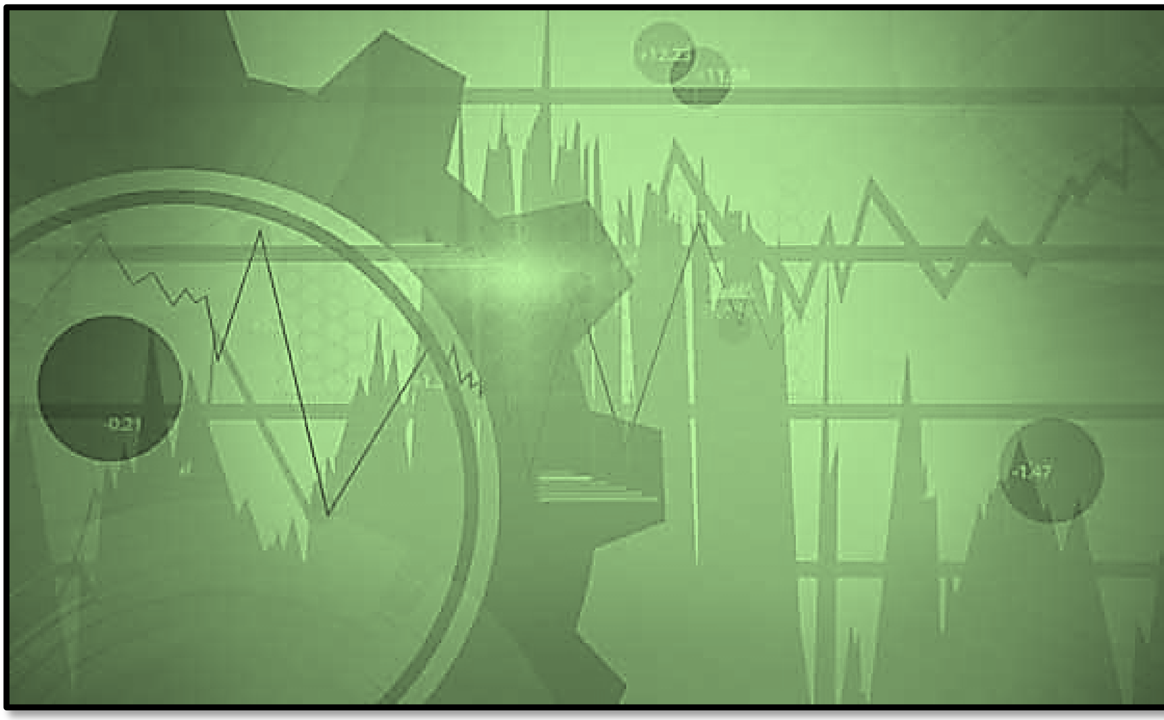
INVESTOR RISK MITIGATION IN ENERGY EFFICIENCY RETROFIT PROJECTS USING AUTOMATED MONITORING AND VERIFICATION TECHNIQUES

Energy and Environmental Policy Analysis (EEPA) Project

SECOND YEAR REPORT MAY 2018



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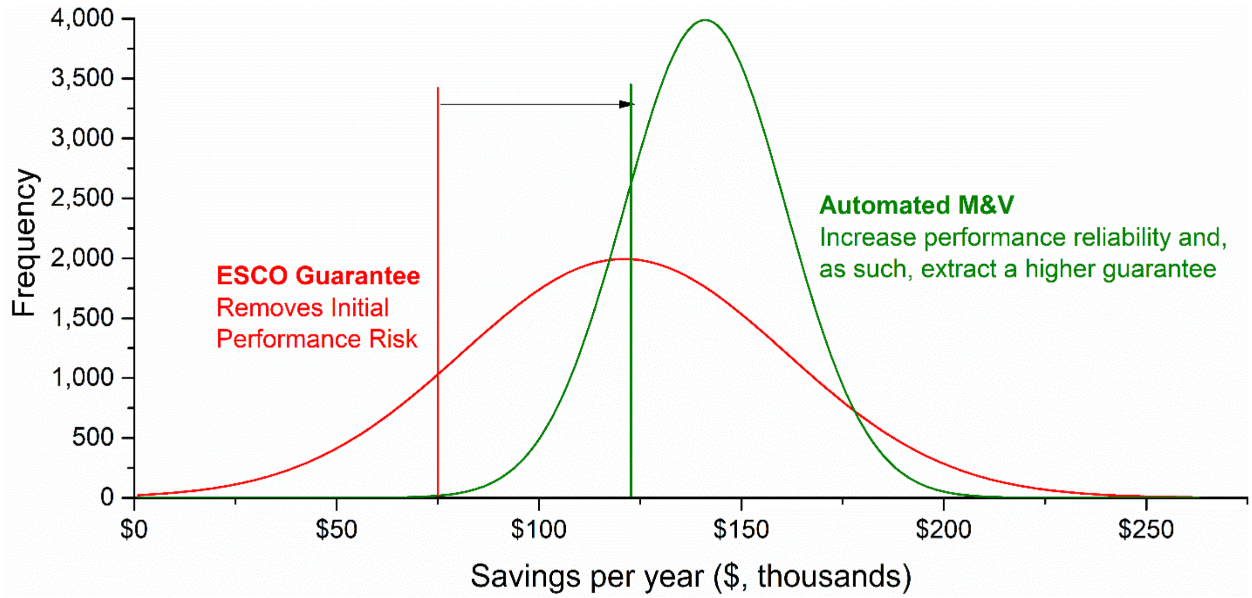
Executive Summary

This Second-Year Report captures research results of the 2nd year of a 3-year research project supported by a grant from the Delaware General Assembly. The first-year research effort outlined a literature review and conceptual understanding of automated M&V in relation to energy efficiency financing from a range of different perspectives (including client, energy service company (ESCO), and investor perspectives). In addition, the first-year report demonstrates a methodological approach capable of parsing out some of the expected benefits of incorporating automated M&V in energy efficiency finance. A preliminary test of the approach – using a small sample size and limited energy conservation measures (ECMs) – was conducted at the end of last year as well. Finally, the first-year research effort concluded with a range of recommended actions for the next installment of the investigation.

This Second-Year Report draws from the findings of the first year – where extensive consideration and examination of the extant literature was included and initial model application was performed – in order to conduct a practical assessment of investor risk mitigation in energy efficiency retrofit projects using automated monitoring and verification (M&V) techniques. Particular emphasis is directed towards the modeling effort conducted so far and application of several of the recommendations of the first-year final report. This report details the work conducted over the September 2017 – May 2018 time period. Research results of the project so far indicate interesting risk mitigation opportunities using automated M&V techniques. The report closes with several recommendations for the 2018-2019 research project.

The context of the modeling approach is assumed to be a proposed energy efficiency project using guaranteed energy savings agreements (GESAs). Within such an agreement, an ESCO guarantees a level of savings in order to underwrite the overall project. However, to incorporate possible performance variation due to behavioral, technological and other dynamics, the ESCO is typically only comfortable with a conservative guarantee. Literature review in the 2016-2017 final report and additional literature evaluated in this report supports this assertion. As such, it is feasible that additional technology components capable of assuring a higher level of performance could help accelerate the energy efficiency sector. As postulated in the 2016-2017 final report, automated M&V could fulfil such a role as advanced data gathering and analytics could potentially mitigate some or all of the technological or behavioral variation. This dynamic is illustrated in ES Figure 1, using hypothetical data.



ES Figure 1. Theoretical benefit of automated M&V in combination with ESCO Guarantee mechanism.

In ES Figure 1, the red distribution is the performance profile that could occur during operation of an energy efficiency project due to technological, behavioral, and meteorological variation. ESCOs could consider a portion of this performance profile sufficiently unlikely to offer a guarantee against that performance risk. The green line, meanwhile, represents the performance profile that could occur during operation of an energy efficiency project that has automated M&V controls installed – performance risk is reduced due to higher control on operation. Looking at this new curve, the ESCO could consider a higher guarantee, thus making the project more attractive to all parties involved. The benefit of a higher guarantee can be positioned against the additional investment cost of the automated M&V controls.

To model this effect, we take a series of steps:

- **Step 1: Model benchmark energy use and costs of several building types:** A hypothetical energy efficiency project is created using benchmark buildings from the U.S. Department of Energy. We model six benchmark building types: small, medium, and large office, primary and secondary school, and hospital. Using DOE software application EnergyPlus, we model the energy use and associated cost of the pre-retrofit building.
- **Step 2: Model 'riskless' energy performance of retrofit:** A next step in the modeling effort is to determine the level of savings obtained from an energy efficiency project that would work exactly according to specification. This case represents what technology upgrade could achieve if operated as determined prior to

allowing for behavioral, meteorological, and other influences that could limit performance. In effect, this level represents what could be seen as an "engineering estimate", conducted along energy efficiency project guidelines.

- **Step 3: Model performance downgrade:** the assumption of riskless performance is doubted by investors and ESCOs. ESCOs typically lower their guarantee below the engineering estimate accompanying equipment specification in order to insulate themselves from the risk of possible variation. The literature review in this report and the 2016-2017 final report discusses empirical evidence of this non-zero risk. To model the risk here, we use a 15% performance downgrade of the operation of the equipment.
- **Step 4: Model performance variation with and without automated M&V technology in place:** The energy efficiency retrofit project could choose to have some or all of its ECMs use automated M&V technology to rein in performance variation. We assume automated M&V eliminates the performance variation in its entirety (i.e., the equipment operates in accordance with the specified parameters when controlled with automated M&V technology components). However, the installation of these components comes at an additional cost.

In this Executive Summary, we outline one hypothetical energy efficiency project for consideration. The project summary provided below is for a hypothetical medium-sized benchmark office building located in Delaware. Step 1 refers to data collection and control, which is excluded from the summary below but provided in the main body of the report.

Step 2: The 'riskless' performance summary for a medium-sized benchmark office building is reported in ES Table 1. At pre-retrofit conditions, this medium-sized benchmark building has an annual utility bill of $125,683. A hypothetical retrofit audit of the building shows options for lighting and plug load upgrade. A $166,000 investment can upgrade the lighting level to an engineering estimate performance level of 6.46 W/m2 while a $31,272 investment can improve plug load performance to 8.07 W/m2.

ES Table 1. Overview of ECMs performance, cost, and savings profile for a medium-size benchmark office when performance is assumed to be riskless.

ECM	Pre-Retrofit Efficiency	Retrofit Cost	Post-Retrofit Efficiency Value	% Reduction	Upfront Capital Investment ($)	Savings / year	Simple Payback (years)
1 - Lighting	16.89 W/m^2	33.32 $\$/m^2$	6.46 W/m^2	~62%	$166,000	$23,949	6.9
2 – Plug Loads	10.76 W/m^2	6.28 $\$/m^2$	8.07 W/m^2	25%	$31,272	$9,446	3.3
3 - Combined ECMs Project	NA	NA	NA	NA	$197,272	$32,975	6.0

Note: Data crosschecked with ESCO industry professional to ensure accuracy. Future installments of research outputs will further improve accuracy by means of interacting with multiple technology providers. Calculation results shown here are for each ECM when modeled independently of each other in rows 1 and 2 while modeled in combined operation for row 3. Savings per year are calculated for an electricity price of 12.41 cents/kWh and a natural gas price of 1.208 dollars per therm, as per Energy Information Administration (EIA) data.

