Distributed evolutionary algorithm for co-optimization of building and district systems for early community energy masterplanning

ABSTRACT

Buildings play a significant role in climate change mitigation. In North America, energy used to construct and operate buildings accounts for some 40% of total energy use, largely originating from fossil fuels [1]. The strategic reduction of these energy demands requires knowledge of potential upgrades prior to a building's construction. Furthermore, renewable energy generation integrated into buildings façades and district systems can improve the resiliency of community infrastructure. However, loads that are non-coincidental with on-site generation can cause load balancing issues. This imbalance is due to solar resources peaking at noon, whereas building loads typically peak in the morning and late afternoon or evenings. Ideally, the combination of on-site generation and localized storage could remedy such load balancing issues while reducing the need for fossil fuels. In response to these issues, this paper contributes a methodology that co-optimizes building designs and district technologies as an integrated community energy system. A distributed evolutionary algorithm is proposed that can navigate over 10^{154} potential community permutations. This is the first time in literature that a methodology demonstrates the co-optimization buildings and district energy systems to reduce energy use in buildings and balance loads at this scale. The proposed solution is reproducible and scalable for future

community masterplanning studies.
Keywords: evolutionary algorithm, energy planning, district energy, net-zero energy

1. Introduction

The energy vision of a community begins at the earliest design stage with a masterplan. Masterplans outline information such as building end-uses, footprint areas and floor plate shapes and it is increasingly common to include energy infrastructure. In order for engineers and architects to assist developers in transitioning to renewable energy targets, the search for integrated solutions must occur at the earliest opportunity where the greatest energy and economic saving opportunities exist. To support decision makers, this paper proposes an optimization methodology using an evolutionary algorithm that aids in identifying integrated design strategies. This problem is difficult as the reduction of energy use in communities requires a systems level approach where all design opportunities are considered as an interacting whole. Such decisions are made within a narrow time frame before the solidification of the final design. Consideration later in the decision process represents a missed opportunity to optimize energy performance. Communities that function using only renewable energy satisfy a strategic need to transition to clean energy supplies, better balance loads and mitigate the environmental impacts of the new and existing building stock.

An increasingly adopted building performance target is net-zero energy (NZE), or the reduction of building energy use sufficiently such that renewable energy generation can meet the remaining on-site energy demands during a typical meteorological year [2, 3]. The importance of NZE is that it is a measurable goal and a guiding principle in transitioning the building sector to renewable energy supplies. However, community energy systems offer several distinct advantages over building solutions in achieving NZE: (i) NZE is easier to achieve since energy deficiencies in larger buildings can be offset by on-site energy generation and storage, (ii) renewable energy resources can be better collected and stored, leading to higher solar utilization fractions [4], (iii) existing or emerging technologies can be integrated at building or district systems aiding the NZE goal without disrupting building operations, and (iv) the prioritization of load balancing between buildings rather than treating the grid as an infinite source and sink of electricity. There is public demand for community energy solutions due to the increased need for a robust electrical grid that better adapts to grid outages and extreme weather events. However, integrated design approaches are needed which both reduce energy use in buildings and balance loads using generation and storage technologies. This is because the reduction of energy use in buildings does not imply a decrease of peak loads and the presence of peaks may require centralized, fossil-fuel driven, peaking power plants. As a potential solution, community integrated modelling approaches must identify optimal outcomes which include energy use reductions and load balancing from a vast number of design possibilities.

Evolutionary Algorithms (EA) are a proven optimization method to solve large building simulation problems due to their ease of implementation and ability to navigate multiple objectives. EAs use pseudo-evolutionary algorithmic operations, such as mutations and crossovers, on representations of buildings to emulate the 'survival of the fittest' found in biological evolution [5]. Conceivably, a distributed model where the performance of buildings are intertwined with district energy systems could co-optimize both problems simultaneously. In literature, distributed EAs have been shown to solve high dimensional problems using divide-and-conquer mechanisms [6]. As such, a distributed EA model may be invaluable to facilitate decision-making to achieve net-zero energy at a community-scale.

