SUPPORT OF ENERGY RETROFIT DECISIONS AT MULTIPLE SCALES

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ABSTRACT

This overview paper chronicles two recent projects conducted by the research group of the author dealing with retrofit decision-making at different levels of aggregation. Inspection of the projects reveals the contrast in resolution and scope of decision making that is typical of different retrofit contexts. At the aggregate level the benchmarking across a portfolio of buildings is supported including the selection of candidates for improvement. At the individual building level a drill-down analysis is supported by two modes of audit models, a calibrated simple normative model and a high fidelity dynamic simulation model. Both models contain explicit representations of uncertainty in the parameters and model assumptions and can thus be used to quantify the spread in energy performance of the proposed retrofit. This result is vital to support risk-conscious decision-making for retrofit stakeholders. This paper summarizes the findings of the two projects.

1. INTRODUCTION

Heo et al. (2012b) summarize the retrofit necessity and energy saving potential pointing to the fact that increasing the energy efficiency of existing buildings is one of the best ways to save energy and reduce CO_2 emissions. McKinsey & Company estimate a potential of 1.1 Quads in energy savings in retrofitting existing private and public buildings, not considering plug loads (Granade et al., 2009). In a meta-analysis on retro-commissioning projects for 643 existing buildings, Lawrence Berkeley National Laboratory found that existing buildings contain energy inefficiency problems in heating and cooling plants, distribution systems, lighting

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systems, and building envelope that, when retrofitted, yielded a median energy savings of 16% (Mills, 2009). These studies and energy data trends point to energy retrofits of existing buildings as essential to achieving reduction targets in energy consumption and CO_2 emissions from the commercial building sector.

In response to this need, federal, state, and city governments have established retrofit initiatives and programs to promote the reduction of energy consumption by the building sector. President Obama launched the "Better Buildings Initiative" with a target of reducing energy consumption by 20% in commercial buildings by 2020 through cost-effective retrofit interventions (White House, 2011). In response to the initiative, organizations so far have committed to enhancing the energy performance of 1.6 billion square feet of floor area (EERE, 2012). Reaching these targets will rely on the decisions made by public agencies in planning policy and incentives, utilities in executing energy efficiency programs, financiers in providing capital to the market, energy service companies in developing their business models, and building owners in investing in energy efficiency retrofits. These stakeholders face decisions that span individual buildings, portfolios of buildings, and large aggregates of buildings and are constrained by various degrees of available information about each building. Their decisions will be based on evaluations of the cost, benefits, and risks associated with the implementation of energy efficiency technologies. Currently, there are gaps in the analytic tools available to support these decisions.

The energy service company (ESCO) business model highlights one gap in decision support. For their retrofit projects, ESCOs typically perform an audit to evaluate the potential energy savings of feasible energy efficiency measures (EEMs). The audit involves collecting data about actual building physical and operational characteristics, establishing an energy baseline of the building, and evaluating the effects of EEMs. Moreover, ESCOs need to quantify risks associated with EEMs because their service is based on some form of energy savings guarantee or performance contracting that guarantees certain savings and compensates the customer for what has not been realized according to the contract clauses. In practice, they often rely on their historical experience and expert judgment to estimate energy-saving potential of candidate EEMs and quantify underperformance risks. The rule-of-thumb approach based on expertise tends to limit the set of EEMs to those with proven records while not properly evaluating all possible EEMs including advanced retrofit technologies. Properly supporting energy retrofit decisions can be realized by a formal method that can evaluate all feasible EEMs while accounting for all major sources of uncertainty.

Improving the energy efficiency of a large set of buildings requires a new generation of scalable and adaptable modeling methodologies. A new retrofit analysis framework discussed below is based on simplified and normative energy models that greatly enhance the cost-effectiveness of the analysis process cutting down on data collection, modeling, and computation effort.