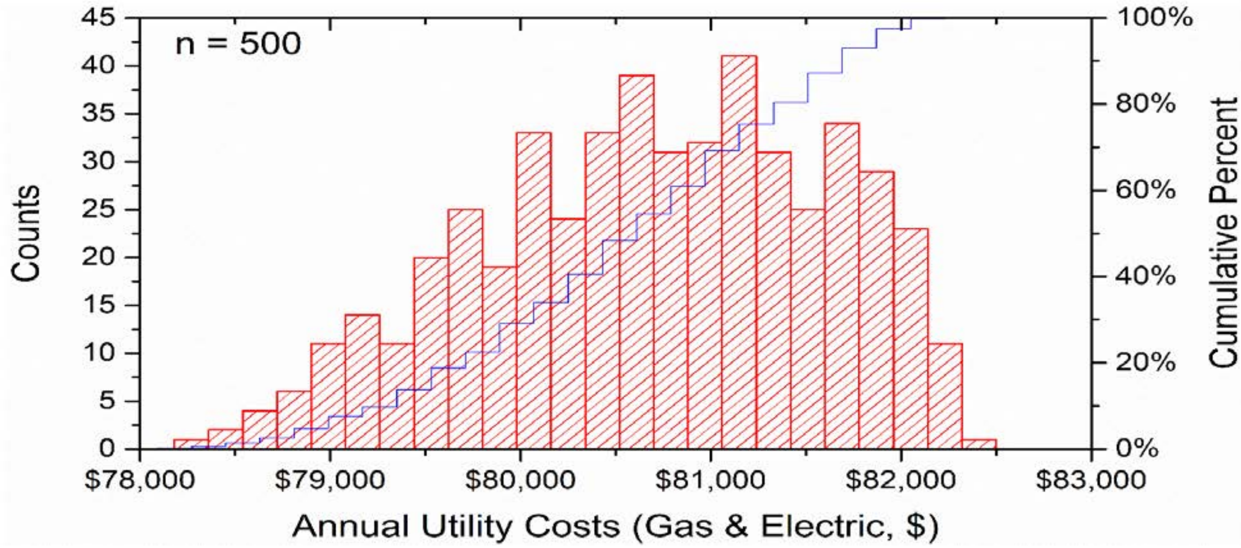
Step 3: Next, the operation of each ECM independently at a level 15% below the "engineering estimate" is calculated. Accordingly, ES Table 2 shows the performance level for ECM 1 – Lighting when operated at an efficiency of 7.43 W/m2 (15% below the 6.46 W/m2) and for ECM 2 – Plug Loads at 9.28 W/m2. Such a project overview yields lower annual savings for the same cost and, as such, has a simple payback period that is longer than illustrated above. This result represents the case where an ESCO is assumed to be comfortable guaranteeing performance – the vertical red ESCO guarantee line in ES Figure 1.

ES Table 2. Overview of ECMs performance, cost, and savings profile for a medium-sized benchmark building located in Delaware. The Table shows the performance level at a 15% downgrade.

ECM	Pre-Retrofit Efficiency	Retrofit Cost	Post-Retrofit Efficiency Value (15% downgrade)	% Reduction	Upfront Capital Investment ($)	Savings / year	Simple Payback (years)
1 - Lighting	16.89 W/m^2	33.32 $/m^2	7.43 W/m^2	~56%	$166,000	$21,763	7.6
2 – Plug Loads	10.76 W/m^2	6.28 $/m^2	9.28 W/m^2	~14%	$31,272	$5,223	6.0
3 – Combined ECMs Project	NA	NA	NA	NA	$197,272	$26,763	7.4

Note: Data crosschecked with an ESCO industry professional to ensure accuracy. Future installments of research outputs will further improve accuracy by means of interacting with multiple technology providers. Calculation results shown here are for each ECM when modeled independently of each other in rows 1 and 2 while modeled in combined operation for row 3. Savings per year are calculated for an electricity price of 12.41 cents/kWh and a natural gas price of 1.208 dollars per therm.

If no automated M&V controls are implemented, it is possible that performance is closer to specification than the established ESCO guarantee. In other words, actual realized savings could be higher than the guarantee – we estimate the possible performance range of the energy efficiency project for the medium-sized benchmark building as illustrated in ES Figure 2 below. Using the triangular distribution of performance variation reveals that higher levels of performance are available if strategies to mitigate behavioral, technological, and other risk factors are put in place. The difference between ES Table 1 and ES Table 2, along the probability distribution illustrated in ES Figure 2 represents the opportunity for automated M&V to accelerate the energy efficiency sector. We assume here that full implementation of automated M&V technology yields the upper value of energy savings – the maximum distance between the ESCO guarantee and specification.



ES Figure 2. Variation in annual utility costs due to assumed post-retrofit performance variation for both lighting and plug loads.

Step 4: ES Table 2 can be amended to yield a new profile for the energy efficiency project where automated M&V controls are installed to avoid expected performance variation (see ES Table 3). The additional cost of the automated M&V technology is partially mitigated by the higher guarantee of savings. In particular, the results provided in ES Table 3 below shows that the additional savings per year from plug load controls lowers the overall simple payback from 6 years to 5.7 years. The additional cost for lighting controls, as modelled here, appears to extend the payback period from 7.6 years to 8.4 years. Whether the additional cost is worthwhile depends on assumptions of project lifetime and other financial parameters.

ES Table 3. Overview of automated M&V contribution and specifics.

ECM	**Old ESCO Guarantee (ES Table 2)**		**Automated M&V Application**			**New ESCO Guarantee**	
	Savings / year	Simple Payback (years)	Automated M&V Cost ($)	Performance Level with Automated M&V	Capital Investment with Controls ($)	Savings / year	Simple Payback (years)
1 - Lighting	$21,763	7.6	$35,297	6.46 W/m²	$201,298	$23,949	8.4
2 – Plug Loads	$5,223	6.0	$22,369	8.07 W/m²	$53,641	$9,446	5.7
3 – Combined ECMs Project	$26,763	7.4	$57,667	NA	254,939	$32,975	7.7

Note: Data crosschecked with an ESCO industry professional to ensure accuracy. Future installments of research outputs will further improve accuracy by means of interacting with multiple technology providers.

When combined together, the overall payback period is only slightly longer than under old ESCO guarantee conditions (7.7 years instead of 7.4 years). The additional $6,212 in savings each year plus the other benefits that accompany installation of automated M&V could weigh up against the slightly longer payback period from the client's, ESCO, and investor perspective. For instance, from the client's perspective, the controls enable direct insight into performance and direct evaluation of deviation – the data essentially provides the client with extra capability to ensure the guarantee is met and to challenge the ESCO if necessary. The ESCO can promise a higher annual guaranteed level of savings and, as such, perhaps attract additional clients. Finally, the investor experiences a higher level in certainty of operations and, depending on assumptions of project lifetime and other financial parameters, perhaps a higher rate of return.

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1.0. Introduction

Present-day energy consumption patterns could be significantly reduced through the use of energy efficiency strategies (e.g. Backlund, Thollander, Palm, & Ottosson, 2012). The size of the United States energy savings potential has been estimated at a significant 23% reduction opportunity by 2020 – equal to $1.2 trillion in energy savings (e.g. Granade et al., 2009). For comparison, estimates by the U.S. Energy Information Administration (EIA) suggest a total energy consumption of 106 quadrillion BTU by 2050, up from a current (2016) 96.5 quadrillion BTU (EIA, 2017). A particular target for energy efficiency retrofits is the built environment: buildings account for about 32% of total global final energy use and 19% of energy-related greenhouse gas emissions (Lucon et al., 2014). While almost 80% of 2005 energy use in buildings globally faces lock-in risk if no new energy efficiency strategies are applied, implementation of state-of-the-art energy efficiency measures in the built environment can significantly reduce energy use: modeling efforts show North American energy use reduction potential of 75%, Western European conservation possibilities of 72%, and Centrally Planned Asia and China energy use could be reduced by as much as 54% compared to a business as usual pathway (Ürge-Vorsatz et al., 2012).

However, insufficient capital deployment for energy efficiency and conservation continues (Parker & Guthrie, 2016). While a series of challenges exist for the energy efficiency sector, a repeated criticism of energy efficiency retrofit projects is the neglect of substantive consideration of risk management techniques such as quantitative uncertainty analysis (QUA) or quantitative risk analysis (QRA) (Heo, Augenbroe, & Choudhary, 2013; Mathew, Koehling, & Kumar, 2006; Reddy, Maor, & Panjapornpon, 2007; Walter, Price, & Sohn, 2014). Indeed, a series of expert interviews revealed that it is "common" in the energy efficiency industry to neglect uncertainties in the savings calculation (Kim, Anderson, & Haberl, 2016). [1]

It is important to note that, in the context of raising capital investment for energy efficiency projects, uncertainty can be debilitating to private investors. For instance, the Energy Efficiency Financial Institutions Group (EEFIG) emphasized that "uncertainty is treated very differently from risk by financial institutions who consider themselves consummate risk managers but whose credit committees are usually highly "uncertainty averse". The result is a lack of appetite for energy efficiency investments, low motivation for new entrants to offer energy efficiency finance and increased financing costs (to overly compensate for the unknowns)" (Energy Efficiency Financial Institutions Group, 2015, p.

[1] The study by Kim et al. does not provide an indication of the magnitude or frequency of this neglect.

69). A strategic shift from uncertainty to risk management is needed as a *conditio sine qua non* for the investment community is reasonable assurance of energy efficiency performance and financeability.

Implementation of guaranteed energy savings agreements (GESAs) addresses this issue. Indeed, according to Goldman et al., the ESCO market has shifted and now predominantly uses guaranteed savings in energy performance contracting (EPC) projects (Goldman et al. 2005). Under a GESA-based approach, the ESCO guarantees a level of performance of the new equipment. This guarantee is intended to satisfy both the investor and the project host (e.g. the building owner) by limiting exposure to (external) risks. The guarantee, in other words, is the key component in EPC contracts where capital works upgrades are covered by future cash flow. However, the approach depends on the level of performance the ESCO is willing to guarantee.

The ESCO, as such, is faced with a key choice: on the one hand, conservative guarantees align with the ESCO's risk averse character but, on the other hand, high-energy savings guarantees can get more favorable financing rates or convince the client to engage in the contract (Deng et al. 2015). In other words, a higher guarantee attracts more investment and convinces more clients to collaborate with the ESCO but, at the same time, can expose the ESCO to too much risk – failure to deliver a level of performance in line with the guarantee can have serious consequences for the ESCO.

As such, typically, a guarantee level appears to be set lower than the expected actual performance of the equipment. This is supported by empirical evidence. For instance, analysis results of a Oak Ridge National Laboratory database found that, in aggregate, the 102 projects in the database saw savings 8% higher than the cost saving guarantee (Shonder & Hughes, 2007). Similarly, an analysis by Hopper et al. found greater savings than the guarantee in 72% of the cases evaluated from their NAESCO/LBNL database (Hopper et al. 2005).