Community energy systems could have a transformative effect for the public. In the near future, there may be an opportunity for a community of net-generating buildings to act like a smart grid node, which can be throttled depending on future demand. Net-generating communities could be a key technology in cities where policy makers must decide whether to refurbish aging generation infrastructure such as a nuclear fleet, or face public resistance to additional centralized generation near urban centers. To overcome these challenges and facilitate the extraction and use of optimal community design principles, this paper proposes an optimization methodology capable of navigating energy saving trade-offs between buildings and district energy systems for energy masterplanning.

2. Literature Review

This section reviews key previous work in support of the proposed optimization methodology. These topic include: optimization algorithms, district energy technologies and previous community integrated energy modelling case-studies. The focus is placed on cold-climate technologies, given that the case-study is located in southeastern Canada, as described in Section 3.1.

Distributed EAs (dEA) are an evolutionary approach where EA nodes share population information to achieve a larger optimization goal. In a detailed literature review, Gong et al. (2015) categorized dEA models as master-slave, island, cellular, pool, hierarchical and multi-agent [6]. The salient feature of an island GA is that the population of one generation is divided into several sub-populations, or 'islands', where genetic operations are performed on each sub-population separately and individual information is exchanged periodically between sub-populations, called 'migrations'. This approach is useful to decompose intractable optimization problems into smaller, easier to solve problems. For example, Ooka and Komamura (2009) utilized a dEA using the island model to solve a heating, ventilation and air-conditioning (HVAC) sizing, scheduling and control optimization problem [7]. Building optimizations problems are particularly challenging as they involve a computationally expensive fitness function. This is further complicated in community optimization problems as they involve many buildings requiring hours of simulation time. Several innovations have been made to mitigate fitness function time requirements in building models. Brownlee and Wright (2015) used radial basis function networks to reduce the number of calls to the building energy simulation [8]. Khanmirza et al. (2016) used a simplified thermal network with mechanical system controls optimized using a multi-objective genetic algorithm [9].

There is a growing body of research which evaluates the energy and economic performance of communities. Lu et al. (2014) proposed a multi-objective (exergy, life-cycle cost) optimization approach for a net-zero exergy district [10]. The proposed methodology required load profiles as inputs, meaning that energy saving trade-offs between buildings and district systems were not considered as part of the optimization study. Llanos et al. (2017) proposed a load estimation method for microgrid applications using self-organizing maps as opposed to first-principle models [11]. Bucking and Cotton (2015) proposed a preliminary modelling methodology focused on buildings in a community setting using net-energy consumption and life-cycle cost objective functions [12].

Community energy systems are emerging as a practical solution to better harvest renewable energy and potentially balance loads. Previous research has proven that EAs are a versatile tool to solve integrated building design problems. Based on the reviewed literature, this paper will propose an integrated modelling methodology to co-optimize buildings and district energy systems. This new optimization algorithm will show it is possible to solve this problem using a dEA approach with building sub-population migrations that are linked together using district infrastructure. A key contribution is a methodology that navigates simultaneous trade-offs between reducing energy demands of buildings and balancing community loads using centralized district equipment to assist community energy masterplanners.

3. Methodology

The methodology is described starting with energy models, district models and the proposed optimization algorithm. The case-study is presented first, as aspects of the methodology require it for background knowledge.

3.1. Case Study

Figure 1 shows the masterplan considered in this paper. Three building types are included: a multi-residential building, commercial office and townhouse archetypes. The case-study supports of a 70 acre NZE development located in Southwestern Ontario [13].

