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

Energy and Environmental Policy Analysis (EEPA) Project

FINAL REPORT JUNE 2019 (Revised)

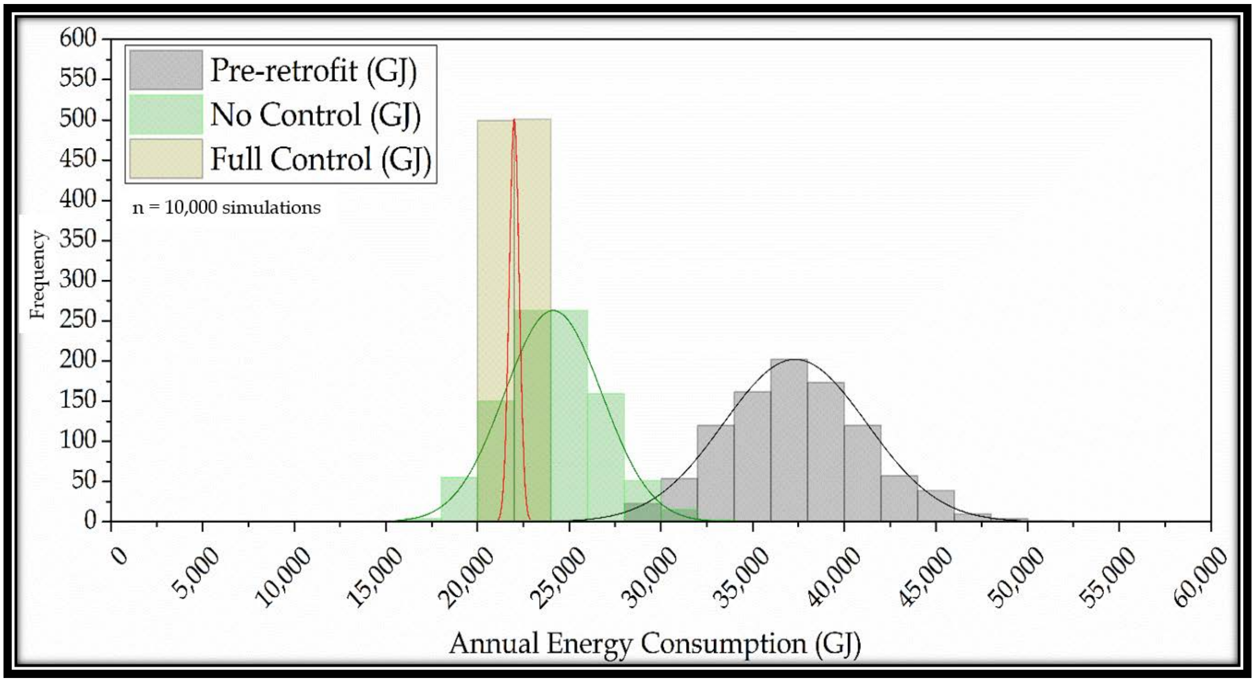

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TABLE OF CONTENTS

PART II: INTER-PARTY TRUST: CONTROLS, INSURANCE, AND THE ENERGY SAVINGS GUARANTEE

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

This 2018-2019 Final Report documents the research outputs of an investigation into the potential of risk mitigation in energy efficiency retrofit projects by technology-based control of project performance. The report describes a model of the dynamics associated with investment in energy efficiency projects when applying technology control [1] of project performance under several scenarios.

The energy efficiency retrofit market is subject to trust concerns between parties [1]. In particular, the ability of projects to deliver on promised savings is sometimes drawn into question [2; 3]. Trust concerns can be partly addressed through energy saving performance guarantees which now represent the dominant performance risk mitigation tool used in the market [4; 5]. The performance guarantee is based on the project's characteristics, especially the suite of energy conservation measures (ECMs) that are installed as part of the project. Contractual stipulations arrange the conditions of the guarantee. Two dimensions stand out in this regard:

1. All else being equal, a higher energy savings guarantee should reduce project performance risk. Therefore, methods that yield a higher energy savings guarantee could help accelerate the market [2; 3; 6].
2. The value and strength of the guarantee *itself* is sometimes questioned by the project host – i.e., there is mistrust by the project host that the energy service company (ESCO) will actually make the project host whole in cases of under-performance [6; 7]. This position can result in a dispute and litigation to compel an uncooperative ESCO to compensate performance short-falls [6; 8-10]. Therefore, methods that advance inter-party trust could help accelerate the market.

We explore these two dimensions in this research, with an emphasis on methods to raise the guarantee. In particular, we review the ability of smart, automated, and connected technologies that can a) intelligently monitor and control the performance of energy-consuming devices to reduce performance variations, b) provide additional degrees of control over the project's operations, and, by doing so, c) possibly convince the ESCO to

[1] In this report, technology control (e.g., occupancy sensors to control lighting functions) is used interchangeably with the term automation. We also sometimes ascribe the term 'smart' to this technology suite to describe their automated control protocols based on pre-determined algorithms.

raise the guarantee. To evaluate options regarding the strength and value of the guarantee, the report spends some time on energy efficiency performance insurance.

RESEARCH OBJECTIVE I

This research investigates the use of *smart controls* to restrict performance variation with the aim of extracting a higher energy savings guarantee.

The research is built around the hypothesis that use of *smart controls* can strategically reduce performance variation, which yields a higher energy savings guarantee and, critically, accelerates the energy efficiency retrofit market. To evaluate this contribution, we focus on the dynamics of the energy savings guarantee setting process. The guarantee originates from the ESCO, which sets the guarantee based on its own confidence in the expected performance of the energy efficiency technologies installed as part of the project. This level of confidence is dependent on many variables, including a) the ESCO's experience with the technologies used in question; and b) the ESCO's tolerance for risk.

The incentive for the ESCO in this regard is double-edged. On the one hand, the ESCO can be inclined to set the guarantee below the expected savings of the project – a lower guarantee results in a lower risk of dispute and need for performance shortfall compensation. On the other hand, a higher guarantee makes the ESCO more competitive to win the project bidding process.

One way to accelerate the market could therefore be to identify a way for the ESCO to set a higher guarantee while not engaging in higher levels of risk. The level of possible project performance variation plays a major role in this context: all else being equal, a project with a high level of possible performance variation will produce a lower guarantee relative to a project with a low level of performance variation. Thus, the installation of performance control technology – which limits the range of possible performance variation – is a method that could result in a higher guarantee at the same level of risk.

RESEARCH OBJECTIVE II

This research explores the contribution of *smart controls* to advance inter-party trust that the guarantee is meaningful and will be observed in accordance to expectation. A role is reserved for energy efficiency performance insurance (to be explained in greater depth in the future).

Controls that can monitor and operate devices in real-time offer additional degrees of control over the overall project's performance beyond simply narrowing possible performance variation. The presence of controls could advance inter-party trust if the information and data generated is available to all parties. Deeper understanding of project performance could help to move beyond 'black box' moral hazards that currently occur in the energy efficiency retrofit market. In this way, performance-focused controls can help reduce conflict and save time and costs in reaching consensus about viable projects for the ESCO and client alike.

Energy efficiency performance insurance is introduced in this report as a possible tool to remove problems associated with inter-party trust: under-performance risk – and associated disputes and litigation between ESCO and project host – can be off-loaded to the third-party insurance company. But, this arrangement elevates transaction costs of the overall project. This research attempts to quantify some of these costs. Research objective II is explored but research outputs are preliminary – further research is required to more closely disentangle the various dynamics.

RESEARCH APPROACH

The research follows several steps to pursue the research objectives:

Part 1: Controls and the Energy Savings Guarantee (Section 1.0 to 4.0 of this report)

Section 1.0: Identify and characterize building performance variation, including underlying causes and risks

- There is concern regarding performance uncertainty, captured in the literature as an energy savings "credibility gap" or "performance gap" [11-14].
- Expected or experienced manifestation of performance risk leads some clients to emphasize concern "about ESCO's guaranteed savings not being achieved, causing problems to third party financing" as a top worry [6]. In a similar vein, "uncertainty of payments based on energy savings" is listed as a key market and financial barrier according to a survey of industry professionals and scholars [7].
- Commonly occurring operational issues that result in low performance are identified [15; 16]. When controls are present to avoid low performance, (frequent) re-tuning of these controls is necessary over the lifetime of the project if they are not automated (or '*smart'*) to maintain "optimal" performance [15].

- Investment at scale is available when performance can be guaranteed [2; 3].

Section 2.0: Review technology controls literature about their impacts on energy savings

- There is a general consensus in the literature that building controls can improve energy saving profiles of energy efficiency projects [17].
- "Optimal" control of building operations could save up to 60% of energy consumption, with most reported savings in the 10%-30% range [17].
- Automated building control techniques can yield actionable value by monitoring and correcting, in real-time, the energy performance profile of the building [18; 19].
- Under-adoption of whole-building automated control technologies is attributed to the high cost associated with whole-building deployment [19]. However, automated control technologies at the end-use level have become available that might overcome this barrier. As such, as opposed to purchasing a whole-building system at considerable cost, strategic deployment of control options is now possible.

Section 3.0: Identify and characterize the energy savings guarantee setting process

- Extant literature shows that realized savings can deviate from the guarantee. For example, review of a large database finds that 72% of projects experienced greater savings than were guaranteed by the ESCO (517 projects) – some by as much as 50% more [5].
- This deviation is partly explained by the fact that, to limit their downside risk exposure, ESCOs typically set the guarantee below predicted performance using ESCO-specific risk tolerances [20-22]. Yet, no "rule of thumb" for setting the guarantee is available [23].
- From the perspective of the ESCO, strategic guarantee placement can be modelled using stochastic performance profiles [23].
- Stochastic performance profiles for hypothetical projects with and without the use of *smart controls* are used to quantify the ability of these technologies to increase the guarantee.

Section 4.0: Summarize the results

The model prepared for this report is complex. Perhaps a practical way to describe it is to use an example of a building whose owner is weighing energy efficiency options and the possible use of technology controls. The owner is interested in investing in a project provided that a performance guarantee can be put in place that covers investment costs. Simultaneously, an ESCO is evaluating what it can guarantee. The model to represent this owner-ESCO decision-making process is described briefly here by using an example of a large office building. In Section 3.0., several building types are analyzed in order to demonstrate the model's ability to examine a broad range of project types.

The owner-ESCO decision-making process can be graphically represented in its hypothetical form (Figure ES 1). For a hypothetical project, Figure ES 1 shows that the project's savings can exceed a low guarantee but will likely fall short when a (very) high guarantee is used. Under a guaranteed savings structure, savings above the guarantee are awarded to the project host while savings that fall short of the guarantee negatively impact the ESCO. This is illustrated in Figure ES 1 by the green and red areas, respectively. From the perspective of the project host, savings that exceed the guarantee are welcome but, critically, these savings are not guaranteed and, as such, are not available to underwrite the initial investment. However, savings that fail to reach the level of the guarantee prompt the project host to argue for compensation that could be disputed by the ESCO. The project host, overall, is interested in a high guarantee.

Surplus savings above the guarantee means that the project over-performed relative to the guarantee. In this case, the ESCO is not at risk of claims for compensation. While this sounds appealing, it also means that the project bid by the ESCO could have been more competitive. Insufficient savings to cover the guarantee lower the overall return on the project and could even represent a net-loss for the ESCO. From the perspective of the ESCO, this should be avoided whenever possible. As illustrated in Figure ES 1, a hypothetical range of possible guarantee values that are acceptable to the ESCO can be identified.

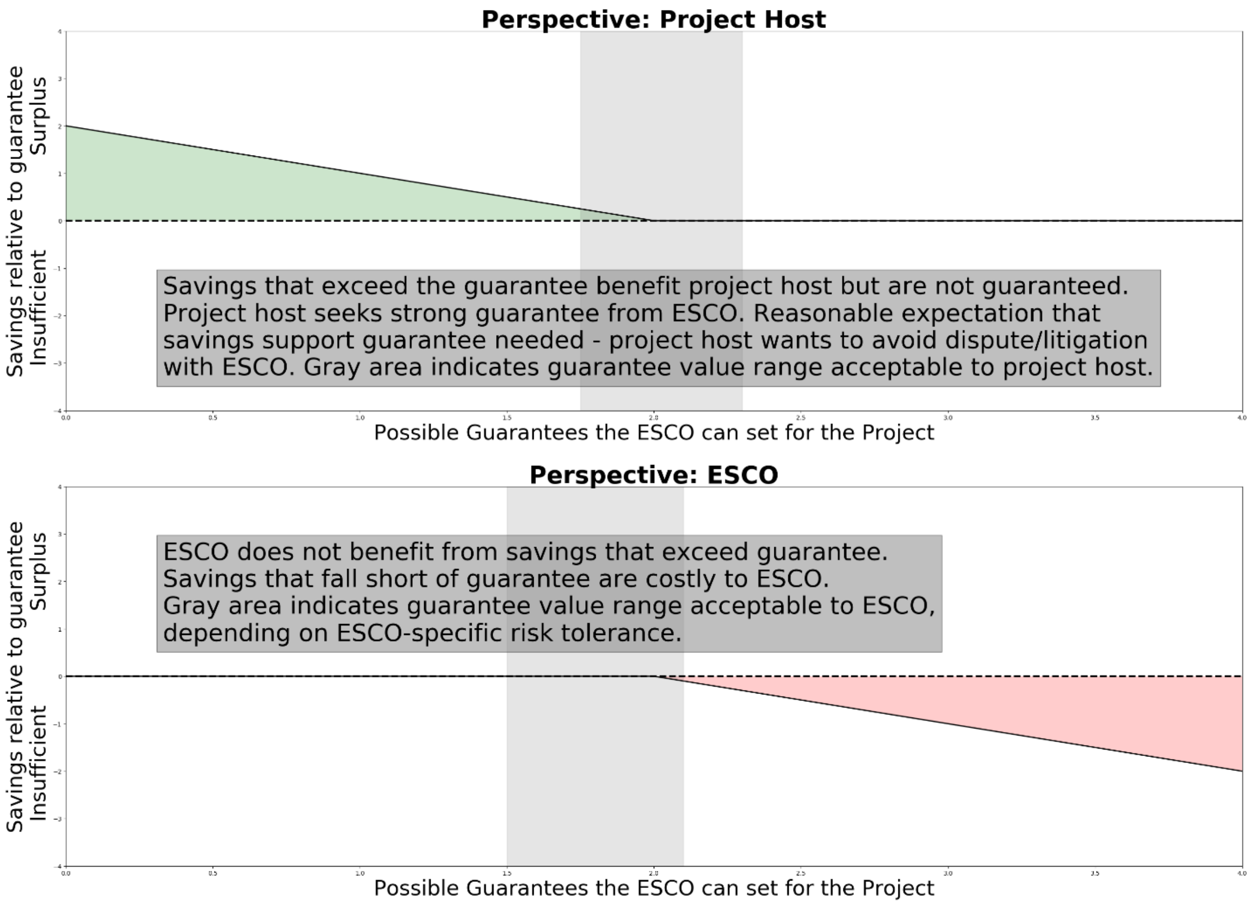

Figure ES 1 Overview of the owner-ESCO decision-making process regarding setting the energy savings guarantee

For the large office a post-retrofit scenario provides an average annual consumption level of 24,057 GJ compared to the pre-retrofit average consumption level of 37,034 GJ – an average savings of about 35%. Yet, as illustrated in Figure ES 2, the probability of savings is such that, under highly unfavorable circumstances, the project *could* have annual performance levels that are below pre-retrofit performance. Figure ES 2 also illustrates the performance profile when control technologies are installed in the project.

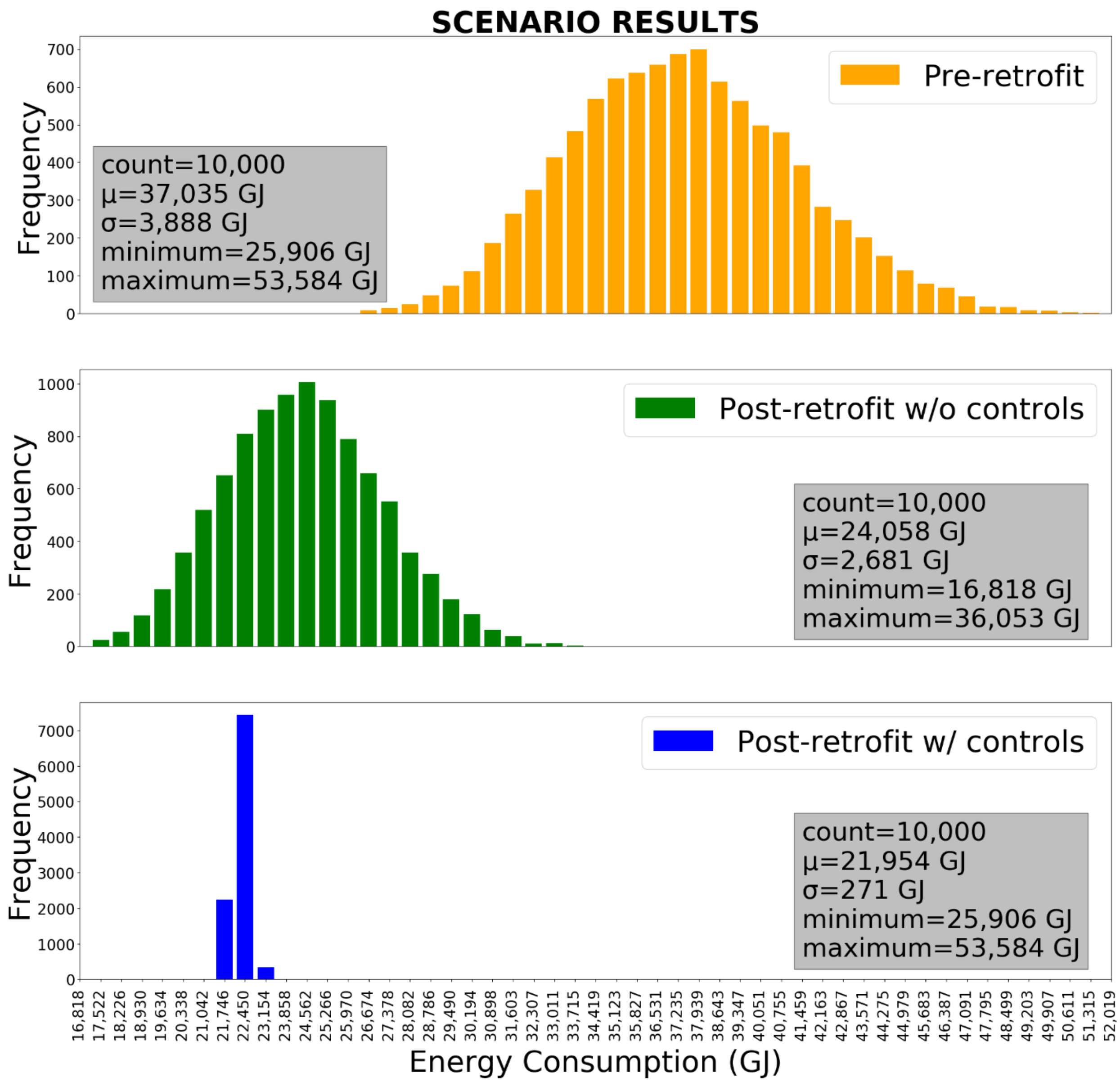

Figure ES 2 **Pre-and post-retrofit energy consumption without and with performance controls (10,000 simulations each) for the large office building**

Next, the ESCO determines the placement of the energy savings guarantee.

