A Comparison of Methods for Early-Stage Retrofit Analyses

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ABSTRACT

There are often several phases of energy efficiency analysis on a portfolio of existing buildings prior to retrofits or operational changes being implemented. The earliest stage of analysis involves sizing the energy efficiency opportunity that exists in each building. This process provides utilities and program administrators with a mechanism to prioritize buildings and determine whether deeper (and more time consuming) analysis is warranted. During early stage efficiency analyses, most practitioners focus on prioritizing buildings with high-level metrics such as Energy Use Intensities (EUI) or ENERGY STAR scores. These aggregated performance indicators are often inadequate for identifying good candidates for energy efficiency programs.

Focusing on buildings with limited energy savings potential leads to increased program costs and low project conversion rates in the later stages of delivering energy efficiency services. This study presents three different approaches for early-stage retrofit analyses designed to improve simple benchmarking alternatives. The first approach involves classical, detailed energy modeling efforts to construct a calibrated building dynamic energy model. The second approach also constructs a building energy model (quasi-steady state) to evaluate interactive EEMs, but utilizes a streamlined approach and less asset data from the building in question. Instead, algorithms infer unknown variables based on publicly available data, previous audits, and historical monthly energy consumption to determine savings potential and opportunities. The third approach utilizes sub-hourly interval energy consumption data and site location to determine specific facility insights. These specific insights provide suitable information for software driven rapid energy model construction and optimization. This paper describes these three approaches and illustrates how they can be used for early-stage retrofit analyses in a portfolio of six buildings. Despite the significant differences in the amount of required input data and time, the projected savings across three approaches are similar, demonstrating that rapid energy modeling and analytical approaches can play a prominent role in targeting buildings and identifying energy efficiency opportunities at scale.

Introduction

Utilities and efficiency program administrators have been facing the challenge of identifying energy savings in existing buildings for decades. Total utility energy efficiency program investment in the US has almost tripled from 2008 to 2012, from approximately $2 billion to almost $6 billion (Nowak, Kushler, Witte, & York, 2013). To reach increasingly aggressive energy efficiency mandates, utilities must become more sophisticated and proactive in how they target their commercial customer base with their energy efficiency programs.

Aligning the right customers with the right efficiency programs has historically been an obstacle. Some utilities have relied on leads either from inbound requests, customer bill complaints, or by simply focusing on basic benchmarks such as total consumption or EUI. These passive approaches have limited results; simply prioritizing efficiency potential based on annual energy consumption is normally an inadequate indicator for actual savings opportunities.

ENERGY STAR scores and EUI metrics have been shown to be functionally ineffective in assessing the energy savings potential of a particular building. Figure 1 illustrates the results of a random sample of 500 building energy audits conducted over the past two years regarding the energy savings potential of the building type and the respective ENERGY STAR score. Additionally, Figure 2 illustrates the results of offices in terms of annual EUI.

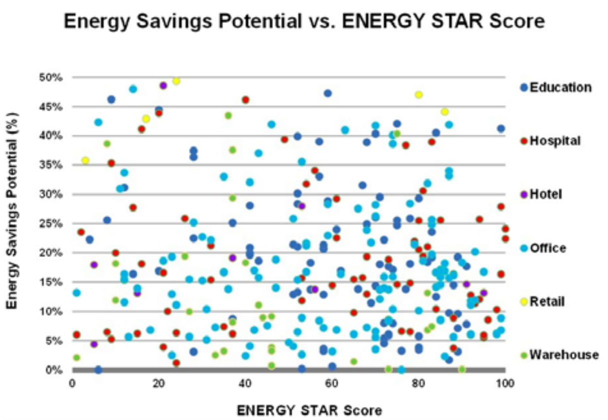


Figure 1. Relationship of uncertainty, applicability and level of effort.

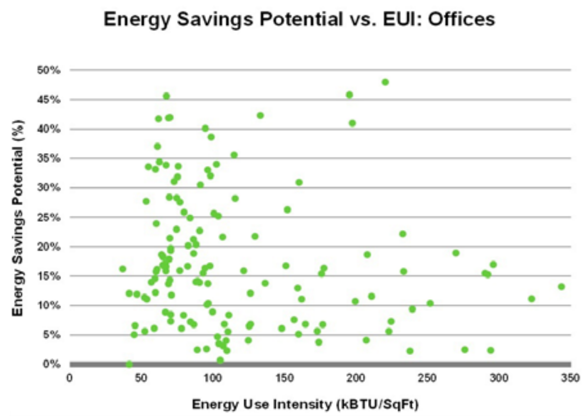


Figure 2. Applicable approaches with different levels of asset and consumption data.

