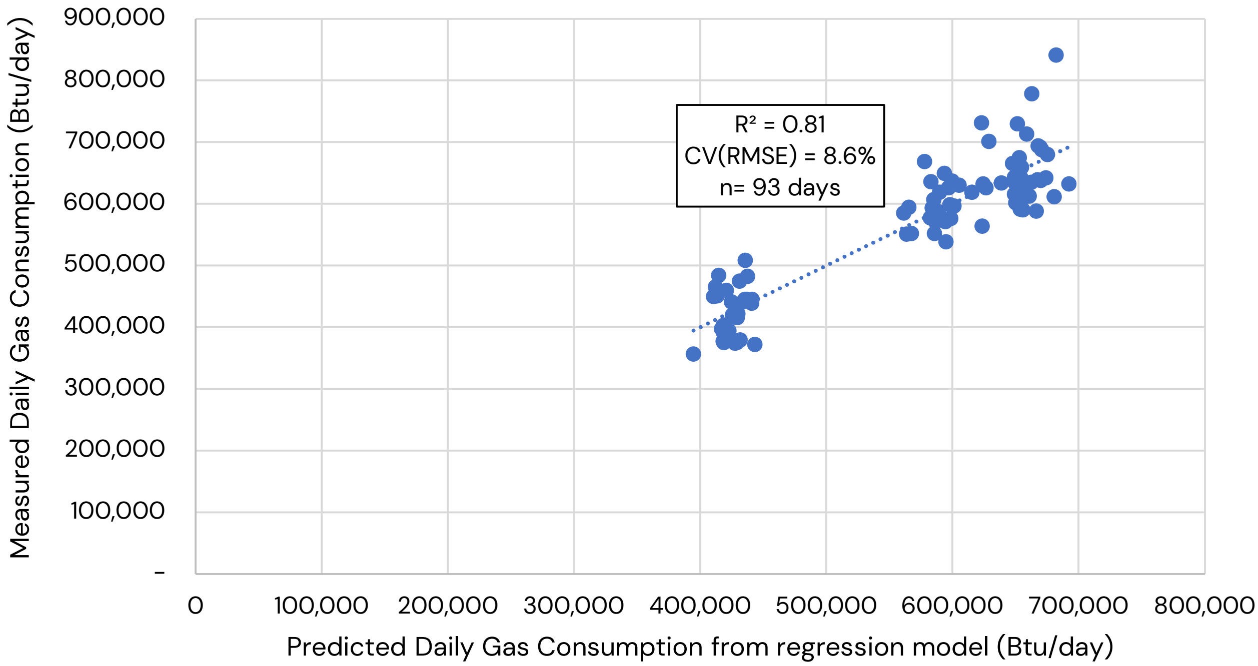


Figure 11: Site #1 Constant Temperature period predicted vs. measured gas consumption scatter plot comparison.

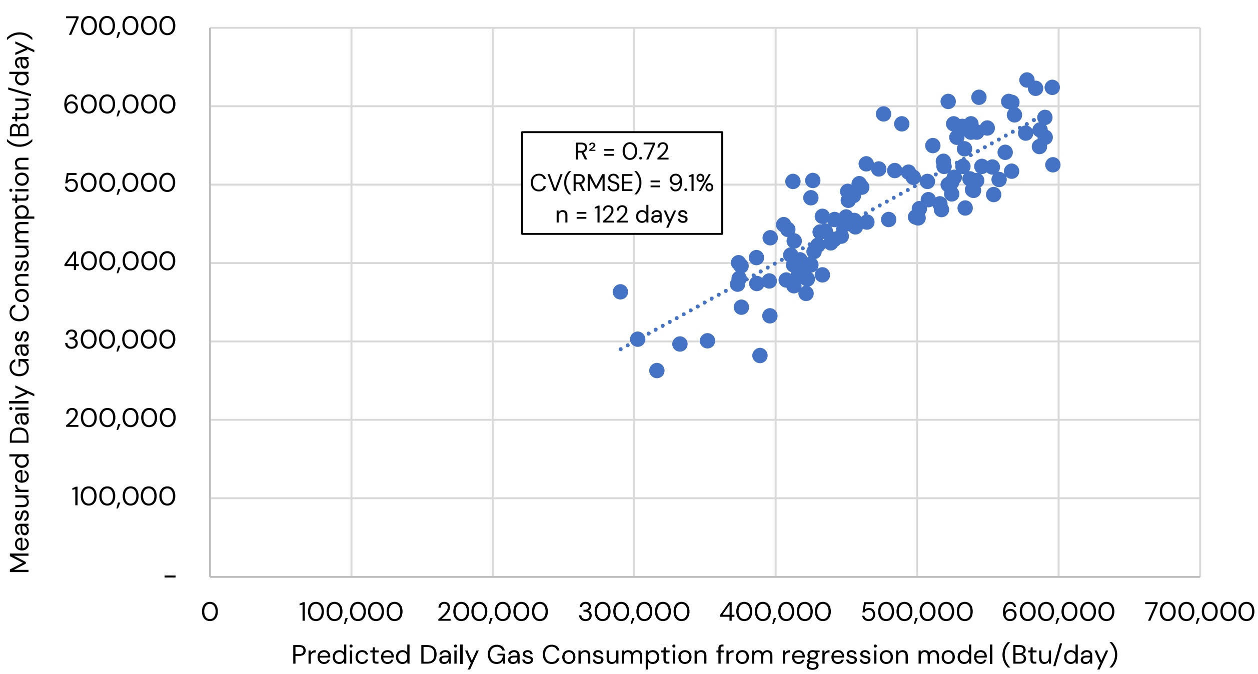


Figure 12: Time series of daily pump electrical consumption across all periods at Site #1.