Based on the results reported in Figure ES 2, the ESCO can set an energy savings guarantee. This guarantee is dependent on the energy efficiency project profile introduced above and – importantly – on the ESCO's tolerance for risk. Using the guarantee placement model built for this report, the cost savings profile of the hypothetical project yields a strategic estimate of the guarantee an ESCO might be willing to provide over 20, say, 20 years. We calculate this estimate both for the scenario where no controls are installed and for the scenario where the project does make use of these advanced technologies. Figure ES 3 shows the results for the large office building. The illustration shows that the ESCO, in a project without controls, would set the guarantee at ~$47,500. The use of controls improves the project's profile in such a way that a $116,000 guarantee becomes feasible.

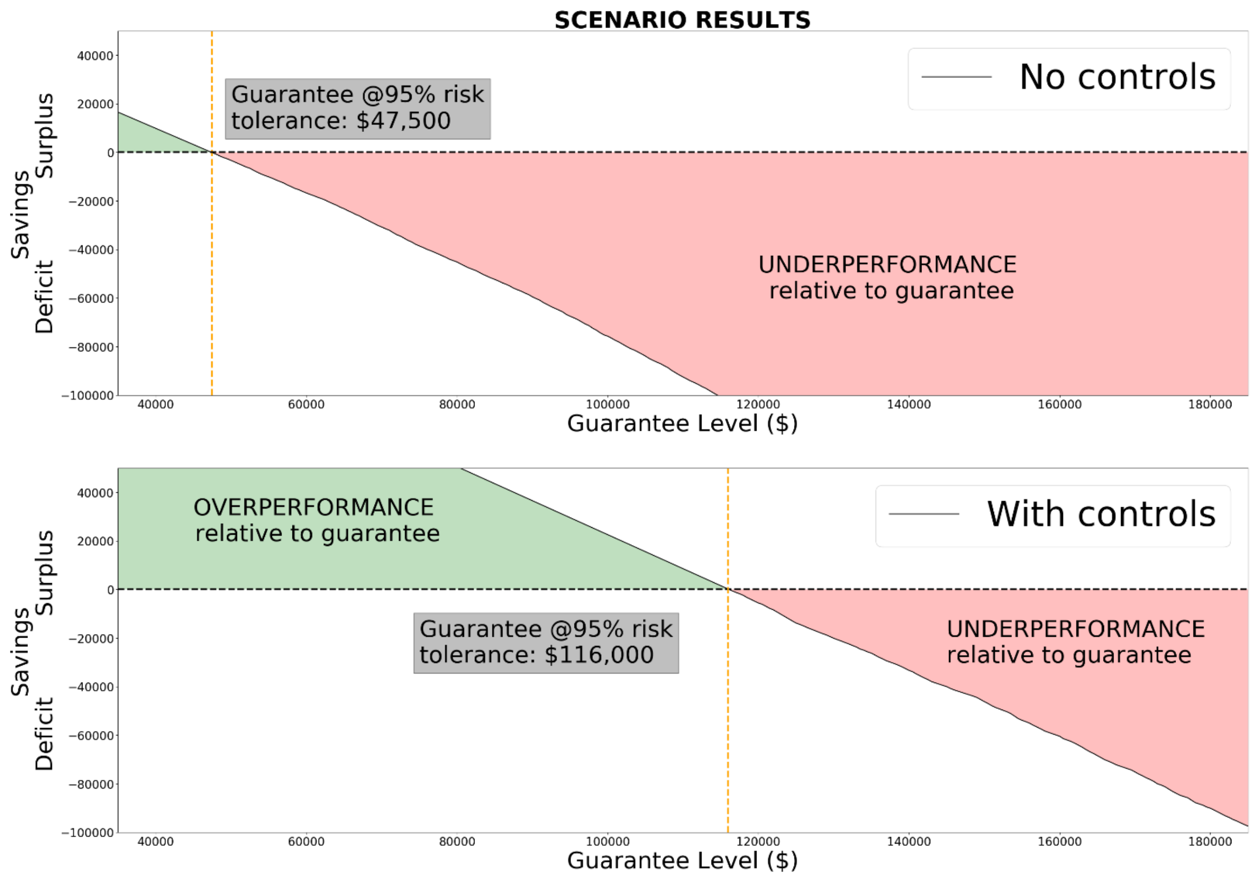

Figure ES 3 **Guarantee placement with and without controls for the large office building**

Part 2: Controls, Energy Efficiency Performance Insurance and the Energy Savings Guarantee

Section 5.0: Interparty trust-building through the use of controls

- The actual value of the guarantee can matter less than the client's perception of the trustworthiness of the ESCO's promise.
- Controls can help to improve this situation by creating large amounts of performance data, where under-performance can be correlated to potential causes.

Real-time performance monitoring can shine a light on the ESCO 'black box' tools that sometimes generate mistrust by the project host.

- Trust-building and other benefits accrue from the use of automated technology options, including operational and engineering risk reduction; monitoring and verification risk reduction; economic risk reduction; and financial risk reduction.
- The energy savings guarantee is, effectively, a risk-transfer contract between ESCO and client. Other forms of financial risk mitigation are also possible.
- We provide a preliminary discussion of financial risk mitigation in the form of energy efficiency performance insurance.
- Energy efficiency insurance has been suggested as a possible financial risk mitigation tool in the energy efficiency retrofit sector [25; 26; 79].
- Insurance product valuation is inherently about valuing risk. The problem of valuing risk reduction can be modeled by considering a hypothetical financial insurance instrument available to the project [27].
- A hypothetical insurance product can be modeled using stochastic performance profiles [25].
- We explore a model proposed by Töppel &Tränkler [28].
- By simulating many values of insured coverage, a cost curve for insurance can be obtained.
- We provide a preliminary calculation of the cost of guarantee setting from the perspective of the ESCO. This cost calculation can be used in subsequent research to further define the benefit-cost ratio of controls in EPC projects.

Conclusions

- Tests of our multi-stage model confirm that the model captures the interlocking dynamics associated with energy efficiency insurance, guarantee setting, and performance control technology implementation.
- Our results indicate that such technology implementation can deliver substantial benefits for the investor in the form of, especially, a large increase in the energy savings guarantee.

PART 1

ENERGY SAVINGS GUARANTEE WITH AND WITHOUT CONTROLS

1.0. Problem: Building Performance Variation

Significant growth characterizes the U.S. energy efficiency market [4; 29]. However, the 2014 $5.3 billion energy efficiency market can be contrasted against an estimated $92 to $333 billion overall potential [29-31]. Nominal revenue stagnation between 2011 and 2014 [30] adds to the impression of a seeming incapability to successfully unlock the rest of the market. Critically, market potential could be unlocked if investment at scale can be achieved by explicitly considering current barriers that deter investment and the enabling conditions that would make energy efficiency attractive [2; 3]. A principal barrier in this regard is performance and operational uncertainty [2], captured as the energy savings "credibility gap" or "performance gap" [11-13]. For example, financial institutions consider themselves consummate risk managers but are highly "uncertainty averse" resulting in "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)" [2].

The finding that financial institutions are hesitant to invest in energy efficiency due to their operational uncertainty is a principal motivation for this research project. As such, it is worthwhile to expand on the underlying dynamics. To that end, this section briefly evaluates:

- The risks in energy performance contracting (EPC), including a description of commonly occurring performance variation problems; and
- Energy savings uncertainty profiles and the role of guaranteed energy savings agreements;

1.1. Risks in Energy Performance Contracting (EPC)

Inherent risks accompany energy performance contracting and clear risk allocation is critical to avoid dispute or litigation [6; 9; 10]. Energy savings uncertainty from the perspective of the investor can be attributed to various risks, including monitoring and verification risk, financing risk, and technology risk (see Table 1). Expected or experienced manifestation of these risks lead clients to indicate "worry about ESCOs' guaranteed savings not being achieved, causing problem to third party financing" as a top concern according to Ref. [6]. In a similar vein, "ambiguity between owner and ESCO regarding realization of estimated savings" and "uncertainty of payments based on energy savings" are listed as key market and financial barriers according to a survey of industry professionals and scholars [7].

1.2. Energy Savings Uncertainty as a Result of Risk Profiles

Conventional risk screening tools used by investors (e.g. simple payback) could downgrade or miss valuable investment opportunities [34-36]. As a first risk mitigation option, contractual agreements are used and, principally, performance contracts between ESCO and client can be formulated as either so-called 'shared savings' contracts or 'guaranteed savings' contracts. [2] Shared savings contracts allow the ESCO to take a share of the savings above a target level and, in this model, ESCOs typically provide project financing [6]. Under the guaranteed savings model, the ESCO guarantees a level of performance sufficient to pay back installation and financing costs if proposed ECMs are implemented and monitored and verified according to IPMVP guidelines. When actual savings fall short of the guarantee, the ESCO compensates the shortfall to the client or otherwise makes the client whole. The ESCO does not benefit from performance levels that are above the guarantee. Importantly, the ESCO market now mostly uses the guaranteed savings model [4; 5].

[2] Other contractual agreement forms, such as "first out" or "chauffage", are also available. These are not considered in this report.

Table 1 Overview of relevant risks

CATEGORY	MANIFESTATION	CAUSES	CONSEQUENCES	MANAGEMENT
FINANCIAL RISK	Payment default	Energy saving is not achieved as expected	Inability to service loan and possible termination	Guarantee on energy saving; performance bond
TECHNOLOGY RISK	Poor system/ equipment performance	Design deficiency	Reduction in actual energy savings	Careful design; acceptance tests
OPERATIONAL RISK	Unexpected consumption pattern	Changes in baseline conditions such as weather, operating hours, load on system conditions	Change in measured energy savings	Contract design, especially for baseline adjustments; M&V protocols
	Degradation of equipment	Faster rate of equipment degradation due to, for instance, poor maintenance	Consuming more energy to achieve same level of performance, resulting in reduction of energy savings	Monitoring and diagnostics
	Faulty operation	Improper system operation	Reduction in actual energy savings	Operation staff training; provision of system operational procedure guidelines;
	Frequent breakdowns	Improper or lack of maintenance	Reduction in profit of ESCO and disturbance to client	Planned maintenance
M&V RISK	Poor data quality	Low resolution of operating data; missing data	Increase in uncertainty on energy savings calculation	Prior agreement in the expected quality of data
	Modeling errors	Incorrect assumptions on technical projects	The model might be invalid for estimating baseline energy use, leading to disputes about actual energy savings	Prior agreement on the use of modeling method and assumptions
	Inconsistency of data	Improper M&V design	Dispute over actual energy savings	Project M&V plan design
	Imprecise /inaccurate metering	Measurement error	Increase in uncertainty in energy saving calculation	Regular calibration; sub metering
ECONOMIC RISK	Fuel cost increases	Electricity/gas price volatility	Reduction in actual cost savings	Hedges; baseline adjustment in fuel cost

Note: selection adapted from analysis by Refs *[6; 10; 32; 33]*.

Under the guaranteed energy savings model, clients are typically responsible for obtaining financing either from internal funds or from external third-party investors (e.g. a bank or financial institution) [6; 37; 38]. Responsible for about 15 TWh of the 34 TWh in electricity savings achieved in 2012 [39], the public/institutional market sector is the dominant market [30]. This market segment often finances up to 100% of project costs [4]. The guaranteed savings model is compelling especially for public/institutional property owners which typically operate in a capital deficient, maintenance-deferred environment [40]. The guarantee, supported by a creditworthy ESCO, represents a financial commitment that addresses downside risk, making it easier for these property owners to attract the capital needed for the project.

To limit *their* downside risk exposure, ESCOs typically set the guarantee below predicted performance [20] using ESCO-specific risk tolerances on individual energy conservation measures (ECMs) [21]. [3] In other words, no "rule of thumb" for setting the guarantee is available [23]. However, a benchmarking database of about 6,100 projects operated by Lawrence Berkeley Laboratory (LBNL) in partnership with the National Association for Energy Service Companies (NAESCO) shows realized savings often exceed from the guarantee in both ways, sometimes significantly (Figure 1). Discrepancies between predicted and actual metered building energy use found in evaluations lead us to examine guarantee placement by ESCOs. For example:

- U.S. federal level non-EPC and EPC project compliance was found to have insufficient realization rates [46; 47].
- An evaluation of 8,541 buildings in Greece found that, on average, calculations underestimated actual EPC savings by 44% [44].
- Review of a NAESCO database found that 72% of projects experienced greater savings than were guaranteed by the ESCO (517 projects), some by as much as 50% more [5].

[3] To further limit downside risk, the ESCO is less likely to recommend high-impact, high-cost technologies, leading the guaranteed savings approach to relatively safe and often less aggressive ambitions [40; 41]. This is partly due to the fact that the performance contractor is compensated based on the value of capital acquisition – thus linking profits to size of the expenditure – as opposed to a direct connection to energy savings [40]. ESCOs, knowing that especially the governmental sector can access low-cost capital via tax-exempt municipal lease or bonds, increasingly focus on capital improvement and project size as a result [40].

- Analysis of a U.S. Department of Energy (DOE) Super Energy Savings Performance Contract (Super ESPC) Program found that, for the aggregate of 102 projects, the value of annual cost savings exceeded the cost savings guarantee by 19% [48].

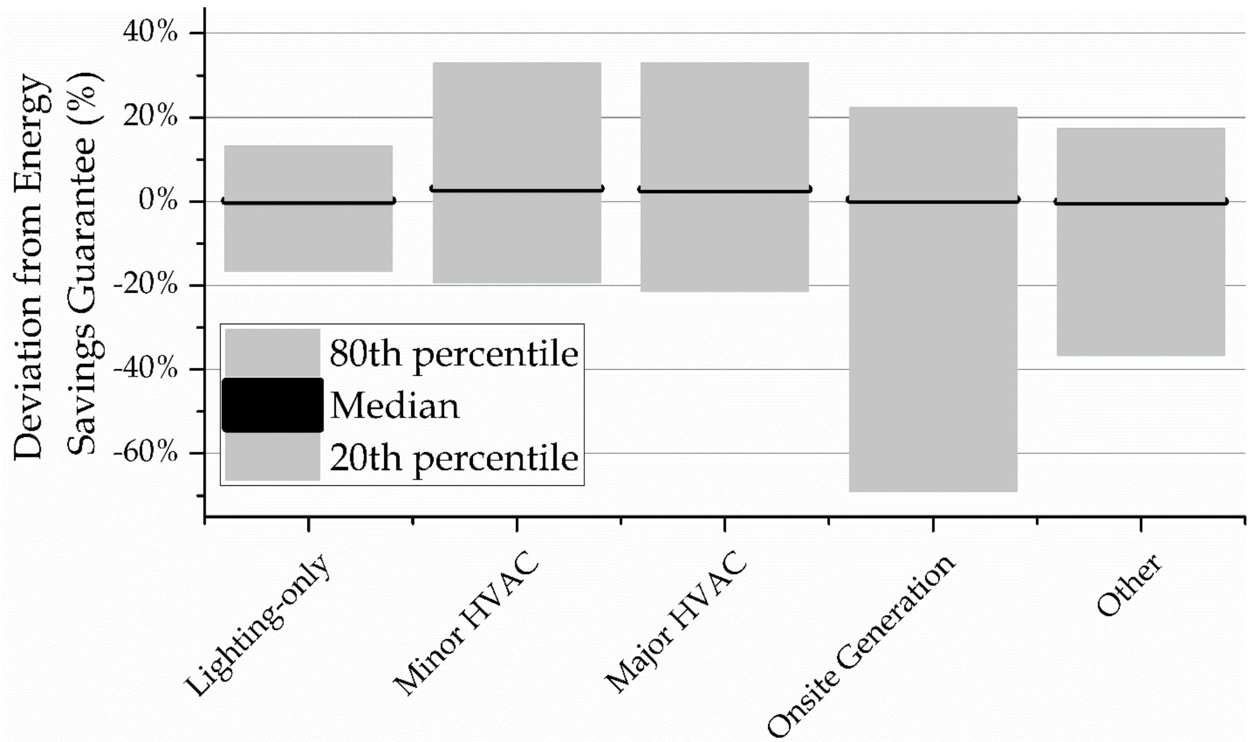

Figure 1 Realized energy savings against guarantee at public properties (1990-2017)

Note: Presented here is the 20th percentile (lower end), median (black horizontal bar), and the 80th percentile (high end) (n = 1,652). Source: https://eprojectbuilder.lbl.gov/home/#/benchmark.

On the other hand, researchers report that potential clients of energy performance contracting express reservations about the guarantees. Specifically, potential clients worry that performance contracts may under-perform against guarantee, leading to what has been described as a "credibility gap" [11; 13; 42-45].

In this regard, performance contracts raise conflicting concerns: over-performance or under-performance of the guarantee? Our research question is whether risk management under a guaranteed savings contract can be improved so as to reduce ESCO tendencies to shift project risks to other parties; and can we manage risk around the guarantee in a manner that reduces the "credibility gap" harbored by potential clients? Our focus is on "smart controls" as one tool to address these twin problems.

Important elements regarding energy savings guarantees are:

- Contractors will not typically assume risks that they cannot manage in a direct fashion;
- Savings guarantees shift unbounded risks (any risks not captured in the guarantee) to other parties;
- Savings guarantees are usually well below the achievable savings in order to build-in risk protection for the ESCO;
- Guarantees always carry a cost.

2.0. BUILDING CONTROLS FOR AUTOMATED PERFORMANCE CONTROL

Inadequate building operations due to the convergence of the risks listed in the table above can result in inefficient performance both in terms of excess energy consumption but also in terms of discomfort to the buildings' inhabitants. Commonly occurring operational problems identified in the literature include:

- Continued system operation (such as heating, ventilation, and air conditioning (HVAC), exhaust fans, or lighting) beyond necessary hours;
- Improper technology set points (e.g. thermostat set points); and
- Inadequate economizer operations [15-17].

Implementation of building controls could therefore help prevent significant energy waste. For instance, an assessment by the U.S. Energy Information Administration (EIA) documented in 2012 that over 85% of commercial buildings in the United States have inadequate control infrastructure in place [49]. It has been broadly established that advanced control measures can improve performance and save 10%-30% of energy consumption [17; 50-53]. For instance, for lighting, a combination of improved lighting devices and controls can reduce commercial lighting energy use by 81% [54]. A meta-analysis looking at the savings generated by lighting controls in commercial buildings by isolating the control function contribution found savings ranging from 28%-40% with combined operation of sophisticated controls achieving higher saving rates [55].

An emerging paradigm in building controls is the introduction of automated performance control technology options, that can measure and control building operations in real-time [19; 56-58]. As a general definition, technologies within this paradigm rely on "web-based analysis software, data acquisition hardware, and communication systems […] to store, analyze, and display whole-building, system-level, or equipment-level energy use" and, at minimum, provide hourly but typically provide sub-hourly interval meter data with graphical and analytical capabilities and assessment [18; 19].

The use of such techniques is currently largely in the pilot stage and used primarily for program targeting and opportunity identification [57]. The technology platforms are mostly used in commercial and industrial applications [56; 57; 59-62] but "cloud computing platform[s] for real-time energy performance [monitoring and verification are] applicable to any industry and energy conservation measure" [63].

Combined, the suite of technologies that makes up the automated performance control paradigm can, thus, yield actionable value in EPC projects by monitoring and correcting real-time performance [18; 19]. Clients that have used such technology suites indicate a high level of satisfaction: 19 out of 21 cases evaluated reported automated measurement, verification, and control as critical in achieving energy savings [19]. A 2018 market analysis by a leading industry actor found that building control improvements are "the most popular investment for the next 12 months among U.S. organizations" as 68% of survey respondents indicated plans to invest in (additional) controls [70]. A 2014 estimate suggested the intelligent building control market could reach an annual $59 billion (in 2009 dollars) by 2019 [71].