2. URBAN SCALE ENERGY RETROFİT MODELİNG

The following summary is based on (Heo et al, 2012b) which articulates a scalable methodology as the core of a retrofit decision-making environment to support two distinct levels of analysis:
(1) Aggregated level decision-making by policy makers and planners. This analysis inspects buildings in a large portfolio to inspect the effects of different energy improvement scenarios over time. At this level, one can decide which level of intervention in certain categories of buildings is necessary to reach an overall energy improvement target.
(2) Individual level decisions by the building owner, i.e. the selection of the right mix of energy efficiency measures (EEM) while adequately recognizing financial risks associated with them. At this level explicit information about performance risks related to certain EEMs is made available to enable risk-conscious selection of measures.
In our framework, decisions at both levels are informed by normative building energy models for the reasons indicated above. At the individual level the normative energy models are refined through a Bayesian calibration to allow a more accurate prediction of the effect of each EEM choice on energy efficiency improvement. More information about the normative energy model can be found in (Heo et. al., 2011) and (Hogeling and Dijk, 2008).
The Bayesian calibration approach starts with specification of prior probability distributions for uncertain parameters and based on measurement data generates a set of accepted parameter values as posterior distributions. The calibration process is described in detail elsewhere (Heo, 2012a).
The retrofit decision framework draws from an exhaustive list of common retrofit technologies in the current market, stored in a database. The database includes 30 retrofit technologies for envelope, HVAC, lighting, DHW, appliance, and building energy management systems. The database further defines the input parameter adjustments that are required to represent the retrofits in the normative energy model. The details have been summarized by Zhao et al. (2011).

3. A RETROFIT EVALUATION AND DECISION ENVIRONMENT

Figure 1 shows the components and interfaces of the overall system in the Retrofit Decision-Making Environment. The two level analyses are based on normative energy models, but have different approaches in treating normative models and translating decision-making contexts.
The aggregate-level layer strictly follows the normative model standard and scenarios to benchmark buildings and evaluate the effectiveness of retrofit scenarios. This layer uses the energy model without calibration and is based on a deterministic analysis as this is deemed adequate for comparative raking and benchmarking.
The individual-level layer tackles the questions of what energy savings are achievable in absolute terms from EEMs and at with what level of confidence can we guarantee these savings. Hence, we apply two additional calibration steps in this

layer: (1) operational adjustment based on site visits and measurements, and (2) parameter estimation based on the Bayesian approach, such that the resulting baseline model can accurately reflect a building as operated and reliably predict potential energy savings from candidate EEMs. This layer no longer follows normative scenarios for building usage and operation, but makes operational adjustments to the model parameters such that the model is in alignment with actual building operation. Furthermore, this layer calibrates the model on the basis of the Bayesian approach to enhance the reliability of the baseline model and quantify uncertainty in the energy use predictions. Then, we incorporate uncertainties associated with the EEMs to provide probabilistic predictions of retrofit scenarios.