Despite their widespread usage, neither ENERGY STAR scores nor EUI are capable of providing the accuracy and level of detail to effectively prioritize buildings based on their energy efficiency savings potential. ENERGY STAR, the more detailed of the two approaches, evaluates building energy performance by normalizing energy use type, building size, location, and other operational and general asset characteristics. EUI more broadly measures energy consumption per square foot and is often used to compare buildings of the same use type.

While both ratings are common tools for benchmarking a building's energy use, they have minimal correlation to the actual potential a building has for energy savings, particularly across a large and diverse portfolio. The primary reason is that both ENERGY STAR and EUI are driven by a single point benchmark (annual energy usage). The problem is, however, there is great diversity in the way a building uses energy throughout a year. Two buildings may end up with the same amount of energy consumption at the end of 12 months, but they may take two very different paths to get there. Buildings can be relatively efficient (or inefficient) during different times of day; in response to different types of weather; or by each end use, such as lighting, heating, cooling, and plug loads, among others. To be clear, this is not to say that there is no value in either benchmarking methodology. When used in the correct context, both can provide a direct comparison of two buildings in terms of energy usage, e.g., which building consumes more energy and, perhaps more importantly, create awareness about energy efficiency amongst stakeholders. However, this is not the same thing as asking which building has the greatest potential for energy efficiency savings. One building can use more energy than another and yet be running efficiently.

Forward-looking utilities are addressing this problem by using data analytics to better identify, target, and secure these commercial building efficiency opportunities. However, as utilities move from being reactive on a relatively small scale, to proactive on a portfolio-wide scale, assessments must be made across a large customer base with very limited information about the respective facilities.

In most cases, utilities know little more than the building address and the energy consumption, and during the early stages of customer engagement, often lack critical insight into the facility prior to making commitments to deploy energy audits and engineering services. In addition to prioritizing buildings, with the ability to engage customers with customized efficiency opportunities, personalized to their specific buildings, utilities have a much greater chance at securing customer interest and participation in an energy efficiency program. As utility programs evolve through this paradigm change from reactive to proactive, and as all stakeholders strategize how to utilize their efficiency programs to drive deeper energy savings at scale, utilities will need to leverage the right data and solutions at each step of their process.

Based on results from a utility funded pilot, this paper compares three different approaches for early-stage retrofit analysis. The first approach, a whole building dynamic simulation with detailed asset data, involves classical energy modeling efforts to construct a building simulation, including calibrating the model to observed consumption and evaluating interactive EEMs. The second approach, quasi steady-state models with minimum asset data, utilizes less asset data to infer unknown variables based on publically available data and previous audits in the database. Similar to the first approach, the model simulates current performance, is calibrated to observed consumption and then determines achievable performance by analysis of interactive EEMs. The third approach, interval-based inverse modeling with automated forward modeling, utilizes sub-hourly interval consumption data and site location to determine unique insights and recommendations about the building.

This paper describes these three approaches, compares outputs such as savings estimates and end use disaggregation from each approach, and estimates potential incremental savings realized in the context of an efficiency program. The objective of this exercise to help inform stakeholders of the benefits of each approach so they can best apply them to their program needs.

Three Approaches for Retrofit Decision Analysis

Approach 1: Whole Building Dynamic Simulation with Detailed Asset Data

Several transient building simulation software packages (e.g., eQuest, EnergyPlus, TRNSYS) have been extensively vetted and well-used in the industry over the past few decades. These software packages are high-fidelity energy models that can accurately simulate the actual building behavior, given sufficient information and time from a skilled energy modeler. Transient building simulation software emulates the performances of energy systems in a building by solving the full set of dynamic heat balance equations using non-linear numerical methods. These types of software packages therefore are considered a “best practice” for modeling a building and its energy and control systems to a high degree of detail.

