RISK MODEL FOR ENERGY PERFORMANCE CONTRACTING IN CORRECTIONAL FACILITIES

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ABSTRACT

Energy performance contracting provides guaranteed minimum energy savings to building owners, enabling them to finance project costs using utility savings over the duration of the project. This has been an attractive project delivery method for organizations with reduced budgets for capital projects, particularly among correctional facilities which frequently have lengthy periods of deferred maintenance and ongoing building operations and maintenance concerns. This research builds on a previously developed project factors risk framework for energy service companies undertaking building retrofits. This paper proposes a risk analysis and evaluation model that includes quantitative, expert-based, and probabilistically derived information. Expected cost was used to evaluate risks over lengthy project life cycles and a new metric was developed for use in the model—expected life cycle value. Model results reveal that the most critical risk factors relate to the reduced availability of "low-hanging fruit" energy conservation measures, work scopes based on traditional design-bid-build procurement, unavailable or inaccurate facility information, facility age and current code requirements, and conducting the investment grade audit too quickly. The life cycle cost-based risk model employed in this paper is proposed as an advancement over traditional risk management methods, and it is expected to be applicable, with modification, across other municipal and state government subdomains, especially high security projects.

KEYWORDS

energy performance contracting (EPC), energy efficient building practices, building retrofits, project performance risks, risk modeling, scenario failure mode and effect analysis (SFMEA)

INTRODUCTION

Commercial buildings account for nearly half of the primary energy consumption in the United States. Although correctional facilities (prisons and jails) account for less than 1.5% of the overall commercial building stock floor space, they are in the upper half of all commercial building

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types for energy intensity, consuming approximately 50 trillion BTUs annually (U.S. Energy Information Administration 2016b). Average energy intensities between 64,766 and 190,362 British thermal units (BTUs) per square foot (sf) were recorded for buildings coded as "prison or correctional facility" in the 2012 CBECS survey (U.S. Energy Information Administration 2016a). Correctional facility data, obtained from Wisconsin and the EPA Portfolio Manager, shows these facilities had average energy intensities between 93,200 BTU/sf and 168,131 BTU/sf (U.S. Environmental Protection Agency 2016; Wisconsin Department of Administration 2018), respectively.

Despite high energy intensities, many public agencies have reduced capital budgets to fund retrofit programs, even among projects that enhance efficiencies and thus save funds (Bharvirkar et al. 2008). The continued operation of inefficient mechanical, electrical, and plumbing equipment can lead to increased utility costs, thereby exacerbating this situation (Bhattacharjee et al. 2010). These factors have contributed to the increased use of energy performance contracts (EPCs), particularly in what has been termed the MUSH (municipalities, universities, schools, and hospitals) market (Hopper et al. 2005).

Energy performance contracting is a project delivery mechanism that finances retrofits using projected utility savings gained through improved energy efficiency. As a result, capital is not required at project startup; rather, the work can be financed over a period of years, termed the contract performance period. EPCs are generally executed by an energy service company (ESCO), which performs the work and receives payment as a result of accumulated utility savings which exceed baseline consumption. These savings frequently accumulate over a 12–15 year project performance period.

The MUSH and federal markets (which include correctional facilities) are the dominant sources of revenue for ESCOs. Additionally, nearly 70% of public and institutional EPC projects are executed using the guaranteed savings model (Larsen et al. 2012). The guaranteed savings contractual form releases the ESCO from financing-related risks (due to 3rd party financing for the project owner); however, the performance guarantee must ensure that a wider range of costs are recoverable, to include debt service, measurement and verification (M&V) fees, and any maintenance obligations or other incremental costs stipulated by the contract (IFC 2011). If actual savings are less than the guaranteed amount, the ESCO pays the shortfall amount to the owner using previously agreed upon utility rates and escalation factors. As a result, the predominant savings model in EPC building retrofits is also the primary source of risk to ESCOs—the energy performance guarantee which relies on predicted energy savings over lengthy periods of time, often up to 15 years (Deng et al. 2014).

While the literature is replete with energy efficiency decision making and risk models, the vast majority are based on technical performance of energy conservation measures (Lucchi 2016), social factors, such as cognitive bias (Delgado and Shealy 2018), or optimization across energy performance, cost, and related factors (Penna et al. 2015). Fewer entries exist that address risk factors specific to EPC retrofits (Hu and Zhou 2011; Lee et al. 2015; Berghorn and Syal 2016; Garbuzova-Schlifter and Madlener 2016; and Wang et al. 2018), and none focuses specifically on the challenges unique to correctional facilities. These challenges typically originate from security concerns, as enumerated in Berghorn (2014). They include lost daily productivity due to check-in/check-out procedures, tool counts, and the need for facility escorts; tampering with installed energy conservation measures (ECMs); and unique physical building and operational characteristics.

Xu et al. (2011) and Xu and Chan (2012) focused on understanding risk and critical success factors in hotel buildings. Their research found that due to numerous interrelated project complexities, such methods should be built for unique building types. Furthermore, their work found that project management, EPC implementation strategy, knowledge of EPC and M&V, and contractual form were among the most important risk and performance indicators.

This research develops a project management-focused risk management model for ESCOs when undertaking EPC building retrofits in correctional facilities. Building from the risk identification framework developed by Berghorn (2014) and Berghorn and Syal (2016), this work presents a risk analysis and evaluation framework, which in turn is developed into a risk model that can be used by ESCOs for decision making when evaluating building retrofit projects.

METHODS

Figure 1 depicts the steps involved with developing the approach used for developing the risk model. The model utilizes expert knowledge and project-specific quantitative data, as described by Duah (2014). Therefore, a method that combines both types of information must be considered in developing an EPC contractor's risk model. Since all levels of project decisions have a greater impact on overall project design and performance at the lowest overall cost, information availability and quality during the project is also critical. This is premised on the notion that risks can best be controlled during the earliest project phases, when the costs of change are lowest and the potential impact of those changes is the greatest (Horsley et al. 2003; Kishk et al. 2003). As a result, the presented model utilizes a risk analysis and evaluation framework that incorporates multiple sources of information (quantitative, expert knowledge, probabilistically generated data).

Risk Category and Risk Management Method Selection

Risk Category Selection

The analysis performed by Berghorn and Syal (2016) considered 11 risk categories (Table 1). A consensus of 18 expert panelists highlighted the importance of two categories (investment grade audit quality and selection and installation of energy conservation measures) which were the subject of risk analysis and evaluation in the risk model. Experts were asked how often they considered each risk category in their project planning processes, they were asked to rank the relative importance of each category, and then to provide a re-ranking of the top six categories as identified by the first two scores. These two categories received consensus importance rankings

FIGURE 1. Risk Model Development Process.

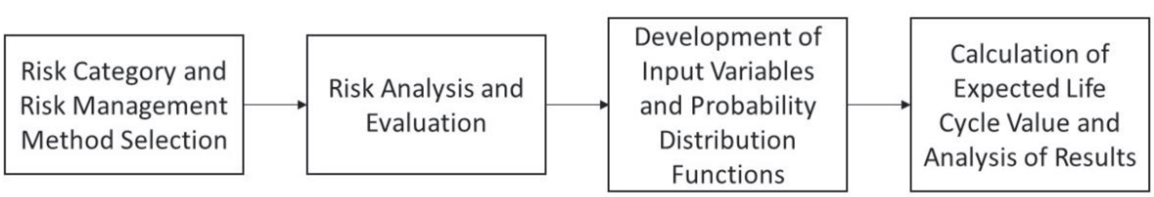


TABLE 1. EPC Contractor Risk Categories.