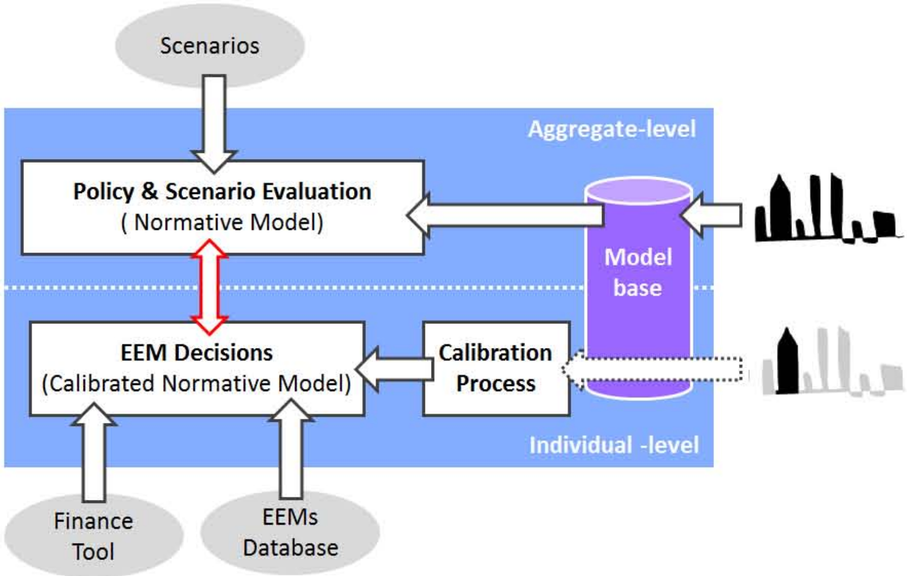

Figure 1. Scheme of the analysis environment

4. EXAMPLE ANALYSIS

Table 1 shows a typical example of the aggregate level analysis for a portfolio of seven buildings. It shows EPCs calculated for all buildings. These data show a significant range of energy performance amongst the seven buildings and indicate buildings with the greatest thermal loads and least efficient energy systems. The EPC_{need} and EPC_{del} are normalized outcomes of the energy demand and energy consumption. They are used as benchmark data point to the possible improvements that could be achieved by upgrading both the building envelopes, the mechanical and lighting systems etc. in the buildings.

The value of benchmarking with the normative energy model is the capability to evaluate the performance of buildings independent of differences in how they are occupied or operated. Further comparison of model benchmark outcomes against those based on measured energy consumption (for example Energy Star Portfolio Manager) will provide a deeper understanding of the actual versus normative energy use in the buildings and the focus areas for energy improvements.

Table 1. EPCs of seven case buildings

BUILDING	**EPC_{need}**	**EPC_{del}**	**EPC_{pri}**
Building 1	1.0	1.0	1.0
Building 2	1.8	1.6	1.9
Building 3	1.5	1.8	1.8
Building 4	1.5	1.8	1.4
Building 5	1.3	1.4	1.3
Building 6	1.5	1.5	1.4
Building 7	1.3	1.3	1.1

As the next step we chosse a set of retrofit palettes by grouping specific retrofit technologies. Then, we associate different palettes with different sets of buildings to create competing retrofit scenarios. Table 2 shows a typical result for retrofit palette 1 and retrofit palette 2 applied to the seven buildings.

Table 2. Specification of the two retrofit palettes

PALETTE	**ENERGY EFFICIENT MEASURES İN PALETTE**
1	High-efficiency Chiller / Energy Recovery Occupancy Sensor / Infiltration Reduction /
2	High-efficiency Chiller / Energy Recovery Occupancy Sensor / Infiltration Reduction / Triple Glazing, Low-e

We can now evaluated different retrofit scenarios in relation to a policy target or a mandated 30% energy reduction. Figure 2 for example shows that scenarios 1 and 2 reduce the total delivered energy expressed as Energy Use Intensity (EUI) by 10% and 20%, respectively, in comparison to the baseline. The results suggest the need for more aggressive retrofit strategies to achieve the 30 % savings target (green bars).

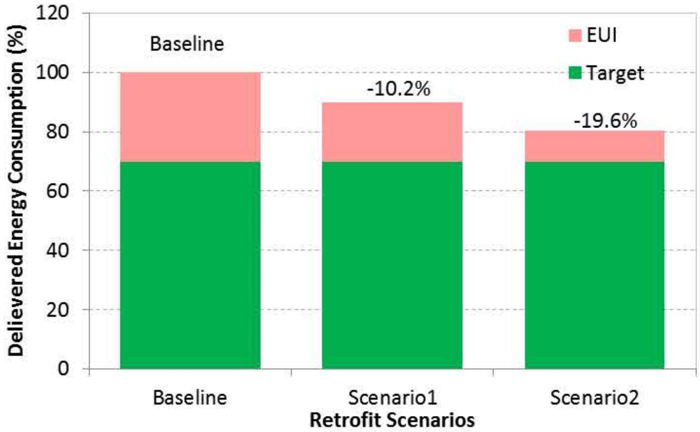

Figure 2. Effects of retrofit scenarios on energy consumption at aggregate level

5. DRILL DOWN INTO A SPECIFIC BUILDING RETROFIT MEASURE

The above approach is suited for large scale energy improvement planning. In many cases the underlying building energy model may not be accurate enough to correctly analyze an EEM in a specific building, especially when accurate information about energy savings potentials and costs of EEMs is necessary to make the right investment decisions. In those cases the normative model parameters need to be identified suchj that the model reflects the observed energy performance of the building. The calibration approach starts with an initial assumption of the parameter values. As we are using a Bayesian technique we need to estimate the prior distributions (rather than a single value) of these parameters.