The dynamic simulation approach for retrofit analysis requires detailed asset data and usually monthly energy consumption data (O’Neill et al., 2011; Raftery et al., 2011). Collecting reliable building asset information is often a challenge when stakeholders begin trying to proactively engage customers to discuss potential savings opportunities in buildings.

In practice, protocols and guidelines such as the International Performance Measurement and Verification Protocol (IPMVP) and ASHRAE Guideline 14 have specified the whole building calibrated simulation approach to identify energy savings. Guideline 14 provides explicit statistical criteria to with which to evaluate relative accuracy of an energy model, to be considered a sufficiently calibrated model.

The typical procedure of the approach requires the engineer to review drawings, collect consumption and weather data, construct building geometry, create HVAC systems and zoning, calibrate the model, create design options, iterate the model to optimize the potential energy savings, and prepare reports. In the context of an energy efficiency program, utilities and program administrators are most likely to leverage this approach in response to a customer compliant (e.g., about a high bill), or by requests for a utility funded audit driven by traditional customer engagement methods such as mass marketing or delivery and validation of incentive applications by account executives.

There are two drawbacks of this approach for early-stage savings analysis: scalability and objectivity. First, it takes tremendous amount of time to collect asset data, and usually even longer to create and calibrate the model. According to a U.S. Department of Energy (DOE) FEMP report (U.S. DOE, 2004), typical model construction time ranges between 3 (three) person-days to 6 (six) person-months, and costs between thousands and hundreds of thousands of dollars, depending on the project size. Second, the creation of whole-building energy models requires deep expert knowledge and experience. Based on different assumptions (e.g., plug load power intensity), different users using different software packages may generate significantly different simulation results (Guyon, 1997).

Researchers (Long et al., 2013; New et al., 2012) have been working on improving whole building dynamic simulation scalability by modularizing model creation and applying super-computing techniques, which are an important step towards applying this type of approach to mass scale prioritization and remote opportunity identification.

Approach 2: Quasi-Steady State Model (QSM) with Minimum Asset Data

QSMs for buildings are computationally less intensive mathematical representations that offer the potential for near high-fidelity analysis, with a significant reduction in processing time. They are based on first order thermodynamics and aggregated building specifications (e.g., simplified geometry, less zoning, and aggregated system performance parameters). These models, while still based on energy-balance methodologies, enable significant computational efficiency and streamlined assumptions to overcome the drawbacks of the first approach. Because of these inherent benefits, QSMs have been used for large-scale building stock energy modeling (Reichmuth & Turner, 2010; Zhao, et al., 2011), intensive model calibration (Heo, Choudhary, & Augenbroe, 2012), standardized performance rating (Corrado & Fabrizio, 2007; Corrado et al., 2007), and are increasingly being leveraged for ASHRAE Level I, II and even supplementing Level III on-site energy audits.

In the context of early stage retrofit analysis, QSMs focus less on predicting actual usage of the building and more on comparing and sizing the impact of EEMs under typical building design and operational conditions. Unknown model input parameters are inferred based on a much smaller set of publically-available asset data such as use type, vintage, floor area, and heat source from previous audits of similar buildings. The model can then be iterated to quickly rank hundreds of EEMs based on their environmental and economic impacts (Heo et al., 2012).

Approach 3: Interval-Based Inverse Modeling with Automated Forward Modeling

Given a physical system, inverse modeling uses observed measurements (energy consumptions) to replicate the actual values of model parameters (building characteristics). Forward modeling, in contrast, predicts consumption results given actual model parameters.

Traditional simplified inverse modeling based energy data analyses methods use weather data and other optional variables (e.g., occupancy) to build various regression models, such as a change-point model (ASHRAE, 2002; Kissock, Haberl, & David E. Claridge, 2003). If the building is not sub-metered, which is usually the case, algorithms have been developed to disaggregate end use categories from interval usage data (Akbari, 1995; Birt et al., 2012). These traditional methods have then been significantly advanced by various DOE run National Labs, as well as private companies in the past several years, enabled by the rapid development of big data computing technologies and related analytical advancements.