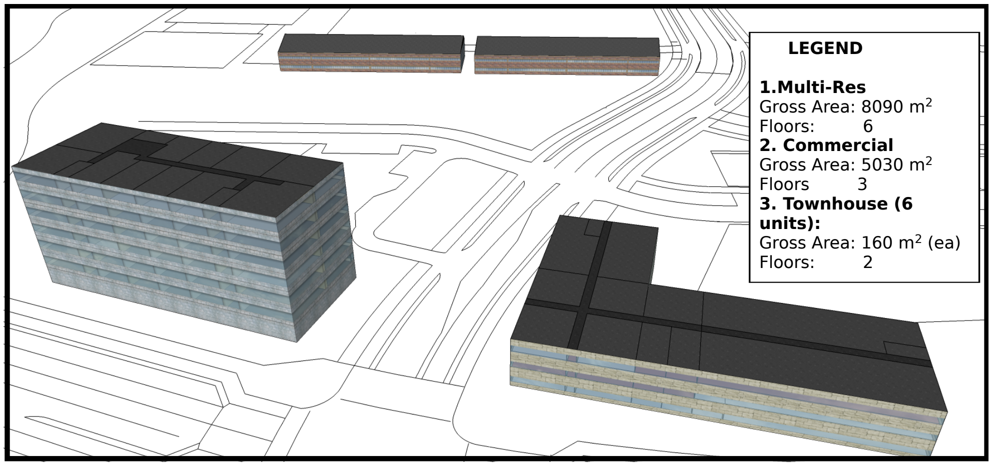

Figure 1: Masterplan and building renderings of phase one.

3.2. Energy Models

Energy models identify the mismatch in building energy use to on-site energy generation over an annual period. This section describes how building energy models and their resulting sub-hourly load profiles were developed for electricity and natural gas meters. Load profiles for each building were later combined and used for district systems analysis.

A combination of tools were used to create load profiles for various buildings types: (i) OpenStudio for drawing geometry and window positions [14]; (ii) WINDOWS for specifying glazing spectral properties [15]; (iii) THERM for specifying envelope properties [16]; (iv) EnergyPlus for energy performance simulation [17]; and (v) a custom scripting process for technology implementation and modelling best-practices. This is a first-principles approach which quantifies all heat and energy transfers in a building.

A programmatic approach assigned EnergyPlus objects and technologies required to achieve NZE in a cold-climate to each zone or envelope/glazing surface. The time savings were significant and less error-prone than user-driven text file manipulations. Renewable energy generation was considered on vertical and roof surfaces using BIPV. Additional PV generation infrastructure was also considered on ground mounted racks and parking structures.

The objective function for building EA nodes is given by equation 1 This equation is important as it quantifies a building achieves a renewable energy balance.

$$f(\mathbf{x}) = (E_{heat} + E_{cool} + E_{DHW} + E_{elec} - E_{PV})/A_{bldg} \tag{1}$$

where: $\mathbf{x} = (x_1, x_2, \cdots, x_N)^T$ is a design variable vector as described in Tables 1–2, $f(\mathbf{x})$ is the equivalent annual net-energy use intensity (EUI) of the building (kWh_{eq}/m^2), $E_{heat,cool}$ is the equivalent annual heating and cooling load of the building, E_{DHW} the equivalent domestic hot-water (DHW) energy use, E_{elec} is the gross annual electricity use in lighting, appliances and plug-loads (kWh), E_{PV} is the electricity generated by BIPV (kWh), and A_{bldg} is the gross building area (m^2). Note the unit 'kWh_{eq}' is short form for equivalent kilowatt hour and implies that several fuel types may be used (eg. electricity and natural gas). NZE is achieved when $f(\mathbf{x}) = 0$ implying an annual renewable energy balance and a building is net-positive energy if $f(\mathbf{x}) < 0$.

Table 1 shows the decision variables considered for the townhouse units shown in Figure 1. The solution space size for a single townhouse was 10^{21} permutations. This was calculated by multiplying the number of steps for each variable present in Table 1. Each of the six townhouses was allowed a unique set of decision variables.

Discrete variables describe key building design parameters. This is an appropriate choice as building materials and technologies are largely not available in

Table 1: Sample of Influential Model Variables for Townhouses

VARIABLE	DESCRIPTION	UNITS	START	STOP	STEPS
aspect	Aspect ratio (south facing width to depth ratio)	–	0.7	2.2	16
azi	Building orientation/azimuth	degrees	-45	45	32
wall_ins	Effective resistance of wall insulation	m^2K/W	3.5	13.0	8
ceil_ins	Effective resistance of ceiling insulation	m^2K/W	5.6	15.0	8
base_ins	Effective resistance of basement wall insulation	m^2K/W	0.0	7.0	8
slab_ins	Effective resistance of slab insulation	m^2K/W	0.0	2.3	4
infil	Natural infiltration rate	ACH	0.025	0.179	8
occ_loads	Occupant loads (percent of Canadian average consumption) [18]	% CAD_{avg}	50	80	8
ovr_south	Width of Southern Window Overhangs	m	0.00	0.45	4
pv_area	Percent of PV area on roof	%	0	90	8
pv_eff	PV efficiency	%	12	15	4
roof_slope	South facing roof/PV slope	degrees	30	47	8
wwr_s	Percent of window to wall ratio, south (also N,E,W)	%	5	80	8
GT_s	Glazing type, south (also N,E,W)	–	1	4	4
FT	Window Framing Types (1:Wood, 2:Vinyl)	–	1	2	2
slab_th	Concrete slab thickness	m	0.1	0.2	8
vwall_th	Concrete wall thickness (basement)	m	0.00	0.35	8
zone_mix	Air circulation rate between thermal zones	L/s	0	400	4