Table **3** gives a snapshot of a particular example, showing the minimum, and the maximum value for model input parameters, compiled on the basis of industry reports, standards, and technical reports.

Table 3. Range of uncertainty in model parameters

PARAMETER	BASE	MIN	MAX
Roof U value (Btu/h·ft²·°F)	0.09	0.08	0.10
Roof Solar Absorptance	0.63	0.43	0.83
Roof Emissivity	0.91	0.87	0.85
Wall U value (Btu/h·ft²·°F)	0.09	0.08	0.10
Wall Solar Absorptance	0.63	0.43	0.83
Wall Emissivity	0.91	0.87	0.95
Window U value (Btu/h·ft²·°F)	0.32	0.29	0.36
Window Solar Transmittance	0.22	0.16	0.26
Envelope Heat Capacity (Btu/ft²·°F)	0.81	0.60	1.02
Heating Temperature—Occupied	72	68.5	75.5
Heating Temperature—Unoccupied	65	61.5	68.5
Cooling Temperature—Occupied	70	66.5	73.5

Cooling Temperature—Unoccupied	75	71.5	78.5
Occupancy Density (ft^2/person)	208	46	245
Occupant Metabolic Rate (W/person)	80	70	130
Appliance Power Density (W/ft^2)	1.63	0.56	3.16
Lighting Power Density (W/ft^2)	1.34	1.11	1.58
Cooling System Mean Partial Load Index	0.84	0.83	0.99
Cooling Distribution Loss Factor	0.00	0.00	0.15
DHW System Efficiency	0.91	0.88	0.95
DHW Distribution System Efficiency	0.60	0.54	0.66
Infiltration Rate (ACH)	0.15	0.10	1.25

For a detailed account of the calibration technique we refer to (Heo, 2012a). The outcomes of the calibration method are the posterior distributions. To explain the idea, Figure 3 shows the calibration results (blue histograms) of two parameters against the prior beliefs (red lines). The heating temperature during the occupied hours proves to be likely to be 2°F higher than the expected prior estimate, while that during the unoccupied hours does not change much from the prior estimate.

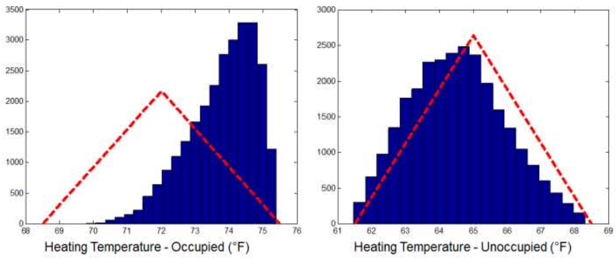

Figure 3. Calibration results for the setpoint temperatures in occupied and unoccupied zones (prior – red, posterior – blue)

The resulting calibrated model can now be used to study the different retrofit palettes. The outcomes are energy saving probabilities rather than deterministic predictions. Thus, the outcomes present (1) the energy savings achievable with the retrofit palette and (2) the magnitude of risk associated with those savings. Figure 4 shows a box plot of energy savings from the two retrofit palettes introduced above. The bottom and top bars of the box indicate the lower and upper quartiles, and the range between the whiskers includes about 99% of the distribution. The box plot suggests that the possible savings from retrofit palette 1 range between 9% and 12%, while the savings from retrofit palette 2 fall between 12% and 17%.

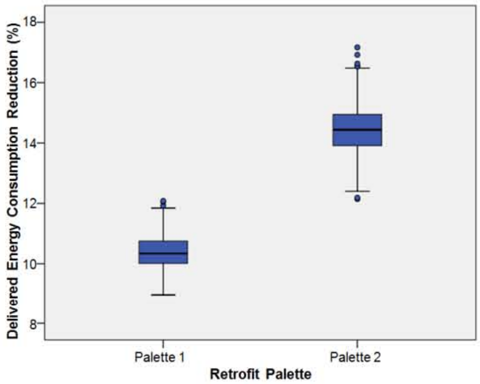

Figure 4. Effects of retrofit palettes on energy saving

6. DEEP RETROFIT DECISIONS SUPPORTED BY DYNAMIC SİMULATİON MODELS

Retrofit decisions cannot always be based on the calibration of simplified models. In some cases one has to resort to dynamic simulation models. This is for example the case when the EEM itself contains large physical uncertainty that obviously not be resolved through pre-retrofit calibration. An obvious example is a deep façade retrofit where the quality of the new façade improvement with respect to air leakage can only be guaranteed within certain limits of performance. The following is a summary of the work reported in (Sanguinetti, 2012).

