Optimization under Economic Uncertainty: A Methodology to Determine the Effects of Solar Variability on Energy and Economic Indicators

ABSTRACT

Energy models are commonly used to examine the multitude of pathways to improve building performance. As presently practiced, a deterministic approach is used to evaluate incremental design improvements to achieve performance targets. However, significant insight can be gained by examining the implications of modelling assumptions using a probabilistic approach. Analysing the effect of small perturbations on the inputs of energy and economic models can improve decision making and modeller confidence in building simulation results. This paper describes a reproducible methodology which aids modellers in identifying energy and economic uncertainties due to variabilities in solar exposure. Using an optimization framework, uncertainty is quantified across the entire simulation solution space. This approach improves modelling outcomes by factoring in the effect of variability in assumptions and improves confidence in simulation results. The methodology is demonstrated using a net-zero energy commercial office building case-study.

Keywords: optimization, solar variability, life-cycle cost, net-zero energy

INTRODUCTION

Building performance modelling is an effective tool to explore trade-offs before construction using several performance indicators. Coupled with optimization approaches, designers have the added confidence that they have fully explored opportunities to reduce building energy use, improve occupant comfort and productivity while evaluating upgrades using economic indicators. However, as practitioners we have yet to use the full potential of building performance models to evaluate the significance of uncertainty in our assumptions. Uncertainty arises from the many assumptions made early in the energy modelling process. Better quantifying the implications and relative significance of uncertain parameters allows modellers to focus on the assumptions with the most significant performance implications. The paper contributes to the ASHRAE 2020 vision which calls for the development of tools which facilitate the widespread adoption of market-viable net-zero energy (NZE) buildings, or buildings which produce as much renewable energy as they consume over a year (ASHRAE, 2008).

This is the second part of a series of papers on optimization studies under uncertainty. An earlier contribution analyzed how economic uncertainty varies across the entire search space due to assumptions in cost model inputs such as inflation rate, utility rates and material costs required to achieve NZE (Bucking, 2016). This paper examines a different uncertainty pathway by quantify the significance of solar variability on energy and economic indicators. Uncertainties originate from estimates and predictions of solar insolation, cloud coverage as well as renewable energy yields. This paper quantifies variations in passive solar performance and photovoltaic panels (PV) yields, which may change due to the duration or intensity of solar radiation or deviations in equipment performance.

Given that NZE buildings are largely driven by solar resources (both active and passive) and commonly use PV to offset on-site energy demands, quantifying the significance of uncertainty propagation is of importance to the building simulation community. Although the methodology focuses on the early-design phases, it could be equally applied to the detailed and pre-operational phases of design.

The goals of this paper are to: (i) support an optimization analysis with an estimate of uncertainty in energy use intensity (EUI) and economic performance metrics due to variabilities in solar radiation and RE yields using PV; (ii) identify and rank which uncertain inputs affect models outcomes most significantly; and (iii) exemplify the proposed methodology using a NZE case-study.

Contributions can be summarized as follows: (i) demonstration of how uncertainty analyses can be performed in conjunction with optimization studies; (ii) quantification of uncertainty originating from solar variabilities in the design of a NZE office building; and (iii) proposed methodology to identify and rank significant model inputs on energy and economic performance indicators under a cold-climate context.

LITERATURE REVIEW

An uncertainty analysis estimates the effect of variations in model inputs collectively with regards to a model outcome. Uncertainty analyses are commonly performed using a Monte Carlo analysis (MCA). A MCA repeatedly samples input distributions to form representative models, which once simulated result in an outcome distribution that approximates the effect of uncertainty in the model (Liu, 2001). The transformation of model inputs into probability distribution functions (PDFs) allows for an examination of cumulative changes in an outcome due to variations in inputs.

Since NZE building performance is driven by passive and active solar design, variations solar irradiation can have a marked impact on energy and economic indicators. The following key factors are reviewed with the goal of identifying variabilities in solar yields: (i) extraterrestrial solar variations, (ii) terrestrial solar variations, and (iii) variations in PV electricity generation.

Variations in extraterrestrial solar radiation impinging the Earth's atmosphere can be caused by: solar activity called the solar cycle, and orbital distances and axial tilt called Milankovitch cycles. The solar cycle has an average period of approximately 11 years and is indicated by the presence of sun spots. Although the underlying mechanisms are not well understood, as the number of sun spots increase, the total irradiance of the sun is observed to decrease. The magnitude of these variations can be as large as 9 W/m^2 but typically fall in the range of ± 1.3 W/m^2 or roughly 1% of the solar constant (1367 W/m^2). Although extraterrestrial variations in solar radiation are key contributors to the occurrence of ice-ages on Earth, they occur over periods of tens of thousands of years and can be ignored for a typically building's life-cycle.

