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RESEARCH ARTICLE

A methodology for identifying the influence of design variations on building energy performance

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In building performance simulation, understanding the potential for parameter variations to cause a disproportionately large change in a performance metric is an important aspect of the modelling and design process. This is especially true if the proposed building is expected to meet a performance target such as net-zero energy consumption. In the context of this paper, variations refer to design modifications which lead to large changes in a performance metric. This paper proposes a methodology to identify influential variations around a performance criterion. This methodology aids in the understanding of possible discrepancies between predicted and realized building performance. A net-zero energy house case-study demonstrates the methodology. A variability analysis of the case-study indicated that combinations of variations caused energy consumption to be larger than on-site generation in 20% of variational scenarios. A back-tracking search identified that 8 of 26 variables were responsible for significant changes in net-energy consumption. In particular, energy-related occupant behaviour, solar orientation, and variables related to the sizing of a roof-based photovoltaic system can significantly influence net-energy consumption. The case-study helped quantify two optimal approaches for passive solar design—one relying on high insulation levels and lower window areas, and the other relying on good insulation levels and large window areas.

Keywords: variability analysis; Monte Carlo; back-tracking search; optimization; net-zero energy

1. Introduction

1.1 Background

Creating a net-zero energy (NZE) building, or a building that generates as much renewable energy on-site as it consumes over a year (Torcellini et al., 2006), is a challenging task. Pivotal design decisions to reduce building energy consumption are made within a narrow time frame before the solidification of the final design. These design-stage decisions commit 80–90% of a building's life-cycle operational energy demand (Ramesh et al., 2010; UNEP-SBCI, 2007).

Designing a NZE building requires a systems level approach where all aspects are considered as an interacting whole. This requires designers to balance energy efficiency and conservation opportunities against renewable energy generation. For example, trade-offs between insulation

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levels, building layout and massing, orientation, glazing properties and sizing, natural ventilation, daylighting, renewable energy integration and HVAC system selection and sizing must be considered before the architectural design is finalized. Consideration later in the decision process represents a missed opportunity to optimize building performance. However, some modifications to early designs may be required. Potentially, these changes can affect energy consumption in unpredictable ways due to breakages in system level interactions.

The objective of this paper is to propose a methodology which estimates the effect of variations around a performance criterion. The proposed methodology identifies and ranks variations which most significantly affect a desired performance goal. This added simulation step can inform designers on how robust their design is to variations in usage and construction and aids in understanding potential discrepancies between predicted and realized building performance. A case-study demonstrates the methodology by identifying system level variations which significantly affect the net-energy consumption of a net-zero energy house (NZEH). As discussed later, such information could be used to streamline quality control processes. Although a residential case-study is used, the methodology equally applies to commercial and industrial building types.

1.2 Review of Uncertainty, Sensitivity and Optimization Techniques in Building Simulation

Kim and Augenbroe (2013) defined several areas of uncertainty in building simulation research: (i) statistical uncertainty or uncertainty which can be estimated using historical data. Examples are variations in climate, exterior temperatures, solar radiation and cloud coverage; (ii) uncertainty caused by discrepancies in the model and the as-built building; (iii) measurement errors such as thermal or optical proprieties of building materials; and (iv) statistical uncertainty where no historical data exists. Examples include occupant behaviour such as occupancy, utility usage, window operation and conditioning schedules. This paper explores the effect of variations caused by discrepancies in the model and the as-built building. Causes of such variations could include: (i) early appraisal of unknown and influential model inputs, such as energy related occupant behaviour; (ii) late-stage design modifications; and (iii) modifications to a design due to unavailable or less expensive building materials.

Hopfe and Hensen (2011) suggested several additional benefits of performing an uncertainty and sensitivity analysis: (i) parameter screening to reduce model complexity; (ii) analysis of model robustness and validation; (iii) quality assurance measures to identify sensitivity of specifications; and (iv) decision support analysis.

An uncertainty analysis estimates the effect of variations in inputs collectively with regards to an output. A common technique to perform an uncertainty analysis is a Monte Carlo analysis

(MCA). A MCA repeatedly samples input distributions to form representative designs, which once simulated result in an outcome distribution that approximates the effect of uncertainty in the model (Liu, 2001). The decomposition of model inputs into probability distribution functions (PDFs) allows for an examination of cumulative changes in an outcome due to variations in inputs. Sampling refers to the formation of a representative design by selecting the value of each model input using a probabilistically weighted distribution of possible values. A limitation of a MCA is that it cannot attribute the significance of individual parameter variations on model uncertainty. A sensitivity analysis is commonly used for this purpose.

A sensitivity analysis determines the importance of individual variations in model inputs with respect to a model output. A variable is sensitive if a small variation causes a disproportionately large change to an outcome. In building performance simulation, a sensitivity analysis identifies and ranks sensitive variables in a building model using a simulation objective, such as energy consumption. A variety of suitable methods exist to conduct a sensitivity analysis. Regression analyses, such as standardized regression coefficients (SRC) (Saltelli et al., 2000), attribute sensitivity coefficients to model inputs by building a regression model of uncertainty results. The Morris method (1991) determines which variations are: (i) negligible, (ii) linear and additive, or (iii) non-linear or involve interactions with other factors. The Morris method uses two statistical quantities, the mean and standard deviation, calculated from a Morris design sampling strategy (Saltelli et al., 2008), as sensitivity measures. These quantities are calculated by using a sampling strategy of many local sensitivities. The mean represents the overall influence of the input on the output. The standard deviation estimates the ensemble effects of input variations on the output. A variable with a small mean but large a variance indicates the influence of non-linear couplings between other variables is significant. The Sobol method (1993) attributes the variance in a model's output to its parameters and their interactions. This method calculates the first order, total order and second order sensitivities and reports confidence intervals for each factor. Other techniques such as Fourier methods, one-at-a-time methods are applicable to building energy research (Tian, 2013).

An optimization algorithm may be used to extract performance variations from the solution space for an uncertainty analysis. The use of optimization approaches to explore and identify variations from the energy model solution space is a departure from other optimization studies where algorithms primarily identify optimal designs. The role of optimization algorithms in the paper are to map out variable couplings and build plausible variation scenarios. Although several families of optimization algorithms exist, one well studied optimization approach in building simulation is the Genetic Algorithm (GA), from the Evolutionary Algorithm (EA) family. GAs have become popular due to their ease of implementation and proven ability to solve multimodal and multi-objective problems. Computational pseudo-evolution was first demonstrated by Goldberg (1989) using biological inspirations. Performing genetic operations, such as mutations and crossovers, on representations in combination with selection operators emulate the 'survival of the fittest' found in biological evolution. For further information on optimization techniques for building simulation refer to the extensive review presented by Evins (2013).

Before describing the methodology and case study, a literature review of relevant previous research is presented.

1.3 Literature Review

This section describes previous research which influenced the proposed methodology as presented in this paper. Previous work focused on uncertainty analysis to improve: (1) information for decision making; (2) confidence in simulation results; and (3) sensitivity and uncertainty techniques for building simulation.