1. Client Pre-Qualification • Financial factors • Facility/technical factors • People factors	5. Commissioning 6. Operations and Maintenance Practices 7. Measurement and Verification of Savings 8. Project Management Over the Project Life Cycle
2. Project Development	9. Construction-Specific Concerns
3. Energy Audit Quality	10. Volatility of Energy Prices
4. Equipment Selection and Installation	11. Performance of the EPC Industry

Source: Berghorn and Syal (2016)

of either "1" or "2," indicating the top two ranks, across all three score types. One panelist referred to these as the risks that "keep me awake at night." Additionally, panelists agreed that since the investment grade audit (IGA) establishes the energy baseline for the project, as well as the basis of design for the project, the quality of this analysis can disproportionately impact actual savings.

These varied and significant risks highlight the need to develop a comprehensive framework for addressing all of the elements of risk that impact specific project objectives. Syal et al. (2014) and Duah (2014) emphasized the need to capture expert knowledge and judgements related to the energy retrofit process; in this paper, that is applied within the context of a risk management system. While this research uses an expert-based risk evaluation and analysis process, the following studies were considered to guide method development:

- Qualitative techniques, based on the recommendation of McKim (1992);
- Applicability across the development and design phases (Grimaldi et al. 2012), as this is where the majority of risk-based decisions are made in EPC projects, and when changes can have the greatest impact at the lowest incremental cost (Horsley et al. 2003; Kishk et al. 2003);
- Techniques favoring the use of expert knowledge;
- Techniques enabling the incorporation of monetary value as the measure of risk criticality (Thaheem and DeMarco 2013) and the use of life cycle costs as part of risk evaluation; and
- Iterative, consensus-based techniques to address Raftery's (1994) observation that construction professionals could benefit from being made aware of their decision-making process.

Risk Management Method Selection

Failure mode and effects analysis (FMEA) was selected as the primary risk management method as it met the above criteria and due to being well suited to all phases of the project life cycle (Onodera 1997). There is also a body of literature supporting the incorporation of monetary value and life cycle costs as a measure of risk severity during the evaluation phase (Kmenta and Ishii 2000; Rhee and Ishii 2002; Marenjak et al. 2003; Rhee and Ishii 2003; Rhee and Spencer 2009; Chen and Zhang 2012; Liu et al. 2013; Thaheem and DeMarco 2013).

FMEA was developed in the 1960s for the aerospace industry and has since been used by the defense, nuclear, space exploration, automotive, software systems, healthcare, and construction industries (Dhillon 1992; Latino 2004; Liu et al. 2013; Rahimi et al. 2013). Built environment applications of FMEA have included an assessment of barriers to innovation in construction (Murphy et al. 2011), analyzing moisture-related risks in buildings (Nielsen 2002), an analysis of the effects of interior insulation on moisture-related damage to walls (Morelli and Svendsen 2012), and risk of failure in building envelope systems (Layzell and Ledbetter 1998).

Despite the wide application of this method, the use of FMEA is limited by its complexity, its focus on end effects to the exclusion of causes, disagreement about the definition of failure mode detection, the inability for a single FMEA analysis to accurately evaluate risks based on the life cycle phase where they are realized, and criticism leveled at the risk priority number (RPN) (Bowles 2004; Kmenta and Ishii 2004; Gargama and Chaturvedi 2011; Grimaldi et al. 2012; Liu et al. 2013).

Cost-based methods have been proposed, among other alternatives, to address these shortcomings (Kmenta and Ishii 2000; Rhee and Ishii 2002; Rhee and Ishii 2003; von Ahsen 2008; Liu et al. 2013). An appropriate cost-based method was sought that could adequately address risk costs over a lengthy project life cycle during the earliest project phases, since a priori risk costing may not be incorporated in bids in order to improve competitiveness (Laryea and Hughes 2011).

Kmenta and Ishii (2000) developed scenario-based FMEA (SFMEA) as a methodological improvement over traditional FMEA by using failure scenarios and expected cost (EC) as the measure of risk criticality. Rhee and Ishii (2002) and Kmenta and Ishii (2004) further refined SFMEA by incorporating life cycle costing, which enables the analysis to represent multi-level cause-effect relationships (e.g., end effects during early project phases may become risk causes during later phases).

A foundational characteristic of SFMEA is its creation and analysis of multiple "failure scenarios," which are cause and effect chains of varying length to represent risk causes, intermediate effects, and end effects throughout the analysis (Kmenta and Ishii 2000; Kmenta and Ishii 2004). The use of failure scenarios has been applied in construction and engineering research (Esmaeili and Hallowell 2013; Pallin 2013; Hamilton et al. 2014).

Kaplan and Garrick (1981) and Gilchrist (1993) were among the first to propose cost as an acceptable measure of risk consequences, so for each failure scenario, Kmenta and Ishii (2004) posited that risk can be calculated as the expected cost (Rasmussen 1981; Kmenta and Ishii 2000).

The expected cost is shown mathematically as:

$$\text{Expected Cost (EC) of risk } i = p_i \times c_i$$

where p_i is the probability of risk i and c_i is the cost of risk i.

The conditional probability of a given failure scenario can then be calculated using Bayes' theorem (Bolstad 2013), which states the probability of a given scenario can be found by multiplying the probability of the cause by the conditional probability of the end effect. This also demonstrates the utility of SFMEA throughout the project life cycle, as early-, mid-, and late-phase project risks can be analyzed simultaneously. SFMEA allows the same expert panel to examine multiple levels of causes and effects, using the same evaluative criteria and language to describe risks.

Risk Analysis and Evaluation

The selected risk categories were analyzed and evaluated during a workshop, convened with EPC and ESCO experts with domain-specific knowledge for correctional facility retrofits. While this focuses the analysis and evaluation based on the expertise of the participants, it also limits findings based on their domain knowledge. The qualification and background of the expert panel is described below.

Panelist Selection and Qualification

Recommended FMEA panel sizes range from four to nine (Stamatis 2003; McDermott et al. 2009); however, the most critical aspect of its composition is that key project functions and technical disciplines are represented. Following this guidance, a four-member panel was assembled that had significant experience in corrections EPC projects. Two members each had over 30 years of experience in delivering correctional facility retrofit projects (17 years specifically using EPC delivery, average of seven EPC correctional facility EPC projects, each). The other two panelists had worked on an average of four correctional facility EPC projects, and each had over 10 years of experience with EPC projects, in general.

SFMEA Workshop Framework

The framework for the SFMEA risk analysis and evaluation workshop consisted of five steps: (1) review selected risk categories in the refined risk framework; (2) construct failure scenario maps; (3) evaluate risk criticality for each scenario; (4) recommend and evaluate mitigation strategies; and (5) calculate the expected life cycle value.

