AMI Intelligence Connected Building Energy Modeling

Final Report

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Disclaimer

Executive Summary

This report covers the development and refinement of a low-cost, high-impact building energy modeling tool tailored for medium-sized commercial buildings. The project team designed this energy modeling tool — the California Commercial Building Energy Modeling (CCBEM) — to be run by utility customers for no cost and to output energy-efficiency measure recommendations that would decrease annual energy usage. It requires simple inputs from the customer and ingests historical utility data to improve the accuracy of the model. Energy modeling for building sites of this scale would typically require up to four weeks of analysis; the new CCBEM tool can generate building models in less than 30 minutes.

This report also reviews the project team's process of recruiting volunteer test sites, which provided their real-world energy usage data to further train the tool and improve the accuracy of its assumptions. For each of nine test sites, the Project Team analyzed the tool's output to determine whether the ingestion of the advanced metering infrastructure (AMI) data improved the CCBEM tool's modeling accuracy compared to conventional modeling processes. The team concluded that with future refinements and expansions, the tool has the potential for widespread use in California. Through the ingestion of AMI data, the CCCBEM significantly simplified and reduced the time investment in building energy-efficiency models for the nine, medium-sized buildings tested.
Background

OpenStudio is a software development kit created by the Department of Energy (DOE) and the National Renewable Energy Laboratory (NREL) and is the platform on which the CCBEM was created. OpenStudio allows access to EnergyPlus, a DOE-published Building Energy Modeling (BEM) engine, and this connection allows the tool to make educated assumptions about measure control impacts on energy usage when needed. OpenStudio also allows the integration of Recurve's Open EE Meter, which is a toolkit containing routines for estimating energy-efficiency savings.

Methodology

Participant Engagement

As part of developing a tool that can scale across all instances of medium-size commercial buildings, the project team recruited nine volunteer sites that span three building types (outpatient health care centers, retail pharmacies, primary schools) and two distinct climate zones (north California and south California). The project team chose these three building types for their differing energy signatures due to their occupancy, functionality, and size. The buildings involved represented a range of energy footprints determined by the buildings' ages, levels of complexity, and states of repair.

Tool Development

There are three primary components of the new tool: the user interface, the output details and reporting metrics, and the database housing configuration.

User Interface: The Project Team designed the CCBEM's user interface (UI) with simplicity in mind: the objective is to demonstrate the effectiveness of an energy modelling tool that can be used by utility engineers and public end-users alike. The UI is divided into three tabs:

Job Information: Contains the name of the building, location information, temperature and electricity unit measurements, and a field to upload AMI data.

Configuration: Contains qualitative characteristics: the age of the site's heating, ventilation, and air-conditioning (HVAC), lighting, and plug systems. In addition, it contains fields for square footage, ratios of room types to the total square footage, floor height, and window-to-wall ratio.

- **Measures**: Presents the opportunity for the user to experiment with measure changes detailed in Table 1: CCBEM Upgrade Measure Options. These changes are also referred to as "strategies" within the report.

The tool includes 10 potential efficiency measures that are widely applicable to most small-to-medium commercial buildings.

Develop Model Workflows

Collecting each site's usage data from past and present helped align the baselines for comparing usage indicators on each model. The comprehensiveness of the collected data enabled the project team to make the best baseline possible, by isolating the appropriate deviations from the prototype buildings and adjusting them to be California specific. This in turn informed the quality of CCBEM's output.

Heating and cooling factors were outside of the project's scope, meaning that the ideal CCBEM output would contain accurate assumptions of heating and cooling electricity usage based on the exact lighting, plug, and internal HVAC features as well as the total annual electricity usage.

The process of improving the tool through iterative testing used data from sites as it came in and prototypical data to draft and test the application architecture. The project team ran the three or four versions of CCBEM energy models, totaling a maximum of 2 hours and 40 minutes of processing time, for each site.

Database Hosting Configuration

- A demonstration hosting configuration has been provided for the project to facilitate tool development and testing. The project team will deliver a source code for a Streamlit application, along with instructions for running it locally on a Windows computer. If public website hosting is desired, a stakeholder could either link to the URL for Streamlit application or add on a user interface to integrate it with their website.
- Analyzing Site Data
- For each test site, the CCBEM used the following sets of data:
    - The building characteristics collected from the phone interview and site visit
    - The historical AMI data offered by the test site
- From these sets of data, three models were created for data analysis:

- M1: A prototypical projection using only the age of the building's HVAC system, the type of the building's HVAC system, the age of the building's lighting systems, and other parameters available in the configuration panel.
- M2A: The project team uses the AMI data to extract a day-to-day schedule of use for the test building and then replaces the schedule within M1, resulting in a model that is theoretically much closer to the true energy profile of the building.,
- M2B: Applies a base-use (energy usage in kWh) adjustment to the lighting and equipment loads in the previous model. The base-use adjustment is a product of assumptions made given the site's past AMI data.

M3: A version of M2B that has been altered in ways that simulate energy efficiency upgrades. Comparing M2B and M3 is how potential savings are communicated to the user.

LIMITATIONS

The better the match between the utility data and M2B, the more accurate the tool is for those specifications. Local occupancy meters were initially intended to verify the schedule inferred from the past energy usage data. However, due to gaps in the occupancy data and an unanticipated excess of outliers in the meter data, the loggers were unable to be used for this purpose. The plug load instances were spot checked in some locations and the HVAC system run hours were conferred to support the fault accuracy.

Several test sites were comprised of more than one building. To preserve the CCBEM's time advantage over conventional modeling efforts, the program team compromised on multi-building sites and simulated them as a single building, averaging their equipment vintages and combining their square footage. This enabled the project team to exercise the tool and improve its calibration for use in single-building scenarios. The Project Team explored the sensitivity of the perimeter-to-floor area ratio and its impact on energy use when modeling multiple buildings as a single building.

Findings

- By ingesting AMI data at each of these sites, the CCBEM tool was able to achieve a net mean bias error as low as 3.4, compared to the ASHRAE 14 requirement of 5, on one of the test sites. Further development may result in more consistently low net mean bias errors.

- The CCBEM tool generates models in less than 30 minutes.

- The CCBEM tool can accept electricity usage data in the 8760 format, the predecessor to AMI, used in older buildings.

- At present, the CCBEM tool is unable to easily discern the presence of solar generation when presented with consumption data rather than net-metered data.

- The CCBEM tool's models can get very close to real-world usage data while only using the lighting and plug measures allowed in the project's scope. This creates a successful foundation of a tool that can be adapted to more particular climate zones and seasonality.

- To increase the tool's accuracy for more building types, more data throughput is needed, and that quantity cannot be obtained from individual volunteer sites within the time available for this project.
- Looking ahead, the next stage in further refining this tool includes focusing on additional building end-uses, running it on a greater number of building sites, integrating more data sources, and improving the user-friendly interface for wider adoption throughout the state of California.

The project team's recommendations include:

- We strongly recommend keeping the tool open-source, which allows utilities to make their own modifications using OpenStudio.
    - By decentralizing ownership of the CCBEM source code and blueprint, the project team will enable utilities across the state of California to adapt the tool for their website and incorporate their own incentives as recommendations for the tool's output.
- The project team recommends expanding on the process of automating solar detection within the tool, as it is crucial for increasing the accuracy of models of Californian buildings.
- The project team recommends getting alignment from all relevant stakeholders on key performance indicators such as annual electrical energy usage, annual GHGe, coincident demand performance, efficiency estimates, metrics for economic stimulus, community enhancements, and disadvantaged community access improvements.
- The project team recommends that the tool be tested with the missing parameters of heating and cooling, as well as more specific values, settings, and seasonality to greatly improve the tool's level of detail and accuracy.

Abbreviations and Acronyms

Acronym	Meaning
AMI	Advanced Metering Infrastructure
BEM	Building energy modeling
CCBEM	California Commercial Building Energy Modeling Tool
CDD	Cooling degree days
CV	Coefficient of variation
CVRMSE	Coefficient of the variation of the root mean square error
DAC	Disadvantaged communities
DOE	Department of Energy
GHGe	Greenhouse gas emissions
HDD	Heating degree days
HTR	Hard-to-reach
IOU	Investor-owned utility
kWh	Kilowatt-hours
NAN	Not A Number
NMBE	Net mean bias error
NREL	National Renewable Energy Laboratory
ROI	Return on investment
RMSE	Root mean square error
SI	Système Internationale

Acronym	Meaning
UI	User interface
UX	User experience

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Introduction

Commercial building energy-efficiency upgrades are often made without the benefit of data-driven insights, making it difficult to ensure building managers and owners achieve their desired outcomes. These outcomes are commonly either a reduction in their monthly electricity expenses or a reduction in a building's carbon footprint. Alternatively, some building managers who lack the necessary building energy data may instead choose the least risky course of action and do nothing. Modeling a building's energy usage allows building managers to estimate savings based on a prescribed upgrade pathway. Further, the data presented through modeling allows building managers to prioritize upgrade projects on the basis of savings impact. There are time and financial barriers that limit who can take advantage of energy modeling and, in turn, who can confidently invest in a building's energy efficiency. Barriers include the cost of modeling, which can range from $30,000 to $200,000 (Roth, Energy.gov 2016), equipment costs, and installation costs. Upfront costs can make the prospect of upgrading buildings unfeasible for many small or medium business owners with buildings in disadvantaged or hard-to-reach communities and who may not have the capital. While implementing energy-efficiency measures will reduce operating costs, upfront measure analysis costs can lengthen the payback period.

Since 2009, many utilities in California have rolled out smart metering technology for their customers that provides real-time digital information pertaining to energy usage, known as Advanced Metering Infrastructure (AMI) data (Song 2011). AMI data comprises a minimum of 15 parameters that include tamper notification, voltage event flags, outage counts, and other items that relate to energy usage. However, the primary focus of this project centers around the single parameter of time-of-use kilowatt hours. Before the advent of AMI, this level of sub-hourly energy consumption data was available to utilities for the purpose of calculating demand charges. It was not, however, readily available to building managers, contractors, or energy consultants. The need for quick, equitable energy savings analysis through modeling that employs this new AMI data is growing rapidly. The project team has created a user-friendly tool that is capable of ingesting and processing AMI data to create a building energy model, hereafter referred to as the California Commercial Building Energy Modeling Tool (CCBEM). Automated modeling tools like the CCBEM, with their increased availability and quicker turnaround time, represent the future of energy analysis and are worth investment due to the massive time and cost savings compared to traditional modeling. These tools require more substantial development time investments before they pay dividends, but the long-term potential is significant.

Objective

The objective of this project was to create and refine an open-source, user-friendly energy modeling tool that can rival the quality and detail of more traditional, expensive, commercially available means of energy modeling in a fraction of the time. It is designed to provide immediacy, ease-of-access, and a lower cost that is more attractive to personnel who manage building operations for whom procuring energy modeling services is a barrier. The project team presented the tested CCBEM to utilities and other potential hosting entities to gauge interest in adoption or building on the application. Through public use of CCBEM, or a similarly developed tool, the project team will bring energy modeling opportunities to those who were previously unable to access them, including disadvantaged communities (DAC) and hard-to-reach (HTR) customers.

Background

The CCBEM links historical data intelligence with forward-projecting OpenStudio model simulations. OpenStudio is a software development kit created by the Department of Energy (DOE) and the National Renewable Energy Laboratory (NREL). It is designed to allow third parties to design Building Energy Modeling (BEM) applications that use EnergyPlus, a BEM engine also designed by DOE and NREL. EnergyPlus enables detailed simulations and calculations of moisture, heat transfer, lighting metrics, and control strategies among many other physical aspects of building management. EnergyPlus is continuously maintained and fully supported by the DOE, ensuring that any application utilizing its features that has been created through OpenStudio will remain functional (Roth, Energy.gov 2014a). Using EnergyPlus on its own would require interacting with large, inelegant files without a focused user interface (UI). OpenStudio acts as an intermediary, presenting EnergyPlus inputs and outputs as a dynamic data model with an application-friendly interface. Therefore, by creating a building energy modeling application using OpenStudio, EnergyPlus's powerful simulation and calculation functions are made available to a wider audience in an easily understood manner. OpenStudio is fully compatible with other analysis engines, such as OpenEEMeter, which was developed by Recurve in 2019. OpenEEMeter is a toolkit for calculating normalized metered energy consumption and avoided energy use. The OpenEEmeter library contains routines for estimating energy-efficiency savings, making it an integral part of any energy modeling (Roth, Energy.gov 2014b). By employing an iterative process that involves design, simulation, and analysis, applications developed using OpenStudio provide valuable insights into how choices on building equipment and operation influence energy consumption and associated costs.

Methodology and Approach

Outside of this CalNEXT project, the project team routinely assesses the market of building simulation modeling tools available, especially those built on EnergyPlus or OpenStudio. No one is currently offering a tool to utilities or the public that can quickly develop an energy model, calibrate it to AMI data, and make low-cost to no-cost efficiency recommendations to medium complexity commercial buildings.

To develop a tool that can scale across all instances of medium-sized commercial buildings, the project team recruited nine volunteer sites interested in testing the tool as part of the CCBEM development process. The subsequent tests focused on three building types: outpatient health care centers, retail pharmacies, and primary schools. The information gathered by testing the CCBEM on California buildings in two distinct climate zones allowed the project team to further refine the CCBEM to increase the modeling accuracy.

Outpatient health care centers, retail pharmacies, and primary schools were chosen for their differing energy signatures based on size, occupancy, and functionality. The owners of these buildings may also have connections to other buildings of the same type in different locations (e.g. the building manager of a school in location “A” could relate to another school in location “B”), thereby lowering the cost of enrolling customers for the study. Participating buildings were in both Northern and Southern California to demonstrate the tool’s efficacy in modeling buildings in colder climates and warmer ones. The buildings involved represented a range of energy footprints from poor to nominal to high performance. These energy footprints were roughly determined by the buildings’ ages, levels of complexity, and states of repair.

Participant Engagement

Core to this project was the use of real-world data to both test the tool’s functionality and demonstrate its effectiveness. The volunteer recruitment process included the following tactics:

- Leveraging existing contacts
- Impromptu in-person visits
- Email or phone calls.
- Search engine and mapping.
- Social media

The project team used search engine and map software in conjunction with CalEnviroScreen, to locate potential participants in DAC or HTR communities. CalEnviroScreen is a publicly available screening tool, sponsored by the California government, for identifying California communities that are disproportionately affected by moderate-to-severe pollution. For school buildings, the team successfully made connections through internal contacts. For medical facilities and pharmacies, social media sites such as LinkedIn proved to be the most helpful. Once in contact with a potential volunteer, the project team initiated the following procedure:

1. Conducted a phone interview with facility manager.
2. Collected at least one year of the test building’s past AMI data from pilot participant.
3. Provided facility manager with a contract agreement to conduct AMI data collection.
4. Scheduled a visit to the test site to document site conditions and install an occupancy logger device.

The phone interview was designed to collect qualitative data points about the test site that relate to the entry fields in the CCBEM. From the phone interview, the project team collected information such as the building’s HVAC system type and general information for an inference, e.g., draftiness of the building. Once the interview was completed and sufficient past AMI data is acquired, the preliminary run of the CCBEM was then completed. During the site visit, the team installed the occupancy logging device and verified the building information from the survey. Once the occupancy logging device was installed, data was collected for four weeks, a sufficient period for obtaining consistent occupancy patterns that inform model creation. The project team has compiled an analysis for each site and information will be presented to the participants.

Limitations

In simple terms, the accuracy of the CCBEM tool is measured by how well the utility data matches the model regressions the tool generates. Local occupancy meters were initially intended to verify the schedule inferred from the past energy usage data. However, due to gaps in the occupancy data and an unanticipated excess of outliers in the meter data, the loggers were unable to be used for this purpose. The plug load instances were spot checked in some locations and the HVAC system run hours were conferred to support the fault accuracy.

Several test sites were comprised of more than one building, such as some of the school sites having separate buildings for some classrooms. Modeling each building on the same meter would have been outside of the project's scope as it would require accounting for variability of equipment across each building, which would inflate the level of effort required to accurately model these sites. The project team felt that seeking only single-building sites would be an unnecessary limitation on site acquisition. A primary design principle for developing the tool is to achieve a balance between building energy model accuracy and the time it takes to get building energy model results. To preserve the CCBEM's time advantage over conventional modeling efforts, the program team compromised on multi-building sites and simulated them as a single building, averaging their equipment vintages and combining their square footage. While this may have resulted in a diminished accuracy specific to sites that include more than one building, it enabled the project team to exercise the tool and improve its calibration for use in single-building scenarios.

Tool Development

The project team developed the CCBEM in parallel to the site recruitment. There are three primary components of the tool that were developed:

User Interface

The CCBEM consists of a UI and two analysis engines: OpenEEMeter and EnergyPlus. CCBEM's UI is designed with simplicity in mind: The objective is to demonstrate the effectiveness of an energy modelling tool that can be used by utility engineers and public end users alike. The UI is divided into three tabs:

- Job Information: This panel contains the fields that define the modeling instance, such as the name of the building, location information, temperature and electricity unit measurements, and a place to upload the site's AMI data.
- Configuration: This panel contains fields referring to qualitative characteristics of the site's internal systems, such as the age of the site's HVAC, lighting, and plug systems. In addition, it contains fields for the user to fill out related to square footage, ratios of room types to the total square footage, floor height, and window-to-wall ratio.
- Measures: This panel presents the opportunity for the user to experiment with the 10 measure changes detailed in Table 1. Adjusting these settings and then running the tool will present the user with the estimated impact of those changes, depicted in tabular and graphical formats.

Splitting the user inputs across three different tabs reduces visual clutter and organizes them according to their purpose. EnergyPlus and OpenEEMeter use the metric system (Système Internationale, or SI) for calculations, but most facility managers are apt to enter data using the imperial system (IP). For this reason, the CCBEM automatically converts all IP into SI for the engines to use. All analysis results are then converted back into IP for an easier user experience.

Data entered in some fields, such as “HVAC System Type,” limit the available fields and options. The tool includes 10 potential efficiency strategies that allow the user to compare an upgrade measure’s relative impact on their building’s energy usage. Listed in Table 1, these options were selected because they are simple, low-cost changes that can be made to a building’s systems without requiring equipment inspection or a building walkthrough first. They are widely applicable to most small-to-medium commercial buildings. Efficiencies demonstrated by the tool are expected to be approximately five kBtu/ft^2/year, which may provide a range of 5–20 percent overall improvement, depending upon the specific customer. If the user identifies any of these options they are interested in pursuing, based on the projected savings, they can either make the changes themselves or contact their utility’s energy-efficiency program for assistance. To program the model with cost saving estimates, the team used a report that postulated all control contractor sequence-based measures cost $0.03 per square foot (NREL 2014).

Table 1: CCBEM Upgrade Measure Options

Recommendation	Definition
Temperature Setback Adjustment	Adjust delta temperature that the building is set to when in unoccupied mode
Cooling Set Point Adjustment	Increase the target temperature for cooling the building.
Heating Set Point Adjustment	Decrease the target temperature for heating the building.
Economizer Installation	An economizer uses cool outside air to cool the indoor space.
Demand Control Ventilation Modes	Adjusts ventilation intensity based on occupancy.
Daylighting Control	Reduces overhead lighting use by leveraging ambient light.
Chilled Water Pump Differential Pressure Reset	Resets down the hydronic differential pressure setting based on low cooling demand, saves pumping electrical power through pump affinity laws.

Recommendation	Definition
Hot Water Pump Differential Pressure Reset	Resets down the hydronic differential pressure setting based on low heating demand, saves pumping electrical power through pump affinity laws.
Hot Water Supply Temperature Reset	Resets down the hydronic circulation loop temperature setpoint where there is a low heating demand. This saves boiler energy and impacts pumping power.
Chilled Water Supply Temperature Reset	Resets up the hydronic circulation loop temperature setpoint where there is a low cooling demand. This saves energy and impacts pumping power.
Supply Air Temperature Outdoor Air Reset	Is an air side system efficiency strategy that uses the outdoor air temperature to adjust the air temperature as supplied by the HVAC equipment. This lowers the supply air temperature as the outside air temperature increases. Usually booked by minimum and maximum ranges. This saves HVAC energy through reduced heating and cooling loads based on setpoint reset.
Supply Fan Static Pressure Reset	When the system control module recognizes that all VAV boxes are partially closed, the system reduces the fan speed to lower the static pressure in the duct system until at least 1 of the VAV boxes is completely open.

Develop Output Details and Reporting Metrics

Since this project involved collecting utility data from different sites and sources, the project team anticipated the possibility of inconsistent time period measurements. A predecessor to AMI data, 8760-format data measures electricity usage in hourly intervals over a calendar year; there are 8,760 hours in a non-leap year. Buildings measuring their energy usage in this format are generally older with meters that have not been updated to operate with AMI. Data in the AMI format has the potential for more granularity with the ability to measure usage in intervals as small as 15 minutes. While the CCBEM tool was designed with AMI data in mind, the project team allowed the tool to accept and normalize 8760 data. To normalize data, a common scale with which to measure the same data from different sources is created, making proportional adjustments to the data to fit on that scale. This effectively converts 8760 usage data to AMI usage data. Through this process, the project team developed CCBEM so that it can be adapted to any time-period measurement that a building's utility uses. Once the data is entered in the user input fields and the program runs, the model uses regression methods to identify customer specifics about when and how they use their facility. Then, the CCBEM displays the results of the regression analysis. The CCBEM is designed to infer plug and lighting loads based on a building's occupancy schedule and non-occupancy loads. Within the project scope's boundaries, the tool recognizes electrical energy usage as the main indicator of building efficiency and upgrade effectiveness. Collecting each site's AMI data from past and present helps align the baselines for comparing these indicators on each model. The comprehensiveness of AMI data enabled the project team to make the best baseline possible, by isolating the appropriate deviations from the prototype buildings and adjusting them to be California specific. This in turn informed the quality of CCBEM's output.

Prior to receiving data from volunteer sites, the project team completed a test run using OpenStudio's typical building model to determine a baseline of accuracy, determining that the tool was ready for testing in the project. The Project Team ran the CCBEM tool at least three times for each test site, with different parameters depending on the building's internal HVAC, lighting, and plug features. The modeling accuracy achieved over the course of this project was accomplished through intentional limitation of the tool's available data. Heating and cooling factors were outside of the project's scope, meaning that the ideal CCBEM output would contain accurate assumptions of heating and cooling electricity usage based on the exact lighting, plug, and internal HVAC features as well as the total annual electricity usage. Later in this report, the Project Team postulate further on the potential increase in accuracy in a scenario where users feed the CCBEM tool data related to heating and cooling equipment and usage.

Iteration was the key to training the CCBEM program; the more datasets the tool could ingest and analyze, the more the project team could make specific adjustments, which increased the accuracy of future models. Over the course of this project, the number and variation of these test runs allowed the team to address bugs and recognize potential improvements to the CCBEM's primary components. While the project was able to recruit only half of the planned number of test sites, the Project Team collected enough data to facilitate significant tool improvements, as discussed later in this report.

To improve the tool, the Project Team used prototypical data to draft and test application architecture, and then data from sites as it became available. Enrollee site tests took between 20 to 40 minutes of processing time for the CCBEM's EnergyPlus simulations to run sequentially within the app. The project team ran the three or four versions of CCBEM energy models that will be outlined later in the report, totaling a maximum of 2 hours and 40 minutes of processing time for each site. In the realm of conventional energy modeling services, where a customer would receive their model after several days or weeks, the CCBEM's processing speed is notable.

Database Hosting Configuration

A demonstration hosting configuration has been provided for the project to facilitate tool development and testing. The current scope does not include long-term hosting costs associated with a full-scale productive environment. While this project will not result in a permanently hosted tool that utilities and others can access, the optimized tool that results from this project will have its source code made available to utilities for them to modify and host themselves or provide to third-party program administrators; encryption is included in the business fees associated with those hosting services. In preparation for this, the project team developed the tool with Amazon Web Services server-hosting in mind.

The project team will deliver a source code for a Streamlit application, along with instructions for running it locally on a Windows computer. The Streamlit application could also be run on a server to allow multiple users to access it via a browser. If public website hosting is desired, a stakeholder could either link to the URL for Streamlit application or add on a user interface to integrate it with their website.

Analyzing Site Data

For each test site, the CCBEM used the following sets of data:

- The building characteristics collected from the phone interview and site visit.
- The historical AMI data offered by the test site.

From these sets of data, the Project Team created three models for data analysis. The first energy model, M1, is a purely prototypical projection of a building's energy usage, using only parameters derived from the building characteristics. These characteristics include the age of the building's HVAC system, the type of the building's HVAC system, the age of the building's lighting systems, and other parameters available in the configuration panel. Each selectable parameter references data available from Department of Energy prototype models, with the CCBEM using this to simulate the parameter's relative impact on its own M1 model.

To verify this model's accuracy, the project team compared it to the past AMI data for quality-of-fit. A successful version of the CCBEM would be able to accurately create an energy-usage model using only those parameters that match a model created with real-world AMI data.

The team created the second energy model, M2A, by making modifications to M1 informed by the site's past AMI data. The project team used the AMI data to extract a day-to-day schedule of use for the test building and then replaced the schedule within M1. The team only produced this M2A model if the M1 model showed a statistical accuracy of 70 percent (r^2 value of 0.7) or over. If the accuracy is too low, the CCBEM will not run an M2A model. The next model, M2B, takes either M1 or M2A depending on the above, and applies a base-use (energy usage in kWh) adjustment to the lighting and equipment loads in the model. The base-use adjustment is a product of assumptions made given the site's past AMI data.

Our final model, M3, is a version of M2 that has been altered in ways that simulate energy-efficiency upgrades such as those listed in Table 1. The CCBEM then provides comparisons of energy usages in M2 and M3 and the estimated electrical energy savings resulting from the prescribed building upgrades.

The better the match between the tool's inferred model for the building's energy usage and actual utility data, the more accurate the tool is for these specifications. The AMI intelligence modules were intended to be optimized by using local occupancy meters to check the accuracy of the inferred schedules that were automatically generated from the ingested AMI data. The project team analyzed the statistical differences between the inferred and generated schedules in aggregate for all nine sites, as well as subcategories like building type or climate zone. However, due to gaps in the occupancy data and an unanticipated excess of noise in the meter data, it was unable to be used for this purpose. “Noise” is a collective term for outliers that could be attributable to several unknown factors, here including solar energy. The plug load instances were spot checked in some locations and the HVAC system run hours were conferred to support the fault accuracy.

Site Engagement

Initially, the project team targeted 20 sites to test and prove the AMI intelligence in various situations. This would have allowed for a matrix of three site types by two possible site locations by a range of three building vintages. The project team’s recruitment efforts were partially successful, enabling us to capture data at nine sites across all three categories: Two non-hospital health care facilities, one pharmacy, and six K-12 school sites. While not meeting the original target these nine sites did allow the project team to test the tool at three site types, two site locations and a variety of buildings vintages, which was sufficient to test and prove the AMI intelligence. Table 2 offers some characterization of these volunteer sites, from which all necessary data was collected.

Table 2: Test Site Characterization and Status

Site #	Site Type	Site Location	Building Age	Square Footage
1	School	North	>60 Years	25,925
2	School	South	>80 Years	43,213
3	School	North	>60 Years	34,698
4	School	South	<5 Years	70,000
5	School	South	>10 Years	30,422
6	Pharmacy	North	>20 Years	600
7	School	South	>50 Years	270,000
8	Medical	South	>50 Years	24,600
9	Medical	North	>10 years	77,491

The project team encountered many obstacles in site recruitment. It was convenient to use email for communication with prospective test sites and this approach worked well in some cases, but prospective contacts often mistook initial communications as a scam, perhaps because these communications discussed collecting data and other operational details from a building in exchange for a gift card. It was also challenging to find legitimate email contact information for prospective volunteers: The project team used Google, LinkedIn, and internal referrals to acquire email contacts, but given the response rate, some of them were either inactive or incorrect.

For in-person recruitment, the project team expected locally owned businesses to be receptive to monetary compensation and the prospect of saving money because of the insights gained from volunteering their data to the CCBEM. However, monetary incentives were less effective than the Project Team expected, and feedback from contacts included:

- They did not have enough spare time to participate.
- They did not have the personnel resources.
- They were already participating in similar projects.
- They were concerned about the impact of the project on their daily operations.
- They were concerned about having inadequate facilities or infrastructure to support the project requirements.
- They were not interested in participating in the research.
- They did not understand the project's goals due to their lack of knowledge in the energy-efficiency space.

The project team's efforts to recruit corporate businesses were difficult due to hierarchical complications and interference. When contacted, the managers would be supportive of participating, but then someone higher up in the organization would override their decision and end their involvement in the project.

In another case, the project team was unable to use data from a volunteer site because the site did not complete their enrollment process.