Deep façade retrofit decisions should be related to a confidence level in the expected energy performance after the retrofit. If the confidence level can be computed, it can be used in a financial gain model with explicit quantification of the probability that a certain RoI will be achieved. Growth in the financial sector of the sustainable building market has in fact shown that the approach to the retrofit decision has changed from a lifecycle cost to an investment opportunity (Bernstein et al. 2008; Managan et al. 2012). In addition to owners and developers, a third group of stakeholders is beginning to play a key role in the investment decision. For example, the Property Assessed Clean Energy (PACE) and Managed Energy Services Agreement (MESA) models are two alternative financing models that involve the key stakeholders in the energy retrofit investment decision: the owner, the finance provider and the municipality or ESCO. From this investment perspective, the expected revenue must be evaluated against a quantification of the risks for each of the involved stakeholders. The ultimate decision will be the one that offers the most gain to each partner, without exceeding the risk accepted by any.

Two sources of uncertainty affect the façade retrofit evaluation: exogenic sources, such as the effect of the financing model on the cash flow calculation; and endogenic sources, such as the physical behavior of the façade retrofit components. Figure 5 shows how these uncertainties can be classified by their impact on investment and building performance assessments. Financial uncertainties in the investment assessment are linked to four sources: government financial incentives, interest payment depending on the financing model, initial investment of retrofit construction, and the cost savings due to improved building performance. Cost savings from the façade retrofit are obtained using an energy model for the building performance assessment. Four other sources affect this calculation: uncertainty in the scenario assumptions, physical behavior of the building systems, simplifications, and errors inherent in the energy model abstraction (Sanguinetti, 2012).

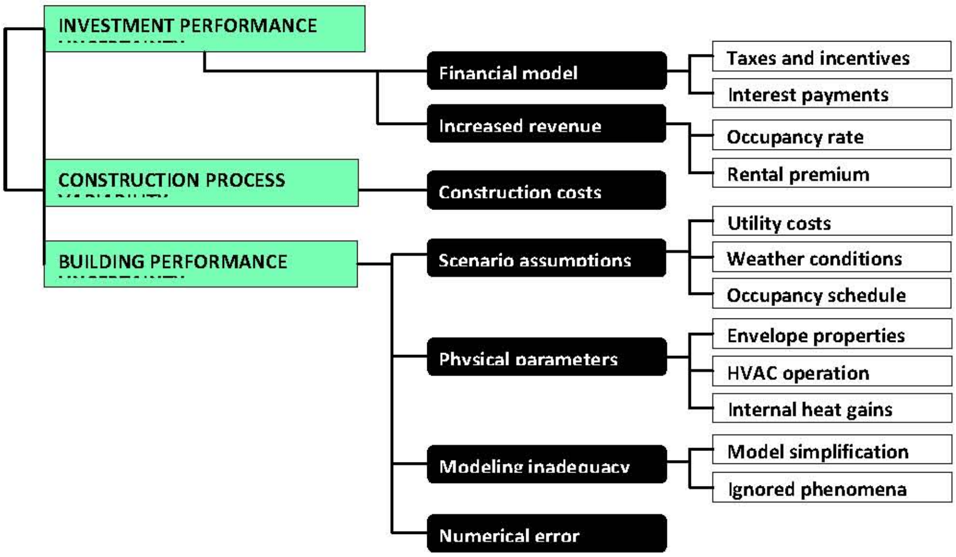

Figure 5. Sources of uncertainty in a facade retrofit evaluation

The integrated framework proposed in (Sanguinetti, 2012) accommodates varying approaches to investment risk. For the selection of a façade retrofit alternative, the final evaluation for retrofit selection involves:

- Determination of two reference values: minimum risk threshold, Tr, and a confidence target, Tc.
- Quantification of confidence and risk for each scenario could then be stated as follows:

$$P_{confidence} = \Pr\ y \geq Tc$$
$$P_{risk} = \Pr\ y < Tr$$

where y is the normalized improvement in the Net Present Value (NPV) of the façade, i.e. NPV of the retrofit investment divided by the NPV of a base case or existing (reference) condition.