Step 1: Review Selected Risk Categories

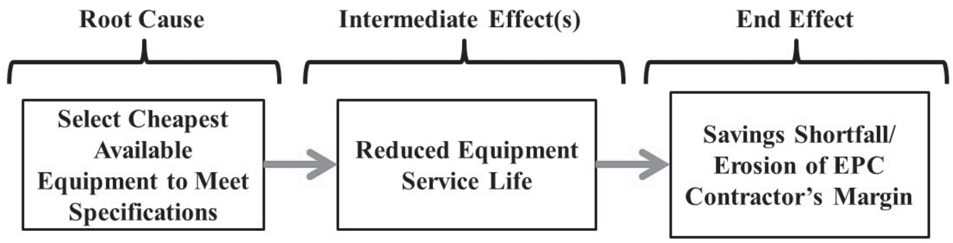
Twenty-seven risk causes related to the IGA quality and ECM selection and installation risk factors from the refined framework were reviewed, based on risk importance scoring in the EPC risk framework in Berghorn (2014) and Berghorn and Syal (2016). Examples of these potential risk causes included misunderstanding retrofit needs due to lack of correctional facility EPC experience, missing/incomplete facility information, owner's misapplication of design-bid-build (DBB) principles on EPC retrofits, and accessibility of retrofit measures to inmates/physical security of work.

Step 2: Construct Failure Scenario Maps

Failure scenarios consist of a root cause, an end effect, and possibly one or more intermediate effects (Figure 2). The probability of the cause and that of the end effect given any intermediate effects, termed the conditional probability of the end effect, constitutes the risk likelihood.

To familiarize them with their task, panelists were first provided with example scenario maps from a different project context, so as not to bias their efforts. They next undertook an iterative process that began with the identification of a single root cause followed by intermediate and end effects connected to that root cause. The scenario maps were revised repeatedly throughout the facilitated process as long as consensus was achieved among panelists.

FIGURE 2. Example Failure Scenario.



Panelists were able to lengthen the chain in either direction either as a result of detecting and including a new root cause, new intermediate effects, or a new end effect. Multiple related scenarios were organized into risk maps which described the interrelationships among causes, intermediate effects, and end effects in a single system, thereby creating a one-to-many relationship among causes and effects. Figure 3 depicts a scenario map which includes the scenario from Figure 2, and demonstrates how the cause-effect chain may be lengthened, how additional intermediate effects may be evaluated, and the one-to-many relationship potential among causes and end effects in failure scenario maps.

Step 3: Evaluate Risk Criticality Using Expected Cost

The determination of EC relies on an assessment of the probability of the risk cause (prior probability) and the conditional probability of the end effect (posterior probability). Panelists assessed these probabilities based on their experience with such projects and facility types. Cost data was provided as a percentage of the project's margin if risks were fully realized (i.e., not completely mitigated). EC can also be used to assess costs over the project life cycle. Figure 4

FIGURE 3. Example Failure Scenario Map.

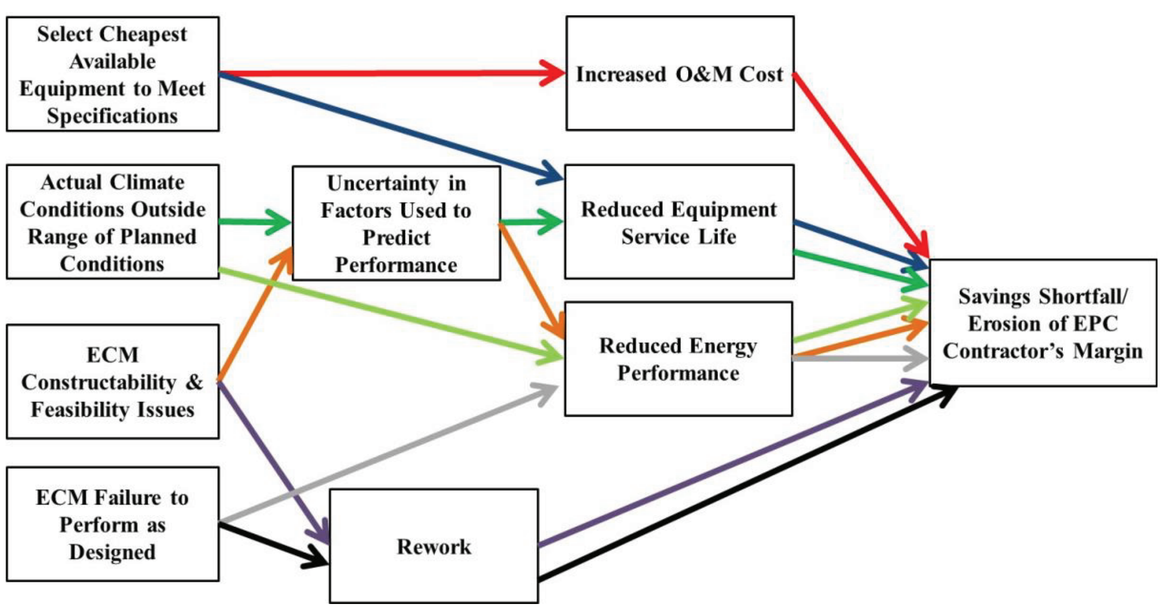
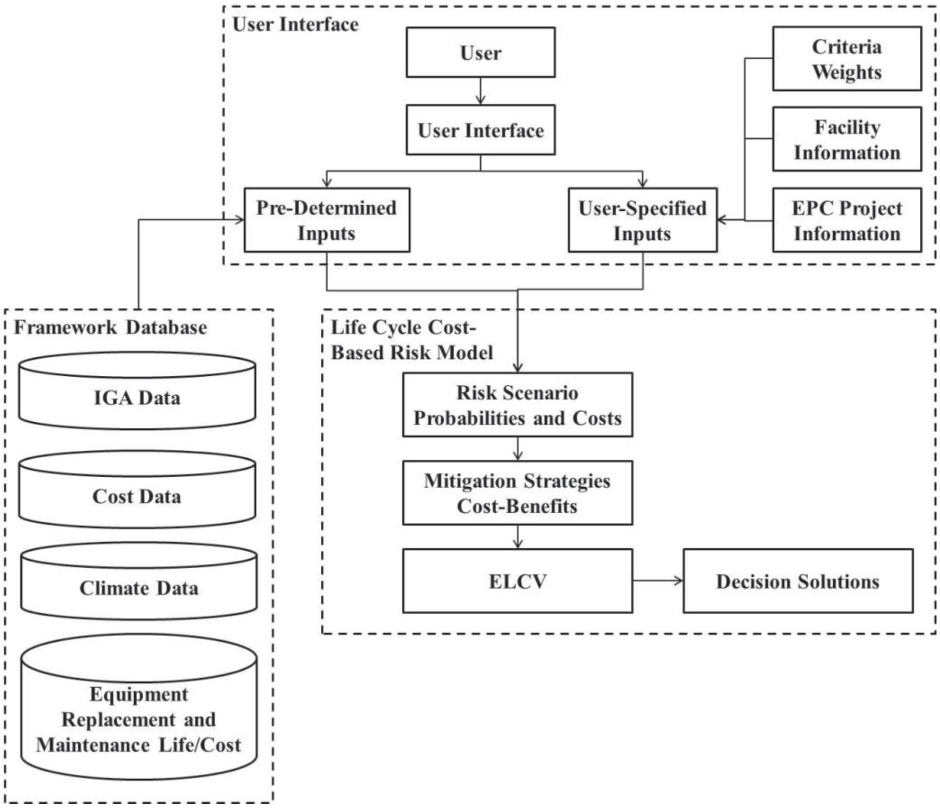


FIGURE 4. Use of Risk Scenarios and Expected Cost Over Project Life Cycle.



shows a risk scenario map that evaluates a root cause originating during the energy audit phase, but having intermediate and end effects spread across four of five EPC project phases.