Terrestrial variations in solar radiation reaching horizontal surfaces through the atmosphere can be caused by: aerosols suspended in air, variable cloud coverage, uncertainties in ground based measurements, and influence of suspended particulate matter. Wild et al. (2015) suggested that climate change will cause a global decrease in solar irradiation due to the increase of aerosols in the atmosphere except for key regions such as China where it is predicted that solar exposure will increase due to improvements in outdoor air quality.

Thevenard and Pelland (2011) described several variabilities in PV energy yields. Uncertainties were estimated for: the power rating of PV modules, losses due to snow and dirt coverage, and other miscellaneous losses such as inverter efficiency drift. The cumulative uncertainty in PV yields including solar and electricity uncertainties was estimated as 8.7% for short-term yields and 7.9% for long-term yields.

CASE-STUDY: A NET-ZERO ENERGY OFFICE BUILDING

The case-study used in this paper is a 3-story NZE office building with 5,030 m^2 (54,142 ft^2) of gross floor area with retail space on the first floor. The design specification requires a mandatory L-shape to allow for pedestrian access to first floor retail space from both streets, see Figure 1.

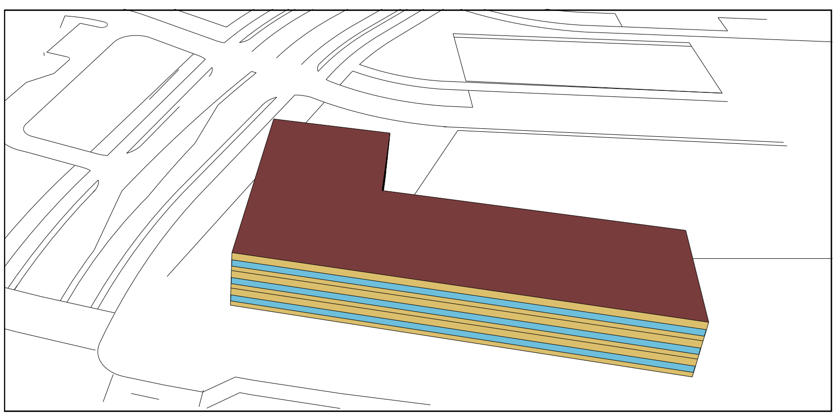

Figure 1: Rendering of preliminary office building design.

The case-study is part of a 70 acre NZE development located in Southwestern Ontario (S2E, 2014). It is a mixed-use community with 2000 living units, including semi-detached townhouses, mid-rise and high-rise apartments/condos.

This cold-climate case-study is particularly interesting in the context of a solar variability analysis since: (i) the climate requires conditioning of outdoor air from $-30\,^{\circ}C$ ($-22\,^{\circ}F$) to $35\,^{\circ}C$ ($95\,^{\circ}F$) necessitating passive solar strategies such as appropriate window areas and shading strategies, (ii) an abundance of solar resources in Southwestern Ontario (latitude of $43\,^{\circ}$) where under or over-estimations could lead to significance differences in building energy utilization, (iii) the added factor of building integrated photovoltaics (BIPV) on facade and roof surfaces and on-site energy generation, and (iv) the building is under construction in 2016 implicating an additional opportunity to validate the proposed methodology.

Over 30 unique variables were considered in the office building design problem, see Table 1. A building design is defined as a unique set of building attributes or characteristics as described by these 31 design variables. Note that the approach must potentially explore over 10^{21} unique building designs for this case-study. This is called the solution space size and is calculated by multiplying the number of steps for each variable present in Table 1. However, optimization algorithms search a minuscule fraction of this total solution space to identify optimal solution sets.

To limit the size of the search space, the variables shown in Table 1 are constrained. For example, infiltration through walls is constrained from 100% to 75% with respect to the reference building. This recommendation is based on an ASHRAE 90.1 infiltration sub-committee (Gowri et al., 2009) which recommends infiltration reductions of 25% with respect to present energy codes with a potential upper limit reduction of 42%. However, measured infiltration can vary in the field up to a factor of ten (Li et al., 2014; Lin and Hong, 2013). Thus, the constrained values are a subset of a much larger set of values found in existing buildings.

Several mechanical system configurations were considered. Mechanical options included: variable-air-volume distribution with natural gas fired boilers or

