Design Optimization Methodology for a Near Net Zero Energy Demonstration Home

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Abstract

This paper applies an energy optimization methodology to identify improvements to a monitored near net-zero energy house located near Montreal, Canada. The method leverages design variable interdependencies to expedite the optimization process via a hybrid deterministic-evolutionary algorithm. This paper presents several recommendations and lessons learned, which can be applied to the design optimization of net-zero energy homes.

1. Introduction

A well implemented optimization methodology can greatly facilitate the process of designing a net-zero energy building. Net-zero energy (NZE) refers to generating as much on-site renewable energy as energy consumption over a year. A major challenge in designing a NZE building is determining optimal combinations of interdependent design variables such as the optimal level of insulation and south-facing window area and type.

Using only trial-and-error approaches, it requires many years of experience for designers to identify and understand the relative strength of coupling between design variables. Evolutionary-based optimization algorithms have been shown to navigate these interactions. Thus data from an optimization run can be used to identify and visualize design variable interactions.

The goals of this paper are: 1) using a systematic optimization approach, to redesign an existing near-NZE home based on an energy model calibrated to monitored energy data, 2) to evaluate the potential of hybrid deterministic-evolutionary algorithms, including their application to the optimization process, and 3) to extract information regarding variable interdependencies and apply it to expedite the optimization process.

The intricacies of energy simulation and interpretation of energy simulation results are discussed in a companion EuroSun paper [1].

1.1. EcoTerra, a Near Net Zero Energy Demonstration Home

EcoTerra, located in Eastman, Quebec, Canada, is one the 15 winners of the Canada Mortgage and Housing Corporation EQuilibrium Housing Demonstration Initiative (see Figure 1a). The primary goal of the house design was to be cost competitive with other pre-fabricated homes and to greatly reduce the home's energy needs compared to the Canadian building stock.

This house represents the first pre-fabricated home design with a customized building integrated photovoltaic-thermal (BIPV/T) roof linked to a hybrid thermal energy storage system [2].

Approximately forty percent of the gross heating demand is met by passive solar gains. Most of the auxiliary heating is provided by a ground source heat pump. The remainder is supplied by the thermal energy contribution of the roof integrated 2.84 kWe BIPV/T system, which can produce up to10 kWp of useful heat.

The thermal energy from the BIPV/T is delivered directly (open-loop air system) to a concrete slab in the basement, which serves as an active charge-passive discharge storage device, or to a domestic hot water (DHW) pre-heat tank through an air-water heat exchanger. The house's net yearly energy consumption is less than 50 kWh/m^2, one fifth of the average national energy consumption (see breakdown of power, cooling, heating and hot water consumption, Figure 1b).

Fig. 1 a) EcoTerra House and b) Energy Consumption with respect to national averages and Energy Production

Data has been recorded since early 2008 with over 100 temperature sensors distributed within the roof, slab and thermal zones. The PV generation, DHW, and heat pump electrical demand of the home have been monitored separately. This information permits the study of each design parameter and offers a unique opportunity to evaluate the present operation as well as to assess the impact of design adjustments in similar future home design projects.

2. Method

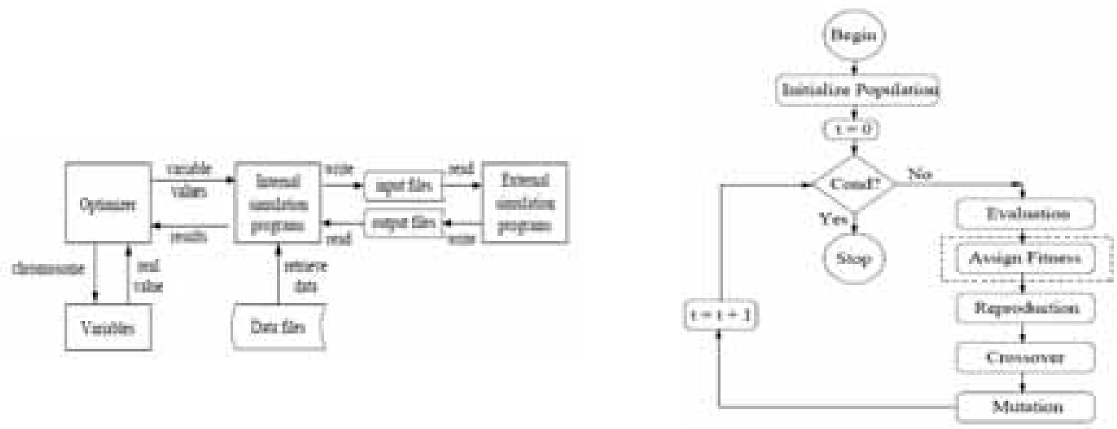
The design of net-zero energy solar buildings is highly dependent on local climate and site constraints. Any deviations in heating or cooling degree days, or the amount of solar exposure would require the optimization process to be repeated on a new design. Yet, restarting the entire optimization process is unnecessary as there will be similarities between many optimal design parameters in high performing designs. The relative importance of each design variable can be identified and used as an advantage in future optimization studies.