Uncertainty analysis techniques can improve decision making during building design. De Wit (2001) demonstrated the potential for thermal comfort uncertainty estimation in a naturally ventilated office building. De Wit and Augenbroe (2002) showed the effect of variations in heat transfer and climate variables on thermal comfort and energy consumption to facilitate rationale design decisions under uncertainty. Hopfe et al. (2007) showed the effect of variations to physical parameters in an energy model on heating and cooling energy use in relation to unmet building loads. Heiselberg et al. (2009) identified a few influential design parameters using sensitivity techniques to optimize a building's sustainability. Breesch and Janssens (2010) estimated the performance of natural ventilation strategies using building energy simulation while considering uncertainties using a MCA with SRC. Domínguez-Muñoz et al. (2010) showed the significance of uncertainty on peak cooling load calculations under various weather and building use scenarios using a Monte Carlo analysis with SRC. They showed that peak load uncertainty was sufficiently addressed using three variables related to charging and discharging of thermal mass. Tian and de Wilde (2011) proposed a methodology to model uncertainties in building energy consumption and greenhouse gas emissions under climate change projections. A case-study showed that heating energy consumption is likely to decrease and cooling energy consumption will increase. Hu and Augenbroe (2012) used a MCA to estimate the effect of uncertainty in the power systems of an off-grid house on thermal comfort and power reliability. Rysanek and Choudhary (2013) explored the technical and economic uncertainties of building retrofits using optimized greenhouse gas emissions and a cost criteria. The study provided decision-makers information for identifying retrofit opportunities in existing buildings under various uncertainties. Wang et al. (2012) explored uncertainties in climate, physical and mechanical system parameters on the energy consumption of an office building. They found that mechanical system operations significantly influenced energy consumption. Booth and Choudhary (2013) identified a limited number of energy saving measures using uncertainty techniques to cost-effectively reduce GHG emissions and energy consumption in the UK housing stock.

Another area of research was improving simulation results by including confidence factors using uncertainty and sensitivity analysis. Aude et al. (2000); Borchiellini and Fürbringer (1999) utilized uncertainty and sensitivity techniques to validate energy models. Purdy and Beausoleil-Morrison (2001) calculated the sensitivity of variations to individual building model inputs to improve modelling decisions by varying each input independently using a stationary building model. Struck et al. (2006) utilized the Morris method with linear partial correlation coefficients to estimate the importance of material properties variations on annual cooling and heating loads. Hopfe et al. (2007) compared the results of four building performance simulation tools using uncertainty analysis. Corrado and Mechri (2009) used the Morris method to estimate the sensitivity and uncertainty of building energy rating systems. Spitz et al. (2012) applied a Monte Carlo uncertainty and sensitivity analysis using 139 physical parameters within an energy model. The Sobol method attributed 6 significant variables to uncertainty propagation. Hopfe and Hensen (2011) applied a MCA and sensitivity analysis using step-wise and rank regressions to three groups of uncertain parameters: (i) physical, (ii) design, and (iii) scenarios. Burhenne et al. (2010) analyzed uncertainty associated with model parameters of a building using a solar thermal collector for heating and domestic hot water.

Additional research has been aimed at improving uncertainty analysis for building simulation problems. Lomas and Eppel (1992) recommended differential sensitivity methods for sensitivity predictions in building thermal simulation programs rather than stochastic sensitivity approaches. Macdonald (2002) described how to embed uncertainties within a simulation tool's conservation equations using a differential and factorial analysis (Macdonald and Clarke, 2007; Macdonald and Strachan, 2001). De Wit (2001) used the Morris method to identify and rank which variations contributed to uncertainty in building energy model outputs. Macdonald (2009) recommended about one hundred samples for a MCA, independent of the number of model inputs, to estimate the mean and variance of the outcome distribution. O'Brien et al. (2011) extracted one-way and two-way interactions from a net-zero energy house model. Heo et al. (2011, 2012) updated PDFs using a Bayesian approach in the calibration of an energy model for energy performance contracts. Previous studies estimating the effect of uncertainty in building simulation indicated that few input parameters affect energy performance outcomes significantly (Corrado and Mechri, 2009; Déqué et al., 2000; Hopfe and Hensen, 2011). In one study, about 100 of the 1009 input parameters of a building model had statistical significance (Eisenhower et al., 2011).

Brohus et al. (2012) quantified the uncertainty of building energy consumption using stochastic differential equations and applied the method to an arbitrary number of loads and zones in a building. Burhenne et al. (2013) proposed a cost-benefit analysis using a MCA with Monte Carlo filtering to find which variables drive model uncertainty. Infiltration was identified as having the largest effect on the solar fraction of a solar thermal system. Sun et al. (2013) defined uncertainty quantification of micro-climate variables affecting building simulation results.

There is limited research exploring the robustness of a building design around a performance criterion. For example, Hopfe et al. (2012) added uncertainty functionality to an EA to estimate the robustness of building performance simulations. Jelle et al. (2013) developed a robustness classification system for materials, assemblies and buildings. Hoes et al. (2011) proposed an EA selection operator to rank potential designs based on their robustness to uncertainties in occupant behaviour.

To explore influences of input variations for a performance criterion such as NZE requires experimental evidence or expert knowledge. Associating arbitrary PDFs to model inputs, such as normal or triangle distributions, offers no indication that sampled designs represent or fall within the desired performance range. To overcome this problem, optimization techniques extracted PDFs from the solution space of acceptable designs. A MCA was selected for uncertainty propagation. Based on the recommendations of Macdonald (2009), a random sampling method was selected for the MCA to allow for an unbiased sampling of the solution space. Most of the sensitivity techniques used in literature were not suitable to extract and rank the relative importance of variation combinations to model inputs while retaining a performance criterion such as NZE. Based on the reviewed papers, only Monte Carlo Filtering techniques using regression analysis met this restriction. However, Monte Carlo Filtering is only suitable to explore first order effects (Saltelli et al., 2008). Thus a new technique is proposed in this paper to explore first and higher order effects.

2. Methodology

This section proposes a methodology to estimate the effect of variations about a performance criterion. In a later section, the methodology is used to identify system level variations which most greatly affect the net-energy consumption of a NZEH.

To accomplish this, the methodology required the following distinct steps: (i) an optimization training dataset was formed using an optimization algorithm, (ii) discrete PDFs were created from this dataset for designs which satisfied the NZE performance criterion, (iii) new designs were created from independent random samplings of these PDFs and simulated using an objective function (due to system level effects, not all of these samplings resulted in NZEHs), (iv) a back-tracking search identified the variations responsible for non-NZE compliant samples.

The methodology is divided into three sections described by the following components: (i) creation of optimization dataset using an Evolutionary Algorithm and extraction of PDFs, (ii) a Monte Carlo analysis using samplings of discrete PDFs, and (iii) importance factor calculations using back-tracking searches.

2.1 Formation of PDFs from an Optimization Training Dataset

This section describes the steps required to build PDFs from a training dataset built using an optimization algorithm; this training dataset will be used within a MCA.

The use of optimization data is a reasonable approach to build PDFs. The reasons for using optimization data to build PDFs are: (i) algorithms can systematically seek out variable limits and combinations which result in high-performing designs; (ii) algorithms converge towards optimal variable combinations and the frequency of PDFs is calculated from the frequency of optimal solutions in the dataset; and (iii) the shape of distributions and optimal variable combinations is a property of the solution space and not the algorithm search technique.

The steps, summarized in Figure 1, are as follows: (i) model formation, (ii) discretization of variables, (iii) formation of optimization training dataset using a customized evolutionary algorithm (Bucking et al., 2010), and (iv) extraction of PDFs for each model variable from compliant designs in the optimization training dataset. These steps are described in greater detail below.

Before proceeding, it is assumed that a model exists to evaluate the performance criterion. Simulation of this model allowed for comparisons of design performance.