The nine sites that were recruited offered the project team enough data to effectively calibrate the CCBEM, as evidenced by significant improvements in functionality and accuracy, described later. These nine participants have also provided real-world feedback for the tool's output, providing the team with insight into how potential users would approach and view the tool if something similar were made available by their utilities, and further informing future UX (user experience) improvements to the CCBEM. However, in the process of modeling the sites' data, the project team discovered that some sites did not declare the presence of solar energy on their meter. We had asked each test site if any equipment existed on the property that would impact the AMI data. Three of the sites indicated the existence of solar energy, which allowed for some amount of corrective calibration, but there were other sites that did not indicate solar, and only one of the nine sites had data that showed solar production finely enough to correlate with the AMI data presented. From the perspective of the CCBEM's intelligence module, the sites with solar energy have lighting, HVAC, and plug usage amounts that should theoretically correlate to large amounts of energy being supplied to the building from the meter. In reality, the building's solar generation supplies some of that energy, but the tool does not know to look for this and its assumed amount of base electricity usage is then so large that it throws off the model. In hindsight, the project team should have eliminated test sites that did not have a way to show 15-minute intervals of solar generation. This granular measurement, if supplied to the project team, would have made it easier to train the tool to compensate.

Running the Application

To begin using the CCBEM tool, the user inputs the AMI data, time zone, building age, and appropriate climate area selection into the Job Information panel detailed in Figure 1. The project team uploaded AMI data into the tool in the form of a comma-separated value file, the recommended format for users of this tool. In the tool's configuration panel shown in Figure 2, a user can enter building specification parameters. Required information includes square footage of finished space, the HVAC system type and vintage, the lighting system, and the building envelope. The project team did not include Title 24 as part of the vintage options in the configuration panel, but this can be included by the user of the tool as a customization.

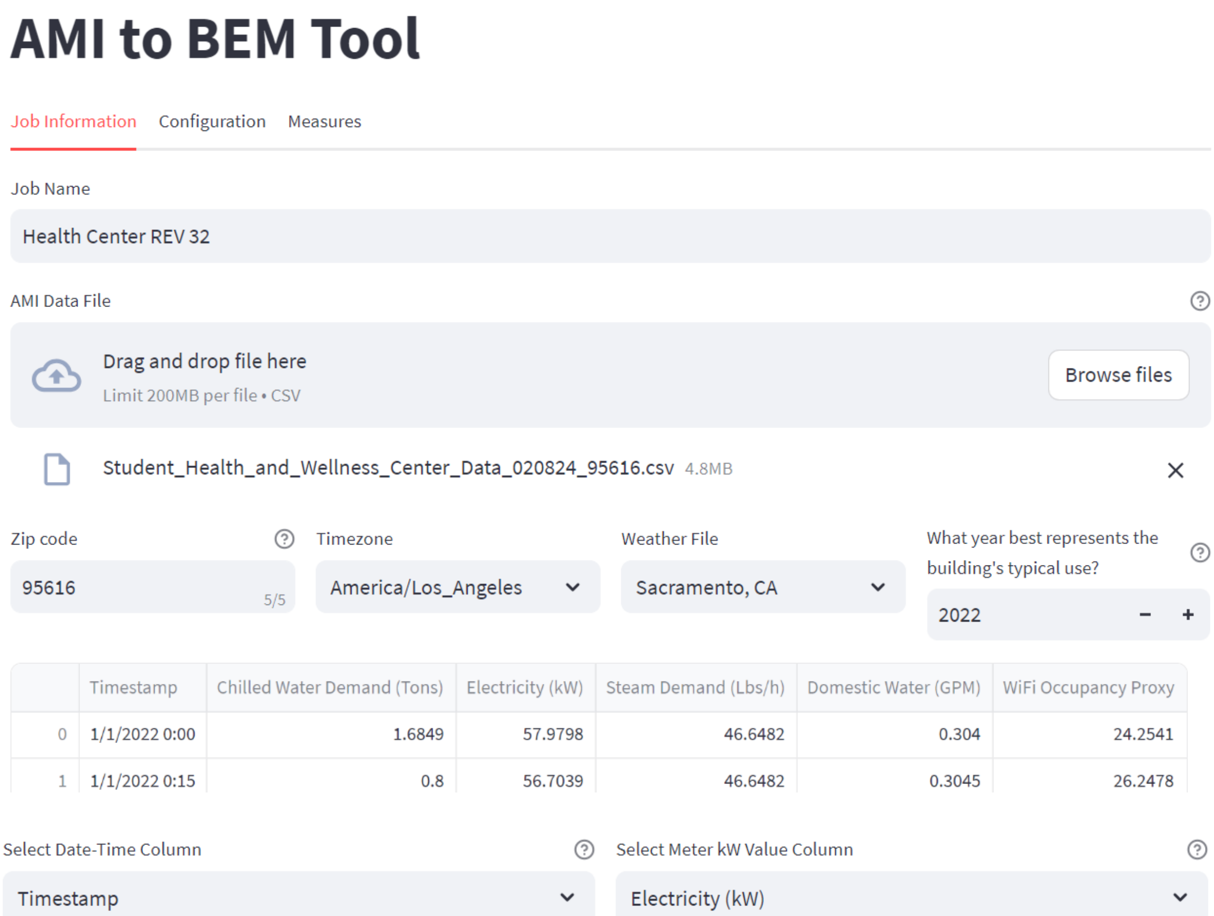


Figure 1: CCBEM AMI input.

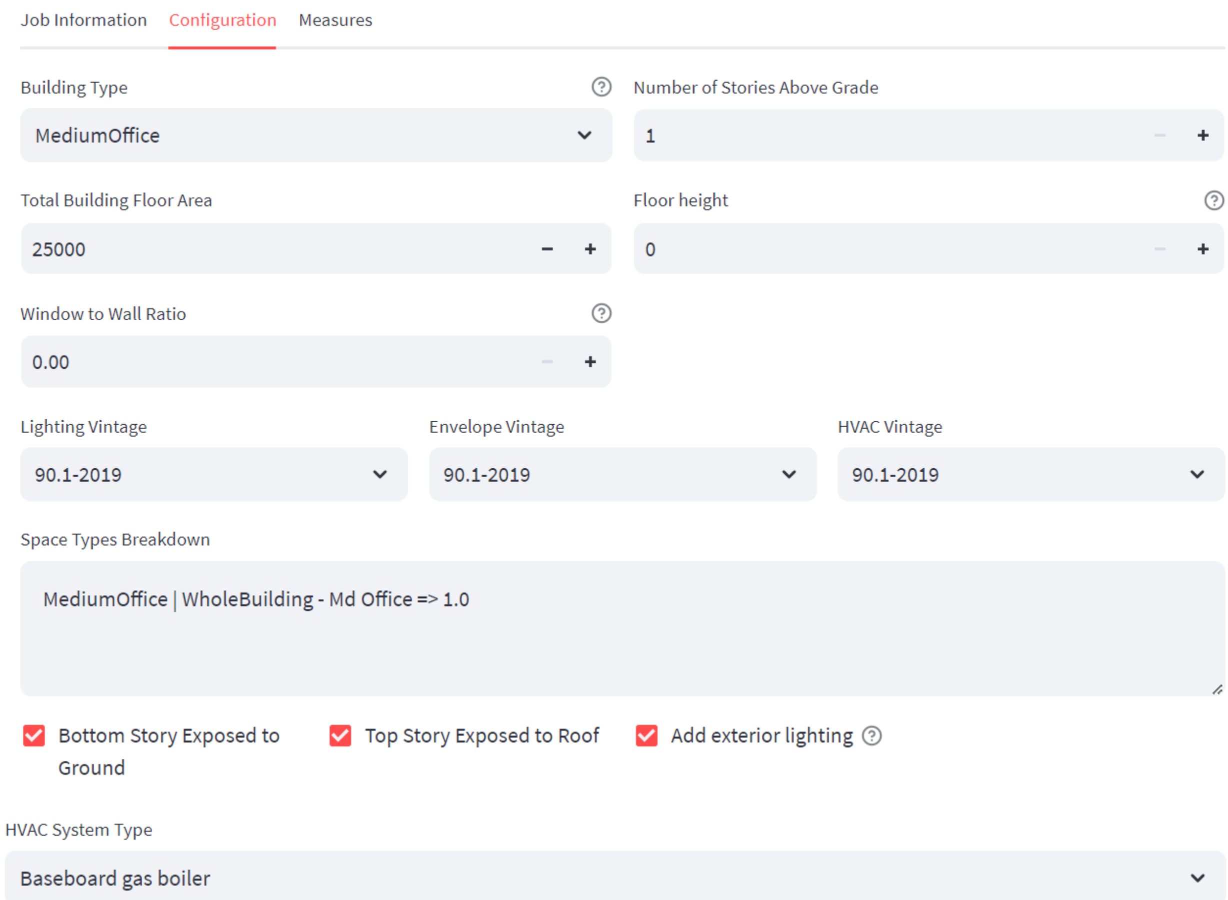


Figure 2: CCBEM configuration panel.

The tool creates a prototype energy model, M1, of the test building using this information. To verify this model's accuracy, the team compared it to the past AMI data for quality-of-fit. The second energy model, M2, was then created by making modifications to M1 informed by the site's past AMI data uploaded on the Job Information panel. From there, the Project Team extracted a day-to-day schedule of energy use for the test building and replaced the schedule within M1.

To create the M3 models for each site, the project team navigated to the "Measures" tab pictured in Figure 3 and selected the upgrade measures that they wanted to test.

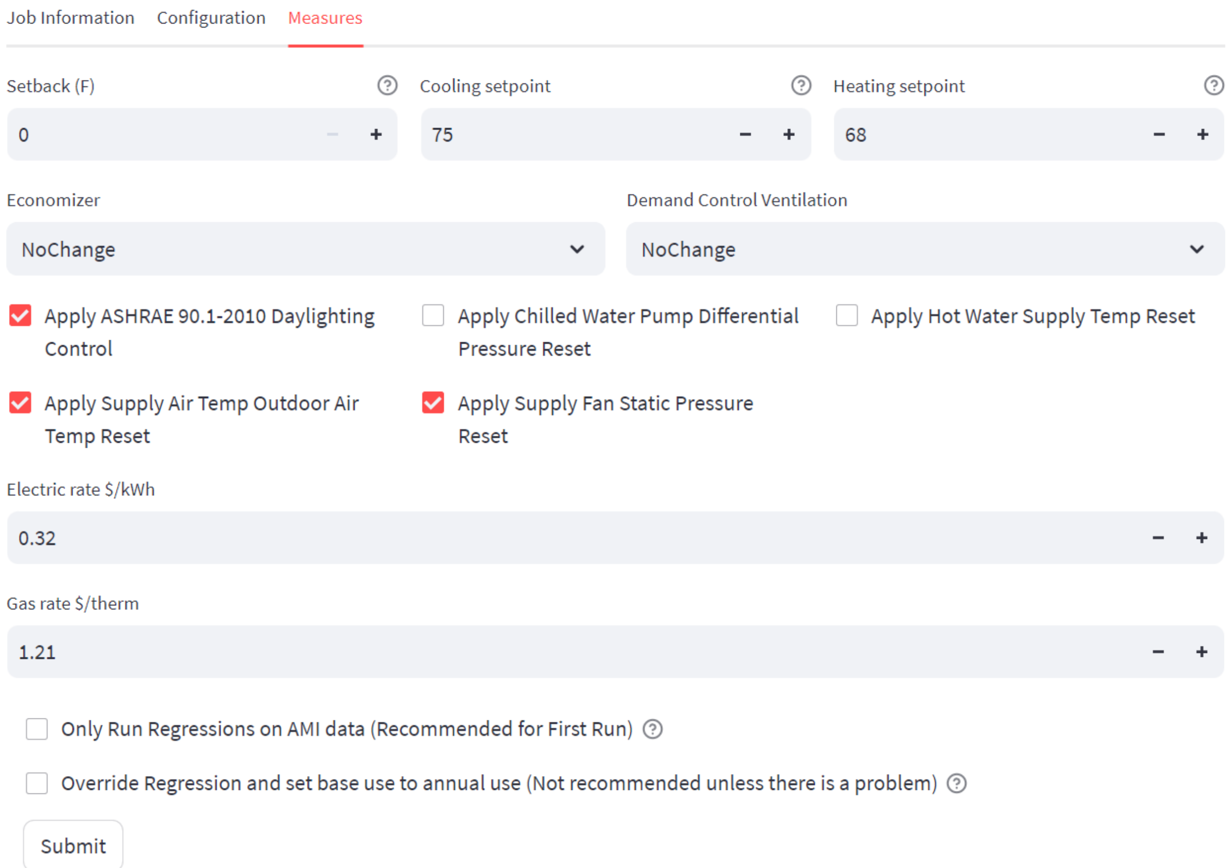
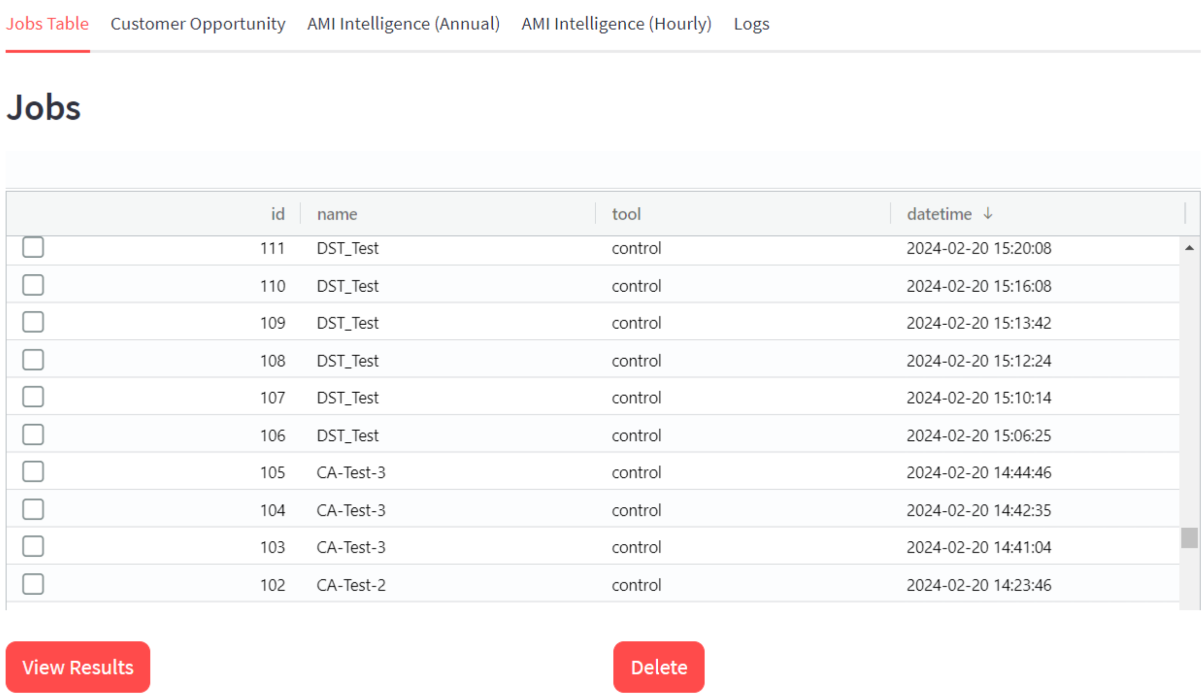


Figure 3: CCBEM upgrade measure input.

By testing each hypothetical measure's impact on projected energy usage, the project team could identify the most impactful upgrade path for each site. For the scope of this project, the Project Team changed only measures related to lighting and plugs and not, for example, measures relating to heating and cooling. The results were stored in a searchable database, shown in Figure 4, that allowed the project team to download the results for further analysis. This ease-of-access to past results gives the tool its intended feel of a sandbox environment, where exploration and experimentation let users take full advantage of the CCBEM tool's resources.



	id	name	tool	datetime ↓
☐	111	DST_Test	control	2024-02-20 15:20:08
☐	110	DST_Test	control	2024-02-20 15:16:08
☐	109	DST_Test	control	2024-02-20 15:13:42
☐	108	DST_Test	control	2024-02-20 15:12:24
☐	107	DST_Test	control	2024-02-20 15:10:14
☐	106	DST_Test	control	2024-02-20 15:06:25
☐	105	CA-Test-3	control	2024-02-20 14:44:46
☐	104	CA-Test-3	control	2024-02-20 14:42:35
☐	103	CA-Test-3	control	2024-02-20 14:41:04
☐	102	CA-Test-2	control	2024-02-20 14:23:46

Figure 4: CCBEM database feature.

When using this program outside of the context of this project, the user will be looking for actionable recommendations for upgrading their building. Once the user has run the program and it produces the M3 model, it also provides information in tabular format about the potential savings resulting from the selected measures. A sample of these outputs can be seen in Appendix C. The user can take this information to their utility to receive advice on moving forward with these upgrade measures. Alternatively, if they are confident enough for measure changes such as heating or cooling setpoints, they can make them independently. By design, most available measure changes are non-intrusive and can be made in-situ.

Error Messages

The CCBEM displays error messages when there are data inconsistencies in its modeling process. The CCBEM's ability to recognize these inconsistencies is a direct result of the inclusion of the sites' past AMI data; errors may emerge from directly comparing the M1 model to the utility data. The Project Team expected a certain level of inaccuracy for the M1 models over the course of this project and found that there are certain scenarios in M1 development that require re-tuning of the inputs.

In one example (Figure 5), the display tells the user that the HVAC regression model must be re-run since the "inputs are not consistent with bills" and recommends revising the inputs. In another example, the system was more specific, detailing the numerical inconsistency detected (Figure 6). In this case, the model was assuming the presence of heating in its attempt to match the curve of its annual energy usage regression to the curve of the utility data provided. However, it verified against the utility data that there was no heating present on the bill, indicating to the CCBEM that the model was inaccurate as a result, the details of which are present in the tabular output (Figure 6).

Different type of regression: True

The model HVAC needs to be revised and re-run since underlying inputs are not consistent with bills

Re-run model and align hvac system with the hvac system reflected in bills

Figure 5: CCBEM error example 1: explanatory.

0 kwh of electric heating detected, 1,265 kwh of electric cooling detected, and 9,066 kwh of base use detected

See outputs below and in folder for more information

Ensure the HVAC system selected for the model has **electric heating = False and electric cooling = True** as indicated above

Figure 6: CCBEM error example 1: numerical.

	hdd	cdd	r2	cv_rmse	annual_kwh	adj_est_kwh	heating_kwh	cooling_kwh	base_kwh
model	hdd_64_bin	cdd_58_bin	1.00	0.04	17,098.59	17,098.59	1,679.49	6,382.55	9,036.55
bills	nan	cdd_64_bin	0.97	0.05	10,330.49	10,330.49	0.00	1,264.80	9,065.68

Figure 7: CCBEM error example 1: tabular display.

In this error case (Figure 8, similar outputs are presented to the user as the former error. The exception here is that this error is indicating that the model has assumed the existence of both heating and cooling where it does not exist on the meter data in order to best match the regression curve to the AMI meter curve. In Figure 9 and Figure 10, the numerical and tabular data expound on the error messages given.

It should also be noted that while heating and cooling are not within the project's scope to make measure changes, heating and cooling energy usage are still in the tool's output. These categories of usage are displayed as observed by the regression of the meter data. The location in the building or the device responsible for the usage is unknown, but the tool recognizes that there is a portion of usage on the meter that can be shown to increase or decrease as a function of outdoor air temperature changes. In essence, while the tool can sort usage by equipment category for lighting and plugs, within the project's scope, the tool estimates heating and cooling electrical usage based on simple outdoor temperature rules. Making this mechanism more exact is part of the project team's recommended further development for this tool.

Different type of regression: True

The model HVAC needs to be revised and re-run since underlying inputs are not consistent with bills

Re-run model and align hvac system with the hvac system reflected in bills

Figure 8: CCBEM error example 2: explanatory.

0 kwh of electric heating detected, 0 kwh of electric cooling detected, and 17,061 kwh of base use detected

See outputs below and in folder for more information

Ensure the HVAC system selected for the model has **electric heating = False and electric cooling = False** as indicated above

Figure 9: CCBEM error example 2: numerical.

Bills and Model Regressions Compared:

	hdd	cdd	r2	cv_rmse	annual_kwh	adj_est_kwh	heating_kwh	cooling_kwh	base_kwh
model	hdd_50_bin	cdd_64_bin	1.00	0.01	145,271.57	145,271.57	39,290.55	61,230.32	44,750.70
bills	nan	nan	nan	nan	17,060.63	nan	nan	nan	17,060.63

Figure 10: CCBEM error example 2: tabular display.

Findings

As defined by ASHRAE 14, the target accuracy for energy modeling software should be a net mean bias error (NMBE) of 5, which is a value few of these test sites reached. By testing this tool on these nine sites, the project team was able to make adjustments that resulted in energy models that were several times more accurate once AMI data was ingested into the program. In terms specific to the project, this means that because of the iteration opportunities and the amount of data the program was allowed to train on, the NMBE between the M1 models and the M2B models reduced by an average of 280 percent, sometimes reaching as low as 3.4. However, as discussed previously, there were several instances where some test sites were equipped with solar panels, which distorted the net meter data that the CCBEM ingested, leading it to make inaccurate assumptions about the total energy consumption of the buildings. This meant that, in the cases of these sites that included solar, the Project Team had to manually adjust to the tool between the M1 and M2A-B models, so the process was not fully automatic.

Site 1

After running the model, the building owner would have concluded that instituting simple control strategies around economizing ventilation would have made $44,134.84 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- Meter regression in Table 7 identified a regression focused on heating degree day (HDD), where the site was described as having gas heat. HDD estimates the amount of energy needed to heat a building, and HDD dependence may indicate the presence of solar contribution on the meter data.
- Despite the solar mismatch, the “baseload” adjustment portion of the AMI intelligence informed a model with an error reduction of 810 percent.
- When adding back into the meter an estimated solar consumption, the AMI intelligence nearly achieved automatic calibration, with an error reduction of 520 percent, and stopped 0.75 percent short of achieving the ASHRAE Guideline 14 calibration statistics.

Site Overview

Site 1, an elementary school in Contra Costa County in the north of California, has a total of 25,925 air-conditioned square footage divided between five buildings: a multipurpose building, a kindergarten building, a grades 1-5 building, an administrative building, and a library. According to the customer intake survey, there is no cooling and just boiler and baseboard heating, so no cooling setpoint is listed. The intake also reads “Packaged Single Zone ACs with gas heat.” For the prototype, the team proceeded with the assumption that there is no cooling. Configuration is shown in Figure 11.

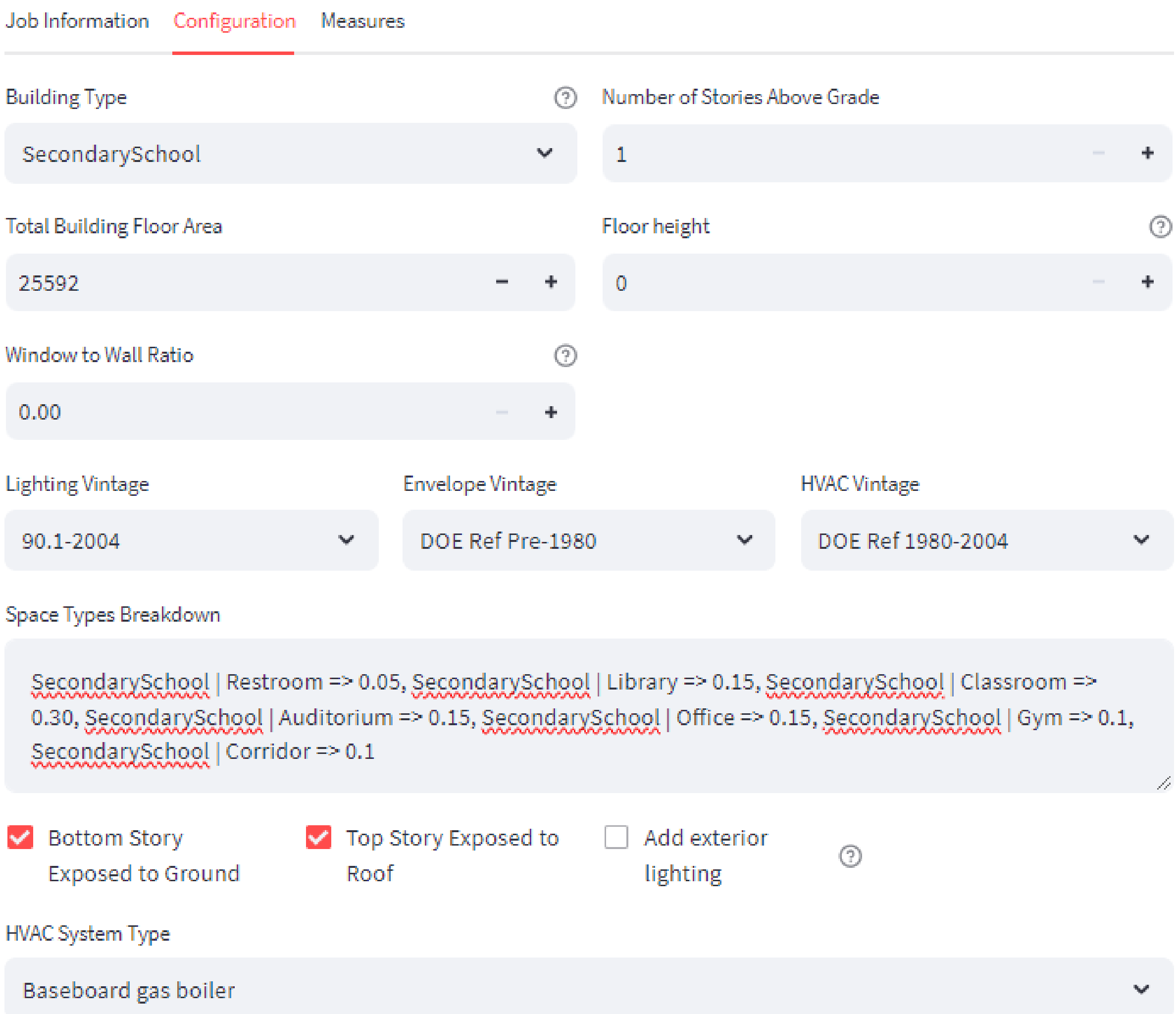


Figure 11: Site 1 configuration panel.

In terms of measures, this site was assigned daylighting, hot water temp reset and DCV measures (). These measures are typically cost-effective and yield substantial energy savings in this building type.

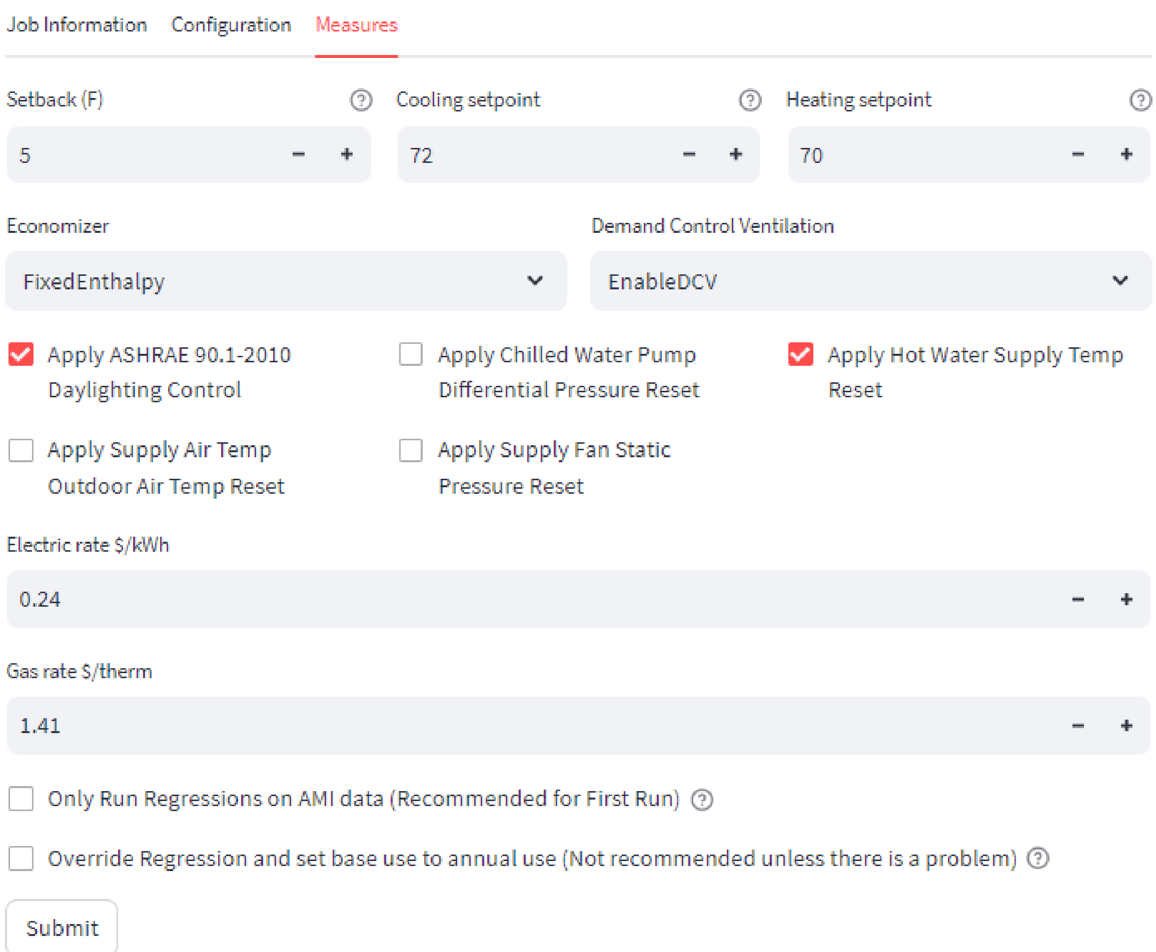


Figure 12: Site 1 measures panel.