Table 1: Sample of Influential Model Variables for Commercial Office Building

Variable	Description	Units	Start	Stop	Steps
infil	Infiltration through walls: percentage compared to reference	%	75	100	8
lpd	Light Power Density: percentage compared to reference	%	50	100	8
eleceq	Electrical equipment power density: percentage compared to reference	%	50	100	8
azi	Building orientation relative to south	degrees	-39.4	45	16
base_ins	Basement insulation	m^2K/W	0.18	7.04	8
		ft^2 °F-h/Btu	1.0	40.0	8
ceil_ins	Ceiling insulation	m^2K/W	3.52	11.40	16
		ft^2 °F-h/Btu	20.1	65.0	16
wall_ins	Wall insulation	m^2K/W	3.52	10.57	8
		ft^2 °F-h/Btu	20.0	60.0	8
wintyp_n	Window type north [1: Double Glz low-e. 2: Triple Glz Low-e]. Also variables for east, west, south.	–	1	2	2
wwr_s	Window to wall percentage south	%	10	80	8
wwr_n	Window to wall percentage north. Also variables for east, west	%	10	50	4
use_doas	Use a Dedicated Outdoor Air System for ventilation control	bool	0	1	2
hvac_sys	HVAC system [1: VAVelec. 2: VAV. 3: PTHP. 4: VRF]	–	1	4	4
dhw_sys	DHW system [1: DHW NG Plant. 2: DHW HP Plant]	–	1	2	2
pvbal_sc	Ballasted PV space scaling factor	–	0.1	2.5	8
pvbal_ang	Ballasted PV angle	degrees	0	35	8
pvfrac_s	PV percentage on south. Also variables for east, west, roof	%	0	80	16
pvfrac_a	PV parking lot array area	m^2	0	400	8
		ft^2	0	4306	8
blind_type	Blind shading type [1: ExteriorShading; 2: InteriorShading]	%	1	2	2
blind_maxt	Max tolerable temperature in zones before blind deployment	degC	21	28	8
		degF	70	82	8
blind_maxsr	Max tolerable solar radiation in zones before blind deployment; 0=OFF	W/m^2	0	1400	8
dhw_ld	Percent of DHW loads relative to reference	%	60	100	8
use_nv	Use natural ventilation for night cooling	bool	0	1	2

electric heating, package terminal air source heat-pumps (PTHP), distributed water-source heat-pumps, and a variable refrigerant flow system (VRF) (Raustad, 2013). A dedicated outdoor air system (DOAS) option was considered to provide fresh-air to all spaces.

Photovoltaic panels (PV) were the primary electricity generation strategy to achieve NZE. Building integrated PV is a proven technology which can redirect excess heat to reduce DHW and heating loads (Bucking et al., 2014; Candanedo et al., 2010; Doiron et al., 2011). BIPV was considered on the south, east and west facades as well as on the roof surface directly or in ballasted racking. In the event that additional PV was required to achieve an annual energy balance, it was placed on a racking system beside the building or on adjacent parking lot structures. The case-study used 16% efficient panels (CanadianSolar, 2014). A panel efficiency degradation factor of 0.7% per year was specified (Jordan and Kurtz, 2013; Phinikarides et al., 2014). Energy yields were modelled using the four-parameter equivalent circuit approximation with a temperature dependency which affected PV yields (DOE, 2011).

METHOD

This section describes energy and economic models as well as the Monte Carlo methodology. The proposed methodology can quantify uncertainties in energy and economic building indicators using probable variations in solar radiation and electrical equipment performance.

The uncertainty analysis was achieved by post-processing multi-objective optimization results using a Monte Carlo analysis. This process required both an energy and economic model. The energy model described the incremental energy savings required to achieve NZE over a reference building. Thus two energy models were required—a proposed and reference design. ASHRAE standard 90.1-2010 (ASHRAE, 2010) defined the reference building using current energy code best-practices.

The proposed methodology links in the following manner: (i) energy model definition of building performance; (ii) use of optimization algorithm to exhaustively search through all design permutations; (iii) input distributions define uncertainties in key decision variables; (iv) a Monte Carlo analysis samples input distributions to examine the global effect of uncertainties; and (v) statistical regression models are used to rank decision variables. These elements are further discussed in the following sections.

Energy Model

The energy model identified the mismatch in energy consumption to energy generation over an annual period. This information aided in determining the need for additional technologies to satisfy the annual energy balance. The energy model created sub-hourly load profiles with 15 minute time-steps. This information was useful to evaluate the potential application of various technologies and must be emphasized early in the feasibility stage of the project.

The proposed methodology requires a full building model to quantify the uncertainties in passive solar and renewable energy generation using BIPV. Thus the model must characterize the total surface areas where PV could be placed such as roofs, walls and in racking on or beside the building. If the objective were to quantify only passive solar performance, a smaller building model such as an office space could be a viable alternative to a full building model which requires additional simulation time.

A combination of tools were used to create building load profiles: (i) Windows for specifying glazing spectral properties (LBNL, 2014b); (ii) Therm for specifying envelope properties (LBNL, 2014a); (iii) EnergyPlus for energy modelling (Crawley et al., 2000; DOE, 2014); and (iv) a custom scripting process for technology implementation and modelling best-practices. Further details regarding how the modelling methodology can be used for other building archetypes and community simulation studies can be found in Bucking and Cotton (2015).

Economic Model

The economic model used a life-cycle approach to associate incremental costs to incremental energy savings. Various performance indicators were calculated using annual cash flow differences and cumulative cash flows over a defined life-cycle period.

