A Comprehensive Risk Management System On Building Energy Retrofit

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Abstract— **Due to the fluctuations in energy prices and the global warming effects as a result of pollution emission in the energy generation/conversion processes, energy conservation has gained much attention recently. The buildings in US consume significant amount of energy. Thus undertaking a building retrofitting project, in which new technology and features are added to the existing structure, can potentially both yield a good return on investment due to the future savings in energy consumption and reduce the negative environmental impact due to reduction in greenhouse gas emission.**

In this project, we study how to optimally perform energy retrofitting of existing building structures. Most existing methods either focus solely on minimizing energy consumption, while overlooking the financial incentives and occupant comfort, or aim at optimizing the energy related expenses under one particular deterministic setting and omitting the stochastic risks, such as volatility in energy pricing, weather uncertainties, in the operating environment. Hence, the building owners may not find the recommendation for building construction/recommendation relevant and profitable over its lifetime, and may not be willing to undertake such projects. This work proposes a novel risk management system on building energy retrofit, which uses a comprehensive optimization framework and considers both deterministic and stochastic factors. In one case study, we show that this system can improve the performance of the building under uncertainties while satisfying constraints imposed by occupant.

Keywords-building retrofit; energy consumption; risk management; system learning; optimization; uncertainty; robust decision making

I. INTRODUCTION

The recent high volatility in energy prices and the surfacing causality between global warming effects and greenhouse gas emission have attracted much attention to controlling and reduction of energy consumption. According to [11], the buildings account for about 40% of energy consumption in US, which costs approximately $350 billion a year. Thus on a macro-level, improvements in building energy performance can potentially have significant impact on the total energy consumption. For each individual building owners, researches [5], [12], [10] have established that the energy performance of a building is closely related to the long term operating expense associated with it. Several demonstrations, both in simulation [6], [8] and in practice [7], have established that one can optimize the energy use of a property through building construction/retrofitting projects, in which new technology and features are added to the existing structure.

In this work, we present a holistic approach to optimally perform energy retrofitting of existing building structures. Most existing methods [5-8], [12] either focus solely on minimizing energy consumption, while overlooking relevant financial incentives and occupant comfort, or aim at optimizing the energy related expenses under one particular deterministic setting and omitting the stochastic risks, such as volatility in energy pricing, weather uncertainties, in the operating environment. Consequently, not all the building owners are interested/motivated to participate in this new energy control and optimization trend, building retrofit projects in particular. The two main obstacles are: (1) the lack of clear and convincing financial and other incentives, and (2) the inability of existing models to capture uncertainty in the future – thereby yielding a retrofit solution that may not be optimal over its lifetime. Hence, it is crucial to the success of implementation and sustainability of the building retrofit projects that the building owners are well informed about their potential risk and rewards regarding the future energy savings under uncertainty. This calls for an intelligent comprehensive energy retrofit risk management system that can process fundamental stochastic and/or deterministic risk/reward factor.

In this work, we describe an energy retrofit risk management system that processes fundamental stochastic and/or deterministic risk/reward factor. Using these inputs, the energy retrofit risk management system builds a portfolio of scenarios along with their associated probabilistic view of total future value. In a case study of a sample system we implemented, we will discuss the relationship between consumptions of electricity and natural gas, human comfort level and various retrofitting parameters (focusing on lighting renovation and HVAC tuning) under the presence of both weather and energy price uncertainties. Specifically, we employ stochastic meta models [8] using retrofitting parameters to predict key building performance metrics, examples of which include electricity and natural gas consumptions and occupant comfort. We then optimize over the retrofitting parameters with respect to the various measures under uncertainty. The output of the system is the set of retrofit packages, such as lighting and HVAC

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recommendations, which yield better expected net present value, occupant comfort level and are also more robust to future uncertainties than the state of the art. Moreover, we will discuss how this system can be applied to different categories of buildings (for instance offices, hospitals, factories, warehouses and schools).

Our work is closely related to the recent work [13], where the authors incorporated technical and economic uncertainties in their decision making model. For each candidate retrofit profiles, the authors evaluate the best and worst potential outcomes and make decision based thereon. The major shortcoming of their approach is the lack of probabilistic measures, which is essential to many financial planning activities that building owners might be interested in. Our approach overcomes this by generating a probabilistic model of the future outcome, which highlights the trade off between potential risk and reward of the retrofit projects.