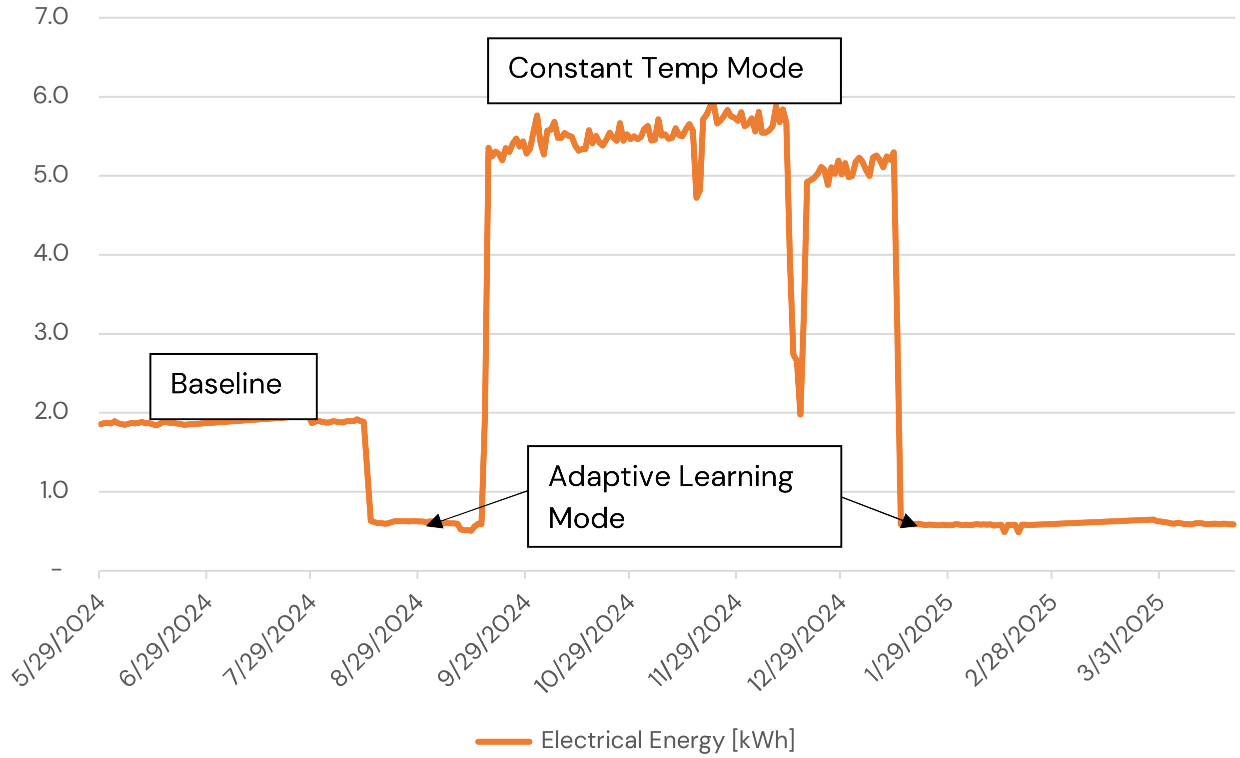
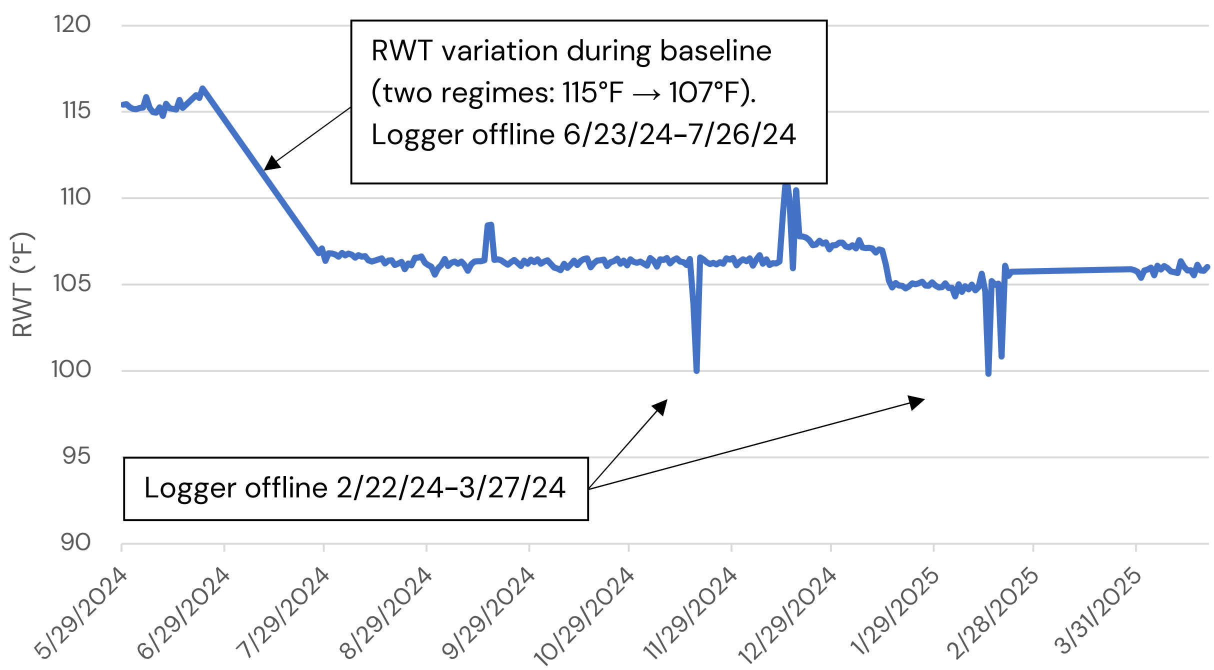