There are four key elements to achieve NZE cost-effectively: (i) energy conservation and efficiency measures to reduce operational energy costs, (ii) net-metering laws which enable the real-time sale of renewable energy at time-of-use utility prices, (iii) escalation of fuel prices which accelerates economic savings, and (iv) upfront financing to distribute the upfront capital cost to achieve NZE across the life-cycle. Note that in some cases NZE can be achieved cost-effectively without financing, however this is not a general rule. Renewable energy purchasing programs, such as feed-in tariffs, can provide additional financial aid for on-site energy production and accelerate economic returns.

Operational energy costs were calculated by post-processing hourly EnergyPlus results. Table 2 shows the time-of-use electricity billing rate (London Hydro, 2015). An electricity escalation rate of 3.0% was used and a demand charge of \$6.83/kW was used with an escalation rate of 3.0% (London Hydro, 2015). A marginal natural gas rate of $18¢/m^3$ with an escalation rate of 2.0% was used. Note that all monetary amounts refer to Canadian dollars (CAD).

Table 2: Commercial Time of Use Billing

Pricing Schedule	Hours	TOU	Price (¢/kWh)
Summer Weekdays	21:00–07:00	off-peak	7.2
	07:00–11:00	mid-peak	10.9
	11:00–17:00	on-peak	12.9
	17:00–21:00	mid-peak	10.9
Winter Weekdays	21:00–07:00	off-peak	7.2
	07:00–11:00	on-peak	12.9
	11:00–17:00	mid-peak	10.9
	17:00–21:00	on-peak	12.9
Weekends and Holidays	00:00–24:00	off-peak	7.2

Equation 1 defines the incremental cost of materials and operational energy costs over the life-cycle using net-present values (NPV).

$$g(\mathbf{x}) = C_{NPV} + E_{NPV} + R_{NPV} - S_{NPV} - I_{NPV} \tag{1}$$

where: $g(\mathbf{x})$ is the net-present value of all cash-flows; C_{NPV} is the capital costs of materials and equipment; E_{NPV} is the operational energy costs; R_{NPV} is the replacement cost for materials and equipment; S_{NPV} is the salvage or residual value using a linear depreciation method; and I_{NPV} is the income generated through incentives such as feed-in tariffs.

Materials were scheduled for replacement using an expected serviceable lifetime (RSMeans, 2014). As per *EN 15459: Energy performance of buildings—economic evaluation procedure for energy systems in buildings*, life-cycle costs were calculated over a 25 year time horizon (EN15459, 2007). Longer time horizons were not considered as the proposed building upgrades consistently had paybacks within this timeframe.

Including replacement costs creates an additional challenge—the possibility that costs are incurred just before the end of the life-cycle which results in a misleadingly large NPV (Anderson et al., 2006). Salvage values were incorporated using a linear depreciation method (Doty and Turner, 2012). This ensured that materials replaced late in the life-cycle were effectively resold in the final year.

A feed-in tariff (FIT) incentivized the creation of on-site renewable electricity generation. This income is intended to provide an attractive return on investment for building owners to accept the financial cost of additional material and labour associated with the PV system install. For this study, a tariff of 54.9 ¢/kWh was used for 20 years of the life-cycle based on an incentive program incentive program in Ontario (OPA, 2014). As of June 21, 2016, this incentive was reduced to 31.4 ¢/kWh in Ontario to account for the improved economic viability of PV systems.

Equation 2 shows a key performance indicator called the net-present value. This equation can be solved for NPV or several interesting economic metrics by setting NPV to zero.

$$\mathrm{NPV} = \sum_{t=0}^{N} \frac{C_t}{(1+\bar{r})^t} \tag{2}$$

When set to zero, equation 2 can be solved for the internal rate of return (IRR), $\bar{r}$, or tolerable initial cost, C_t, which yields an acceptable IRR. The cost model compared cash-flows to an investment with 2.14% return based on a 10 year GIC from 2002 to 2012 and used an annual inflation rate of 2.0% (Bank of Canada, 2009).

It is recommended that a cost model be built by post-processing EnergyPlus results. Note that life-cycle economic models can be built directly into Energy-

Plus, however, running economic scenarios requires model resimulation which can add unnecessary analysis time. Decoupling energy and economic models enables the expedited evaluation of economic scenarios. Another advantage is that maximum flexibility in the programming of financing, utility billing structures, depreciation methods and material cost specification is attained.

The SQLite interface to EnergyPlus results is an effective means to retrieve key information for take-off cost analyses. For example, area information of exterior windows and walls is required to estimate envelope costing. Similarly, mechanical system initial costs were calculated using cost per peak load. For example, adding insulation not only reduced operational energy costs but also reduced the initial size and thus cost of mechanical equipment. RSMeans data was used when manufacturer cost data was not available (RSMeans, 2012, 2014). A price point of $3.0 per watt was used for a ground mounted PV system. BIPV was priced at $2.3 per watt since it eliminated the need for an exterior finish.