To complete the study, an energy model, database and an optimization algorithm were necessary (see Figure 2). The optimization algorithm, a hybrid deterministic-evolutionary algorithm, was developed using a LISP variant, Clojure [3]. SQLite was used as a database to store variable mappings and fitness evaluations.

The primary objective of the study was to minimize net annual electricity consumption using a single objective function. Although cost interactions could easily be handled in a multi-objective optimization, associating costs to various upgrades would be more susceptible to approximation, whereas electricity consumption has been monitored explicitly and can be predicted with a calibrated energy model. Time-of-use electricity billing and feed-in tariffs will change design variable interactions and are a subject of future research.

Design variables included in the optimization have been restricted to upgrades that could be done by a simple renovation and control strategies to reduce electricity consumed for heating and cooling loads (such as blind controls, free cooling and modifications to temperature schedules). Adding more PV was allowed if the type and efficiency remained the same (6% efficient amorphous silicon), but changes to the roof slope were prohibited. An exhaustive list of design variables used for the optimization and parameters for the EcoTerra design are presented in Table 1.

Fig. 2 a) Summary of Methodology [4] and b) Overview of Optimization Algorithm [5]



The following subsections elaborate more on the energy model, optimization algorithm, strategies to integrate deterministic searches into an evolutionary algorithm and methods to extract information regarding variable importance and interdependencies.

2.1. Energy Model

The objective of the study was to minimize the net-annual energy consumption of a near net zero energy home. Heating, cooling, fan loads, PV generation and lighting loads were simulated using EnergyPlus version 5.0 [6]. Heating and cooling loads were modelled implicitly using a heat pump with a seasonal coefficient of performance equal to three. A time step reduction from one hour to fifteen minutes was necessary to ensure peak loads were similar to existing heat pump products. Thermal comfort was ensured by actively controlling the air temperature with mechanical heating and cooling. Daylighting was used to offset dimmable lighting loads during occupancy, but at the expense of additional heat loss through window area. The average simulation time, per fitness evaluation, was approximately 4.5 minutes.

Occupant based loads such as lighting, appliance and DHW become increasingly more important as designs converge to NZE. To show the sensitivity of simulations to occupant behaviour, three profiles were created. The first profile corresponds with the national energy consumption average in Canada

[7]. The second profile represents a high energy user, 1.5 times the national average. The third profile represents the behavioural patterns of the current EcoTerra occupants, roughly one-half of the national average. Occupant loads result in internal gains in each of their respective heating zones.

The EcoTerra energy model is covered in greater detail by O'Brien et al. [2].

Table 1. Definition of Optimization Variables and Parameters used for EcoTerra Design

Design Variable	Units	Start	Stop	No. Steps	EcoTerra	Description
wall_ins	RSI	3.5	12	8	5.89	Thickness of Wall Insulation
ceil_ins	RSI	5.6	15	8	8.2	Thickness of Ceiling Insulation
base_ins	RSI	0	7	8	5.2	Thickness of Basement Wall Insulation
slab_ins	RSI	0	2.32	4	1.32	Thickness of Slab Insulation
ovr_south	cm	0	45	4	0	Width of Southern Window Overhangs
int_loads	--	1	4	1	1	Occupant load profile (low, avg, high)
pv_area	%	0	90	8	50	Percent of PV on roof
wwr_s	%	1	80	8	35	Window to Wall Ratio South (also N,E,W)
GT_s	--	1	4	1	4	Glazing type (also N,E,W)
set_heat	°C	18	25	4	22	Heating Setpoint (18 implies radiant floor)
set_cool	°C	25	28	4	26	Cooling Setpoint (28 implies NV)
FT	--	1	2	1	1	Window Framing Type (ex. Wood, Vinyl)
blind_irr	W/m^2	0	1000	4	500	Incident Solar Radiation for Blind Deployment
slab_th	cm	10	20	8	10	Concrete Slab Thickness (Thermal Storage)
vwall_th	cm	0	35	8	10	Vertical Slab Thickness (Thermal Storage)
zone_mix	L/s	0	400	4	400	Air Recirculation Rate
infil	ACH	0.025	0.179	8	0.047	Infiltration Rate (ACH under normal conditions)

2.2. Optimization Algorithm

A simple Genetic Algorithm (GA) was used as it allowed a large degree of flexibility with respect to deterministic search integration.