Figure 13: RWT comparison across periods at Site #1.



Site #2: Results

Table 37: Site #2 Performance Summary

	Baseline	Adaptive Learning	Constant Temp
Reporting Period	10/26/24 – 12/09/24	01/28/25 – 5/12/25 05/21/25 – 05/21/25	05/27/25 – 08/31/25
Number of Days	45	104	97
Avg. RWT (°F)	122.4	94.0	93.8
Avg. SWT (°F)	126.3	128.27	119.64
Avg. CWT_m (°F)	76.4	73.3	77.4
Avg. OAT (°F)	54.2	53.6	59.0
Avg. ΔT $(SWT - CWT_m)$	68.3	40.3	34.9
Avg. Daily Gas (Btu/day)	348,585	317,277	273,085
Avg. Daily Gas (therm/day)	3.5	3.2	2.7
Avg. Daily Electric (kWh/day)	0.76	0.16	0.12
Gas Model R^2	0.0012	0.57	0.70
Gas Model CV(RMSE)	7.6%	11.6%	10.9%
Gas Model NMBE	-0.0000%	0.0723%	-0.0000%
Normalized Gas Savings (Btu/day)	—	65,304.4	28,219.32
Normalized Gas Savings (%)	—	18.7%	8.08%
Electric Savings (kWh/day)	—	0.61	0.65
Electric Savings (%)	—	79.4%	84.7%

Table 38: Site #2 Baseline Model Statistics from Equation 23.

Coefficient	Value	Std. Error	t-statistic	p-value
ε_0 (Intercept)	310,778.35	298,928.10	1.04	0.304
ε_1 $(SWT - CWT_m)$	598.05	3,523.85	0.17	0.866
ε_2 (OAT)	3.84	1,756.12	0.002	0.998

Table 39: Site #2 Post Regression Model Statistics using Adaptive Learning mode from Equation 24.

Coefficient	Value	Std. Error	t-statistic	p-value
τ_0 (Intercept)	75,771.33	72,514.14	1.04	0.298
τ_1 $((SWT - CWT_m)/RWT)$	513,375.01	53,868.94	9.53	<0.001
τ_2 (OAT)	-1,066.81	923.00	-1.16	0.250

Table 40: Site #2 Post Regression Model Statistics using Constant Temperature mode from Equation 25.

Coefficient	Value	Std. Error	t-statistic	p-value
δ_0 (Intercept)	139,855.34	74,546.58	1.88	0.0637
$\delta_1\,(\mathrm{RWT} - \mathrm{CWT_m})$	6,193.07	467.66	13.24	<0.001
$\delta_2\,(\mathrm{OAT})$	-3,502.75	1,062.04	-3.30	0.0014

Figure 14: Site #2 Baseline period modeled vs. measured gas consumption comparison.