Results

The AMI intelligence acted as if it saw electric-dependent heat within the model, where the system was explicitly described as gas heat. Also, the site information indicated the presence of a lot of solar (~60 kW), which showed up in the "double horned" shape of the meter data (Figure 13).

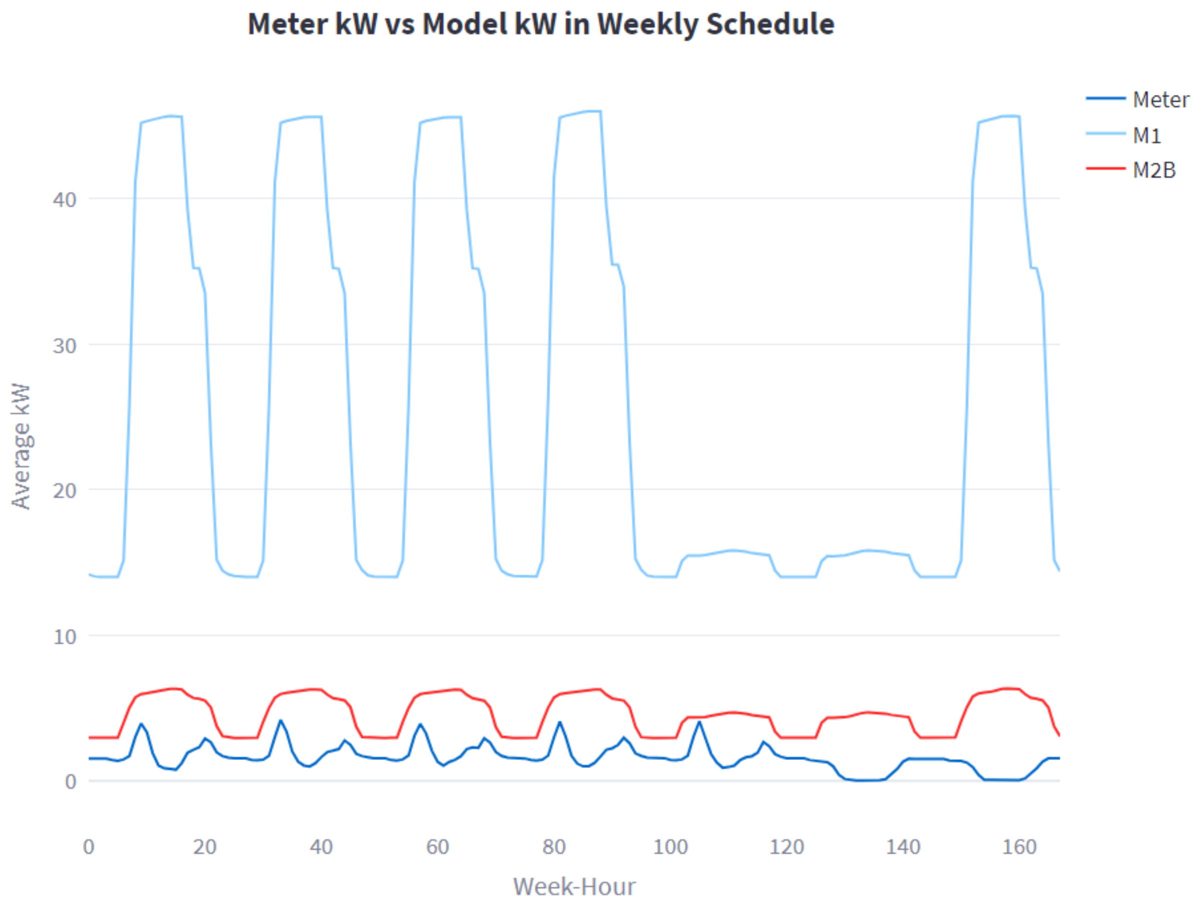


Figure 13: Site 1 full regression line graph.

Table 3: Site 1 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	NAN	NAN	NAN
Bills	NAN	cdd_68_bin	0.76	0.15

Table 4: Site 1 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	227,207.1	NAN	NAN	NAN	227,207.1
Bills	14,120.0	14,120.0	4,802.1	0.00	9,317.9

Despite the distortion resulting from unanticipated solar energy intake, the prototype M1 (Table 3, Table 4) had a much larger error than the M2B, indicating CCBEM's ingestion of AMI data directly resulted in a more accurate simulation of the site's energy usage profile. In specific terms, the inclusion of the AMI data allowed for a model with 800 percent more accuracy (Table 5).

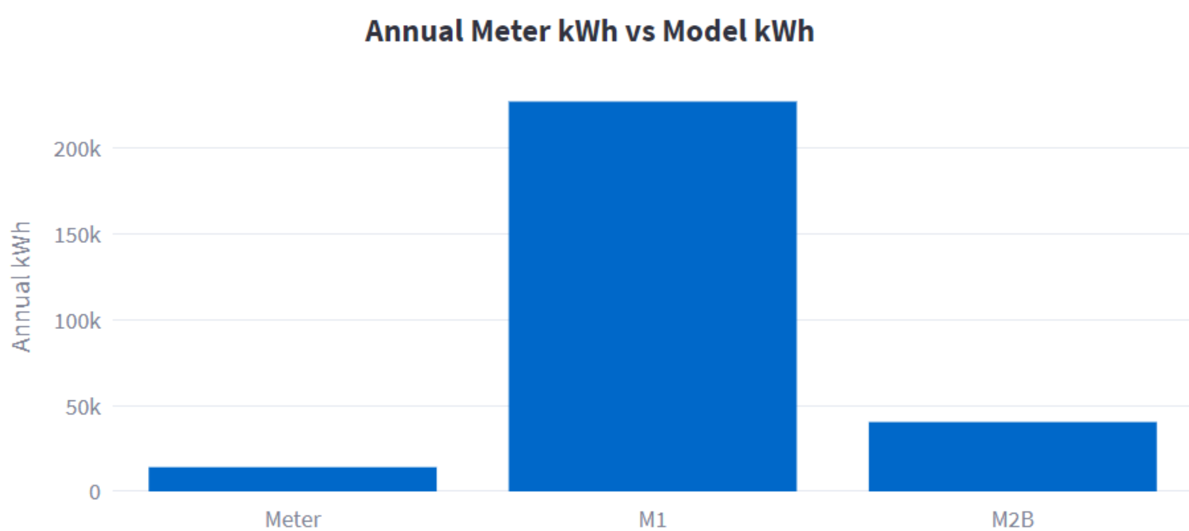


Figure 14: Site 1 model accuracy comparison.

Table 5: Site 1 Calibration Results

Model	CVRMSE	NMBE
M1	1,589.2	-1,646.5
M2B	196.9	-203.3

The analysis team discovered that the reason the M2B model did not achieve a closer level of accuracy was because of an inability to automatically account for solar energy. The manual estimation of solar energy consumption relied on the solar intensity — watts per area — in the file for reference on the hourly profile of production and aligned the actual monthly production using the NREL PV watts tool for production estimates. This is represented in .

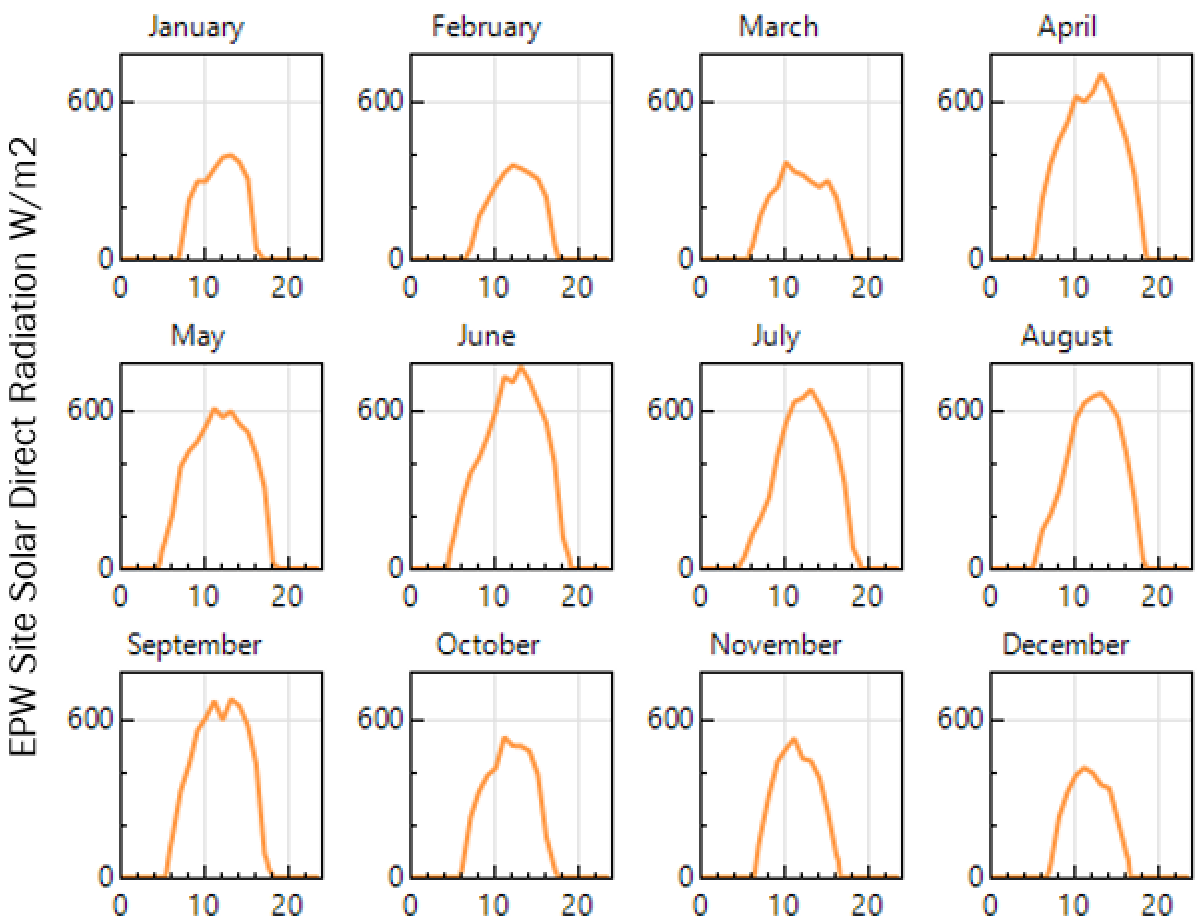


Figure 15: Site 1 solar profile data.

Running another model with this data ingested resulted in a regression with an almost-complete match that comes close to achieving ASHRAE 14 calibration criteria for CVRSME. That including this solar data had an immediate positive impact on the model's accuracy speaks once more to the potential of the tool once it includes more dimensionality, beyond lighting and plug measures.

Table 6: Site 1 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_54_bin	0.83	0.05
Bills	NAN	cdd_52_bin	0.97	0.08

Table 7: Site 1 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	39,497.8	39,497.8	0.00	2,708.0	36,789.7
Bills	38,299.7	38,299.7	0.00	16,398.5	21,901.2

Table 8: Site 1 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	0.00	0.00	115,044	0.00	79,071	0.00
M2B	0.00	0.00	4,717	0.00	3,242	0.00

In Table 6 and Table 7, HDD and heating_kwh are NAN and 0 respectively, indicating electric heating was not statistically significant in the model or bills. Cooling degree days (CDD) and cooling_kwh are identified and the balance points of the CDD are very close, which is a good sign and shows the model is similar in both. The high coefficients of determination (r^2) indicate that the data fits the model very well in both cases. In statistical analysis, the maximum value for r^2 is 1.00, which indicates that the model perfectly represents or predicts the dependent variable. Therefore, a value above 0.70 is typically considered a good fit. Root mean square error (RMSE) measures the average magnitude of the errors between the model's values and actual values. It provides a measure of how spread out these prediction errors are, ranging from 0 to theoretically infinity. A lower RMSE indicates a model with fewer errors. Coefficient of variation (CV) is a standardized measure of dispersion of a frequency distribution, similar to standard deviation, expressed as a percentage. Combining the two into the measure seen in Table 9 and subsequent tables (CVRMSE), this value measures the RMSE in proportion to the actual size of the data set, a more exact measurement for this study's purposes. The CVRMSE values both appear excellent in the models indicating there is little error in the model's predictions when compared to the data, anything under 15 percent is considered excellent and less than 30 percent is considered acceptable.

Finally, the quantities of use identified in each category (annual_kwh, heating_kwh, cooling_kwh, and base_kwh) are what the team compares between the model and bills to see, numerically, where they are similar and where they differ. In an ideal scenario, the model would match the real-world values precisely. In the case of Site 1, the annual use is very close, the base use is pretty close, but cooling is substantially different. In , the regression models are a good fit, similar in identifying heating and cooling, have close balance points, and have low error in their predictions. In accordance with the scope's limitations, cooling and heating were not adjusted, meaning that the CCBEM's intelligence appears to be doing a good job adjusting base use and tuning the model in this case.

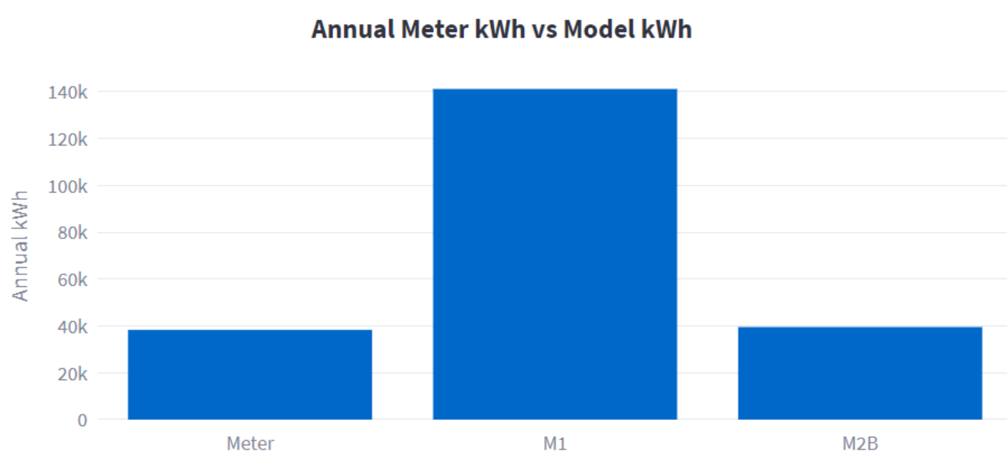


Figure 16: Site 1 model accuracy comparison post-solar data integration.

Table 9: Site 1 Calibration Results Post-Solar Data Integration

Model	CVRMSE	NMBE
M1	285.3	-292.8
M2B	15.8	-3.4

If the team were to re-analyze this site, the Project Team would edit the solar data introduced into the tool to fully reflect time-of-week, instead of treating weekend days as having the same solar usage as weekdays. However, re-analysis on that particular scale would be outside the scope of the project. The solar estimation did not account for weekday versus weekends, and this is shown by the meter data falsely adding consumption on the weekend (Figure 17, hours 100 to 140). This contributed to autocalibration not directly achieving the CVRSME, even with the added solar.

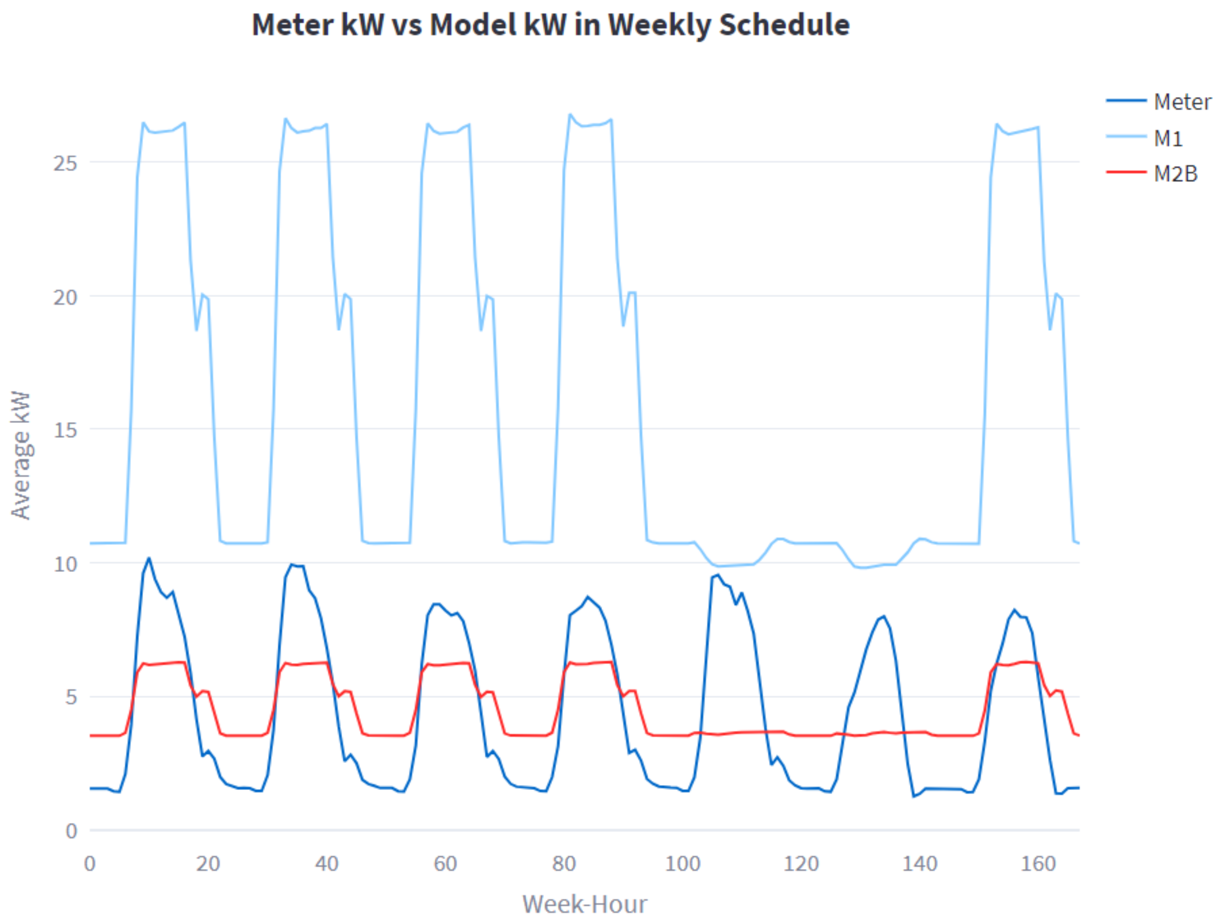


Figure 17: Site 1 model hourly accuracy comparison post-solar data integration.

With the acceptable calibration results the customer opportunity for this site can be considered with confidence. Upon calibration of the baseline to the meter data the CCBEM estimates that a small incremental cost to institute some simple control strategies around economizing and adjusting ventilation based on demand (Table 10) yields significant savings (Table 8) and rapid returns (Table 11 and Table 12). Ideally, at this point, the customer would look into pricing these measures out with a controls contractor.

Table 10: Site 1 Selected Measures

Efficiency Measure Combination	Notes
• Economizer • Demand Control Ventilation • Hot Water Supply Temp Outdoor Air Reset • Daylighting Control	The team tried some simple-loop-type measures for the water-related aspects, and then selected some outdoor-air-related measure for the ventilation. However, actual ventilation parameters were unknown.

Table 11: Site 1 Customer Opportunity Report: Savings

Energy	Savings
Electricity	188,571 kWh
Natural Gas	-207 therms

Table 12: Site 1 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$1535.52
Annual Cost Savings	$44,134.84
Simple Payback	.04 years

Site 2

After running the model, the building owner would have concluded that instituting simple control strategies around fan resets and daylighting would have made $61,281.01 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- Meter regressions and building regressions both identified electric heating and cooling with similar balance points. This was an indication that the regression model worked well for both the bills and energy model.
- As seen in Table 16 the base kWh detected in the M1 model was adjusted and between M1 and M2B, base kWh went from 338 MWh in the model to 77 MWh, a 77-percent reduction, and coming very close to matching the bills at 62 MWh.
- The annual M1 consumption in Table 14 was reduced from 433 MWh to 193 MWh, a reduction of 55 percent. The consumption meter showed annual use of 86 MWh. These results show the AMI intelligence is working and if heating and cooling are accounted for, calibration should be achieved.

Site Overview

Site 2 is a primary school in Riverside County with five classroom buildings, a kitchen, and a library. Most buildings are more than 30 years old except the library, which was built in 2021. The lighting is all LED so a lighting vintage of 2018 was used. Because the HVAC systems are older, the project team used an average vintage of pre-2000. The group of buildings was modeled as one segmented primary school with building average vintages weighted by square footage of building area. This was done because the prototypical school model breaks the building into separate buildings by space types and would therefore capture the separate buildings already. Configuration is shown in Figure 18. The system chosen was PSZ-Heat Pump (Figure 18).

For the measure changes, the standard set was employed with building weighted average cooling and heating setpoints with a 3°F setback.

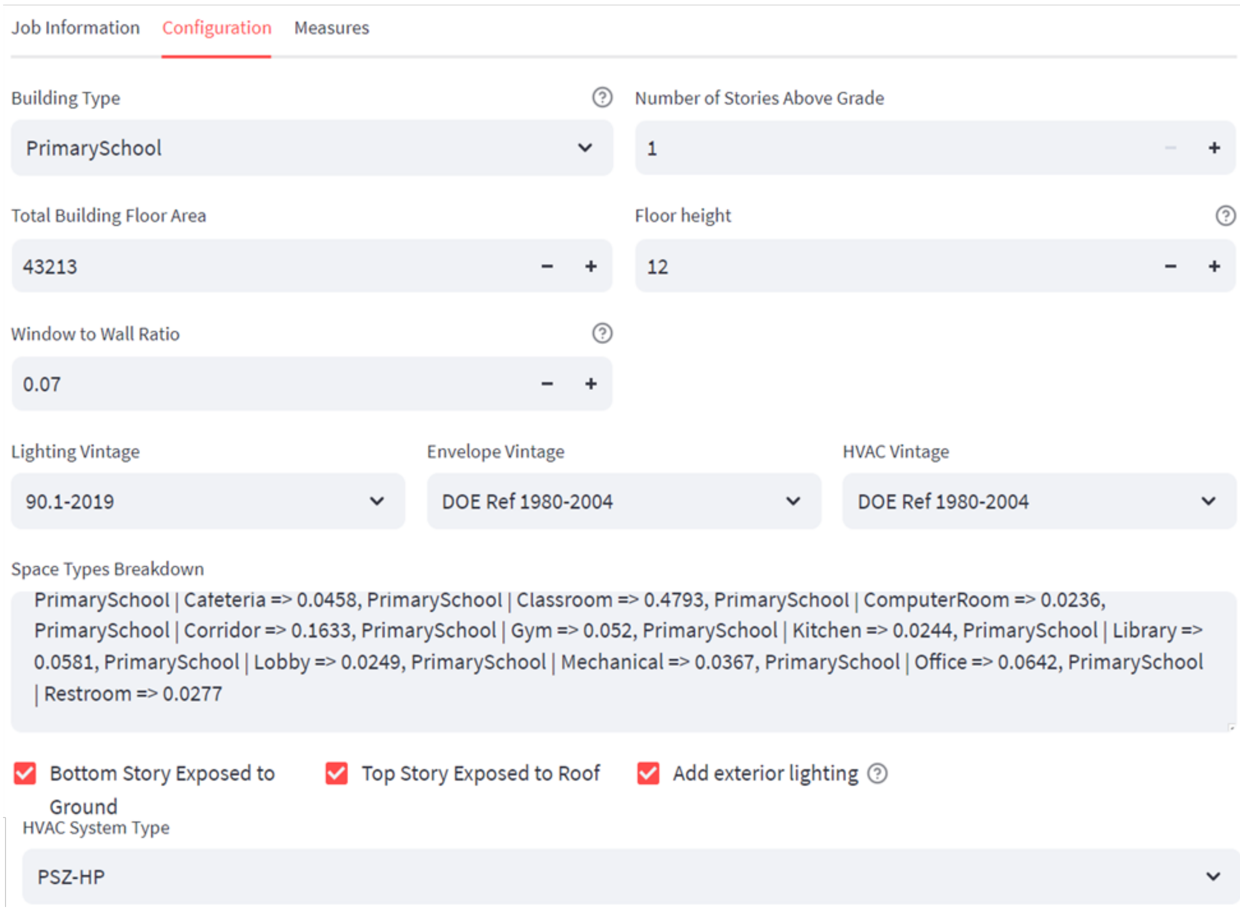


Figure 18: Site 2 configuration panel.

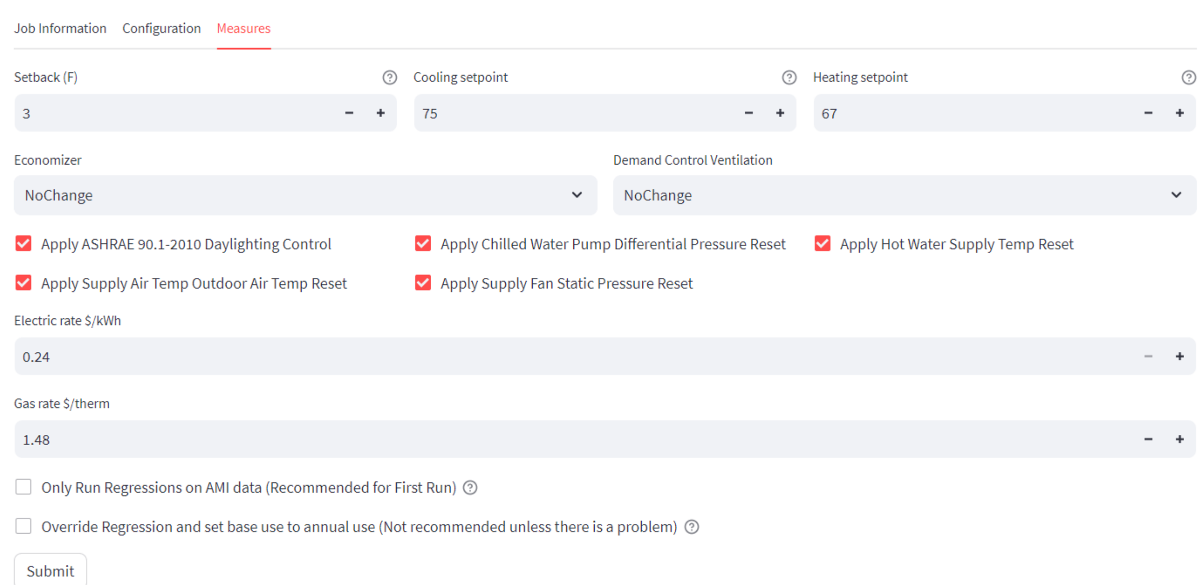


Figure 19: Site 2 measures panel.

Results

The annual regressions of the bills and models showed similar balance point temperatures, good regressions, and good heating and cooling detection (Table 13). The hourly regression was below an r^2 of 0.7, which indicated that the building schedule was not adequately adjusted to the AMI data and the prototypical schedules were retained. The base kWh detected in the M1 model was adjusted and between M1 and M2B, base kWh went from 338 MWh in the model to 77 MWh, coming very close to matching the bills at 62 MWh (Table 14). Since heating and cooling adjustments are out of scope, the annual use is not as close. However, with only adjustments to lighting and plugs, the CCBEM is arriving incredibly close to the AMI utility data, according to Figure 20.

Table 13: Site 2 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_60_bin	cdd_66_bin	1.00	0.00
Bills	hdd_58_bin	cdd_66_bin	0.99	0.02

Table 14: Site 2 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	433,233.4	433,233.4	5,537.3	89,641.1	338,045.0
Bills	86,221.8	86,221.8	7,499.8	16,448.9	62,273.1

Table 15: Site 2 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_62_bin	0.99	0.02
Bills	hdd_58_bin	cdd_66_bin	0.99	0.02

Table 16: Site 2 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	193,133.5	193,133.5	67.354.6	48,852.6	76,926.4
Bills	86,221.8	86,221.8	7,499.8	16,448.9	62,273.1

The hourly AMI data magnitude moved substantially closer to the metered use between M1 and M2B post-AMI intelligence. It appears that the model may be offset by a day in these graphs, which should be further investigated.