The methodology requires discrete variables. This step is beneficial as it improves the convergence properties of the optimization algorithm. Furthermore, the resolution of most variables in building applications is finite in application. Although continuous parameters would result in higher resolution estimates of variability, they require additional binning which is sensitive to bin size. Thus, the methodology requires that appropriate design parameter increments be selected.

In a MCA, attributing representative distributions with physical interpretations to the input parameters of the model is difficult. There is no evidence that samplings of common distribution functions such as normal or triangle distributions will represent a performance criterion or fall within a desired performance range. To overcome this difficulty, a training dataset was utilized based on searches from an optimization algorithm.

Optimization algorithms identify which sets of design parameters resulted in a NZEH. The se-

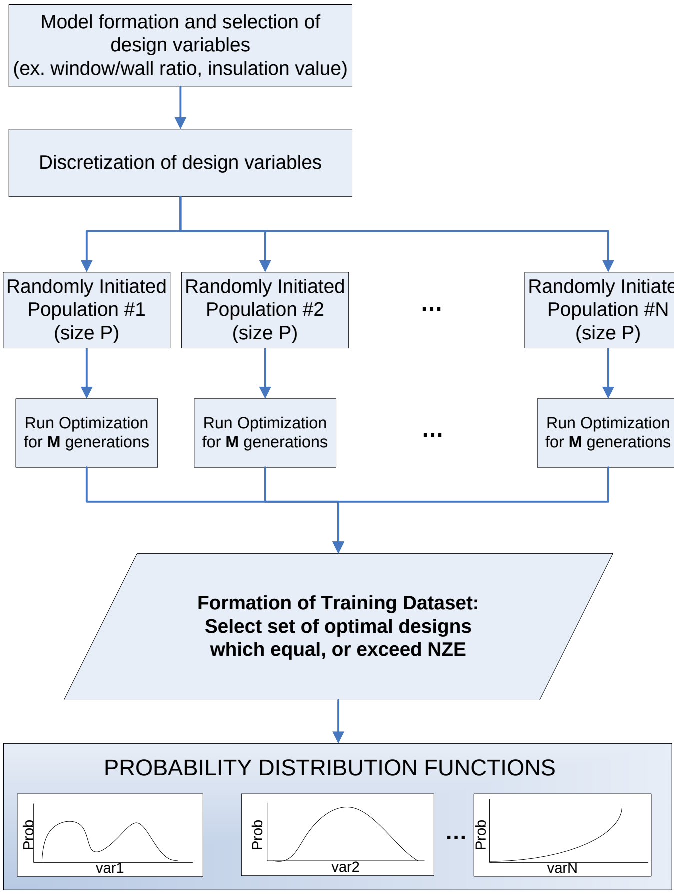

Figure 1. Formation of PDFs from the optimization dataset

lection of the optimization tool will not affect the training dataset if the algorithm can optimize large solution spaces involving interacting variables and pathways leading to optimal regions can be queried from a database. For the case study, a previously developed evolutionary algorithm (Bucking et al., 2013) navigated the design space. Training data was built by running the optimization tool, starting with a randomly selected initial population, at least N times for M generations using a population of P designs to approach optimal landscapes from different directions. Wright and Alajmi (2005) suggested a population size, P, of 10 to 15 is appropriate for most building simulation applications. The selection of the number of generations, M, is problem specific and must be large enough to allow for convergence to global optimums. Finally, repeating optimization runs, N, at least 20 times is a sufficient sample size of optimization results to build PDFs. Therefore, the procedure requires $N \cdot M \cdot P$ simulations to build the training dataset. After navigating the design space, the training dataset was formed by selecting a subset of designs from the database which equalled or exceeded a specified performance criterion.

A SQLite database (SQLite, 2012) stored data originating from the optimization tool; SQL queries formed the training dataset. SQLite allows for concurrent writes from simultaneous simulations originating from multi-core and distributed computers. To save computation time, a database query confirmed if a set of parameters has yet to be simulated before calling the simulation tool. SQL queries allowed for the quick recollection of design parameter sets which exceeded the NZE performance criterion.

PDFs were extracted by: (i) selecting all combinations of variables that equalled or exceeded the NZE performance criterion from the training dataset, (ii) counting the number of occurrences of each discretized interval, and (iii) normalizing the sum of counts to equal one. For the case study, the performance criterion was NZE or better, i.e. all building designs where the on-site renewable energy generation equalled or exceeded on-site energy consumption over one year. To aid in visualizing the limits of and weightings of PDFs, kernel density functions (Scott, 1992) smoothed and interpolated the data, see Figure 2. However, discrete probabilities were used for samplings in the MCA.

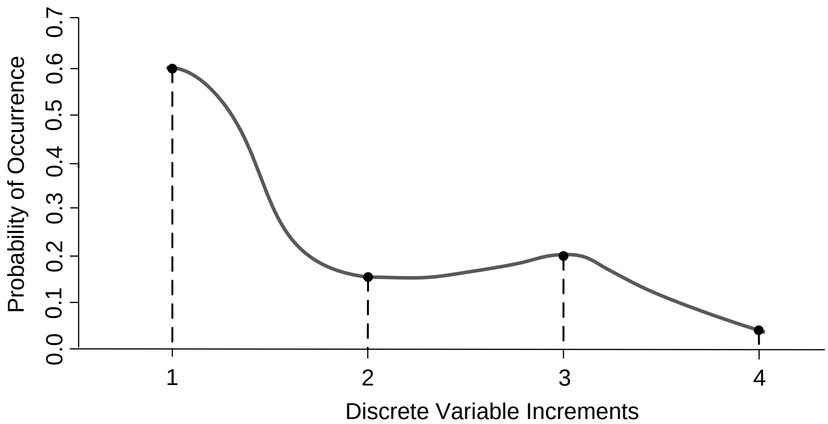

Figure 2. Kernel density function fitted to discrete probabilities of one variable

The extraction of PDFs from the training dataset ensured that all variable distributions were representative of NZEHs. An immediate benefit is the identification of parameter limits and most probable values for each variable. This is discussed more in the results section. Due to variable couplings, the sampling of a set of trained PDFs may not result in a NZE compliant design. This became evident if the Monte Carlo samplings from trained PDFs resulted in some non-NZE compliant designs. In fact, by intentionally sampling model variables as though they were independent variables indirectly identifies non-linear effects and inter-variable interactions which cause non-NZE compliant designs.

The optimization dataset offered many insights into variations which caused a performance criterion to be exceeded. Using the trained PDFs as an input, a Monte Carlo analysis enabled the exploration of model variations around this performance criterion.

2.2 Monte Carlo Analysis

A Monte Carlo analysis was selected to identify the global effects of variations on the previously defined PDFs. A MCA does not require modifications to the model and can directly use the trained PDFs from the optimization training dataset for samplings. Monte Carlo analyses are commonly referred to as uncertainty analyses since they estimate the cumulative effect of sampling uncertain input distributions. For this paper, a MCA conducts a variability study since the input distributions represent parameter sets of NZE buildings and not physical uncertainties in model inputs.

Figure 3 summarizes the steps required to estimate the global variability of a model. A random sampling technique of trained PDFs was used for the MCA, based on the recommendations of previous studies comparing sampling methods (Lomas and Eppel, 1992; Macdonald, 2009). This methodology used a Monte Carlo sample size of 1000. This was ten times larger than previously recommended by Macdonald (2009). Larger sample sizes helped to explore the effect of sample size on importance factor convergence as discussed in section 2.3. In a MCA, 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.