Critically, any performance above the guarantee benefits only the client: agreement on debt service payments, interest rates, etc. is based on the ESCO guarantee. The investor, as such, yields no additional benefit from performance levels beyond those stipulated in the original contracts and installment payment agreements. To accelerate investment in the sector, therefore, pathways that allow for a guarantee of higher performance by reducing risk exposure are needed. As outlined in the previous 2016-2017 report, automated M&V technology components offer to fulfill this function: automated and sophisticated technology control of the energy system of a building could reduce exposure to behavioral, technological, meteorological and other risks and enable the ESCO to submit a higher guarantee. The higher guarantee, in turn, convinces more clients to participate in energy efficiency projects and, importantly, attracts higher levels of investment.

A conceptual and modeling approach is developed and applied throughout this report in order to quantify investor risk mitigation in relation to building energy performance uncertainty in energy efficiency retrofit projects. The methodological approach makes use of EnergyPlus (an existing whole building energy simulation program sponsored by the U.S. Department of Energy), a Monte Carlo assessment approach to quantify probability distributions of both savings and costs for a selection of energy conservation measures (ECMs). Risk reduction effects provided by the use of automated M&V techniques is then quantified to determine risk mitigation recommendations for use in the energy efficiency retrofit industry. The analysis described in the following sections suggests automated M&V provide suitable risk mitigation options and could be integral in enabling and accelerating the energy efficiency retrofit investment decision-making process in particular and the energy efficiency sector in general.

This report first establishes the characteristics of an emerging suite of automated M&V techniques (Section 1). Next, the methodological approach is described in detail (Section 2). Results are provided in Section 3 while a discussion of the findings is central to section 4. Section 5 of the report concludes the report.

2.0. Emergence of Automated Monitoring and Verification (M&V)

The use of advanced data gathering and analysis methods can streamline and automate monitoring and verification efforts - so-called "automated M&V" (also referred to in the extant literature as "intelligent efficiency" or "M&V 2.0" – and provide a potential means to reduce investor uncertainty and risk (Franconi et al., 2017; Granderson, 2013; Lin, Singla, & Granderson, 2017). Shaped by rapid advancements in two general fields (data analytics and improved data collection), new software and hardware capabilities could establish a new paradigm of real-time and comprehensive measurement and control regarding energy use profiles throughout the built environment (Franconi et al., 2017; Goldberg et al., 2015).

The paradigm, in general terms, relies on enhancements in computing power, speed, and communications, to automatically measure *and* control the performance of a variety of devices and equipment at all levels of use (device-level, sub-meter level, whole-building level, community-level) in real-time (Granderson, Piette, Ghatikar, & Price, 2009; Granderson, Lin, & Mary, 2013; Rogers, Carley, Deo, & Grossberg, 2015). For example, a whole-building application of the automated M&V techniques – commonly called an "energy management information system" – can measure and control a wide variety of functions such as lighting, heating, cooling, and plug load use (e.g. computers, vending machines) and even non-energy functions such as security control. Broadly, these types of systems can be defined as "web-based analysis software, data acquisition hardware, and communication systems used to store, analyze, and display whole-building, system-level, or equipment-level energy use" (Granderson & Lin, 2016). At minimum, these systems provide hourly interval meter data with graphical and analytical capabilities for assessment and response (Granderson & Lin, 2016).

Much of this paradigm is already being rolled out. For example, over 30 electric companies in the U.S. are now at 100% deployment of "smart meters" (an essential hardware component of the new paradigm and often supported by intelligent software) as they have replaced old infrastructure (Cooper, 2016). Further growth of the paradigm will occur: the market is projected to grow rapidly from a 2015 level of 64.7 million installed smart meters in the United States to 90 million smart meters by 2020 (Cooper, 2016). At a strategic level, however, the use of automated monitoring and verification is currently still in the "pilot stage" (Goldberg et al., 2015). These pilots currently occur mostly in commercial and industrial facilities with a high energy use throughput (Franconi et al., 2017). However, automated M&V is not limited in terms of sectoral application, particularly when relying on the storage capacity and computational speed of the cloud: "cloud computing platform[s] for real-time energy performance M&V is applicable to any industry and energy conservation measure. With the M&V cloud platform, real-time and long-term energy performances can be obtained" (Ke, Yeh, & Su, 2017).

The pilot stage can further be characterized as one of targeting and opportunity identification – i.e. seeking out energy efficiency retrofit opportunities among the building stock (Goldberg et al., 2015; Lin et al., 2017). Importantly, such efforts *enable* savings through identification of suitable retrofit candidates but their application for *quantifying* savings in post-retrofit conditions is currently limited. It is this stage where this research effort directs its attention – the research is less focused on determining the better investment opportunity among a variety of candidate buildings and more focused on characterizing and enhancing the investment opportunity of a particular building by quantifying its energy savings profile and risk. To explore this further, it is first necessary to discuss the category of automated M&V technologies in more detail. A portion of this work was done in the 2016-2017 research effort which is briefly summarized below. In addition, we rely on work done in this field by researcher teams from the Lawrence Berkeley National Laboratory (LBNL) as they have established a foundation of knowledge in this field (Franconi et al., 2017; Granderson et al., 2009; Granderson, Piette, & Ghatikar, 2011; Granderson et al., 2013; Granderson, 2013; Granderson et al., 2015; Granderson, Price, Jump, Addy, & Sohn, 2015; Granderson et al., 2016; Granderson & Lin, 2016; Granderson, Touzani, Fernandes, & Taylor, 2017; Lin et al., 2017).

2.1. Automated M&V Costs

A continuing problem in automated M&V research is the broad range of cost estimates of the technology (California Energy Commission, 2002; Granderson & Lin, 2016). A key reason for this broad range is the very wide scope of technological capabilities, software specifics, hardware options, and market deployment strategies. Overall, automated M&V market is relatively immature – much of the research estimates still rely on pilots, experimental designs, and short histories of data. In their attempt to quantify the cost for whole-building energy efficiency management systems, Granderson & Lin (2016) provide an example of this broad range:

- Upfront costs ranging from $1,700 to $300,000. In normalized terms, this cost range is equivalent to 0.08 cents/square ft to 77 cents/square ft.
- Annual ongoing costs ranging from $1,000 to $140,000, equivalent to 0.04 cents/square foot to 15 cents/square foot.

- A 5-year cost of ownership from $31,000 to $790,000 or 2 cents per square foot to $1.1 per square foot.
- Median values for upfront costs, annual costs, and 5-year ownership costs were 1 cent, 1 cent, and 6 cents per square foot, respectively.

Business model evaluation of the energy information systems in use today found that the most common application is a so-called "software-as-a-service" (SaaS) offering (Granderson & Lin, 2016). This model focuses on the delivery of automated M&V on a subscription-type basis (as opposed to actual procurement and ownership of the software or hardware by the customer). Payment of SaaS offerings is typically done through an up-front expenditure (for, among others, licensing and system configuration) and a recurring monthly or yearly subscription fee (Granderson & Lin, 2016).

2.2. Automated M&V Savings

Estimates of cost savings due to the use of automated M&V are scarce as well. Granderson & Lin (2016) report energy savings ranging from -3% to 47% with a median of 17% for individual buildings. For portfolios of buildings, savings ranged from 0% to 33% with a median of 8%. In terms of cost savings, Granderson & Lin (2016) found a range from $0 to $1.5 per square foot (median: $0.4/sq. ft.) for individual buildings and $0 to $0.9 per square foot for a portfolio of buildings (median: $0.4/sq. ft.). However, indicative of the immaturity of the market, many of the automated M&V applications in Granderson & Lin's (2016) sample only had one or two years of post-installation data. Additionally, the contribution of the automated M&V application of the energy information system can't be separated from other energy efficiency activities performed at the locations sampled. A final point in consideration is that the sample cases differ in their original energy use intensity – a factor directly related to how much energy you can save is how much was originally being used. Nevertheless, Granderson & Lin (2016) report a high level of satisfaction among the users of energy information systems in their sample: 19 out of 21 cases reported they positioned the energy information system as critical in achieving their energy savings.

Other benefits also accompany the installation of automated M&V technology. For instance, automated M&V requires substantially fewer measurements in order to calculate models that demonstrate a high goodness-of-fit (Walter et al. 2014). As noted by Granderson et al. (2017), "common practice in the industry for whole-building M&V is to use 12 months of data for both the pre- and post-periods, however, this may be an artifact of historically having access exclusively to monthly whole-building data". Automated

M&V allows for shorter periods of analysis due to the speed and data volume provided by advanced data analytic capability.

Additionally, reductions in the time lag between installation and performance evaluation can improve project goal achievement (Franconi et al., 2017) and customer satisfaction. For instance, Goldberg et al. (2015) note how automated analysis of energy consumption patterns and data could begin providing useful feedback within one month of measure installation.

The use of automated M&V furthermore has the promise of reducing labor time (and, as such, costs). A study by Granderson et al. (2017) estimated time requirements for automated M&V compared to conventional M&V processes and found needed labor time to conduct automated M&V at around 1 day for various processes, down from an original 4-6 days.

Other possible benefits of this new method include:

- **Portfolio level analysis and benchmarking:** the automated and high-speed character of automated M&V allows for simultaneous analysis of large volumes of data in a standardized manner. As such, automated M&V opens up the opportunity of conducting M&V at the portfolio-level: analyzing many buildings with various degrees of retrofitting at the same time to draw useful conclusions about each individual building and the pool as a whole. This is a particularly useful attribute of automated M&V when considering large-scale financing of energy efficiency which typically includes many different buildings, building types, weather conditions, etc.
- **Anomaly and fault detection and timely identification of energy waste:** automated energy anomaly detection using algorithmic baseline consumption models enable continues performance assessment (Haves, Wray, Jump, Veronica, & Farley, 2013).
- **Database building:** the widespread use of advanced data collection tools and data analytics could improve existing databases on energy efficiency performance. The advanced nature of the data could, for instance, show why performance profiles differ for the same technology but under different conditions. An assessment of energy efficiency finance limitations, for instance, explicitly notes how current limitations in data availability, quality, and access restrict investment in the sector (Energy Efficiency Financial Institutions Group, 2015; Parker & Guthrie, 2016).
- **Standardization and transparency:** the availability of data could prompt standardization and certification efforts. In addition, automated M&V offers a

substantial opportunity for two-way data provision and analysis where developer and client have same-level access and understanding of the building's energy conditions. Through interface options such as online dashboards, clients could have direct insight into not only the functioning of their property but also into the savings profile (and potential shortfalls in that profile). As Goldberg et al. (2015, p. 60) note: "the majority of vendors of automated M&V tools have stated that they will provide full transparency of the equations, and the process of constructing a comparison group where relevant".

- **Cost-effectiveness:** automated M&V at scale with large speed and provision could represent a cost-effective pathway to rigorous and long-term M&V at potentially lower prices than conventional advanced M&V options.
- **Automatic conversion of energy consumption data into monetary information:** automated M&V can include real-time utility tariff information to explicitly show the cost of energy used and saved. Provides a motivational stimulus to users (Granderson & Lin, 2016) but also investors as the system can communicate tangible dollar values of energy savings or energy waste.
- **Utility billing validation:** automated M&V systems validate utility bills through, for instance not only continuous monitoring of peak load but also management of peak load consumption timing and scale to address demand charges. Additionally, streamlining of utility-related processes can minimize personnel requirements and can assist identification of metering or billing errors by automatically crosschecking consumption patterns with utility bills.
- **Automatic sustainability reporting:** automatic conversion of energy use data into dimensions and metrics required to meet corporate or organizational sustainability reporting standards.