The rest of the paper is organized as follows: Section II contains the description of our general approach in designing the comprehensive risk management system. In Section III we present in detail a sample risk management system we created, apply the system to five categories of buildings: offices, hospitals, factories, warehouses and schools and demonstrate the system performance via some simulated data. We include our concluding remarks in Section IV.

II. Risk Management System: General Model

The goal is to design a building retrofit risk management system with the following properties: it takes as input the stochastic and deterministic factors, which may affect the building performance; it then processes the data, builds a model for the building and optimizes over the model; and finally it gives as output some recommended retrofit profiles along with their probabilistic view of the future outcomes. Examples of the stochastic factors refer to the uncertain elements. Examples include but not limited to occupancy schedule, future weather conditions, and future energy prices. Deterministic factors refer to the fundamental properties of the system, which are known with certainty. Examples of deterministic factors include physical building properties (such as geographic location, building architecture), lighting composition (such as lights location, lights efficiency, lack/presence of automatic lighting control) and HVAC (Heating Ventilation Air Condition) system parameters. Using these inputs, the energy retrofit risk management system builds a portfolio of scenarios along with their associated probabilistic view of total future value, which can then be used to optimize the energy performance and occupant comfort under uncertainty. The intended user for this system is a service provider, whose responsibility is to perform the retrofit project and need to present to the building owner an estimate of the future potential improvement (under uncertainties) due to the retrofitting. We use the term "provider" and service provider interchangeably. We also may refer to the building owner as the client. We remark that this system can also be used directly by the building owners, when the parts pertaining service providers are simply ignored.

An outline of the system is presented in Fig. 1. The figure can be roughly partitioned into three columns: the column headed by the block "building properties" can be viewed as the inputs; the middle column with "quantize variables" block on top is the core of the system, which performs the computational tasks of model construction and stochastic optimization; the right column lead by the block "recommended retrofit variables" contains the outputs of the system. We next describe the elements of the three columns in detail.

We start by the column of inputs. The building properties block represents the deterministic factors and can include geographic location, the orientation, the shape and architecture, the size and the roof structure of the building, the size and orientation of the windows, lighting location and composition, HVAC system of the building and many other characteristics. The uncertainties block is a novel inclusion of our system, since it enables us to give a probabilistic view of the future, which can capture both the expected value and the associated risks characterized usually in variance, instead of the standard expected value calculation. The uncertainties block can include prediction error in weather conditions, use pattern variations and energy price fluctuations. The one below is the contract element, which specifies the retrofit variables (the elements in the block below) that can be modified. These are the variables under consideration, which are also the variables to be optimized over. This block can also include the fixed/promised return of the retrofit project, along with (reward/penalty) terms regarding the uncertain factors, which might affect the return. The provider and client goals can be written both in terms of expected return and risk tolerance levels for financial, environmental and other measures. Historical data contains the existing knowledge about energy prices, material costs, previously learned models of other buildings, technology efficiency levels, weather forecasts, status of other projects (which will affect the risk level the provider is willing to take for the current project) and any other relevant information.

The middle column of the flowchart contains the risk management system, which maps the inputs to the outputs. The system identifies the retrofit variables based on the previous column and determines a suitable quantization level of the variables for computational relevance and convenience. Simulations and numerical studies are then performed with respect to the chosen variables. Once numerical values are obtained regarding the energy consumption, pollution emission levels, human comfort levels and other building performance metrics, which the users are interested in, the system moves on to the next machine learning block.

In this step, machine learning techniques [4] are used to construct a model mapping the retrofit variables to the building performance under various (uncertain) scenarios, which we refer to as the "meta model". We chose the meta model technique over the traditional brute-force search approach due to its computational efficiency and the powerful ability to predict outcomes which are not simulated (interested readers may refer to [8] for more details on the meta model approach). Thus reducing the computation load significantly, which has been one of the major bottlenecks

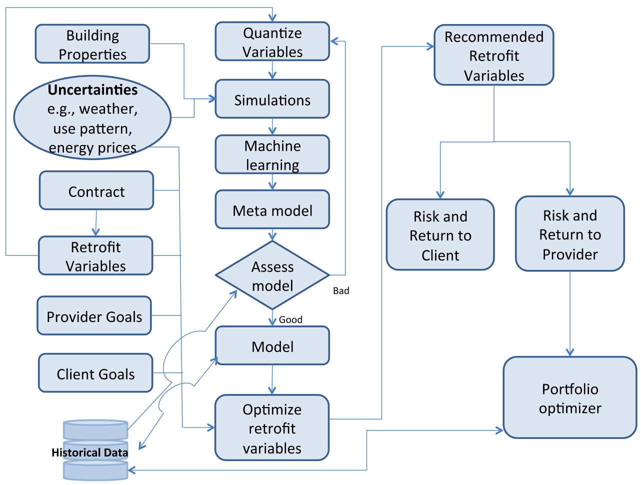

Figure 1. Overall design of the risk management system.