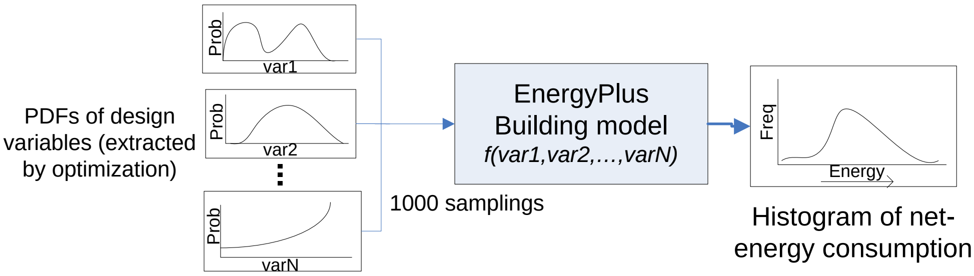

Figure 3. Monte Carlo analysis

Monte Carlo methods rely on the sampling of predefined input distributions to estimate the cumulative variability of a model. Data points are formed by simulating samplings using a performance objective. The binning of all sampled data points forms an outcome distribution which represents the cumulative effect of input variability on the model output. The expected variation within a confidence interval, typically 95%, can be extracted from the outcome distribution and indicate the importance of potential variations. Regions of the outcome distribution that result in unacceptable performance are of particular interest. However, the MCA is unable to identify which variations to model inputs cause non-compliant Monte Carlo samples. A separate back-tracking analysis is proposed for this purpose.

2.3 Calculation of Importance Factors using Back-tracking Searches

A back-tracking search ranked the relative importance of variations to model inputs for Monte Carlo samplings that were non-NZE compliant. The proposed back-tracking search was created for the requirements of this paper. This search identifies input variations which caused non-compliant Monte Carlo samples.

In this section, importance factors are introduced to represent the relative significance of variations to each variable affecting a performance criterion. A variable with an importance factor of zero indicates that variations to this variable do not affect the performance criterion. The sum of all importance factors equals one; thus, each factor is the relative contribution of each variable to unexpected changes in the performance criterion.

Figure 4 shows a back-tracking search using a simplified example.

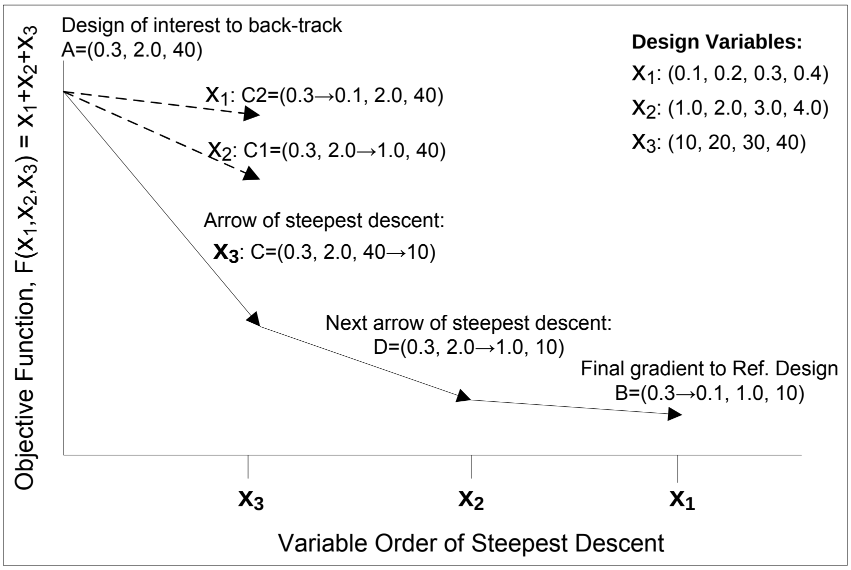

Figure 4. Simplified back-tracking search

A back-tracking search identifies the order in which each variable should be changed to result in the steepest objective function gradients from a selected design, A, to a known reference design, B. In Figure 4, starting from the initial design, A, three potential variable changes are tested. The variables, x_1, x_2, x_3, are changed from the value found in the selected design to the value known in the reference design. Thus three new intermediate designs, C, C_1, C_2, are created and evaluated using the objective function. The variable x_3 resulted in the steepest change in the objective evaluation and is identified as the variable with the highest importance as listed in the x-axis. The objective function gradient from design A to design C is recorded. Now, the variable x_3 can be excluded from the remaining back-tracking searches. Starting from the intermediate design, C, the variable x_2 with the next steepest gradient is identified for design D. This process is repeated until all variables of design A are back-tracked to design B.

A back-tracking search requires a reference design. Selecting the optimal design, a positive NZEH with maximum production, as a reference point ensures that the extraction of steepest objective function gradients is consistent across the entire solution set. This is because the optimal design is unique for a single objective optimization problem. Furthermore, using the optimal design as a reference point also ensures that back-tracking searches identify all influential variations in the solution space. Note that the back-tracking of incremental improvements of the initial design to the reference design is equivalent to the back-tracking of incremental degradations of the reference design to the initial design.

Figure 5 shows the method for calculating importance factors using back-tracking searches. Designs of interest, shown as shaded region in histogram, refers to candidate building designs for the back-tracking searches, i.e. designs which are non-NZE compliant. To calculate importance factors, using each design of interest ($j = 1, \cdots, M$): (a) perform a back-tracking search from the design of interest to the reference building to identify steepest performance gradients and incremental performance improvements for each variable change; (b) calculate *local* importance factors by dividing the incremental objective function gradient of each variable ($E_{\text{grad } i,j}$ where $i = 1, \cdots, N$) by the difference in the objective functions between the design of interest (E_{DOI}) and the reference building design (E_{Ref}), see equation 1; (c) continue to the next design of interest and repeat from step (a) until all non-NZE compliant designs have been back-tracked; finally, (d) calculate and rank *global* importance factors by normalizing all local importance factors calculated in steps (a–c), see equation 2. The sum of global importance factors for all variables should be equal to one. These factors are global in the sense that they represent the average effect of variations on non-compliant Monte Carlo samples.

$$IF_{\text{local } i,j} = \frac{E_{\text{grad } i,j}}{E_{DOI} - E_{Ref}} \tag{1}$$

$$IF_{\text{global } i} = \frac{\sum_j IF_{\text{local } i,j}}{\sum_i \sum_j IF_{\text{local } i,j}} \qquad \text{where, } \sum_i IF_{\text{global } i} = 1 \tag{2}$$

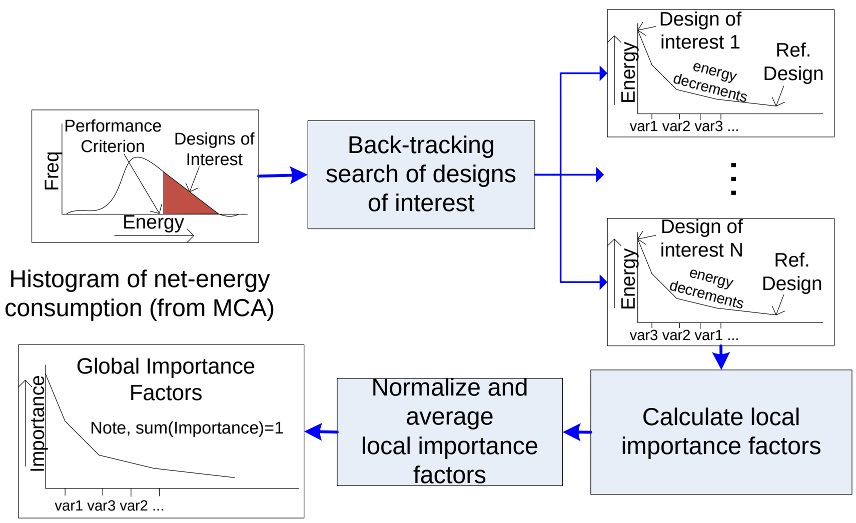

Figure 5. Calculation of importance factors using back-tracking searches

To investigate if the back-tracking of all designs of interest were required, a convergence analysis of importance factors was performed. After back-tracking each additional design of interest, the average of all local importance factors for each variable was recorded. The calculation of importance factors converged if the inclusion of results from additional back-tracking searches does not change the average of local importance factor for each variable. This characteristic is important in understanding how many back-tracking searches are required to confidently calculate global importance factors.