Whole-building energy management systems integrate a variety of end-uses. A survey of zero net-energy buildings that use building controls found that 91% of the commercial buildings surveyed relied on control systems that integrate multiple end-uses with 67% using a fully integrated controls architecture capable of controlling all end-uses centrally and automatically [72]. However, it is important to emphasize that even these systems often still rely on the occupant for some part of the successful operation of the controls: 74% of the buildings surveyed have integrated controls system sequences that are not fully responsible for driving performance, relying instead on the occupant [72]. Under these cases, persistence of savings is uncertain and "optimal" operation likely requires frequent re-tuning [15].

However, relative to the potential, significant under-adoption of the technology suites can be observed and this is often attributed to the high cost associated with whole-building applications [19]. The suite of technologies is typically deployed as "software as a service" (so-called SaaS) offerings, delivering capabilities on a subscription-type basis [19]. In other words, up-front expenditures for items such as licensing and system configuration are accompanied by recurring subscription fees which spread out the cost of the entire system over its lifetime [19]. Nevertheless, up-front cost estimates range from $10 to $3,400 per "point" with most in the $100 to $500 per point range [19]. In addition, the recurring costs range from $5 to $3,100 per point [19]. Put together, 5-year ownership estimates ranged from $140 to $16,000 per point [19]. A "point" is a single datum that is trended, stored, and available for normalization and data analysis across use cases and comprehensive, whole-building systems can have thousands of points. For example, a use cases overview of a major controls company shows how a project involving three federal office buildings contained 18,000 points [73]. Therefore, at the median 5-year ownership costs found by Ref [19] of $1,800 per point, a fully integrated energy management system could cost as much as $32 million. The wide range in costs is illustrative of the relative immaturity of the market but also suggests significantly higher costs for more advanced systems and the use of different pricing models.

For these reasons, it is worthwhile to consider partial integration using separate control technology options (i.e. not part of a whole-building systems package). Acquiring only the level of controls necessary to ensure limited performance variation represents a strategic approach to building performance that might prove sufficient to boost investor and client confidence. Versions of partial integration deployment strategies can be observed in the market: the survey of zero net-energy buildings found that partial integration of end-uses occurred in 24% of the buildings while 9% had no whole-building controls architecture at all but, instead used controls only at the end-use level [72]. At this level of operation, there is an expectation of significant cost reduction to the point where control technology cost can be brought down from an estimated $150-$300 per node to $1-$10 per node using low-cost, self-operated, and wirelessly connected end-use level devices [74].

3.0. ENERGY SAVINGS GUARANTEE SETTING PROCESS

So far, we've established that the energy efficiency savings performance can be uncertain. One way to consider this uncertainty is to reflect on energy savings performance as a stochastic distribution of possible savings. The savings with highest probability can be seen as the expected performance level. Yet, deviation from this expected performance is what prevents project confidence.

A key way the energy efficiency retrofit sector attempts to limit the influence of this uncertain performance profile is to establish energy savings guarantees. In this case, the ESCO guarantees a certain level of performance and, if the project fails to materialize this level of performance (i.e. if realized savings are below the guarantee), the ESCO is responsible to either a) improve the performance of the project by deploying additional effort or b) provide other means of compensation. Effectively, energy savings guarantees are contractual risk transfer agreements provided by the ESCO that mitigate the risk surrounding lower-than-expected energy bill savings. The guarantees bolster the client's confidence in the project's ability to deliver actual energy bill savings.

However, as documented briefly above, ESCOs seek to limit their own downside risk exposure as well. This is done by setting the guarantee below predicted performance [20] using ESCO-specific risk tolerances on individual energy conservation measures (ECMs) [21]. In other words, no "rule of thumb" for setting the guarantee is available [23]. Instead, ESCOs deploy in-house models to strategically determine the placement of the energy savings guarantee. A broad distribution of energy savings – i.e. a higher probability for adverse circumstances – presents a higher risk for the ESCO that performance levels will be below the guarantee (e.g. [75]) and, as such, all else being equal, is accompanied by a lower guarantee. Relevant possible adverse circumstances are listed above in Table 1.

3.1. Energy Savings Guarantee Setting Model

In this research, we evaluate an energy efficiency retrofit project where the ESCO is sufficiently confident in the project's ability to save energy that it will provide an energy savings guarantee. Nevertheless, as mentioned above, we model a risk-averse ESCO by using a low risk tolerance. In addition, funding sources for energy saving projects can come from a variety of resources. Here, the project is financed via third-party sources – such as, for instance, the capital markets – and this debt is paid back through the cash flow from the guaranteed energy savings (i.e. the project is "self-financing"). As such, several important dimensions stand out for the ESCO when considering placement of the guarantee:

- **Cash flow resulting from the project:** The cash flow of the project is determined by the realized energy bill savings which is a product of the energy price and the amount of energy units saved per year by the project relative to a baseline energy bill before the retrofit took place. These two sub-dimensions of energy price and energy savings can be identified separately:
  - **Energy Price:** We evaluate electricity and natural gas prices over time. Electricity prices are assumed to follow a contractually fixed trajectory starting at a current electricity price and escalating annually. Natural gas prices are determined stochastically by allowing a drift coefficient and volatility coefficient to set the trajectory (see Ref. [23]).
  - **Profile of realized saving:** The realized savings are determined stochastically resulting in a distribution that approximates a normal distribution. Following Deng et al. [23], two assumptions underpin the profile of realized savings. First, we assume that the estimate of expected annual savings is guided by the system engineers' best knowledge. Second, we assume that the volatility effect of realized savings is annually independent.
- **Under- or over-performance of guarantee decisions:** various contractual forms are available to decide on the profit (or loss) sharing structure. Under the assumed conditions of the energy efficiency project, under-performance is entirely on the shoulders of the ESCO while over-performance benefits entirely the client. In other words, there is no sharing of the profit if savings exceed the guarantee and the ESCO will compensate any shortfall.
- **Risk tolerance:** All risk-transfer contracts – of which energy savings guarantee is one – are affected by the same underlying risky energy bill savings and costs (see "cash flow resulting from the project" above). Therefore, the financial risk experienced by the ESCO, client, and third-party investor are subject to the specification of the contract terms. Following Töppel &Tränkler [28], we assume that the parties involved treat the contract options with an equivalence-based perspective: decisions are made based on the expected returns and the risk profile;

no preference for a particular risk-transfer contract approach is embedded into the modeling. Nevertheless, the investor, ESCO, and client are positioned as risk-averse: if premium levels to reduce risk are the same, parties will select the premium option that reduces the most risk. Risk is measured based on standard deviation and "value-at-risk" [76].

The model to determine the energy savings guarantee is described in detail in Appendix A. In essence, the strategic guarantee is, as discussed in Appendix A, the highest possible guarantee where the ESCO can reasonably expect the savings to be equal to or larger than the guarantee. This can be graphically represented. For the hypothetical example (see Figure 2), we assume 3 performance variables with different variations (for example, advanced lighting, zonal, programmable thermostats, and improved cooling technology). The hypothetical example shows the results of four simulations to illustrate the stochastic character of performance. As can be visually approximated in Figure 2 (actual analysis below shows exact numbers), the last value where $D_{E,total}(G(t), \beta) = 0$ (see Appendix A) is roughly under a scenario where the ESCO guarantees annual energy savings worth $50,000.

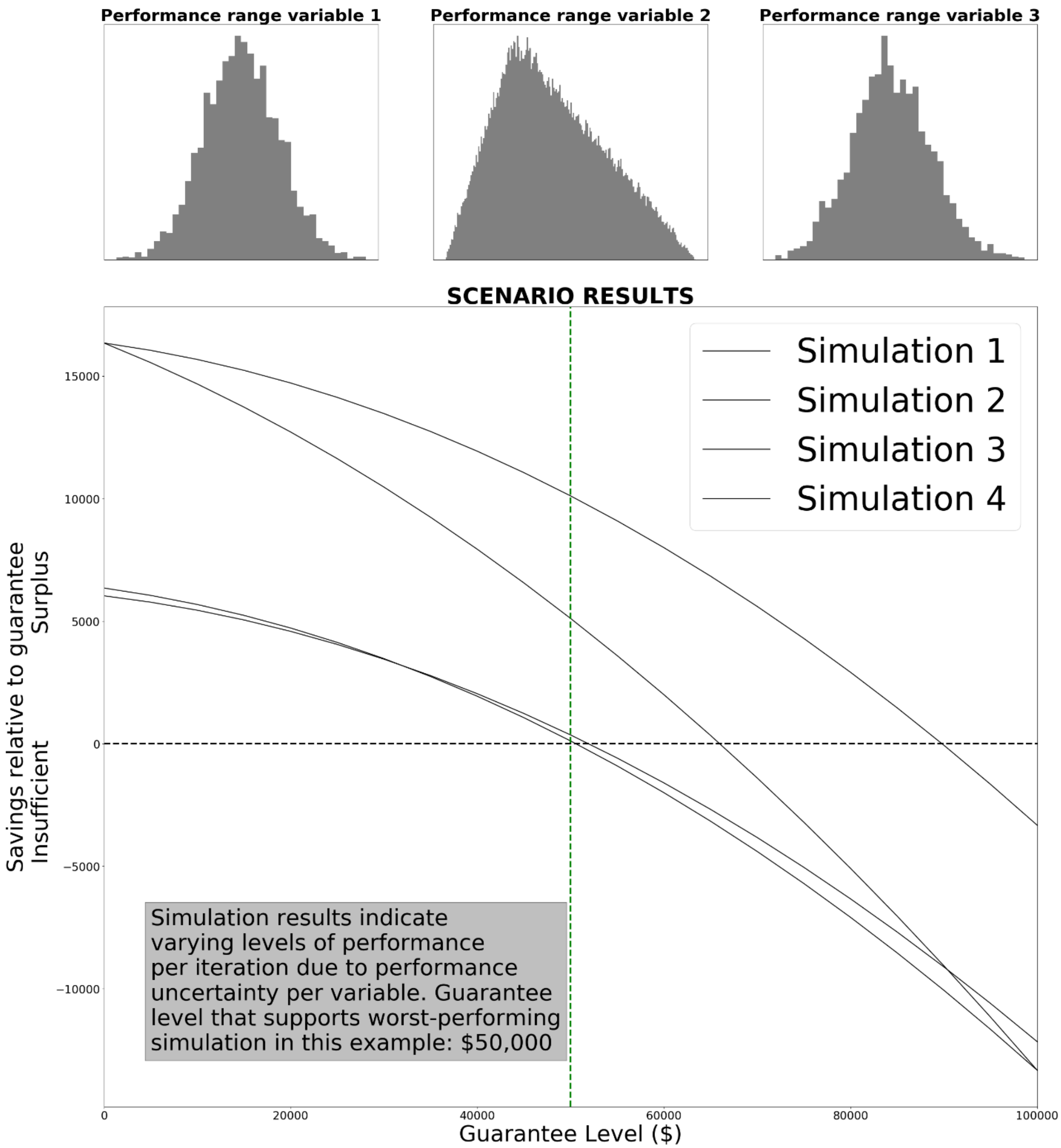

Figure 2 **Hypothetical distribution of model simulation results for four evaluations**

While only four simulations are included in Figure 2, the analysis performed in Section 4 simulates tens of thousands of simulated outcomes. This generates a challenge: when simulating such a large number, there will undoubtedly be a few simulations with exceedingly low performance and, hence, very low $D_{E,total}(G(t), \beta) = 0$ values. This is where the ESCO's risk tolerance becomes important. For example, hypothetically, the

ESCO can be comfortable with a risk tolerance where 95% or 99% of 10,000 simulations show a present sum profit difference $D_{E,total}(G(t), \beta) = 0$, accepting a (small) risk that the performance ends up being below the guaranteed energy savings. In our model, we've inserted a final step that takes the percentile values of each guarantee level G(t) to model this risk tolerance. We use a risk tolerance of 95% in our analysis.

3.2. Software stack

The primary software element is the Department of Energy's (DOE) Energy Plus software: a leading building energy simulation tool in the energy efficiency industry [35; 80; 81]. Advantages of Energy Plus include first-principles, text input-output workflow that can be automated [82] and availability of benchmark building model databases (16 building types across 16 locations and three construction periods) [83; 84]. Within Energy Plus, we made use of DOE's prototypical commercial building models that describe typical building layout, geometry, energy consumption, etc. for buildings in the Delaware region constructed before 1980 [84; 85].

Parametric evaluation of the building models was conducted using jEPlus software (version 1.7.2), an open-source parametric analysis tool specifically designed for Energy Plus [86] that provides flexible and structural analysis opportunities and smooth operations [87]. The tool has been used in similar investigations to determine sensitivity or optimize energy systems [88-91]. This set-up enables Monte Carlo analysis for risk estimation and management of, among others, renewable energy projects, system planning, or system optimization [92-98] and for energy efficiency projects in general and M&V efforts specifically [22; 37; 88]. Latin Hypercube Sampling (LHS) was used to run 10,000 simulations per jEPlus model run. LHS is a powerful tool that enables efficient stratification across the uncertain performance range [99]. This parametric evaluation takes the possible performance levels described in the previous section and models their effect on overall energy consumption and resulting energy and cost savings.

Outputs of the jEPlus modeling tool are then inserted into the calculation models introduced in the previous sections.

3.3. Prototypical Building Selection

Within Energy Plus, we made use of DOE's prototypical commercial building models that describe typical building layout, geometry, energy consumption, etc. for buildings in the Delaware region constructed before 1980 [84; 85]. The energy performance of these buildings is simulated in Energy Plus version 8.6.0. Six commercial benchmark building models are evaluated in the 2018-2019 study. These buildings were selected as they reflect a possible building portfolio operated by the public sector, the dominant user currently of energy savings guarantees (see earlier sections):

Large Office: The large office benchmark building is a 46,320.38 square meter, 12-story office building (including basement) with total annual baseline consumption of 26,358.15 GJ of electricity and 7,265.8 GJ of natural gas to fulfill its end-use functions or 725.9 MJ/m^2. Notably, over half of the building's energy consumption serves interior lighting (9,422.03 GJ or 28.1%) or interior equipment (8,384 GJ or 25.2%). Heating is third most responsible for annual energy consumption (7,265 GJ or 21.6%).

Medium Office: The medium office benchmark building is a 4,982 square meter, 4-story office building (including basement) with total annual baseline consumption of 3,438.2 GJ of electricity and 534.4 GJ of natural gas to fulfill its end-use functions or 797 MJ/m^2. Notably, over half of the building's energy consumption serves interior equipment (1,066 GJ or 26.6%) or interior lighting (1,231 GJ or 31%). Fans represent 708 GJ of annual energy consumption or about 17.7%). Heating is fourth most responsible for annual energy consumption (534.4 GJ or 13.5%) followed closely by exterior lighting (280 GJ or 7%).

Small Office: The small office benchmark building is a 511.16 square meter, 1-story office building with total annual baseline consumption of 363.33 GJ of electricity and 156.43 GJ of natural gas to fulfill its end-use functions or 1,016.79 MJ/m^2. Notably, most of the building energy's consumption is accounted for by heating (30.14%), interior lighting (19.7%), interior equipment (16.8%) and fans (16.3%).

Hospital: The hospital benchmark building is a 22,422.24 square meter, five-story hospital building with total annual baseline consumption of 33,182 GJ of electricity and 15,000 GJ of natural gas. At 24.4% of the total annual consumption, heating represents the key energy consuming end-use function, followed by interior lighting (18.2%), cooling (14.8%), and interior equipment (14.2%).

Primary School: The primary school benchmark building is a 6,871 square meter, single-floor school building with total annual baseline consumption of 4,108 GJ of electricity consumption and 2,454 GJ of natural gas use. Heating (31.8%) is followed by interior lighting (27.8%) as main energy use functions in the building. Interior equipment (22.2%)

and cooling (9.8%) are other key end-use functions in terms of their contribution to annual energy consumption.

Secondary School: The secondary school benchmark building is a two-story, 19,592 square meter building with total annual baseline consumption of 10,380.04 GJ in electricity consumption and 7,772.15 in natural gas consumption. Like with several of the other benchmark buildings, heating represents the main end-use function in terms of energy consumption (38.4%), followed by interior lighting (22.5%), interior equipment (12.5%), and fans (10.1%). A brief overview of several key metrics is provided in Table 2 for each of the six benchmark building models tested in this analysis.

Table 2 Key metrics of the benchmark building models

Building	**GJ /yr**		**MJ/m2**	**Electricity (MJ/m2)**			**NG (MJ/m2)**	
	Source	**Site**		**Lighting**	**HVAC**	**Other**	**HVAC**	**Other**
Large office	102,191	33,624	725.9	203.41	143.72	221.91	156.86	0
Medium office	12,879	3,972	797.4	247.15	228.9	214.07	107.27	0
Small office	1,470	519	1016.79	285.79	253.4	171.62	306.04	0
Hospital	136,523	49,540	2,209.45	388.11	680.25	411.52	668.98	60.58
Primary school	17,373	6,563	955.28	293.42	115.41	189.17	323.17	34.11
Secondary school	45,605	18,152	926.5	226.63	179.77	123.41	378.66	18.04

3.4. ECM Selection, Cost, and Control

Possible ECMs were identified using research results from Lawrence Berkeley National Laboratory (LBNL), specifically the Commercial Building Energy Saver (CBES) project (http://cbes.lbl.gov/ and Refs [100-102]). This ECM selection was further supported by data from the Building Component Library and several articles using a similar methodological approach [21; 82; 88; 103]. Finally, our research team had access to guaranteed energy savings agreements (GESAs) provided by ESCOs for other projects in Delaware and across the United States. Data from these GESAs was used to complete ECM profile selection by looking at buildings in those projects that share similarity with the benchmark buildings. The ECMs used in the remainder of the analysis are briefly summarized in Table 3. Critically, based on a review of existing control literature, the selected ECMs listed in Table 3 can be accompanied with a control function.

Table 3 ECMs used in the analysis

#	ECM	Main parameter in E+	Unit
1	Replace lighting with LED upgrade	Lighting load	W/m2
2	Appliance upgrade	Plug load	W/m2
3	Change zone thermostat set-point	Set-point in Celsius	C
4	Install high-efficiency chillers	Reference COP	fraction
5	Install high-efficiency boiler	Nominal thermal efficiency	Fraction
6	Install high-efficiency fans	Fan total efficiency	Fraction
7	Install high-efficiency water heater	Heater thermal efficiency	Fraction

Large Office: Application of the suite of ECMs identified in Table 3 and Appendix 3 yield a post-retrofit performance profile with, on average, annual consumption levels of 16,629.48 GJ and 5,515.283 GJ for electricity and natural gas consumption, respectively – a reduction in energy use of approx. 34%. In particular, the electricity intensity for lighting has been reduced from 203.41 MJ/m2 to 93.94 MJ/m2 – a reduction of over 53%.

Medium Office: Post-retrofit performance profile with, on average, annual consumption levels of 2,187.64 GJ and 700.27 GJ for electricity and natural gas consumption, respectively – a reduction in energy use of 27%.

Small Office: The ECMs together reduce electricity use to 223.41 GJ and natural gas consumption to 163.86 GJ. This is equivalent to an overall, facility-wide energy consumption reduction of 25%.

Hospital: The applied measures combined reduce, on average, the use electricity to 22,522 GJ and 12,478.4 GJ for natural gas. Accomplishing a reduction in energy use of over 29%.

Primary School: After application of the ECMs, the total use of electricity and natural gas decreased to 2,429.86 GJ and 1,925.25 GJ respectively. The implemented ECMs achieved therefore, a total consumption reduction of 33.6%.

Secondary School: Post-retrofit performance reduced the use of electricity to 6,366.22 GJ and the use of natural gas to 7,064.48 GJ. The overall consumption of electricity was decreased by 26%.