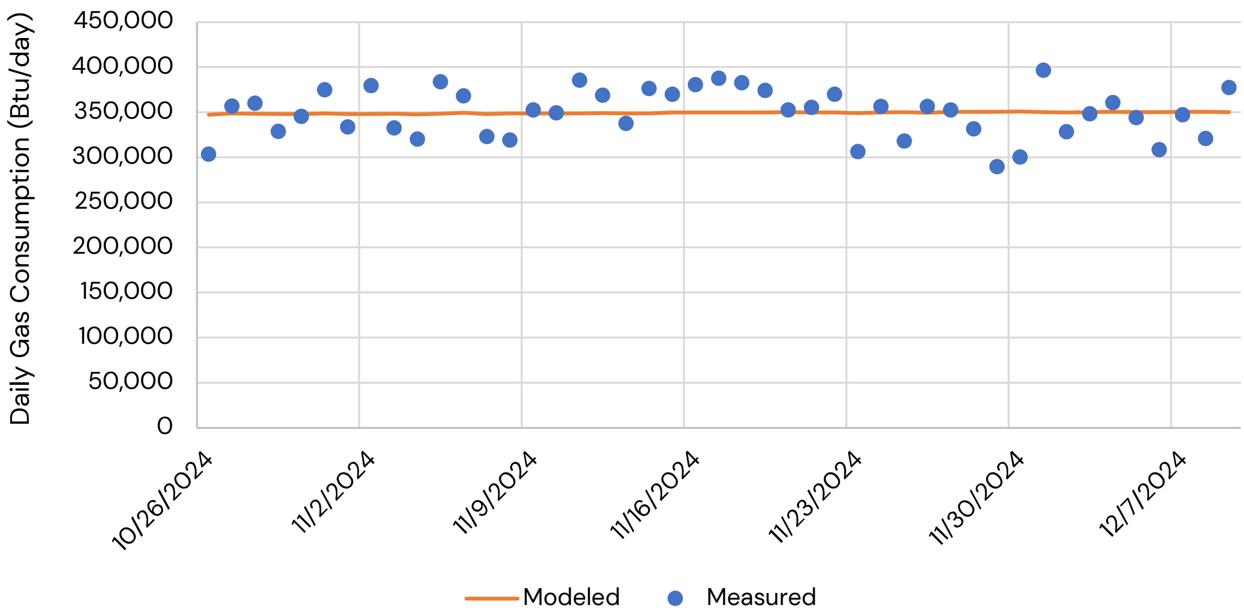


Figure 15: Site #2 Adaptive Learning period predicted vs. measured gas consumption scatter plot comparison.

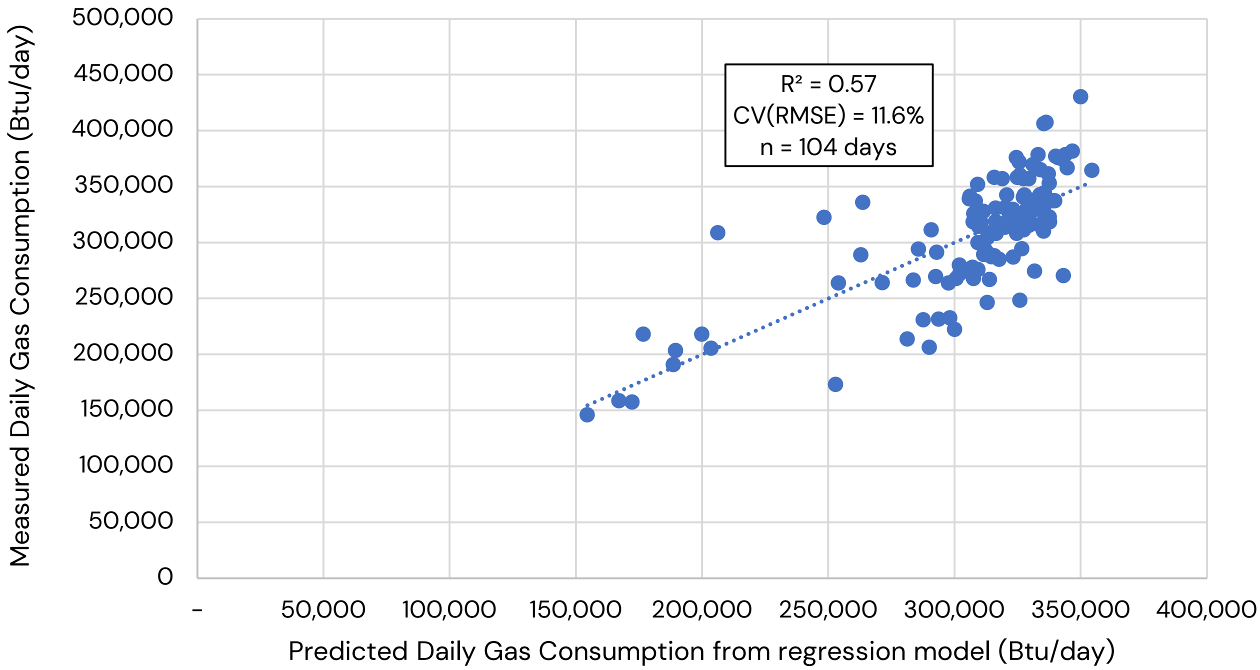


Figure 16: Site #2 Constant Temperature period predicted vs. measured gas consumption scatter plot comparison.