The resultant EC for each risk scenario was discounted based on the time in the project life cycle when the risk is realized. The single present value (SPV) is used to calculate the present value of a one-time future amount given a discount rate. As given by Fuller and Petersen (1995), the equation to determine the present value of a given EC using SPV is:

$$EC_{PV} = \frac{EC_t}{(1+d)^t}$$

where EC_{PV} = the present value of the EC, EC_t = the future expected cost at time t, d = the discount rate, and t = the time in years when the risk is realized.

Step 4: Recommend and Evaluate Mitigation Strategies

The EPC risk framework completed by Berghorn and Syal (2016) included control measures and mitigation strategies for many potential risk causes. The primary focus of the paper was the development of the model framework. Mitigation, while important, was not the main goal, therefore a separate ESCO expert with significant risk management experience was asked to provide mitigation strategies for each risk scenario. An efficacy score was assigned to each mitigation strategy, which is a measure of the amount of the initial risk that is controlled by investing in a given mitigation strategy.

Step 5: Calculate the Expected Life Cycle Value (ELCV)
The expected life cycle value ELCV is defined as the amount of risk that has been effectively mitigated. It can be calculated based on the EC in current dollars or the EC_{PV}, accounting for the year where the risk is realized and discounted to the present year. Its formula is:

$$ELCV = EC - Cost_{mitigation} - Risk_{remaining}$$

or

$$ELCV_{PV} = EC_{PV} - Cost_{mitigation} - Risk_{remaining}$$

where

$$Risk_{remaining} = \left(1 - Efficacy_{mitigation}\right) \times EC \textit{ or } Risk_{remaining} = \left(1 - Efficacy_{mitigation}\right) \times EC_{PV}$$

Potential values of ELCV or $ELCV_{PV}$ are variable within the upper limit of the EC and the lower limit of the cost of risk remaining after mitigation, therefore values approaching zero are desirable; negative values indicate a poor cost-benefit relationship between mitigation costs and net benefits.

Risk Workshop Data Collection and Analysis

The data collection strategy consisted of facilitated, open-ended responses from panelists with consensus as the goal for elicited risk measures. If consensus could not be reached, median values of the range of panelists' responses were used. With a small data set ($N = 4$), outliers could unduly influence results, therefore, a more robust measure of central tendency was needed. Additionally, such a small data set limits the overall generalizability of findings from this study; however, this was the first attempt to analyze EPC retrofit risks specifically within the domain of correctional facility projects, and the work therefore has merit as an exploratory study.

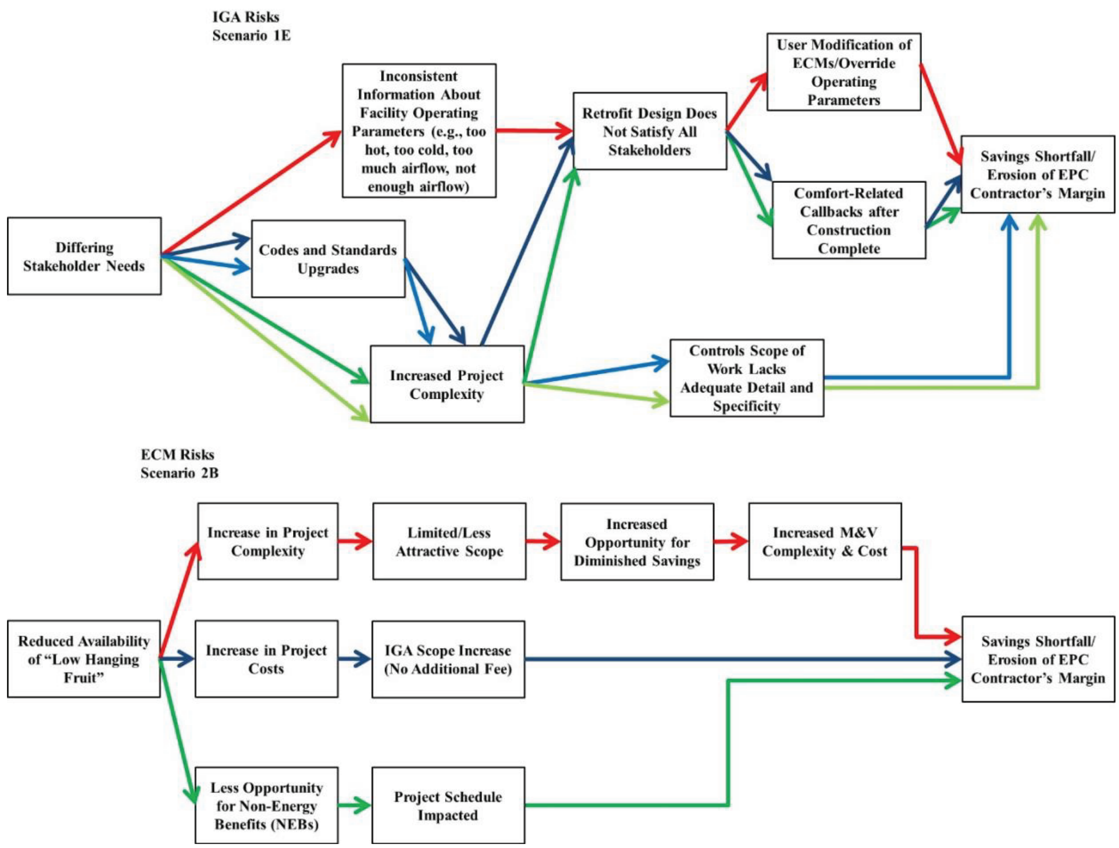
Additionally, in the authors' experience, the professional network of individuals working on such projects is relatively small, with much cross-pollination of individuals across firms as they move through their careers. While the data set for this study is small, it reflects the composition of professionals engaged in correctional facility EPC retrofit work.

Data Collection and Analysis—Risk Scenarios and Scenario Maps
Panelists agreed upon sixteen risk root causes identified in the risk framework; seven potential causes were reconfigured as intermediate effects, and five were not considered by the panel (one was deemed to be a duplicate entry). Once root causes were agreed upon, panelists constructed 12 risk scenario maps, consisting of 77 individual risk scenarios. Two example scenario maps are provided in Figure 5.

Data Collection and Analysis—Expected Cost
Panelists assigned measures of risk criticality to the 77 developed risk scenarios; group consensus was developed from individual responses. During the process of assigning prior probabilities, panelists identified several facility-related factors that influenced the way these probabilities were assigned.