Table 4 Key metrics of the post-retrofit benchmark building models

Building	GJ /yr		MJ/m2	Electricity (MJ/m2)			NG (MJ/m2)	
	Source	Site		Lighting	HVAC	Other	HVAC	Other
Large office	65,490	22,145	478.09	93.94	88.41	176.66	119.08	0.0
Medium office	8,588	2,888	579.66	129.21	141.08	168.82	140.56	0.0
Small office	977.82	387.26	757.62	151.59	156.75	128.72	320.57	0.0
Hospital	94,166	35,000	1,561	161.0	509.91	333.55	495.94	60.58
Primary school	10,791	4,355	633.84	132.06	74.94	146.64	246.09	34.11
Secondary school	30,479	13,430	685.51	103.94	123.96	97.04	342.54	18.04

3.4.1. ECM 1: Replace Lighting with LED Upgrade

Around 18% of U.S. electricity consumption (~6% of all U.S. electricity consumption) is used to provide indoor and outdoor lighting [54]. (Interaction effects between lighting (artificial and daylighting) and heating and cooling loads are also important to emphasize. These interactive effects are modeled by EnergyPlus software). The 2017 U.S. lighting market characterization report by the DOE shows that, in 2015, the residential sector accounts for 71% of all lighting installations (6.2 billion lights) followed by the commercial buildings sector at 24% (2.1 billion lighting installations), the outdoor sector (3%, 258 million) and the industrial sector (2%, 172 million) [104]. However, the commercial sector is responsible for about 40% of annual electricity use dedicated to lighting in the U.S. – this is due to the higher average daily operating hours (see Table 5).

Table 5 Overview of U.S. lighting market in 2015

Sector	Total lamps and luminaires	Average daily operating hours	Average Wattage per lamp or luminaire	Annual electricity use (TWh)
Residential	6,218,969,000	1.9	38	149
Commercial	2,076,460,000	8.9	36	237
Outdoor	257,546,000	13.4	166	202
Industrial	171,682,000	12.1	65	53
Total	**8,724,657,000**	**4.1**	**42**	**641**

Source: [104]

Our focus here is on the buildings commonly found in the commercial sector as operated by the public sector (i.e. office spaces, schools, hospitals). The commercial sector is shifting from T12 to higher-efficiency fluorescent lamps and LED lights [104]. Indeed, LED technology is seen as the most likely technology to dominate the sector moving forward [54]. However, linear fluorescent remains the predominant lighting technology (78% of lighting) in this sector and only about 10% of the sector's lighting is provided through LED technology [104]. Average lighting wattage of linear fluorescent lighting across the various building types of the commercial sector is estimated at 34 Watts while LED lighting average wattage is estimated at 19 Watts – a reduction of around 45% in wattage [104]. Best-in-class LED technology can deliver even higher energy savings – these savings remain even when comparing it to best-in-class linear fluorescent lighting [105].

Lighting efficiency is expressed in lumens per watt (lm/W) and laboratory LED devices have demonstrated efficiencies approaching 300 lm/W [54]. The most efficient commercial products today have efficiencies between 120 and 160 lm/W [54]. In addition, LED technology is accompanied by features typically unavailable in other technology options while retaining a high level of efficacy (e.g. spectral control, intensity control, and optical distribution control) [105]. Following the Commercial Building Energy Saver (CBES) Project (http://cbes.lbl.gov/ and Refs [100-102]), we assume ECM 1 can lower indoor lighting consumption in the large office benchmark to 6.46 W/sq. m.

The cost of LED products has rapidly decreased [106]. For example, a 2017 research plan by DOE documents the price trend of the technology (Figure 3). The price estimates documented in Figure 3 are used in this analysis and represent typical retail prices for LED packages purchased in quantities of 1,000 from major commercial distributors [105]. Using price point estimates for 2020 for cool white LED packages at 218 lumens per Watt and $0.45/kilolumen and using a 6.46 W/square meter application for the large office's 46,320 square meters, yields a $0.63/square meter cost for ECM 1 in the large office. Using the same calculation for the other benchmark buildings yields similar figures (Table 6).

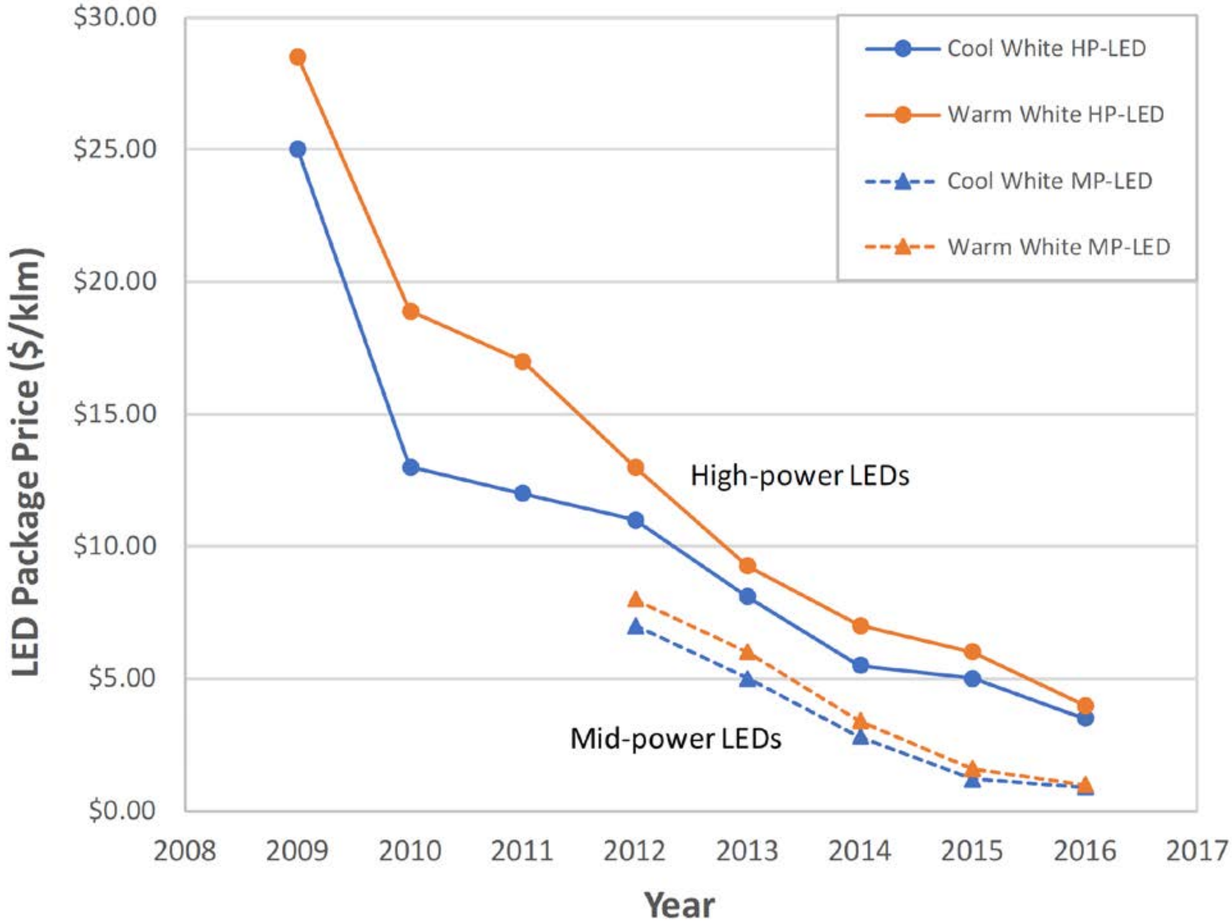

Figure 3 **Price and quality improvement of LED technologies**

Source: [105]

Table 6 **Cost per square meter for ECM 1: LED lighting**

Building Benchmark	Square meters*	Application level (W per sq. meter)	Cost ($/sq. meter)	ECM Cost ($)
Small office	511	7.79	$0.76	$391
Medium office	4,982	6.76	$0.66	$3,303
Large office	46,320	6.46	$0.63	$29,354
Hospital	22,422	Various	Various	$9,695
Primary school	6,871	Various	Various	$5,399
Secondary school	19,592	Various	Various	$11,592

* Note: for several buildings, only a selection of the square meters were included in the ECM. For example, the hospital building benchmark has highly specific rooms (e.g. emergency rooms, operating rooms) that are not available for retrofit. The ECM cost calculation is only for those rooms where the lights were indeed retrofitted.

In terms of performance variation controls, LED technology stands out as the technology enables a "whole new lighting system paradigm by the broad transition of lighting infrastructure to inherently controllable [solid state lighting] systems" [105]. Yet, despite this significant opportunity and the existing availability of lighting controls, the deployment of controls has so far been limited (Table 7). In fact, the majority of buildings, according to Ref [105], have no lighting controls at all. LEDs are "poised to be the catalyst that unlocks the energy savings potential of lighting controls due to their unprecedented controllability and increasing degrees of automated configuration" [105]. This is another reason to select ECM 1: LED lighting. Lighting control systems that can leverage occupancy sensing, daylight harvesting, personal area controls, etc. can enable energy savings of 20%-60% (depending on use case) [17; 51; 55; 107-109]. In addition to the sensors and controls listed in Table 7 (occupancy sensors, daylight sensors, etc.) which are relatively well understood, novel control applications such as presence detectors (video-based occupancy sensors), air quality sensors, Wi-Fi, Bluetooth, or temperature sensors are expected to be added to the control function spectrum.

Table 7 **Installed stock penetration rate of lighting controls in buildings and outdoor lighting applications**

Installed stock penetration (%)	Commercial	Residential	Industrial	Outdoor
None	68%	86%	94%	41%
Dimmer	3%	11%	4%	<1%
Daylighting	<1%	<1%	<1%	39%
Occupancy sensor	6%	<1%	2%	<1%
Timer	4%	<1%	<1%	20%
Energy management system	15%	<1%	<1%	<1%
Multi	4%	<1%	<1%	<1%
Connected	<1%	<1%	<1%	<1%

Source: [105].

3.4.2. ECM 2: Appliance Upgrade

The category of "plug loads" represents all appliances within a building. As such, it is an inherently nebulous category, including many different types of devices such as computers, vending machines, water coolers, phones, etc. [4] Plug loads account for approximately 12% of total energy consumption in all U.S. office buildings according to

[4] No consistent definition of the concept of "plug loads" appears to be available. A study into the topic found that other terms for similar definitional boundaries as "plug loads" are "miscellaneous equipment", "process loads", "receptacle loads", "office equipment", or "miscellaneous electronic loads" [110]

the Commercial Buildings Energy Consumption (CBECS) reports published by the U.S. Energy Information Administration. In California, plug loads represent about 18% of total electricity consumption in office buildings [110]. A U.S. Department of Energy Building Technologies Program report published in 2010 estimated that so-called "plug and process loads" accounted for about 33% of total U.S. commercial building electricity use [111]. In addition, the relative importance of "plug loads" in energy efficiency projects is expected to increase as a) energy efficiency efforts have reduced the relative importance of other loads such as lighting and b) office equipment energy consumption is expected to rise over time [112].

A study into the power consumption from plug loads per square meter (the metric used in our EnergyPlus modeling) found that for a certification for major renovation ("LEED-NC"), median plug load power intensity was 10.8 W/m2 while average plug load power intensity was estimated at 4.0 W/m2 [110]. These numbers are similar to our modeling efforts for plug loads documented below.

An important realization, like with lighting, is that office workspace plug load energy consumption is "strongly linked to occupancy" [112](see also Refs. [113; 114]). An analysis of 137 plug load functions in a California office found that desktop computers consume most power per person *and* demonstrate the largest fluctuations in power consumptions [112]. The analysis furthermore found that office occupants are more likely to turn their plug load equipment off right before a long break than they are to do so overnight during the week [112]. Similarly, a study that reviewed the operation of ten offices found that over 75% of the plug-in equipment electricity consumption took place during unoccupied periods [115]. The result is that office plug load equipment is often unnecessarily on (overnight), wasting energy.

(Advanced) plug load control refers to control technology at the device-level that can control the performance of plug loads especially when they are not in use. Implementation of appliance control strategies demonstrate realized savings. For example, an appliance-based home performance control strategy has been shown to yield energy savings of 5%-16%, cost reduction of 10%-24%, and peak reduction of 38%-53% [116]. Examples of the type of intervention strategy include [110-112; 117]:

- smart (e.g. load sensing) power strips for office equipment;

- occupancy-based sensors for vending machines;
- time switches for water coolers;
- adjust power management savings to reduce energy use during non-working hours;
- control plug loads remotely; and
- wire plug loads on same circuit.

ECM cost data on plug load energy efficiency improvement is provided by CityBES.org [118; 119] and sets the intervention price at $0.491 per square foot (~$5.29/square meter). The costs are reported for each benchmark building in Table 8.

Table 8 **Cost per square meter for ECM 2: Plug Loads**

Building Benchmark	Square meters	Cost ($/sq. meter)	ECM Cost ($)
Small office	511	$5.29	$2,701
Medium office	4,982		$26,330
Large office	46,320		$244,805
Hospital	22,422		$118,502
Primary school	6,871		$36,314
Secondary school	19,592		$103,545

3.4.3. ECM 3: Change Zone Thermostat Set-Point

Our third ECM changes zone thermostat set-points by widening the thermostat deadband and modifying the night setback. Widening of the thermostat deadband – the range of temperatures where no heating or cooling is required – avoids frequent switching from heating to cooling, saves energy by lowering effective heating and raising the effective cooling setpoint [117]. A study on the topic found that increasing the cooling setpoint for their case study examples by 5 °F reduced cooling energy on average by 29% [120]. Similarly, reducing the heating setpoint 2 °F reduced heating energy by 34% [120]. Another study found energy savings ranging up to 60% without compromising thermal comfort to the occupants of the buildings [121]. These findings, however, depend heavily on the climatic conditions of the location in question.

Controlled operation of zone thermostats can be performed in a variety of ways. Conventional building control strategies are inefficient [122] and simple programmable thermostats appear to be insufficient to realize the expected energy savings as well [123]. Now, the industry is turning to "smart" thermostats that can incorporate multiple features such as web-based or smart-phone user interfaces, energy-use feedback, networked control of multiple zones, occupancy-sensing, learning, fault detection, diagnostics of operations, and demand response [123]. Occupancy-responsive thermostats are one option currently available on the market that can respond to their environment. A study into the performance of such occupancy-responsive, learning thermostats found that they reduced energy consumption by about 9% during periods of regular use of the building in question and about 20%-30% during prolonged periods of low occupancy (for example, a vacation period for a school) [123]. Similarly, the deadband widening control intervention tested by PNNL found 8.1%-15.6% in annual site energy savings for a variety of building types [117]. The PNNL team also tested an occupancy-based thermostat control intervention in the large hotel benchmark building and found a reduction of about 3.3% in annual site energy consumption [117]. A well-insulated space in the heating season can save about 3%-10% with an occupancy-based thermostat control strategy according to another study [124].

Costs for this ECM, without controls, are relatively low [119] as it is a thermostat setting modification rather than equipment replacement. CityBES database reports a unit cost of $49.10 for each thermostat. When adding control functions (e.g. occupancy-based thermostat-level sensors), new equipment needs to be installed which comes at higher cost.

3.4.4. ECM 4, 5, and 6: Install High-Efficiency HVAC Equipment (Chiller, Boiler, Fans)

Thermostats form one technology component in the heating, ventilation, and air conditioning (HVAC) category. Several other technology components are also replaced in the hypothetical energy efficiency project: chillers, boilers, and fans.

ECM 4 is an intervention where the existing chiller is replaced with a high-efficiency version. Important considerations in this regard are the type and size of the chiller that is being replaced. These considerations influence the cost profile of the ECM and its control options, the efficiency range of the equipment, and its operations in the benchmark building model. HVAC equipment sizing for all reference building models is determined from design day runs by EnergyPlus with a specified sizing factor [85]. The large office comes with two 2 air-cooled electric chillers which are both replaced for high-efficiency chiller equipment. The associated ECM cost data is represented in $/ton of refrigeration

(Table 9). At $439.48/ton[5], replacement of the 2 air-cooled electric chillers in the large office (at ~560 tons each) comes down to ~$491,935. This $/ton data point is consistent with a market survey performed by E Source which estimates air-cooled chillers >= 150 tons at $350-$500/ton [125]. The other benchmark buildings are represented in Table 9.

Chiller controls can come in a variety of configurations. Chiller sequencing control, for instance, enables optimization of performance across multiple chillers while retaining indoor thermal comfort. For example, when making use of the complementarity across multiple load indicators, the performance robustness of chillers can be improved [126]. Electricity load savings can be extracted with smart control strategies [127; 128]. A control strategy focusing on morning start periods, for instance, found energy savings on the order of 50% during that period (4.5% of total A/C system consumption) [128].

Table 9 **Overview of building benchmark cooling equipment before and after retrofit (ECM 4)**

Building	Chiller Capacity	Pre-Retrofit Efficiency	Retrofit Cost	Post-Retrofit Efficiency Value	ECM Cost ($)
Large Office	2 air-cooled electric chillers at 1,968,310.37 W or ~560 tons (rounded up) each	5.11	439.48 $/Ton	6.274	$491,935
Medium Office	Not Applicable				
Small Office	Not Applicable				
Primary School	Not Applicable				
Secondary School	Not Applicable				
Hospital	1 air-cooled electric chillers at 3,450,464 W or ~980 tons (rounded)	5.11	428.64 $/Ton	6.274	$420,548

There are approximately 120,000 commercial boilers in the U.S. of which about 79,000 are gas-fired units under 10,000 MBH [129; 130]. [6] Combined, commercial boiler systems in the United States use approx. 1,040 trillion BTUs of natural gas annually of which 709 trillion BTUs are used to heat 20 billion square feet of commercial floor space according

[5] A "ton of refrigeration" is defined as 1 short ton ice melted in 24 hours. Approximately 3,504 W or 12,000 Btus per hour.

[6] MBH is a unit commonly used when referring to boiler capacity and one MBH represents 1,000 BTU/hr.

to a 2011 report [129]. This comes down to around 51% of total natural gas expenditures for non-mall commercial buildings [129]. Classification of boilers takes many forms but both ASHRAE and FEMP separate between "small" commercial boilers (those between 300,000 BTU/hr and 2.5 million BTU/hr) and "large" commercial boilers (>2.5 million BTU/hr) [129].

Energy efficiency upgrades of boilers before end-of-life can deliver significant energy savings but also come at high capital costs [129]. An important consideration in this regard is that commercial boilers have the longest lifetime of all major commercial HVAC technologies, estimated between 24 and 35 years [129]. Payback times for boiler replacement, as such, can be extended further out than for other ECMs. For the purposes of this project, ECM 5 focuses on the boiler in the facilities in question. For the large office, the design size nominal capacity in the large office building is ~3,072,498.94 W / ~10,484 MBH with a flow rate of 0.037743 m^3/s [85]. At $34.96/MBH, this comes down to a ECM installed cost of $366,503. Boiler control options can achieve energy savings in heating systems and improve boiler performance efficiency [131]. A study into the matter found a 20% energy saving opportunity for boiler controls in the built environment [132].

Table 10 Overview of boiler replacement costs (ECM 5)

Building	Boiler Capacity	Retrofit Heating Efficiency	Retrofit Cost	ECM Cost ($)
Large Office	Nominal operating capacity of 3,072,498.94 W or about 10,484 MBH.	95%	$34.96/MBH	$366,503
Medium Office	Not Applicable			
Small Office	Not Applicable			
Primary School	Nominal operating capacity of 877,080 W or about 2,993 MBH.	95%	$34.96/MBH	$104,626
Secondary School	Nominal operating capacity of 1,717,600 W or about 5,861 MBH.	95%	$34.96/MBH	$204,884
Hospital	Nominal operating capacity of 1,680,500 W or about 5,734 MBH.	95%	$34.96/MBH	$200,459

Another ECM deployed in our hypothetical energy efficiency project is the use of high-efficiency fans to replace current fans (ECM 6). The fans in the system provide the critical function of ventilation and air flow that support and provide suitable indoor air quality [133]. CityBES provides a cost estimate for high-efficiency fans dependent on the capacity maximum air flow that the fan can ventilate. The ECM cost overview is provided in Table 11. Control strategies for efficient fan operation and performance are available and can deliver energy savings [134-136].