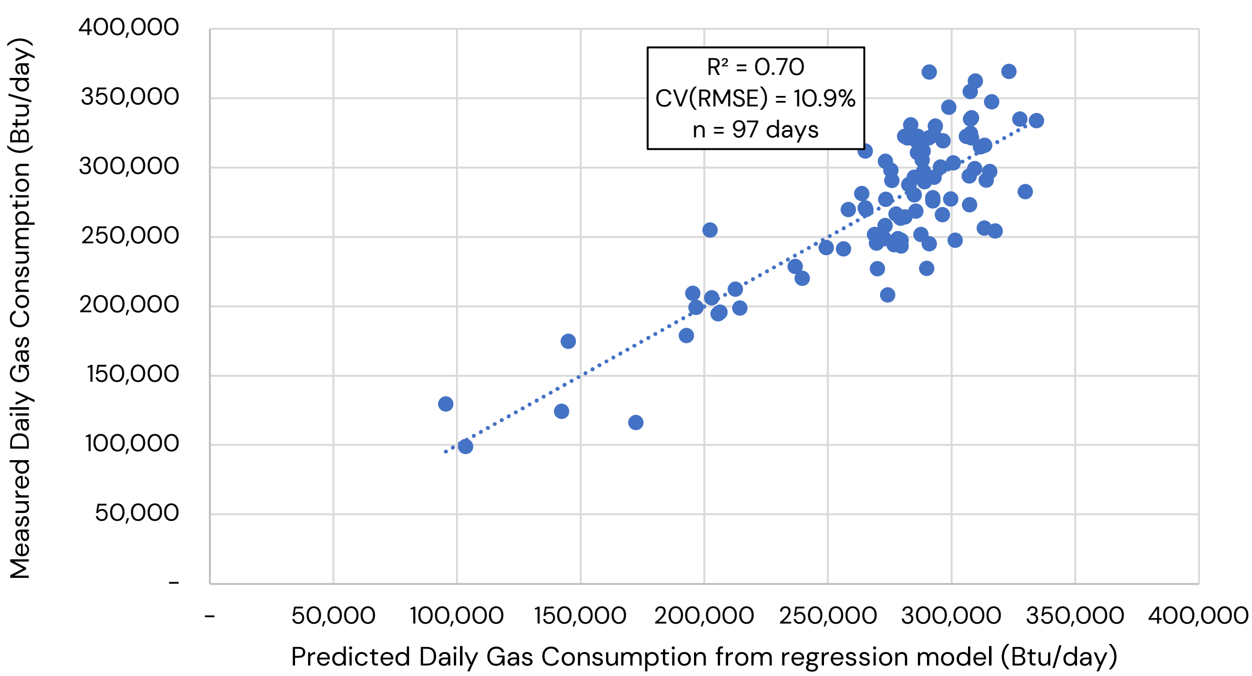


Figure 17: RWT time series for across periods at Site #2.

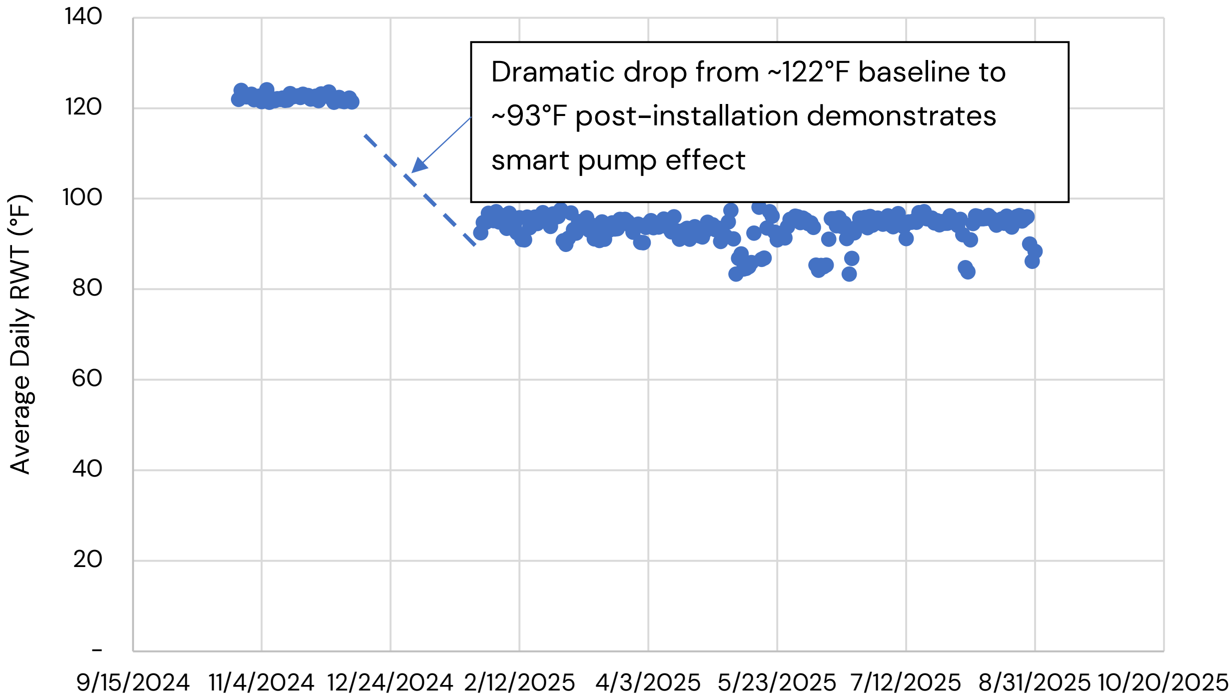
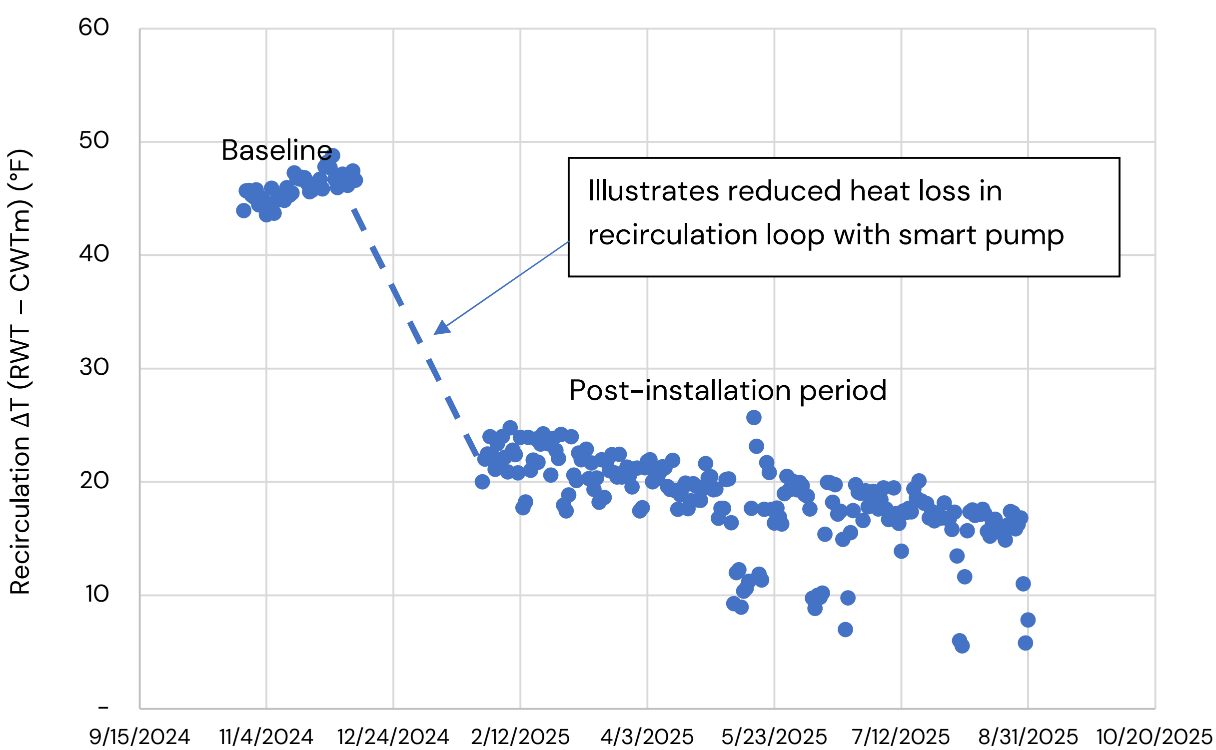


