Optimization under Economic Uncertainty using a Net-Zero Energy Commercial Office Case-Study

ABSTRACT

Energy modelling and optimization studies can facilitate the design of cost-effective, low-energy buildings. However, this process inevitably involves early assumptions of unknowns such as predicting occupant behaviour, future climate and econometric assumptions. As presently practised, energy modellers typically do not quantify the implications of these unknown into performance outcomes. This paper describes an energy modelling approach to quantify economic risk and better inform decision-makers of the economic feasibility of a project. The proposed methodology suggests how economic uncertainty can be quantified within an optimization framework. 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 located in London, ON.

Keywords: optimization, uncertainty analysis, life-cycle cost, net-zero energy

INTRODUCTION

Energy models are an effective means to explore building performance opportunities at the early-design stage. Coupling energy models with optimization approaches provides a robust tool to explore and identify cost-effective, deep-energy savings. However, the building design problem is ill-defined meaning that modellers must work with uncertainties such as predicting occupant behaviour, future climate and econometric assumptions to achieve a performance-optimized building design. Quantifying the uncertainty of key modelling assumptions can be influential in the early decision-making process.

This paper focuses on quantifying economic uncertainty—one particular subset of many broad categories of uncertainties in performance-driven building modelling. The goal is to quantify the potential economic risk and better inform decision-makers of a building's economic feasibility. Economic indicators are of particular interest to building owners and developers since they provide some assurance that an attractive payback is achievable. As presently practised, modellers typically do not quantify the implications of risk into performance outcomes.

Economic uncertainties can be defined using several methods: (i) distributions of historical data such as previous cost estimates, or observed variations in market inflation; (ii) economic projections originating from analysts and supplier quotations; and (iii) distributions using best-case or worst-case scenarios (extreme analysis). Specification of economic uncertainties originating from historical data or supplier quotations are preferred.

An uncertainty analysis estimates the effect of variation 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.

The goal of this paper is to: (i) support an optimization analysis with an estimate of uncertainty in economic performance metrics; (ii) identify and rank which cost inputs affect models outcomes most significantly; and (iii) exemplify the proposed methodology using a case-study with a performance criterion.

There is limited previous research exploring the robustness of a building design around a performance criterion. For example, Hopfe et al. (2012) added uncertainty functionality to an optimization to estimate the robustness of energy performance. Jelle et al. (2013) developed a robustness classification system for materials, assemblies and buildings. Hoes et al. (2011) proposed an evolutionary algorithm selection operator to rank potential designs based on their robustness to uncertainties in occupant behaviour. This paper evaluates uncertainty as an integral part of the optimization approach and uses a net-zero energy office building case-study to demonstrate the process.

Achieving net-zero energy (NZE) in an office design is possible by exploring load reduction, energy efficiency and generation measures. However, achieving NZE *cost-effectively* involves careful consideration of highly-coupled trade-offs between energy and cost and necessitates optimization techniques. This case-study demonstrates two key outcomes of modelling studies: (i) a 'bang-for-buck' optimization study to ensure that cost-effective design decisions are made, and (ii) consideration of market variations within an econometric framework to improve investor confidence.

This paper contributes the following: (i) demonstrate how uncertainty analyses can be performed in conjunction with optimization studies; (ii) quantify uncertainty in the design of a net-zero energy office building; and (iii) identify significant economic parameters under a cold-climate context.

CASE-STUDY: A NET-ZERO ENERGY OFFICE BUILDING

This paper applies the proposed methodology to a net-zero energy office building. The building is a 3-story 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. A primary design strategy is to identify a balance of energy conservation, energy efficiency and energy generation measures which meet a combined internal rate of return (IRR) greater than 5% over market inflation.

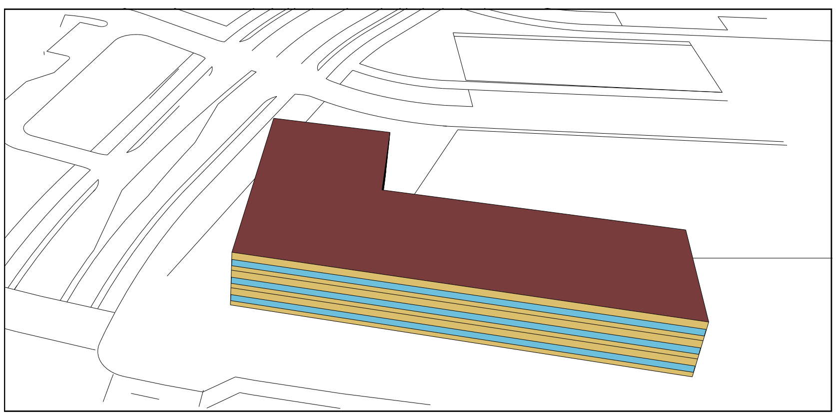

Figure 1: Rendering of preliminary office building design.