Cost was calculated as the proportion of the EPC contractor's margin that would be at risk if the given risk scenario was left unmitigated. The end effect "savings shortfall/erosion of EPC contractor's margin" appeared in most scenarios. Remaining end effects included

FIGURE 5. Example Risk Scenario Maps Developed by SFMEA Panel.



"difficulty getting financing," "reduced project value for EPC contractor," "legal impacts," "remove/modify," "manage in place," and "modify affected system(s)." Panelists agreed in all cases that these consequences could be adequately addressed in terms of the proportion of the EPC contractor's project margin that would potentially be at risk. In order to convert relative costs to actual costs, a $2,000,000 project with a 20% margin was assumed.

Data Collection and Analysis—Most Critical Risks

Values of EC were ranked from 1 (highest criticality value) to 77 (lowest criticality value); the ten most critical risks are identified in Table 2. Five root causes were responsible for these top ten risks: (1) reduced availability of "low hanging fruit," (2) prepare technical scope of work based on standard public DBB procurement, (3) facility information unavailable/inaccurate, (4) misunderstanding existing conditions, and (5) EPC contractor lack of experience with facility type. Low hanging fruit is typically defined as no-cost or low-cost ECMs, or those with very fast payback periods, such as lighting retrofits.

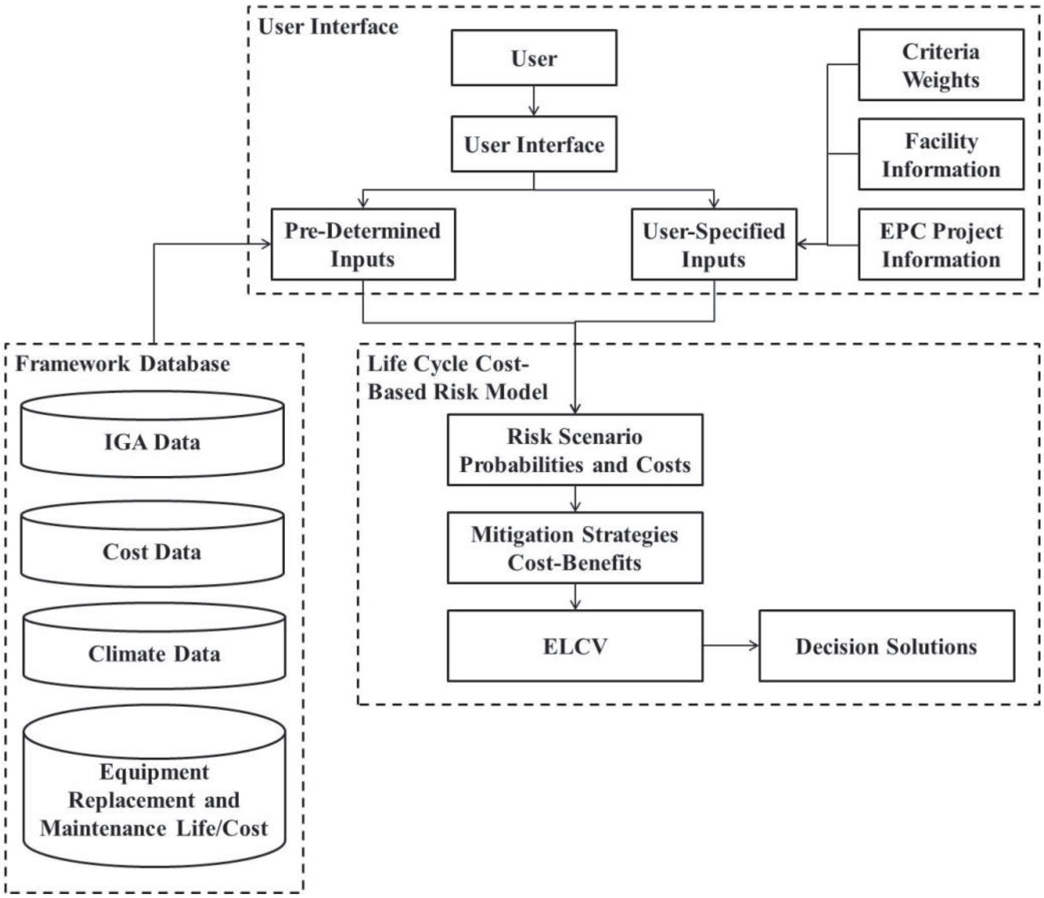
Development of Input Variables and Probability Distribution Functions

Figure 6 represents the development of the model from the risk analysis and evaluation framework. The risk model is the central component of the framework and incorporates elicited and

TABLE 2. SFMEA Panelist Consensus Assessment of Most Critical Risks.

EC Rank	Risk Cause	Intermediate Effect 1	Intermediate Effect 2	Intermediate Effect 3	End Effect	EC
1	Reduced Availability of "Low Hanging Fruit"	Increase in Project Complexity	Limited/Less Attractive Scope	Increased Opportunity for Diminished Savings	Savings Shortfall/Erosion of Contractor's Margin	$153,600
2	Prepare Technical Scope of Work Based on Standard Public DBB Procurement	Incorrect Vendor Selection	Disconnect Between IGA and Retrofit Design		Savings Shortfall/Erosion of Contractor's Margin	$104,625
3	Reduced Availability of "Low Hanging Fruit"	Increase in Project Costs	IGA Scope Increase (No Additional Fee)		Savings Shortfall/Erosion of Contractor's Margin	$102,400
4	Facility Information Unavailable/ Inaccurate	Missing Facility Information			Savings Shortfall/Erosion of Contractor's Margin	$91,350
5	Facility Information Unavailable/ Inaccurate	Inaccurate Baseline	Energy Model Calibration Errors		Savings Shortfall/Erosion of Contractor's Margin	$86,275
6	Reduced Availability of "Low Hanging Fruit"	Less Opportunity for Non-Energy Benefits	Project Schedule Impacted		Savings Shortfall/Erosion of Contractor's Margin	$76,800
7	Prepare Technical Scope of Work Based on Standard Public DBB Procurement	Require Contractor to use Fixed Overhead & Profit Rates	Overstate Project Soft Costs		Savings Shortfall/Erosion of Contractor's Margin	$67,500
8	Prepare Technical Scope of Work Based on Standard Public DBB Procurement	Divide Procurement into Separate Phases	Disconnect Between IGA and Retrofit Design		Savings Shortfall/Erosion of Contractor's Margin	$64,125
9	Misunderstanding Existing Conditions	Presence of Asbestos-Containing Materials (ACM)			Remove/Modify	$64,000
10	EPC Contractor Lack of Experience with Facility Type	Failure to Understand Facility Operations and Client Goals	Overestimate Productivity Rates	Underestimate Project Costs	Savings Shortfall/Erosion of Contractor's Margin	$63,000

FIGURE 6. Risk Analysis and Evaluation Framework for EPC Retrofits.



constructed knowledge from Berghorn and Syal's (2016) risk framework, risk-scenario data from the SFMEA panel, and quantitative information from the framework database.