Table 17: Site 2 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	8,652	24,945	93,770	48,074	180,210	0.00
M2B	20,520	7,967	17,272	48,074	33,195	0.00

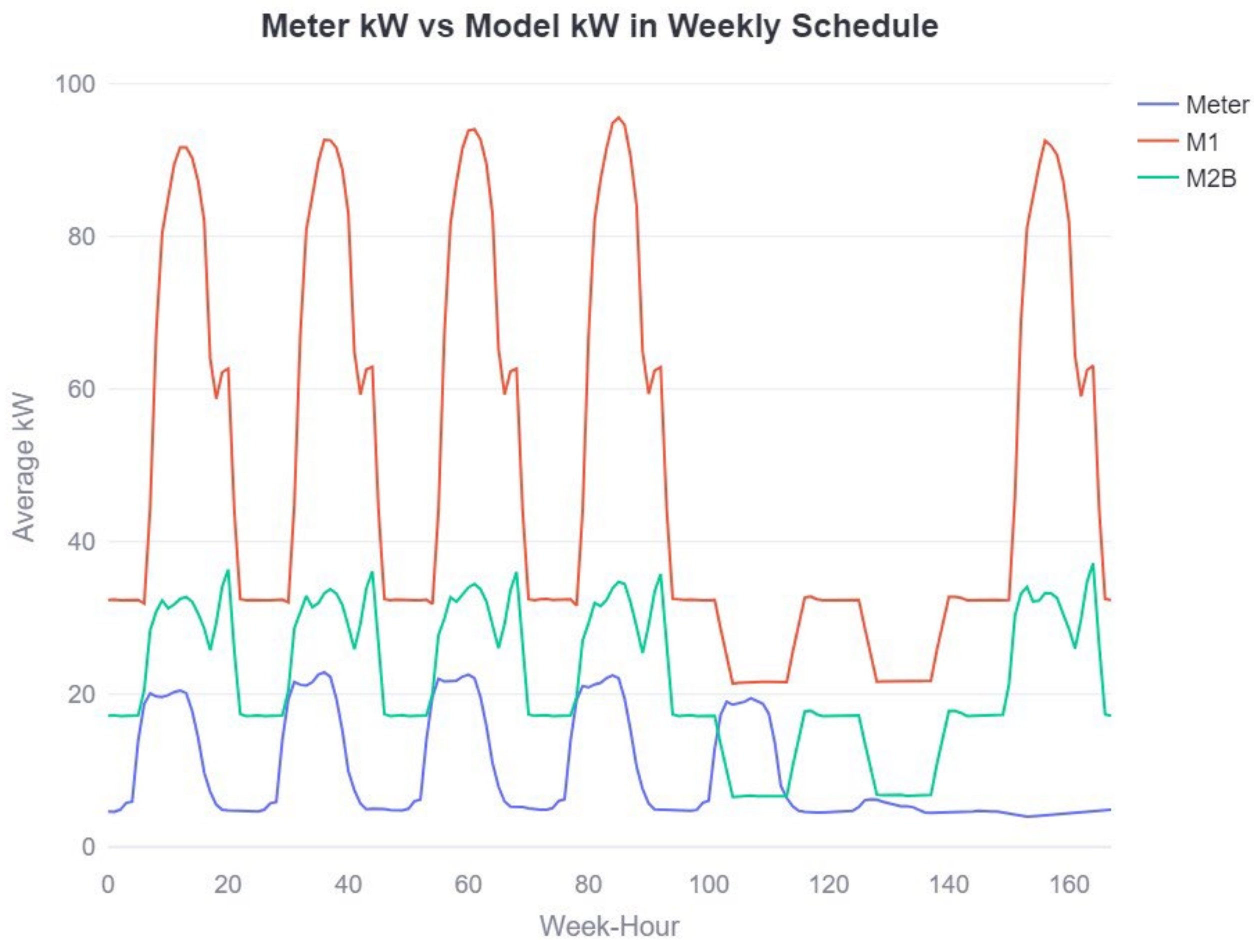


Figure 20: Site 2 full regression line graph.

The AMI intelligence reduced the annual M1 consumption from 433 MWh to 193 MWh and the consumption meter showed 86 MWh.

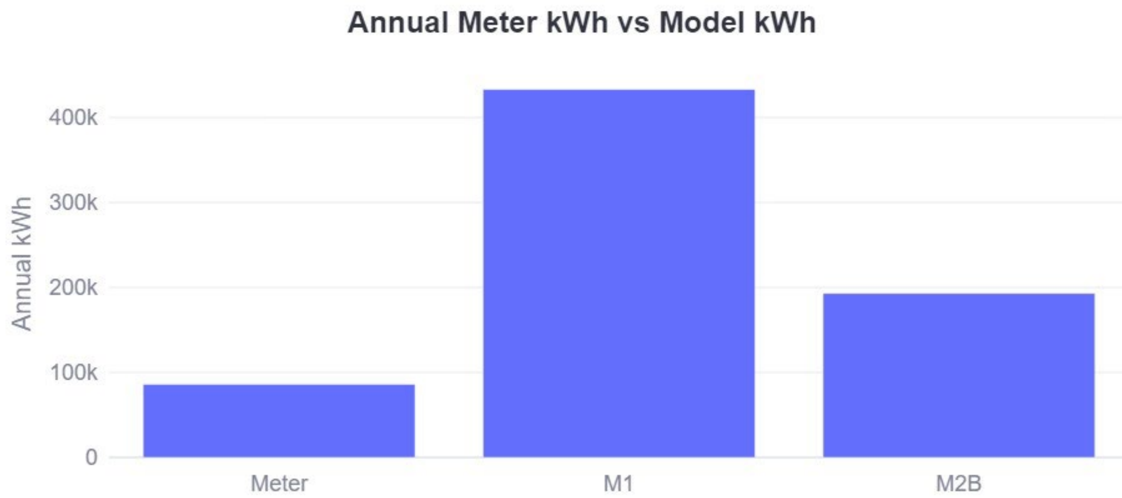


Figure 21: Site 2 model accuracy comparison.

Table 18: Site 2 Calibration Results

Model	CVRMSE	NMBE
M1	4425.6	-439.1
M2B	137.0	-135.3

In summary, the AMI intelligence at this site greatly benefited the CCBEM tool's analysis and, with some tuning of the intelligence to account for other out-of-scope end-uses such as heating and cooling, the tool will have an easier time calibrating to similar sites in the future. According to the model, the measure changes included in the model and detailed in Table 19 are projected to save Site 2 over 250,000 kWh of annual electricity usage which translates to nearly $61,300 (Table 17, Table 20).

Table 19: Site 2 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset • Supply Air Temperature Setpoint Outdoor Air Reset	This building was very new and likely would have had a lot of these measures and sequences required by code. The team was curious to see if there were any clear indicators in the AMI data that these measures were not already implemented but could find nothing conclusive.

Table 20: Site 2 Customer Opportunity Report: Savings

Energy	Savings
Electricity	257,483 kWh
Natural Gas	0 therms

Table 21: Site 2 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$2592.84
Annual Cost Savings	$61,281.01
Simple Payback	.04 years

Site 3

After running the model, the building owner of Site 3 would have concluded that instituting simple control strategies around pump and fan pressures would have made $75,327.19 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- This was a solar net-metered AMI meter with a lot of solar production, which masked the actual consumption of the building.
- Even with poor building energy use data, the AMI intelligence reduced the annual M1 consumption in M2B from 478 MWh to 145 MWh, a 70 percent reduction Table 26).
- Given actual building consumption instead of the net-meter data, the AMI intelligence would have performed much better, and it would be good to try sites like this again with better data.

Site Overview

Site 3, a middle school in Contra Costa County in the north of California, has a total of 34,698 air-conditioned square footage split between six buildings: three buildings devoted to classrooms, a library, an administration building, and a gym. The classroom buildings were built around 1955, and the rest of the buildings are no older than 1995. Lighting is generally fluorescent with a few of the newer buildings having LED; to represent an average, the Project Team used a lighting vintage of 2007. The HVAC systems are older and some buildings do not have cooling, and so the Project Team used an average vintage of 2004 HVAC. The Project Team modeled the group of buildings as one segmented primary school with building average vintages weighted by square footage of building area. Figure 22 shows model configuration where the system chosen was PSZ-AC with baseboard gas boiler.

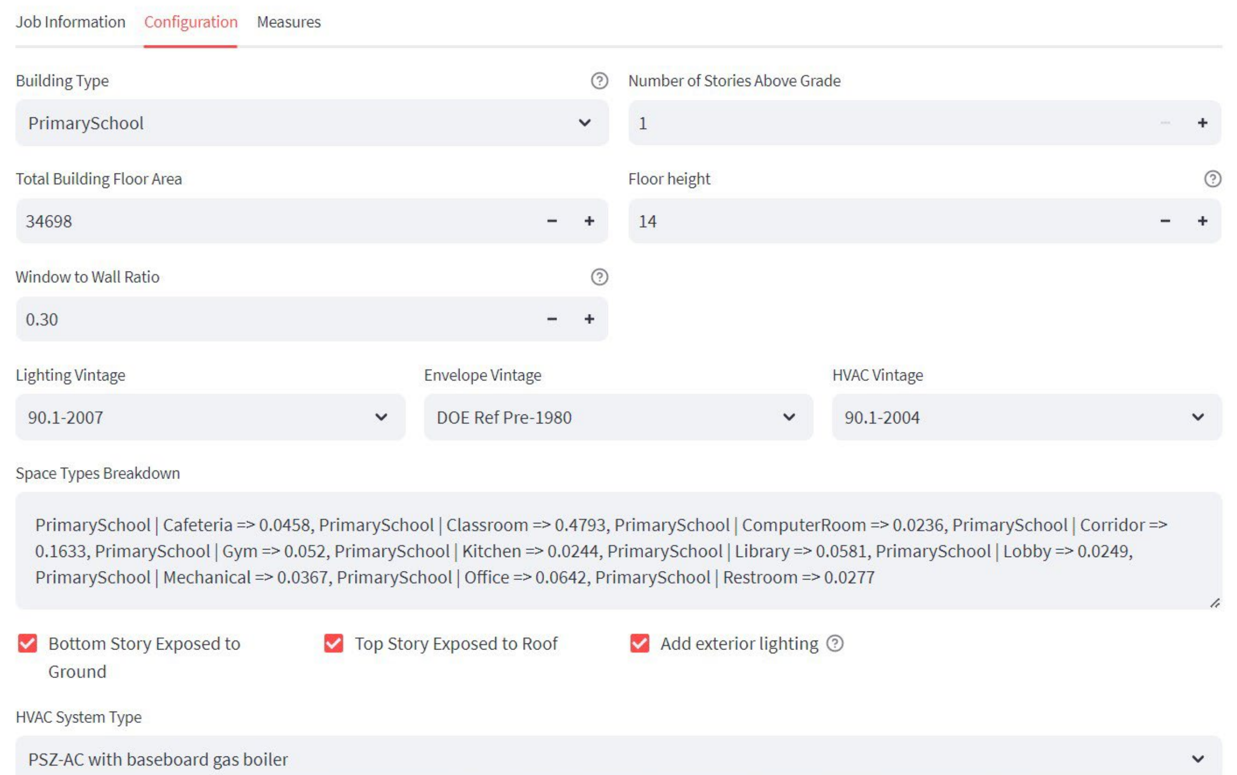


Figure 22: Site 3 configuration panel.

For the measure controls, the project team selected all controls options and used building weighted average cooling and heating setpoints with those buildings without cooling set as 85°F.

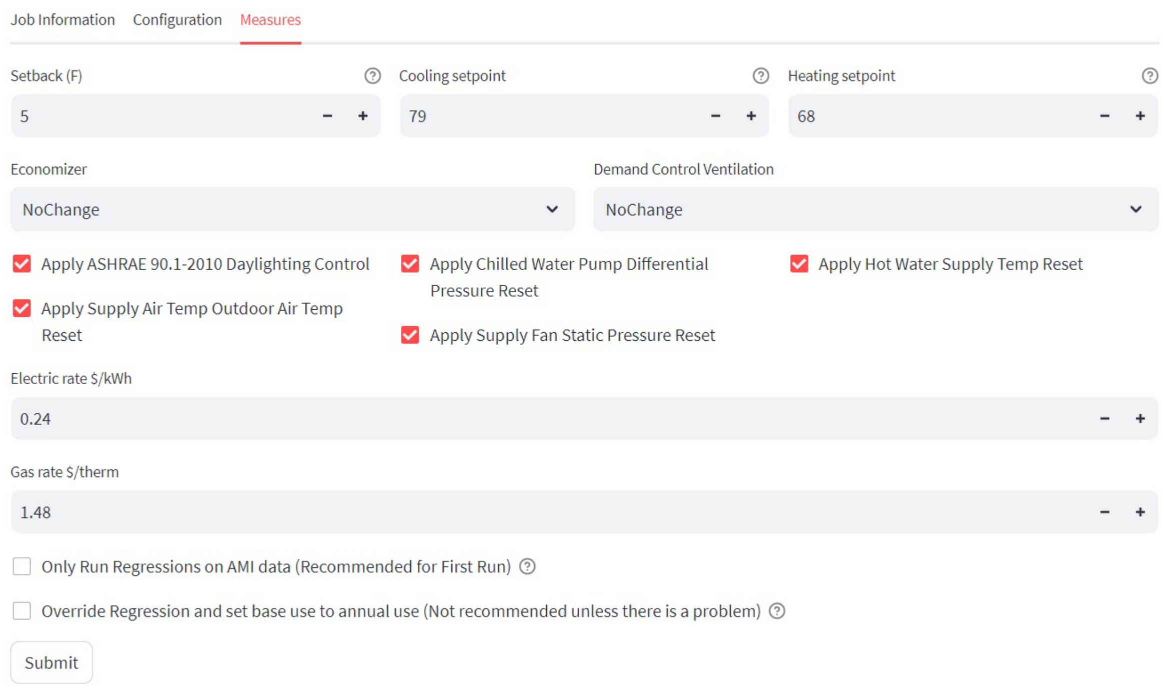


Figure 23: Site 3 measures panel.

Results

The regression of the bills in Table 22 and Table 23 failed to detect any heating or cooling signatures, but they were detected in Table 24. On-site solar use did not allow us to view the true building consumption which caused the regression of the bills to fail. Additionally, site bill consumption looked extremely low when compared to the model since solar production was offsetting site consumption to a substantial degree.

Table 22: Site 3 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_62_bin	0.99	0.04
Bills	NAN	NAN	NAN	NAN

Table 23: Site 3 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	477,890.8	477,890.8	0.00	64,360.1	413,530.7
Bills	17,060.6	NAN	NAN	NAN	17,060.6

Model accuracy made a dramatic leap forward from prototypical M1 to post-AMI intelligence M2B. However, site solar production showed a falsely low meter profile (Figure 24) which the intelligence was not able to adjust the lights and equipment enough to meet.

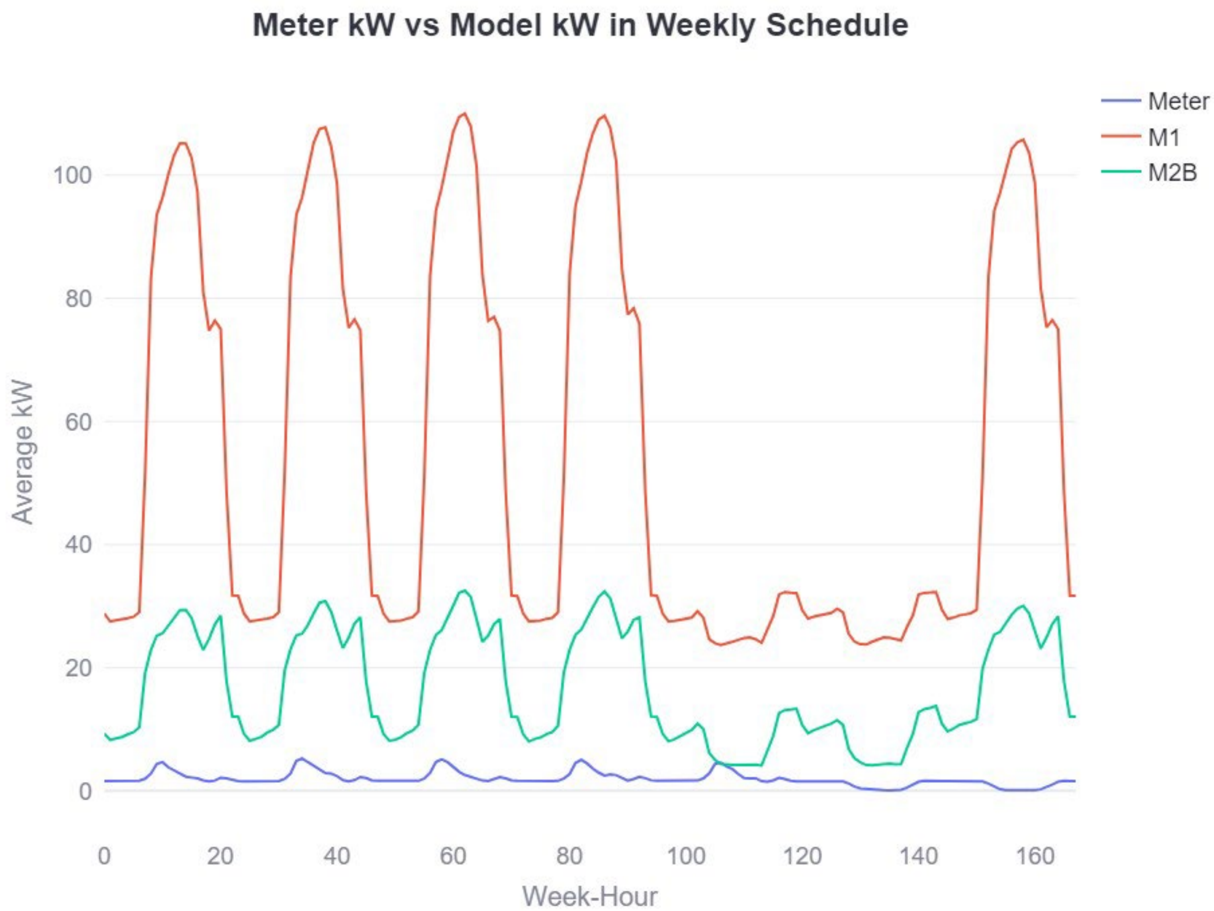


Figure 24: Site 3 full regression line graph.

Table 24: Site 3 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_62_bin	1.00	0.01
Bills	NAN	NAN	NAN	NAN

Table 25: Site 3 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	145,271.6	145,271.6	39,260.6	61,230.3	44,750.7
Bills	17,060.6	NAN	NAN	NAN	17,060.6

This was also true in the annual AMI comparisons; the model got closer to the meter as illustrated in Figure 25 and Table 27, but it was unable to get as low as would be optimal.

Table 26: Site 3 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	0.00	21,043	157,540	27,265	163,978	0.00
M2B	0.00	8,272	6,506	27,265	6,772	0.00

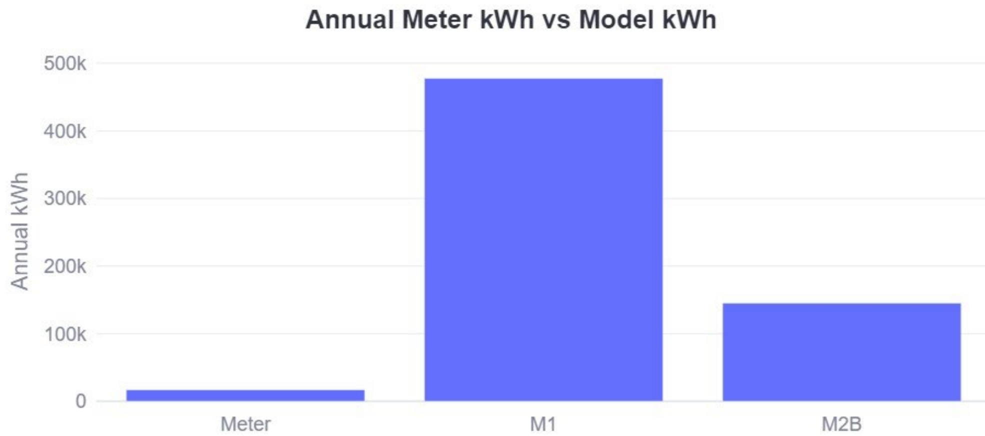


Figure 25: Site 3 model accuracy comparison.

Table 27: Site 3 Calibration Results

Model	CVRMSE	NMBE
M1	2,838.4	-2,947.0
M2B	787.4	-819.9

The AMI intelligence reduced the annual M1 consumption from 478 MWh to 145 MWh and the net consumption meter showed 17 MWh. The projected Site 3 savings in Table 29 due to these prescribed measures in Table 28 are over 300,000 kWh in annual electricity usage (Table 26), equivalent to over $75,000.

Table 28: Site 3 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset • Supply Air Temperature Setpoint Outdoor Air Reset	Some buildings were older and could likely use some controls tuning such as the ones selected. All of the controls were selected to understand the impact from a wide range of measures.

Table 29: Site 3 Customer Opportunity Report: Savings

Energy	Savings
Electricity	318,907 kWh
Natural Gas	-387 therms

Table 30: Site 3 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$2081.88
Annual Cost Savings	$75,327.19
Simple Payback	.03 years

Site 4

After running the model, the building owner would have concluded that instituting simple control strategies around adjusting the temperature setback would have made $103,016.07 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- This was a very new building, constructed circa 2019. It may not have many efficiency opportunities without knowledge of actual failures, which were not easily captured in the introductory survey.
- Hourly meter intelligence indicated that solar production was present on the meter, distorting the auto calibration. Despite this interference, the AMI intelligence module reduced the prototypical error by 370 percent in the M2B model as seen in Table 36.

Site Overview

Site 4, a high school in Riverside County in the south of California, has a total of 70,000 air-conditioned square footage spread across seven buildings. The equipment is very new, circa 2019, so all vintages were set to that year. Figure 26 shows configurations.

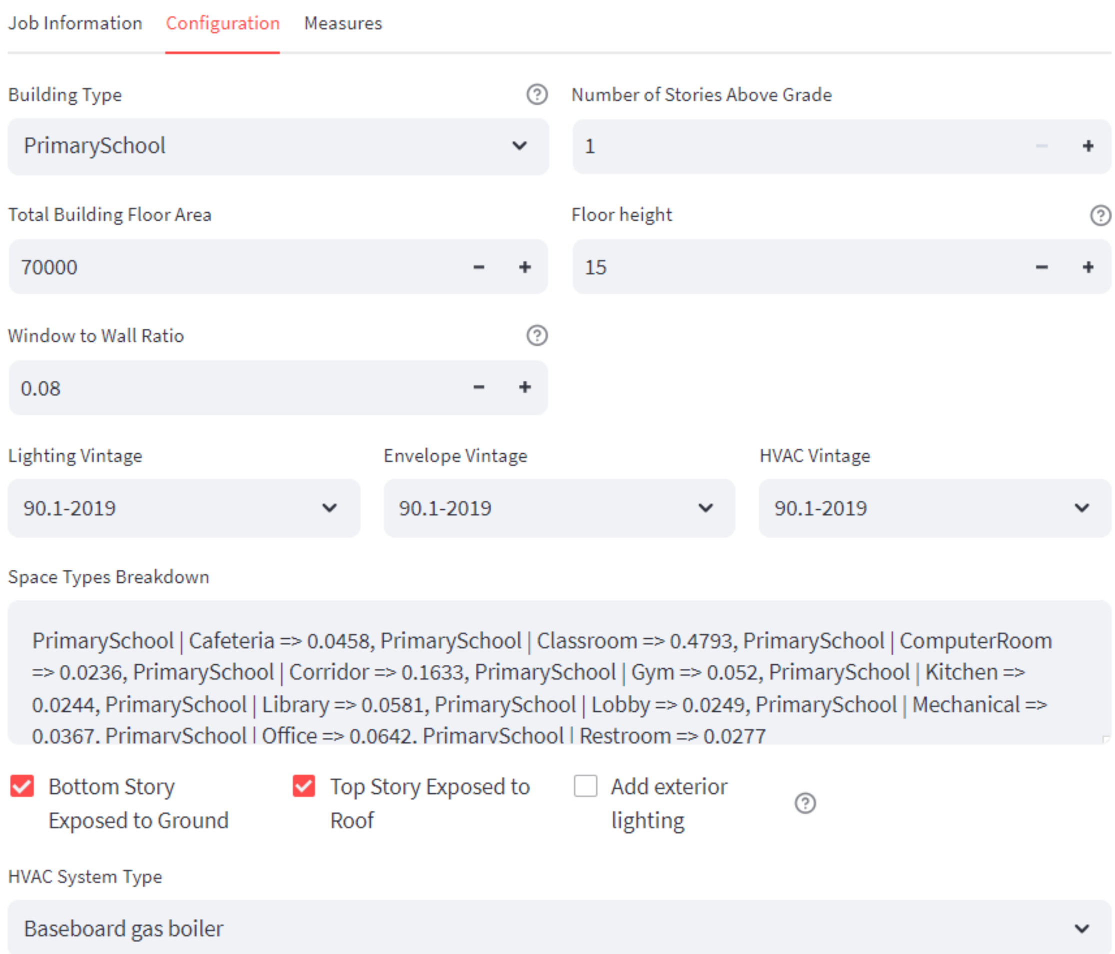


Figure 26: Site 4 configuration panel.

Given how new the equipment is in the building, the programming team was unsure what measures would be available; they set the measure changes with very economical setpoints (Figure 27).

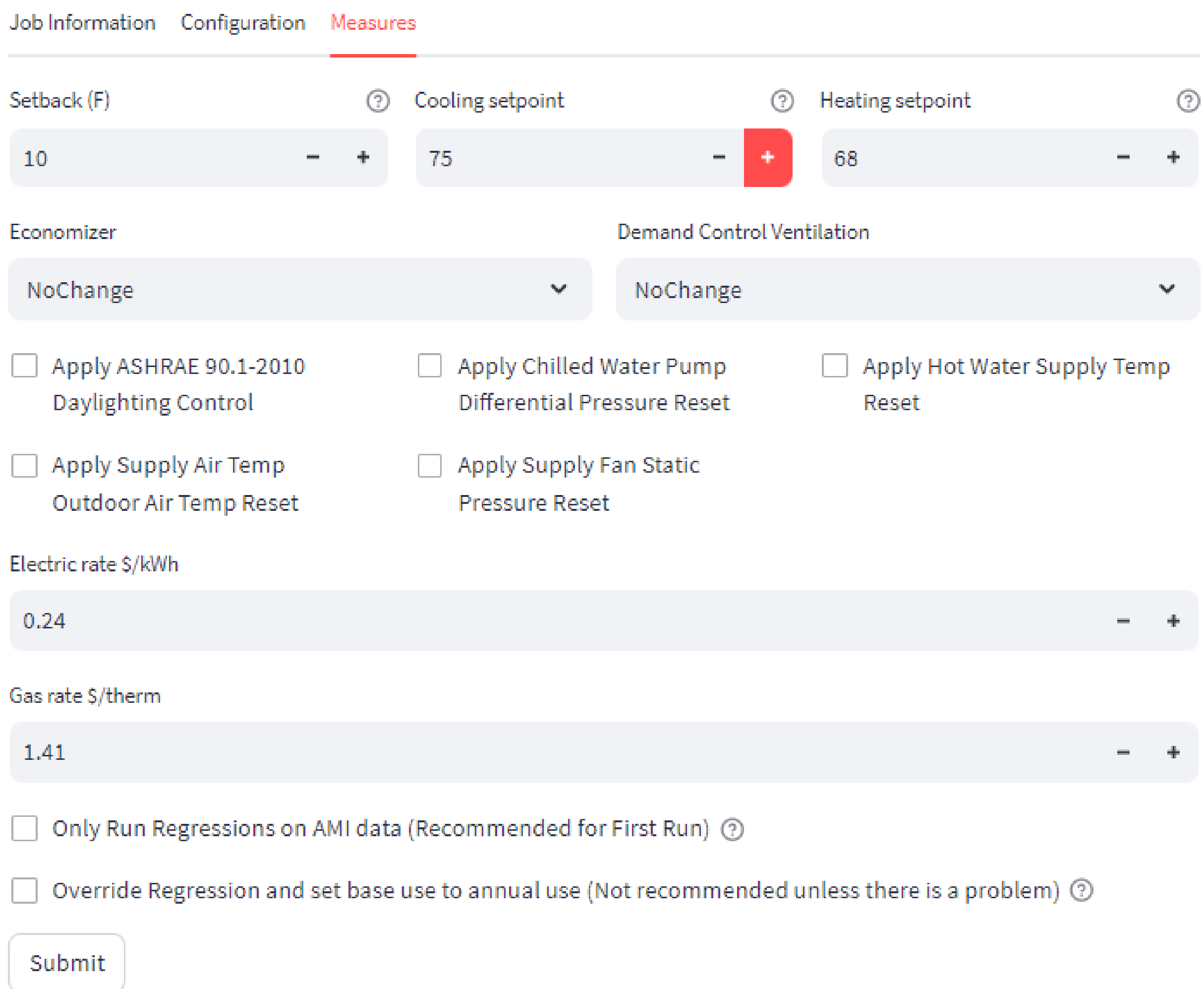


Figure 27: Site 4 measures panel.

Because the model was designed for data surrounding energy consumption rather than net metering, there was a significant error in the prototype model that indicated to the project team that solar energy was most likely involved. The Project Team reached out to the site and confirmed that there was solar present.