continuous ranges. For example, insulation thickness is often only available in 13mm (0.5in) increments. Both lower and upper ranges are determined from a mix of building codes, best practices and user expertise. If an optimization search converged to a lower or upper bound, this suggests that the range of the parameter should be expanded. Alternatively continuous variables could be used in the methodology if appropriate crossover and mutation operators were selected.

Table 2 shows the decision variables considered for the multi-residential and office building. District heating systems, if needed, provided pre-heated water for heating and hot-water systems. As a mechanical system option, heat pumps could lift or drop water temperatures using circulated water within a common loop in the office and multi-residential system. Water-source and variable refrigerant flow heat pumps were considered as potential mechanical solutions. It was assumed that the district system could supply heat at 15 °C during the winter and 30 °C during the summer months. This delivered heat was treated as a load that a district system must meet.

EnergyPlus results were reported using metered comma separated files and SQLite databases. Metered outputs for electrical and gas consumption were stored in a database entry for each model instantiation so that after a building's performance was evaluated, the annual performance and sub-hourly meter files could be accessed with a query. This eliminated the need for future resimulation. The combined meter files for several buildings is described in Section 3.3.

Table 2: Sample of Influential Model Variables for Office and Multi-Residential Building

Variable	Description	Units	Start	Stop	Steps
infil	Infiltration through walls: percentage compared to reference	%	75	100	8
lpd	Lighting 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
ceil_ins	Ceiling insulation	m^2K/W	3.52	11.40	16
wall_ins	Wall insulation	m^2K/W	3.52	10.57	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 (Commercial) [1: VAVelec. 2. FCU, 3: BaseBoard 4: VRF]	–	1	4	4
hvac_sys	HVAC system (MultiRes) [1: PTAC 2: BaseBoard 3: FCU 4: VRF 5: VRFdist 6. PTHP 7. WSHP 8. WSHP dist]	–	1	8	8
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
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
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

abbrev: Variable Air Volume (VAV), Fan-coil Unit (FCU), Variable Refrigeration Flow (VRF), Packaged Terminal AC (PTAC), Packaged Terminal Heat-Pump (PTHP), Water Source HP (WSHP)

3.3. District Energy Systems

The performance of district systems were evaluated using the sum of sub-hourly building energy meters as an input load profile. Specifically, district models used four meters as inputs: building district heating, gross electric demand, PV generation and natural gas consumption. Each load profile was previously stored in a database entry when a given building's performance was simulated as explained in Section 3.2. Figure 2 describes the district technologies considered.

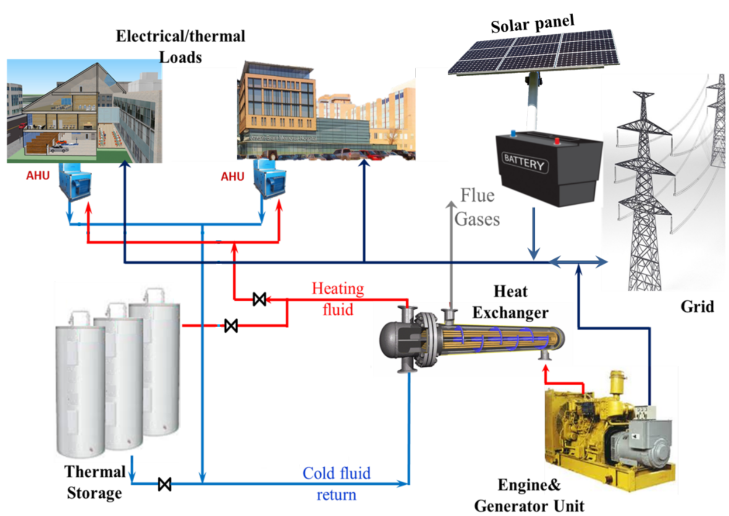

Figure 2: District energy model schematic. Lines connecting PV panels/battery and CHP to buildings indicate electricity transmission. Lines connecting CHP unit to air handling units (AHU) and storage indicate thermal energy transferred.