Optimization Method

Figure 2 presents the evolutionary cycle common to an evolutionary algorithm (EA). In Figure 2, a set of binary genomes, or simplified representations of building designs, form the population. The population is initialized by randomly creating the specified population size and the fitness of each individual is evaluated; in this paper an energy simulation program evaluates building energy use. This population becomes the parent population as it enters the evolutionary cycle. Parent selection is used to select genomes for variation operators such as recombination and mutations. The fitness of new individuals, called children, is evaluated. Survivor selection, or replacement, selects which genomes from the old and new population will survive in the next generation. The process is repeated until a termination criterion is reached, typically a set number of evolutionary cycles sometimes called iterations or generations.

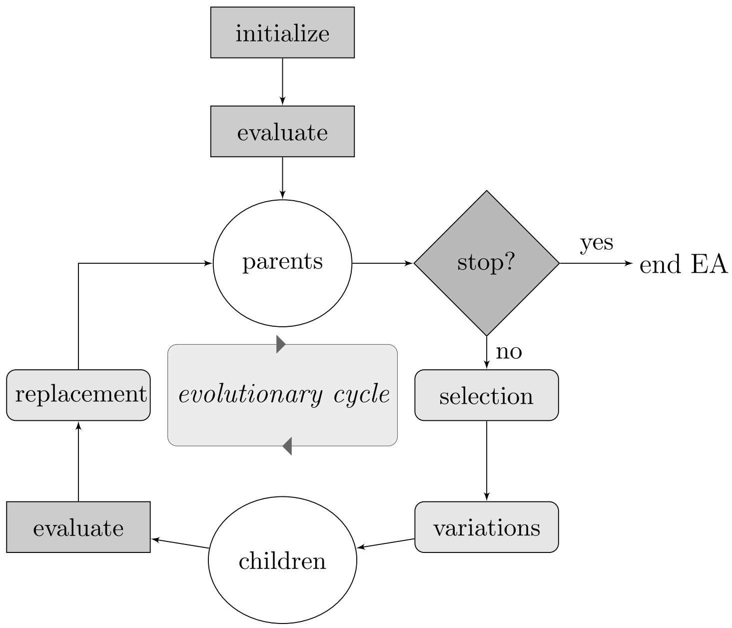

Figure 2: Overview of an evolutionary algorithm

Table 3 highlights key configuration parameters of the multi-objective evolutionary algorithm configuration used in the case-study. The proposed algorithm configuration aids in expediting optimization studies while improving optimization results (Bucking et al., 2013).

A 79-bit binary representation was necessary to represent the variables ranges described in Table 1. Binary representations improved algorithm convergence properties with the negative trade-off of losing resolution on variable ranges. A differential mutation operator, originally created by Storn and Price (1995), was adapted to work within a binary evolutionary algorithm. This operator was found to improve convergence properties of the optimization algorithm (Bucking et al., 2013).

Table 3: Summary of Multi-Objective Algorithm Configuration

Algorithm Parameter	Setting
Representation	71 bit grey-coded binary string
Solution Space Size	2.36×10^{21} unique designs
Objective 1	Net-energy consumption (kWh)
Objective 2	Life-cycle cost over a 25 year period ($)
Population Size	10 growing to 50, i.e. generation gap of 20%
Recombination	50% bit-by-bit uniform, 50% variable uniform
Recombination Prob	100%
Mutation	40% bit-by-bit mutation, 60% differential mutation
Mutation Prob	2.0%
Parent Selection	Non-dominated sorting (NSGA-II) (Deb et al., 2002)
Elitism?	Yes, built into NSGA-II
No. of Children	10
Survivor Selection	Best parents and children, ($\mu + \lambda$), using crowded comparison operator
Diversity Control	None required since using NSGA-II

The elitist non-dominated sorting genetic algorithm (NSGA-II) was selected as a multi-objective parent selection operator (Deb et al., 2002). This selection operator preserves elite individuals through non-dominance and explicitly maintains population diversity using crowding distances.

Multi-objective building design problems require population sizes of 40–50 individuals to spread across Pareto fronts; however early objective function evaluations rarely contribute the identification of non-dominated individuals. To reduce the number of early energy simulations, an over-selection operator required only ten new fitness evaluations of building performance. This is referred to as a *generation gap* of 25% indicating that 75% of the population was selected from previous generations (Eiben and Smith, 2003).

A *SQLite* database (SQLite, 2012) stored design variable sets, algorithm parameters and building performance metrics such as breakdowns of annual energy consumption from energy simulations. *SQLite* allows for concurrent writes from simultaneous building simulations originating from multi-core and distributed computers. To save computation time, a database query confirmed if an identical representation has been simulated previously before calling the energy simulation tool. SQL queries allowed for the quick recollection of previously simulated design parameter sets, economic performance indicators and corresponding energy consumption.