2.3. Accuracy of Automated M&V

Insight into the accuracy can be obtained by investigating the use of interval data (hourly or sub-hourly) to determine whether the amount of data reduces model error. Analysis of this kind shows that model accuracy improves with additional data but also shows that a saturation effect occurs after which point model error (on a building-by-building basis) no longer improves (Walter et al. 2014). In other words, model error information gained from analysis on only one or a few months can help predict model error across using years of data (Walter et al. 2014). [2] The analysis method used by Walter et al. (2014)

[2] Walter et al. (2014) carefully note that this finding can not necessarily be extrapolated to other models than the one they used or to other buildings than the ones in their data set. Nevertheless, the finding

further allows for a determination of how much data is needed for specific intended M&V applications – different applications come with different guidance on accuracy requirements some of which can be met using interval data from very short timeframes.

Other analysis similarly shows how the current industry standard of using 12 months pre- and post-retrofit data can be reduced to at least 9 months both before and after project implementation when using hourly model training data (Granderson et al. 2015; Granderson et al. 2015; Granderson et al. 2016). For instance, across a dataset of 537 geographically diverse commercial buildings, Granderson et al. (2016) show that automated M&V models "hold great promise for scaling the adoption of building measured savings calculations using Advanced Metering Infrastructure (AMI)" as, even with only six months of hourly data to train the model, all models realized a predictive accuracy in line with accepted protocol guidelines. A similar investigation showed that model training using six months of interval data was "just as accurate as those based on a 12-month baseline period" (Granderson et al. 2015).

Testing models available in the public domain, Granderson et al. (2015) showed that fully automated prediction of energy consumption use in a future period – in other words, no re-calibration or adjustment by an engineer – demonstrated median model error of under 5% and mean errors of less than 9%. Semi-automated prediction of energy use, allowing for instance for pre-screening of buildings that are not particularly predictable or other measures that an engineer could deploy, could further improve the predictive accuracy of these models. Similarly, testing ten different models with varying levels of complexity and computational efficiency resulted in a qualitative statement that three models had "medium" accuracy while the remaining seven were seen as "high" accuracy (Granderson et al. 2016). Particularly when applying automated M&V on a population basis, so referring to a portfolio of buildings, predictive modeling of consumption patterns using automated M&V models yields the conclusion that these models are "compellingly accurate" (Granderson et al. 2017). Aggregation of savings in a building data sample "resulted in a decrease in the uncertainty, with the aggregated value falling below that of the best 10th percentile of the individual buildings" (Granderson et al. 2017).

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provides an important insight: interval data could potentially reduce required timeframes to months instead of the current industry standard of 12 months.

3.0. Modeling Method to Determine Investor Risk Mitigation Contribution from Automated M&V

To establish a conceptual and modeling approach for investor risk mitigation using automated M&V techniques, a methodological approach was developed that makes use of several key building blocks:

- A building energy simulation software package, relying primarily on the Department of Energy's EnergyPlus simulation tool;
- A Monte Carlo assessment framework to determine risk profiles;
- A cloud computing setup to enable large-scale analysis and simulation; and
- A conceptual understanding of risk in energy efficiency projects.

3.1. Building Energy Simulation Software

Detailed building energy simulation tools provide capability to assess building ECM configurations. The use of such software is common in the energy efficiency industry (Kim et al., 2016). A leading software option is the Department of Energy's (DOE) EnergyPlus simulation tool, which works off of DOE-2 algorithms (Fumo, 2014; Heo, Choudhary, & Augenbroe, 2012). EnergyPlus uses text input and output that can be integrated into an automated workflow, relies on first principles, is non-proprietary, is highly configurable, and avoids inaccuracies (Hygh, DeCarolis, Hill, & Ranji Ranjithan, 2012). In addition, EnergyPlus provides a range of benchmark building models, improving ease of use (Deru, Griffith, & Torcellini, 2006). Indeed, the DOE building benchmark database represents "one of the largest" databases as it encompasses benchmark buildings for 16 building types across 16 locations and three construction periods (Corgnati, Fabrizio, Filippi, & Monetti, 2013). For the research conducted in this investigation, we used EnergyPlus Version 8.7.0

3.2. Monte Carlo Assessment framework

Another key component of the modeling approach used here is the introduction of probabilistic change in variables in order to capture any potential uncertainty in the estimates. To run the parametric evaluation of the uniform distributions, the sets of data were automatically incorporated into EnergyPlus using jEPlus, an open-source parametric analysis tool specifically designed for EnergyPlus simulations (Y. Zhang & Korolija, 2010). The jEPlus software provides flexible and structural parametric analysis opportunities and smooth operations (Park, Norrefeldt, Stratbuecker, Grün, & Jang, 2013) and has been used in similar investigations to determine sensitivity or optimize energy systems (Lee, Lam, Lee, & Chan, 2016; Ramos Ruiz & Fernández Bandera, 2017; Singh, Lazarus, & Kishore, 2016; B. Zhang, Liu, Rai, & Krovi, 2016). For the research conducted in this investigation, we used jEPlus Version 1.7.0.

The parametric approach enables Monte Carlo analysis for risk estimation and management. Various forms of this method have been applied in similar investigations for instance in determining risk profiles of renewable energy projects, system planning, or system optimization (Arnold & Yildiz, 2015; Byrne, Taminiau, Kim, Seo, & Lee, 2016; Byrne, Taminiau, Kim, Lee, & Seo, 2017; Gurgur & Jones, 2010; Momen, Shirinbakhsh, Baniassadi, & Behbahani-nia, 2016; Pereira, Edinaldo José da Silva, Pinho, Galhardo, & Macêdo, 2014). Various authors have pushed for application of the approach for energy efficiency projects in general and M&V efforts specifically (e.g. Jackson, 2010).

3.3. Cloud computing for large-scale analysis

The parametric simulation of the whole building commonly requires the evaluation of many scenarios, each with their own configuration of the variables. The jEPlus software introduced above enables the analysis of a large number of scenarios. However, such simulation is accompanied by a large computing demand and a high simulation time barrier. The use of "cloud computing" (using remote computational power to run the simulations) significantly reduces the total simulation time as it can efficiently allocate simulations to multiple processor cores. Examples of the use of cloud computing for similar purposes as outlined in this article are available in the literature (e.g. Lee, Lam, Yik, & Chan, 2013; Zhang et al. 2016).

To run the simulations in this investigation, we relied on Amazon Web Services (AWS) computing stations to perform the analysis. The "instance" (AWS jargon for the remote computer) used here was a Windows 2016, 8 vCPU, 32 GiB memory general purpose system. For the research reported in this report, we simulated two Energy Conservation Measures (ECMs) across 4 different scenarios. A full simulation was run for each hour of the year for each case in the building energy model. Next outputs of the research effort will include additional building types and additional ECMs.

3.4. Modeling Risk and Uncertainty in Energy Efficiency Retrofit Cases

The ECMs were modeled under different scenarios for a benchmarked pre-1980 large office building, as defined by EnergyPlus. [3] Three scenarios are tested:

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[3] The EnergyPlus database maintains several benchmark reference building models for a variety of building types, regions, and construction time periods. Regarding time periods, EnergyPlus separates benchmark models across pre-1980, post-1980, and new construction. We use the pre-1980 benchmark building model here to illustrate the

- *Riskless Scenario:* operation of ECMs is modeled according to equipment specifications without deviation in performance.
- *Performance Variation without Automated M&V Controls Scenario:* performance variation is introduced under this scenario by means of a 15% downgrade along a triangular distribution. No automated M&V controls are implemented to mitigate the performance variation. Only downside risk is tested.
- *Risk Mitigation with Automated M&V Controls Scenario:* Equipment performance variation is addressed by the additional installation of automated M&V technology components (hardware and software) leading to a full elimination of performance variation. The installation of automated M&V technology comes at an additional upfront cost.

The central idea behind the three scenarios is that any retrofit demonstrates a distribution of performance around the equipment specifications due to behavioral, technological, and meteorological dynamics. This variation introduces uncertainty in energy savings and thus, this modeling approach focuses towards narrowing down variation in retrofits through a combination of control mechanisms.

The Riskless Scenario involves modeling post-retrofit building operation with retrofit performance values in line with specifications for our our 2 defined ECMs:

- Lighting Power Density (LPD) ("ECM 1 – Lighting") and
- Plug Load Density ("ECM 2 – Plug Loads")

The Riskless Scenario fixes performance of the two ECMs and post-retrofit savings and costs are calculated against pre-retrofit operation. This modeling effort case can be seen as representative of a conventional calculation of future energy savings (e.g. Kim et al., 2016) or what can be called an "engineering estimate".

Next, using the jEPlus software platform, each of the ECMs was varied under a triangular distribution with a 15% downgrade in performance as the lower bound for 500 simulations. The result is a distribution of possible performance. The lowest level of performance is one where both ECMs operate 15% below specification. This, therefore, represents the maximum expected risk level and is assumed to be the level where an ESCO is comfortable providing an energy savings guarantee. This calculation represents

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energy savings potential of existing building stock that has been constructed according to outdated standards and guidelines for energy use – this section of the building stock represents an especially attractive target for the energy efficiency market due to their relatively high energy intensity. In addition, the large office space building type was selected for its general applicability – other categories provided by EnergyPlus are more specific (e.g. primary school, outpatient health care, quick service restaurant, etc.).

the second scenario: *Performance Variation without Automated M&V Controls Scenario.* Notably, under this scenario, no automated M&V controls are put in place under this scenario and only the downside risk (i.e. a 15% downgrade in performance) is tested – as accounted for by the literature review above and in the next section below, the investment community is interested in having a clear understanding of this downside risk profile. In other words, the *potential* upside of a risk distribution is not an effective argument to attract investment and, as such, is not included in the modeling effort.

Finally, a third scenario models the risk mitigation effect of using automated M&V controls on the ECMs. The scenario assumes that the combined application of automated M&V software and hardware is capable of enabling ECM performance in line with equipment specifications. In other words, at an additional investment cost, use of this new and advanced technology can fully eliminate the performance risk. Within this scenario, 4 different cases were constructed through a combination of controls on the two ECMs (see Table 4). These cases test the various selections of automated M&V controls available: a) the choice of no controls, b and c) the deployment of one control on either ECM, or d) the installation of controls on both ECMs. Using jEPlus modeling as described above, each of the four cases yields a performance profile with cost and savings against the pre-retrofit model.

3.5. Incorporating Investor Risk Considerations

Automated M&V application can substantially influence the risk profile of an energy efficiency project: as more variables are controlled with sophisticated technology and software, project risk decreases. This risk reduction effect of automated M&V is fairly straightforward – especially when considering our current modeling approach where the control succeeds fully at fixing the variable at its "engineering estimate" value. A follow-up analysis could document how the results differ when allowing for:

- instead of elimination of variability, a reduction in variability, or
- time dynamics throughout the lifetime of the project, and
- additional benefit arising from the use of automated M&V.

The risk reduction effect provides insight into possible investment options. In our modeling approach, full automated M&V control of both ECMs delivers an energy efficiency retrofit project directly in line with the Riskless Scenario estimate as both ECMs are fixed at their "engineering estimate" value. However, a second consideration is the cost of such an automated M&V scenario. Enhanced levels of risk reduction come at additional investment cost as automated M&V controls need to be purchased, installed, and operated. Using numbers derived from the literature and professionals in the ESCO industry, we assess how this cost profile changes under different automated M&V options.