Figure 18: Recirculation ΔT (RWT – CWT_m) comparison at Site #2.



Site #3: Results

Table 41: Site #3 Performance Summary

	Baseline	Adaptive Learning	Constant Temp
Reporting Period	04/30/25 – 06/24/25	06/26/25 – 09/24/25	09/25/25 – 1/12/26
Number of Days	55	91	109
Avg. RWT (°F)	113.2	99.9	103.3
Avg. SWT (°F)	119.7	124.9	134.7
Avg. CWT (°F)	71.6	77.3	71.8
Avg. OAT (°F)	59.8	63.6	54.9
Avg. ΔT (SWT − CWT)	48.1	47.7	62.8
Avg. Daily Gas (Btu/day)	460,216	355,820	490,454
Avg. Daily Gas (therm/day)	4.60	3.56	4.91
Avg. Daily Electric (kWh/day)	3.16	0.21	0.21
Gas Model R^2	0.93	0.93	0.82
Gas Model CV(RMSE)	1.8%	1.6%	4.2%
Gas Model NMBE	0.0000%	0.0000%	0.0000%
Normalized Gas Savings (Btu/day)	—	85,085	81,784
Normalized Gas Savings (%)	—	19.3%	14.3%
Electric Savings (kWh/day)	—	2.95	2.95
Electric Savings (%)	—	93.3%	93.2%

Table 42: Site #3 Post Adaptive Learning Regression Model Statistics from Equation 36.

Coefficient	Value	Std. Error	t-statistic	p-value
Intercept	-117,193.20	53,390.95	-2.20	0.0351
SWT − RWT	10,919.84	1,826.56	5.98	<0.001
$\dot{V}_{return}$	238.32	30.77	7.74	<0.001

Table 43: Site #3 Post Constant Temperature Regression Model Statistics from Equation 37.

Coefficient	Value	Std. Error	t-statistic	p-value
Intercept	279,205.84	52,578.88	5.31	<0.001
SWT - CWT	- 3,449.32	1,438.98	-2.40	0.0218
$\dot{V}_{return}$	395.49	57.69	6.86	<0.001

Table 44: Site #3 Post Adaptive Learning Cold City Flow Rate Regression Model Statistics from Equation 38.

Coefficient	Value	Std. Error	t-statistic	p-value
Intercept	-255.91	40.93	-6.25	<0.001
$\dot{Q}_{gas}$	0.001	0.00012	10.24	<0.001

Note: *This model did not include OAT as the P-value was greater than 0.05 showing the OAT is not statistically significant. This is due to the dynamic nature of the Adaptive Learning model that varies with demand instead of OAT.*

Table 45: Site #3 Post Constant Temp Cold City Water Flow Rate Regression Model Statistics from Equation 39.

Coefficient	Value	Std. Error	t-statistic	p-value
Intercept	-522.41	72.32	-7.22	<0.001
$\dot{Q}_{gas}$	0.0010	0.0001	11.94	<0.001
OAT	3.92	0.91	4.29	<0.001

Table 46: Site #3 Baseline Regression Model Statistics from Equation 43.