Within this framework the selection of the most desirable retrofit alternative could be based on $P_{confidence}$ and P_{risk}, assuming that the decision maker can express his attitude towards expected gain and acceptable risk in the choice of these two (subjective) factors. Note that these factors represent a poor man's formulation of utility theory based decision-making.

7. CASE STUDY OF DEEP FAÇADE RETROFİT

Sanguinetti (2012) performed an analysis of three energy retrofit scenarios involving changes in the facade of the apartment building shown in Figure 6.

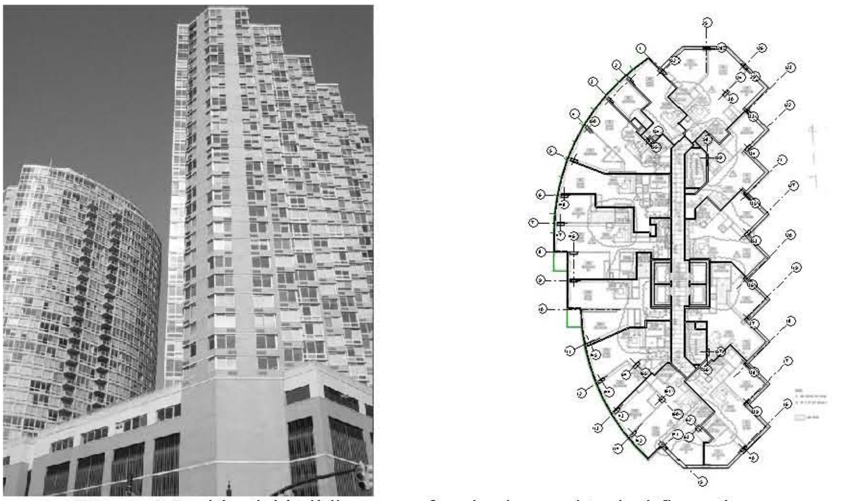

Figure 6. Residential building case, facade view and typical floor plan

A façade retrofit was proposed to increase energy efficiency and improve thermal comfort. Apartment renters complained of high utility bills. The façade was to be retrofitted to update the aesthetic appearance of the building and reduce the impact on energy consumption. Adding a new internal layer to the façade or replacing façade components were considered viable alternatives based on the potential to reduce energy use and the associated implementation costs. Table 4 provides list of three considered energy efficiency scenarios for the façade, including a description of the retrofit measures and financial models.

Table 4. Retrofit scenarios considered in the case study

Scenario	Retrofit measure	Retrofit delivery	Financing model
1	Low-e storm window through DOE bulk program (~25% reduced leakage)	Typical energy efficiency	PACE
2	Low-e storm window and air seal (~60% reduced leakage)	Deep retrofit	PACE
3	Window and packaged terminal heat pump (PTHP)	Deep retrofit	MESA

The analysis for each retrofit scenario involves an energy performance and comfort study of the pre- and post-retrofit situation. Given the fact that considerable uncertainty resides in the façade properties after the retrofit, special care was given to this in the whole building model. Therefore a sensitivity analysis was conducted to identify the most sensitive window parameters impacting the energy performance of the façade. A base case model of the window assembly was created in Therm 5 (LBNL 2012) and subjected to a detailed analysis. A result of THERM is shown in Figure 7.

Figure7. Example visualization of heat transmission at window head (before and after retrofit)

The analysis led to a good estimate of the uncertainties in the U-value and Solar Heat Gain Coefficient (SHGC) which were consequently used as input parameters in the whole building energy model, which was simulated for a full year of weather data. Uncertainties were propagated into the outcomes using a standard Monte Carlo approach. A similar (but more detailed) set of parameter uncertainties as listed in table 3 was included in the Monte Carlo approach. They are classified into physical façade parameters, building system and operation parameters, and financial cost parameters. For the cost analysis parameters, the National Residential Efficiency Measures Database (NREL 2012) was consulted to determine the associated first costs for each scenario. The National Institute of Standards and Technology (NIST) escalation rates for the cost of electricity were used for Net Present Value calculations. Other financial parameters were fixed including the 5% discount rate stipulated for (in this example) PACE financing.