for providing better retrofit optimization solutions. The meta model is then passed through an assessment stage based on comparison against historical data and certain metric specified by the user. If the model is not good, then the quantization level is re-adjusted and the model building process is repeated. Once a good model is obtained, we are ready to use it generate the optimal retrofit profile. There is also some interaction with the database at this stage. The information (such as historical distribution of the uncertain factors) from the database can be used to refine our model and the established outcome model is stored in the database for future references. Note that if a similar building model already exists in the database, then using the old model as a warm start can speed up this stage of model building.

The optimization of the retrofit profiles can now be performed with respect to client goals and/or provider goals, using techniques including but not limited to linear programming, nonlinear programming, stochastic programming, coordinate descent algorithms and Pareto frontier characterization [3], [14], [15].

In the right column of the flowchart are the outputs of the system. From the optimization above, a group of recommended retrofit profile packages are obtained, which yields some expected risk and return estimations for both the client and the provider. The solution provided by the general system lies on the efficient frontier (i.e., the Pareto frontier of the risk-reward curve). The users (client and/or provider) can then choose from the set of packages according to its own preference for the tradeoffs between risk and reward, or provide a risk and reward selection criterion for the system to optimize over, in which case the system will yield one retrofit profile as a result. The components included in the risk and reward analysis could be related to financial, environmental, occupancy comfort level and other building performance metrics. A provider could be involved in many projects simultaneously. By combining certain projects together, the provider may be able to diversify and reduce the overall risk associated with the portfolio. Therefore, it is advantageous for the provider to optimize the risks (and/or reward) over the multiple projects using the historical database. The current project information is also stored in the database for future references.

III. Case Study

In this section, we illustrate the risk management system in more detail by describing a particular sample risk management system we built , which analyzes the relationship between electricity and gas consumption, human comfort level and various retrofitting parameters (focusing on lighting renovation and HVAC tuning) under the presence of both weather and energy price uncertainties. Specifically, the meta model is used to predict electricity, gas consumption and comfort. We then optimize over the retrofitting parameters with respect to different building performance measures for the next 10 years. We applied our analysis on five categories of buildings: offices, hospitals, factories, warehouses and schools and our results indicate that the retrofit package our method recommends yields less expected cost and is also more robust to future uncertainties.

The rest of the section is organized as follows: section III-A contains the background information for the tools we used and assumptions we used for the sample system; section III-B includes the description of the details of the sample system; section III-C presents some initial findings we obtained using the sample system.

A. *Preliminaries: Tools and Assumptions*

In this section, we describe some preliminary information: items 1-4 are tools we used in the sample system construction and some assumptions we made. Items 5-7 specify the uncertainties we incorporated in our system.

1) EnergyPlus: In order to assess and optimize the performance of various retrofit profiles, we need first obtain large amount of information on the performance of some typical profiles (for instance, energy consumption under various lighting composition and HVAC settings for a building at a particular location). This information is usually impossible to obtain from real data, since each building is unique in its location and architecture and hence the standard technique is to perform large-scale simulation. We used EnergyPlus (v 7-1-0) as our main simulation tool, which is one of the most popular software for this purpose. EnergyPlus is a government issued freely available multi-platform comprehensive software. It takes the building features, occupancy schedule, lighting composition, local weather and other information as input and simulates the hourly (can also simulate for higher frequencies) building performances for a year (8760 hours), including the prediction for various annual building performance measures (gas, electricity, greenhouse gas emission, occupancy comfort level etc.) as output. Information of a typical building layout, local daylight distribution and

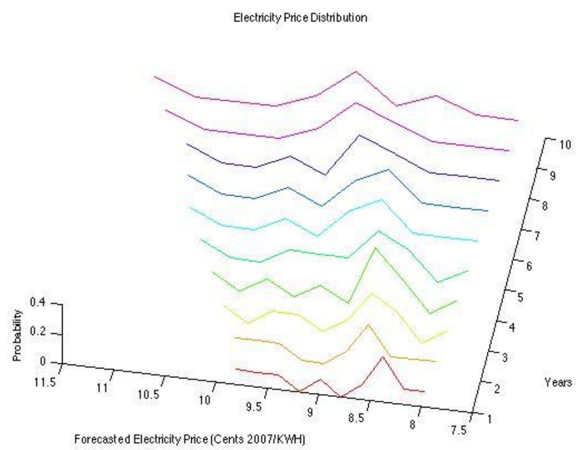

Figure 2. Forecasted electricity prices for ten years.

relevant weather data were obtained from the EnergyPlus software distribution package.