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.

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 small portion of this total solution space to identify optimal solution sets.

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 °Fh/Btu	1.0	40.0	8
ceil_ins	Ceiling insulation	m^2K/W	3.52	11.40	16
		ft^2 °Fh/Btu	20.1	65.0	16
wall_ins	Wall insulation	m^2K/W	3.52	10.57	8
		ft^2 °Fh/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

Several mechanical system configurations were considered. Mechanical options included: variable-air-volume distribution with natural gas fired boilers or 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., 2014a; Candanedo et al., 2010; Doiron et al., 2011). Building integrated PV 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 an racking system beside the building or on adjacent parking lot structures. The case-study used 16% efficient Canadian Solar panels, model number CS6P-250 (CanadianSolar, 2014). A panel efficiency degradation factor of 0.7% per year was specified (Jordan and Kurtz, 2013; Phinikarides et al., 2014).

METHOD

This section describes both energy and economic models as well as the multi-objective optimization methodology and the Monte Carlo analysis (MCA).

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 net-zero energy over a reference building. Thus two energy models were required—a proposed and reference design. ASHRAE standard 90.1 (ASHRAE, 2010) defined the reference building using current energy code best-practices.

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 building energy balance. The energy model created sub-hourly load profiles. This information was useful to evaluate the potential application of various technologies and smart control strategies and must be emphasized early in the feasibility stage of the project.

A combination of tools were used to create load profiles for various buildings types: (i) OpenStudio (OS) for drawing geometry and window positions (NREL, 2014); (ii) Windows for specifying glazing spectral properties (LBNL, 2014b); (iii) Therm for specifying envelope properties (LBNL, 2014a); (iv) EnergyPlus for energy modelling (Crawley et al., 2000; EnergyPlus, 2014); and (v) a custom scripting process for technology implementation and modelling best-practices. Further details regarding the modelling methodology can be found in Bucking and Cotton (2015).

Economic Model

The economic model used a life-cycle approach to assign incremental costs with 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 achieving a cost-effective NZE building: (i) energy conservation and efficiency measures to reduce operational energy costs, (ii) net-metering laws which enable the resale of renewable energy at time-of-use utility prices, (iii) escalation of fuel prices which accelerates economic savings, and (iv) upfront financing to absorb the additional capital cost to achieve NZE. 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.

Table 2: Commercial Time of Use Billing

Pricing Schedule	Hours	TOU	Price (¢)
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.

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

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 based on 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, 2010).

Including replacement costs creates a potential problem—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).

In some limited cases, initial costs (including technology costs) were financed over a 10 year timespan with a 5% annual interest rate with payment beginning in year one. A leveraging rate of 40% was used to finance the added capital cost of the project.

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 a incentive program incentive program in Ontario (OPA, 2014).

Equation 2 shows the life-cycle cost as net-present value (NPV). This equation can be solved for NPV or several interesting economic metrics by setting NPV to zero.

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

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 a 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 EnergyPlus, however, running economic scenarios requires model resimulation which can add unnecessary analysis time. Economic scenarios using a post-processing approach expedites uncertainty analyses of cost-modelling assumptions. 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. Although this information could be calculated directly from the EnergyPlus input description file, it is simpler to query using SQLite.

Optimization Method

Figure 2 presents the evolutionary cycle common to an evolutionary algorithm. 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.