Table 11 **Overview of Fan Replacement Costs (ECM 6)**

Building	Fan Capacity (cfm)	Retrofit Cost ($/cfm)	ECM Cost ($)
Large Office	Fan 1: 38,987 Fan 2: 397,184 Fan 3: 39,877 Fan 4: 17,417	Fan 1 : $0.176 Fan 2 : $0.176 Fan 3 : $0.176 Fan 4 : $0.390	$90,470
Medium Office	Multiple	Multiple	$32,196
Small Office	Fan 1:1,335 Fan 2:1,865 Fan 3:1,271 Fan 4:1,632 Fan 5:1,610	Fan 1: $0.59 Fan 2: $0.59 Fan 3: $0.59 Fan 4: $0.59 Fan 5: $0.59	$4,537
Primary School	Fan 1:593 Fan 2:2,882 Fan 3: 424 Fan 4: 1,716 Fan 5: 2,564 Fan 6: 4,810 Fan 7: 17,968 Fan 8: 17,862 Fan 9: 13,646 Fan 10: 14,408	Fan 1: $1.16 Fan 2: $0.59 Fan 3: $1.16 Fan 4: $0.59 Fan 5: $0.39 Fan 6: $0.39 Fan 7: $0.18 Fan 8: $0.18 Fan 9: $0.18 Fan 10: $0.18	$17,986
Secondary School	Multiple	Multiple	$50,319
Hospital	Multiple	Multiple	$41,514

3.4.5. ECM 7: High-Efficiency Water Heater

The final ECM under consideration in this research project is to replace the current water heater with a high-efficiency version (ECM 7). CityBES again provides relevant cost estimates per capacity unit. The ECM intervention cost profile is summarized for each building benchmark in Table 12.

Table 12 **ECM 7 water heater cost overview**

Building	Water Heater Capacity (gallons)	Retrofit Cost ($/gallon)	ECM Cost ($)
Large Office	200	$20.82	$4,163
Medium Office	100	$21.76	$2,176
Small Office	40	$21.76	$858
Primary School	264	$20.82	$5,500
Secondary School	792	$20.82	$16,499
Hospital	793	$20.82	$16,499

3.5. Modeling Performance Variation

To reflect performance uncertainty, we modelled variation in the performance of each ECM and variation in their scheduling in each of the six buildings. The scheduling variation is introduced to model many of the ECM's reliance on occupant behavior. Overall, this performance variation serves the function of introducing uncertainty and risk in post-retrofit performance in each of the six energy efficiency retrofit projects. This uncertainty and risk translates to an uncertain distribution of possible energy savings.

A series of scenarios are developed to model performance variation under different circumstances:

- **Model 1: Pre-retrofit.** This is the condition of the building before any energy efficiency project has been initiated. The pre-retrofit condition is stochastically modeled to simulate uncertainty in performance using the existing equipment. To model this uncertain performance profile, we apply variation in all schedules and in the performance of the equipment itself.
- **Model 2: Post-retrofit without controls.** This scenario represents the operational condition of the building after an energy efficiency retrofit project has been conducted. All the energy efficiency equipment has been installed. However, no performance variation control technology is used. As such, variation in all schedules and in the performance of the equipment itself is included in this scenario.
- **Model 3: A series of control scenarios.** We simulate several control packages to determine suitable performance control applications.
  - **Full Portfolio: Post-retrofit with full control (all controls installed).** In this scenario, we apply a performance control function to all high-efficiency equipment installed as part of the energy efficiency retrofit project. This

means that we lower the variation in operational schedules of each unit of equipment that is under control and limit the operational variation of the equipment itself as well.

- **Portfolio 1: Post-retrofit with control on major energy consumers.** Here, we argue that control functions could perhaps be best placed on only those functions that consume a lot of energy. As such, the operational variation of interior lighting and plug loads is controlled while all other end-uses remain subject to a higher level of performance variation.
- **Portfolio 2: Post-retrofit with control on major uses of expensive energy.** Here, we apply control functions on expensive energy consumption end-uses. As such, the boiler and heater equipment performance is sharply controlled while all other end-uses remain subject to a higher level of performance variation.
- **Portfolio 3: Post-retrofit with control on devices sensitive to user inputs.** Some devices likely experience higher levels of user manipulation and, as such, are perhaps more worthwhile controlling programmatically instead. Therefore, in this scenario we apply control functions on temperature setpoints, lighting load, and water heater equipment operations.

3.5.1. Distributions and Variance

To model performance variation, we applied different distributions. This is in line with existing research efforts into this topic (e.g., see Refs [21; 22; 37; 88]). Each variable is assigned a distribution profile based on lessons learned from the literature [21; 22; 37; 88] but are also based on physical constraints and limits. For example, efficiency values can't exceed 100% and, as such, distributions of efficiency performance can perhaps be captured better by a triangular distribution than a normal distribution.

-<u>Normal or Gaussian Distribution</u>: This distribution is defined by a mean and a standard deviation value. With this distribution we were able to display symmetric probabilities around a mean allowing us to get increasingly more likelihood of outcome close to the mean than far away in an exponential manner. The results in this distribution are however, likely to be in any point from –infinity to +infinity.

-<u>Triangular Distribution</u>: The distribution is defined by a max, a min, and a mode. Where the mode is the most probable outcome. The likelihood of getting a value away from the mode is linearly decreased. This function allows us to generate skewed distributions and contain the values between the min and the max. This function was useful for distributions that can't exceed certain values (e.g. occupancy cannot surpass 100%). The distribution profiles are given in Table 13.

Table 13 Distributions of performance variation for each variable

Variable	Distribution
Interior lighting load	Normal
Plug load	Normal
Business day heating	Triangular
Non-business day heating	Triangular
Business day cooling	Triangular
Non-business day cooling	Triangular
Chiller performance	Normal
Boiler performance	Normal
Fan performance	Normal
Lighting schedule	Triangular
HVAC schedules	Triangular
Plug load schedules	Triangular

The values for the distributions were found in the literature. We were able to find the mean/mode, max, min and standard deviation of the efficiencies of the building devices before and after applying ECMs. The values for the schedule distributions were obtained from the benchmark building files. A set of dummy variables were added, however, to increase variability when dealing with interior lightning, HVAC and equipment schedules. In this process, a deviation around the mean values provided in the file was added in order to account for unforeseen behavior.

Importantly, we made the lighting schedule dependent on the occupancy schedule. This was done while keeping in mind the following:

- Lighting schedules correlate with occupancy: the main function of lighting is to provide illumination when people are present.
- However, lights can be left on in an empty room.

We are able to generate a lighting schedule by adding a certain allowed variance with respect to occupancy schedule. The added light usage was more linearly likely to happen in smaller additions than in larger additions (e.g. it was more likely that the light usage surpassed occupancy by 5% than by 15%) (Figure 4).

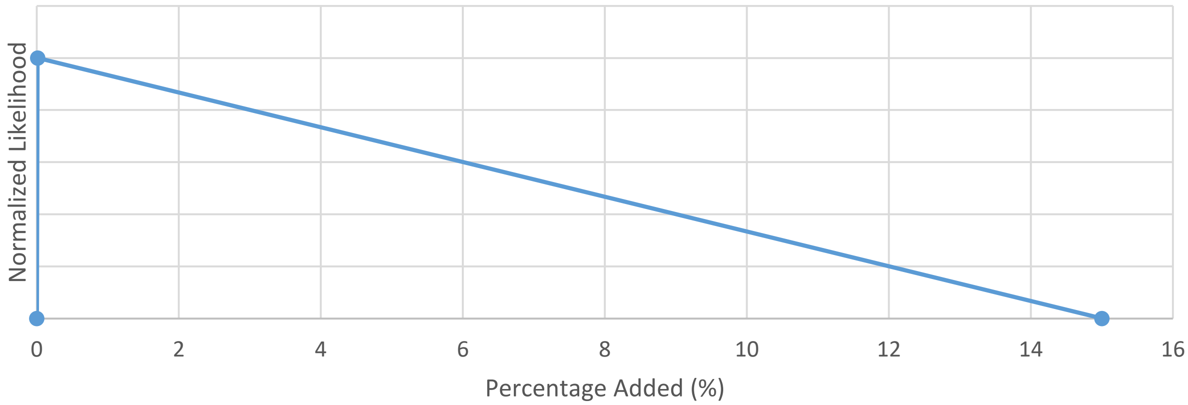

Figure 4 **Lighting in building benchmark room compared to occupancy**

When adding the previous distribution to the occupancy distribution, the overall light usage is provided in *Figure 5*. In *Figure 5*, the black line resembles the occupancy in the building depending on the hour of the day, and the blue area represents the percentage of light used in the building. Again, the likelihood of getting a value close to the black line goes down the further away you are from it. Two sets of assumptions were made in this process. The first one deals with the fact that there is high increment in the light usage between 1-7 and 22-25. These hours represent night time, and even though the occupancy in the building is kept at a minimum, we find likely that some lights are kept on unintentionally all night, and therefore cannot be proportional to the occupancy at these hours. The second assumption considers that in the valley found in the middle of the day (lunch time), occupancy in the building decreases by a half, however, the lights in the office are usually kept on.

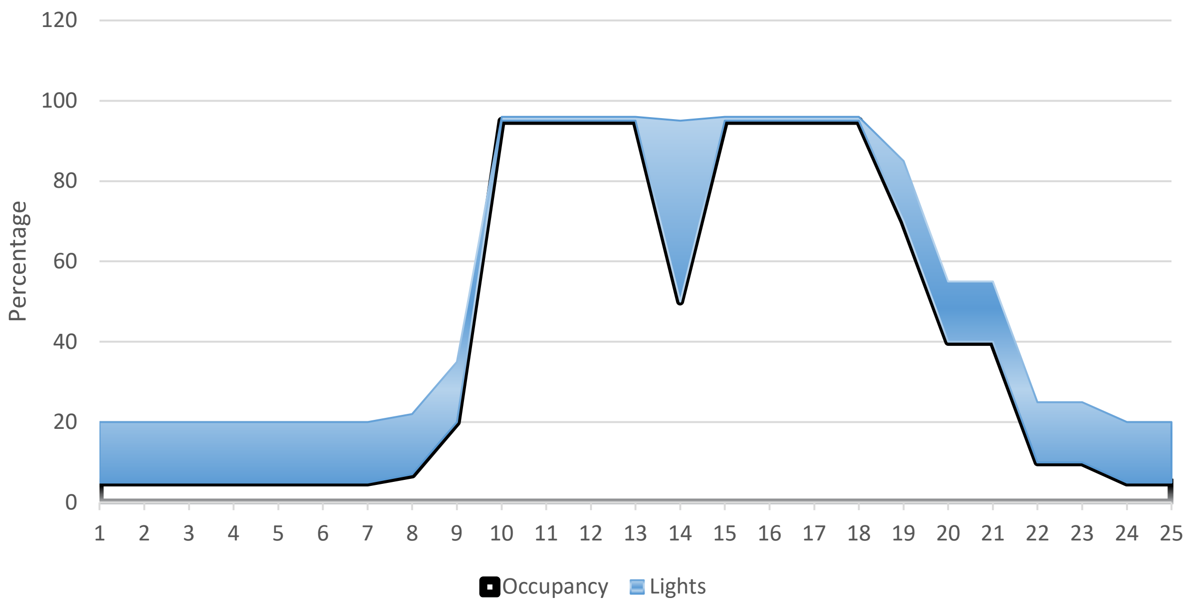

Figure 5 Light and occupancy schedules

The same process was followed with HVAC and Equipment schedules. A sketch of the variables is included below in *Figure 6* for illustrative purposes.

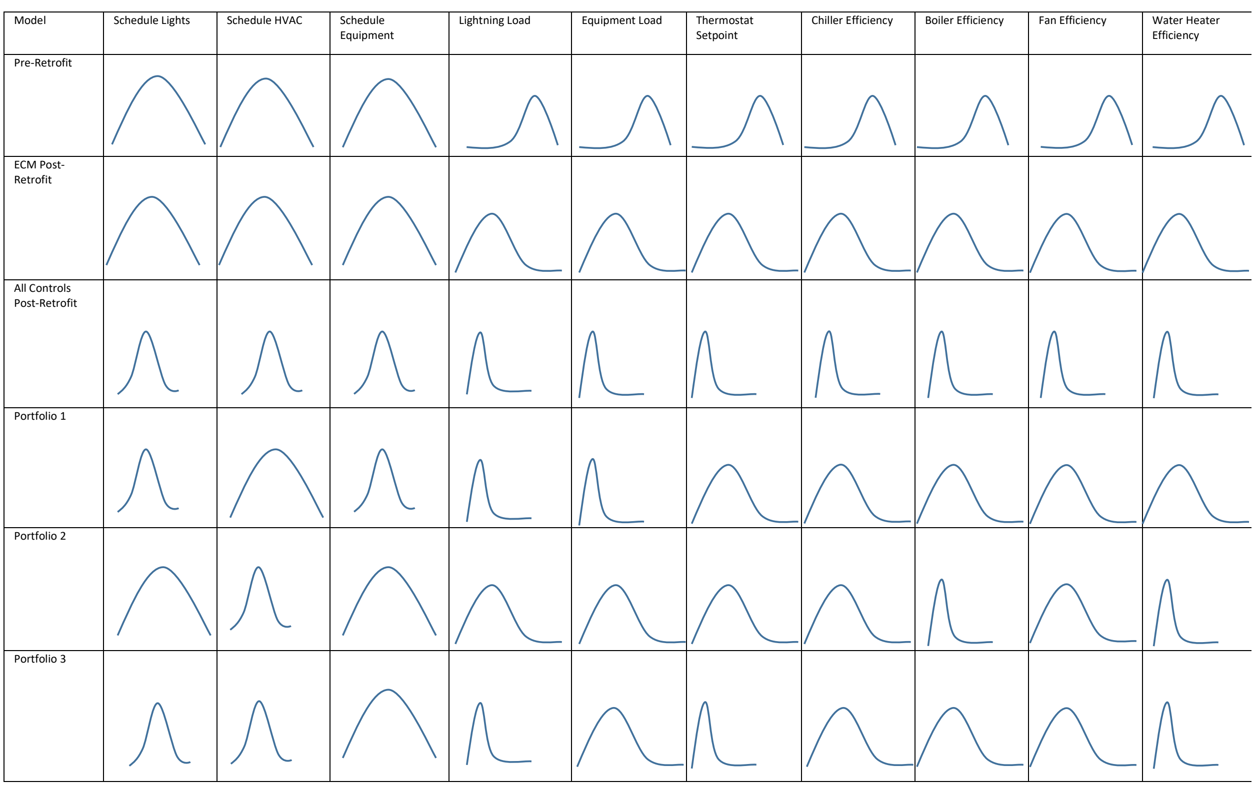

Figure 6 Sketch of the variables associated with the investigation

Performance variation in input parameters for the large office benchmark building is given in Table 14. The performance variation captured in Table 14 for the large office building benchmark illustrates operational variation. The outcome – a performance range of the energy efficiency retrofit project – enables statements of probability of savings. For instance, the resulting distribution can show that there is a 90% chance that a 10 year simple payback will be achieved and a 20% chance that an 8 year simple payback is realized. This output is used in the following sections such as in Section 4.0 where the profile is used to determine the ESCOs placement of the savings guarantee.

Table 14 Pre- and post-retrofit performance variation inputs for the large office

	ECM		Distr.	Pre-retrofit				Post-retrofit				Ref.
				Input	**SD**	**Min**	**Max**	**Input**	**SD**	**Min**	**Max**	
1	LED upgrade (lighting load) (W/m2)		Normal	16.14	0.565	N.A.	N.A.	6.46	0.226	N.A.	N.A.	[88]
2	Appliance upgrade (plug load) (W/m2_		Normal	10.76	4.549	N.A.	N.A.	8.07	3.412	N.A.	N.A.	[88]
3	Thermostat set-point	Heating (C)	Triangular	21	N.A.	19.630	22.370	20	N.A.	18.696	21.304	[88]
				15.6	N.A.	14.583	16.617	14.6	N.A.	13.648	15.552	[88]
		Cooling (C)		24	N.A	22.435	25.565	25	N.A.	23.370	26.630	[88]
				26.7	N.A	24.959	28.441	27.7	N.A.	25.894	29.507	[88]
4	High-efficiency chillers (reference COP)		Normal	5.11	0.024	N.A.	N.A.	6.2	0.029	N.A.	N.A.	[88]
5	High-efficiency boiler (thermal efficiency, %)		Normal	0.76	0.011	N.A.	N.A.	0.95	0.014	N.A.	N.A.	[22]
6	High-efficiency fans (total efficiency, %)		Normal	Various	0.050	N.A.	N.A.	0.65	0.033	N.A.	N.A.	5% SD
7	High-efficiency water heater (thermal efficiency, %)		Normal	0.8	0.012	N.A.	N.A.	0.95	0.014	N.A.	N.A.	[22]

Note: SD stands for Standard Deviation.

4.0. Results: Influence of Controls on Savings Guarantee

The models and modeling approach described in the previous sections above yield an understanding of the risk profile of energy efficiency investment and what options are available for mitigation of that risk. This section describes the outputs of the various models above and extracts key findings. To that end, for each of the six building benchmark models studies, we report the following:

1. **Energy efficiency project profile**: the investment cost and energy savings profile of the hypothetical project is evaluated. We model performance uncertainty of the project using the stated level of performance variability for each relevant variable. We report on the distribution of expected savings in energy and dollar terms.
2. **Strategic placement of the energy savings guarantee:** Based on the uncertain profile of energy savings, we use the energy guarantee savings model to determine where a risk-averse ESCO could be expected to place the guarantee.
3. **Comparing scenarios with and without performance control technologies:** we contrast the guarantee placement for the scenarios with and without performance control technologies.

4.1. Energy Efficiency Project Profile

A first-level understanding of the hypothetical projects evaluated here is to review the total project investment amount for each of the building benchmarks (Table 15). Due to their various sizes and other specific characteristics, the total project investment amount is substantially different from, say, the small office to the hospital to the large office. The large office represents the largest project in terms of total project investment at about $1.23 million.

This project investment generates energy savings compared to pre-retrofit conditions. However, as discussed above, the profile of energy savings is uncertain due to performance variation. To illustrate this, the pre-retrofit conditions and post-retrofit performance in project performance year 1 are illustrated in energy units in

Figure 7. A broad range of possible energy consumption levels exists across the 10,000 simulations modeled here for both the pre-retrofit and the post-retrofit without application of performance control. For the large office, in terms of energy savings, the post-retrofit scenario provides an average annual consumption level of about 24,057 GJ

compared to the pre-retrofit average consumption level of 37,034 GJ – an average savings of about 35%.

Table 15 Energy efficiency project investment profiles

Building Benchmark Model	Project Investment ($)
Large Office	$1,227,232
Small Office	$7,500
Primary School	$168,794
Secondary School	$386,839
Hospital	$807,219

As illustrated in Figure **7**, the probability of savings is such that, under highly unfavorable circumstances, the project *could* have annual performance levels that are below pre-retrofit performance. In other words, in the most efficient operation of the pre-retrofit benchmark building and the most inefficient operation of the post-retrofit model, no energy savings would occur – in fact, energy consumption levels in GJ for that year would be higher compared to the baseline. However, the above described scenario of no energy savings is unlikely. Other building models, like the hospital, do not have such overlap.