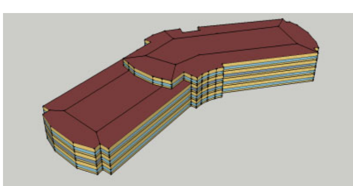
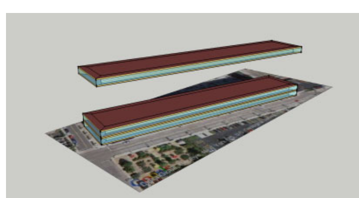
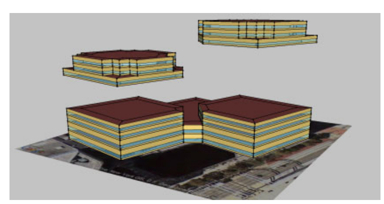
Interval energy consumption data has become more and more accessible due to changes in the markets such as energy deregulation, the advancement of energy efficiency and demand response programs, as well as with the development smart grid technologies. To provide sufficient insights from inverse modeling, at least a full year of hourly or sub-hourly interval energy data is ideal to allow for statistical significance.

Interval-based inverse modeling is the most scalable approach amongst the three in that it is the most rapid (analysis can happen in minutes per building) and cost-effective. It is also as purely objective approach compared to the other two approaches, because it detects information directly from interval consumption data, and frequently determines key parameters, such as operating and occupancy hours, much more accurately than what is reported by building owners , managers and operators.

It is important to note that these statistical models must be trained using large sets of building data. Utilities and data analytics companies that have acquired these large data sets usually consider them proprietary and develop their own models for internal use. Furthermore, data quality, both in terms of format and content, is still evolving; initiatives like the White House-sponsored Green Button effort could help eliminate these challenges by standardizing both the format and content of energy interval data.

Case Studies

In this study, we selected six actual buildings and applied the three approaches to each building. These buildings consist of four large office buildings and two secondary schools, all of which are located in ASHRAE climate zone 5. Table 1 lists additional building information and the Figure 3 shows the modeled buildings made in Approach 1.

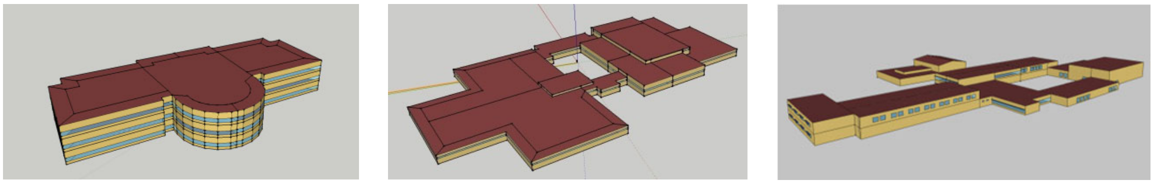


Figure 3. Order by row: Office #1-4, School #1-2.

Table 1. Summary of building information

Building	Building Area (ft^2)	Heating Type	Cooling Type
Office #1	237,000	Electric	Electric
Office #2	612,000	Non-Electric	Electric
Office #3	452,000	Non-Electric	Electric
Office #4	93,000	Electric	None
School #1	137,000	Non-Electric	Electric
School #2	161,000	Electric	None

We also collected all available data needed for each of the three approaches under review, although not all data was used for each approach. The purpose of the case study is to demonstrate how these approaches can be used in a project, and to determine which approaches are more applicable with different levels of data adequacy and time constraints.

Approach 1: Whole Building Dynamic Simulation with Detailed Asset Data

This approach builds a unique energy model specific to the actual building specifications including the detailed building geometry, operational schedules, lighting and equipment loads, as well as HVAC equipment and controls. The tool used to complete the early stage retrofit analysis is Open Studio, which leveraged a Trimble SketchUp plug-in for geometry creation and utilizes EnergyPlus as the back-end whole building energy simulation.

The inputs for each building type were different based on the building type and the observed consumption. Each model was calibrated to very closely match annual, daily and sub-hourly electric interval consumption data. The table below shows the calibration levels for each model. ASHRAE Guideline 14-2002 requires Coefficient Variance Root Mean Squared Error (CVRMSE) to be less than 15% and the Normalized Mean Bias Error (NMBE) to be less than 5% to be able to qualify as a calibrated model. Each model was calibrated to exceed this criterion as the following table shows. Table 2 depicts calibration results for all the buildings. Figure 4 shows monthly calibration results for Office #3 as an example.