2) YALMIP: We Used YALMIP and MATLAB to solve the meta model buildign (machine learning) problem.

3) SPOT and CalcZone: For lighting fixture and daylight control profiles, we obtain the lighting power density (LPD) reading, which is necessary to simulate the lighting profiles and electricity consumptions after retrofit project, by using simulation software SPOT (Sensor Placement Optimization Tool) and CalcZone.

4) CostWorks: The cost estimation (material and labor) of preforming the retrofit project was obtained using

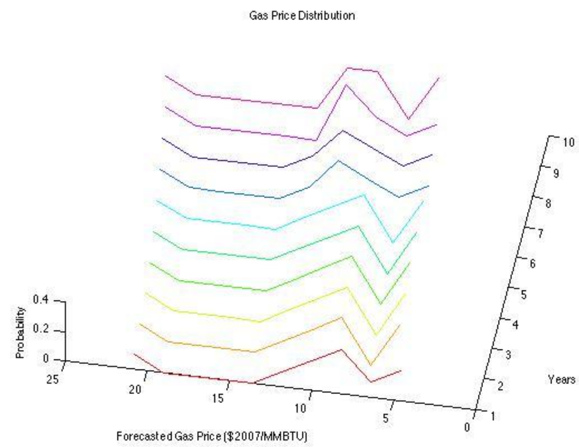

Figure 3. Forecasted gsa prices for ten years.

simulation software CostWorks (which was configured to include labor unions).

5) Weather files: To model the weather conditions, an hourly weather file of the particular location, included in EnergyPlus, is used to model the weather situation of that particular location, which includes temperature, daylight, humidity, wind speed and many other detailed features. We use the current weather file as the prediction base for the next 10 years weather situation. To capture uncertainty in the future weather, we run our simulations using 30

Model	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
NEMS	8.64	8.84	9.04	9.24	9.52	9.79	10.07	10.34	10.62	10.66
E2020-EC	10.09	10.60	11.11	11.62	11.76	11.89	12.03	12.17	12.31	12.40
CEPE-Swiss	12.13	12.16	12.19	12.22	12.29	12.36	12.43	12.50	12.57	12.67
CIMS	8.92	9.11	9.30	9.49	9.80	10.11	10.42	10.73	11.04	11.12
GCAM	10.62	10.81	11.00	11.18	11.37	11.55	11.74	11.93	12.11	12.27
IMACLIM	21.68	21.83	21.98	22.13	22.44	22.76	23.07	23.39	23.70	24.21
MITRE-INFORUM	5.51	5.69	5.87	6.06	6.29	6.53	6.77	7.01	7.25	7.32
NEMS-GPRA	8.43	8.54	8.66	8.77	8.99	9.20	9.42	9.64	9.85	10.03
RFF-Haiku	5.45	5.63	5.81	5.99	6.18	6.37	6.56	6.75	6.94	6.93
AEO	3.70	4.24	4.41	4.62	4.67	4.79	4.93	5.16	5.39	5.77

Table 2: Predicted electricity price for the next 10 years (2007 Cents/KWH).

Model	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
NEMS	8.42	8.49	8.57	8.64	8.74	8.83	8.92	9.02	9.11	9.16
E2020-EC	8.10	8.19	8.27	8.36	8.32	8.28	8.24	8.20	8.16	8.17
CEPE-Swiss	7.86	7.83	7.79	7.75	7.72	7.69	7.66	7.62	7.59	7.57
CIMS	8.44	8.52	8.60	8.68	8.80	8.91	9.02	9.13	9.24	9.29
GCAM	9.65	9.67	9.69	9.71	9.73	9.75	9.77	9.78	9.80	9.78
IMACLIM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MITRE-INFORUM	8.89	8.85	8.82	8.78	8.80	8.81	8.83	8.85	8.86	8.88
NEMS-GPRA	8.32	8.36	8.40	8.44	8.46	8.48	8.50	8.52	8.54	8.54
RFF-Haiku	8.59	8.67	8.74	8.81	8.93	9.05	9.17	9.29	9.41	9.45
AEO	9.90	10.00	10.20	10.40	10.60	10.80	10.90	11.00	11.30	11.50

Table 1: Table 1: Predicted gas price for the next 10 years (2007 Dollar/mmbtu).