District energy systems allowed for the export and import of electricity to and from a smart grid. Electricity was generated using PV panels or a CHP system. Furthermore, electricity could be exported to the smart grid from buildings using BIPV, discharged from batteries or generated from district infrastructure.

The heat from CHP systems could be used immediately or stored for later usage via thermal storage. CHP units had a 30% electrical efficiency and a 60% thermal efficiency for a combined peak unit efficiency of 90%, as specified by the manufacturer [19]. As a mechanical system option, heat pumps could draw heat from a common district water loop to supplement heating demands.

Thermal storage and electrical batteries were modelled using an ideal energy bin approach. This allowed for the auto-sizing of storage components using an energy balance without requiring particular charge/discharge specifications. The thermal storage model assumed water was stored above freezing and below boiling points. The theoretical battery and thermal storage volume was determined based on peak annual utilization. A two-pipe loop was assumed to transport only pre-heated water. As presently implemented, the model does not consider the distance between buildings and district resources. Thus the results assume a masterplan with buildings in close proximity. Although the district system could be expanded to include chilled water using an absorption chiller and four-pipes, this was not considered due to the reliance on heat pumps in the energy models.

Electric batteries had a 95% draw and charge efficiency and were sized using the annual peak demand. Although these are purely theoretical constructs, the storage models provide an estimate of how well thermal and electrical storage can aid in regulating loads using energy balances. The modelling approach ensured that storage started and finished with a full charge to equalize technology comparisons.

District systems were configured and controlled using one of five strategies:

1. District heating demands (if existent) are met using a 80% efficient district

boiler

2. CHP was sized to meet instantaneous heating demands. CHP electricity was used instantly. No thermal/electrical storage.

3. CHP was controlled to meet seasonal thermal demands by using thermal storage. CHP was operated to shed peak electrical loads using the method shown in Figure 3. No electric batteries.

4. CHP was sized to meet instantaneous heating demands. CHP and PV electricity was stored in batteries. Stored electricity was used if there was demand in the future timestep.

5. CHP was sized to meet instantaneous heating demands. CHP and PV electricity was stored in batteries. Batteries are used to shed peak loads using the method shown in Figure 3.

Figure 3 shows a load duration curve for balancing electrical loads as used for district control options 3 and 5. Typically, load duration curves determine how often peak loads occur during a specified period. In this paper, load duration curves determined how much on-site generation could be stored and strategically used to shed peaks at an optimal power level over a given year, see Figure 3. Note, the load duration curve was unique for each community permutation. An iterative solution was required to choose an exact balance point as load duration curves ignore time series information needed to size batteries and thermal storage.

The objective function used to determine community performance was the average power of net-electricity and natural gas use in equivalent units plus the

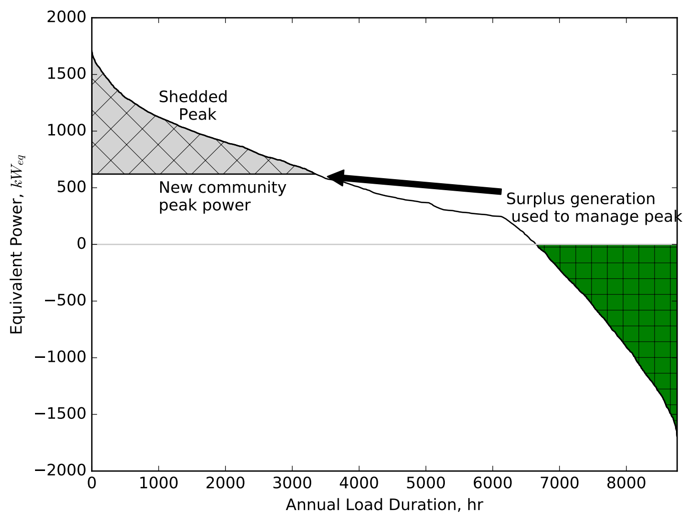

Figure 3: Peak Load Management Controller for District Modes 3 and 5. Negative power implies net-generation.

square root of mean square error, see equation 2.

$$g(\mathbf{x}) = P_{avg} + \sqrt{\frac{\sum(P_i - P_{avg})^2}{N}} \tag{2}$$

where: $g(\mathbf{x})$ is the community objective function (kW_{eq}), P_{avg} is the community average equivalent power (kW_{eq}), P_i is the instantaneous community equivalent power (kW_{eq}), and N is the number of load profile timesteps.