Risk Scenario Probability Input Variables

Prior and posterior probabilities for each of the 77 risk scenarios were derived from SFMEA panelist-assigned values. For each risk scenario, the minimum, maximum, and mean panelist values of P_{cause}, P_{effect}, and cost were recorded and developed as a triangular distribution from which variables were later drawn in the model. The triangular distribution was selected since it can be used with smaller sample sizes ($N = 4$ in this case), and either mean or median values (U.S. Environmental Protection Agency 2001).

Project Variables: Variables related to ECM service life-related costs were generated from a probability density function (PDF) that was generated based on ECM-specific service life values using the "Service Life Data Query" feature of the ASHRAE Service Life and Maintenance Cost Database (ASHRAE 2014).

Facility Variables: Cause probabilities were developed through expertise elicited from SFMEA panelists.

External Environmental Variables: Prior probability values were generated from a PDF that was generated based on historical annual heating degree-day (HDD) and cooling degree-day (CDD) values. The risk model provides the ability to identify the climate zone of the project location—for climate zones 4 and above, the model utilizes HDD; CDD are utilized for projects located in climate zones 1 through 3.

Example Rules: The above relationships were developed in the model through conditional statements using IF-THEN-ELSE logic. This enabled the model to represent the knowledge elicited from the SFMEA panelists to calculate EC values for each affected scenario. As an example, the probability of encountering lead-based paint that requires remediation resulting from the facility's age would be represented as:

IF (gross floor area) built or renovated before 1980 > 0 THEN Pcause = 1.0 × area ELSE

IF (gross floor area) built or renovated after 1980 THEN Pcause = 0.0 × area

Calculation of Risk Scenario Costs: As with the calculation of probabilities, costs for each scenario are derived from SFMEA panelist-assigned values, user inputs, or externally-derived data.

In cases where risk causes were "Misunderstanding Facility Conditions" and "Facility Age and Current Code Requirements," construction estimates were used whenever possible to determine risk costs, utilizing industry standard cost databases such as those developed by RS Means (RS Means 2017). Data for asbestos abatement costs per building square foot were derived from Azen et al. (1992) and Whitestone Research (2009), with costs converted to present year dollars using consumer product indices.

Mitigation Strategies Cost-Benefits

The second element of the model is focused on determining the costs and benefits of mitigation strategies for each risk scenario. The model provides the ability to select appropriate strategies for each of the 12 groups of risk scenarios. Required measures for each mitigation strategy are the efficacy of the strategy and the cost of the strategy. Efficacy is the assessment of how effective the measure is at mitigating the original source of risk. For example, conducting an asbestos survey in a building may not adequately characterize 100% of the asbestos-containing materials, thereby leaving some residual amount of unmitigated risk. There may be a relationship between efficacy and cost, where increased intensity of the mitigation strategy may result in greater efficacy at a higher cost. This cost-benefit relationship is the central component of interest for this part of the model. An important consideration is the ability to make decisions about risk control and mitigation strategies at given levels of cost.

Calculation of the Expected Life Cycle Value

The third element of the model is the calculation of the net effects of project risks and mitigation strategies using the ELCV metric. Values of unmitigated value at risk, mitigated value at risk, and ELCV are calculated and presented in terms of EC and percentage of the ESCO's margin. This also results in the calculation of a cost-benefit relationship for each scenario, where values below one represents mitigation strategies that cost more to implement than the value they mitigate. This element of the model examines the value of ELCV-related cost parameters throughout the project life cycle, by assigning to each scenario the project phase where end effects are realized.

Decision Solutions

The final element of the model is the use of ELCV-related data in providing advice about the risk management process. The model highlights instances of negative cost-benefit ratios and negative values of ELCV, which indicate that elected mitigation strategies cost more to implement than the value of the mitigated risk. The decision solutions element, therefore, supports the ability of the decision-maker to find optimal combinations of risk mitigation strategies to maximize the value of the ELCV. To support this process, the model also provides a graphical representation of the unmitigated value at risk, the mitigated value at risk, the ELCV, and the average cost-benefit value across each project phase.

Framework Database

The database providing facility-, probability-, and cost-related data utilizes data sources in four primary sub-databases: (1) IGA data, (2) cost data, (3) climate data, and (4) equipment replacement and maintenance life/cost. Relevant IGA data is provided directly by the model user through the interface. Cost data was derived from industry standard construction cost estimating databases (RS Means 2017) and research that has been directed to defining asbestos remediation costs per square foot of building area. Equipment service life data was obtained from the ASHRAE Service Life and Maintenance Cost Database combined with cost data from the IGA.

Climate data consisted of annual normal HDD and CDD values as well as 62 years of CDD and HDD data. These data were then used to calculate probabilistic energy savings in the case of extreme climate conditions (e.g., ≥95th percentile climate years). Each model run selected an input value of HDD or CDD from the climate PDF; if a value from the 95th percentile or above was chosen, that value was retained and its impact on the project was calculated using the results of the multivariate regression model developed by Griffin (2008). Griffin's model found that for every one unit increase in HDD, energy consumption per square foot increases by 0.032 thousand BTUs (KBTUs) (or 0.00032 therms). He also observed a 1:0.007 relationship for CDD and KBTUs. While developed for Air Force installations, and thus not specific to correctional facilities, Griffin's work was useful in preliminary model development due to similarities between military installations and correctional facilities (government ownership, large multi-building campuses, wide variation in building ages, and high security operational profiles).

PILOT APPLICATION OF THE LIFE CYCLE COST-BASED RISK MODEL

To demonstrate the function of the model, its use was tested on a correctional facility case study location. The following characteristics were used when selecting the case study location:

- Highly experienced key informants (ESCO and correctional facility staff); and
- Locations were sought that recently (i.e., within the past five years) entered the energy savings phase of an EPC project, such that data would be readily available and key informants would have recent knowledge of project characteristics.
- Capacity and willingness of ESCO and corrections staff to participate in the study.

A correctional facility located in the Southern Lower Peninsula of Michigan was selected as the case study for this research. It was selected because it was representative of a number of similar correctional facility EPC retrofit projects completed during the last ten years. Project data was obtained from agency and contractor reports, as well as the knowledgeable informant and a member of the ESCO staff who developed the retrofit project at the case study location.

Risk Model Results

The pilot model was run with 75 of the 77 identified risk scenarios. The pilot run excluded scenarios related to asbestos abatement and management in-place due to the State of Michigan separately funding asbestos-related mitigation on such projects.

The model was iterated 10,000 times using ModelRisk by Vose Software (Vose Software 2014). Probabilistic variable values for equipment service life and climate (HDD and CDD) were drawn from their individual PDFs; the HDD data for the case study location were distributed bi-modally, with a slight left skewness; the CDD data for the same location followed a normal distribution. Deterministic parameter values (risk scenario inputs) were calculated using the risk modeling function of ModelRisk, drawn from a triangular distribution based on panelist values.