Table 31: Site 4 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_56_bin	1.00	0.00
Bills	hdd_70_bin	NAN	0.77	0.11

Table 32: Site 4 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	674,687.1	674,687.1	13,707.4	261,288.6	399,691.1
Bills	129,136.8	129,136.8	23,135.6	0.00	106,001.2

Table 33: Site 4 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_58_bin	1.00	0.00
Bills	hdd_70_bin	NAN	0.77	0.11

Table 34: Site 4 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	273,267.3	273,267.3	19,735.8	124,045.3	129,486.2
Bills	129,136.8	129,136.8	23,135.6	0.00	106,001.2

Table 35: Site 4 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Lighting (kWh)	Ext. Lighting (kWh)	Int. Equipment (kWh)
M1	0.00	87,576	150,175	0.00	291,912

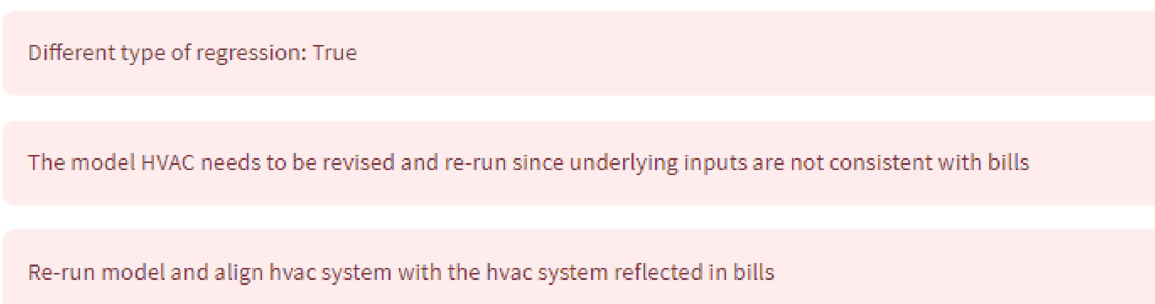


Figure 28: Site 4 CCBEM error messages.

Because of this mismatch between consumption and net meter, the CCBEM output delivered a warning to revise the system type in the input. The “NAN” readout for the meter indicated that none of the regression curves for any of the cooling setpoints fit the meter’s curve at all. Looking at the post-AMI-ingestion model, the inclusion of this data was a net positive for the CCBEM tool even if it wasn’t a complete success. It was correcting the error by reducing the magnitude.

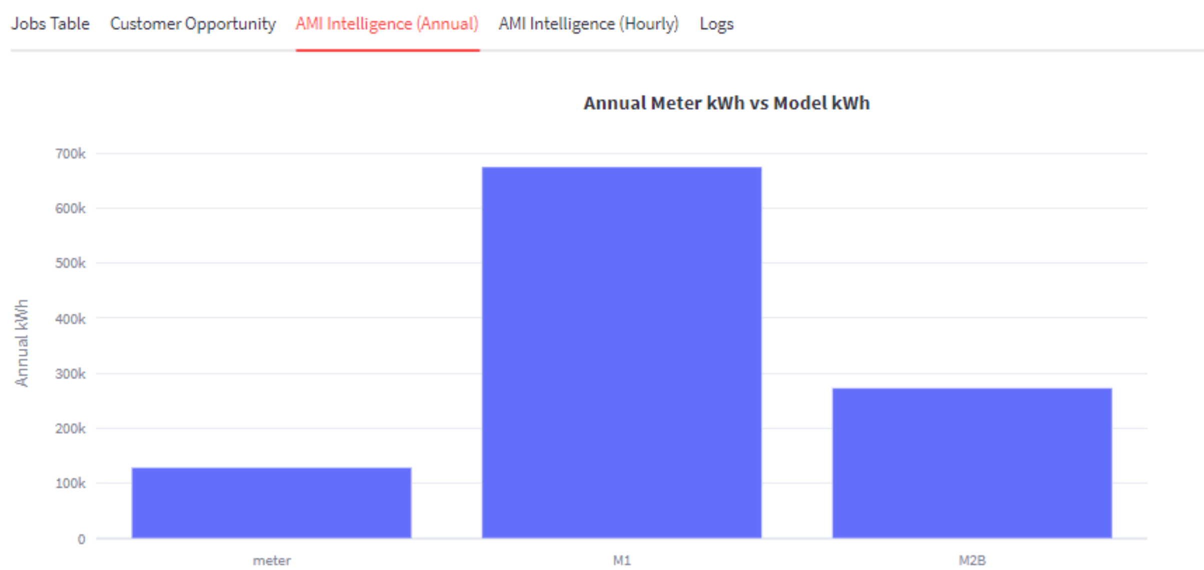


Figure 29: Site 4 model accuracy comparison.

Table 36: Site 4 Calibration Results

Model	CVRMSE	NMBE
M1	446.3	-460.9
M2B	123.5	-121.8

Results

The calibration error was reduced by 360 percent, despite the fact that the AMI data was training the tool to read net meter data rather than consumption data as originally intended. It is possible that with more iterations and more AMI data ingestion, the accuracy of the model could hew even closer to the real-world meter. The measures prescribed in the model are projected to save Site 4 almost 500,000 kWh of electricity usage annually, estimated to be over $100,000 (Table 39).

Table 37: Site 4 Selected Measures

Efficiency Measure Combination	Notes
• Deeper Temperature Setback - 10°F	This building was very new and likely would have had a lot of these measures and sequences required by code. With that in mind, the team tried only using a deeper setback (10°F).

Table 38: Site 4 Customer Opportunity Report: Savings

Energy	Savings
Electricity	437,340 kWh
Natural Gas	-15 therms

Table 39: Site 4 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$4200
Annual Cost Savings	$103,016.07
Simple Payback	.04 years

Site 5

After running the model, the building owner would have concluded that instituting simple control strategies around water pump resets would have made $41,545.57 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- This appeared to be a net-metered AMI meter with some solar production, which obscured the building's true energy use and impaired the regression analysis.
- Despite the data issues, base kWh went from 178 MWh in the model to 63 MWh, a 65-percent reduction, and coming very close to matching the bills at 53 MWh as seen in Table 43.
- The AMI intelligence reduced the annual M1 consumption in M2B from 287 MWh to 132 MWh, a 54-percent reduction as seen in Table 44..

Site Overview

Site 5 is a primary school in Riverside County with three classroom buildings, a library, multipurpose rooms, and an administration building. The lighting is all LED, and so the Project Team used a lighting vintage of 2018. HVAC was also older, so the team assumed it hadn't been updated since the buildings were completed and used an average vintage of pre-2000. The group of buildings was modeled as one segmented primary school with building average vintages weighted by square footage of building area. Calibration is shown in Figure 30. The measure chosen was PSZ-AC with gas coil.

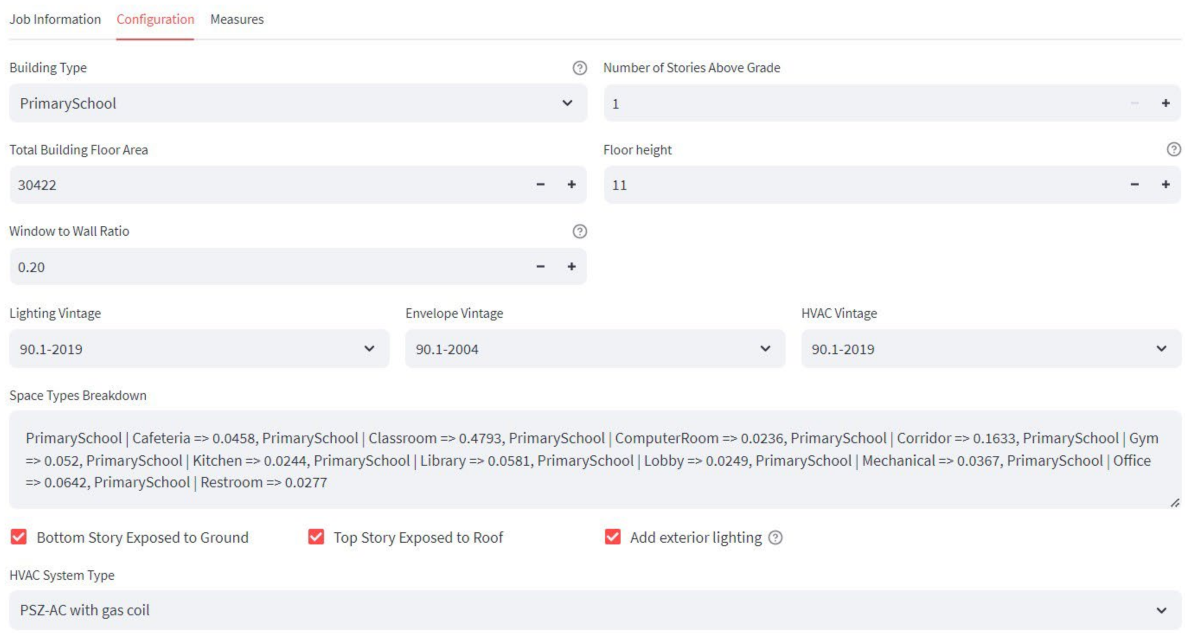


Figure 30: Site 5 configuration panel.

For the measure controls in Figure 31, the project team selected all controls options and used building weighted average cooling and heating setpoints with a 3°F setback.

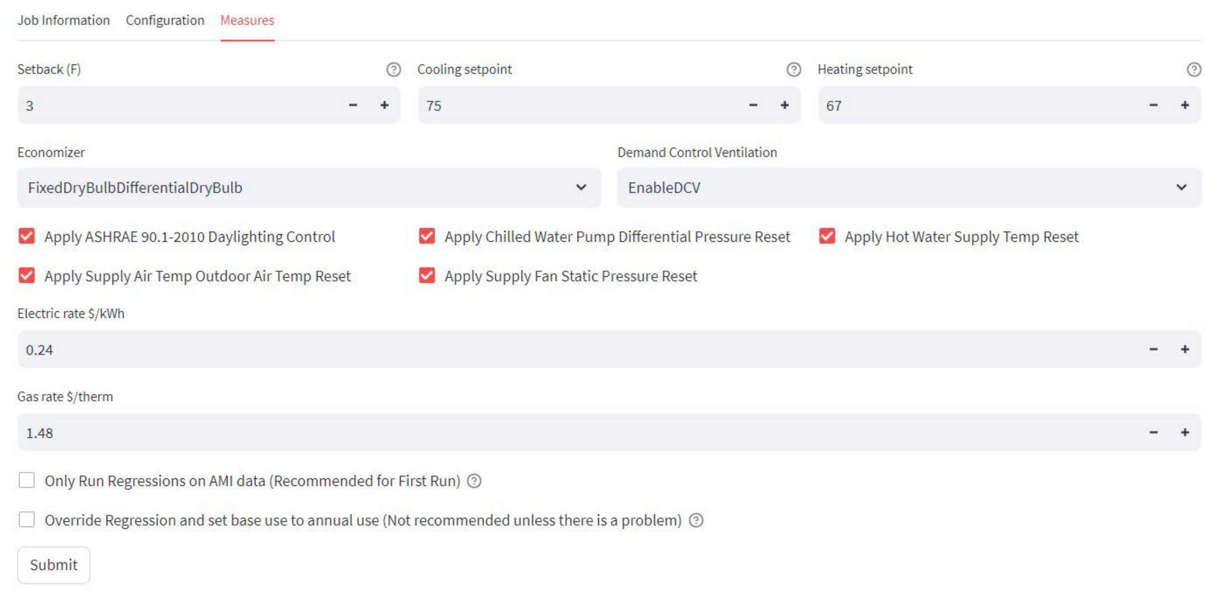


Figure 31: Site 5 measures panel.

Results

The annual regressions of the bills and models showed differing balance point temperatures, but adequate regressions and heating/cooling detection. The hourly regression indicated that the building schedule was not adjusted to the AMI data and prototypical schedules were retained. The differential between the balance point temperatures is greater than optimal and is indicative of unaccounted-for solar energy input (Table 40, Table 41). The project team reached out to the site and confirmed the presence of solar on their systems. Overall, regressions performed well, and base consumption was brought down substantially between M1 and M2B (Table 42, Table 43), approximately threefold (Figure 32).

Table 40: Site 5 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_58_bin	1.00	0.00
Bills	hdd_58_bin	cdd_66_bin	0.95	0.03

Table 41: Site 5 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	286,743.0	286,743.0	14,202.0	94,895.7	177,645.2
Bills	62,881.8	62,881.8	5,471.7	4,630.6	52,779.5

Table 42: Site 5 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_58_bin	1.00	0.01
Bills	hdd_58_bin	cdd_66_bin	0.95	0.03

Table 43: Site 5 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	131,699.1	131,699.1	13,728.1	54,684.7	63,286.2
Bills	62,881.8	62,881.8	5,471.7	4,630.6	52,779.5

The base kWh detected in the M1 model was adjusted and between M1 and M2B, base kWh went from 178 MWh in the model to 63 MWh, coming very close to matching the bills at 53 MWh. As with the other sites, the total base kWh usage was not as close between meter and model, but for the end-uses the project team is adjusting, the numbers are significantly closer after AMI ingestion.

Table 44: Site 5 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	0.00	33,239	58,913	16,854	126,865	0.00
M2B	0.00	17,387	17,503	16,854	37,692	0.00

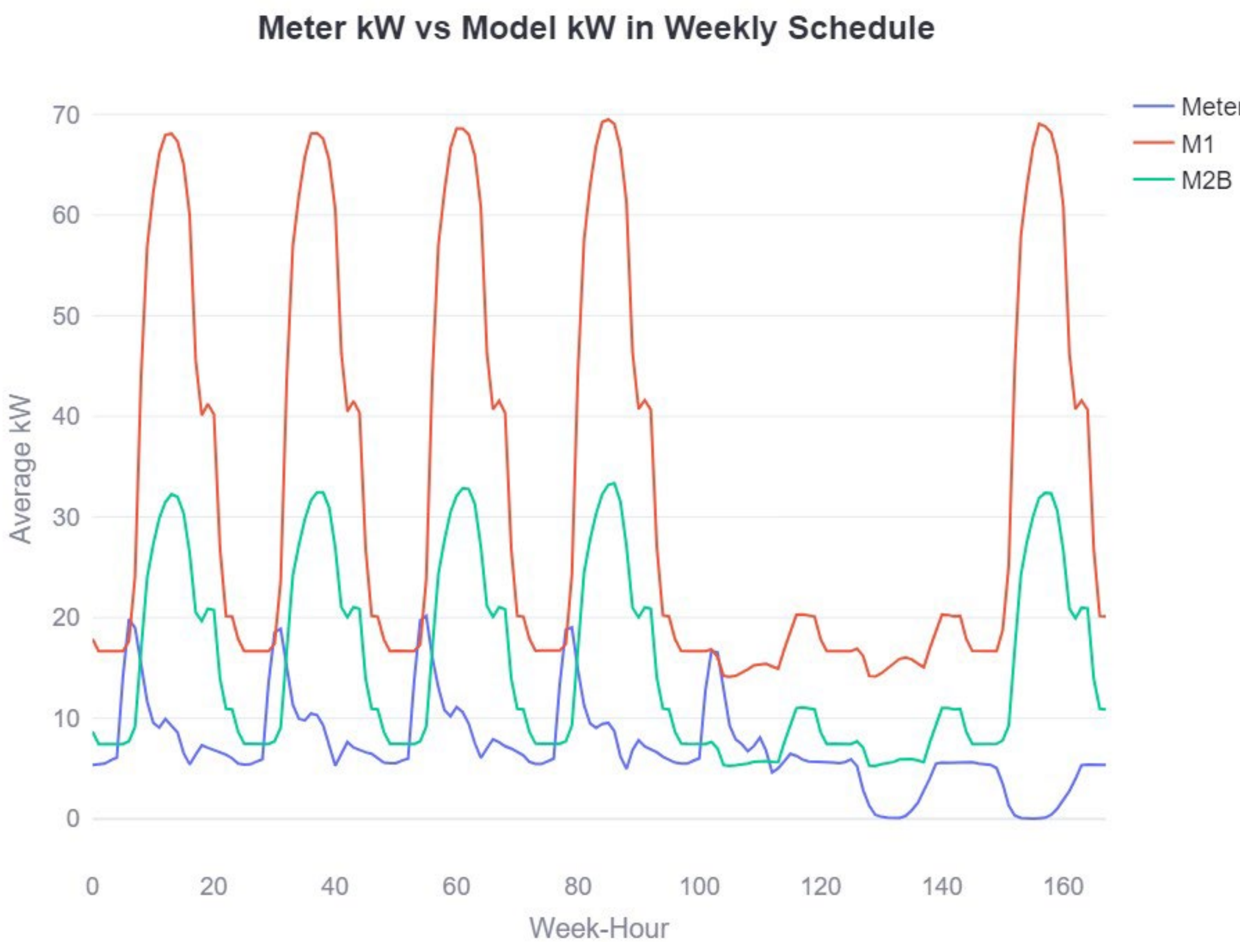


Figure 32: Site 5 full regression line graph.

The hourly AMI data magnitude moved substantially closer to the metered use between M1 and M2B post-AMI intelligence (Figure 32). It appears that the model may be offset by a day in these graphs which warrants further investigation and adjustment. The graph makes it clearer than Table 44 that there may be solar on the meter as well, obfuscating the actual building consumption and AMI intelligence.

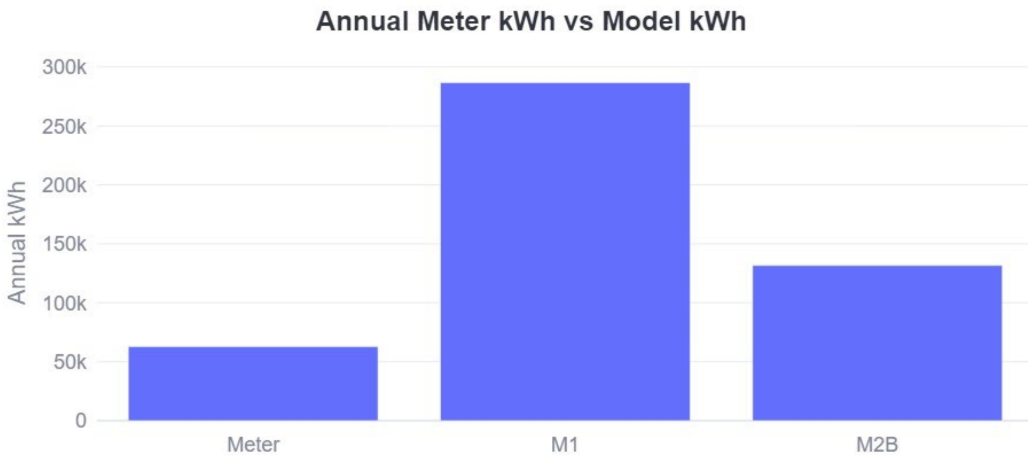


Figure 33: Site 5 model accuracy comparison.

The AMI intelligence reduced the annual M1 consumption from 287 MWh to 132 MWh and the consumption meter showed 63 MWh (Figure 33). According to the model, the included measure changes in Table 45 should save Site 5 close to 200,000 kWh in annual electricity usage (Table 44, Table 46).

Table 45: Site 5 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset	This building was very new and likely would have had a lot of these measures and sequences required by code.

Table 46: Site 5 Customer Opportunity Report: Savings

Energy	Savings
Electricity	173,217 kWh
Natural Gas	-17 therms

Table 47: Site 5 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$1825.32
Annual Cost Savings	$41,545.57
Simple Payback	.04 years

Site 6

After running the model, the building owner would have discovered an error in this current iteration of the CCBEM related to the tool not recognizing a scenario where the initial prototype model is more accurate than expected.

Key Points

- This was a small 600-square foot pharmacy within a larger building and the consumption meter captured only terminal HVAC use and not the larger HVAC systems serving the space, presenting the CCBEM's usual analysis method with a challenge.
- As seen in Figure , despite the data issues, base kWh went from 3,155 kWh in the model to 9,036 kWh, a 86 percent increase, basically matching the bills which had base kWh at 9,065 kWh. This is very promising and with some future work on the heating and cooling areas, tuning could be much closer.

Site Overview

Site 6 is a small pharmacy in Santa Clara County built in 1998. The lighting is all LED, meaning that a lighting vintage of 2019 was used. HVAC was older, so assuming it has not been changed since the building was completed, an average vintage of pre-2000 was used for HVAC. The building was modeled as a retail standalone prototype building with 100 percent retail area. The system chosen was water-source heat pumps with fluid cooler and boiler. It is likely that the water loop heating and cooling equipment is not on the AMI meter since it serves more than one space; this wasn't stated in the job information from the survey. It is likely that the water-source heat pump terminal units would be on the AMI meter.

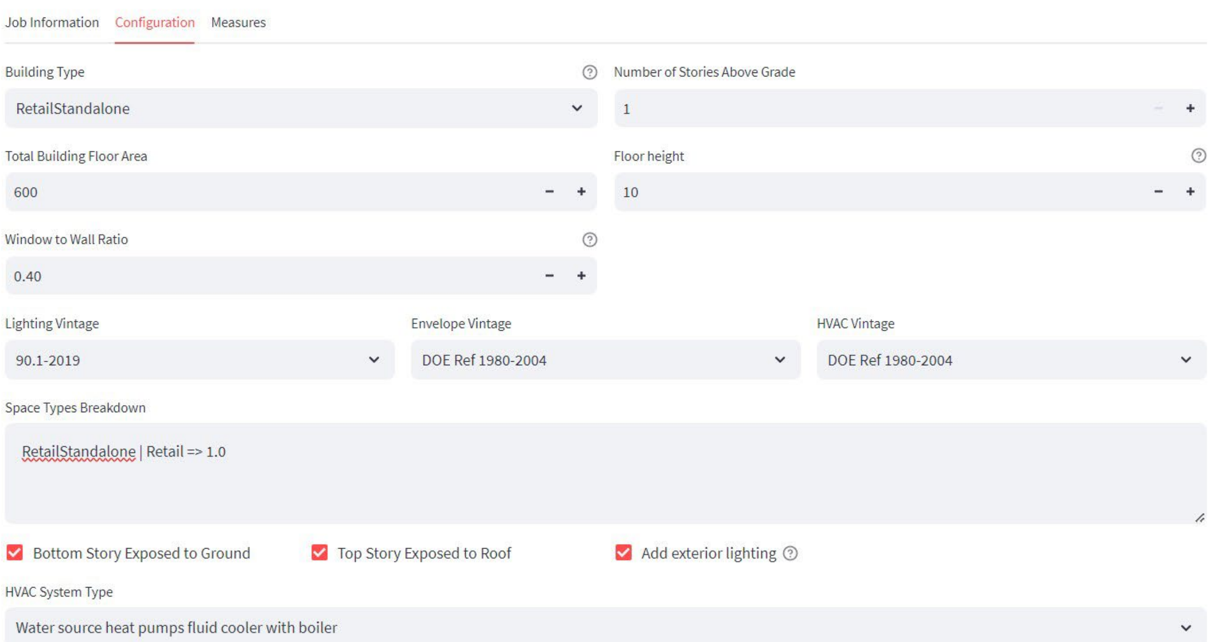


Figure 34: Site 6 configuration panel.

For the measure changes, the team selected all controls options except economizer or DCV and used stated cooling and heating setpoints with a 5°F setback.

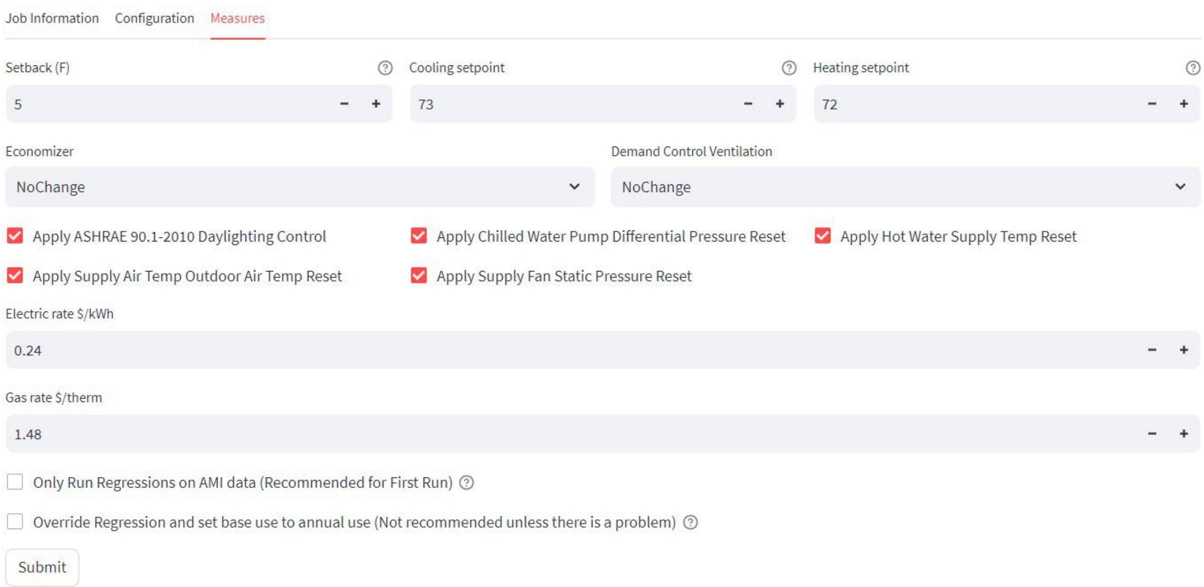


Figure 35: Site 6 measures panel.

Results

The annual regressions of the bills and models showed slightly different cooling balance point temperatures, different heating detection, but good regressions. The hourly regression was below an r2 of 0.7, so the building schedule was not adjusted to the AMI data and prototypical schedules were retained. Since the main heating and cooling systems in the building were not likely reflected in the bills but were reflected in the model, the team believed this caused much of the discrepancy. The base kWh was adjusted very well in this model calibration and the base kWh are nearly identical in the M2B model.

The base kWh detected in the M1 model (Table 48, Table 49) was adjusted and between M1 and M2B, base kWh went from 3,155 kWh in the model to 9,036 kWh, coming very close to matching the bills at 9,065 kWh (Table 50,). Since heating and cooling adjustments are out of scope of this study, the annual use is not as close, but those areas the team adjusted are extremely close.

Table 48: Site 6 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_68_bin	cdd_60_bin	1.00	0.03

Output	HDD	CDD	r2	CVRMSE
Bills	NAN	cdd_64_bin	0.97	0.05

Table 49: Site 6 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	10,483.3	10,483.3	3,756.5	3,571.6	3,155.2
Bills	10,330.5	10,330.5	0.00	1,264.8	9,065.7

Table 50: Site 6 M2B Model Regression Results: Statistical

Output	HDD	CDD	r2	CVRMSE
Model	hdd_64_bin	cdd_58_bin	1.00	0.04
Bills	NAN	cdd_64_bin	0.97	0.05

Table 51: Site 6 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	17,098.6	17,098.6	1,679.5	6,382.6	9,036.6
Bills	10,330.5	10,330.5	0.00	1,264.8	9,065.7

Table 52: Site 6 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	991.0	1,249	2,274	2,687	819.0	0.00
M2B	719.0	1,905	6,533	2,687	2,354	0.00

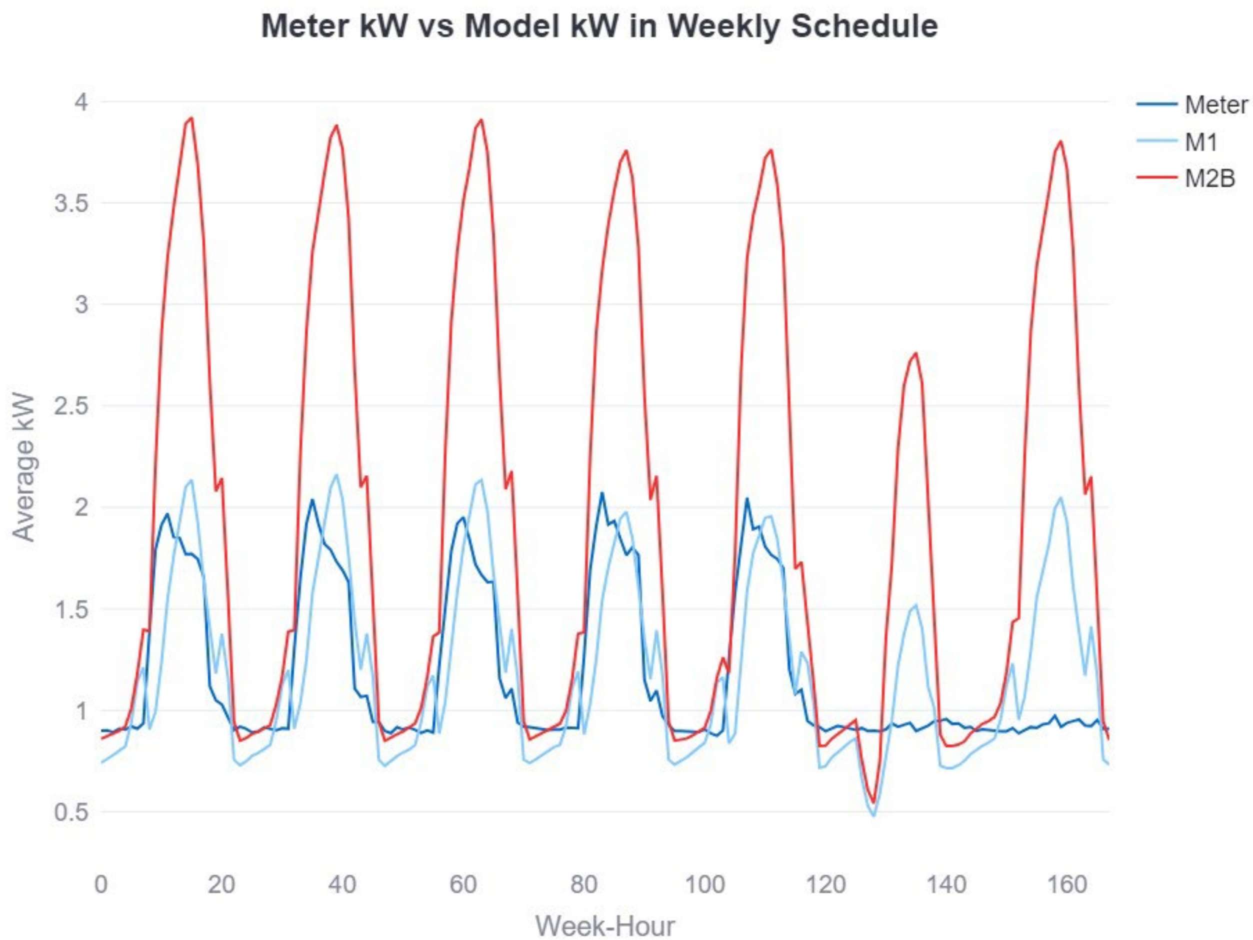


Figure 36: Site 6 full regression line graph.