Adding the average equivalent power ensures that communities with the lowest average power are preferred. A sum of squares penalizes peaks with the square of their distance from the average and instantaneous signal equally discerning positive and negative distances from the average signal. This added term is equivalent to adding a standard deviation of signal to the community average power.

The community objective function, shown in equation 2, is an important deviation from the annual EUI objective function used for buildings shown in equation 1. If an annual energy usage objective function was used to rank district system performance, the optimization results at the building and community scales would be identical, ignoring the load balancing challenges of the problem. Therefore, the goal of the community algorithm was to effectively balance peak loads, whereas the building algorithm's goal was to reduce annual energy consumption. The combination of these two objective functions was key to identifying optimal community solutions. However, objective function scaling was required to ensure that high performing buildings at the community scale also appeared to perform well at the building level, see Section 3.4.2.

3.4. Optimization Algorithm

This section describes the representation and workings details of the dEA proposed in this paper. A distributed evolutionary algorithm was developed to solve a building and district co-optimization problem. First, the structure of the EA nodes and optimization algorithm parameters are described. Later, the synchronization of EA islands into a centralized community EA algorithm is described. Figure 4 shows how the problem is solved using several distributed computing platforms and how data synchronization is achieved. Based on the categorizations of Gong et al. (2015), the proposed algorithm is a hybrid master-slave model with population migrations via islands as individuals migrate to and from a centralized repository [6].

Figure 4 describes how information transfer was handled between building and community EA nodes. For simplicity, assume that each building EA node operates on an independent computer or server. Alternatively, a large central cluster could solve the problem on a single computing platform. At each algo-

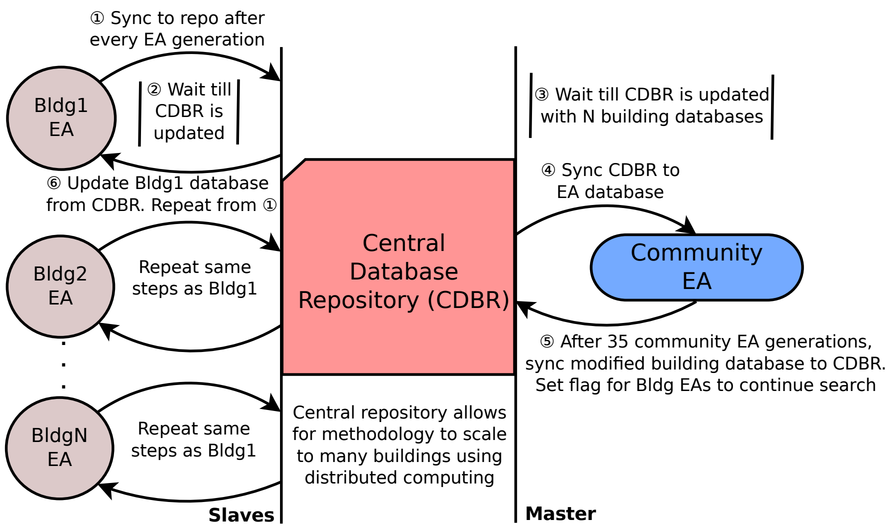

Figure 4: Database Synchronization between Building and Community EAs

rithm iteration, the EA node synchronizes with a central repository where building load profile databases are shared. Once all building nodes have completed and uploaded their results, the community EA is initialized. After the community EA has completed, modified databases are resynchronized with the central repository and a completion flag is set. Building EA nodes identified that a new database is available, synchronize with the updated information and repeat the process until the problem has converged. The solution is a hybrid method as the algorithm conducts fitness evaluations both in the master (community) and slave (building) nodes deviating from a pure master-slave model where fitness evaluations are conducted by slave nodes [6]. Additionally, populations of individuals are migrated from building EA nodes to the master community node for EA operations as per the island model. A description of how building and community EA nodes are configured is described in the following sections.