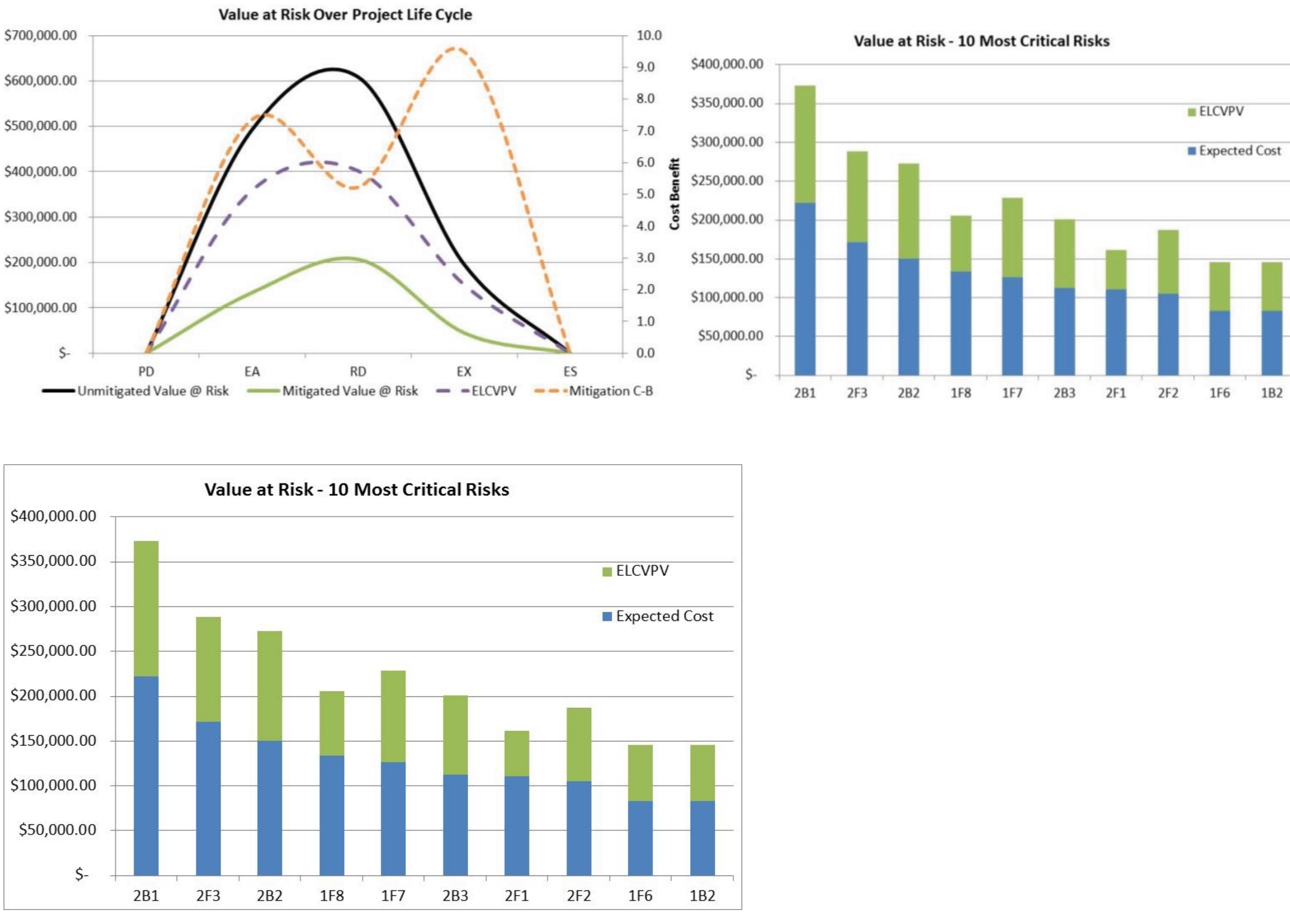
Based on the deterministic and probabilistic model inputs, the most critical risk scenarios were assessed based on their expected cost values. These were generally aligned with the SFMEA panelist evaluation of risk criticality—the top eight risks were identical in both cases; however, the causes of the 9th and 10th most critical risks from the model test run were related to "IGA Conducted Too Quickly" and "Facility Age and Current Code Requirements."

Figures 7 and 8 depict the results screen obtained from the pilot model run. Some observations of interest for decision makers immediately become clear from these results. First, the ten most critical risks were responsible for a potential erosion of 218.1% of the ESCO's margin if left unmitigated. Seventy percent of the initial unmitigated risk was recovered over the project life cycle through the implementation of risk mitigation strategies, resulting in a present value of the ELCV of $912,383, or 153.3% of the ESCO's margin. It is important to note that while 64.8% of the margin remains at risk, the improvement described above was after mitigating just 10 out of 75 risk scenarios in the model. Further mitigation efforts will improve the values of Mitigated Value at Risk and present value of the ELCV.

FIGURE 7. Pilot Model Run Results Screen.

A. RISK CRITICALITY			6B. RISK CONTROL AND MITIGATION						6C. ELCVPV
Rank	Scenario #	Expected Cost	Scenario #	Mitigation Strategy	Efficacy	Mitigation Cost	Remaining Risk	Cost-Benefit	ELCVPV
1	2B1	$ 221,890.99	2B1	Use cost contingency factors 2B	90%	$ 48,449.63	$ 22,189.10	4.12	$ 151,252.27
2	2F3	$ 171,293.78	2F3	Identify risks for each ECM and the ECM portfolio 2G	80%	$ 20,000.00	$ 34,258.76	6.85	$ 117,035.02
3	2B2	$ 150,060.16	2B2	Assign a team member to align outsourced design team witl	90%	$ 12,000.00	$ 15,006.02	11.25	$ 123,054.15
4	1F8	$ 133,867.15	1F8	Use cost contingency factors 2B	90%	$ 48,449.63	$ 13,386.71	2.49	$ 72,030.81
5	1F7	$ 126,430.08	1F7	Interview all facility staff and report findings to them to "grc	90%	$ 12,000.00	$ 12,643.01	9.48	$ 101,787.08
6	2B3	$ 112,545.12	2B3	Third-party internal review based on historical projects 1F	85%	$ 7,500.00	$ 16,881.77	12.76	$ 88,163.35
7	2F1	$ 110,512.12	2F1	Use cost contingency factors 2B	90%	$ 48,449.63	$ 11,051.21	2.05	$ 51,011.28
8	2F2	$ 104,986.51	2F2	Robust construction management practices 2F	90%	$ 12,000.00	$ 10,498.65	7.87	$ 82,487.86
9	1F6	$ 83,089.95	1F6	Assign a team member to align outsourced design team witl	90%	$ 12,000.00	$ 8,309.00	6.23	$ 62,780.96
10	1B2	$ 83,089.95	1B2	Interview all facility staff and report findings to them to "grc	90%	$ 12,000.00	$ 8,309.00	6.23	$ 62,780.96
	UNMITIGATED VALUE AT RISK	$ 1,297,765.83			MITIGATED VALUE AT RISK	$ 385,382.10			ELCVPV $ 912,383.73
	% Margin:	218.1%			% Margin:	64.8%		% Margin:	153.3%

FIGURE 8. Pilot Model Run Results Screen Plots.



In making risk management recommendations, the first risks to examine are those with cost-benefit ratios of less than one, and those approaching a value of one (approximately break-even). Such cases were not present in the modeled results, so risks with the lowest overall cost-benefit relationships were given greatest attention. The ELCV results and decisions screen also provides insight into these relationships graphically, as shown in Figure 8.