In Figure 36: Site 6 full regression line graph. the hourly modeled use diverged from the metered use between M1 and M2B post-AMI intelligence. It appears that the model set the base kWh very well, but since heating and cooling were higher in the model than the bills and not adjusted (out of scope of this study) the overall annual kWh were brought higher.

In the annual AMI comparison, best illustrated in Figure 37, the original M1 model was quite close to the metered AMI consumption. When the Project Team increased the base kWh without accounting for the heating and cooling, the model diverged in M2B from the metered annual consumption. The base energy usage was very close in M2B though which is a promising sign since this is the only area the Project Team focused on in this study.

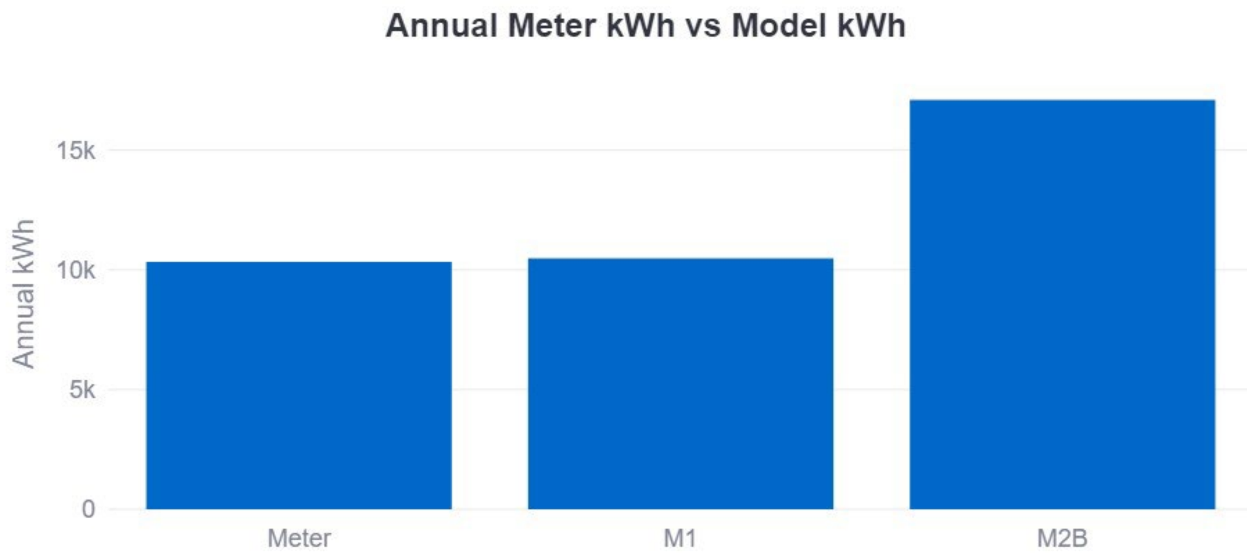


Figure 37: Site 6 model accuracy comparison.

The AMI intelligence increased the annual M1 consumption from 10,483 kWh to 17,098 kWh and the consumption meter showed 10,330 kWh.

In summary, the AMI intelligence at this site worked very well to adjust the base consumption (Table 52). With some tuning of the intelligence to account for other end-uses (heating and cooling), the tool should be able to calibrate sites like this in the future, especially if all heating and cooling equipment is integrated into the tool's intelligence module. As M2B went awry as shown, the projected savings in and Table 55 reflect this inaccuracy, estimating that the prescribed measure changes will cost the site more than $1500 annually. It is still valuable information for the volunteer test site that heating and cooling present an outsized influence on their annual electricity usage, giving them a direction in which to look for potential measure upgrades, such as the ones in Table 53.

Table 53: Site 6 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset	This building was new, and so it was deemed likely these strategies were implemented. The team was curious to see if they would be identified as opportunities by the CCBEM.

Table 54: Site 6 Customer Opportunity Report: Savings

Energy	Savings
Electricity	-7292 kWh
Natural Gas	4 therms

Table 55: Site 6 Customer Opportunity Report: Savings

Simple Payback	
Incremental Cost	$36
Annual Cost Savings	-$1742.92
Simple Payback	-.02 years

Site 7

After running the model, the building owner would have concluded that instituting simple control strategies around fan and water pump resets would have made $278,476.66 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- Meter review showed noisy meter data, likely influenced by solar contribution as a net meter.
- This site was a large building indicated to have fairly modern lighting and HVAC systems.
- Initial meter-to-M1-model comparison shows drastic differences.
- Even with distorted data, the AMI Intelligence module improved the NMBE by 180 percent (Table 61).

Site Overview

Site 7, a high school in Riverside County in the south of California, has a total of 270,000 air-conditioned square footage spread across seven buildings. Given the size, the team used the "SecondarySchool" building profile and reflected the new light and HVAC vintages.

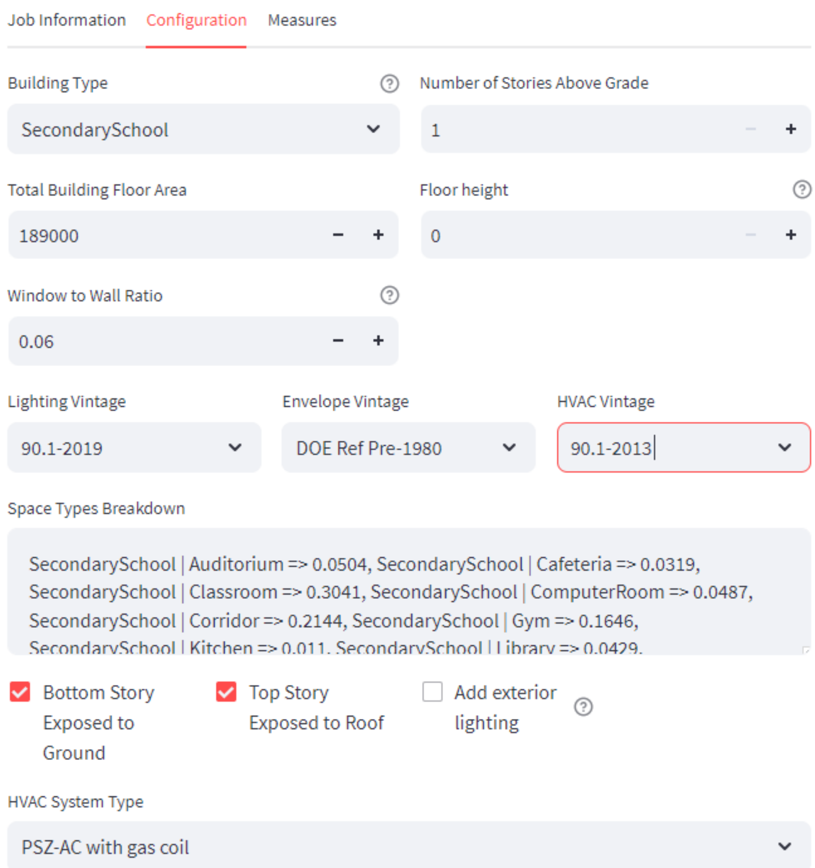


Figure 38: Site 7 configuration panel.

According to the preliminary survey, the site has a differential enthalpy economizer in which two sensors measure both indoor and outdoor air enthalpy and dampers ensure the lowest enthalpy is achieved (Figure 38). In terms of measure settings, this translates best to the standard array of controls for testing (Figure 39).

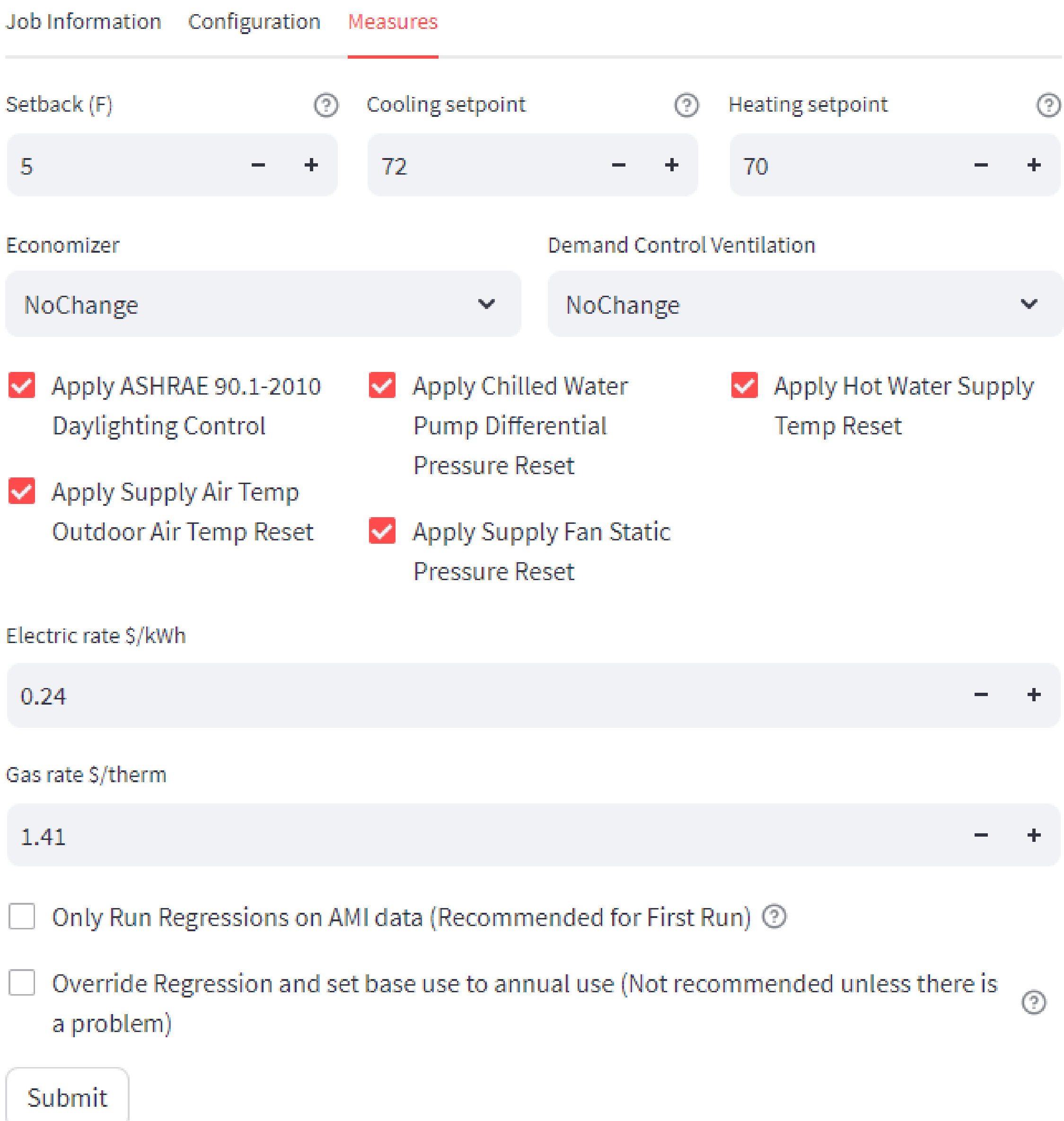


Figure 39: Site 7 measures panel.

According to the prototype output tables (Table 56, Table 57), overall usage is much lower in the meter data than the model of a site of this size. This site, when surveyed, reported a gas heating system, but it displays seasonal heating energy usage. The CCBEM was not looking for that to be included in the regression and worked around it, causing a distortion. This discrepancy highlighted in and Table 57 indicate that solar contributions are impacting the meter, a dimension that the tool as developed under this scope is not equipped to automatically handle. The project team reached out to the site and confirmed the presence of solar. However, as seen in Table 58, Table 59, and the calibration results in Table , the AMI intelligence module is still capable of reducing the error nearly twofold, despite the solar element.

Table 56: Site 7 M1 Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_60_bin	0.98	0.07
Bills	hdd_62_bin	cdd_66_bin	0.94	0.03

Table 57: Site 7 M1 Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	2,449,816.1	2,449,816.1	0.00	1,110,872.0	1,338,944.1
Bills	311,545.6	311,545.6	17,069.6	21,372.2	273,103.8

Table 58: Site 7 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_66_bin	0.99	0.07
Bills	hdd_62_bin	cdd_66_bin	0.94	0.03

Table 59: Site 7 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	1,421,040.5	1,421,040.5	0.00	775,647.6	645,392.9
Bills	311,545.6	311,545.6	17,069.6	21,372.2	273,103.8

Table 60: Site 7 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	0.00	717,437	412,761	0.00	572,527	0.00
M2B	0.00	560,297	84,203	0.00	116,796	0.00

Table 61: Site 7 Calibration Results

Model	CVRMSE	NMBE
M1	743.4	-748.8
M2B	411.2	-388.6

Results

Calibration error improved by 180 percent. The AMI hourly intelligence indicated the presence of solar, based on both the HDD-62 regression fit on the actual meter data and on the AMI hourly intelligence plot of the weekly data (Figure 40) where the “double horned” profile indicates possible solar influence on consumption.

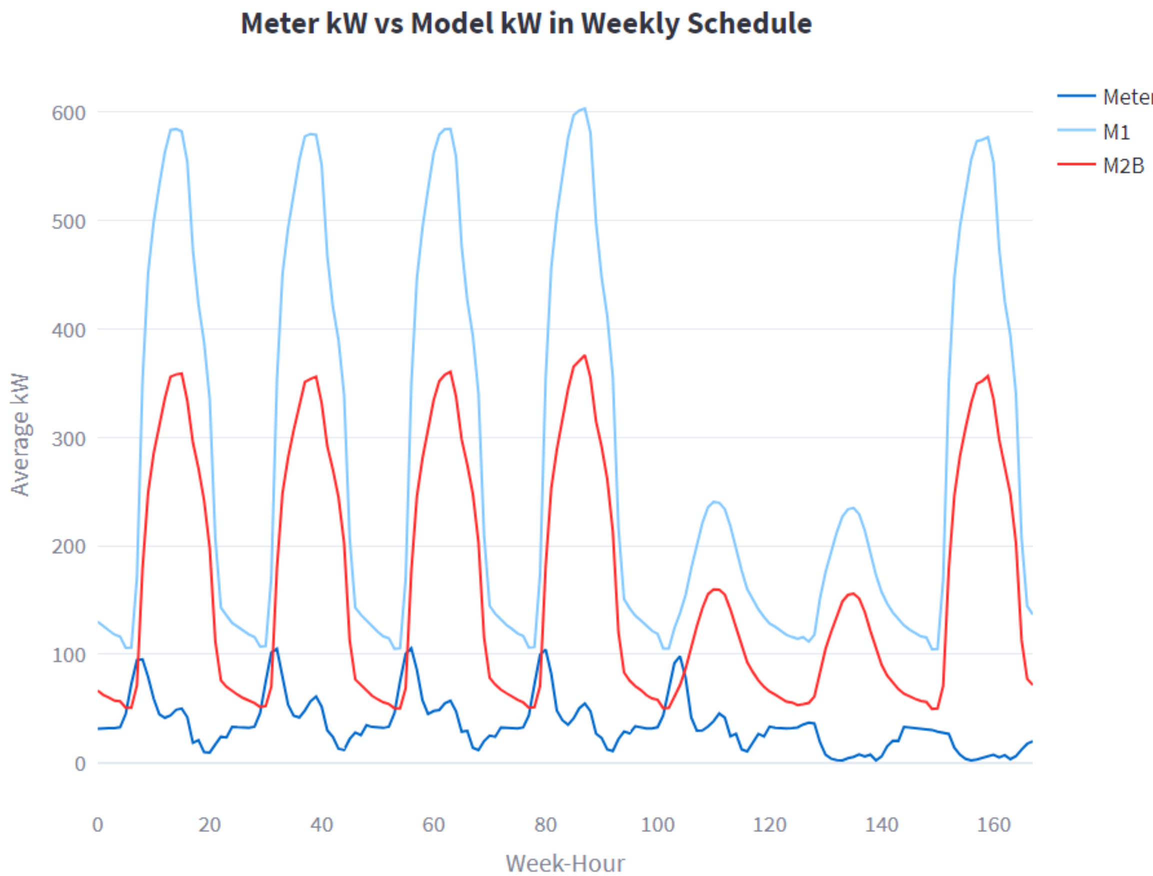


Figure 40: Site 7 meter to model weekly kW schedule, with "double-horned" daily spikes on meter indicating possible solar.

Despite the difficulties using the meter data to automatically calibrate the energy models, the customer opportunity for this site, addressing economizer and demand control ventilation as a low-cost measure, is projected to yield substantial returns: more than 1 million kWh of annual electricity usage (Table 60), equivalent to approximately $278,477.

Table 62: Site 7 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset • Supply Air Temperature Setpoint Outdoor Air Reset	This building was indicated in the intake form as having Differential Enthalpy Economizers already included in its sequences. This meant that there were not many available measures left with respect to air-related controls, so the team focused on resets for the fans and pumps.

Table 63: Site 7 Customer Opportunity: Savings

Energy	Savings
Electricity	1,184,805 kWh
Natural Gas	-470 therms

Table 64: Site 7 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$11,340
Annual Cost Savings	$278,476.66
Simple Payback	.04 years

Site 8

After running the model, the building owner would have concluded that instituting simple control strategies around the economizer would have made $21,367.27 in annual savings. Upon careful analysis, the project team identified the following key points:

Key Points

- The initial model was substantially different from the AMI meter data.
- Solar production was not noted at this site, but about a month of missing data caused data visibility issues.
- Even with data visibility issues, the model improved substantially with AMI calibration and the NMBE reduced by 308 percent (Table 70).

Site Overview

Site 8, a student medical center at a university in Los Angeles County, has one floor and 24,600 air-conditioned square footage. The building is more than 50 years old with upgraded lighting and a circa-1990 dual-duct HVAC system. Without further information on the HVAC system, the program team used the setting for VAV Chiller Boiler. The building seemed to have lighter duty usage than others, so the program team used the Medium Office Building setting.

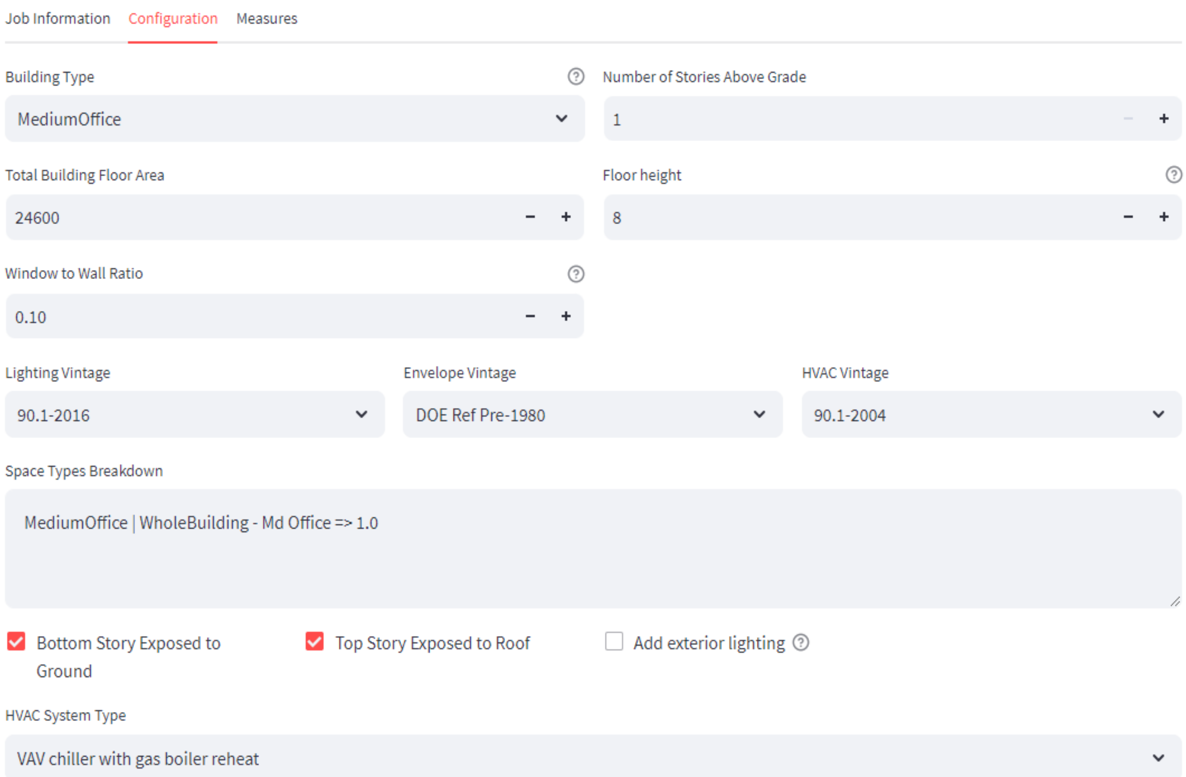


Figure 41: Site 8 configuration panel.

A short list of very basic measure controls was input for this site, all related to lighting and fan pressure (Figure 42).

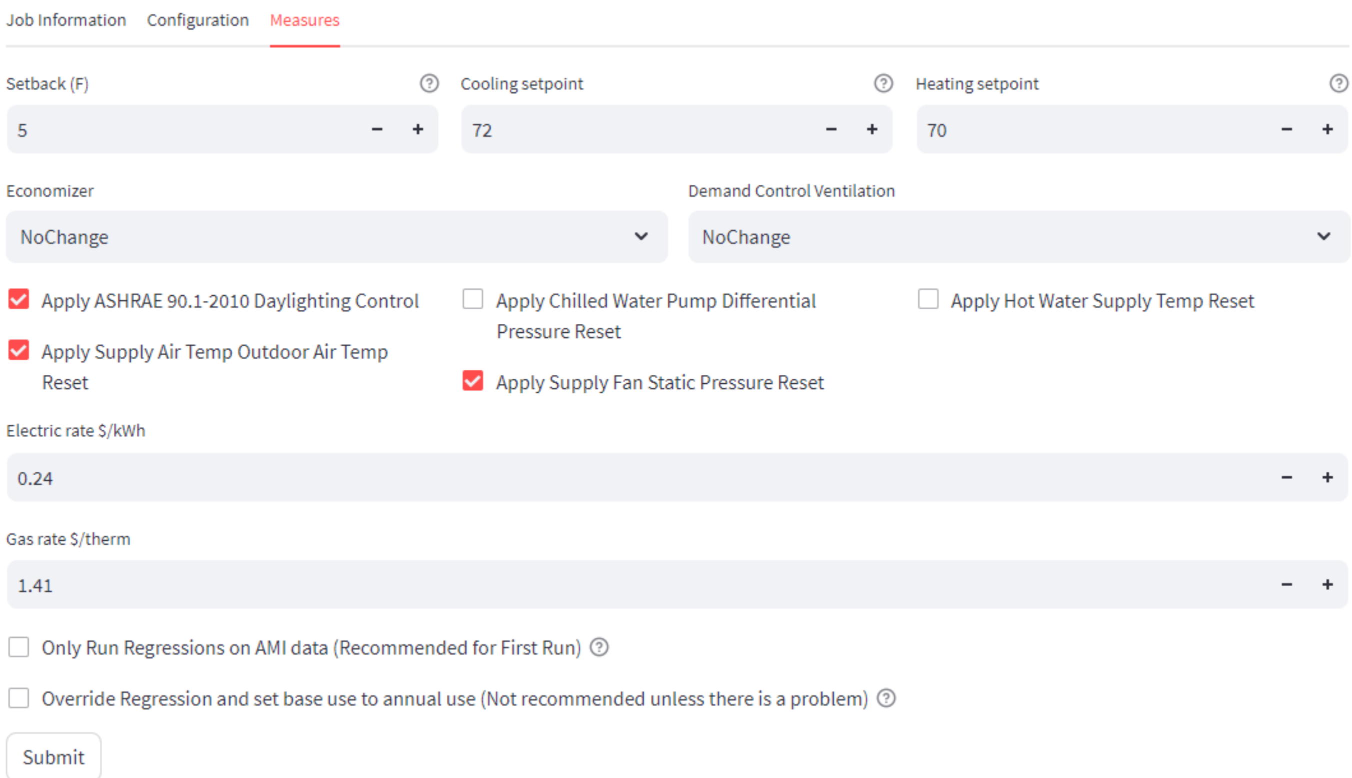


Figure 42: Site 8 measure panel.

Results

Running these parameters through the program resulted in the regression seen below in Table 65 and Table 66. As seen in the tables, there was a mismatch between the assumed heating and cooling degree days (HDD/CDD) and the actual billing data. From the information presented to the CCBEM tool, it assumed that there was a CDD of 70 and an HDD of 60. The "hdd_60_bin" and "cdd_70_bin" reflected in the table are regressions based around that HDD/CDD that the CCBEM has decided most closely matches the regression of the site's data. The mismatch here may result from the regressions not being able to adapt as well as needed due to the month of missing meter data. In the case of substantial heating and cooling differences in the regressions as seen here, the tool will issue warnings to focus the user's attention back to model inputs and the underlying meter data.

Table 65: Site 8 M2A Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_60_bin	cdd_70_bin	1.00	0.00
Bills	NAN	cdd_50_bin	0.98	0.02

Table 66: Site 8 M2A Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	158,143.4	158,143.4	1,538.5	99,974.6	56,630.3
Bills	31.405.2	31.405.2	0.00	8,193.8	23,211.4

Table 67: Site 8 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	hdd_50_bin	cdd_58_bin	1.00	0.02
Bills	NAN	cdd_50_bin	0.98	0.02

Table 68: Site 8 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	79,253.6	79,253.6	22,140.7	78,345.6	21,232.8
Bills	31.405.2	31.405.2	0.00	8,193.8	23,211.4

Table 69: Site 8 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Lighting (kWh)	Ext. Lighting (kWh)	Int. Equipment (kWh)
M1	0.00	34,372	49,688	0.00	75,604
M2A	0.00	34,238	54,217	0.00	51,471

Different type of regression: True

The model HVAC needs to be revised and re-run since underlying inputs are not consistent with bills

Re-run model and align hvac system with the hvac system reflected in bills

Figure 43: Site 8 CCBEM error message.

After inputting the AMI time-of-day energy usage, the regression in Figure 44 was produced.

Figure 44: Site 8 full regression line graph.

As shown in Figure 44 and elaborated upon in Table 67 and Table 68, the M1 curves are significantly different from the AMI meter data. After introducing the AMI data into the model, the regression curves representing the M2B model are, on average, almost three times closer to the real-world data and far closer than the M2A model. This is further illustrated in Figure 45.

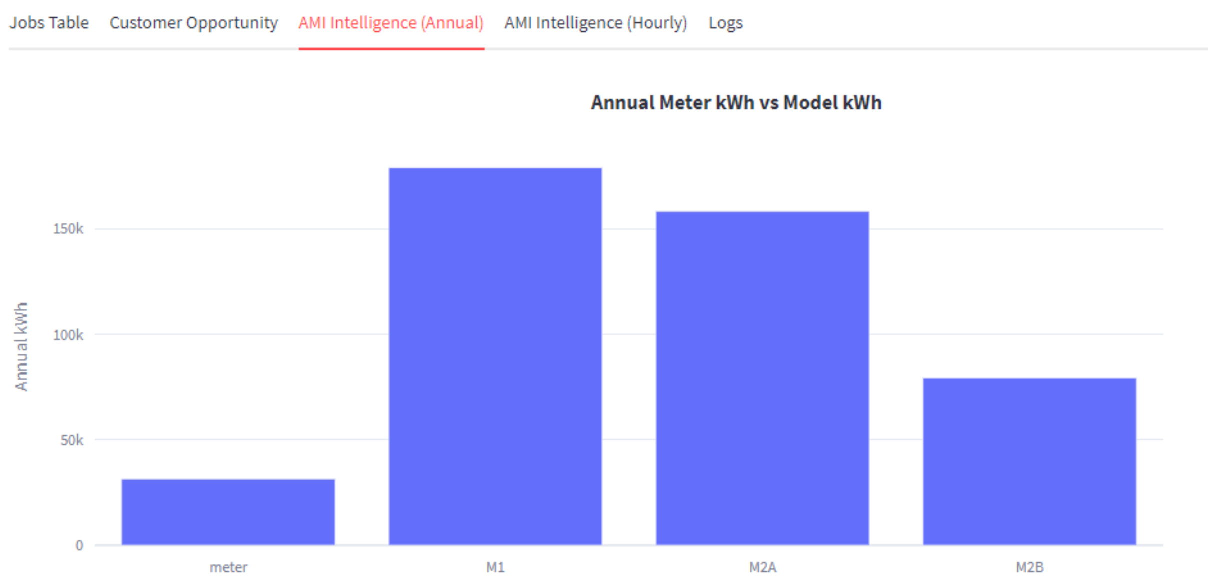


Figure 45: Site 8 model accuracy comparison.