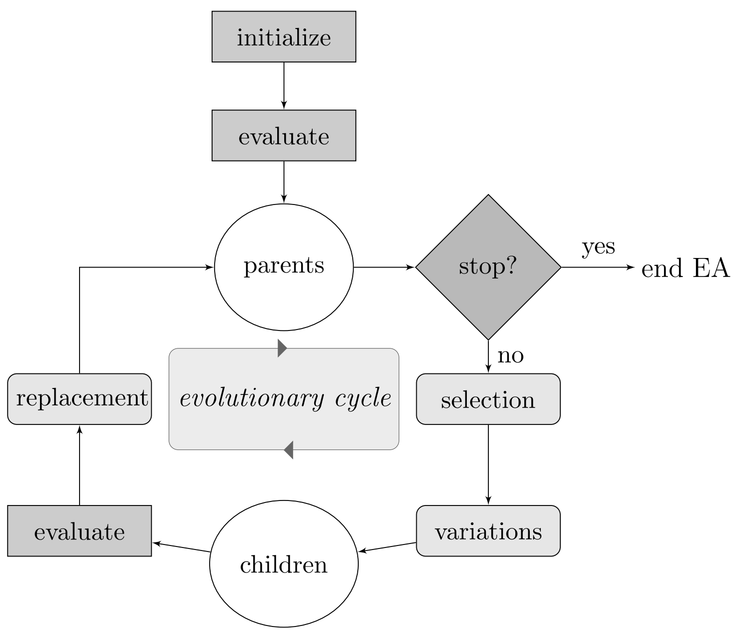

Figure 2: Overview of an evolutionary algorithm

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

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

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).

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 economic risk and better inform decision-makers of the economic feasibility of a project. The quantification of economic uncertainty plays a role in improving investor confidence. This methodology could be further extended to include energy performance indicators as suggested in Bucking et al. (2014b).

Traditional deterministic models require all variables to be unique prior to simulation. Probabilistic models require probability distribution functions (PDFs) to be assigned to input variables. Ideally, input distributions are formed using historical or measured data. In a Monte Carlo analysis, the probabilistic inputs are sampled randomly to select individual values, then evaluated in the model to form output distributions. Sampling refers to identifying economic parameters by selecting the value of each input using a probabilistically weighted distribution of possible values. Several hundred Monte Carlo samples are sufficient to develop convergence in output distributions (Liu, 2001).

Calculating uncertainty in the economic model required the following steps: (i) conduct a multi-objective optimization study as described on page 11; (ii) assign distributions using historical data to each input in the economic model 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; (v) calculate error bars in performance outcomes using a 95% confidence interval; (vi) build regression model using NPV; (vii) repeat MCA for all building design in the optimization set; and (viii) plot error bars on optimization results.

Figure 3 summarizes how error bars were calculated using a Monte Carlo approach. PDFs were defined using historical contracts and projected supplier quotations. These distributions were sampled roughly 300 times and evaluated in the cost model resulting in a distribution of outcomes. 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 then calculated using a 95% confidence interval. A 95% confidence interval implies that error bars span from 5% to 95% of the outcome distribution. It is very likely that actual economic performance indicators lie somewhere in the 95% interval. The process was repeated for all building designs found in the optimization dataset.

The economic model was intentionally over-sampled in the MCA to explore the convergence properties of economic performance indicators. Larger sample

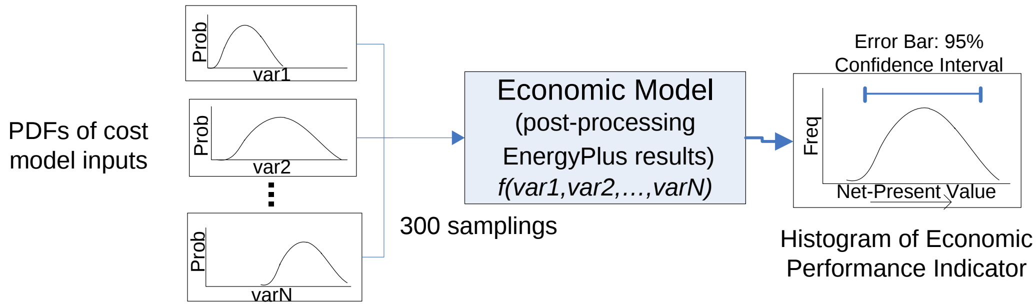

Figure 3: Monte Carlo analysis

sizes helped to explore the effect of sample size on outcome distributions. Larger sample sizes tend to yield more normal distributions, due to the central limit theory of statistics; otherwise, they do not affect Monte Carlo outcomes.

Table 4 describes a subset of the 70 economic variables used in the analysis. Normal distributions were defined for all variables. Variable types included: (i) life-cycle economic variables such as inflation and discount rate; (ii) variations of initial and replacement costs using multipliers; (iii) duration of expected material serviceable life-times; and (iv) utility and financing rates.

The sensitivity of variables within the MCA was calculated using a generalized linear model (GLM) regression approach. A GLM is a generalized approach for calculating regression models using generalized least squares (Reddy, 2011). GLMs calculate many interesting statistical metrics such as: (i) student t-tests and p-values indicating the statistical significance of a variable in the GLM, (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.