Figure **7** also illustrates the performance profile when performance control technologies are installed in the project. It is clear from Figure **7** that the performance variation is substantially reduced in our modeling approach as the resulting distribution is much more narrow. In addition, the application of performance variation control technology also improves the overall functioning of the equipment, leading to higher average savings overall. For example, for the large office, the average energy consumption in GJ without application of performance variation control technology is 24,058 GJ while the average energy consumption is 21,954 with application of this technology option.

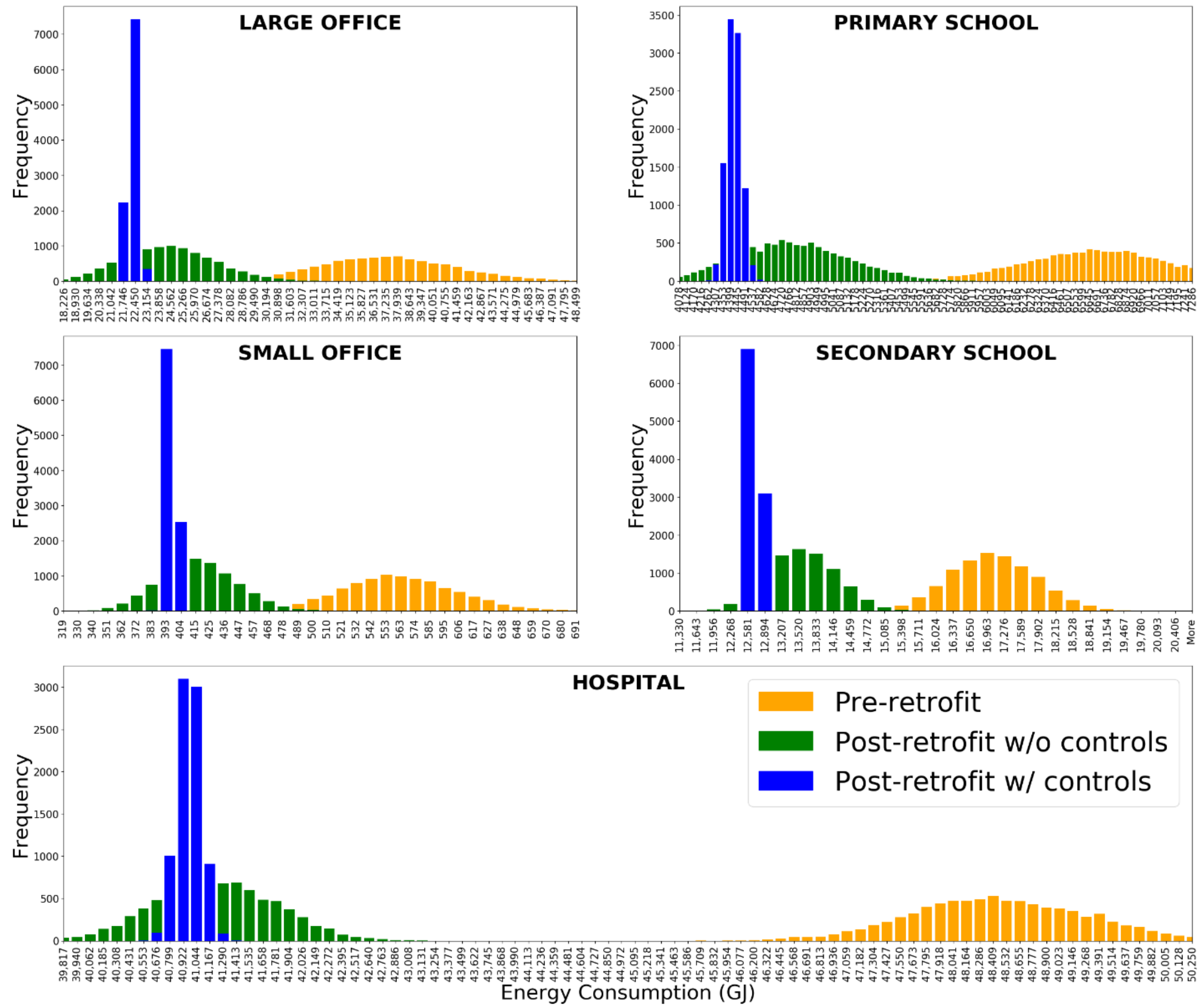

Figure 7 **Benchmark Pre- and Post-Retrofit Energy Consumption without and with Controls (10,000 simulations each) for the benchmark buildings**

Using Equation 8 and Equation 9, the probability that savings occur can be calculated for performance year 1 and beyond. The probability that a certain amount of savings in dollar terms can occur is integral in the calculus of energy savings guarantee placement. As such, the possible distribution of savings, in dollar terms, is illustrated for each building benchmark for each of the 20 years of the hypothetical projects (*Figure 8*). We compare the probability of savings to occur between the post-retrofit without controls and the post-retrofit with controls installed. As *Figure 8* shows, the distribution of possible savings is narrower when controls are applied and, importantly, the low end of the distribution is substantially above the low-end of the distribution when no controls are applied. This makes the hypothetical project more attractive to the investor. When incorporating various dynamic effects – such as equipment degradation, inflation, fuel price volatility, contracted electricity price escalators, etc. (see Appendix A), overall project performance is expected to increase over time (*Figure 8*).

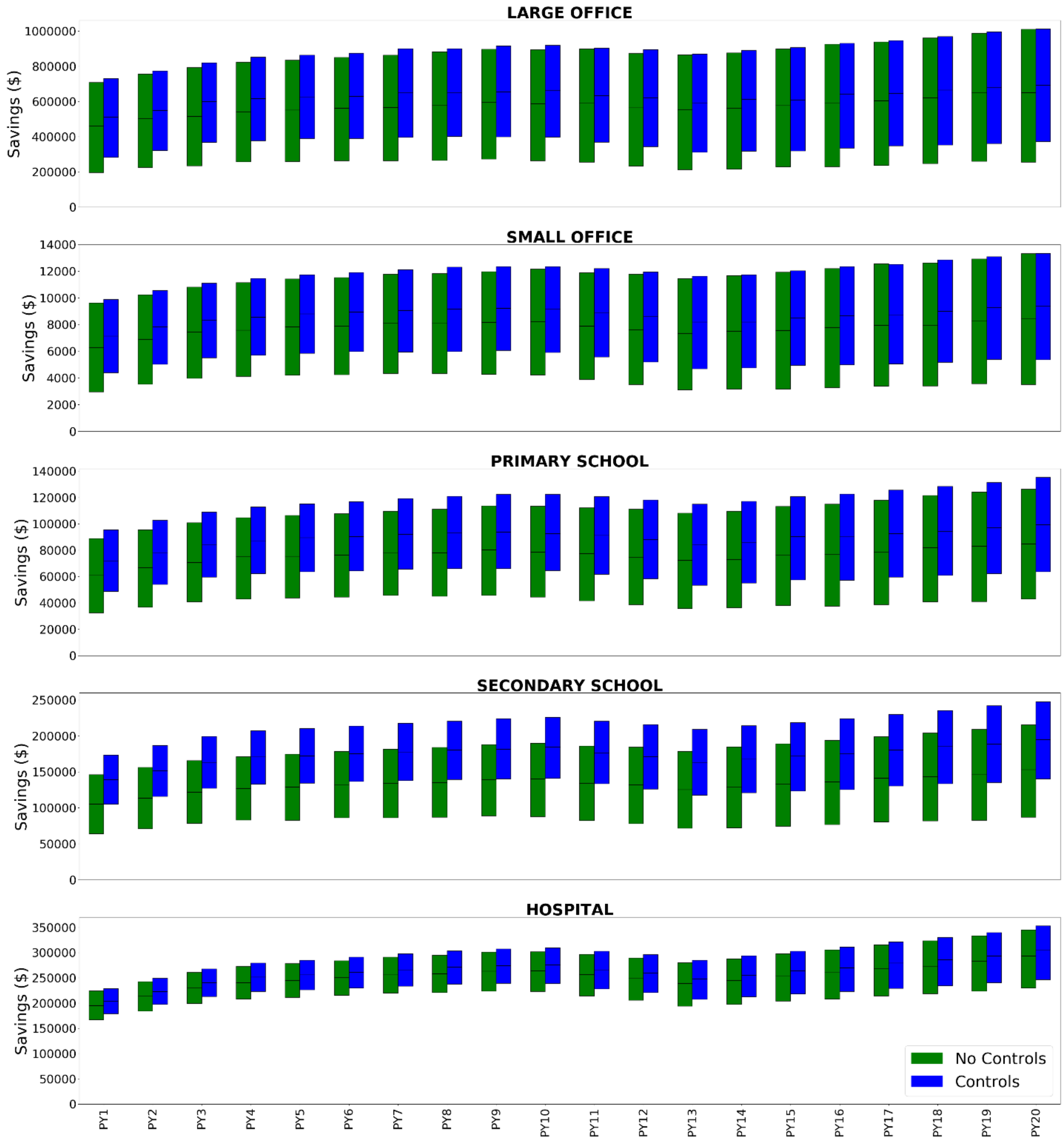

Figure 8 **Annual energy savings for the building models (10,000 simulations in each year) for all performance years**

4.2. Strategic Placement of the Energy Savings Guarantee

Now, we introduce the ESCO's perspective by asking the ESCO to guarantee the performance of the ECMs. This guarantee is dependent on the energy efficiency project profile introduced above and – importantly – on the ESCO's tolerance for risk. We assume a highly risk averse ESCO with a risk tolerance of 95%. This means that 95% of the 10,000 simulations of the project need to exceed the guarantee in **each** year of the 20-year project in present value terms. The ESCO's risk for profit losses, therefore, is virtually eliminated by this risk-averse placement of the guarantee. In other words, the ESCO can reasonably expect the energy efficiency project to perform in accordance with the annual savings guarantee.

Using the guarantee placement model, the cost savings profile of the 20-year project yields a strategic estimate of the guarantee an ESCO might be willing to provide. Again, we compare the guarantee placement for the post-retrofit scenario where no controls are installed and for the scenario where controls are in place. The use of performance control technology is proposed as a viable risk mitigation pathway for energy efficiency performance projects. To consider the effect of using these controls, we calculate the upward movement expected in energy savings guarantee placement when the controls improve performance and reduce risk. This process is illustrated in Figure 9. Effectively, the scenario where controls are applied enables the ESCO to reasonably expect a higher level of performance, leading a higher guarantee (`$95,000 compared to the no controls scenario of ~$50,000).

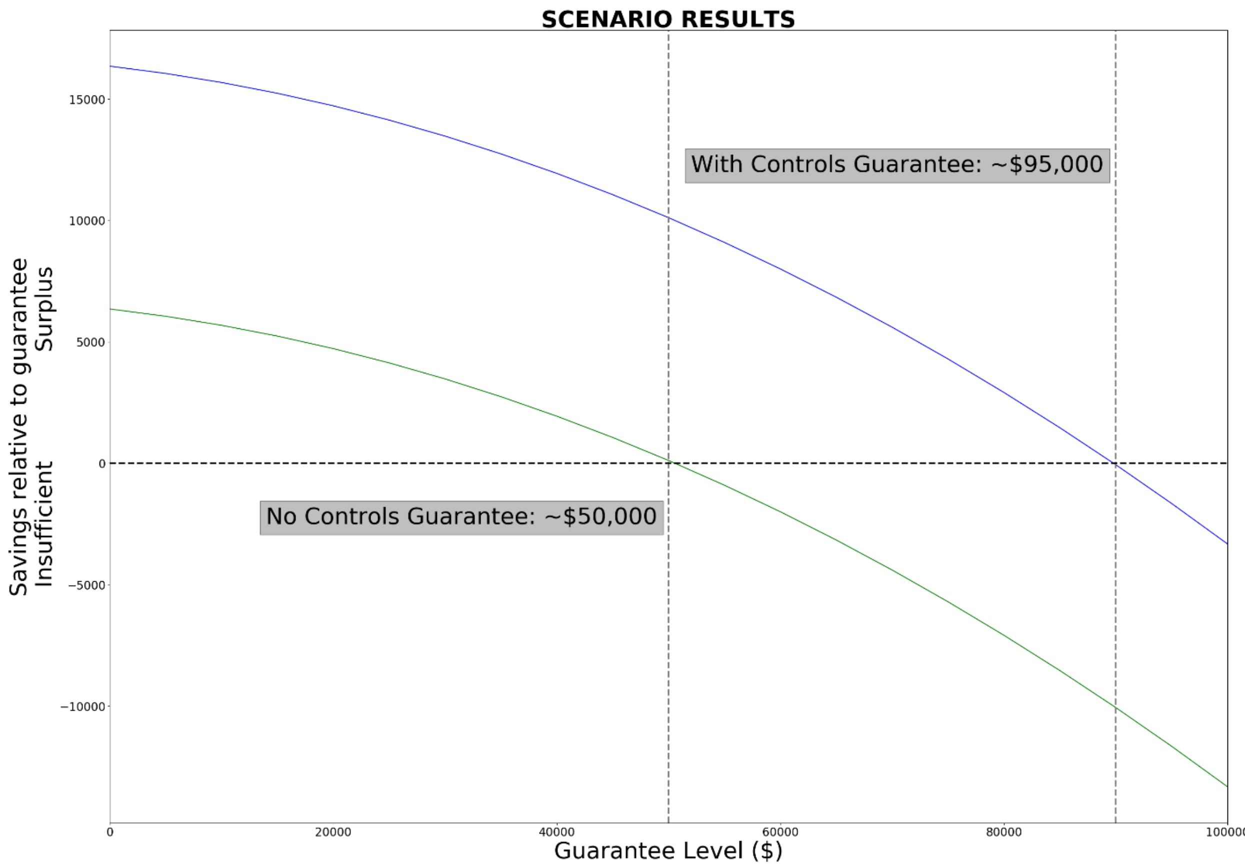

Figure 9 **Guarantee placement with and without automated controls (hypothetical)**

Please note that the values for the axes of each graph in Figure 10 are the same as those in Figure 9 and, therefore, are not repeated here. The "full control" scenario applies a 90% performance standard for variation reduction on all 7 ECMs. [7] The "full control" scenario results in two improvements: 1) a much narrower performance range; and 2) actual performance improvement of the devices leading to higher average savings levels. For example, for the large office benchmark building, the energy efficiency project profile extracts an ESCO guarantee of ~$116,000 in annual savings when controls are applied. In this scenario, the project's performance is such that the guarantee can be more than double the guarantee in a scenario where no controls are in place. The secondary school building benchmark model, the small office, and the primary school model show a similar potential. The hospital building has large areas that are not subject to energy

[7] It is challenging to determine the extent controls enable performance uncertainty reduction – some level of behavioral, technological, and other risks remain even after controlling for various aspects of the devices' operation – so the 90% reduction in performance range is currently an assumption. Further research will need to evaluate this question in more detail perhaps through sensitivity analysis.

efficiency improvements in this envisioned project (e.g. operating rooms, emergency rooms, patient rooms, etc.) leading to a smaller difference between the two scenarios.

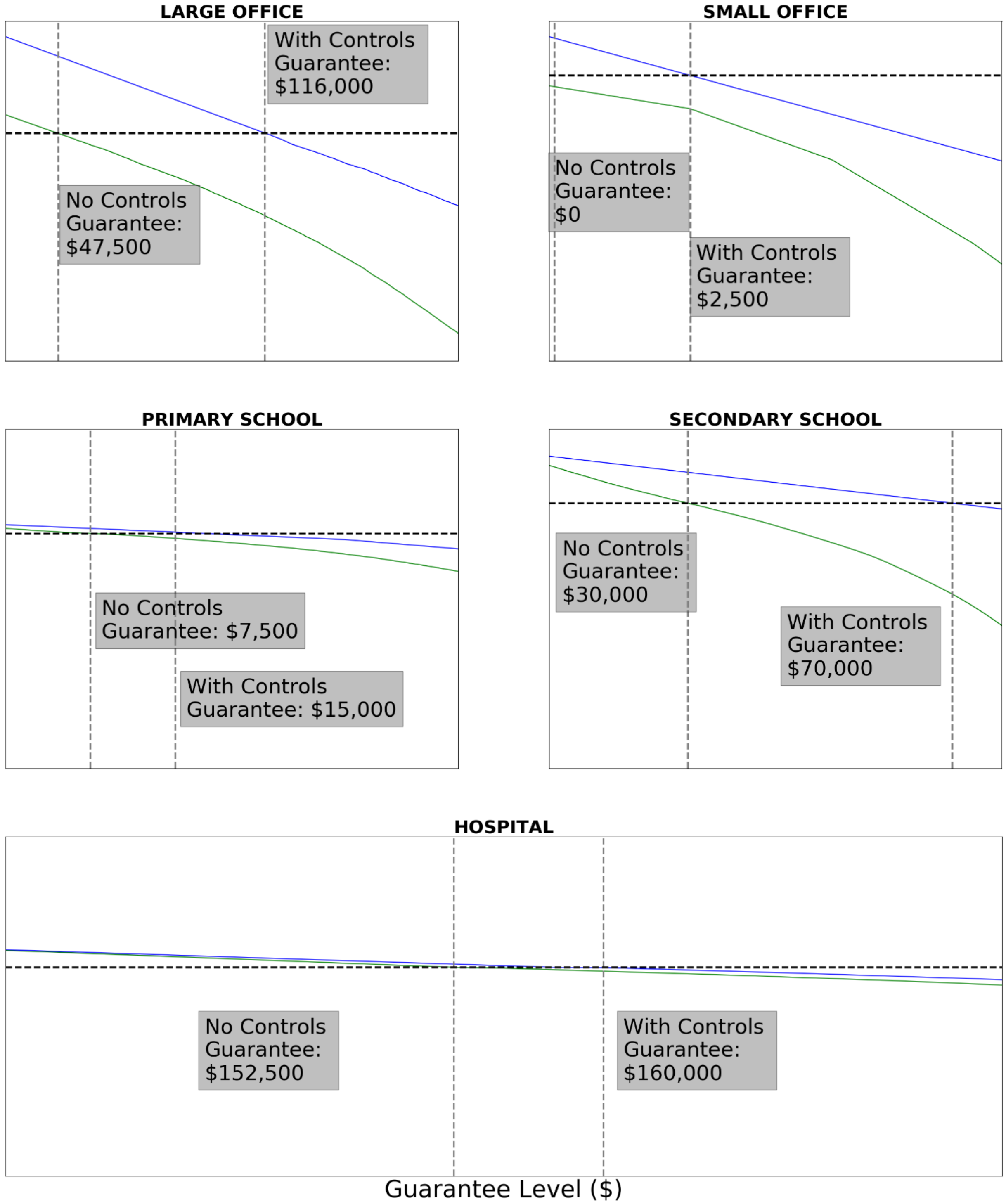

Figure 10 **Guarantee design for "no control" and "full control" scenarios for the building models**

4.3. Comparing Projects with and without controls

As per the above illustrations, the implementation of performance control technologies can extract higher guarantees from ESCOs and narrow the dollar savings distribution. These are critical benefits. Table 16 summarizes some of the main contributions of the controls under the approach modeled here. In particular, the control function modeled here:

a) Improves overall savings by achieving a lower average consumption;
b) Lowers performance risk by achieving a significantly lower standard deviation of the distribution; and
c) Significantly raises the guarantee, in some cases by over 100%.