Coefficient	Value	Std. Error	t-statistic	p-value
ε_0 (Intercept)	165,253.01	47,302.96	3.49	<0.001
ε_1 $(\dot{V}_{cold})$	496.36	33.07	15.01	<0.001
ε_1 $(SWT - CWT)$	7,021.43	765.73	9.17	<0.001
ε_2 (OAT)	-2,474.24	376.25	-6.58	<0.001

Table 47: Site #3 Post Regression Model Statistics using Adaptive Learning mode from Equation 44.

Coefficient	Value	Std. Error	t-statistic	p-value
α_0 (Intercept)	- 264,512.15	123,389.79	-2.14	0.0478
α_1 $(SWT - CWT)$	634.62	49.52	12.82	<0.001
α_2 $(\dot{V}_{cold})$	9,934.20	2,533.71	3.92	0.0012

Table 48: Site #3 Post Regression Model Statistics using Constant Temperature mode from Equation 45.

Coefficient	Value	Std. Error	t-statistic	p-value
ϵ_0 (Intercept)	236,020.89	201,992.09	1.17	0.2503
ϵ_1 $(\mathrm{SWT} - \mathrm{CWT})$	- 9,448.17	3,317.80	-2.85	0.0072
ϵ_2 $(\dot{\mathrm{V}}_{\mathrm{return}})$	665.83	70.75	9.41	<0.001
ϵ_2 (OAT)	2,833.42	1,033.43	2.74	0.0095

Figure 19: Site #3 Baseline gas consumption regression model scatter plot comparison.

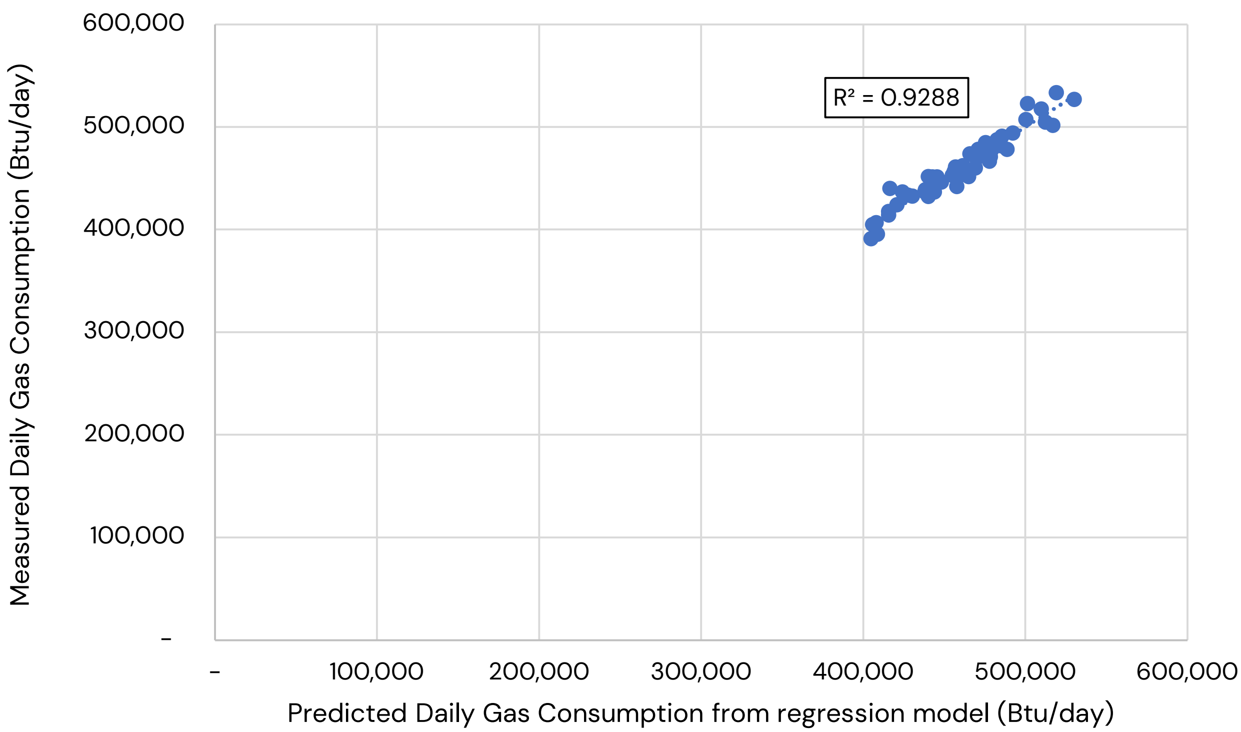


Figure 20: Site #3 Adaptive Learning period predicted vs. measured gas consumption scatter plot comparison.