The value at risk over the project life cycle plot (left side of Figure 8) shows that the ten most critical project risks are concentrated in the energy audit (EA) and retrofit design (RD) phases, so early decisions regarding risk management are critical. The value at risk—10 most critical risks plot (right side of Figure 8) indicates that to further reduce the project's mitigated value at risk, relatively poorer performing mitigation strategies can be targeted for more intensive activity, with the intent to increase efficacy or lower cost solutions to risk management and control.

The most important risks were found to occur during the earliest project phases; lower risk importance scores were assigned to risk categories occurring later in the project. Reasons for this included the inability to address risks contractually once the energy savings guarantee was signed, thereby requiring risks to be addressed early in the project life cycle. However, the greatest cost-benefit relationship for mitigation measures was found during the later project phases of execution (EX) and energy savings (ES). This further indicates the need to make long-term risk management decisions during the earliest project phases, in order to maximize project performance during the length performance period. ESCOs typically mitigate project risks by multiplying anticipated savings by a factor less than one, in an attempt to hedge against project and performance risks (Hu and Zhou 2011; Wang et al. 2018). By focusing instead on risk criticality during the EA and RD phases, ESCOs can focus instead on maximizing project scope and savings by proactively addressing risks.

Sensitivity Analysis

Sensitivity analysis was conducted to determine the impact of inputs on the results of the life cycle cost-based risk model. Key areas of interest included the sensitivity of the model to changes in deterministic and probabilistic parameters. Monte Carlo analysis was used for this step, since the use of probabilistic inputs in the model made it difficult to assess risk criticality in a single model run because the results changed with each iteration.

The Monte Carlo results were analyzed to determine whether probabilistic or deterministic variables had greater influence on model outcomes. Additionally, the analysis was used to identify which probabilistic model inputs had the greatest impact on the model.

Deterministic inputs to the model were found to have the greatest overall contribution to uncertainty of the model output, which may be the result of having just four probabilistically derived risk scenarios in the pilot model, compared to 71 deterministic scenarios. Parameter values for equipment service life had little effect on the model outcome, regardless of whether they were drawn from the high or low range of the distribution. Climate extremes were found to be seven times more critical than unplanned or early failure of key mechanical equipment.

Recommendations

The model determined the ten most critical risks for the case study project to be related to five root causes discussed briefly, below: (1) reduced availability of “low-hanging fruit” ECMs, (2) work scopes based on traditional DBB procurement, (3) unavailable or inaccurate facility information, (4) facility age and current code requirements, and (5) conducting the IGA too quickly.

These root causes point to the need for ESCOs to expand ECMs beyond traditionally deployed technologies such as lighting retrofits and water conservation measures. This includes continuing the trend to increase use of non-energy benefits in EPC retrofits (Stuart et al. 2016). Moving away from DBB procurement models will require institutional commitment to adopt design-build or integrated project delivery procurement methods, in order to integrate retrofit contractors into early phase engineering decisions during the RD phase. Additionally, reliance on standardized fees for engineering and architectural design, often found in DBB contracts, may lead to artificially increasing the cost of an EPC retrofit to the ESCO, thus eroding the potential energy savings scope of work. Incomplete and inaccurate facility information, as well as age and code update requirements highlight the need for ESCOs to clearly and appropriately allocate responsibility for risks that may arise from these root causes. Finally, great care should be taken during the IGA, particularly when focusing on information needs to address critical risks identified through the model (e.g., facility condition information, establishment of the energy baseline, and modeled performance in light of climate extremes).

Despite the maturity of state and federal EPC markets, making these recommended changes, particularly for correctional projects, can be difficult due to the nature of these facilities and the complex political and regulatory environments in which they exist (Stuart et al.

2016). Collectively, these point to the need for the greater collaboration among parties to the EPC retrofit process and changes to the regulatory structure in which correctional facility EPC retrofits exist.

SUMMARY

This paper introduced a risk analysis and evaluation framework and risk model for EPC contractors undertaking correctional facility retrofit projects. The framework of the model was built on SFMEA (Kmenta and Ishii 2000; Kmenta and Ishii 2004) which uses expected cost as the measure of risk criticality. This represents a methodological improvement over the reliance on existing methods found in the literature. Additionally, SFMEA enables analysis of risk across project life cycles in a single methodological step, something which was critical to the assessment of EPC retrofit project risks, since project performance periods can range from 12 to 15 years, or longer. This research improved the SFMEA method through the direct inclusion of a life cycle cost measure of criticality and developed this method into a functional model of EPC project risks related to IGA quality and ECM selection and installation.

The development of the life cycle cost-based risk model is proposed as an advancement over traditional risk management methods in that latent project risks, those that may not occur until many years into the project, can be examined during the early stages of the project life cycle. Furthermore, model development utilized a combination of expertise, quantitative information, and probabilistic functions to create and define model parameters. Key limitations of the model are the fact that it was developed with a relatively small expert panel (N = 4), pilot testing on a single case study, and the lack of emphasis given to mitigation measures. Correctional facility EPC retrofits are not well-represented in the national buildings data, nor are they readily available for study, despite the growing use of such projects and the relatively high energy use of such facilities. The pilot application represents a preliminary effort to apply the model to specific cases; further case study development and application are expected in the future in order to refine the model and incorporate enhanced treatment of risk mitigation.

The model is expected to help ESCOs make informed decisions about the approach they take towards risk management. By clearly demonstrating the financial implications of unmitigated risks, the cost and efficacy of selected mitigation strategies, and their net benefit on levels of risk by phase and to the overall project, risk management-related decisions should be improved. The ELCV, a metric to evaluate the cost-benefit relationship of risk mitigation strategies and their impact on the project was developed, and taken with the life cycle cost-based risk model, represents a significant contribution to energy efficiency, EPC, and risk management domains.

The research approach employed in this study to analyze and evaluate risks based on their expected costs over the project life cycle can be replicated in other MUSH building types, particularly those with high security operations goals. A limitation of this model is that specific risk categories and scenarios would have to be developed for the individual building being analyzed; however, the ability to incorporate expertise, quantitative information, and probabilistic inputs strengthens the ability to represent the system under review, and leads to the creation of robust findings. While the frameworks used in this research relied strictly on knowledge elicited from domain experts, the approach can be expanded to elicit knowledge from end-users, stakeholders, and regulators for incorporation with the model.

LIST OF ABBREVIATIONS

BTU	British thermal unit
CBECS	Commercial Buildings Energy Consumption Survey
CDD	Cooling Degree Days
EC	Expected Cost
ECPV	Expected Cost Based on Present Value
ECM	Energy Conservation Measures
ELCV	Expected Life Cycle Value
EPC	Energy Performance Contract
ESCO	Energy Service Company
FMEA	Failure Mode and Effects Analysis
HDD	Heating Degree Days
IGA	Investment Grade Audit
KBTU	Thousand BTUs
MUSH	Municipalities, Universities, Schools, and Hospitals
Pcause	Probability of the Cause of a Risk Scenario
Peffect	Probability of the End Effect of a Risk Scenario
RPN	Risk Priority Number
SFMEA	Scenario-Based Failure Mode and Effects Analysis
SPV	Single Present Value

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