Importance factors have the following advantages: (i) they identify, rank and give the relative importance of changes to influential variables using a performance criterion, (ii) they identify the significance of first order and second order effects, (iii) they are generalized for a set of design considerations and climate zone, and (iv) they estimate the impact of variations for Monte Carlo samplings which unexpectedly do not equal or exceed a performance criterion.

Important factors have several useful properties. In addition to identifying which variations can cause large deviations from the NZE target, it is possible to identify the significance of primary and secondary effects of variations. Global importance factors, or averaged local importance factors, determine the overall influence of the variable on the output. The standard deviation of local importance factors estimates the ensemble effects of variations. Ensemble effects are caused by non-linearities and/or interactions with other variables. An importance factor with a large variance indicates that the effect of variations is strongly affected by the values of other parameters. By contrast, low values imply that the effect is almost independent of other sampled parameters. Note that primary effects are de-emphasized in this methodology since back-tracking searches are intentionally conducted on designs with sufficient system-level interactions to cause non-NZE building designs. Similar to the Morris method (1991), the mean and standard deviation of importance factors can be plotted against each other to visualize primary and secondary effects.

The following section presents a case study to demonstrate the proposed methodology.

3. Case Study

The proposed methodology was demonstrated using a variability analysis for a NZE house. Rather than creating a hypothetical building, a house model was modified from a previous study (O'Brien, 2011). The model, developed in EnergyPlus, was calibrated using monitored data from an occupied near-NZEH located in Eastman, Québec (Doiron, 2010; Doiron et al., 2011). The two-story ÉcoTerra house was the first of 15 houses completed under the Canada Mortgage and Housing Corporation EQuilibrium Housing Demonstration Initiative. Alouette Homes prefabricated the home and Natural Resources Canada, Canada Mortgage and Housing Corporation, and Hydro Québec partially funded the project. The Canadian Solar Building Research Network provided research and development support. A balance of passive solar design strategies, roof-top photovoltaics and a geothermal heat-pump provided on-site renewable energy generation. For this case study, the primary energy factor associated with electricity from the grid was not considered since the site-NZE definition was selected (Torcellini et al., 2006).

This case study used twenty-six discrete variables, summarized in Table 1. All variables can be considered as design/construction or operation variables (including human factors). For example, in many cases, the orientation and aspect ratio can both be selected and the house can be designed and built to a certain air-tightness (defined by infiltration). Similarly setpoints can be considered as design or operation parameters, or if modified continuously by the occupants, they are an occupant factor parameter. Variable descriptions are shown for the south orientation only; also, the PV slope is equal to the roof slope since the house has a building-integrated photovoltaic system that covers the south-facing roof. Design of experiment techniques (Goos and Jones, 2011) and previous studies (Charron, 2007; O'Brien, 2011; Verbeeck, 2007; Wang, 2005) aided in identifying influential variables. The performance objective selected was the net-annual electricity consumed (Net) during a typical meteorological year, i.e. the energy balance of building energy consumption with renewable energy (RE) generation, see equation 3. Negative values of net-energy indicate a greater production of electricity compared to consumption. Thus, satisfying or exceeding the NZE criterion can be stated succinctly as Net ≤ 0 or RE $\geq$ Consumption.

$$\text{Net} = \text{Consumption} - \text{RE} \tag{3}$$

Table 1. Sample of influential model variables for a NZEH

Variable	Units	Min.	Max.	No. Steps	Description
aspect	–	0.7	2.2	16	Aspect ratio (south facing width to depth ratio)
azi	degrees	-45	45	32	Building orientation/azimuth
wall_ins	m^2K/W	3.5	13.0	8	Effective resistance of wall insulation
ceil_ins	m^2K/W	5.6	15.0	8	Effective resistance of ceiling insulation
base_ins	m^2K/W	0.0	7.0	8	Effective resistance of basement wall insulation
slab_ins	m^2K/W	0.0	2.3	4	Effective resistance of slab insulation
heating_sp	$^\circ$C	18	25	4	Heating setpoint
cooling_sp	$^\circ$C	25	28	4	Cooling setpoint
infil	ACH	0.025	0.179	8	Natural infiltration rate
occ_loads	% CAD_{avg}	50	80	8	Occupant loads (percent of Canadian average consumption)
ovr_south	m	0.00	0.45	4	Width of Southern Window Overhangs
pv_area	%	0	90	8	Percent of PV area on roof
pv_eff	%	12	15	4	PV efficiency
roof_slope	degrees	30	47	8	South facing roof/PV slope
wwr_s	%	5	80	8	Percent of window to wall ratio, south (also N,E,W)
GT_s	–	1	4	4	Glazing type, south (also N,E,W)
FT	–	1	2	2	Window Framing Types (1:Wood, 2:Vinyl)
slab_th	m	0.1	0.2	8	Concrete slab thickness
vwall_th	m	0.00	0.35	8	Concrete wall thickness (basement)
zone_mix	L/s	0	400	4	Air circulation rate between thermal zones

The combined coefficient of performance (COP) of the Ground Source Heat Pump (GSHP), circulation fans, pumps and auxiliary heaters was specified from seasonal-averages of monitored data. Since the heating system uses a GSHP, the COP does not vary significantly over an annual period. Thermal energy for heating was converted into electrical energy by using a COP_H of 3.77.

Similarly, to convert cooling loads into electrical energy a COP_C of 2.77 was used. Thus, any reference to energy consumption using units of kWh refers to electrical energy. Electric lighting ensured that a minimum illuminance of 200 lx was present in all occupied spaces regardless of the window-to-wall ratio. A heat recovery ventilator with an efficiency of 60%, taken from manufacturer specifications, maintained the ventilation rate at 0.3 air-changes per hour in all occupied spaces. Roller shades were automatically deployed if exterior solar radiation on the exterior window surface exceeded 150 W/m^2 and if exterior temperature on the window exceeded 20 °C. These values ensured that blinds were closed if there was potential for zone overheating. Utility dependencies were not considered because a site-NZE definition was used.

An evolutionary algorithm minimized the annual net-energy consumption of the house. The algorithm used a population size P of 10 with 30 generations (M) within each optimization run. To ensure that the optimal landscape was approached from different angles, 20 optimization runs (N) were executed using randomized initial populations; thus, 6000 EnergyPlus simulations were required ($P \cdot M \cdot N = 6000$). Approaching the optimal landscape from different pathways ensured that the extracted PDFs represented a variety of interactions present in the building model.