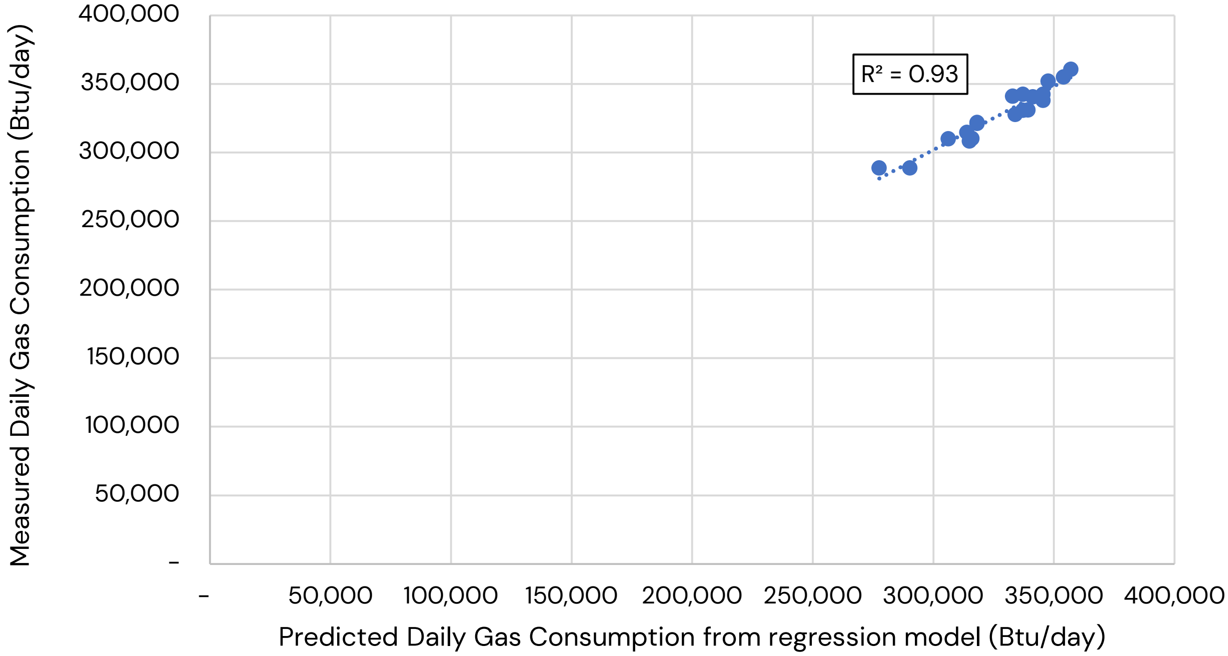


Figure 21: Site #3 Constant Temperature period predicted vs. measured gas consumption scatter plot comparison.

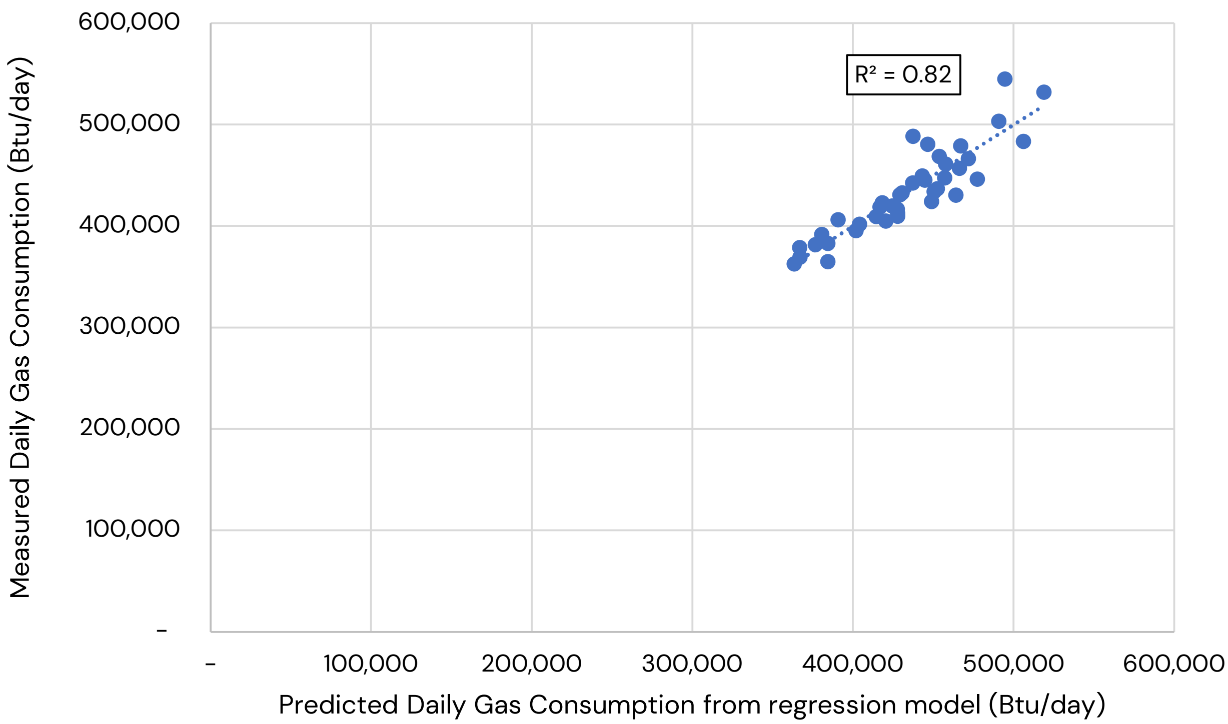


Figure 22: Site #3 Electrical consumption comparison between test periods.