Table 16 Energy Efficiency Guarantees for projects without and with controls

			Large Office	Small Office	Primary School	Secondary School	Hospital
Post-Retrofit w/o Controls	*Energy consumption (GJ)*	Avg.	24,057	411	4,764	13,286	41,157
		SD	2,681	28	344	650	561
	Guarantee Level		$47,500	$0	$7,500	$30,000	$152,500
Post-Retrofit w/ Controls	*Energy Consumption (GJ)*	Avg.	21,954	392	4,396	12,537	40,981
		SD	271	3	46	90	108
	Guarantee Level		$116,000	$2,500	$15,000	$70,000	$160,000
Guarantee increase ($)	*$*		$68,500	$2,500	$7,500	$40,000	$7,500
	%		144%	-	100%	133%	5%

The ESCO can reasonably expect the project to be (much) less risky and, as such, can raise the energy savings guarantee. This benefits the ESCO's ability to win new projects. In addition, a higher guarantee makes the project less risky for both the client and the third-party investor, making it more likely the project will actually come to fruition. For instance, the higher guarantee is attractive to the project client: a higher guarantee enables a project with better financial performance. The ESCO can quantify the benefits of reaching this higher guarantee against the cost of installing the additional controls. A $55,000/year increase in the guarantee, for instance, does not directly translate to a $55,000 profit improvement to the ESCO. Instead, this calculus is dependent on a range of project and ESCO-specific dimensions, including but not limited to:

- The value the ESCO places on winning the project bid;

- Costs associated with installing the additional controls;
- Risk tolerance of the ESCO;
- Quality of relationship between ESCO and client; and
- Costs associated with the guarantee itself.

In Part II of the report, we introduce and use possible method to quantify the cost associated with raising the guarantee from the perspective of the ESCO.

PART II

INTER-PARTY TRUST: CONTROLS, INSURANCE, AND THE ENERGY SAVINGS GUARANTEE (PRELIMINARY)

5.0. INTER-PARTY TRUST THROUGH CONTROLS AND ENERGY SAVINGS INSURANCE

As a risk mitigation strategy, the energy savings guarantee has helped to accelerate the sector and Part I of this report shows how controls could further advance the market by raising the guarantee. Part II of the report explores the following:

1. Inter-party trust-building through the use of controls;
2. Sidestepping inter-party trust concerns through energy efficiency performance insurance;
3. Quantifying the cost associated with raising the guarantee from the perspective of the ESCO;

5.1. Inter-party trust-building through smart controls

If trust is lacking between parties, the actual value of the guarantee matters less than the client's perception of the trustworthiness of the ESCO's promise. The project host, for instance, can be concerned that the ESCO is over-promising on savings without any plans to cover an eventual savings shortfall. Contractual stipulations of energy savings guarantees can be complex and often contain clauses that describe scenarios where the ESCO will not see itself as responsible for performance shortfalls. For example, responsibility for project under-performance can be argued by the ESCO to be anywhere (e.g. weather differences, behavioral changes, etc.) but on the ESCO, leaving the project host with limited recourse to recuperate lost savings. Currently, the project host can engage in costly litigation with the ESCO, creating a clear adversarial relationship.

Controls can help improve this situation by creating vast amounts of performance data, where under-performance can be correlated to potential causes. Real-time performance monitoring, for instance, can identify run-away operation of HVAC equipment and correct quickly when detected. Behavioral pattern changes can be controlled using automated and smart management of devices, improving insight into their effects. For this scenario to play out, however, the data will need to be available to the project host in a format that enables understanding and insight. Too often, energy service company (ESCO) calculations and software are seen as 'black box' tools that generate mistrust by the project host.

In addition, trust-building and other benefits accrue from use of the automated technology options. Many of these benefits can be connected to the risks identified in Table 1 above [56; 57; 61; 64-66] (see section 5.1.1 to 5.1.4).

5.1.1. Operational and Engineering Risk Reduction:

- Time efficiency: automated performance control accelerates whole-building assessment from a typical 4 days to 1 day and reduces time needed for custom engineering calculations from 6 days to 1 day [67]. Automated analysis yields actionable data within the first month of energy conservation measure (ECM) installation [57].
- Time certainty: long lifetime projects expose ESCOs to energy consumption patterns caused by client behavior changes [68]. Automated data analysis could help attribute consumption pattern variation throughout the lifetime of the project making deep energy retrofits more attractive to ESCOs.
- Improved accuracy: A database of 537 geographically diverse commercial buildings, shows that industry standard predictive accuracy can be achieved with only six months of training data [18; 64; 69]. When assessed as part of a portfolio of buildings, predictive accuracy improves further leading to the conclusion that these models are "compellingly accurate" [67].
- Standardization and certification: database development supports and accelerates investor-ready program design – a key need of the sector [2].

5.1.2. Monitoring and Verification Risk Reduction:

- Portfolio level analysis and benchmarking: real-time and high-resolution automated M&V capable of processing "big data" enables analysis of many buildings with various degrees of retrofitting simultaneously.
- Improved sampling: automated M&V scalability and precision allows larger sample sizes, retrieving feedback on the performance of diverse aspects of the retrofit project.
- Fast anomaly and fault detection: real-time data collection and control enables faster anomaly or fault detection and interface options such as online dashboards empower clients and ESCOs to mitigate underperformance.

5.1.3. Economic risk reduction:

- Time-of-day analysis or grid-level location of savings can motivate transmission and distribution planning or microgrid development.
- Automated M&V at scale represents an effective pathway to rigorous and long-term M&V at lower cost compared to whole-building IPMVP options.
- Utility billing validation: automated M&V can include real-time utility tariff and energy consumption analysis to validate utility bills through, among others, a) continuous monitoring and management of peak load consumption; b) streamlining of utility-related processes to, for example, minimize personnel requirements; and c) identification of metering or billing errors by automatically crosschecking consumption patterns with utility bills.

5.1.4. Financial risk reduction:

- Uncertainty mitigation: strategic use of automated M&V can deliver investor-ready program design and enhance the energy savings guarantee (see below).
- Data generated by automated M&V can improve project finance-ability as it supports, among others, a) accurate savings estimates, b) risk management of operational and performance uncertainty, and c) quick remediation of potential energy saving shortfalls.

5.2. Addressing inter-party trust concerns through energy efficiency performance insurance

The energy savings guarantee is, effectively, a risk-transfer contract between the ESCO and the client. Such financial risk mitigation benefits the sector as clients are typically loss-averse (valuing loss mitigation higher than gains). Other forms of financial risk mitigation are also possible. Here, we provide a preliminary discussion of financial risk mitigation in the form of energy efficiency performance insurance. Energy efficiency insurance has been suggested as a possible financial risk mitigation tool in the energy efficiency retrofit sector [25; 26; 79]. In exchange for a premium, an energy efficiency insurance product insures a predefined level of financial performance of the project (e.g. minimum level of savings). This represents a key distinguishing factor: under an energy efficiency insurance approach, the premium is charged independently of realized savings [28]. The premium under energy efficiency insurance, thus, is deterministic (equal annual payments occur no matter the savings profile) while the energy savings guarantee premium is stochastic (it is directly dependent on the performance level). The level of the premium, meanwhile, is dependent on the probability and magnitude of possible risk events.

As with energy savings guarantees, it is important to establish the distribution of costs and benefits. To determine the actuarially fair premium for protection against the risk event of under-performance, we rely on the model proposed by Töppel &Tränkler [28]. Relevant sections of the model are described in Appendix B.

By simulating many iterations of K (see Appendix B), we can obtain a cost curve for insurance. Looking at the cost curve of insurance, we can calculate the actuarially fair annual premium for two scenarios:

- The actuarially fair premium resulting from insuring project performance at the level of the ESCO guarantee when no controls are installed (Guarantee 1). This scenario calculates the premium cost of opting for insurance instead of the ESCO when the ESCO doesn't include controls.
- The actuarially fair premium resulting from insuring project performance at the level of the ESCO guarantee when controls are installed (Guarantee 2). Importantly, no controls are actually installed in this scenario – i.e. we use the distribution of savings from the scenario when no controls are installed but we just set the level of insurance at the higher value. This scenario calculates the cost of opting for insurance instead of the ESCO when the ESCO does include controls.

These scenarios can be graphically located on the cost curve for insurance (Figure 11). Insuring $47,500 in annual savings (Guarantee 1), as such, can be calculated to cost an annual premium of around $1,300 (excluding transaction costs and any deductibles). This value is calculated as the sum of the magnitude of the risk events times their probability. An annual premium of around $3,300 in insurance could cover $102,500 in annual savings (again, excluding transaction costs and deductibles likely accompanying any insurance package). The insurance premium is relatively low – an annual premium of $3,300 for a twenty-year insurance package only comes down to $66,000. However, when insuring $116,000, there is just under a 1 in 3 chance that a claim will be submitted by the client each year. The average size of this claim is about $12,000. The actuarially fair premium as such only captures a portion of the situation – transaction costs, deductibles, insurance company profits, etc. provide additional dimensions. This could be part of future research.

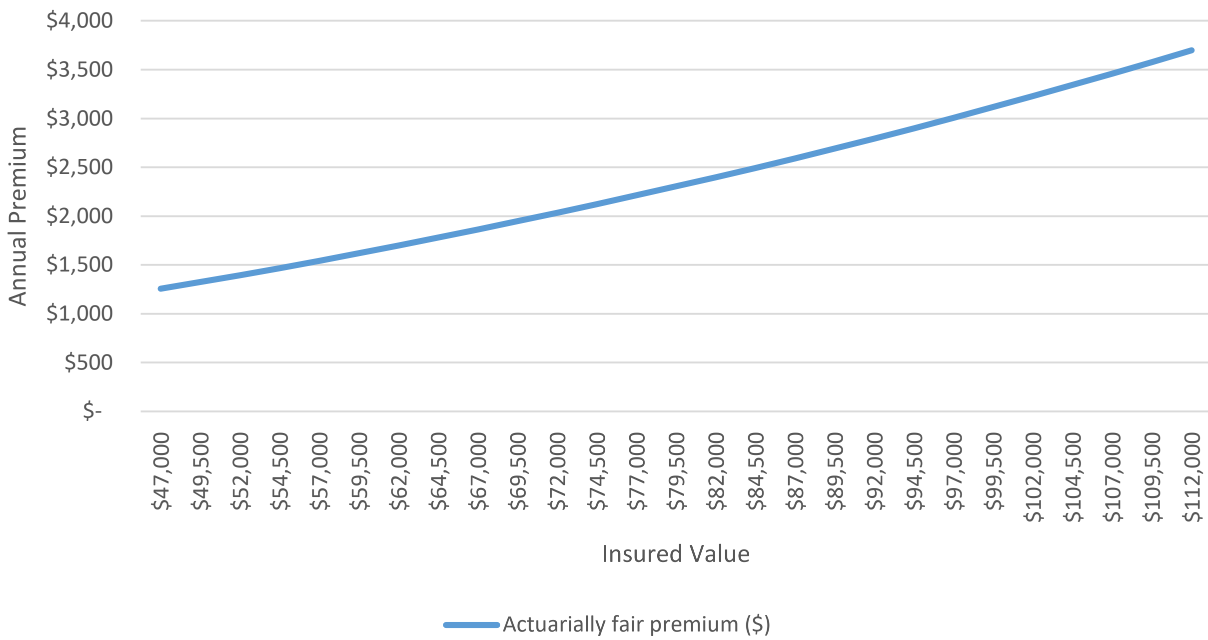

Figure 11 **Insurance premium cost for different levels of insurance coverage for the large office building benchmark model**

5.3. Cost of the guarantee as an indication of the value of controls

The calculations performed above also provide an initial understanding of the expected cost function of the guarantee itself. In particular, assuming the ESCO performs a similar risk calculation of the project – calculating the probability and magnitude that actual performance is below the guarantee – the same model can be applied to determine ESCO guarantee cost. We use a higher interest rate in this case (7%) to reflect ESCO profit considerations. Doing so yields an annual cost associated with the guarantee at ~$1,500 for a guarantee at $47,500 and about $3,700 for a guarantee at $102,500. The ~$2,200 difference can be used as an additional waypoint when contemplating the installation of controls – however, as established in the first section of this report and the first few paragraphs of the second section of the report, this is only one of the dimensions associated with the functions of controls. Future research can be directed at understanding and quantifying the various dimensions.

6.0. Concluding Remarks

The conceptual and modeling approach introduced in this report targets performance uncertainty – a dimension commonly neglected in energy savings calculations [80] despite its potential usefulness in the investment decision-making process [76; 137]. The stochastic profile of energy efficiency projects is illustrated both with and without the use of performance variation control technologies in an attempt to quantify the contribution of such advanced, real-time, high-accuracy control technology. In effect, the use of this technology enables a "deterministic" accounting of project performance through real-time and high-quality measurement [63] that limits the stochastic range of performance. The advancements in advanced data analytics and improved data collection are, indeed, shaping what some call the monitoring and verification (M&V) 2.0 or "automated M&V" paradigm [56; 57]. Automatic and interval performance measurement of a variety of devices and equipment (either at the device-level, sub-meter level, or whole-building level) provides previously unavailable insights into the overall project [19].

In particular, the use of advanced, real-time, high-accuracy control technology could have consequences for the placement of the ESCO guarantee in an energy performance contract project. Raising the guarantee by reducing performance variation is one hypothesized benefit of putting controls in place. We have made an attempt at quantifying this benefit for several common building types in the United States and show that controls can deliver a substantial benefit. We also briefly discuss the potential role played by controls in the realm of energy efficiency performance insurance and provide several preliminary quantifications of the value of such insurance. This will be the subject of further research and the outcomes provided in this report should be seen as a preliminary discussion.

The combined application of probabilistic performance and "deterministic" accounting and management transforms uncertainty into metrics legible for conventional risk management strategies such as the implementation of robust energy savings guarantees or energy efficiency insurance products. These risk management strategies can be attractive to all involved parties. Our multi-stage methodology combines several models with topical data related to automated M&V. The case study evaluation of several hypothetical energy efficiency performance projects enables the model's review of energy performance contracting (EPC) projects with guaranteed energy savings agreements (GESAs) – the most common form of project in the market today [30].

The approach devised and tested in this report could help accelerate ongoing efforts to improve investor and potential clientconfidence and strengthen the energy efficiency market. For example, ongoing efforts to enhance investor confidence include the Investor Confidence Project from U.S.-based Environmental Defense Fund (EDF) or the EEFIG's plan to compile an open source database for energy efficiency finance performance. Motivating investment in energy efficiency makes use of the most cost-effective pathway to reduce CO_2 emissions [139; 140] and, responsible for up to 40% of CO_2 emissions, the building sector represents an especially salient target [2].

The 2018-2019 research effort has so far expanded on previous research conducted under the Energy and Environmental Policy Analysis (EEPA) Project. This 2018-2019 Final Report details findings and the analytical dimensions investigated. In particular, the research effort in 2018-2019 presents the following:

- **Comprehensive analysis:** the research expands the scope of previous work by reviewing seven possible ECMs with accompanying control functions. Moreover, the project evaluation period now covers 20 years. The investigation includes evaluation of several additional building benchmark models. We calculated exhaustive performance profiles through Monte Carlo analysis (in total, several million simulations were conducted).
- **Determine consequences for energy savings guarantee:** We provide preliminary understanding of the role of building controls in the energy savings guarantee setting process and argue that controls could help elicit higher guarantees.
- **Benchmarking research results against insurance costing model:** We deliver a preliminary overview of ways to compare the benefits provided by controls in addition to those of the higher guarantee. As a part of this effort, we constructed a model capable of setting some initial cost estimates on the varying components of a possible EPC project.
- **Standardized and automated computation:** Using KNIME Analytics Software, the research effort developed a workflow-based model capable of automated and consistent computation. This enables reproducibility of results and should allow for consistent research moving forward.

Two findings stand out in the report:

- Tests of our multi-stage model confirms that the model captures the interlocking dynamics associated with energy efficiency insurance, guarantee setting, and performance control technology implementation.
- Our results indicate that such technology implementation can deliver substantial benefits in the form of, among others, a large increase in the energy savings guarantee.

7.0. References

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8.0. APPENDIX A: ENERGY SAVINGS GUARANTEE SETTING MODEL

8.1. Cash Flow of Project Under Energy Savings Guarantee:

Realized energy bill savings (S_t) can be modeled at time (t) as follows:

EQUATION 1: $$\boldsymbol{S_t = C_t^{old} - C_t^{new}}$$

Where Equation 1 describes realized energy bill savings as a function of the energy bill costs before energy efficiency retrofit (C_t^{old}) and after energy efficiency retrofit (C_t^{new}). S_t as such is determined by the amount of energy used and the price paid per unit of energy before retrofit versus the amount of energy used and the price paid after retrofit:

EQUATION 2: $$\boldsymbol{C_t^{old} = P_{E0} * Q_{E0}}$$

EQUATION 3: $$\boldsymbol{C_t^{new} = P_E(t) * Q_E(t)}$$

Where energy bill costs before retrofit (C_t^{old}) are fixed at time = 0 (i.e. the baseline) as indicated by P_{E0} (price of energy at t = 0) and Q_{E0} (quantity of consumption at t = 0) while energy bill costs after retrofit (C_t^{new}) fluctuate over the lifetime of the project. The price fluctuation is addressed by separating out natural gas and electricity (the only two energy sources under evaluation in this project) and considering their price developments over time. As mentioned, electricity is assumed to have been contractually negotiated while natural gas prices are subject to market volatility:

EQUATION 4: $$\boldsymbol{P_{E,natural\ gas} = P_{E0,natural\ gas}\, exp\left[\left(\alpha_E(t) - \frac{\sigma_E^2(t)}{2}\right)t + \sigma_E(t)\epsilon_p\sqrt{t}\right]}$$

EQUATION 5: $$\boldsymbol{P_{E,electricity} = P_{E0,electricity} * (1 + ESC)^t}$$

Where $\alpha_E(t)$ represents an annual price drift coefficient and $\sigma_E(t)$ represent an annual volatility coefficient. Electricity price is escalated at an annual coefficient that is contractually negotiated (ESC).

The amount of energy consumption (Q_E) is modeled stochastically (for description of approach, see Section 0). However, following Deng et al. [23], we assume that there is a specific pattern to the expected savings (i.e. the mean of the distribution) over the lifetime of the project. This pattern accounts for the operationalization of equipment and the resulting degradation over the lifetime of the project. This expected savings estimate is assumed to be calculated by the system engineers as a best estimate. While our numbers differ from Deng et al. [23], we apply the same pattern as given in Table 17.

Table 17 **Pattern of energy consumption expected savings (i.e. mean of the stochastic distribution) throughout the lifetime of the project**

Year of Project (years)	Engineers' estimation of annual savings deviation compared to first year
1	0%
2	+6.85%
3	+12.33%
4	+14.38%
5	+13.70%
6	+13.01%
7	+12.33%
8	+10.96%
9	+9.59%
10	+6.85%
11	+1.37%
12	-4.11%
13	-10.96%
Any following years:	-10.96%

8.2. Under- or Over-Performance of the Guarantee Decisions:

As Deng et al. [23] describe, the guarantee placement decision is influenced by two key parameters. First, the value of the guarantee. Second, the shared percentage if project returns exceed the guarantee. Consider the shared percentage from the perspective of the ESCO as $1 - \beta$ where β is the fraction of savings that will be allocated to the client in the case of over-performance. Based on this consideration, a profit difference ($D(t)$) can be calculated. From the perspective of the ESCO ($D_E(t)$), this yields the following:

Equation 6: $$\boldsymbol{D_E(t) = S(t) - G(t) - max(0, \beta(S(t) - G(t)))}$$

Where $G(t)$ is the annual guaranteed energy cost savings and $S(t)$ is the realized savings. $G(t)$ could be made subject to an annual adjustment (see Deng et al. [23]) but the guarantee here is assumed to be equal in each year of the project. Under the guaranteed energy savings contract used in this project, no profit sharing takes place under the condition of over-performance: all the over-performance value goes to the client, i.e. β =

1. Any over-performance thus limits the profit value of the ESCO by an equal amount ($S(t) - G(t) = \beta * (S(t) - G(t))$). As such, there is no direct financial gain for the ESCO when over-performance is achieved and the ESCO will pursue a guarantee that is as high as possible if it is within its risk tolerance.