Energy related occupant behaviour is an important, but challenging aspect to incorporate into a building simulation. Although occupant behaviour is not actually a design variable, it was included in the case study due to its influence on energy consumption. For example, energy-related occupant behaviour accounted for 37% of ÉcoTerra's gross energy consumption (Doiron et al., 2011). Ideally, monitored data from a large sample of NZEHs would be preferred to estimate energy related occupant behaviour for a given location. Since such data was not available, usage scenarios were created from published data. Previously published hourly occupancy, domestic hot-water (DHW) loads, appliance and lighting usage profiles were used (Armstrong et al., 2009). These were determined from monitored data specific to Canadian housing stock. The amplitude of energy-use profiles were normalized to match published consumption data for lighting, DHW, and appliance loads (NRCan-OEE, 2009). In 2009 Canadians used, on average, 95 kWh/m^2 of total energy for lighting, DHW and appliances. An assumption was made that an above average user of lighting, was also an above average consumer of DHW and appliance loads and vice versa. The lower bound of 50% for DHW, appliance and lighting loads was selected based on monitored data from the ÉcoTerra house.

4. Results

Figure 6 shows the PDFs extracted from the optimization training set. Table 1 provides longer descriptions of short-form notations. The probabilities of each variable, shown in the y-axis, are normalized to one.

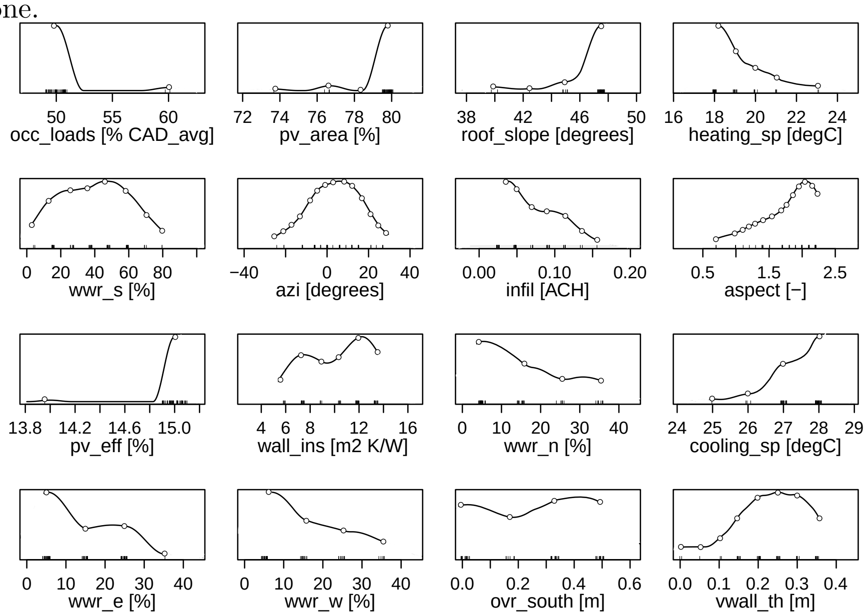

Figure 6. Sample of PDFs extracted from the training dataset

Each PDF resulted in a NZE compliant design given a specific set of other variable combinations. Two-dimensional contour maps are more appropriate to visualize discrete combinations of variables that resulted in NZE compliant designs. For example, Figure 7 shows a probability contour plot, based on several near-optimal designs from the training dataset, for the southern window glazing to wall ratio (WWR) and for the amount of wall insulation. The shaded region shows variable combinations that resulted in a NZE compliant home for this particular case study (RE $\geq$ Consumption). Shading indicates the probability that the combination of parameters appeared in the training dataset; darker shading indicates an increased probability of occurrence.

One important observation from Figure 7 is that some combinations of wall insulation and WWR preferentially appeared in clusters due to coupling; for example, a range of southern WWRs of 31.8–47.9% correlated with wall insulation levels of 6.9–8.3 m^2K/W indicating that these variable pairings has a high probability of occurrence in the NZEH training dataset. Additional pairings can be found for higher wall insulation and lower southern WWRs. This important result demonstrates two very different approaches to design a NZEH: (i) super insulated walls with more variable southern WWR, and (ii) a design with relatively lower wall insulation and appropriately sized southern WWR for passive solar design. Both are valid design strategies to achieve the NZE performance criterion. This result quantifies these two different approaches that until now were described qualitatively: super insulate and be conservative in window areas

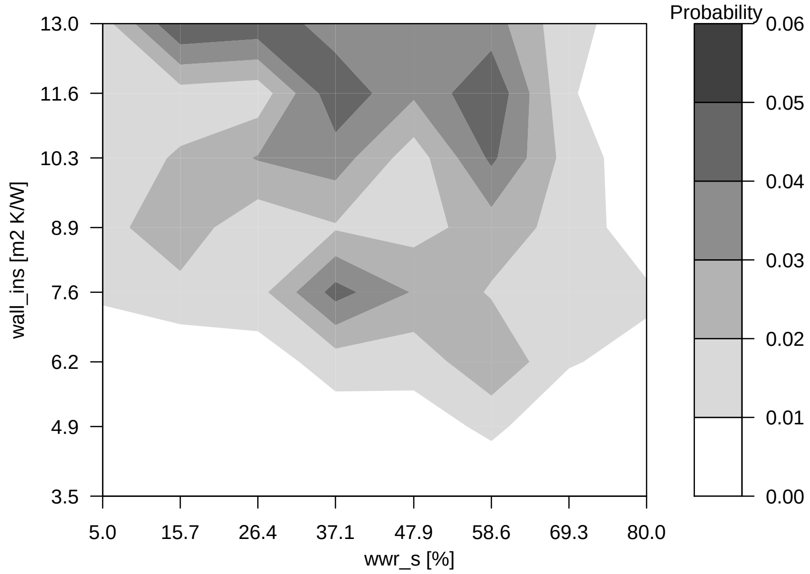

Figure 7. Probability of occurrence for southern WWR and wall insulation parameters resulting in homes that are NZE compliant

versus insulate well—but not excessively—and use larger window areas. The second approach was used in the design of the ÉcoTerra house, but the first approach was used in some of the other EQuilibrium houses.

Once the PDFs were extracted from the optimized training dataset, a MCA was performed which resulted in a histogram of the accumulated effects of design variations, as shown in Figure 8. If all variables were weakly interacting, the sampling of trained PDFs from NZE compliant design in a MCA would result in all NZE compliant design. However, the shaded area in Figure 8 identifies designs where renewable energy generation did not offset the building energy consumption. This is due to variable interactions and non-linearities. The histogram satisfied a hypothesis test for a long-tail distribution (Venables and Ripley, 2002). Long-tailed distributions represent rare events—meaning that deviations from NZE require more than one variable change. The back-tracking analysis proposed, described in section 2.3, identifies the variations responsible for long-tail events.

If one was to approximate a mean and variance, assuming a normal distribution, the expected net annual electricity consumption given all variations would be $-400 \pm 850\ kWh$ using a 95% confidence interval. Negative values of energy indicate the net-production of electricity. For this case study, the combined variations is enough to cause building energy consumption to be larger than renewable energy generated in 20.4% (204/1000) of sampled designs, i.e. RE $<$ Consumption.