Risk mitigation and additional cost can be squared away against each other to determine a selection. This selection would be motivated by the investor's willingness to accept a level of risk. Less risk will come with additional investment to install and operate the automated M&V technology components. However, less risk also increases the prospects for profitability.

3.6. Combined application of building blocks

The combined use of the building blocks represented above yields an energy modeling approach capable of estimating the risk profile around each individual ECM and their combined risk profile. This risk profile can then be compared against the costs.

The steps for this approach are the following:

- **Step 1: Model benchmark energy use and costs of several building types:** A hypothetical energy efficiency project is created using benchmark buildings from the U.S. Department of Energy. We model six benchmark building types: small, medium, and large office, primary and secondary school, and hospital. Using DOE software application EnergyPlus, we model the energy use and associated cost of the pre-retrofit building.
- **Step 2: Model 'riskless' energy performance of retrofit:** A next step in the modeling effort is to determine the level of savings obtained from an energy efficiency project that would work exactly according to specification. This case represents what technology upgrade could achieve if operated as determined prior to allowing for behavioral, meteorological, and other influences that could limit performance. In effect, this level represents what could be seen as an "engineering estimate", conducted along energy efficiency project guidelines.
- **Step 3: Model performance downgrade:** the assumption of riskless performance is doubted by investors and ESCOs. ESCOs typically lower their guarantee below the engineering estimate accompanying equipment specification in order to insulate themselves from the risk of possible variation. The literature review in this report and the 2016-2017 final report discusses empirical evidence of this non-zero risk. To model the risk here, we use a 15% performance downgrade of the operation of the equipment.
- **Step 4: Model performance variation with and without automated M&V technology in place:** The energy efficiency retrofit project could choose to have some or all of its ECMs use automated M&V technology to rein in performance

variation. We assume automated M&V eliminates the performance variation in its entirety (i.e., the equipment operates in accordance with the specified parameters when controlled with automated M&V technology components). However, the installation of these components comes at an additional cost.

4.0. Data Sources and Description

Several data inputs are necessary for the methodological approach outlined in the previous section:

- A hypothetical benchmark building;
- Use of a post-retrofit condition where a selection of variables are modified to a lower energy-using state;
- A listing of ECMs considered and their associated cost profile;
- Variability parameters for each ECM to determine the risk profile.
- A listing of automated M&V options and their associated cost profile.

4.1. Hypothetical benchmark building description

The prototypical benchmark building models provided by EnergyPlus are used throughout the analysis. Our analysis focuses on the small, medium, and large office buildings as well as on the primary and secondary school building types and a benchmark hospital. These six building types are evaluated according to the step-by-step process outlined above (for a full listing of benchmark commercial building models, see: https://energy.gov/eere/buildings/commercial-reference-buildings and Deru et al. (2011). Benchmark building version numbers were updated to version 8.8.0 using the in-built EnergyPlus utility. The hypothetical office building was assumed to be located in Baltimore, MD (the closest location to Delaware available in the database) and, as such, a corresponding typical meteorological weather (TMY) filetype 3 (TMY3) was used.

Table 1. Overview of the six benchmark pre-retrofit building models.

Dimension	Office by varying size			School type		Hospital
	Small	Medium	Large	Primary	Secondary	
Climate Region	*Baltimore, MD*					
Total gross floor area (sq. m)	*511*	*4,982*	*46,320*	*6,871*	*19,592*	*24,422*
# of floors	*1*	*3*	*12*	*1*	*2*	*5*
Aspect ratio	*1.5*	*1.5*	*1.5*			*1.31*
Window-to-wall ratio	*21.2%*	*33.0%*	*38.0%*	*35%*	*32.7%*	*14.6%*

4.2. ECMs considered and their associated cost profile

Drawing from the Building Component Library (BCL) operated by OpenStudio and from several articles using a similar methodological approach (Hygh et al. 2012; Lee et al. 2013; Lee et al. 2016), two energy conservation measures were selected. This selection will be expanded in the next phase of the research. The ECMs and their associated investment cost, taken from the Lawrence Berkeley National Laboratory (LBNL) City Building Energy Saver (CityBES) (https://citybes.lbl.gov/) – an online simulator and database for city-scale building retrofit analysis (Chen, Hong, & Piette, 2017; Hong, Chen, Lee, & Piette, 2016) – are provided in Table 2. The costs for light controls were referred from Whole Building Design Guide (WBDG), a program of the National Institute of Building Sciences (https://wbdg.org). Case studies from General Services Administration (GSA), U.S. Energy Information Administration (EIA), Madison Gas and Electric Company (MGE) were also used to derive information on control costs for other ECMs.

Note that the cost estimates provided here are preliminary numbers. We expect that crosschecking the source material with other findings will present a broader range of retrofit costs that can alter the results.

Table 2. Overview of ECMs considered in the analysis and their cost estimate. Pre- and post-retrofit values presented for the large office benchmark building

ECM	Pre-Retrofit Efficiency	Retrofit Cost	Post-Retrofit Efficiency Value	% Reduction
ECM 1 – Lighting	16.14 W/m^2	33.32 $\$/m^2$	6.46 W/m^2	60%
ECM 2 – Plug Loads	10.76 W/m^2	6.28 $\$/m^2$	8.07 W/m^2	25%

Note: cost data cross-checked with ESCO industry expert. Note also that the large office building has 46,320 square meters of floor space. This brings the installment cost to $1,425,266 for lighting, $290,751 for plug loads, and a total project cost of $1,716,017.

4.3. Post-retrofit model ("Riskless Scenario")

The post-retrofit model of the "large office" building modifies the pre-retrofit model based on the selection of ECMs listed above and their associated energy performance values. The post-retrofit model does not yet include the performance variability and, as such, can be seen as the "engineering estimate" of the performance of the energy efficiency retrofit project. This is the "Riskless Scenario" described above.

4.4. Variability parameters for the Monte Carlo Analysis

Essential in Monte Carlo analysis procedures is the variability assigned to each parameter. Data regarding performance uncertainty and variability, however, is limited. In general terms, two types of errors influence the uncertainty level in determining the energy savings from a project. First, systematic errors (also called bias) reflect the error term in a measurement or analytic method that systematically underestimates or overestimates a value. Second, random errors complicate energy savings assessment and require probability calculations to adjust the savings estimate. Due to their characteristics and relative ease of calculation, "uncertainty is typically calculated and reported through the objective analysis of random errors and the subjective analysis of systematic errors" (SEEAction, 2012).

4.4.1. Model Error or Bias

Common metrics to establish bias in modelling efforts are the monthly and annual Mean Bias Error (MBE, also called ERR) and Coefficient of Variation of the Root-Mean Squared Error (CV RMSE). [4] Guidelines on the acceptable error tolerance have been developed under several frameworks as provided in Table 3. For instance, ASHRAE 14 stipulates that CV $RMSE_{month}$ needs to be within 15% of the use of monthly utility data for a model to be considered 'calibrated' (Coakley, Raftery, & Keane, 2014). Such an approach produces a deterministically calibrated baseline model and can be seen as "optimistic" as several sources of uncertainty are ignored (Heo et al. 2013). Moreover, calibration uncertainty can stem not only from uncertainties associated with the inputs but also with the inaccuracy of the base model itself: "base models themselves often involve a certain level of inaccuracy as they are typically calibrated based on the final modeling outputs, which could be results of different inputs" (Bozorgi & Jones, 2014). Such inaccuracies of the base model are often ignored (Bozorgi & Jones, 2014. p. 418).

Additionally, establishing validity of energy savings through such error indicators for the project as a whole restricts risk management as the standard deviation of the savings estimate a) is not derived from a probabilistic distribution (due to propagating uncertainty throughout its calculation) and b) can't parse out uncertainties associated with individual ECMs (it establishes a uniform risk magnitude for all used retrofit options) (Heo et al. 2013). The approach also motivates the energy analyst to "tune" or "fudge" input parameters until base model error terms fall within acceptable limits (Coakley et al. 2014). Models with the lowest error, deemed 'calibrated' under the figures provided in Table 3 are as such not necessarily the ones with best or realistic performance profiles. [5]

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[4] Earlier efforts to determine the efficacy of building simulation relied on simple percent difference calculations. In 1995, Bou-Saada and Haberl suggested the adoption of standardized statistical indices which better represent the performance of a model (Bou-Saada & Haberl, 1995).

[5] One way to overcome this limitation is to use multiple base models (Bozorgi & Jones, 2014). The base model is the existing, pre-retrofit building model without installed ECMs. Such an approach is a first step into considering the uncertainties associated with energy simulation without requiring additional data inputs. In other words, variation in the data inputs to determine the baseline model provides a probability distribution of likely energy use in the counterfactual scenario that can be used to determine the overall savings level with a precision and distribution statement.

Table 3. Acceptable error tolerance for monthly data calibration in three recognized frameworks (Coakley et al. 2014)

Index	ASHRAE 14	IPMVP	FEMP
MBE (hourly)	+/- 10%	+/- 5%	+/- 10%
MBE (monthly)	+/- 5%	+/- 20%	+/- 5%
CV RMSE (hourly)	+/- 30%	+/- 20%	+/- 30%
CV (RMSE monthly)	+/- 15%	-	+/- 15%

4.4.2. Building Performance Gap

The literature further informs about potential performance uncertainty of energy efficiency projects (see first-year report of this three-year research). A detailed description of this performance uncertainty was provided in the final report of the 2016-2017 research effort. Here, key points are briefly reiterated. Discrepancies between predicted and actual metered building energy use have been found and, together, these discrepancies can be grouped under what has been called the 'performance gap' or 'credibility gap' (Bordass, 2004; Galvin, 2014; Karlsson, Rohdin, & Persson, 2007; Menezes, Cripps, Bouchlaghem, & Buswell, 2012; Sunikka-Blank & Galvin, 2012). For example, energy performance gap analysis for a set of buildings in the south of Germany found overestimates of energy savings by as much as 287% (Calì, Osterhage, Streblow, & Müller, 2016). In other words, some of the buildings in the study consumed almost three times more energy per year than expected.

As a first order approximation, we apply here a 15% performance downgrade in the performance range of the four ECMs to account for behavioral, technological, and environmental variability. The values of the two ECMs used in this investigation are given in Table 4.

Table 4. Overview of the inputs for the two ECMs to incorporate variability

ECM	Post-retrofit efficiency value	15% performance downgrade (triangular distribution)*
ECM 1 – Lighting	6.46 W/m2	7.43 W/m^2
ECM 2 – Plug Loads	8.07 W/m2	9.28 W/m^2

* Note: underperformance is measured in different ways across ECMs due to the difference in units. Lighting and plug loads, both in W/m^2, show underperformance when the value of performance is higher than the nominal value (i.e. a higher level of energy use per square meter).

4.5. Automated M&V Control Cost and Performance

To model the contribution of automated M&V to risk reduction, 4 cases were designed and are described in Table 5. Importantly, we include a chiller control option in all four cases – the analysis found that chiller replacement is cost prohibitive unless at end-of-life. As such, we only consider the chiller automated control option here. When a control is applied, the performance of the variable is fixed at its nominal value. In the table below, a value of 1 suggests that control has been applied to the variable whereas 0 indicates there is no control applied to the variable.