Table 2. Calibration levels for each model

Reference Name	Annual % Difference	CVRMSE	NMBE
Office #1	0.61%	3%	1%
Office #2	1.41%	7%	-2%
Office #3	0.39%	7%	0%
Office #4	0.71%	6%	1%

School #1	0.71%	6%	0%
School #2	1.37%	8%	-1%

ASHRAE Guideline 14-2002 "Measurement of Energy and Demand Savings"

coefficient of variation of the root mean square error

7% CVRMSE	4.063E+09	2.416E+09	4.816E+08	4.185E+08	1.949E+09	2.997E+08	1.421E+09	6.118E+08	1.319E+09	1.527E+09	1.736E+09	6.478E+08
0% NMBE	63,742	49,152	21,946	(20,458)	(44,145)	(17,311)	37,691	24,735	(36,317)	(39,073)	(41,662)	(25,451)

normalized mean bias error

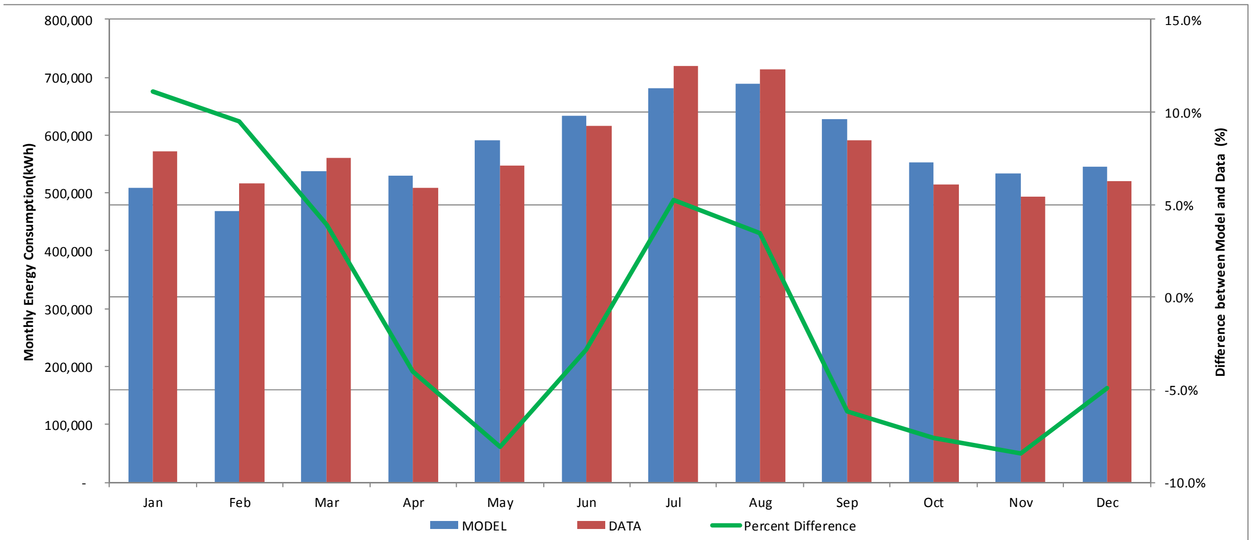


Figure 4. Calibration result of Office #3 using dynamic simulation.

Once the six models were calibrated, individual changes were made to each model to evaluate the savings potential of industry standard EEMs. The energy impact of these measures accurately captured the interactive effects of each change as they were applied to a whole building model. An abbreviated list of the EEMs that were applied to each model where: Decreased Lighting Power Density, Decreased Miscellaneous Equipment Power Density, Improved Chiller Performance (where applicable), Reduced Minimum Flow for VAV boxes, Improved Exterior Wall and Roof Insulation, and Improved Window Fenestration. These EEMs were compared to the base model individually and also as a combined final package to include potential interactive effects. Though it is possible to explore many options with a high fidelity model, it is both computationally expensive and time intensive. The process of creating a detailed energy model for early-stage analysis and energy efficiency potential brainstorming has significant challenges. This is because there is a large set of information that must be collected and built into a relevant energy model. Without a high level of certainty in or availability of building asset information, the cost associated with developing a unique energy model of the facility offers diminishing returns as a means of proactively engaging utility customers in energy efficiency programs.