Monte Carlo Analysis

This section describes how to quantify and propagate solar variabilities using the previously described energy and economic models. The quantification of uncertainties can improve client and practitioner confidence that the proposed passive and active solar design aspects are robust to variations in solar exposure.

Traditional deterministic models require all variables to be unique before simulation. Probabilistic models require probability distribution functions (PDFs) to be assigned to input variables. Ideally, input distributions are formed using previously measured data. In a Monte Carlo analysis, the probabilistic inputs are sampled randomly to select individual values, and then evaluated in the model to form output distributions. Sampling refers to identifying selecting values of input parameters, shown in Table 4, from a probabilistically weighted distribution of possible values. Typically, several hundred Monte Carlo samples are sufficient to develop convergence in output distributions (Liu, 2001). The exact number of required samples necessitates a statistical power analysis.

The following parameters were varied as part of a solar variability study, see Table 4. The variable, *SR_vari*, combines uncertainty in long-term horizontal insolation and year to year climate variability. The uncertainty in PV efficiency and power rating represents discrepancies in PV efficiency and estimations of solar radiation in the plane of the array. Finally, the *PV_misc* variable represents miscellaneous losses due to soiling (dirt/snow), maximum power point tracking and inverter efficiency drifting.

Table 4: Uncertain variables included in solar variability study

Variable	Description	Distribution	Value
SR_vari	Uncertainty in solar radiation data	Normal	6.28%
PV_eff	Uncertainty in power rating and efficiency of PV modules	Normal	4.24%
SR_shade	Uncertainty in shading effecting passive solar performance	Normal	2.50%
PV_misc	Miscellaneous uncertainty in PV/Inverter Performance	Normal	6.02%

Logically, one might expect some one-sided PDFs instead of the two-sided distributions shown in Table 4. For example, it would be unusual for PV and inverter efficiencies to exceed their rated values. In the case-study, photovoltaic yields were scaled down to match energy yields from monitored solar farms. Scaling factors were equally applied to PV areas, cell efficiencies and inverter efficiencies to match an annual performance of approximately 1250 kWh/kW at a 45 degree slope. Thus, it makes sense that values could exceed their scaled rated values and normal distributions were an appropriate choice to model the effect of variations of electrical equipment performance.

The solar and electrical equipment variabilities were implemented by modifying the climate file (EPW) and model input description files (IDF) directly. Since the economic model uses incremental costs over a reference building, both the reference and proposed model required resimulation after changes were made to the climate data. This step was essential as the cash-flow diagram representing the reference building is no longer valid with modified climate data.

The proposed methodology required the following steps: (i) conduct a multi-objective optimization study; (ii) assign distributions to input parameters as described in Table 4; (iii) recreate each energy model using the optimization dataset for use within the MCA; (iv) conduct the Monte Carlo analysis ensuring that both the reference and proposed energy models are resimulated for each sample; (v) calculate error bars in EUI and NPV performance outcomes using a 95% confidence interval; (vi) build regression model using energy and economic performance indicator; (vii) plot error bars with optimization results.

Figure 3 summarizes how error bars were calculated using a Monte Carlo approach. Input distributions were sampled 300 times and evaluated in the energy and cost models resulting in two outcome distributions. A random sampling technique of input distributions was used for the MCA, based on the recommendations of previous studies comparing sampling methods (Lomas and Eppel, 1992; Macdonald, 2009). Error bars were calculated using a 95% confidence interval. A 95% confidence interval implies that error bars span from 2.5% to 97.5% of the outcome distribution, see Figure 3. It is very likely that actual energy and economic performance indicators lie somewhere in the 95% confidence interval. The process was repeated for all building designs found in the optimization dataset.