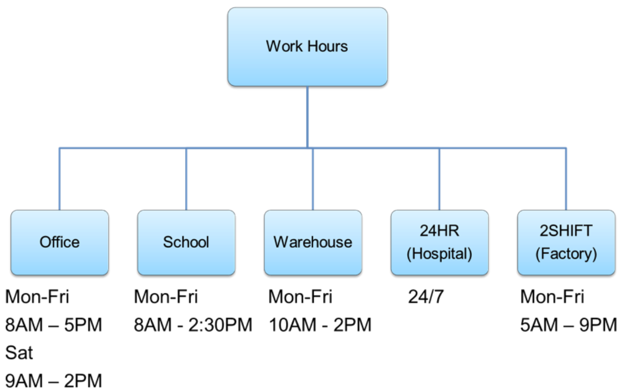

Figure 4. Occupancy schedules for the five categories

randomly generated weather files. Each of the new hourly temperature is generated by an independent normal variable centered around the current hourly reading with standard deviation of 3 degrees Celcius. The value 3 is chosen based on empirical studies. The random variables for the same hour across the 30 files were independently identically distributed. We assumed these 30 files happens with equal probability.

6) Energy Prices: We obtained energy prices from energy model forum [9], which includes predictions for the gas and electricity prices for the next 10 years, under 10 different models (see Table I and II). We also plotted the price predictions in Figs. 2 and 3, where the x-axis is the price, the y-axis is the index of the year number and the z-axis is the predicted probability. We can see the general trend that the electricity price is projected to grow in the next 10 years, while the gas price is forecasted to stay stable.

7) Occupancy Schedule: Another uncertain factor related to the building performance is occupancy data, which affects the performance due to the heat generated and comfort demanded by the occupants. We included typical schedules for five categories of buildings, including office, school, hospital, warehouse and two shift factories, when considering building usage. See Fig. 4 for details on the hours associated with the building types. We assumed January 1st is a Monday for the year simulated and a standard 10 holiday a year schedule, where the holidays are: New Years day, Veterans day, Christmas, Independence Day, Martin Luther King Day, Presidents day, Memorial Day, Labor day, Columbus Day, Thanksgiving Day. For all building types other than hospital and office, we assumed a five work day working schedule, where workdays are Monday through Fridays. Office schedule is assumed to have occupants on Saturday, mimicing commercial bank

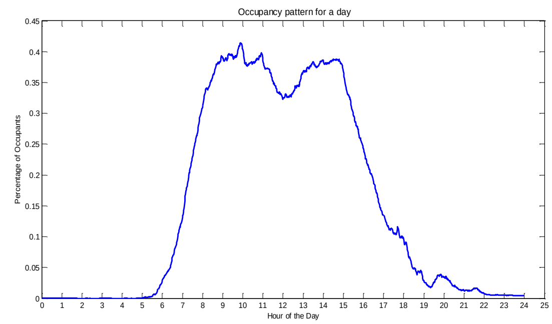

Figure 5. Office occupancy data from Lawrence Berkeley national laboratory.

schedules. Hospital schedule has occupants all the time due to the nature of industry. For each of the given building category and associated schedule, the actual occupancy is uncertain depending on the actual behavior of the occupants (such as lunch and coffee breaks). We extracted probabilistic models of presence from existing literatures [2] for schools and our experiment data from Lawrence Berkeley national laboratory for offices as shown in Fig. 5. The y-axis of Fig. 5 is the probability of presence and the x-axis is the hour of the day. The dip of presence probability in the middle of the day reflects the lunch break.

B. System description

We will now present the sample system by specifying materials for each of the blocks in Fig. 1.

1) Building Properties: The sample system was built for a medium office building (3 stories, 15 zones) in Chicago, where the building properties including window layout were standard and the information was imported from EnergyPlus. We used the location of Chicago city, other location data were also available and the system can be easily modified to accommodate other locations.