Life-cycle cash-flows were calculated using reference and proposed buildings with identical economic parameters. Thus, cash-flows were developed using a

Table 4: Sample of Influential Cost Model Variables for Case-Study

Variable	Units	Min.	Max.	No. Steps	Mean	Description
wall_cost	–	0.8	1.2	8	1.0	Cost multiplier for wall construction by area
opextshd_cost	–	0.73	1.17	8	1.0	Cost multiplier for exterior operable shading by area
pvwall_cost	–	0.75	1.25	8	1.0	Cost multiplier for wall Mounted BIPV by power
pvarr_cost	–	0.9	1.1	8	1.0	Cost multiplier for ground Mounted PV Array by power
ng_rate	–	0.85	1.15	8	1.0	Cost multiplier for natural gas by volume
mech_vrf_peak	–	0.8	1.2	8	1.0	Cost multiplier for VRF HVAC System by peak
mech_pthp_peak	–	0.8	1.2	8	1.0	Cost multiplier for PTHP HVAC System by peak
win_dgclai	–	0.85	1.15	8	1.0	Cost multiplier for Double Glaze Window with Air by area
win_dgclar	–	0.85	1.15	8	1.0	Cost multiplier for Double Glaze Window with Argon by area
win_dgclear	–	0.85	1.15	8	1.0	Cost multiplier for Double Glaze low-e Window with Argon by area
win_tgclar	–	0.80	1.20	8	1.0	Cost multiplier for Triple Glaze Window with Argon by area
win_tgclear	–	0.80	1.20	8	1.0	Cost multiplier for Triple Glaze low-e Window with Argon by area
cost_flr	–	0.90	1.10	8	1.0	Cost multiplier for Fluorescent Lights by area
cost_led	–	0.75	1.25	8	1.0	Cost multiplier for LED Lights by area
mech_repl	yr	20	30	8	25	Replacement time of HVAC System
repl_light	yr	20	30	8	25	Replacement time of Fluorescent Lights
repl_led	yr	20	30	8	25	Replacement time of LED Lights
elecpk_rate	$\$/kW$	5.46	8.20	8	6.83	Cost of Peak Electricity Demand Charges <500kW
elec_on_peak	$\$/kWh$	0.113	0.140	8	0.126	Electricity Time of Use On-Peak Rate
elec_mi_peak	$\$/kWh$	0.098	0.120	8	0.109	Electricity Time of Use Mid-Peak Rate
elec_of_peak	$\$/kWh$	0.069	0.085	8	0.077	Electricity Time of Use Off-Peak Rate
ng_escal	%	2.4	3.6	8	1.0	Escalation of Natural Gas Prices
elecpk_escal	%	2.4	3.6	8	1.0	Escalation of Peak Electricity Demand Charges
elec_escal	%	2.4	3.6	8	1.0	Escalation of Electricity Rates
infla	%	1.75	2.75	8	2.0	Inflation Rate

common set of economic assumptions. As a final step, the difference from the varied incremental economic model and the baseline economic model were used for all uncertainty estimates. This ensured that uncertainty is measured from the varied economic model relative to identical assumptions in the baseline model.

RESULTS AND DISCUSSION

Figure 4 shows the optimization results with error bars originating from the Monte Carlo analysis. Net-present values were annualized, meaning that net cash-flows were normalized by the life-cycle period. Error bars varied from 10–25% of NPV, where the variance depends on the particular building design in question.

Although Monte Carlo analyses were performed on every design in the optimization dataset, results suggest that it might be appropriate to run the variability study on a reduced set of designs and extrapolate results for the remainder of the set. Note that economic risk is not positively correlated to decreasing net-energy use intensity as one might expect. This is likely due to the income generating potential of PV which moderates the added technology costs throughout the life-cycle.