The cost study found that scenario 1, which adds a new low-e storm window and reduces air leakage by approximately 25%, has the lowest cost and the narrower margin of error. Retrofit scenario 2, has the largest margin of error among the three options. Adding a new low-e storm window with an air leakage reduction of 60% will cost as much as replacing the window and changing the PTHP window unit.

The energy study found that a new low-e storm window and with an air leakage reduction of 60%, has the largest percentage of energy savings, ranging between approximately 10 to 23%. Retrofit scenario 3, which replaces the windows and the PTHP units, has the narrower margin of error. There is a lot of overlap in the results between scenarios 1 and 3, which means that in terms of savings, adding a new low-e storm window and with an air leakage reduction of 25% has the potential of producing the same amount of energy savings' as replacing the window and changing the PTHP window unit.

A thermal comfort study was also conducted; for details refer to (Sanguinetti, 2012). The effects of the thermal performance were translated into a rent increase and thus translated to additional contributions to the aggregated net present value of each retrofit scenario.

When all results were brought together and NPV computed for aq 20 year horizon, the following result (Figure 8) was found when plotted on the P_{risk} and $P_{confidence}$ axes:

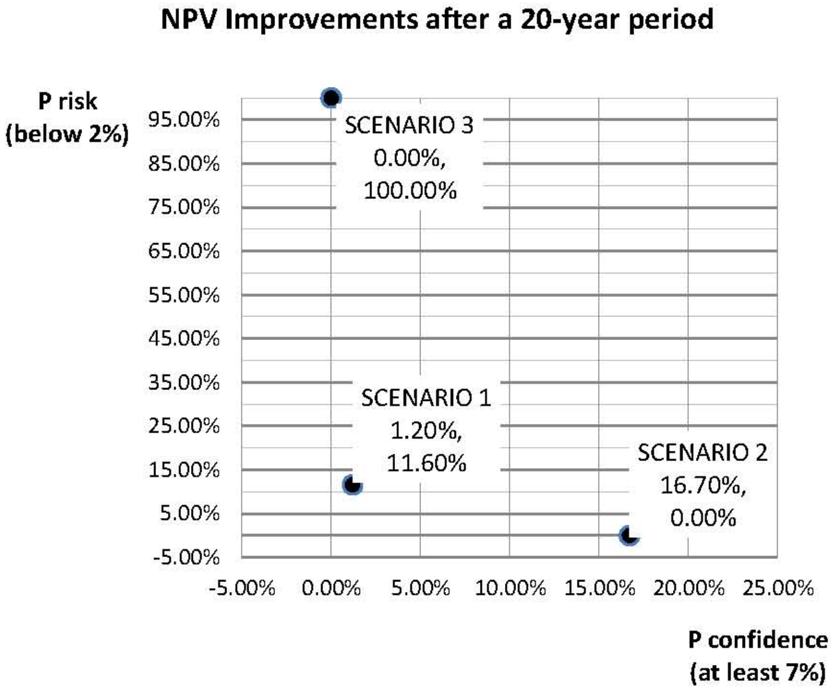

Figure 8. NPV comparison based on confidence target and risk threshold

It is obvious that scenario 2 gets the top ranking, with a 16.7 % confidence in meeting the target NPV improvement and 0% risk of being below 2%. Scenario 1 has a 1.2 % confidence in meeting the target NPV improvement and 11.6% risk of being below 2%. Scenario 3 is the riskiest option because there is a 100% probability of being below 2% improvement.

8. FİNAL REMARKS

We have discussed risk conscious selection of façade retrofits based on expected performance with consideration of uncertainty in energy and comfort assessments as well as uncertainties in cost predictions. Different model fidelities have been proposed for different levels of aggregate decision making. The ultimate decision will be driven by the (subjective) threshold of confidence and risk of the stakeholders involved in the decision. The framework and its embedded models will be tested in more retrofit situations, with different stakeholders, different contracting methods, and multiple retrofit intervention technologies.

ACKNOWLEDGEMENTS

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