2) Uncertainties: The uncertainties included in the sample system are weather, energy prices and occupancy as described in Section III.A items 5-7. For each weather file, the building was simualted separately. Since energy prices is indendent of the energy consumption simualted by the model, and is hence incorporated only at the optimization stage. We now discuss the occupancy uncertainty. For warehouse, factory and hospital categories, due to availability of data, we used either 0 or 1 occupancy rate, depending on the associated schedule in Fig. 4. For school and offices, we each simulated 3 scenarios: first one without occupancy data, where the occupancy rate is also either 0 or 1; second one with occupancy data where the occupancy rate is a real number in [0,1]; the last one is both with occupancy data and with occupancy sensor, where the occupancy rate is a real number in [0,1] and the lights turns off automatically when the building is unoccupied. Note that the second scenario is different from the third, since

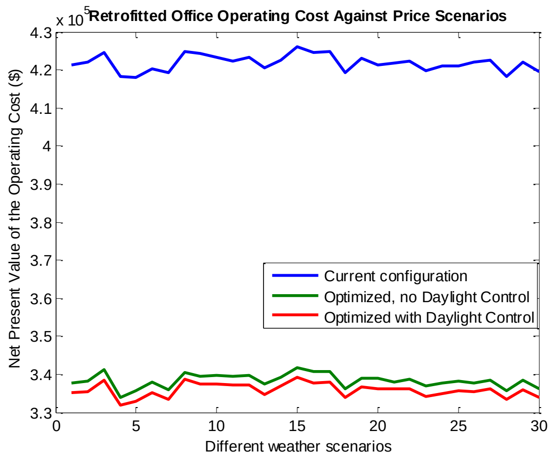

Figure 6. Retrofitted Office: less cost against various weather scenarios

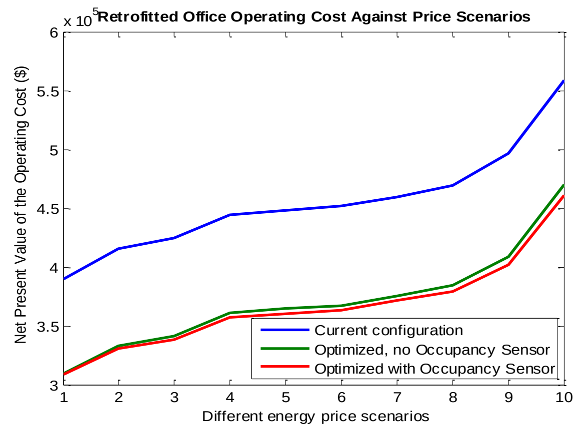

Figure 7. Retrofitted Office: less cost against energy price changes

occupancy rate may affect the heat generated by human actitivies in the building without affecting the lightings. The differnece between the first and the second scenarios highlights the advantage the occupancy data may bring in simulation accuracy, while the differnece between the second and the third scenrios emphasizes the improvements the automatic light switches can contribute to.

3) Contract and retrofit variables: The retrofit variables used here are lighting controls and HVAC paraemters. The lighting control variables include the lighting fixture properties, specified in LPD readings ranging from 7 Watts/Sq Meter, to 16 Watts/Sq Meter and daylight harvesting dimming control which has 3 options: no dimming, 2 step control (off, dim, bright), continuous dimming (the light dims according to the daylight situation). These data were obtained from historical and current industry guidelines and current technology [1]. The HVAC parameters include heating and cooling setpoints, which specifies the desired temperature during winter and summer seasons. The range considered were [18.5, 21.5] for heating and [24, 27] for cooling, which are the government sugested ranges.

4) Provider and client goals: The goal of the system is to minimize the expected net present value of operating cost associated with the building, including electricity and gas cost, with 10% discount rate, while maintain the same risk level as the current configuation and satisfy comfort level requirement, measured in PPD (Percentage of People Dissatisfied for their thermal environment) [6].

5) Quantized variables: For the variables described in 3), we have LPD is quantized into the following sequence: {7.0,7.5,8,8.5,9,9.5,10,12,14,16}, where the smaller numbers corresponds to the updated technology, have finer breakdowns and therefore needs more accurate modeling, while the larger numbers are included to capture existing lighting fixture performances. Heating setpoint was quantized into{18.5, 19.5, 20.5, 21.5} and cooling setpoint in {24, 25, 26, 27}, both in Celcius. The daylight harvesting control was quantized into 3 controls. Hence we have 4 retrofit variables for each of the bulding category, yielding 10*4*4*3=480 potential profiles to simulate.

6) Simulations: Simulations were done for all 9 categories (factory, hospital, warehouse, office with light control, office with occupancy data, office without occupancy data, school with light control, school with occupancy data, school without occupancy data), each with 480 profiles with EnergyPlus, totalling 480*9 = 4320 different retrofit profiles. Each of these profiles were run under 30 different weather predictions.