Approach 2: QSMs with Minimum Asset Data

QSM analytical methodologies allows for quickly inputting a limited amount of known asset data, inferring supplemental unknown asset information from buildings of a similar type, calibrating the model to actual consumption data, and assessing different options for upgrading a building with individual EEMs and packaged groups of interactive EEMs.

For this application, the inputs used to create a QSM were building area, operational start and stop times, building type, lighting load, miscellaneous equipment load, heating fuel type and cooling type. This information was collected during Approach 1 and represents a significant reduction in the amount of data needed to be collected to run a representative energy model. Unknown model input parameters were inferred based on data from thousands of previous energy audits.

To calibrate the model, the approach focuses on changing key variables that impact the energy consumption of the building such as ventilation, lighting and plug loads, and operational start and stop times. The computational time to analyze the QSM in seconds instead of minutes, so analyses and calibration times are greatly reduced over Approach 1. As before, the six building energy models were calibrated (as shown in Figure 5) to meet ASHRAE 14 standards but it took approximately 30 minutes to calibrate each model for Approach 1 as opposed to 6-8 hours per high-fidelity energy model.

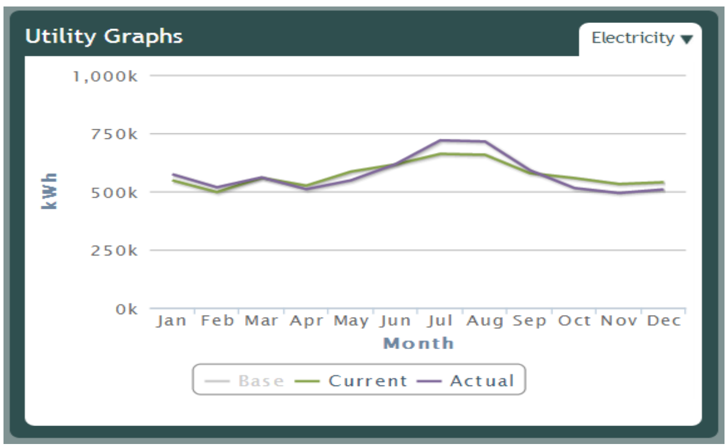


Figure 5. Calibration result of Office #3 using QSM.

Once a calibrated QSM was created, various EEMs were automatically analyzed and the overall building model optimized for cost effective energy savings. QSMs can quickly run through many different combinations of EEMs to find the optimal package(s) for each particular building based on interactive measure effects, depth of savings and implementation cost.

For example, the recommended measures for office #2, targeting a less than 3 year financial payback were: increase cooling set points, decrease heating set points, reduce lighting load by changing lighting to T8 lights, utilize network-based computer power management software, install air-side economizer with dry-bulb changeover control, add demand controlled ventilation, and cycle supply air at night. Other retrofits, such as HVAC replacement or facade retrofit, were considered but did not meet the pre-specified payback threshold. These EEM scenarios were compared to the base model individually and also as a combined final package. This allows the analysis to show the interactive effect of the EEMs on all building systems. More potential EEMs were analyzed in Scenario 2 because the QSM could be run more quickly in terms of computation time and ease of adding new alternatives.

The respective time to complete and process each QSM took approximately 4 hours per building. This is largely because there was less focus on building asset information input and calibration, and more focus on aggregated building information. Interestingly, when building inputs were simplified, it allowed the user to focus more on what impacted the model calibration and what EEMs could deliver the most cost effective energy savings.

Though this approach loses some of the fidelity of a more detailed energy simulation, it served as a useful tool to analyze the six buildings, quickly determine the potential energy savings and provide specific ways to improve the performance of the building.

Approach 3: Interval-Based Inverse Modeling and Automated Forward Modeling

The final approach uses energy interval data and the site location to determine building characteristics when combined with concurrent observed weather conditions. This approach creates a mathematical inverse model to determine what building characteristics would create a consumption pattern that matches to the building's actual consumption. Instead of requiring detailed building asset data, this approach can help to automatically and objectively estimate key building parameters and operational conditions. In this analysis, advanced inverse modeling techniques beyond simple change point models were able to determine the building type, heating type, cooling type, occupancy start and stop time, lighting and equipment loads and the presence of a base load in the building (such as a data center). All of the indicators were determined through an automatic process that required no human intervention.