Although continuous design variables can be integrated into an evolutionary algorithm, all design variables were discretized for the following two reasons: 1) the resolution of any design variable is finite in application. For example, a designer can only specify spatial dimensions in discrete intervals so searching beyond this resolution would not be useful, 2) the use of discrete variables contracts the solution space and converges to optimums more quickly than continuous representations. Two disadvantages of discrete representation are that all variable ranges must be carefully chosen by the designer such that the intervals taken are small enough to sample all important interactions in the solution space, and that the number of parameters must in the binary representation set of 2^N,where N is the number of bits in the representation.

Although there are many freely available algorithms online, none offered the flexibility needed to integrate deterministic searches as per design specifications. In addition, added value was attributed to the ability to significantly reduce simulation time by parallelizing fitness evaluations using concurrent programming techniques. As well, population sizes and the number of generations needed were reduced by monitoring and managing population diversity at each generation.

The complete algorithm design is summarized in Table 2. A 54 grey-coded binary string was used to represent each genotype. Two types of recombination were used. The first shares data between two parents on a bit-by-bit basis using a uniform crossover and the second shares information on a variable-by-variable basis. Uniform recombination on a variable-by-variable basis should be included as it is unlikely that a binary string representing a sensitive design parameter will be transfered from a parent to a candidate child for a representation greater than 50 bits, which is an important aspect in convergence to optimal solutions. Diversity was measured by averaging the number of bits that any individual shared with the fittest member in the population (lowest annual net-electricity consumption). Diversity control becomes important when the population prematurely converges to a local minimum, or the average diversity in the population converges to one. The problem was fixed by injecting noise into the population by increasing mutation rates and decreasing tournament sizes. The concept of injecting noise to escape local minima is found in all optimization algorithms catered to navigating highly multi-modal solution spaces [5].

Table 2. Algorithm Parameter Setting and Design

Algorithm Parameter	**Setting**
Representation	54 bit binary string
Population Size	10
Recombination	50% bit-by-bit Uniform, 50% variable Uniform
Recombination Prob	100%
Mutation	Bit-by-bit mutation
Mutation Prob	1.5%
Elitism?	Yes, best individual
Survivor Selection	Best children only
Diversity Control	Mutation multiplier, shrinking tournament sizes

It is well known that Evolutionary Algorithms work well at finding good combinations of design parameters, but are unable to resolve local minima without a 'lucky' random effect [5]. Resolving local minima, or search intensification, is the expertise of a deterministic search. Deterministic searches were attempted: 1) after initial population fitness evaluation, 2) as a mutation operator and 3) after the termination criteria was reached.

A simple hill climbing algorithm was used for the deterministic search. The hill climbing search increments or decrements each design parameter such that the fitness function is reduced. The process was repeated across each design variable and variable setting until the fitness function could not be further reduced.

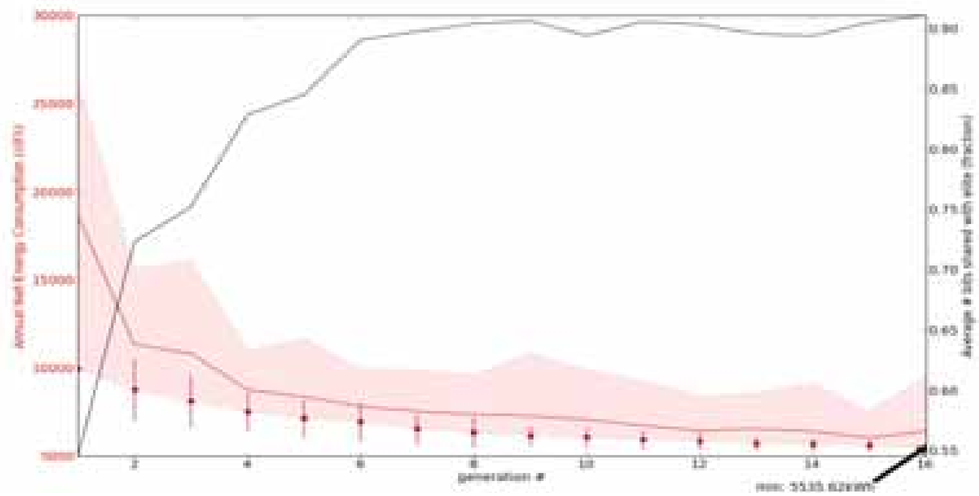
2.3. Data Mining and Extracting Variable Interdependencies