7) Machine learning and meta model building: The data obtained from the previous step were then used to construct a meta model for the building, where the model takes the retrofit variables as input (potentially not in the set of quantized points) and predicts the buidling performance (electricity, gas consumption, comfort PPD readings) as outputs. We used 10 times cross validation techniques, with 70% training data and 30% for testing, the resulting confidence interval of the learned model were all well over 99% and thus the system accepts the model learned as a good model.

8) Optimization: The system uses the meta model built in the previous stage to optimize the goals specified in the provider and client goals. In particular, the optimization has the following form for all building categories except hospitals:

$$\begin{aligned} &\min E[\mathrm{NPV}(\mathrm{Elec+Gas+installation})], \qquad (1)\\ &\text{subject to } \ \mu+0.5\sigma <= 25\% \ (\mathrm{PPD}),\\ &\qquad\qquad \mathrm{risk} <= \text{current level},. \end{aligned}$$

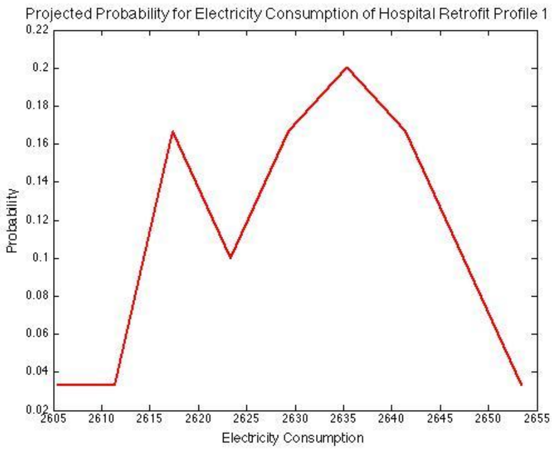

Figure 8. Forecasted electricity consumption for hospital profile number 1.

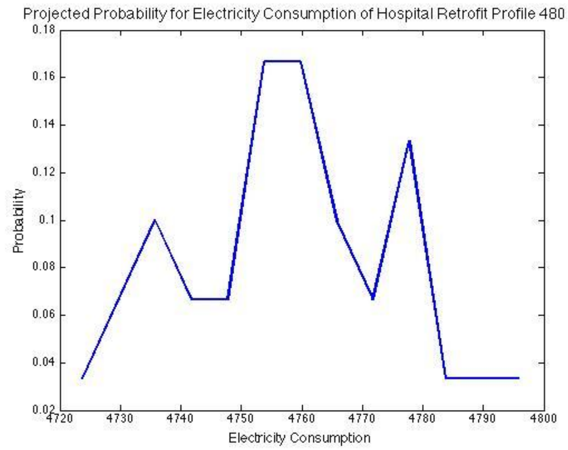

Figure 9. Forecasted electricity consumption for hospital profile number 480.

where the installation cost is obtained from CostWorks and the discounted electricity and gas costs are obtained through the projected 10 year electricity (gas) consumption together with the energy price predictions. The first constraint reflects the comfort level requirement, where the variable μ, indicates the mean value of PPD and σ is the standard deviation across the 8760 hours of the year. This constriant forces that less than 25% people can be dissatisified for most of the time (this event corresponds to the value of PPD<=μ+0.5σ, which captured about 70% of the 8760 hours of the year). For hospital, we tighten this constraint to be

$$\mu + \sigma <= 20\% \text{ (PPD)},$$

which is a stricter requirement on the human comfort level. This adjustment was made to reflect the nature of the hospitals. The second constraint of stays the volatility of the objective function value NPV(Elec+Gas+installation) captured in variance has to be less than the current level. The optimization is done with respect to the retrofit variables. Note that in our particular formulation the objective captures the expected value of the operating cost, and the risks appear in the constraint.

C. *Initial Findings*

We include some preliminary results in this section. One important observation is that through retrofitting the building, the energy consumption level can be reduced and thus the risk associated with the operating cost is also reduced and hence the second constraint of the optimization problem (1) can be met trivially and we can relax the optimization problem by ignoring the second constraint.

We present some of the findings in the Figs. 6-7, both of which indicate significant savings in expectation. Fig. 6 shows that under 30 random weather scenarios, the expected net present value calculations for the building under office schedule when a recommended optimal retrofit project is performed (either with or without daylight control) improves significantly over the current configuration. Fig. 7 shows the uncertainty against energy price, and once again the retrofitted building performance is more robust than the current configuration. This result is promising, since building owners are much more willing to participate in building retrofit project when presented with financial incentives that are robust with respect to future weather realizations.