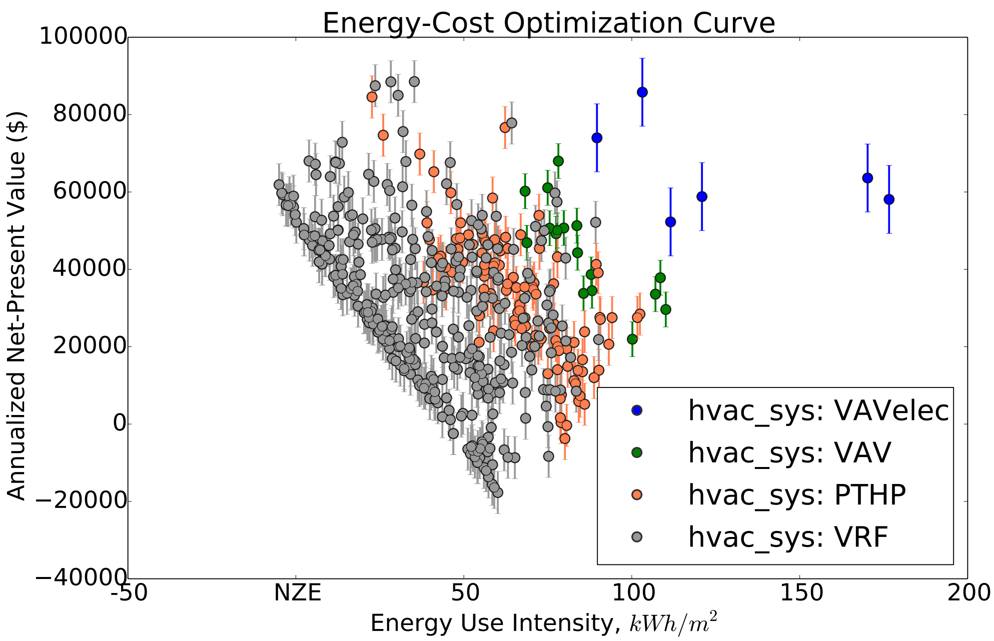

Figure 4: Multi-Objective Optimization Results for Commercial Office Case-Study with Economic Uncertainty (Colored by HVAC System Type)

Figure 4 shows that a NZE design could not be achieved under present market circumstances without additional financing strategies. If the project were to be financed, meaning that the 60% of the upfront costs of equipment and technologies were loaned/leased to the owner, an IRR of 5–10% could be achieved. Since NZE buildings have lower operational costs, attractive rates of return are possible if the financing costs plus operation costs are less than reference building operation costs.

Table 5 shows the optimal and reference building specifications. The optimal design used in this table is the design which achieves NZE with the best net-present value. Note there are a continuum of designs shown in Figure 4 with optimal trade-offs in energy and economic performance.

Note that the optimal building design was oriented 11 degrees off-south because of the L-shape building type. A north window to wall ratio of 40% was selected to increase daylighting access in office spaces. To account for additional heat-loss, triple-glazed windows were selected. Ventilation was supplied independently using a dedicated outdoor air system. A PV array of 400 m^2 (4,306 ft^2) was required to make up for the remaining energy consumption.

Each multi-objective optimization run took approximately 5.1 hours (310 minutes) of simulation time. For convergence to Pareto fronts, roughly 45 algorithm iterations or generations were needed. On average, each model evaluation in EnergyPlus required 6.2 minutes. Since energy simulations could be parallelized on multi-core clusters (conducted simultaneously), each population of 10 building designs was time equivalent to a single energy model evaluation.

The Monte Carlo analysis added two minutes of simulation time per proposed building design. Each Monte Carlo sample required approximately two seconds to post-processing of energy simulation results for economic performance indicators. A convergence study indicated the need for at least 300 MCA samples for convergence of outcome distributions. Samples could be conducted in parallel on multi-core clusters. Note the importance of conducting a cost-analysis by post-processing EnergyPlus results. The proposed methodology would be prohibitively long if an economic model evaluation required five additional minutes