The most effective way to extract variable interdependencies at a defined energy consumption interval, was the mutual information (MI) shared between two design variables [8]. By definition, mutual information measures the interaction of two random variables. Since two weakly interacting variables have a low MI, the inverse of MI can be used as a distance measurement. These distances form a complicated higher dimensional structure. The hierarchy and relative distances between variables can be much better visualized using agglomerative clustering and a dendrogram (see Figure 5)

3. Results and Discussion

The simple GA with incremental diversity control, as described in section 2.2, was used as a baseline comparison (see Figure 3). The simulation was run 20 times and averaged. The red bars represent the standard deviation of the fittest individual at each generation across all runs, the solid red line represents the average fitness of population and the red shaded area represents the average fitness of the best and worst individual in the population across the 20 simulation runs. The solid black line is the average diversity of the population, a measure of the average number of bits shared with the fittest individual in that particular generation.

Fig. 3 Average of 20 runs of a simple GA



Of the three identified locations for deterministic search integration (section 2.2), only one was found to be of significance. Initiating a deterministic search at the end of the evolutionary algorithm successfully resolves designs to local minima, but required a substantial amount of computations (often as much as the original genetic algorithm) for a marginal improvement in fitness. This was primarily because the model had already maximized renewable energy generation and was trying to further reduce heating and cooling loads, but any improvements were devalued by the COP of the heat pump, that is, reduced by a factor of one third. This result enforces the idea that there is little benefit in finding the truly optimal design since the surrounding design space is nearly as good.

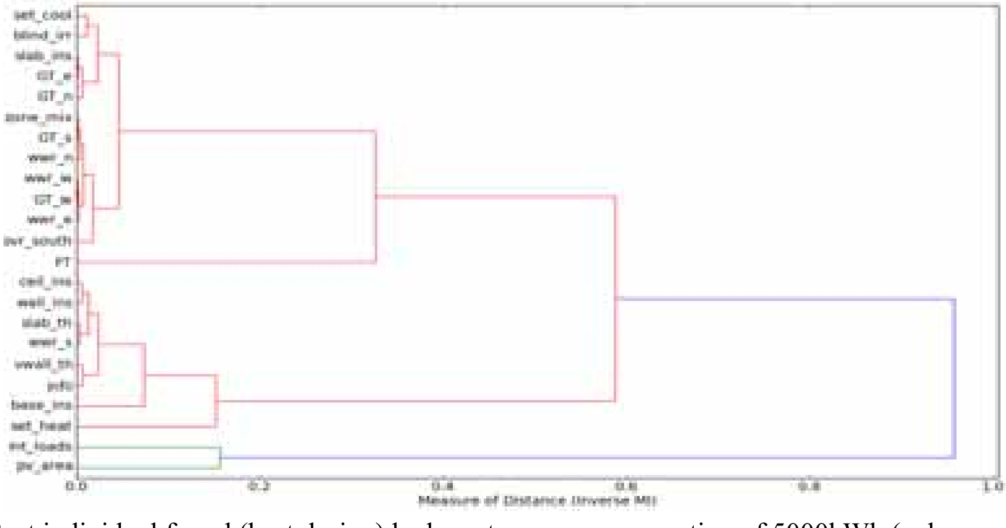
Stochastically incrementing or decrementing the setting of a design parameter as a mutation operator was inadequate to inject diversity into the population. As previously mentioned, the purpose of the mutation operator is to explore new territory in the solution space and if necessary, to intentionally randomize the population to escape from local minima. Randomly incrementing or decrementing the setting of a design parameter was simply not random enough to escape from local minima.