Table 70: Site 8 Calibration Results

Model	CVRMSE	NMBE
M1	497.3	-512.4
M2B	164.6	-166.2

In Table 70, the NMBE has reduced by 308 percent, drawing much closer to the ASHRAE value of 5. After ingesting real-world AMI data to train the CCBEM with simple inputs, the CCBEM tool was able to generate a model with a significantly greater amount of accuracy. The results from this site's models are encouraging and indicate that the Project Team are heading in the right direction but need to work on a module to better adapt to missing data periods. In terms of savings, these listed measures in Table 71 are projected to save Site 8 almost 100,000 kWh of electricity per year according to Table 69 and Table 73.

Table 71: Site 8 Selected Measures

Efficiency Measure Combination	Notes
• Economizer • Demand Control Ventilation • Hot Water Supply Temp Outdoor Air Reset • Daylighting Control	The team tried some simple-loop-type measures for the water-related aspects, and then selected some outdoor-air-related measure for the ventilation. However, actual ventilation parameters were unknown.

Table 72: Site 8 Customer Opportunity Report: Savings

Energy	Savings
Electricity	90,738 kWh
Natural Gas	-7 therms

Table 73: Site 8 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$1476
Annual Cost Savings	$21,367.27
Simple Payback	.07 years

Site 9

After running the model, the building owner would have discovered an error in this current iteration of the CCBEM related to the tool not recognizing a scenario where the initial prototype model is more accurate than expected.

Key Points

- This was the only situation where the AMI intelligence module reduced the overall accuracy of the model.
- Initially, the prototype was only 30 percent off the metered annual energy consumption, although the regressions showed significantly different heating and cooling relationships between the prototype model and the meter (Table 75).
- AMI intelligence over-adjusted the lighting and plug loads when trying to auto-calibrate to match the real-world figure. This overcompensation threw the model awry (Figure 48).

Site Overview

Site 9, a student wellness and health center in the north of California, Yolo County, has three floors with 77,491 air-conditioned square footage. For the CCBEM input, this building was interpreted to be a medium office building per the low duty cycle as seen in Figure 46. However, the HVAC was set to "DOAS with fan coil chiller and boiler" as that was deemed the closest equivalent to the university's actual system of campus steam and chilled water, a configuration not listed as an option in the user interface. This system approximates the campus plant locally at the building. Since the regression identified similar balance points for cooling and no electric heating in the model and bills, the system choice appears to be reasonable.

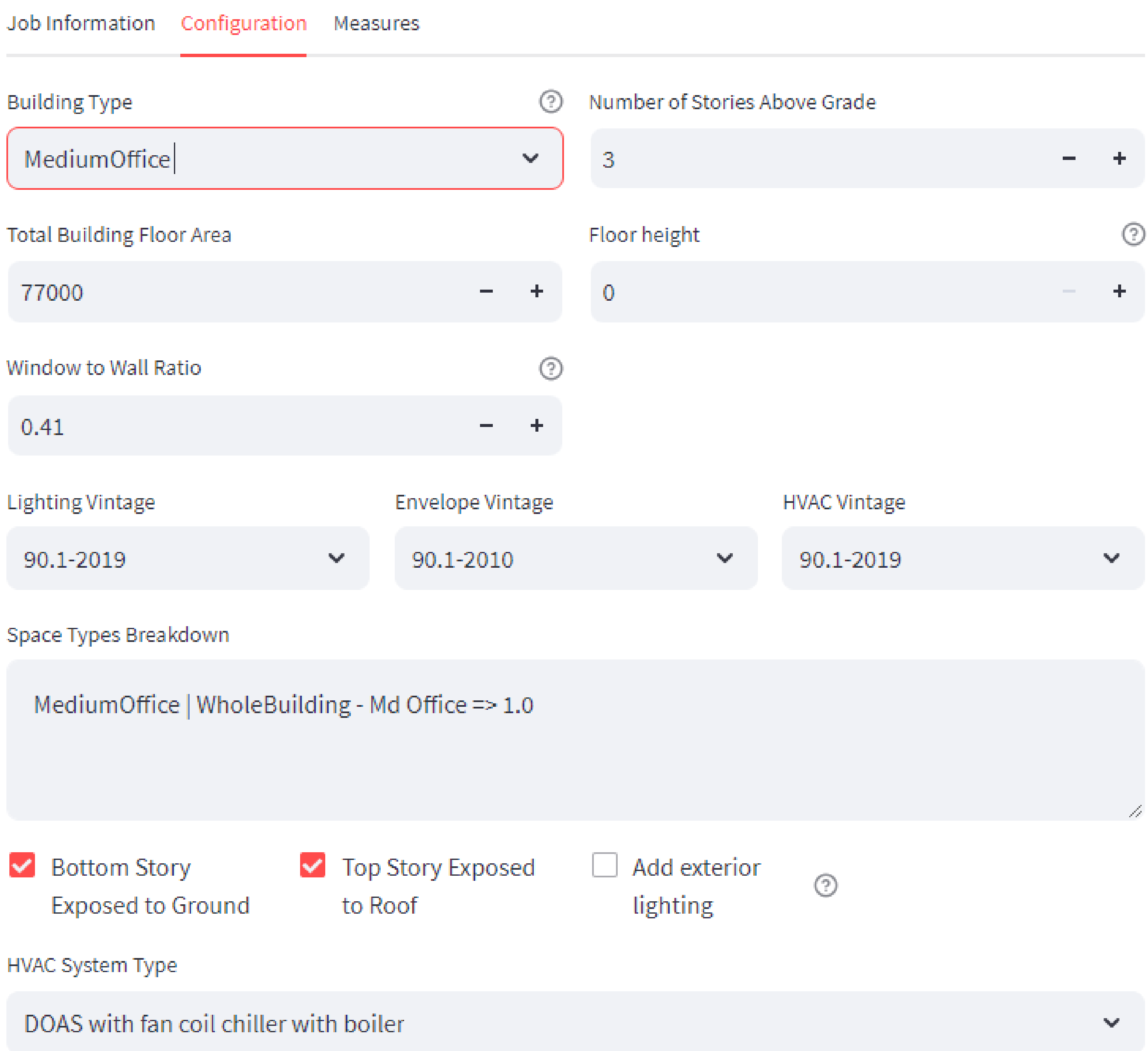


Figure 46: Site 9 configuration panel.

For the suggested measure changes, all of the resets and daylighting measures were selected as a baseline, given the low duty of the building.

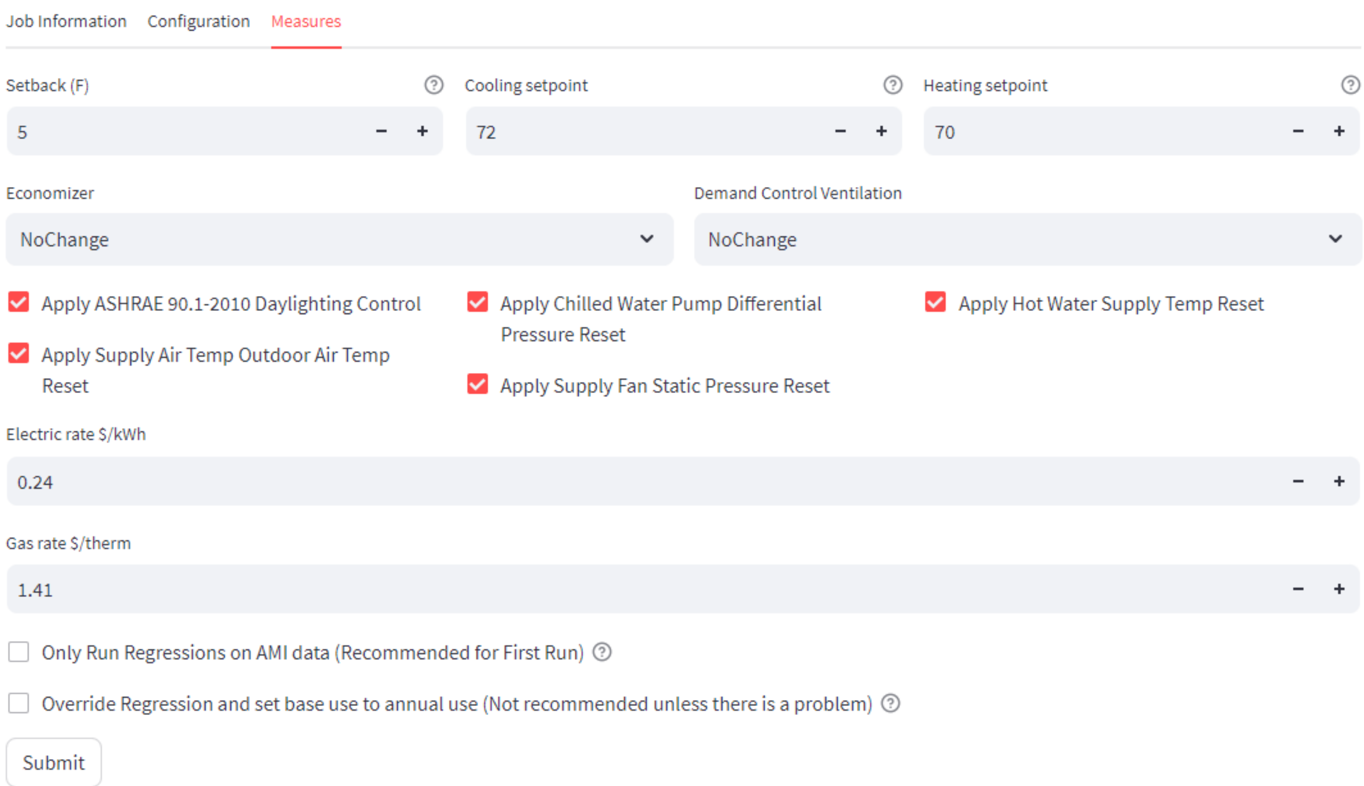


Figure 47: Site 9 measures panel.

For Site 9, the meter presented a lot more energy usage than the prototype model, seen in Figure 48. The first regression comparison in the Table 74 shows that the model was able to match the meter's CDD-50 fit. However, the base usage (Table 75) was so much higher in the meter that as the CCBEM model adjusted the plug loads and lighting loads to come up to the high meter kWh value, it so heavily impacted the modeled cooling energy usage that it compounded the error, leading to the wide discrepancy.

Table 74: Site 9 M2A Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_50_bin	0.99	0.04
Bills	NAN	cdd_50_bin	0.97	0.02

Table 75: Site 9 M2A Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	416,383.5	416,383.5	0.00	224.632.0	191,751.5
Bills	686,494.3	686,494.3	0.00	93,080.4	593,413.9

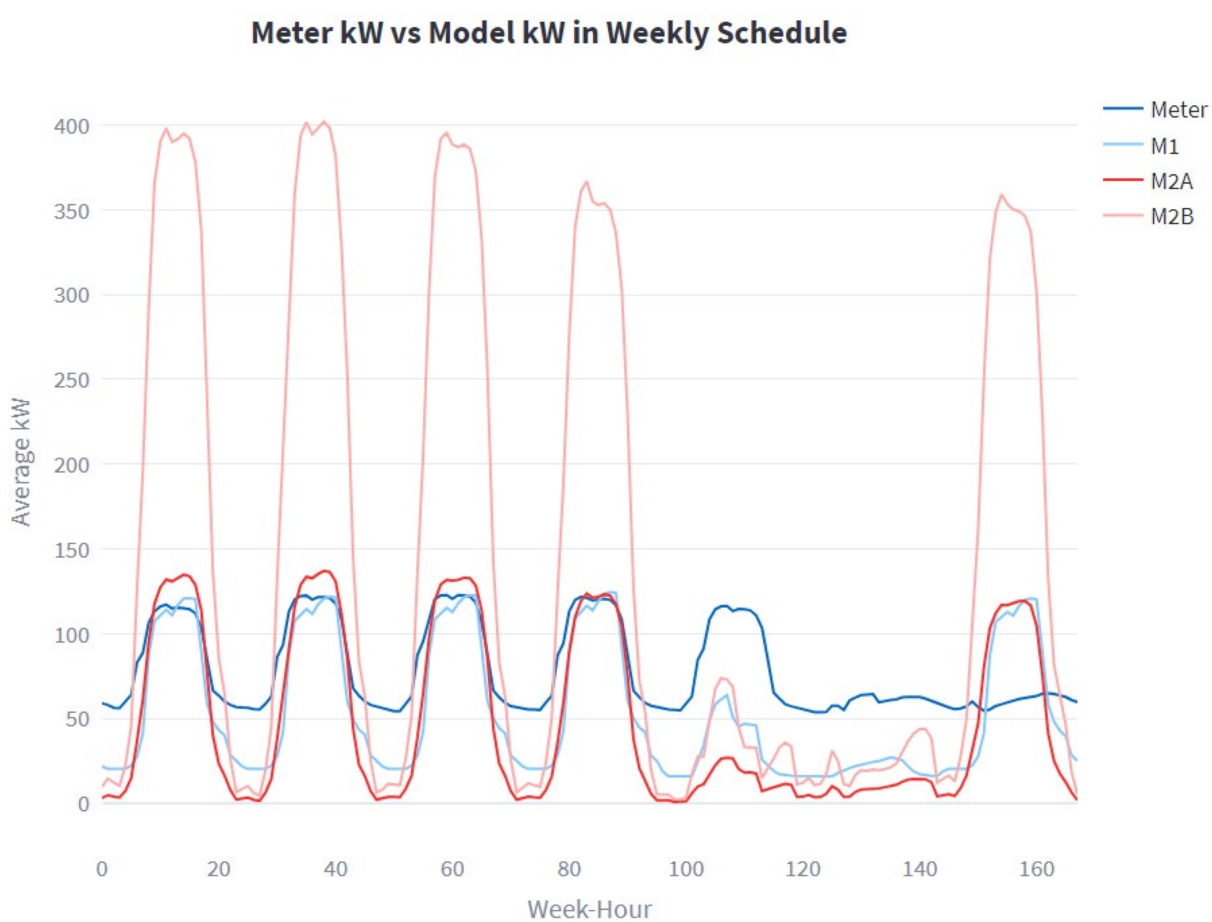


Figure 48: Site 9 full regression line graph.

Table 76: Site 9 M2B Model Regression Results: Statistical

Output	HDD	CDD	r^2	CVRMSE
Model	NAN	cdd_50_bin	0.98	0.06
Bills	NAN	cdd_50_bin	0.97	0.02

Table 77: Site 9 M2B Model Regression Results: Electrical

Output	Annual Electricity (kWh)	Adjusted Estimate (kWh)	Heating (kWh)	Cooling (kWh)	Base Usage (kWh)
Model	1,254,084.7	1,254,084.7	0.00	529,852.38	724,232.3
Bills	686,494.3	686,494.3	0.00	93,080.4	593,413.9

Table 78: Site 9 End Usage

Model	Heating (kWh)	Cooling (kWh)	Int. Light. (kWh)	Ext. Light. (kWh)	Int. Equip. (kWh)	Ext. Equip. (kWh)
M1	0.00	63,562	115,044	0.00	236,576	0.00
M2A	0.00	60,666	137,541	0.00	171,678	0.00
M2B	0.00	199,762	425,650	0.00	531,292	0.00

Results

The AMI intelligence missed the logic case where the initial prototypical model actually matched the meter data closely as opposed to the M2B model in Table 76, Table 77, and Table 78. The logic is programmed for the opposite situation, which was present in most of the above sites: the M1 model is expected to deviate from the real-world meter data to a moderate-to-large degree due to it being an assumption. In this case, it tried to force calibration through by using the light and equipment load parameters. What it actually needed to do was make adjustments to the cooling and heating parameters, but this was outside the scope of the project. In addition to factoring in heating and cooling intelligence, the CCBEM tool would benefit from some sort of logic gate for when the M1 prototype model is within a certain proximity to the meter data. As a result of this data processing error, the projected savings based on the applied measure changes are distorted (Table 80).

Table 79: Site 9 Selected Measures

Efficiency Measure Combination	Notes
• Hot Water Supply Temp Outdoor Air Reset • Chilled Water Pump Pressure Reset • Daylighting Control • Supply Fan Pressure Reset • Supply Air Temperature Setpoint Outdoor Air Reset	This building was built in 2010, so it occurred to the team that upgrades to the DCV, economizer and many controls sequences could already exist. The measures here were chosen out of curiosity to see if they would be identified as an opportunity all the same.

Table 80: Site 9 Customer Opportunity Report: Savings

Energy	Savings
Electricity	-806,707 kWh
Natural Gas	104 therms

Table 81: Site 9 Customer Opportunity Report: Payback

Simple Payback	
Incremental Cost	$4620
Annual Cost Savings	-$189,912.95
Simple Payback	-.02 years

Findings Summary

The modeling team designed a promising tool that builds off of an application that has been used for implementation savings calculations and adds on AMI calibration intelligence. Able to run on most conventional consumer computers, the tool completes its modeling runtimes in less than 40 minutes, dramatically reducing the time investment a building manager would place into this effort through conventional means while also dramatically increasing the accessibility of energy models for their building. Furthermore, as easy as it is to install and run on a home computer, it is just as easy to host on a utility website for the benefit of utility customers. The tool has been set up to read both modern AMI data and older 8760 data, meaning that there is a wide age range of buildings able to take advantage of this software. In terms of modeling accuracy, the inclusion of AMI data for calibration provided steep increases in statistical accuracy over the course of just nine test sites; for a tool that delivers a medium-size building energy model in less than one hour, the level of accuracy achieved during this project has been astonishing. The team concluded that with future improvements, the tool has the potential for widespread usage in California. Through the ingestion of AMI data, the CCBEM significantly simplified and reduced the time investment in building energy-efficiency models for the nine, medium-sized buildings tested.

Over the course of the project, the team found two major areas of complexity in calibrating the CCBEM for Californian buildings: the use of solar energy and the presence of multi-building sites.

Solar Data

The assumption at the beginning of this project was that each test site would present consistent data of energy consumption, but most of the sites put forth net-metered data. The tool can process both, since on the surface they are both comprised of energy amounts tied to time-of-day. However, in areas where solar energy is prevalent and not stated as part of site equipment, this introduced a complication, as solar energy greatly affects the total net energy number. The net-meter amount stated is consumption minus solar production at that date-time, so in essence, it can appear there is less use mid-day than there actually is. The CCBEM tool is unable to automatically discern consumption from energy supply as it is all in one net metered number, so it shows that the building is consuming very little energy when it should indicate that the solar panels are offsetting a lot of usage. Without prior knowledge of solar being on the meter, which would allow for the user to compensate, models will suffer from inaccuracy.

Multi-building Sites

For the sites that included multiple buildings, the team simulated these sites as single buildings with the combined square footage to simplify the modeling process and develop a calibrated baseline for the tool. Initially, Site 2 was modeled using the default prototypical perimeter length of about 1810 ft but noting that there were 16 buildings on-site (including 11 trailers), the highest of any site, the project team explored modeling Site 2 with the true perimeter area of 3,770 ft. The simulated results showed a 12 percent increase in total energy consumption when accounting for the total wall area. Without AMI calibration for this model, it was statistically inaccurate by a factor of 404 percent. Since just a 12 percent increase in simulated energy consumption resulted from the geometry optimization, the project team elected to instead simulate the site as a single building to benefit from the AMI intelligence calibration and the increased accuracy that comes with it. While this, along with every other multibuilding site modeled as a single entity, is geometrically inaccurate, it serves the project's objective of calibrating CCBEM's accuracy; the tool can be trained on individual buildings in later iterations. Keeping the focus on the tool's computation time and regression accuracy rather than strict geometric accuracy streamlined the team's iterative calibration process among the test sites.

Stakeholder Feedback

Once the project scope was completed, the project team presented the CCBEM tool to representatives from SCE and Pacific Gas & Electric. The Project Team ran a sample dataset live, displaying results for the audience.

Site Presentations

Next, the team will provide the output models to the building site owners who volunteered data for this project. In a video call, representatives of the team will present the visual results from the tool and the numerical statistics, pointing out the measure changes that the tool recommends. This step is crucial from a stakeholder engagement standpoint: One of the many reasons that volunteers were reluctant to opt into the project was their uncertainty of the eventual goal. Presenting them their results not only illuminates the benefits of the CCBEM tool but also provides them with recommendations that could represent thousands of dollars in annual energy savings. In this way, the project team can close the loop, justifying and rewarding the participation and cooperation of the volunteer sites. In the presentation, the project team will solicit ideas and suggestions from the participants for further development of the output panel. It is tremendously important that the perspectives of potential future users of this tool or a similar tool are considered, because our goal is to make the recommendations as legible as possible to make easier the measure updates. The Project Team will take detailed notes on feedback and attitudes towards results.

Recommendations

As this project has found, automated modeling tools represent the future of energy analysis and are worth the investment, providing useful insight and saving massive amounts of time and money compared to traditional modeling. These tools, including the CCBEM, require more substantial development time investment before they pay dividends, but the long-term potential is significant. Once refined, these tools can scale up to model far more buildings than is currently possible. The alternative to investing development time in tools like this is maintaining the status quo, where calibrated energy models take three to four weeks to develop. This timeframe is simply not feasible for many projects that aim to assess and compare multiple energy saving measures. To determine which measure is the best for the building and experiment with different combinations could require several sessions of energy modeling and further increase cost. According to modelers on the project team, it takes an average of 80 hours to develop a comprehensive energy model from design drawings and another 40 to 80 hours to calibrate it. A maximum of 160 work hours at $195 per hour, the rate billed for work in California, would result in a total modeling cost of $31,200. This project team's efforts and new tool have reduced modeling time to under 30 minutes, potentially saving tens of thousands of dollars per project. The project team recommends further developing the tool to increase the accuracy of these rapid models, using more diverse parameters as outlined in this section.

Technology Transfer

The project team strongly recommends keeping CCBEM open-source, which allows utilities to make their own modifications using OpenStudio. The alternative of publishing the tool and leasing it out to utilities would limit the tool's capabilities by centralizing the responsibility of updating, hosting, and managing the tool in VEIC. By decentralizing ownership of the CCBEM source code and blueprint, the project team would enable utilities across the state of California to adapt the tool for their customers to use on their website as they see fit, updating it themselves in response to their users' feedback. The non-standardized data received over the course of the project is a result of acquiring the data secondhand from the customer. A direct connection between the utility, which collects the data, and the tool, which processes it, would eliminate the intermediary step of normalizing different data formats, smoothing out processes for the tool and for the customer. Another benefit of enabling individual utilities to adapt the tool is that the utilities could incorporate their own incentives as recommendations for the tool's output, increasing the accessibility and informativeness of the tool for their customers. With alterations to certain climate zone factors, the tool could even be adapted for use by utilities in different states. Regarding the economic viability of a utility adopting a tool like the CCBEM, the project team believes focusing on a target number of users isn't the most relevant metric. Instead, interested utilities should consider the number of projects that could benefit from this tool when implemented through statewide energy-efficiency programs. For instance, if 10,000 buildings could be modeled and analyzed in a calendar year instead of 100, tool development costs could be recovered quickly.

During the presentation with SCE, one attendant expressed concern over data security and whether sharing this tool would mean that a backlog of analyses would be available to every successive user of the application. Each installation of this application is a separate entity, so no two users will be able to view each other's models on their log history. This means that the security of sensitive energy usage data will be up to the user to ensure, through services such as Microsoft Azure. Another question raised pertained to the inclusion of Title 24 standards in the CCBEM configuration panel. This was not included over the course of the project but could be factored into the tool in the future by the user, who could add it as options under HVAC, lighting, and plug vintages. These selectable options would tie directly to EnergyPlus' repository of information around Title 24. The last concern raised was centered around the user-friendliness of program installation and use. The CCBEM tool can run on any modern computer and accepts inputs that relate to knowledge of a commercial building's internal systems. In that sense, this tool can be used by any building manager. The project team has developed a readme, featured in Appendix A, that will be directly available alongside the program download on the open-source repository. Beyond that, the project team has also designed short visual guides to the tool's input and output, featured in Appendix B and Appendix C, which could be included on the open-source repository alongside the readme.

Additional Tool Development

The project team has identified and recommends specific ways to bolster the level of detail in the CCBEM tool's analysis. Increasing the dimensionality of the data would reduce the net mean bias error of the tool to more closely match ASHRAE 14 guidelines. One way to do this is to add seasonality as an analysis factor. Within the project's scope, the CCBEM analyzes the data on an annual scale, meaning that if there are any off weeks, such as those with low occupancy or very little heating and cooling usage, they are not reflected individually. Allowing the tool to take these seasonal energy usage peaks or troughs into account will allow for more specialized measure change recommendations. Further, the team briefly attempted to integrate solar data into the tool to help model the buildings with unaccounted-for solar input that was otherwise distorting the regression. The project team recommends expanding on this effort and exploring the possibilities of automating solar detection within the tool.

The project team recommends getting alignment from all relevant stakeholders on key performance indicators such as annual electrical energy usage, annual greenhouse gas emissions (GHGe), coincident demand performance, and efficiency estimates. It will also be important to get alignment from these groups on metrics for economic stimulus, community enhancements, and disadvantaged community access improvements.

For the duration of the project, the CCBEM tool based its assumptions and analysis on select factors such as lighting and plug settings. Technically, fan settings and air infiltration data were part of the assumptions, but as they were out of scope, the tool operated on basic assumed values for each building. Although the project successfully made the tool functional and effective using these basic assumed values, the project team recommends that the tool be tested with the missing parameters and more specific values, settings, and seasonality, which would greatly improve the tool's level of detail and accuracy.

Appendix A: AMI BEM Tool ReadMe

AMI to BEM Tool

Running the App

ASSUMPTIONS:

These instructions assume the code is run locally on a Windows computer.

FIRST-TIME SETUP INSTRUCTIONS:

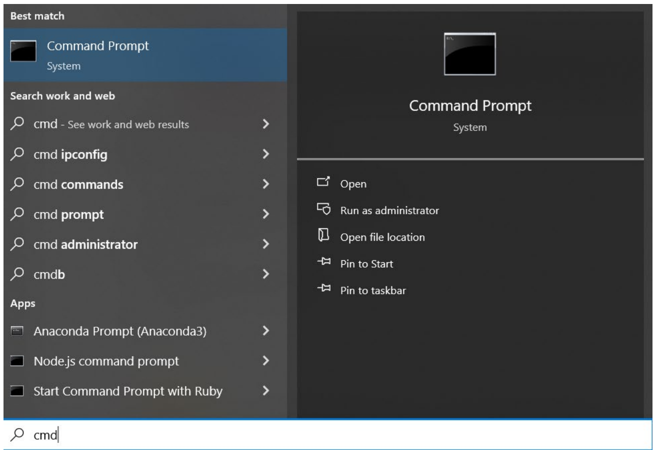
Part I: Install OpenStudio

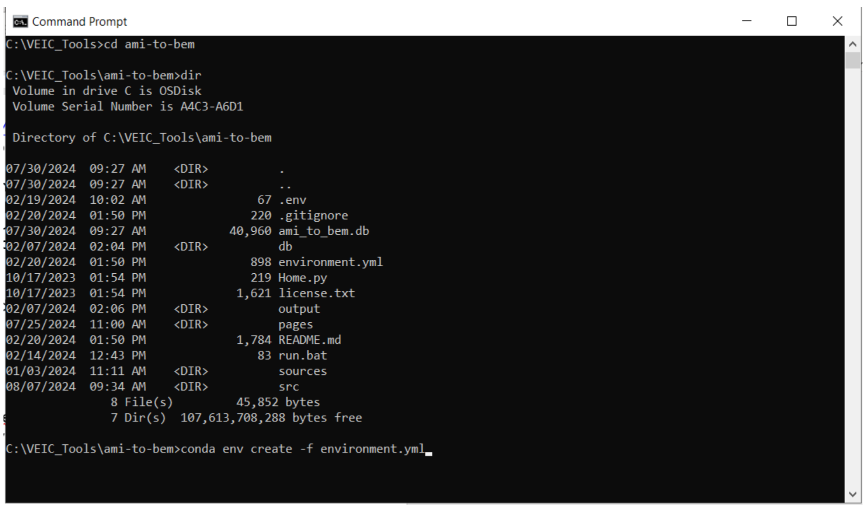
1. Install OpenStudio version 3.6.1 from https://github.com/NREL/OpenStudio/releases/tag/v3.6.1
2. Note the path in which you have installed it, which you'll use to find the full path of the OpenStudio executable. For example, if you installed it in C:\openstudio-3.6.1, your openstudio.exe file will be in C:\openstudio-3.6.1\bin.
3. Include the path to the directory that contains your OpenStudio executable in your PATH environment variable. In the example above, this would be C:\openstudio-3.6.1\bin. If you have other OpenStudio paths in your PATH variable, put this ahead of them.