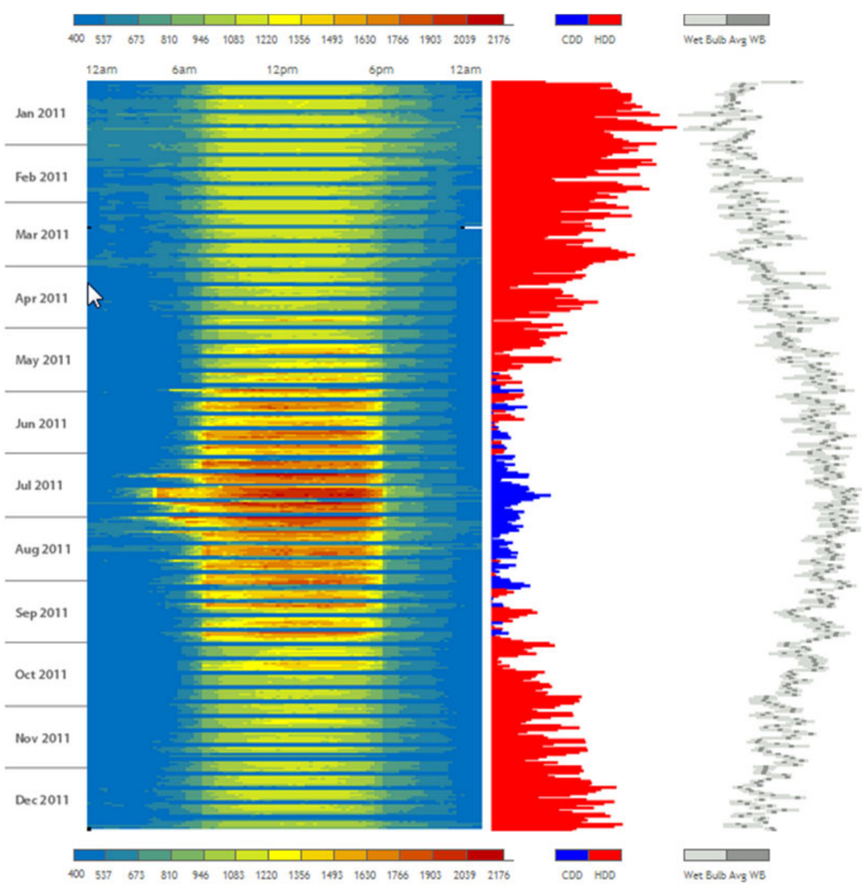


Figure 6. Graphical representation of interval usage and weather data for Office #3.

Insights provided by inverse modeling techniques are then used to generate a unique building energy model on-the-fly of the building in question. This forward modeling exercise is similar to the efforts in Approach 1 in terms of creating an efficient version of the building and allowing the building as-is to be quickly compared against an optimized version of itself. Once the optimized model is created, the next step is to calculate where and when the optimized model is performing more efficiently than the building and what building systems are likely inefficient. From these indicators, building specific recommendations are automatically generated on where the building can improve and what the expected energy savings may be for these changes.

Common insights that were determined from the building's interval consumption data included buildings were active longer than necessary, buildings were both heating and cooling during specific periods of the year, cooling responses being high compared to the thermal load on the building, and higher than expected ventilation consumption.

Results and Discussion

Table 3 lists the total predicted potential energy savings for each building across the three respective approaches with in this study. As can be seen, despite significant differences in the amount of required input data, engineering staff time, and computer processing, the projected savings across three approaches are relatively similar. Each approach also identified similar opportunities to engage customers at the early stages of energy efficiency evaluation.

Table 3. Summary of projected savings across the three approaches

Reference	Approach 1	Approach 2	Approach 3
Office #1	18.1%	12.6%	14.1%
Office #2	19.5%	10.1%	13.7%
Office #3	15.4%	17.0%	15.9%
Office #4	25.3%	24.8%	28.7%
School #1	24.7%	31.0%	20.8%
School #2	17.7%	25.7%	21.4%

To further compare these approaches, Table 4 compares the amount of information needed and average time spent per building for each approach. As described early in the introduction, Approach 1 requires the most detailed asset data and takes longest time to create. Moving towards Approach 3, less asset data are required because of the reduction of energy model complexity and usage of more granular energy data.