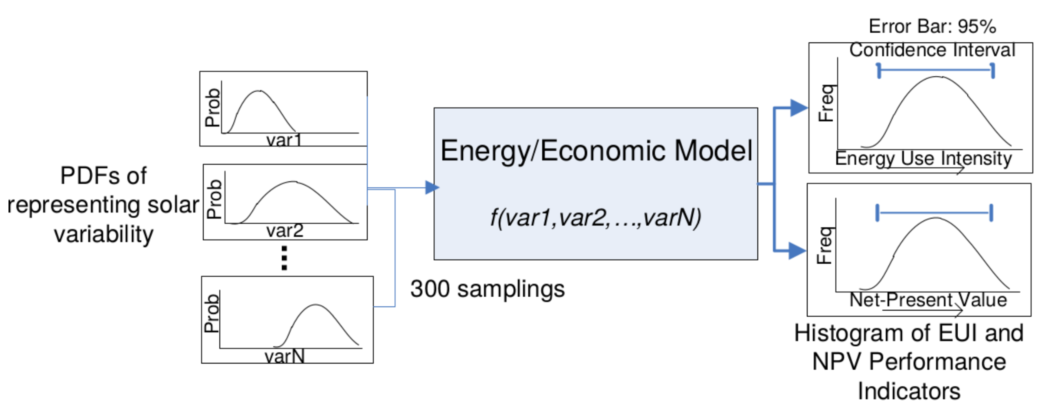

Figure 3: Monte Carlo analysis

The sensitivity of variables within the MCA was calculated using a linear model with ridge regression (LM). LMs can calculate many interesting statistical metrics such as: (i) student t-tests and p-values indicating the statistical significance of a variable in the LM, (ii) parameter fitting of the regression model to training data; (iii) coefficient of determination of the fit (R^2); and (iv) fitting using linear, higher-order terms and interacting regressor values. The p-values were used to rank a variables influence in the Monte Carlo results.

RESULTS AND DISCUSSION

As presently implemented, evaluating the energy and economic impacts of solar variabilities is not computationally efficient and required weeks of simulation time. As a first step, an optimization study is required before proceeding with the MCA study. The optimization study and formation of the Pareto front can be accomplished in 6–8 hours using a 6-core desktop computer. Roughly twelve energy simulation were conducted simultaneously with each model evaluation requiring ten minutes to complete both the reference and proposed designs. However, the MCA study required over five weeks of simulation time. For each of the 500 buildings identified in the optimization study, see Figure 4, the Monte Carlo studies required an additional 300 sampling simulations to establish uncertainty in the input parameters. Since model evaluations are independent of each other, this suggests that the problem could be further parallelized to reduce simulation time.

The analysis for a cold-climate commercial office case-study found that uncertainty in EUI varied between 1.5–5.0 kWh/m^2 (0.5–1.6 $kBtu/ft^2$) and annualized NPV from 2,000–8,000 dollars (CAD) using a 95% confidence interval, see Figure 5. Uncertainty increased slightly as the solution space converged to-

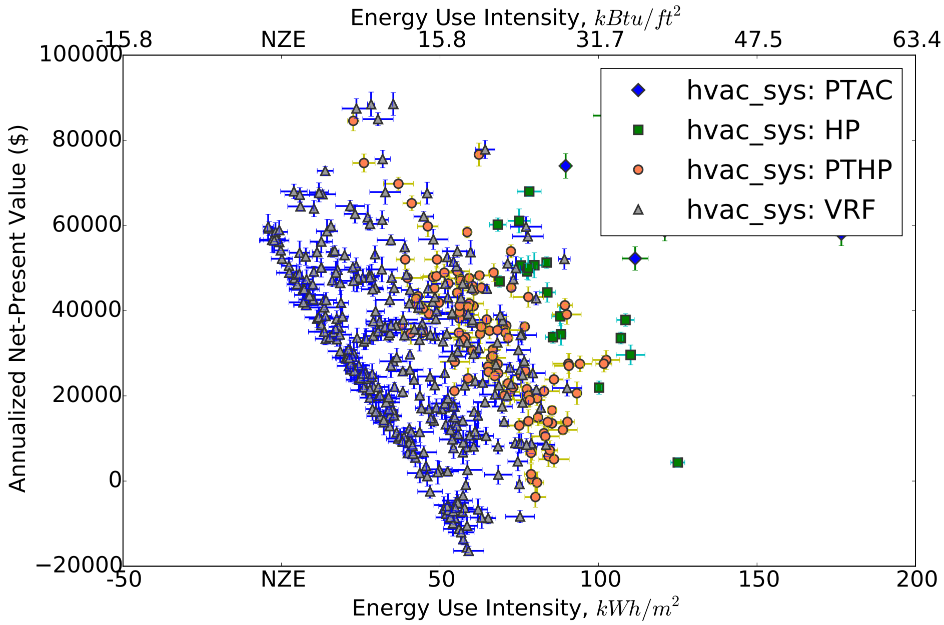

Figure 4: Multi-Objective Optimization Results for Commercial Office Case-Study with Economic Uncertainty (Colored by HVAC System Type)

wards optimal solutions. Logically, this can be rationalized that optimal designs are more highly tuned for passive and active solar utilization and thus should be more sensitive to solar input variations.