You can verify you've completed the above steps correctly by opening a Command Prompt and running `where openstudio`. The first entry it returns should be the path to your OpenStudio v3.6.1 executable.

Part II: Set up Conda

1. Install Miniconda
2. Unzip the project files to a desired folder on your hard drive.
3. Create the conda environment specified in environment.yml. You can do this by opening a Command Prompt (windows icon, search "CMD"), navigating to the project directory, and running `conda env create -f environment.yml`. These steps are shown in the screenshots below.





Part 2: Launch the Application

Option 1:

- Open the project folder in File Explorer
- Double click on `run.bat`

Option 2:

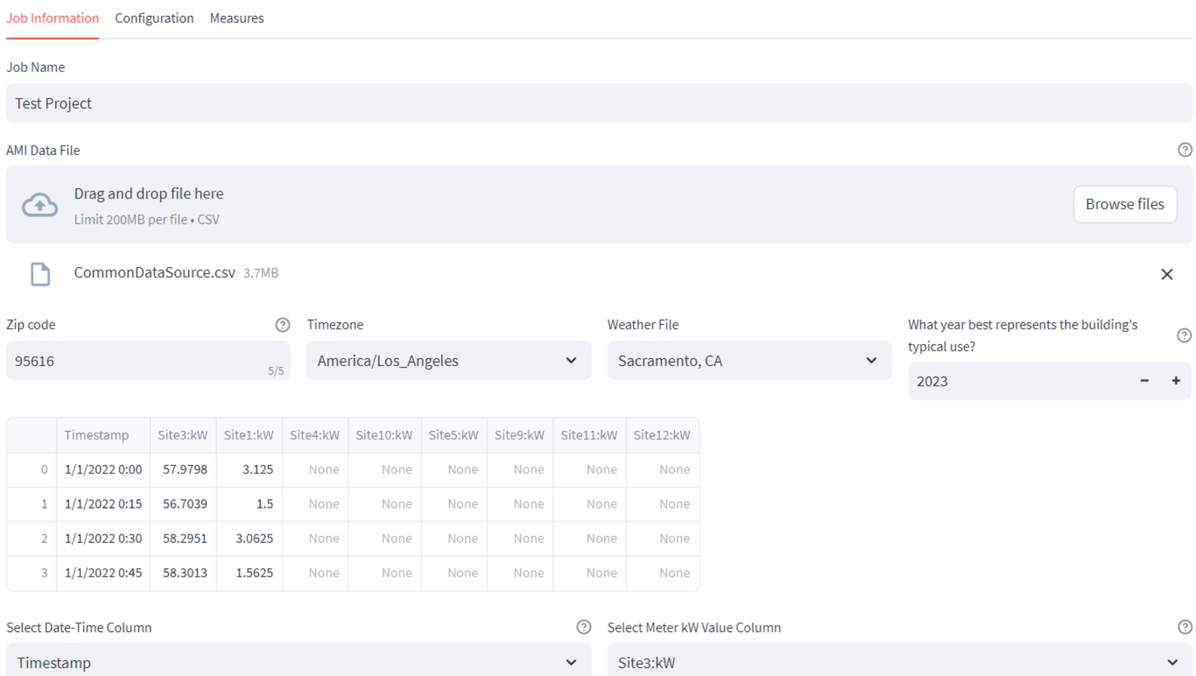
- Open Command Prompt

Run `run.bat`

Appendix B: User Guide for Inputs in AMI to BEM Tool

Guidance on the inputs required for the AMI to BEM Tool are described below by tab within the tool.

Job Information Tab – For entering job name, meter data information, and weather



Job Name – A description of the job to be run. Can include text and numbers and should adequately describe the job.

AMI Data File – An electric consumption meter data file that ideally contains 15-minute interval data and requires at least 1-hour interval data. When one is dropped into this area, a window describing a snapshot of the first five rows of data will appear. This window is there to assist in selecting the date-time column and meter kW column (described below).

Zip Code – The zip code where the project is located. This is used to look up a historical weather data file to compare the meter data to. Rarely, the zip code is not found in the eeWeather library the Project Team are referencing and can result in an error. If this occurs, using a nearby zipcode usually resolves this issue.

Timezone – Timezone where the project is located; this is used to adjust the meter data appropriately to UTC to assist in matching to the weather data.

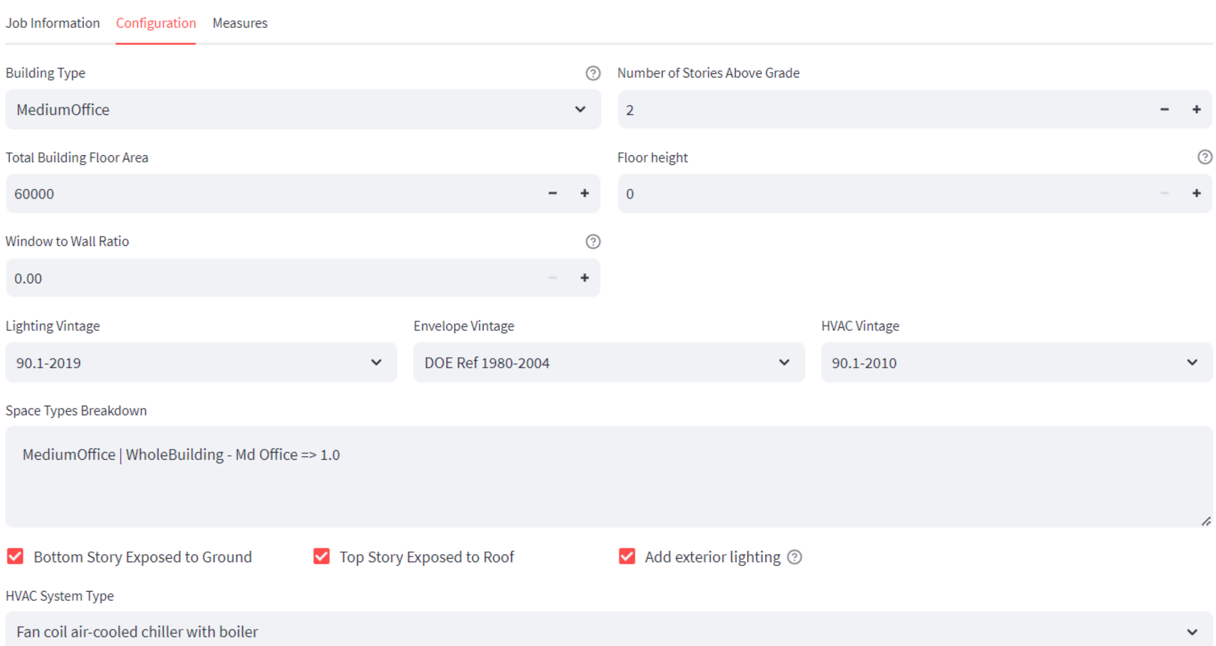
Weather File – The energy model's weather data file which is the nearest weather station. This weather file contains additional information such as solar radiation, wind speed, and enthalpy which is needed by the energy model.

What year best represents the building's typical use? – This should be specified as the year in the meter data that best represents the building's typical use. It is very important that this year actually exists in the meter data and the year is complete. If either of these conditions are not met, it will result in an error.

Select Date-Time Column – The column name in the meter data that has the date-time value in it. This can be called various names such as timestamp, date-time, datetime_local, etc. depending on the meter data source.

Select Meter kW Value column – The column name in the meter data that contains the kW at each interval in the data. Note: This is not the kWh column in the meter data; using the kWh column will result in an inaccurate representation of use in the building. This column can be called various names such as power_kW, kW, etc., depending on meter data source.

Configuration Tab – The energy model inputs that will apply to all energy models.



Building Type - Select the building type that represents the majority of the building's use type.

Building Geometry Characteristics - Enter the number of above-grade stories, the approximate building floor area, the approximate floor to floor height if known, and the window to wall ratio, if known. If floor to floor height or window to wall ratio are not known, leave as 0 and a smart default will be assumed based on the vintage, building type, location, and square footage.

Lighting / Envelope / HVAC Vintage Selection – Select three building vintages for three buildings systems, envelope, internal loads, and HVAC, to improve accuracy. Most buildings are a composition of renovations over multiple years and have different vintages for each building system. For example, many buildings have original envelopes but updated lighting / plug loads, and HVAC systems. Please match the most recent comprehensive renovation with the approximate year of code for each of these areas.

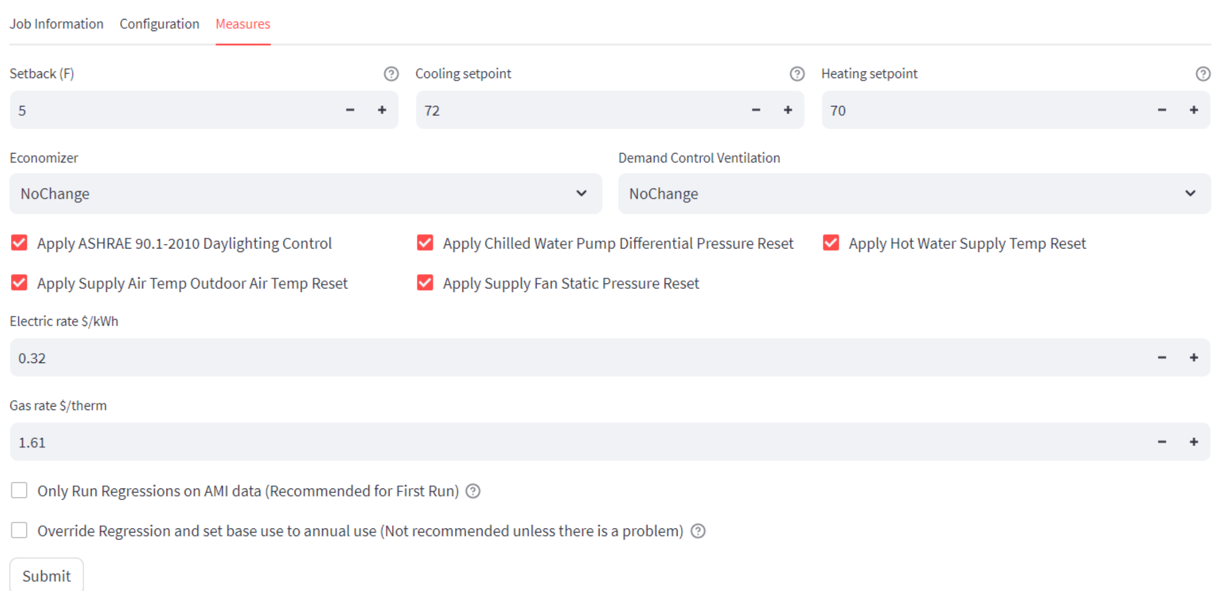
Space Type Breakdown – This is populated based on the building type selected. Adjust and update the breakdown percentages if you know better, ensuring the total is 100 percent. To do this, the Project Team recommend copying and pasting into a spreadsheet.

Bottom Story Exposed to Ground / Top Story Exposed to Roof – Check this box if the lowest story is touching the ground and if the top story is a roof exposed to air. If there is, for example, a parking garage below the building that is not represented, the Bottom Story Exposed to Ground checkbox would be unchecked.

Add Exterior Lighting – Check this if there is exterior lighting on the building.

HVAC System Type - Enter the closest approximation for the HVAC system present in the building. If multiple are present, select the most prevalent type.

Measures Tab – The efficiency measures to be applied to M3



Setback / Cooling Setpoint / Heating Setpoint – If the heating and cooling setpoints are known, the user can enter them here; these are the occupied cooling and heating setpoint temperatures. The night setback can be specified, for example if cooling is at 72°F, a 5°F-setback sets the cooling to be set to 77°F at night. These setpoints are only applied to the proposed design model M3.

Economizer – If an economizer (which brings in outside air to cool instead of using cooling) is to be added to the proposed design model M3, add the type here, otherwise set as no change.

Demand Control Ventilation – If ventilation is going to be controlled with CO_2 controls or by other means in the proposed model, add it here; otherwise set as no change.

Control Strategy Checkboxes – Checkboxes to enable or disable different HVAC controls improvements in the proposed model. These are defined in the bullets below.

- Daylighting Control – Adds daylight sensors to control lighting.
- Chilled Water Pump Differential Pressure Reset – Dynamically adjusts the chilled water pump pressure based on actual cooling demand to optimize energy use and system performance.

- Hot Water Supply Temp Reset – Adjusts the hot water supply temperature based on outdoor air temperature to improve heating efficiency and reduce energy consumption.
- Supply Air Temp Outdoor Air Temp Reset – Modifies the supply air temperature setpoint based on outdoor air temperature and dehumidification requirements to balance comfort and energy efficiency in variable air volume (VAV) systems.
- Supply Fan Static Pressure Reset – Adjusts the supply fan's static pressure setpoint based on zone demands to minimize fan energy consumption while maintaining adequate airflow.

Electric / Gas Rate – If the cost of energy is known, enter these here. This will allow the calculation of financial energy analysis metrics in the results.

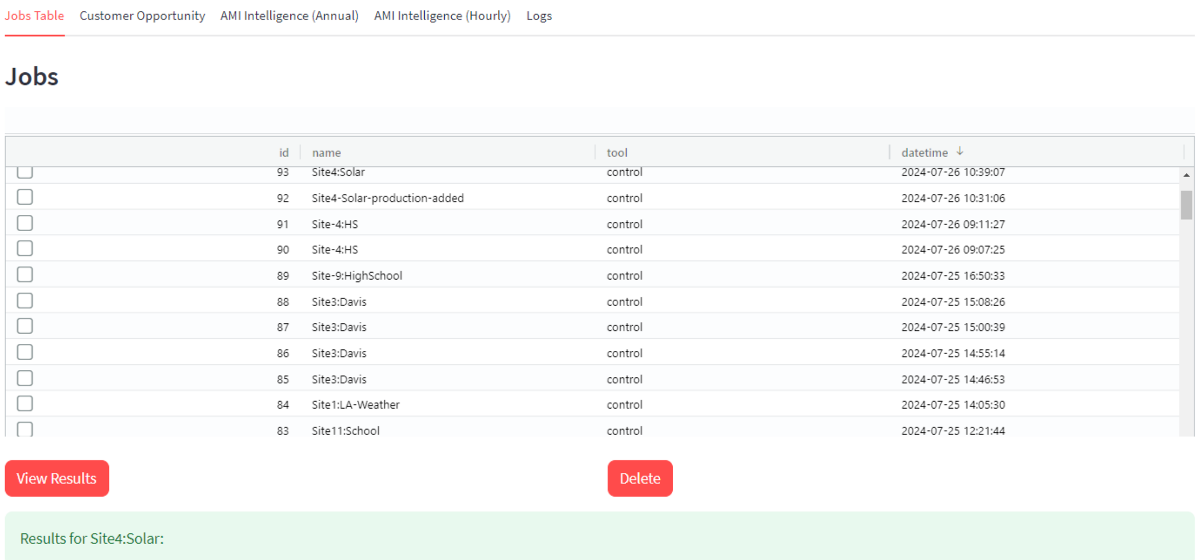
Only Run Regressions on AMI data – If enabled, the run will stop after the regressions are run and before the energy models are created. This allows the user to see what the regression identified and make adjustments to energy model inputs before all of the energy models are run.

Override Regression and Set Base Use to Annual Use – If there is a serious problem with the bill regressions, for example the regressions consistently thinking there is heating and cooling when the user knows there is no mechanical heating and cooling in the building, then the user can override the regression estimates. In this example, one should set the base use equal to the annual use in the utility bill so that the model does not include any mechanical space conditioning. This is not recommended unless there is a serious problem with the regressions in the bills.

Appendix C: User Guide for Outputs in AMI to BEM Tool

Guidance on the outputs generated from the AMI to BEM Tool are described below by tab within the tool.

Job Table – viewing a scrollable list of completed Jobs



id	name	tool	datetime
93	Site4:Solar	control	2024-07-26 10:39:07
92	Site4-Solar-production-added	control	2024-07-26 10:31:06
91	Site-4:HS	control	2024-07-26 09:11:27
90	Site-4:HS	control	2024-07-26 09:07:25
89	Site-9:HighSchool	control	2024-07-25 16:50:33
88	Site3:Davis	control	2024-07-25 15:08:26
87	Site3:Davis	control	2024-07-25 15:00:39
86	Site3:Davis	control	2024-07-25 14:55:14
85	Site3:Davis	control	2024-07-25 14:46:53
84	Site1:LA-Weather	control	2024-07-25 14:05:30
83	Site11:School	control	2024-07-25 12:21:44

View Results – Loads the job analysis data from the output folder of the application, processing takes a moment and then the Customer Opportunity, AMI Intelligence, and Logs tabs will load.

Delete – Removes the job data point and all the associated model and output files from the output directory of the application folder.

Customer Opportunity Tab – Reports information about the efficiency opportunities explored by the tool for the selected job.

Jobs Table | Customer Opportunity | AMI Intelligence (Annual) | AMI Intelligence (Hourly) | Logs

Annual Savings

	0	1
0		Annual Savings
1	Electricity	107235 kWh
2	NaturalGas	-46 therms

Investment Details

Incremental Cost `1536.0`

Annual Cost Savings `25199.0`

Number of EEMs `2`

Measure List

```
[
  0 : "Economizer"
  1 : "DCV"
]
```

Project ROI is 1641.0 %

Annual Savings – A table of estimated savings from the efficiency measures in electricity and natural gas units.

Investment Details – Rough estimates on the economic performance of enacting the efficiency measures as explored by the CCBEM tool.

Incremental Cost – A rough estimate for the incremental cost (cost beyond meeting the code minimums) to enact the select efficiency measures. Calculated by counting the number of selected measures and multiplying the total building total area by the count and an estimate of three cents per square foot per measure.

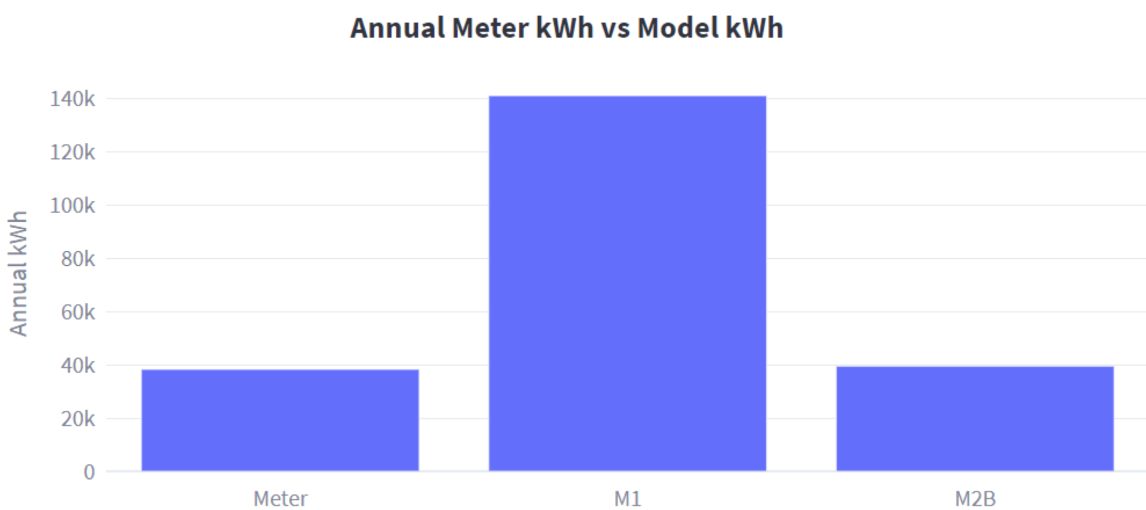
Annual Cost Savings – An estimate based on the energy saved and the user-entered simple utility rates. If the utility rates sections of the input are left blank this will not calculate.

Number of EEMs – This reports back the number of user-selected efficiency measures selected on the measures input tab.

Project ROI – This is the expected simple return on investment for instituting the proposed efficiency measures. This is a simple return calculation expressed as an annual percentage rate.

Monthly Usage Comparison – These chart break down the savings opportunity by month and by certain building system components and may be helpful for exploring the energy modeling outputs.

AMI Intelligence (Annual) – The results of the AMI Intelligence step with an annual perspective.



Calibration Results

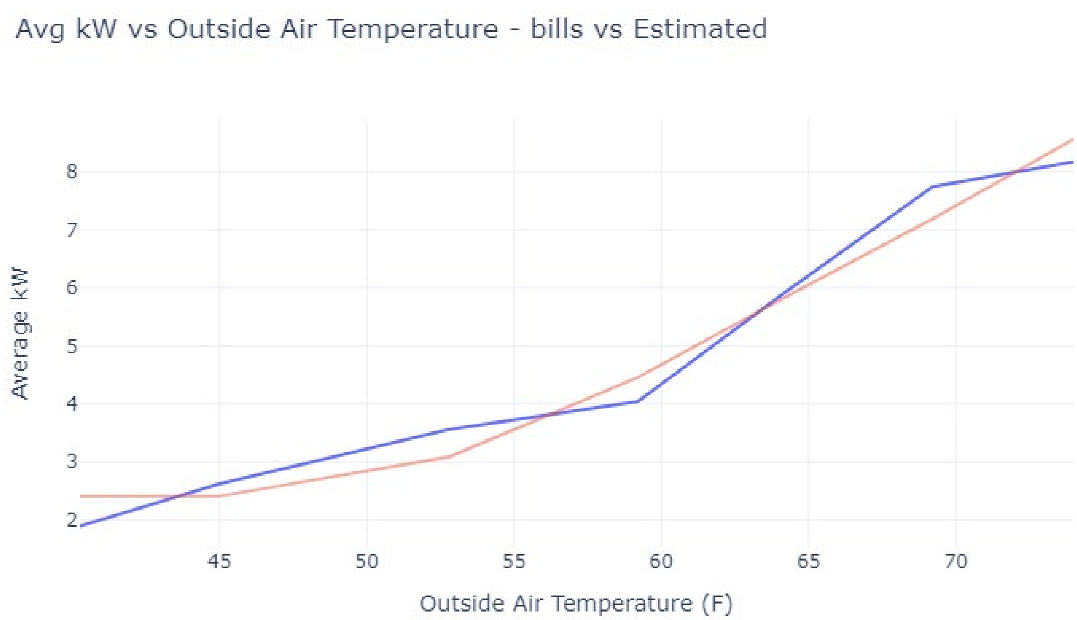
	cvrmse	nmbe
M1	285.3400	-292.7800
M2B	15.7800	-3.4100

Annual Meter kWh vs. Model kWh – This bar chart plots the annual sum of the meter against the annual sum of the calibration models. M1 is the model as prototypically defined by the user inputs and the M2 model(s) are based on the AMI intelligence steps. The results of the initial meter and model regressions determine whether both M2A and M2B models are run. Ideally the AMI intelligence module delivers a model the reflects the actual bills.

Calibration Results – A table of the calibration statistics as calculated by ASHRAE Guideline 14 for comparing a model to actual data. M1 is the prototypical model definition, M2A and M2B are the post-intelligence module statistics.

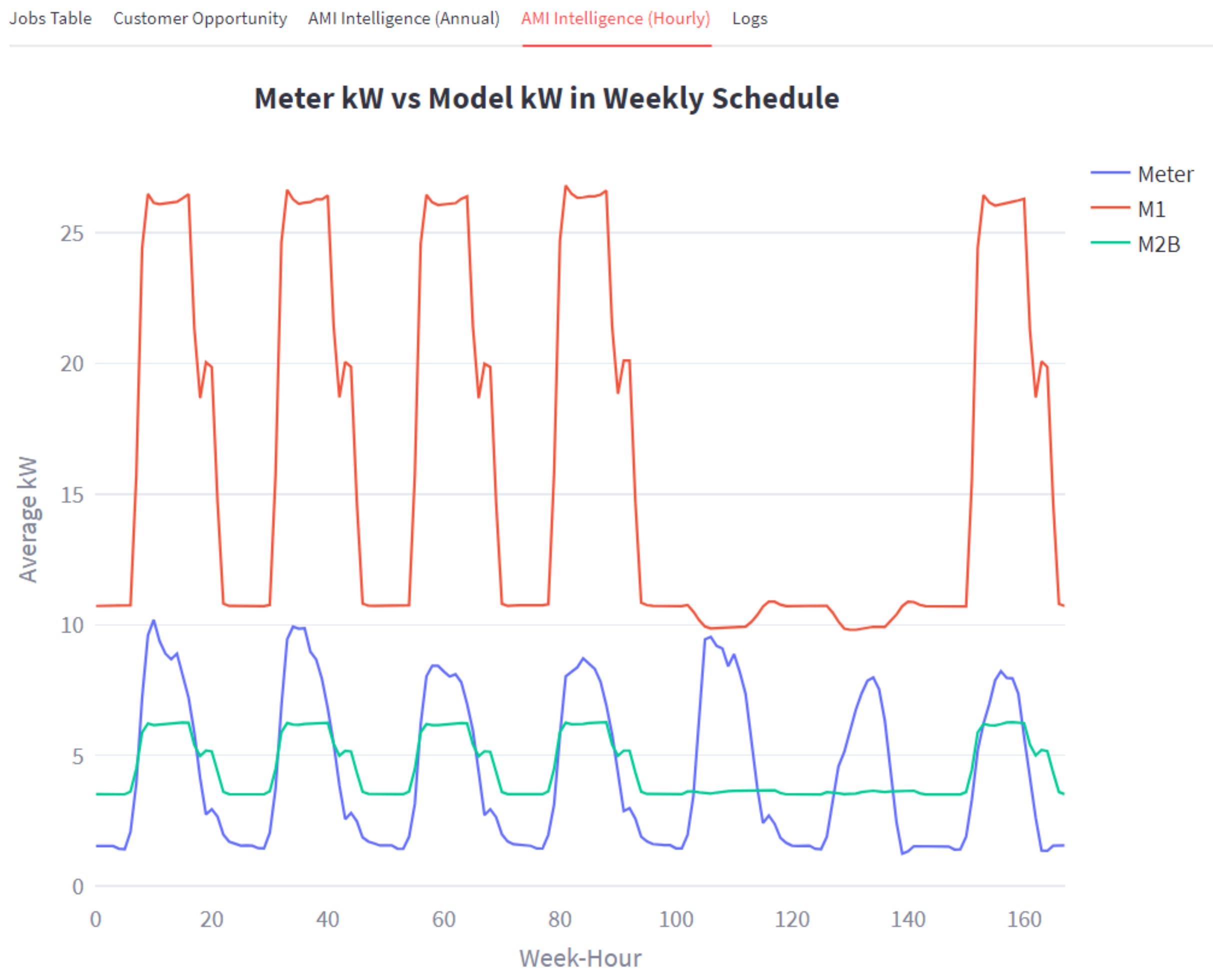
Regression Output Bills – Charts and tables examining the quality of fit and insights from the

HDD/CDD model fit identified for the bills.



Above chart plots the HDD/CDD estimated against the bills on an hourly temperature bin basis.

AMI Intelligence (Hourly) – The results of the AMI intelligence steps with an hourly perspective.



Meter kW vs Model kW in Weekly Schedule – This line chart is a plot of the average 168-hour period – one week – as observed in the meter, prototypical model, and post-intelligence models.

eeMeterHourly Ouputs – This section exposes output from running the open-ee-meter module on the supplied meter data. More information on these outputs can be found within the open-ee-meter documentation.

Appendix D: Site Interview Questions

Am I talking to the correct person?

Identify someone who is familiar with the building specifics and history, like a facilities manager

Contact information

- Business name?
- Building site name?
- Building site address?
- Contact name?
- Contact job title?
- Contact preferred method of contact?
- Contact email address?
- Contact phone number(s)?

General Building Information

- Year built?
- Number of electric utility meters and what areas they cover?
- Year lighting system installed/renovated?
- How extensive are lighting occupancy sensors?
- Building area in square feet?
- Number of floors?
- Ceiling height?
- Square footage by building usage type?
- Office?
- Waiting Area/Lounge?
- Conference/Meetings?
- Clinical?
- Mech/Elec?
- Corr/RR/Support?
- All Others?
- Any major upgrades affecting energy, such as an addition?

Thermal Shell Questions

- Amount of fenestration (lots of glass, little glass)?
- Are the windows single, double, or triple pane?
- Is it noticeably colder in winter near the windows?
- Any updates to insulation since construction?
- How drafty is the building?

HVAC Questions

- Year HVAC system installed?
- Heating setpoint (degrees F)?
- Cooling setpoint (degrees F)?
- General satisfaction with comfort conditions?
- Heating fuel? (gas, electricity, oil, propane, combination - please describe)
- Heat generation? (combustion, heat pump, VRF, electric resistance, combination - please describe)
- Heat distribution? (air based, hydronic, steam, combination please describe)
- AC generation? (Chiller, fan coil, RTU, split system, heat pump, VRF, PTAC, unit ventilator, combination – please describe)
- Automatic controls?

Utility Data

Electric Utilities

- Have two years of AMI data been provided to the team?
- Have there been any major events that have altered how the building energy systems operate? (Examples: extended building shutdown, major system failure)

Heating Fuel Utilities

- Fuel quantities for the same period that the electrical data covers? (There is flexibility on frequency of data collection points required)

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