Another important feature of our system is the ability to present a probabilistic view of the future. Fig. 8-9 show the probability distribution induced by the 30 weather files for the electricity consumption level of the two hospital profiles, with horizontal axis indicating the energy consumption and the vertical axis represents the probability distribution. The recommended profile is to use the most efficient lights, i.e., with lowest LPD of 7.0 Watts/Sq. Meter, set temperature to the coolest in the winter and warmest in the summer and use the most efficient lighting control. This finding suggests the future savings in the operating cost outweighs the current installation cost of the equipment. Profile number 1 (Fig. 8) represents the recommended most efficient profile and has much lower energy consumption and less variance (variance = 133.67), whereas profile number 480 (Fig. 9) corresponds to the least efficient profile, which could reflect the current situation in certain hospitals. This profile has a higher expected electricity consumption and a higher variance of 300.25. These figures can be generated for each of the profiles, and could be used to inform the client in deciding retrofit projects.

We also generated an aggregated probabilistic plot of all 4320 profiles in Fig. 10, where we stacked up the 4320 plots of the type in Fig. 10 together. The sequence we stacked the distribution is profiles 1- 480: school with occupancy sensor, 481-960: office with occupancy sensor, 961-1440 school with only occupancy data, 1441-1920: office with only occupancy data, 1921-2400: school with no occupancy data, 2401- 2880: factory, 2881-3360: warehouse,

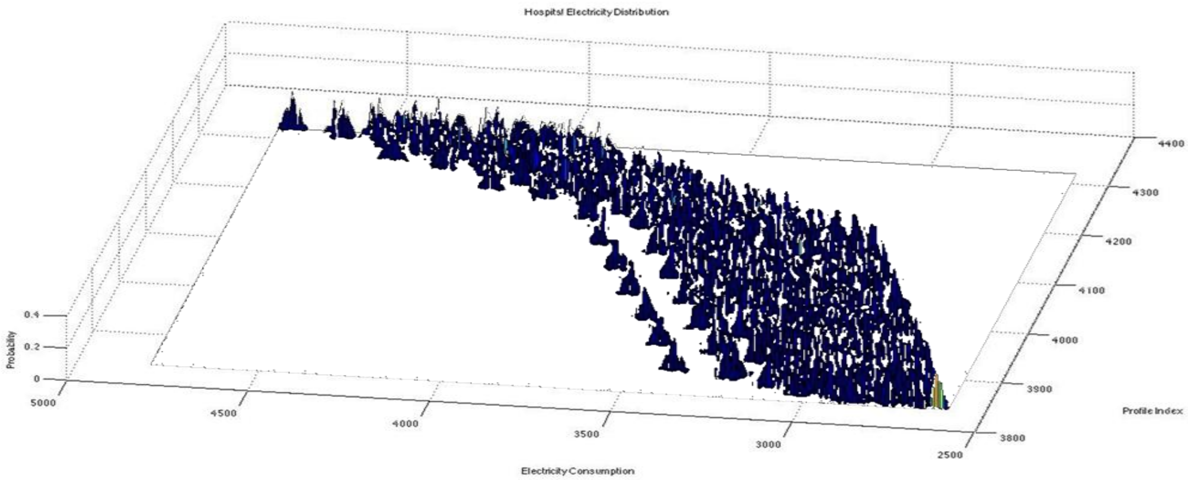

Figure 10. Overlaid probability distribution of all 4320 simulated profiles

3361-3840: office, 3841-4320: hospital. This ordering reflects roughly the least energy consumption (to the left) to the most energy consumption (to the right). This figure could be useful for the provider to determine which category to address first based on the current risk situation of the current provider.

IV. CONCLUSIONS

In conclusion, we have developed a systematic approach to the generic energy retrofit risk management problem, which can address uncertainties in the environment and present a probabilistic view of the future based on the current knowledge. The system uses meta model building technique to overcome large computation burden and can be used to optimize risks, expected returns, environmental impact, occupancy comfort and may other building performance metrics. We also presented a sample system, where the goal is to minimize expected operating cost while maintaining low risk and high occupancy comfort level.

In future developments, we can improve the sample system by including more stochastic factors and incorporate more objective functions and/or constraints. Other objective functions can include expected payback period of the retrofit project, expected IRR (internal rate of return) calculation, variance of energy consumption, where the uncertainty comes from both the weather and the energy prices (electricity and natural gas), and the ratio between the expected value and variance. Other constraints can include reduction in emission level, carbon footprint and reduction in electricity consumption in expectation or in certain probability.

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