8.3. ESCO Risk Tolerance and Setting the Guarantee:

Considering that Equation 6 provides for an annual profit difference calculation, the final step is to determine the project *total* profit difference. To do that, the ESCO's annual profit differences are discounted to a present value using an expected rate of return (r). As such, the previous equations shape the calculation of the total profit difference from the ESCOs perspective ($D_{E,\ total}(G(t), \beta)$:

EQUATION 7: $$\boldsymbol{D_{E,total}(G(t), \beta) = \sum_{t=1}^{N} \frac{D_E(t)}{(1+r)^t}}$$

Guarantee placement, then, can be informed by the total profit difference. A positive ($D_{E,\ total}(G(t), \beta)$ (which can only occur when $\beta < 1$) means that the ESCO provided an energy savings guarantee that ultimately was too low and the project over-performed relative to the guarantee. While this sounds appealing, it also means that the guarantee proposal by the ESCO was not as competitive as it might have been, meaning the ESCO could have lost out on the project. A negative ($D_{E,\ total}(G(t), \beta)$, meanwhile, means that the ESCO had a lower overall return on the project than originally expected. This could even be a net-loss for the ESCO and, as such, a negative ($D_{E,\ total}(G(t), \beta)$ should be avoided whenever possible. An optimal outcome from the perspective of the ESCO, therefore, is a project where ($D_{E,\ total}(G(t), \beta) = 0$. Considering that this is a project where we have set $\beta = 1$, this effectively means that no under-performance can take place in any of the years of the project – a criterion highly relevant to third-party investors.

In other words, the ESCO would attempt to place the guarantee at a level where its profit difference = 0 which is a value sufficiently below the mean of the distribution of expected savings. It also means that a broad distribution of a project's expected savings results in a lower guarantee while a narrow distribution of expected savings elevates the guarantee placement.

8.4. Guarantee Model as Built in KNIME Analytics Software:

The previous sections describe the model introduced by Deng et al. [23] equation-by-equation. We have made several (minor) adjustments, specifically the inclusion of separate prices for electricity and natural gas. To aid replicability of the calculations and our research, we have constructed a KNIME data analytics model that takes the inputs and calculates each step based on the above directions. KNIME Analytics Platform is an open source software that enables the creation of specific and reusable workflow components.

Data inputs:

The model relies on receiving an Excel file which includes the pre- and post-retrofit energy consumption levels for natural gas and electricity use. This Excel file is generated through the modeling steps detailed in Section 0.

Calculating the distribution of savings:

Following Equation 1, realized energy bill savings are achieved by calculating the difference between energy bill costs before energy efficiency retrofit (C_t^{old}) and after energy efficiency retrofit (C_t^{new}). To that end, we first need to determine, in energy units, what the difference between pre-and post-retrofit energy consumption is. To do so, we calculate the mean and variance of the normal distributions of Q for both the pre-and post-retrofit scenarios and for electricity and natural gas. Following the fact that the distribution of a difference of two normally distributed variates is given by a new normal distribution, [8] we derive the mean ($\mu_{Q_{E0}-Q_E(t)}$) of the savings distribution with Equation 8 and the variance ($\sigma^2_{Q_{E0}-\,Q_E(t)}$) of the savings distribution with Equation 9.

EQUATION 8: $$\boldsymbol{\mu_{Q_{E0}-Q_E(t)} = \mu_{Q_{E0}} - \mu_{Q_E(t)}}$$

Where $\mu_{Q_{E0}}$ is the mean of the energy consumption level of the baseline (i.e. pre-retrofit) and $\mu_{Q_E(t)}$ is the mean of the energy consumption level of the post-retrofit scenario.

EQUATION 9: $$\boldsymbol{\sigma^2_{Q_{E0}-\,Q_E(t)} = \sigma^2_{Q_{E0}} + \sigma^2_{Q_E(t)}}$$

Where $\sigma^2_{Q_{E0}}$is the variance of the baseline and $\sigma^2_{Q_E(t)}$ is the energy consumption level of the post-retrofit scenario.

[8] Weisstein, Eric W. "Normal Difference Distribution." From *MathWorld*--A Wolfram Web Resource. http://mathworld.wolfram.com/NormalDifferenceDistribution.html

This is represented in Sub-Model 1 for natural gas Sub-Model 2 for electricity. Sub-Model 1 is graphically represented in Figure 12. The same approach is applied for electricity in Sub-Model 2 (not illustrated here).

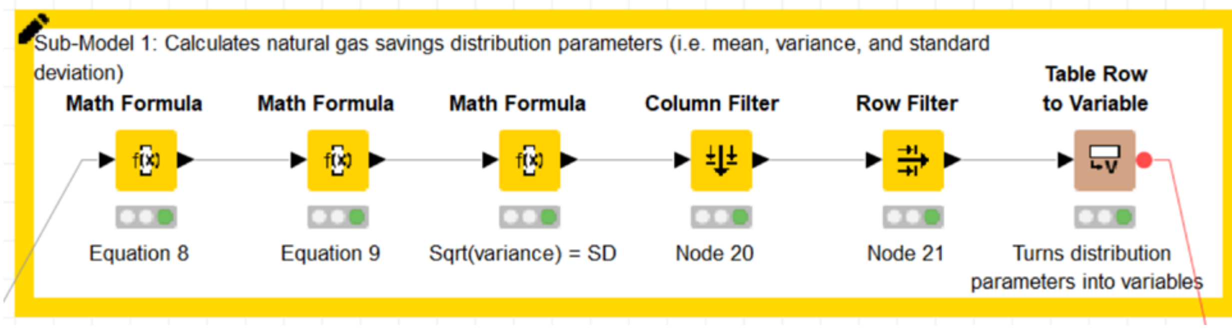

Figure 12 **KNIME Sub-Model 1: Parameters of Natural Gas Savings Distribution**

Next. to create the expected savings distribution for each year of the project, we apply the values provided in Table 17 to modify the distribution year-on-year. The result of Sub-Model 3 is a normally distributed natural gas savings profile for each year of the project Figure 13. The same is done for electricity in Sub-Model 4 (not illustrated here).

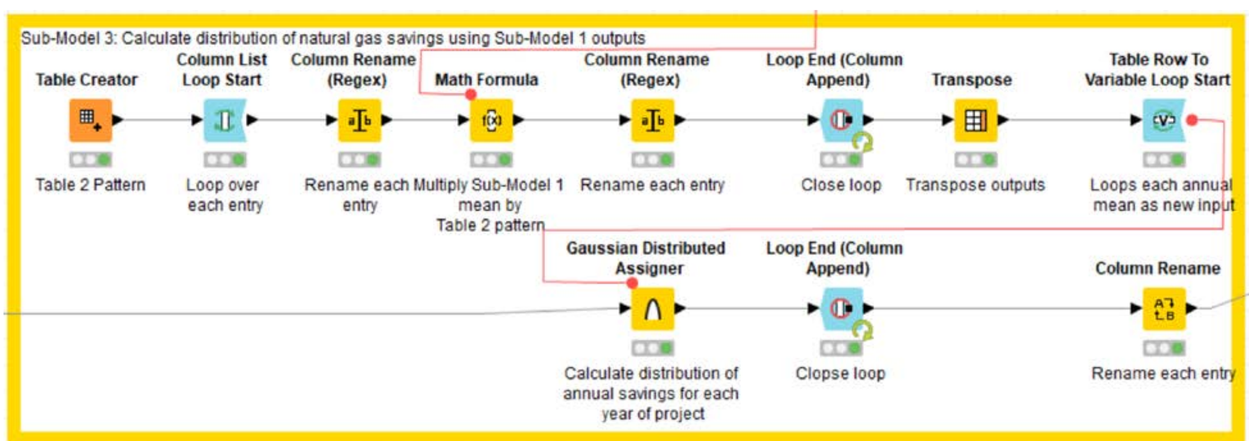

Figure 13 **KNIME Sub-Model 3: Calculate distribution of natural gas savings distribution using Sub-Model 1 inputs**

Calculating energy bill savings:

Using Equation 4, we calculate energy bill savings in KNIME using Sub-Model 5 (Figure 14) for natural gas. The model for electricity is not illustrated here. This model first introduces the drift, volatility, and energy price coefficients and then applies Equation 4 to calculate, for each entry, the energy bill savings based on the volatile energy price and the drift trajectory of the price over time.

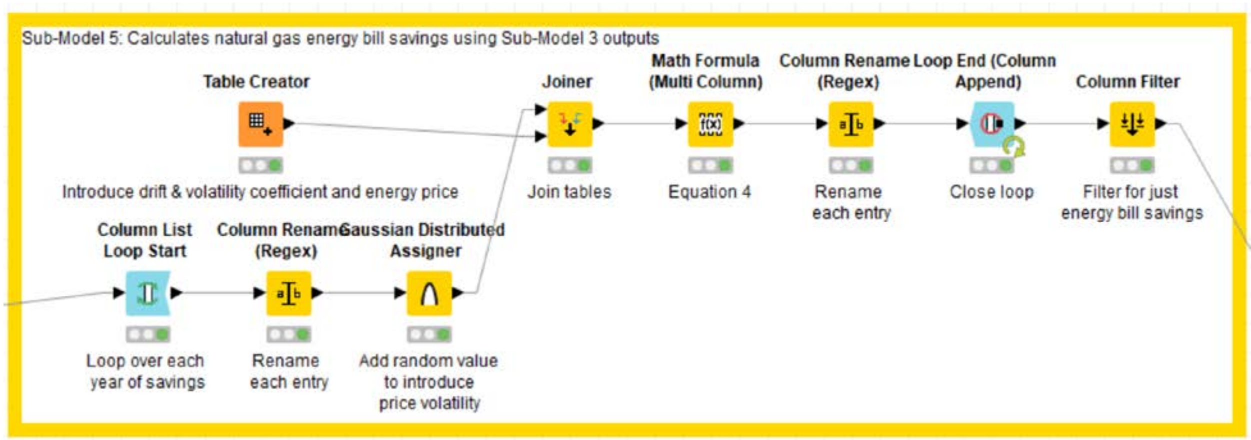

Figure 14 **KNIME Sub-Model 5: Calculates natural gas energy bill savings**

Determining ESCO profit difference by year:

After joining and summing the energy bill savings from electricity and natural gas, the model uses Equation 6 to calculate $D_E(t)$ for each year. Sub-Model 7 contains the steps necessary to operate Equation 6. The output of Sub-Model 7 is a comprehensive table where $D_E(t)$ is calculated for many possible guarantee levels (i.e. values of G(t)).

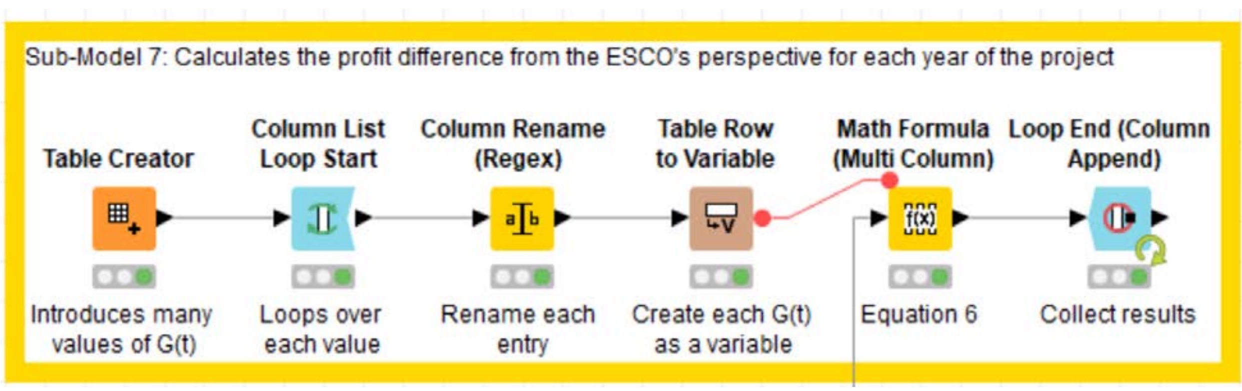

Figure 15 **KNIME Sub-Model 7: Calculates profit difference for each year of the project**

Determining guarantee placement:

The final step, then, in the model is to calculate $D_{E,total}(G(t), \beta)$, the present value of the sum of $D_E(t)$ values calculated in Sub-Model 7. The value where $D_{E,total}(G(t), \beta) = 0$ can be interpolated from the many values of G(t) introduced in Sub-Model 7. The result is a final Sub-Model 8 which documents the analytical steps necessary to determine the strategic guarantee level, relying predominantly on Equation 7.

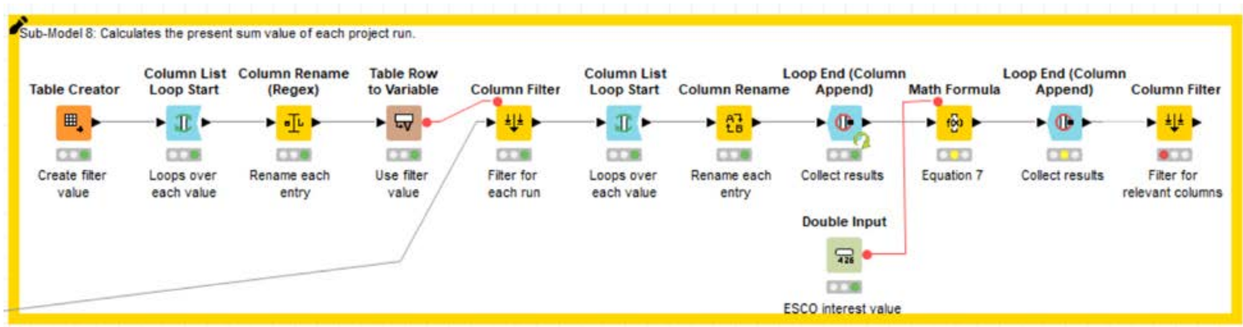

Figure 16 **KNIME Sub-Model 8: Calculates present sum value of ESCO profit against series of possible guarantee levels**

The strategic guarantee level is, in short, the highest possible guarantee where the expression $D_{E,total}(G(t), \beta) = 0$ remains true.

9.0. Appendix B: Energy Efficiency Performance Insurance Model

This model also begins with a description of the cash flow from the perspective of the insurer at time t ≥ 1:

EQUATION 10: $$\boldsymbol{CF_{t,energy\,efficiency\,insurance} = N - (K - S_t)_+ - TC_t}$$

Where K describes the insured level of annual energy bill savings, S_t represents realized annual savings (see Equation 1), and TC_t denotes the transaction costs that occur at time t. The level of transaction costs is dependent on the number of claims in time t and, as such, are stochastic. Actuarially fair premiums (N), can thus be calculated by the following equation which translates annual events to present value:

EQUATION 11: $$\boldsymbol{N = \frac{(1+r)^T * r}{(1+r)^T - 1} * \sum_{t=1}^{T} E\left[\frac{(K - S_t)_+}{(1+r)^t}\right]}$$

Where r is the actuarial interest rate and T the lifetime of the insurance contract. An actuarially fair premium represents insurance with an expected net pay-off of zero. In other words, the premiums paid are equal to the expected value of the compensation received. This expected value, as indicated in Equation 11 is, in turn, defined as the probability of the insured-against event occurring multiplied by the compensation received in the event of a loss. The annual premium paid, therefore, is set equal to the probability of experiencing the risk event times the benefits paid out in the event of the risk event occurring. Figure 17 illustrates the application of Equation 11 in KNIME Data Analytics Software.

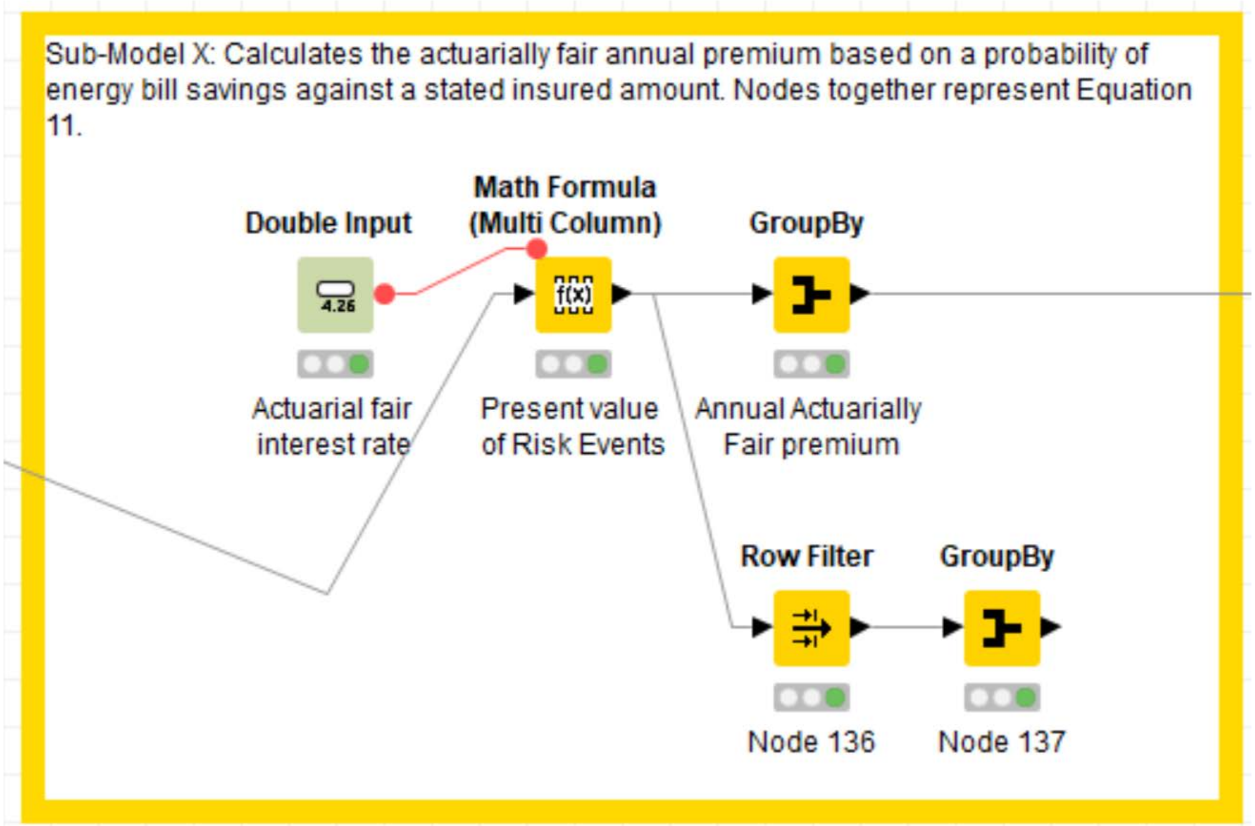

Figure 17 KNIME Sub-Model X: Calculates actuarially fair annual premium based on probability of energy bill savings against stated insured amount

For example, consider K = G(t) at the $50,000 found in the previous hypothetical example (see Figure 2) and the use of actuarial fair interest rate of 1% and a 20-year insurance contract lifetime. In this case, we're evaluating a project with a low risk of underperforming the guarantee. As such, the actuarially fair annual premium is $75,88. The premium is low because a) the probability of the risk event occurring is low (598 cash flows out of a simulated 10,000 or 5.98%) and b) the average present value of the risk event is low ($1,267 in this case).