Table 5. Overview of 4 different cases constructed with automated M&V

Parameters	Case-0	Case-1	Case-2	Case-3
Lighting	0	1	0	1
Plug Loads	0	0	1	1
Chiller controls (large office building only)	1	1	1	1

The cost of the automated M&V intervention is established at the values provided in Table 6. Sources for the data represented in Table 6 are the LBNL CityBES project (Chen, Hong, & Piette, 2017; Hong, Chen, Lee, & Piette, 2016) and the Whole Building Design Guide (WBDG, a program of the National Institute of Building Sciences (https://wbdg.org)). Case studies from General Services Administration (GSA), U.S. Energy Information Administration (EIA), Madison Gas and Electric Company (MGE) were also used to derive information on control costs for the ECMs.

Table 5. Costs of Automated M&V controls for different ECMs. Chiller controls are only tested on the large office building benchmark.

Automated M&V control option	Cost profile	Source
Lighting controls	$7.09/m2	LBNL CityBES project and the Whole Building Design Guide
Plug load controls	$10.77/m2	
Chiller controls	410,724 for large office building	Crosscheck with ESCO industry expert averaged with case study analysis of real-world project

Note: Cost specifications cross-checked with ESCO industry expert.

5.0. Results

5.1. Results per building type

For each of the six building types, the analysis provide in the Executive Summary was conducted. Below, the results of the analysis are provided for each key step with the exclusion of step 1 (data gathering and evaluation).

Step 2: Determine the ‘riskless’ profile of the energy efficiency retrofit project.

As introduced in the Executive Summary and above, the ‘riskless’ scenario essentially represents performance according to specification. Table 6 documents the findings for each of the building types. The differences are minor due to the small selection of ECMs and across-the-board assumptions. Nevertheless, some differences in performance for each investment can be observed due to variations in starting conditions of the building and different equipment use profiles. In particular, the primary school and hospital have starting conditions and energy use profiles that appear to make them favorable candidates for the proposed energy efficiency retrofit project.

Note that for primary and secondary schools and for the hospital, we’re excluding portions of the building that are unlikely to fit the parameters of the proposed efficiency project. For example, the hospital building benchmark has operating rooms, emergency rooms, intensive care units (ICUs) and other very specific rooms that likely are not available for the type of retrofit in mind here. As such, these are excluded from the retrofit, reducing the total project upfront capital investment but also the level of possible savings.

One explanation for the much shorter payback periods for the hospital plug loads is the energy use profile of the hospital – relying on a continuous operating schedule. The primary school benchmark has computer rooms and other rooms with high plug load use levels that could benefit from the proposed retrofit.

Table 6. Overview of research results for each of the six building types under investigation when performance is assumed to be riskless.

Parameters		**Office Buildings**			**School Type**		**Hospital**
		Small	Medium	Large	Primary	Secondary	
Pre-retrofit efficiency (W/m2)	ECM 1	19.48	16.89	16.14	Various*		
	ECM 2	10.76			Various*		
Retrofit cost ($/m2)	ECM 1	$33.32					
	ECM 2	$6.28					
Post-retrofit efficiency (W/m2)	ECM 1	6.46					
	ECM 2	8.07					
Upfront capital investment ($)	ECM 1	$17,027	$166,000	$1,543,382	$179,262	$461,682	$544,354
	ECM 2	$3,208	$31,272	$290,751	$33,770	$86,974	$102,548
	Entire Project	$20,234	$197,272	$1,834,133	$213,032	$548,656	$646,902
Savings/Year ($)	ECM 1	$2,687	$23,949	$201,608	$43,548	$72,682	$132,779
	ECM 2	$817	$9,446	$77,577	$15,642	$10,343	$63,900
	Entire Project	$3,463	$32,975	$277,470	$58,842	$82,439	$190,192
Simple payback (years)	ECM 1	6.3	6.9	7.7	4.1	6.4	4.1
	ECM 2	3.9	3.3	3.7	2.2	8.4	1.6
	Entire Project	5.8	6.0	6.6	3.6	6.6	3.4

Savings per year are calculated for an electricity price of 12.41 cents/kWh and a natural gas price of 1.208 dollars per therm, as per Energy Information Administration (EIA) data.

* *Note: for the schools and hospitals, different rooms have different original energy use conditions. For schools, we only retrofit the following room types: classroom, corridor, offices, library, bathroom, and lobby. For hospital, we only retrofitted the following spaces: office rooms, lobby, corridor, patient waiting rooms, basement, and nurse rooms. We exclude, for instance, emergency rooms or intensive care units as these likely have specific lighting and plug load requirements.*

Step 3: Determine the performance downgrade

We assume here that the ESCO is comfortable agreeing to a performance guarantee that is 15% below specification. Effectively, this means that for the same investment, fewer savings are estimated to be attained. This is modeled for all six building types and reported in Table 7.

Table 7. Overview of six building type performance when a 15% downgrade is applied.

Parameters		**Office Buildings**			**School Type**		**Hospital***
		Small	Medium	Large	Primary*	Secondary*	
Post-retrofit efficiency (W/m2) (15% downgrade)	ECM 1	7.43					
	ECM 2	9.28					
Upfront capital investment ($)	ECM 1	$17,027	$166,000	$1,543,382	$179,262	$461,682	$544,354
	ECM 2	$3,208	$31,272	$290,751	$33,770	$86,974	$102,548
	Entire Project	$20,234	$197,272	$1,834,133	$213,032	$548,656	$646,902
Savings/Year ($)	ECM 1	$2,495	$21,763	$181,520	$30,286	$63,805	$122,632
	ECM 2	$452	$5,223	$42,713	$12,858	$9,305	$53,381
	Entire Project	$2,923	$26,763	$223,325	$53,057	$68,805	$171,033
Simple payback (years)	ECM 1	6.8	7.6	8.5	5.9	7.2	4.4
	ECM 2	7.1	6.0	6.8	2.6	9.3	1.9
	Entire Project	6.9	7.4	8.2	4.0	8.0	3.8

Savings per year are calculated for an electricity price of 12.41 cents/kWh and a natural gas price of 1.208 dollars per therm, as per Energy Information Administration (EIA) data.

** Note: for the schools and hospitals, different rooms have different original energy use conditions. For schools, we only retrofit the following room types: classroom, corridor, offices, library, bathroom, and lobby. For hospital, we only retrofitted the following spaces: office rooms, lobby, corridor, patient waiting rooms, basement, and nurse rooms. We exclude, for instance, emergency rooms or intensive care units as these likely have specific lighting and plug load requirements.*

Step 4: Determine savings with and without automated M&V

The final step in the analysis is to calculate the benefit of automated M&V (Table 8). As is reported in Table 8, under the assumptions listed throughout this report, automated M&V can reduce payback periods for plug loads in most circumstances. For lighting, we're using a fairly high cost for the controls and, as such, in most cases the payback period extends beyond the original ESCO guarantee. The primary school benchmark building appears to be an exception to this findings as it is able to generate sufficient additional savings to deliver an overall shorter payback period despite the additional cost for the investment.

Table 8. Overview of research results for each of the six building types under investigation when performance is assumed to be riskless.

Parameters			Office Buildings			School Type		Hospital*
			Small	Medium	Large	Primary*	Secondary*	
ESCO Guarantee	Savings / year	ECM 1	$2,495	$21,763	$181,520	$30,286	$63,805	$122,632
		ECM 2	$452	$5,223	$42,713	$12,858	$9,305	$53,381
		Entire Project	$2,923	$26,763	$223,325	$53,057	$68,805	$171,033
	Simple Payback (years)	ECM 1	6.8	7.6	8.5	5.9	7.2	4.4
		ECM 2	7.1	6.0	6.8	2.6	9.3	1.9
		Entire Project	6.9	7.4	8.2	4.0	8.0	3.8
Automated M&V application	Automated M&V Cost ($)	ECM 1	$3,620	$35,297	$328,177	$38,117	$98,170	$115,749
		ECM 2	$2,294	$22,369	$290,751	$24,156	$62,213	$73,354
		Entire Project	$5,915	$57,667	$536,154	$62,274	$160,383	$189,103
	Performance level with automated M&V (W/m2)	ECM 1	6.46					
		ECM 2	8.07					
	Capital investment with controls ($)	ECM 1	$20,647	$201,298	$1,753,444	$217,379	$559,852	$660,103
		ECM 2	$5,502	$53,641	$498,727	$57,926	$149,188	$175,902
		Entire Project	$26,149	254,939	$2,252,171	$275,305	$709,039	$836,005
New ESCO Guarantee	Savings/Year ($)	ECM 1	$2,687	$23,949	$201,608	$43,548	$72,682	$132,779
		ECM 2	$817	$9,446	$77,577	$15,642	$10,343	$63,900
		Entire Project	$3,463	$32,975	$277,470	$58,842	$82,439	$190,192
	Simple payback (years)	ECM 1	7.7	8.4	8.7	5.0	7.7	5.0
		ECM 2	6.7	5.7	6.4	3.7	14.4	2.8
		Entire Project	7.6	7.7	8.1	4.7	8.6	4.4

Savings per year are calculated for an electricity price of 12.41 cents/kWh and a natural gas price of 1.208 dollars per therm, as per Energy Information Administration (EIA) data.

** Note: for the schools and hospitals, different rooms have different original energy use conditions. For schools, we only retrofit the following room types: classroom, corridor, offices, library, bathroom, and lobby. For hospital, we only retrofitted the following spaces: office rooms, lobby, corridor, patient waiting rooms, basement, and nurse rooms. We exclude, for instance, emergency rooms or intensive care units as these likely have specific lighting and plug load requirements.*

5.2. Risk Reduction Effect of Automated M&V

Risk reduction effect of using automated M&V: Using the standard deviation of annual savings as an indication of risk allows for the quantification of risk profiles. The result of this analysis is provided in Figure 1 for the large office benchmark building. The case where no controls are implemented reflects maximum risk while the case where both ECMs are under automated M&V control eliminates all risk. The other two cases represent risk profiles where only one of the ECMs is under automated M&V control while the is exposed to performance variation.