Table 5: Optimization Results for Commercial Office

Variable	Description	Units	Ref	Prop
infil	Infiltration Through Walls: Percentage Compared to Reference	%	100.0	75.0
lpd	Light Power Density: Percentage Compared to Reference	%	100.0	50.0
eleceq	Electrical Equipment Power Density: Percentage Compared to Reference	%	100.0	50.0
azi	Building Orientation Relative to South	degrees	0.0	11.0
ceil_ins	Ceiling insulation	m^2K/W	6.58	11.4
		ft^2 °Fh/Btu	40.0	65.0
wall_ins	Wall insulation	m^2K/W	4.15	9.3
		ft^2 °Fh/Btu	24.0	52.0
wintyp_n	Window Type North	–	Double Glz low-e	Triple Glz Low-e
wintyp_e	Window Type East	–	Double Glz low-e	Double Glz low-e
wintyp_s	Window Type South	–	Double Glz low-e	Double Glz low-e
wintyp_w	Window Type West	–	Double Glz low-e	Double Glz low-e
wwr_n	Window to Wall Percentage North	%	50.0	40.0
wwr_e	Window to Wall Percentage East	%	50.0	10.0
wwr_s	Window to Wall Percentage South	%	50.0	30.0
wwr_w	Window to Wall Percentage West	%	50.0	10.0
use_doas	Use a Dedicated Outdoor Air System for ventilation control	bool	No	Yes
hvac_sys	HVAC system	–	VAVelec	VRF
dhw_sys	DHW system	–	DHW NG	DHW HP
pvbal_sc	Ballasted PV space scaling factor	–	0.0	0.0
pvbal_ang	Ballasted PV angle	degrees	0	0
pvfrac_s	PV Percentage on South	%	0.0	80.0
pvfrac_e	PV Percentage on East	%	0.0	80.0
pvfrac_w	PV Percentage on West	%	0.0	80.0
pvfrac_r	PV Percentage on Roof	%	0.0	80.0
pvarray_a	PV Array Size	m^2	0.0	400.0
		ft^2	0.0	4306
blind_type	Blind shading type	–	None	Exterior
blind_maxt	Max tolerable temperature in Zones before blind deployment	degC	Off	23
		degF	Off	73
blind_maxsr	Max tolerable SolarRadiation in Zones before blind deployment	W/m^2	Off	400
dhw_ld	Percent of DHW Loads relative to reference	%	100.0	60.0
use_nv	Use Natural Ventilation for Night Cooling	bool	No	Yes
$f(\mathbf{x})$	Net-Energy Use Intensity	kWh/m^2	185.1	-0.2
		$kBtu/ft^2$	58.6	-0.06
$g(\mathbf{x})$	Annualized Net-Present Value	$	–	-58,800

of simulation time compared to only a few seconds of post-processing time.

The Monte Carlo analysis was implemented by post-processing optimization results. Alternatively, the uncertainty analysis could be conducted as part of the optimization algorithm. Post-processing was preferred since Monte Carlo outcomes did not provide useful information for optimization algorithm functionality. However, both implementations are equally applicable.

Table 6 shows the average ranking of variables used in the NPV uncertainty analysis. The regression analysis typically matched 20 of the 70 cost model inputs with p-values less than 5%. The average coefficient of determination was $R^2 = 0.993$. This table shows the top-ten significant variables in the economic model. The mechanical system and lighting cost estimations and replacement times were identified as significant variables in accurate cost estimates. This was due to the distribution of supplier estimates as defined in Table 4. Not surprisingly, non-linear variables such as escalation rates, inflation and discount rates were of significance. However, historical data does exist implying that variabilities can be appropriately constrained to reduce overall uncertainty. These variables represent a ranked list for additional effort to reduce economic uncertainty.

Table 6: Ranking of Top-Ten Influential Variables in Cost Model using NPV

Rank	Description	Units
1	Mechanical system cost	\$/kW (\$/Btu/h)
2	Inflation rate	%
3	Lighting costs (fluorescent vs. LED)	$\$/m^2$ ($\$/ft^2$)
4	Window material costs	$\$/m^2$ ($\$/ft^2$)
5	Mechanical system replacement time	yr
6	Lighting replacement time	yr
7	PV array costs	\$/W
8	Wall construction cost	%
9	Electricity demand charges	$\$/kW$
10	Electricity escalation rate	%

CONCLUSION AND FUTURE WORK

This paper proposed a methodology for conducting an uncertainty analyses in conjunction with optimization studies and demonstrated this process using the design of a NZE office building. The methodology improves modelling best-practices by quantifying uncertainty in key economic performance indicators. This results in techniques which enables building owners and developers to identify and manage risk ensuring financial returns on energy saving investments.

Future work can be summarized as follows: (i) validate the proposed methodology by comparing predicted and actual performance indicators; and (ii) extend the proposed methodology to include energy performance indicators.

Predicting the energy and economic performance of a building involves inherent uncertainties. Of significance is the quantification of design resiliency to future climate, occupancy, equipment miscalibration and market fluctuations. Many of these unknowns can be quantified using historical or measured data which can be integrated into the modelling process. This marks an important transition away from deterministic modelling approaches performed on a limited number of design scenarios to optimized design approaches which considered uncertainties as an integral part of the modelling process. Energy modelling best-practices need to better assess the implication of energy modelling assumptions. In exchange for the added effort, we will be rewarded with greater certainty in our modelling predictions.

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