Importance factors were calculated for input variables responsible for NZE non-compliance. As shown in Figure 8, 20.4% of the sample was non-NZE compliant. Importance factor calculations involved back-tracking each variable to find which variation caused the largest change in net-energy consumption relative to the reference building, see Figure 9 for the result of one

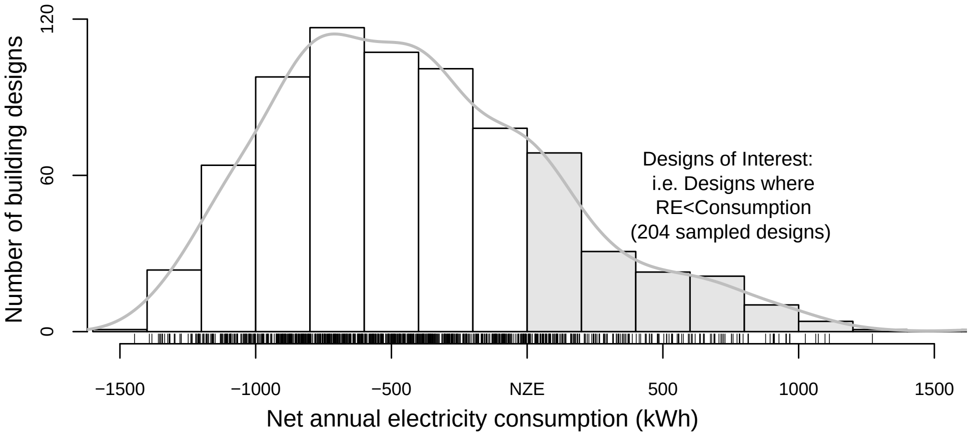

Figure 8. Histogram of 1000 samples from the Monte Carlo analysis

back-tracking search. The reference building used was the optimal design found from the training dataset. The relative importance for each variable was calculated by normalizing each incremental improvement by the performance difference between each design of interest and the reference building. EnergyPlus simulations determined the incremental variable improvements, the performance of the design of interest and reference building.

Consider the back-tracking of a particular design of interest, as shown in Figure 9. Note the net-energy consumption of the design of interest was 374 kWh. A positive NZEH with maximum production was used as the most desirable outcome, and therefore the performance of the reference building was -1446 kWh. The steepest gradient of 797 kWh was obtained by varying the southern WWR from a starting value of 5% to 48.2%, see Table inside Figure 9. The local importance factor for variable wwr_s was calculated to be $797/(374 + 1446) = 0.4381$. A local importance factor of 0.4381 indicates that the variation to southern WWR is responsible for about 44% of the net-energy consumption difference of this particular design of interest relative to the optimal reference building.

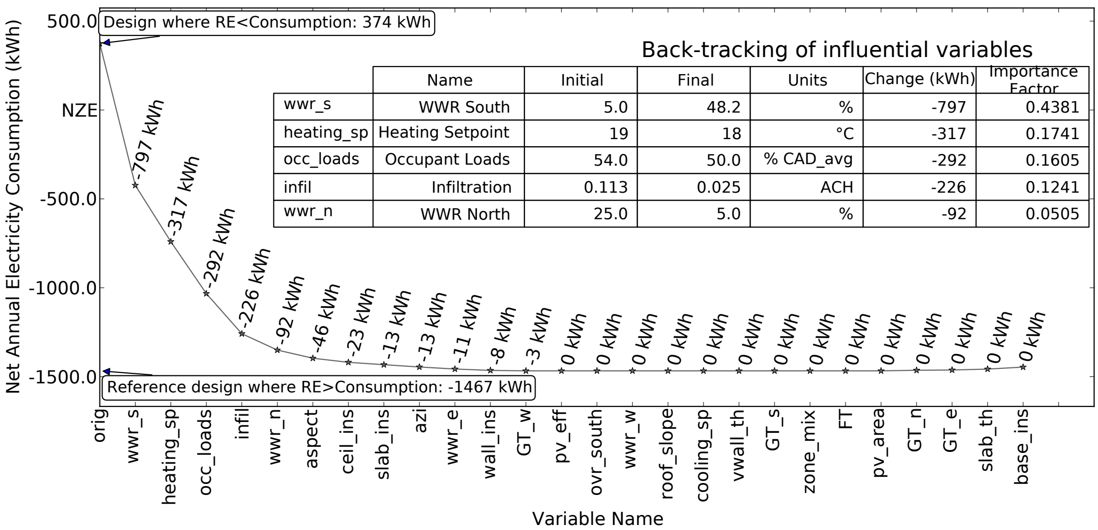

Figure 9. Back-tracking of one NZE non-compliant design to the reference building

Table 2 presents the influential global importance factors for 204 designs of interest. Recall that global importance factors refer to the averaging of all local importance factors; local importance factors were calculated using a single back-tracking search. The average net-change presented in this table is the expected change in net-energy consumption found in the back-tracking search for all 204 designs.

Table 2. Importance factors for influential variables

Variable	Units	Description	Mean Importance Factor	Importance Factor Deviation	Average Net-Change (kWh)
occ_loads	% CAD_{avg}	Occupant Loads (percentage of Canadian Average consumption)	0.1420	0.1258	253
pv_area	%	Percent area of PV on roof	0.1104	0.1490	200
roof_slope	%	Roof slope	0.1043	0.1627	197
heating_sp	°C	Heating setpoint	0.0993	0.1233	182
wwr_s	%	Percent of window to wall ratio, south	0.0868	0.1280	154
azi	degrees	Building orientation/azimuth	0.0828	0.1200	150
infil	ACH	Natural infiltration rate	0.0705	0.0931	129
pv_eff	%	PV efficiency	0.0445	0.1238	82

Table 2 is applicable to other NZEHs with similar variables, RE generation technology, site and situational constraints and climate type as the case study. For different studies, users should repeat the proposed methodology. Calculating the effect of combinations of variations is achieved by adding the average net-changes. This linear assumption may approximate some local non-linear phenomena but is generally acceptable since net-changes originated from the solution space.

Figure 10 shows a plot of importance factor mean and standard deviation. Recall that the mean importance factor represents the overall influences of each variable on the non-compliant MC samples shown in Figure 8. The importance factor standard deviation represents the effect of non-linearities or inter-variable couplings of each variable. This figure shows three clusters of importance factors: (i) cluster A called influential variables, (ii) cluster B, variables with intermediate influence, and (iii) cluster C, non-influential variables. Based on this plot, only 8 of the 26 variables examined were considered influential.

Figure 11 shows the convergence characteristics for the five most influential variables over the back-tracked home designs found to greatly influence the NZE objective. It was found that the calculation of importance factors converged after back-tracking approximately 150 of the 204 building designs. For instance, the value at 50 building designs is the average importance factor calculated for back-tracked building design no. 1 through no. 50. Similarly, the value at 100 building designs is the average of importance factor from design no. 1 through no. 100.