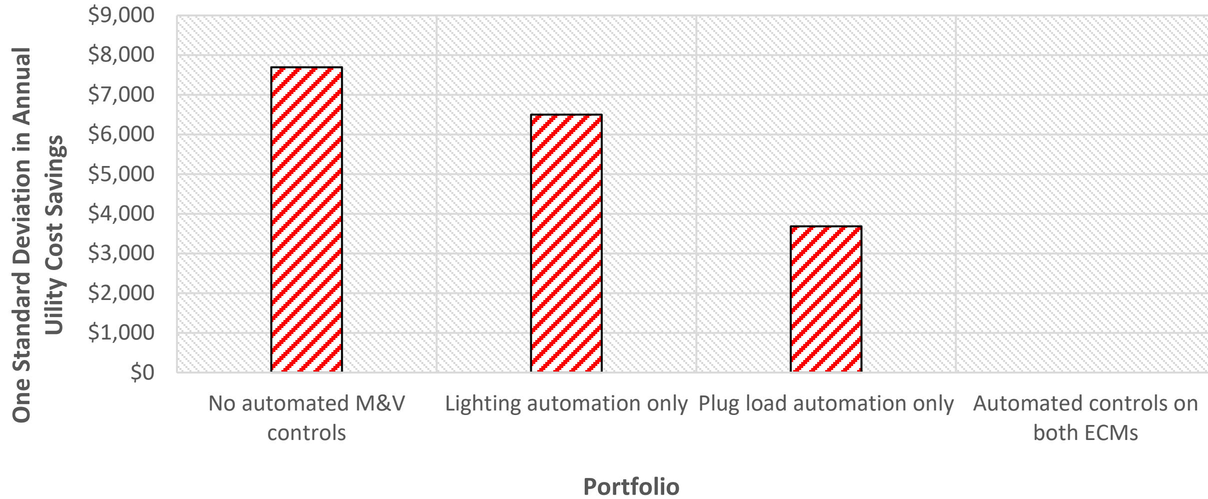

Figure 1. Risk reduction effect of automated M&V for each case. The measure of risk used here is the standard deviation in annual utility cost savings of the resulting performance distribution profile. A higher standard deviation is equivalent to a less certain performance profile – i.e. a higher chance of overshooting the original ESCO guarantee.

Costs associated with each case: The automated M&V control system increases the overall project cost. The case where no automated M&V controls are implemented does not require any additional costs but also doesn't mitigate the risk. The case where both ECMs are subject to automated M&V control is accompanied by the highest additional investment as software and hardware is acquired for lighting and plug load control technology. Lighting control technology comes at a higher additional cost than plug load control technology (see *Figure 2*).

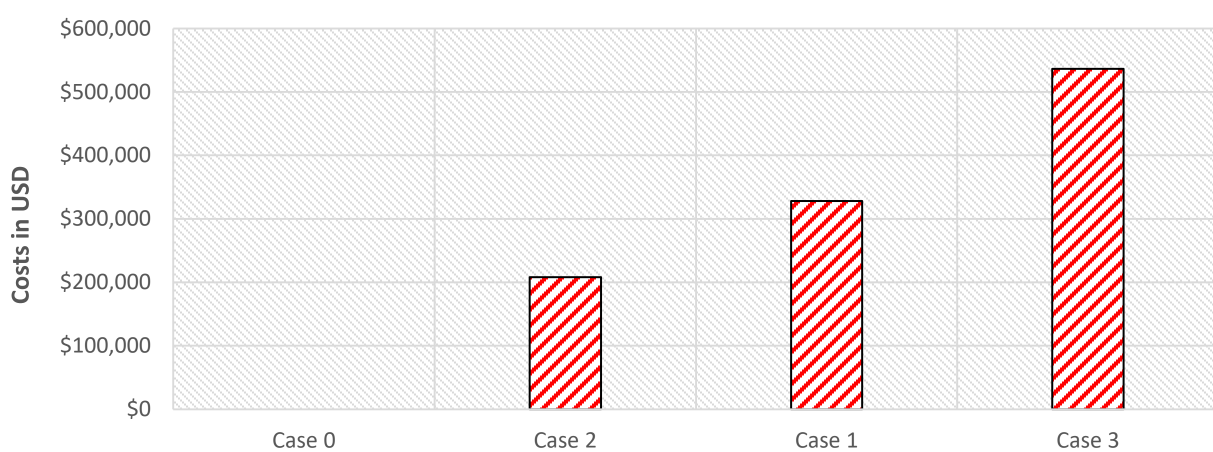

Figure 2. Costs associated with each portfolio of Automated M&V applications.

<u>Comparing risk reduction effect per dollar invested:</u> Finally, combining the above results yields perspective on the return per dollar invested for automated M&V application (*Figure 3*). Using the inputs and modeling described in this report, the analysis suggests adding plug load controls is the most cost-effective but the overall savings of the project are modest compared to the case of lighting with controls.

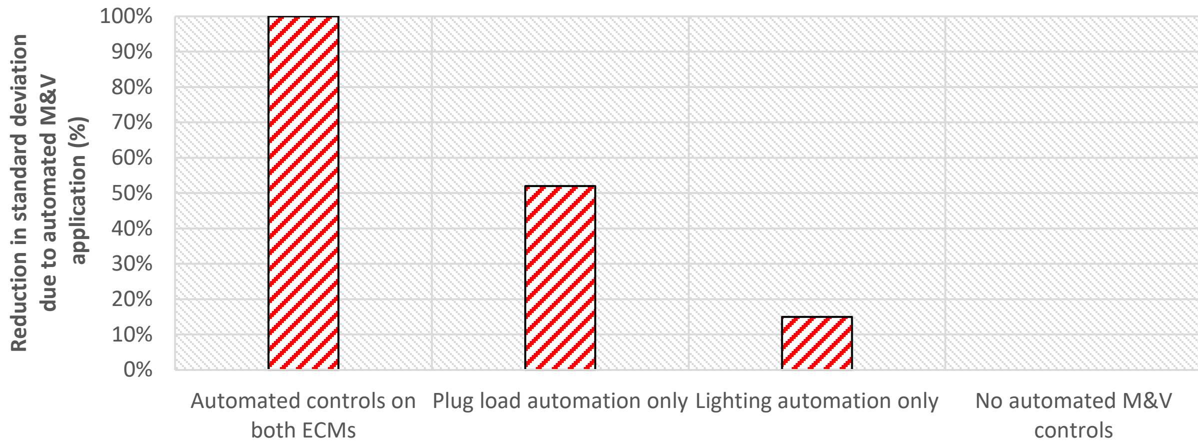

Figure 3. Risk reduction effect from automated M&V applications. Risk reduction is modeled here as the percentage decrease in the standard deviation.

6.0. Concluding Remarks

The conceptual and modeling approach deployed throughout this research effort provides insight into the dynamics of investor risk mitigation using automated M&V techniques. The research so far indicates that the use of automated M&V and Monte Carlo assessment techniques could modify investment decision-making when addressing uncertainty and investor risk.

The research has followed several of the recommendations of the previous research effort. In particular, the research illustrated in this report has:

- **Used cloud computing services such as available through the University of Delaware, Amazon Web Services or Google Computing Engine to accelerate Monte Carlo analysis.** This was a key recommendation of the 2016-2017 research. Calculations performed during 2016-2017 relied on in-house computing power which was deemed insufficient. Through the use of an Amazon Web Services (AWS) computing station, a new set of calculations was performed at considerably higher speed.
- **Financial assessment of automated M&V and probabilistic energy savings:** The Monte Carlo analysis results were used as inputs for a preliminary financial model to determine some of the costs and benefits of automated M&V. In particular, the approach assists in the creation of an investor-ready energy efficiency finance structure that includes automated M&V for (a subset of) specific energy conservation measures.
- **Expand the analysis to additional building types:** This research focused on one building type (i.e. large office) at this point but sixteen benchmark building models are available through EnergyPlus. The same research process as outlined throughout this report could be applied to the other benchmark building models to determine whether automated M&V serves different building types in different ways.

Research efforts for the phase of 2018-2019 research will focus on, among others:

- **Advanced modeling with real-world data:** Enabling access to real-world data could improve the application potential of the software and research architecture outlined in this report.
- **Enable Delaware-specific research models:** Current modeling efforts use existing building benchmarks for Baltimore, MD. One of the research efforts moving forward could focus on the modification of the benchmark building model to

reflect Delaware-specific conditions (such as, for instance, weather, grid context, pricing, etc.).

- **Mapping weather variation (e.g., extreme weather events, climate change):** Research effort can be directed at testing the automated M&V in a broader set of conditions. Weather variations, for instance, could substantially alter energy use patterns (even as they are sometimes short-lived) especially in financial terms (as energy prices can increase exponentially during hazardous weather conditions).
- **Portfolio analysis of buildings of different types:** The inclusion of additional building types also allows for analysis of multiple buildings at once in order to determine the portfolio-based capabilities of automated M&V technologies. In particular, existing research shows that the accuracy of automated M&V commonly improves when applied across building types (Granderson et al. 2016).
- **Mapping technology default rates and continuous commissioning using automated M&V:** While technology variation and default are indirectly captured in the Monte Carlo analysis presented throughout this report through probability distribution functions, direct inclusion of technology default rates and modeling of response options using automated M&V could further improve the model presented here. Such an effort could benefit from the technology performance databases that are emerging such as the U.S. Department of Energy's Technology Performance Exchange (https://energy.gov/eere/buildings/technology-performance-exchange).

References

Arnold, U., & Yildiz, Ö. (2015). Economic risk analysis of decentralized renewable energy infrastructures – A monte carlo simulation approach. *Renewable Energy, 77*, 227-239. doi://dx.doi.org/10.1016/j.renene.2014.11.059

Backlund, S., Thollander, P., Palm, J., & Ottosson, M. (2012). Extending the energy efficiency gap. *Energy Policy, 51*, 392-396. doi://dx.doi.org/10.1016/j.enpol.2012.08.042

Bordass, B.Energy performance of non-domestic buildings: Closing the credibility gap. *In Proceedings of the 2004 Improving Energy Efficiency of Commercial Buildings Conference,*

Bou-Saada, T. E., & Haberl, J. S. (1995). *An improved procedure for developing calibrated hourly simulation models.* (). Montréal, Canada: IBPSA-USA (http://www.ibpsa.us).

Bozorgi, A., & Jones, J. R.Improving energy retrofit decisions by including uncertainty in the energy modelling process. *ARCC Conference Repository,*

Byrne, J., Taminiau, J., Kim, K. N., Lee, J., & Seo, J. (2017). Multivariate analysis of solar city economics: Impact of energy prices, policy, finance, and cost on urban photovoltaic power plant implementation. *Wiley Interdisciplinary Reviews: Energy and Environment,* , n/a. doi:10.1002/wene.241

Byrne, J., Taminiau, J., Kim, K. N., Seo, J., & Lee, J. (2016). A solar city strategy applied to six municipalities: Integrating market, finance, and policy factors for infrastructure-scale photovoltaic development in amsterdam, london, munich, new york, seoul, and tokyo. *Wiley Interdisciplinary Reviews: Energy and Environment, 5*(1), 68-88. doi:10.1002/wene.182

Calì, D., Osterhage, T., Streblow, R., & Müller, D. (2016). Energy performance gap in refurbished german dwellings: Lesson learned from a field test. *Energy and Buildings, 127*, 1146-1158. doi://dx.doi.org/10.1016/j.enbuild.2016.05.020

California Energy Commission. (2002). *Technical options guidebook - enhanced automation.* ().California Energy Commission.

Chen, Y., Hong, T., & Piette, M. A. (2017). *Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis* doi://doi.org/10.1016/j.apenergy.2017.07.128

Coakley, D., Raftery, P., & Keane, M. (2014). A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews, 37*, 123-141. doi://dx.doi.org/10.1016/j.rser.2014.05.007

Cooper, A. (2016). *Electric company smart meter deployments: Foundation for a smart grid.* (No. IEI Report October 2016).The Edison Foundation Institute for Electric Innovation.