Searching sensitive design variables after the initialization of the population was the best way to integrate deterministic searches into a single hybrid deterministic-evolutionary approach. For instance, the fittest individuals always maximized the available roof area to offset unavoidable user loads. The relative importance of each design variable was decided on by randomly selecting a building design and calculating, variable-by-variable, the steepest descent to the best known building design. Variables that interacted weakly with the population were considered to be independent and could be locked after a brief search. Each design variable that was lockable contracted the size of the solution space significantly and expedited the search process. By using a hybrid deterministic-evolutionary algorithm, identification of optimal designs could be reproduced by deterministically searching the PV area and occupant load variables and as few as five evolutionary generations (see Figure 5).

Fig. 4 Average of 20 runs of hybrid GA

Variable interactions for all buildings with energy consumption of less than 6500kWh are shown in Figure 5. Design variables that form their own hierarchy could be highly sensitive to setting variations (will dramatically increase fitness), or could be very weakly interacting with all other design variables. Either situation indicates that variable is susceptible to a deterministic search. For example, the PV area and occupant behaviour interact weakly with other design variables, but exhibit some mutual interactions as PV is used to offset electrical loads. Sub-clusters identify variables that are better handled by the evolutionary algorithm due to variable interdependencies.

Fig. 5 Dendrogram based on agglomerative clustering of mutual information shared by design variables



The fittest individual found (best design) had a net energy consumption of 5000kWh (a decrease in energy intensity from 50kWh/m^2 to 20kWh/m^2). Important changes included adding PV to the remaining area of the roof and modifying the heating and cooling dead-band to the limits of ASHRAE thermal comfort, resulting in a combined net-electricity consumption reduction of 3500kWh [9].

Of the redesign opportunities identified, none required dramatic changes to the passive solar design of the house. For example, fine tuning the thermal storage (slab and basement wall), increasing the slab and wall insulation levels, increasing the southern window area to 50%, increasing air tightness to

0.5ACH at 50Pa from 0.8 ACH at 50Pa, cumulatively amounted only to a 500kWh of annual electricity savings. This indicates that the EcoTerra design was near a local optimum with regards to passive solar design.

The primary inhibitor to NZE is the lack of renewable energy generation. Doubling the PV efficiency from 6% to 12% and changing heating or cooling schedules to the limits of thermal comfort would reduce net-electricity consumption to 400 kWh. A secondary inhibitor was high appliance loads which were approximately 4000kWh/year. Further research on implementing conservation measures on appliance, lighting, and DHW loads and their effect occupant energy behaviour is recommended.

4. Conclusions

It is concluded that the importance of an evolutionary algorithm is to find good design variable combinations quickly and locate near optimal solutions. Deterministic searches are best used to initiating a steepest descent search on sensitive variables prior to the evolutionary search.

The optimization time required was reduced significantly by parallelizing energy simulations, deterministically searching weakly coupled design variables and monitoring diversity at each generation to avoid premature convergence.

The method used was unable to reach NZE without changing user behaviour patterns, adding more efficient PV, or increasing the roof slope to a more optimal slope. Many control strategies were identified to reduce heating and cooling loads, but more research is needed to identify opportunities to reduce occupant behaviour loads such as lighting, DHW, and plug-loads below Canadian national averages.

References

[1] W. O'Brien, A. K. Athienitis , S. Bucking, M. Doiron, T. Kesik, 2010, Applying a Design Methodology for a Net-Zero Energy House to Evaluate Design Processes and Tools, EuroSun 2010, Graz, Austria

[2] Y. Chen, A. K. Athienitis, K. E. Galal and, Y. Poissant, 2007, Design and Simulation for a Solar House with Building Integrated Photovoltaic-Thermal System and Thermal Storage, ISES Solar World Congress, Beijing, China, Vol. I, pp. 327-332

[3] R. Hickey, Clojure Homepage (2010), http://www.clojure.org/

[4] W. Wang, H. Rivard and, R. Zmeureanu, 2005, An object-oriented framework for simulation-based green building design optimization with genetic algorithms, Advanced Engineering Informatics, 19 (2005) 5-23

[5] A. Eiben, J. Smith, Introduction to Evolutionary Computing, Springer, 2003

[6] EnergyPlus Homepage, US Department of Energy Building Technologies Program (2010), http://apps1.eere.energy.gov/buildings/energyplus/

[7] Natural Resources Canada (NRCan), Energy use data handbook tables (Canada), Office of Energy Efficiency (OEE), Editor. 2008

[8] T. Cover, J. Tomas, Elements of Information Theory, Wiley, 2006

[9] ASHRAE Fundamentals 2009, ASHRAE, 2009