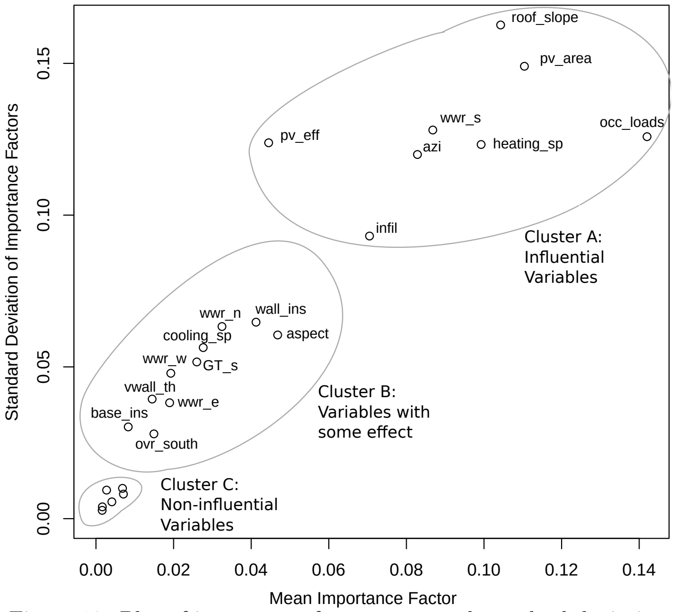

Figure 10. Plot of importance factor mean and standard deviation

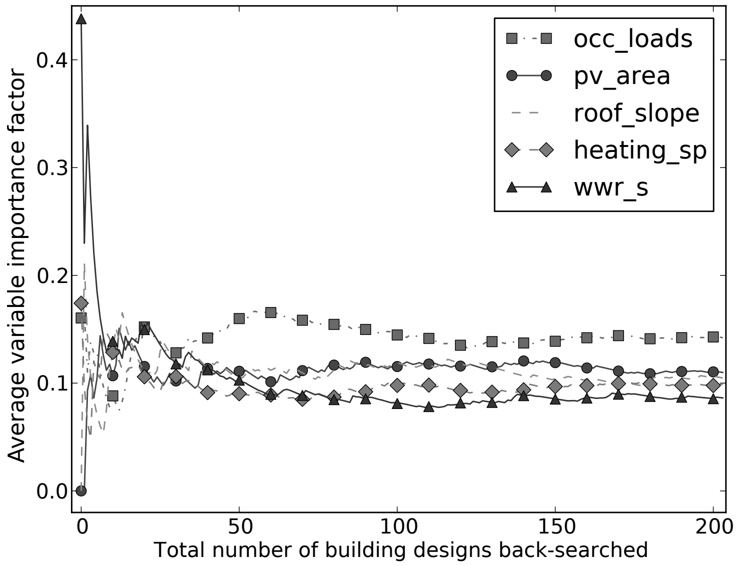

Figure 11. Convergence characteristics for the five most influence variables towards a constant importance factor

5. Discussion

This paper proposed a methodology to identify influential variations around a performance criterion. A net-zero energy house case-study demonstrated the methodology. Although the methodology is focused towards NZE buildings, it is applicable to other high performance building studies. The remainder of this section discusses results from the case study and areas of future work.

The application of the methodology to a NZEH identified several design restrictions specific to the case study. From the set of PDFs shown in Figure 6, limits in variable ranges that resulted in NZE were identified. For instance, if occupants consumed more than 60% of Canadian national electricity averages for appliance, DHW and lighting loads, achieving NZE was not practically possible, i.e. PDFs equalled zero. Other similar design restrictions were noted for the building azimuth angle and PV sizing. For example, NZE compliance is difficult to achieve when the main solar collecting surface of the building is oriented further than 30 degrees from due south. Note that these results are for a particular location and a set of modelling assumptions but they are expected to be valid for similar climatic conditions. For this case study, cut-offs originated due to a limited amount of roof space for PV-based electricity generation. Regardless, Figure 6 shows a remarkable variety of design combinations with the potential to reach NZE. Figure 7 identified that some combinations of wall insulation and WWR preferentially appeared in clusters. For example, a range of southern WWRs of 31.8–47.9% correlated with wall insulation levels of 6.9–8.3 m^2K/W. This result represents two very different design approaches to a NZEH: (i) super insulated walls with more variable southern WWR, and (ii) a design with relatively lower wall insulation and appropriately sized southern WWR for passive solar design. Identifying variable restrictions and optimal combinations of variations in the early design stages of a NZE building will facilitate the quantitative design process.

The convergence of importance factors exhibited an asymptotic relationship regardless of the order of the back-tracked population (see Figure 11). The convergence analysis indicated that at least 150 back-tracking searches were required to build confident estimates of global importance factors.

In the case study, importance factors indicated that only a few design variables associated with a NZEH significantly affect net-energy consumption. In fact, only thirty percent of the variables examined in the case study were influential. Energy related occupant behaviour (occ_loads) was the most influential variable. Occupant behaviour carried more significance than design variations affecting heating and cooling loads due to the COP effect of the heat pump which reduced electricity used by 1/COP. Monitored data from a set of NZEHs would be more appropriate to extract the importance of occupant behaviour. For this study, ranges of occupant behaviour were based on monitored data of a NZEH and average energy consumption data for Canada. Since the occ_loads importance factor was based on these assumptions of occupant behaviour, these results are applicable to the case-study only.

The clustering analysis shown in Figure 10 shows the primary and higher order effects of variations. Variations causing significant higher order effects have larger standard deviations. Variations related to renewable energy generation, particularly, the roof slope (roof_slope), PV efficiency (pv_eff), building orientation (azi) and percentage of roof coverage with PV (pv_area), were the next most influential variables in the case study. Note that the azimuth and roof slope are factors in energy generation since PV is integrated into the roof surface. Although the significance of PV related variables is not surprising given that roof-based PV being the only source of renewable energy used to offset energy consumption, the higher order relationships between clustered variables is not immediately evident. Results suggest that the assurance of PV specifications should have equal or greater prioritization than envelope air-tightness. A key advantage of the proposed methodology is the quantification of primary and higher order effects to improve the robustness of a design and better predict building performance.

6. Conclusion

This paper proposed a methodology which provides new information to designers regarding how robust their performance-based design is to key parameter variations. Importance factors rank and quantify the effects of first order and second order variations of each aspect of the design. This added simulation step can inform designers on how robust their design is to variations in usage and construction parameters and aids in understanding potential discrepancies between predicted and realized building performance. The goal of the paper is to present a methodology which aids designers in understanding the potential for important parameter variations to affect a performance criterion (NZE in the case-study).

Streamlined quality assurance processes guided by importance factors can be used in the design of high performance buildings to identify and prevent costly design mistakes before they occur. By definition, importance factors identify which variables changes are likely to cause a non-compliant performance level for a given climate and building type. Importance factors allow for the prioritization of quality control to focus on the design aspects which most significantly affect a desired performance target. Larger importance factors indicates that changes to the given variable have a greater effect. Also, the size of the anticipated changes can be estimated, as shown in Table 2. Similarly, in the commissioning of new buildings, importance factors could aid in identifying and resolving the causes of discrepancies between predicted and realized building performance.

An area for future work is to utilize PDFs and importance factors to improve energy design guidelines by providing a scientific basis for establishing an optimal combination of design variables. Several approaches used in this paper are applicable in creating more flexible performance-based design guides. For example, PDFs encapsulate all design parameters extracted from an optimized solution set which result in the desired performance level. This can be useful to select parameters which are constrained for the given location. For example, as found by the optimization algorithm, Figure 6 shows that wall insulation, wall_ins, must be at least 6 m^2K/W in Montréal for a house to be NZE. However, the added flexibility of recommending ranges of individual design variables results in a new problem. As shown in this paper, combining sets of high-performing design variables with the assumption that the combination should result in a high performing design is circumstantial due to influential variable linkages and couplings. Importance factors, by definition, identify which design variable changes are responsible for such discrepancies. From the perspective of a design guide, the smaller the importance factor of a design variable, the more confidently it can be used in combination with other design variables.

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