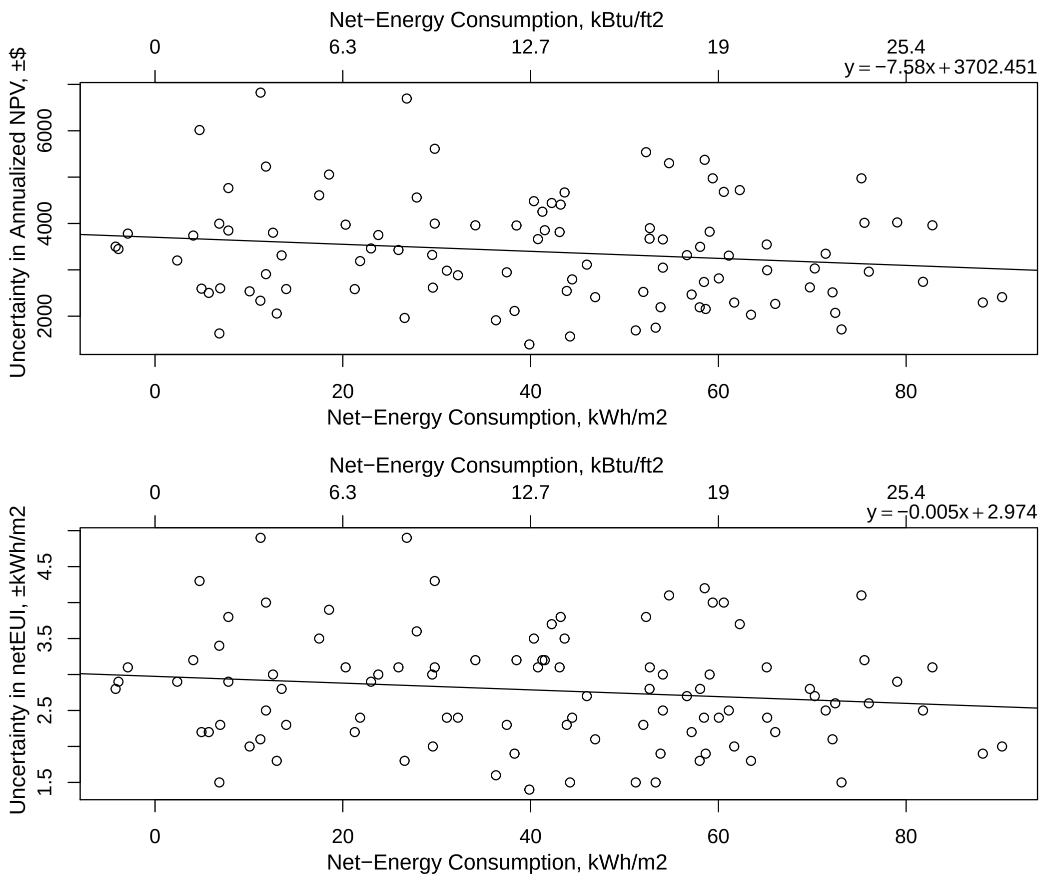

Figure 5: Error bar height versus Energy Use Intensity: Propagated uncertainty in NPV and EUI due to Solar Variations

CONCLUSION AND FUTURE WORK

This paper provides a methodology for quantifying the propagation of uncertainty both in energy and economic models due to variations in solar variabilities. This methodology contributes to the ASHRAE 2020 vision by building modeller confidence in simulation results (ASHRAE, 2008). The approach used an optimization algorithm to ensure the solution space was fully explored. Uncertainty arised from several pathways including: (i) uncertainty in solar radiation used in a climate file, (ii) uncertainty in equipment performance which affects renewable energy yields, and (iii) uncertainty in shading of PV modules. This is an improvement over typical modelling approaches which do not consider the propagation of modelling assumption in energy or economic models.

The case-study found that the uncertainty in EUI and annualized NPV varied slightly while considering variations in solar radiation and PV equipment performance. Furthermore, uncertainty increased as the algorithm converged towards optimal solutions. In the context of a building with an EUI of 200 kWh/m^2 (63.4 $kBtu/ft^2$), a variation of 1.5–5.0 kWh/m^2 (0.5–1.6 $kBtu/ft^2$) may seem insignificant. However, from the perspective of a building or a community which aims to achieve a renewable energy balance, accounting for variations in solar yields could add value to the decision making process. The methodology proposed in this paper could inform designers on how robust proposed designs are to variations in solar radiation enabling added measures to ensure buildings and energy systems perform as expected.

This analysis is not computationally or time efficient to reproduce in regular practice. Five weeks of simulation was required to produce the results shown in this paper after the methodology was completed. Also, since the results are reflective of a single case study it is too soon to make generalizations about the nature of building simulation and uncertainty studies. Although the effects of uncertainty were relatively small, these preliminary results should not deemphasize the significance of conducting studies which test modelling assumptions. If anything, the results should give modellers additional confidence that solar variabilities will not significantly affect energy and economic performance outcomes.

Future work can be summarized as follows: (i) expedite the proposed methodology from months to days or hours so it can be adopted in industry practice, (ii) extend the analysis to include other case studies and climate zones to assess if it is possible to make further generalizations about the effects of uncertainty pathways; (iii) extend the methodology to include other modelling assumptions such as occupancy schedules or HVAC equipment performance; (iv) validate the proposed methodology by comparing predicted and actual performance indicators in the context of solar variabilities; and (v) extend the proposed methodology to include other performance indicators such as comfort and embodied carbon.

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