Table 4. Data & typical time required for different approaches

Data Needed	Approach 1 Dynamic Sim.	Approach 2 QSM	Approach 3 Inverse Modeling
Site Location	√	√	√
1-year Electricity Usage Data	Monthly	Monthly	15-min Interval
Geometry	Detailed drawings	Floor area and shape	Floor area only
Basic Asset Data (e.g., building type, shape, schedule, etc.)	√	√	
Detailed Asset Data (e.g., H/C set points, lighting and plug load intensities, ventilation rate, etc.)	√		

Time Spent Per Building	4-5 days	< 1 day	<1 hour

One of the findings in this study is that consumption data can and should be leveraged as part of the energy efficiency program, particularly during the early stages, to improve the interaction with the customer, and ultimately to get to a better outcome for the utility. Some of these benefits include increased customer awareness of the energy efficiency potential within their specific building and relevant utility incentive programs, as well as providing an effective means of managing the costs to maintain suitable program budget levels during the rapid expansion of programs and offerings. Generally, during the early stages of retrofit analysis, the level of detail of the analytical model can be reduced while maintaining a reasonable level of uncertainty, as shown in Figure 7. More specifically illustrated in Figure 8, when almost no asset data is available, utilities can still detect significant information about building with interval data analytics using Approach 3. In situations where some asset data and monthly consumption data are available, Approach 2 can be used to cost effectively identify insights by inferring more details about the building. To an extreme, for buildings whose detailed asset data are available (perhaps through a previous audit), Approach 1 can generate more building specific results with less uncertainty. It is up to the utility to determine which approach(s) are the most appropriate one to use, depending on the level of asset and consumption data available, expected effort to put on the project, and level of uncertainty needed to make the decision.

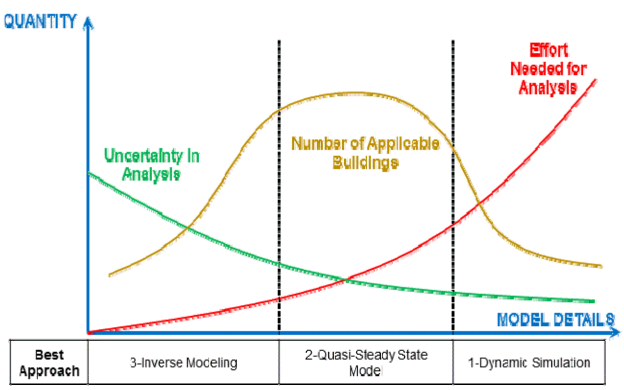


Figure 7. Relationship of Uncertainty, Applicability and Level of Effort

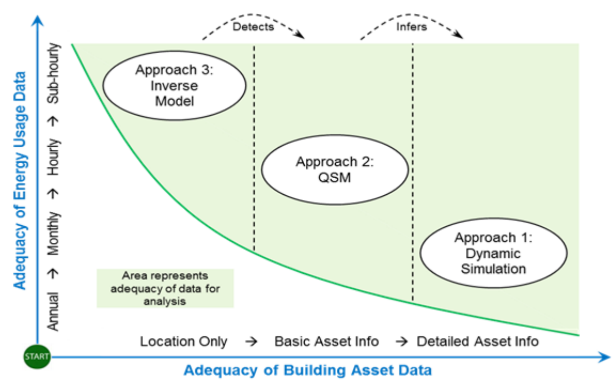


Figure 8. Applicable Approaches with Different Levels of Asset and Consumption Data

Having the ability to engage customers with high efficiency potential and aligning those customers with the right efficiency programs will be a critical step moving forward in the process as utilities evolve from being reactive on a relatively small scale, to proactive on a portfolio-wide scale. Utilities can address this problem by using advanced data analytics to better target commercial building efficiency opportunities across a large customer base; engage those customers on a one to one basis and thereby; drastically improve the early-stage energy efficiency evaluation process.

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