Corgnati, S. P., Fabrizio, E., Filippi, M., & Monetti, V. (2013). Reference buildings for cost optimal analysis: Method of definition and application. *Applied Energy, 102*, 983-993. doi://dx.doi.org/10.1016/j.apenergy.2012.06.001

de T'Serclaes, P. (2010). *Money matters: Mitigating risk to spark private investments in energy efficiency* Organisation for Economic Co-operation and Development. doi:10.1787/5km5zrrvzr42-en

Deru, M., Griffith, B., & Torcellini, P. (2006). Establishing benchmarks for DOE commercial building R&D and program evaluation. *California: National Renewable Energy Laboratory,*

EIA. (2017). *Annual energy outlook 2017 with projections to 2050.* (No. #AEO2017). Washington, DC: U.S. Energy Information Administration.

Energy Efficiency Financial Institutions Group. (2015). *Energy efficiency - the first fuel for the EU economy. how to drive new finance for energy efficiency investments.* ().United Nations Environment Programme Finance Initiative.

Franconi, E., Gee, M., Goldberg, M., Granderson, J., Guiterman, T., Li, M., & Smith, B. A. (2017). *The status and promise of advanced M&V: An overview of "M&V 2.0" methods, tools, and applications.* (No. LBNL-1007125).Lawrence Berkeley National Laboratory and Rocky Mountain Institute.

Fumo, N. (2014). A review on the basics of building energy estimation. *Renewable and Sustainable Energy Reviews, 31*, 53-60. doi://dx.doi.org/10.1016/j.rser.2013.11.040

Galvin, R. (2014). Making the 'rebound effect' more useful for performance evaluation of thermal retrofits of existing homes: Defining the 'energy savings deficit' and the 'energy performance gap'. *Energy and Buildings, 69*, 515-524. doi://dx.doi.org/10.1016/j.enbuild.2013.11.004

Goldberg, M., Marean, M., Puckett, C., Godin, C., Todd, W., Bodmann, S., & Kelly, K. (2015). *The changing EM&V paradigm: A review of key trends and new industry developments, and their implications on current and future EM&V practices.* ().Northeast Energy Efficiency Partnerships & DNV GL.

Granade, H. C., Creyts, J., Derkach, A., Farese, P., Nyquist, S., & Ostrowski, K. (2009). *Unlocking energy efficiency in the U.S. economy.* ().McKinsey & Company.

Granderson, J. (2013). *Energy management and information systems (EMIS) technology classification framework.* ().Lawrence Berkeley National Laboratory.

Granderson, J., & Lin, G. (2016). Building energy information systems: Synthesis of costs, savings, and best-practice uses. *Energy Efficiency, 9*(6), 1369-1384. doi:10.1007/s12053-016-9428-9

Granderson, J., Lin, G., & Mary, A. P. (2013). *Energy information systems (EIS): Technology costs, benefit, and best practice uses.* (). Berkeley, CA: Lawrence Berkeley National Laboratory.

Granderson, J., Piette, M. A., & Ghatikar, G. (2011). Building energy information systems: User case studies. *Energy Efficiency, 4*(1), 17-30. doi:10.1007/s12053-010-9084-4

Granderson, J., Piette, M. A., Ghatikar, G., & Price, P. (2009). *Building energy information systems: State of the technology and user case studies.* (No. LBNL-2899E).Lawrence Berkeley National Laboratory.

Granderson, J., Price, P. N., Jump, D., Addy, N., & Sohn, M. D. (2015). Automated measurement and verification: Performance of public domain whole-building electric baseline models. *Applied Energy, 144*, 106-113. doi://dx.doi.org/10.1016/j.apenergy.2015.01.026

Granderson, J., Touzani, S., Custodio, C., Sohn, M. D., Jump, D., & Fernandes, S. (2016). Accuracy of automated measurement and verification (M&V) techniques for energy savings in commercial buildings. *Applied Energy, 173*, 296-308.

Granderson, J., Touzani, S., Custodio, C., Sohn, M., Fernandes, S., & Jump, D. (2015). Assessment of automated measurement and verification (M&V) methods. *Lawrence Berkeley National Laboratory,*

Granderson, J., Touzani, S., Fernandes, S., & Taylor, C. (2017). Application of automated measurement and verification to utility energy efficiency program data. *Energy and Buildings, 142*, 191-199. doi://doi.org/10.1016/j.enbuild.2017.02.040

Gurgur, C. Z., & Jones, M. (2010). Capacity factor prediction and planning in the wind power generation industry. *Renewable Energy, 35*(12), 2761-2766. doi://dx.doi.org/10.1016/j.renene.2010.04.027

Haves, P., Wray, C., Jump, D., Veronica, D., & Farley, C. (2013). *Development of diagnostic and measurement and verification tools for commercial buildings.* (No. CEC-500-2015-001.).California Energy Commission.

Heo, Y., Choudhary, R., & Augenbroe, G. A. (2012). Calibration of building energy models for retrofit analysis under uncertainty. *Energy and Buildings, 47*, 550-560. doi://dx.doi.org/10.1016/j.enbuild.2011.12.029

Heo, Y., Augenbroe, G., & Choudhary, R. (2013). Quantitative risk management for energy retrofit projects. *Journal of Building Performance Simulation, 6*(4), 257-268. doi:10.1080/19401493.2012.706388

Hong, T., Chen, Y., Lee, S. H., & Piette, M. A. (2016). CityBES: A web-based platform to support city-scale building energy efficiency. *Urban Computing,* doi:10.1145/12345.67890

Hygh, J. S., DeCarolis, J. F., Hill, D. B., & Ranji Ranjithan, S. (2012). *Multivariate regression as an energy assessment tool in early building design* doi://doi.org/10.1016/j.buildenv.2012.04.021

Jackson, J. (2010). Promoting energy efficiency investments with risk management decision tools. *Energy Policy, 38*(8), 3865-3873. doi://dx.doi.org/10.1016/j.enpol.2010.03.006

Karlsson, F., Rohdin, P., & Persson, M. (2007). Measured and predicted energy demand of a low energy building: Important aspects when using building energy simulation. *Building Services Engineering Research and Technology, 28*(3), 223-235.

Ke, M., Yeh, C., & Su, C. (2017). Cloud computing platform for real-time measurement and verification of energy performance. *Applied Energy, 188*, 497-507. doi://doi.org/10.1016/j.apenergy.2016.12.034

Kim, A., Anderson, S., & Haberl, J. (2016). Current industry methods for quantifying energy service projects: Key findings and lessons learned. doi:10.1061/(ASCE)AE.1943-5568.0000191

Lee, P., Lam, P. T. I., Lee, W. L., & Chan, E. H. W. (2016). Analysis of an air-cooled chiller replacement project using a probabilistic approach for energy performance contracts. *Applied Energy, 171*, 415-428. doi://dx.doi.org/10.1016/j.apenergy.2016.03.035

Lin, G., Singla, R., & Granderson, J. (2017). *Using EMIS to identify top opportunities for commercial building efficiency.* (No. LBNL-1007250).Lawrence Berkeley National Laboratory.

Lucon, O., Urge-Vorsatz, D., Zain Ahmed, A., Akbari, H., Bertoldi, P., Cabeza, L. F., . . . Vilarino, M. V. (2014). 2014: Buildings. In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, . . . J. C. Minxc (Eds.), *Climate change 2014: Mitigation of climate change. contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change* (pp. 671). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Mathew, P. A., Koehling, E., & Kumar, S. (2006). Use of quantitative uncertainty analysis to support M&V decisions in ESPCs. *Energy Engineering, 103*(2), 25-39. doi:10.1080/01998590609509457

Menezes, A. C., Cripps, A., Bouchlaghem, D., & Buswell, R. (2012). Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. *Applied Energy, 97*, 355-364. doi://dx.doi.org/10.1016/j.apenergy.2011.11.075

Mills, E., Kromer, S., Weiss, G., & Mathew, P. A. (2006). From volatility to value: Analysing and managing financial and performance risk in energy savings projects. *Energy Policy, 34*(2), 188-199. doi://dx.doi.org/10.1016/j.enpol.2004.08.042

Momen, M., Shirinbakhsh, M., Baniassadi, A., & Behbahani-nia, A. (2016). Application of monte carlo method in economic optimization of cogeneration systems – case study of the CGAM system. *Applied Thermal Engineering, 104*, 34-41. doi://dx.doi.org/10.1016/j.applthermaleng.2016.04.149

Park, S., Norrefeldt, V., Stratbuecker, S., Grün, G., & Jang, Y. (2013). Methodological approach for calibration of building energy performance simulation models applied to a common "measurement and verification" process. *Bauphysik, 35*(4), 235-241. doi:10.1002/bapi.201310070

Parker, M., & Guthrie, P. (2016). Crossing the energy efficiency chasm: An assessment of the barriers to institutional investment at scale, a UK perspective. *Journal of Sustainable Finance & Investment, 6*(1), 15-37. doi:10.1080/20430795.2016.1159650

Pereira, Edinaldo José da Silva, Pinho, J. T., Galhardo, M. A. B., & Macêdo, W. N. (2014). Methodology of risk analysis by monte carlo method applied to power generation with renewable energy. *Renewable Energy, 69*, 347-355. doi://dx.doi.org/10.1016/j.renene.2014.03.054

Ramos Ruiz, G., & Fernández Bandera, C. (2017). Analysis of uncertainty indices used for building envelope calibration. *Applied Energy, 185, Part 1*, 82-94. doi://dx.doi.org/10.1016/j.apenergy.2016.10.054

Reddy, T. A., Maor, I., & Panjapornpon, C. (2007). Calibrating detailed building energy simulation programs with measured Data—Part I: General methodology (RP-1051). *HVAC&R Research, 13*(2), 221-241. doi:10.1080/10789669.2007.10390952

Rogers, E. A., Carley, E., Deo, S., & Grossberg, F. (2015). *How information and communications technologies will change the evaluation, measurement, and verification of energy efficiency programs.* (No. IE1503).American Council for an Energy Efficient Economy.

SEEAction. (2012). *Energy efficiency program impact evaluation guide - evaluation, measurement, and verification working group.* ().State and Local Energy Efficiency Action Network.

Singh, R., Lazarus, I. J., & Kishore, V. V. N. (2016). Uncertainty and sensitivity analyses of energy and visual performances of office building with external venetian blind shading in hot-dry climate. *Applied Energy, 184*, 155-170. doi://dx.doi.org/10.1016/j.apenergy.2016.10.007

Sunikka-Blank, M., & Galvin, R. (2012). Introducing the prebound effect: The gap between performance and actual energy consumption. *Building Research & Information, 40*(3), 260-273. doi:10.1080/09613218.2012.690952

Ürge-Vorsatz, D., Eyre, N., Graham, P., Kornevall, C., Harvey, L. D. D., Majumdar, M., . . . Yi, J. (2012). Energy end-use: Buildings. In International Institute for Applied Systems Analysis (Ed.), *Global energy assessment: Toward a more sustainable future* (). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Walter, T., Price, P. N., & Sohn, M. D. (2014). Uncertainty estimation improves energy measurement and verification procedures. *Applied Energy, 130*, 230-236. doi://dx.doi.org/10.1016/j.apenergy.2014.05.030

Zhang, B., Liu, Y., Rai, R., & Krovi, V. (2016). Invariant probabilistic sensitivity analysis for building energy models. *Journal of Building Performance Simulation,* , 1-14. doi:10.1080/19401493.2016.1265590

Zhang, Y., & Korolija, I.Performing complex parametric simulations with jEPlus. *9th SET Conference Proceedings, Shanghai, China,*