3.4.1. *Building EA Nodes*

Building design parameters were represented using a binary string, see below. Parameters in this representation refer to those described in Tables 1–2.

$$\overbrace{\text{“}\underbrace{010}_{\text{aspect}}\ \underbrace{110}_{\text{wall\_ins}}\ \underbrace{000}_{\text{ceil\_ins}}\ \ldots\text{”}}^{\text{Binary Representation}} \rightarrow \overbrace{(1.3, 8.93, 5.60, \ldots)}^{\text{Vector Representation}} \tag{3}$$

Table 3 highlights key configuration parameters of the building EA nodes used in the case-study. Innovations such as a differential mutation operator are described in a previous contribution [20].

Table 3: Summary of Islanded EA Configuration for Building Nodes

Algorithm Parameter	Setting
Representation	70 bit (townhouse), 79 bit (office), 83 bit (multi-res) grey-coded binary string
Solution Space Size	1.2×10^{21} (townhouse), 6.0×10^{23} (office), 9.7×10^{24} (multi-res) unique designs
Objective 1	Net Energy Use Intensity (kWh_{eq}/m^2), see equation 1
Population Size	10
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	Tournament Selection
Elitism?	Yes
No. of Children	10
Survivor Selection	Best parents and children, $(\mu + \lambda)$
Diversity Control	Yes, increased probability of mutation occurring, see [20]

Figure 5 describes how the building EA functions for a single generation. A set of binary genomes, or simplified representations of building designs are initialized by randomly creating the specified population size forming the initial population. The fitness of each individual is evaluated using an energy simulation program. This population becomes the parent population as it enters the evolutionary cycle. Parent selection chooses genomes for variation operators such as recombination and mutations. The fitness of new individuals, called children, is evaluated. The EA node then waits to synchronize with other buildings in the community. Based on how well the building performs as part of the community district system, the fitness of each individual is scaled using the method described in the next section. Scaled building performance indicators are used in survivor selection to determine which genomes from the old and new population will survive in the next generation. The process is repeated, synchronizing with the community node every iteration until a termination criterion is reached, typically a set number of evolutionary cycles or generations.

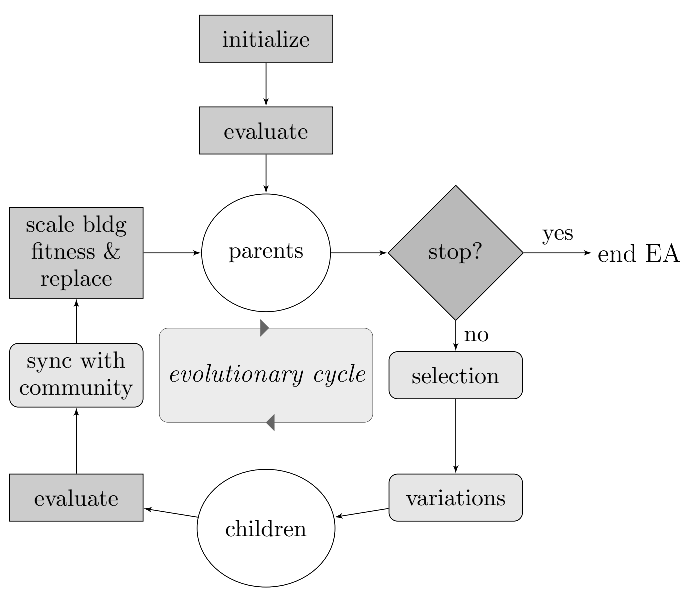

Figure 5: Distributed Building Evolutionary Algorithm Node with Data Synchronization

3.4.2. Community EA

Community details were represented using vectors with indices to a particular building database entry. This simplified community representations allowed for the querying of building load profile data from a database without energy model resimulation. Thus, a combinatorial approach represented buildings within the community EA using the following representation:

$$\text{“}\overbrace{\underbrace{\#20}_{\text{bldg1}}\ \underbrace{\#100}_{\text{bldg2}}\ \ldots\ \underbrace{\#50}_{\text{bldgN}}\ \underbrace{1}_{\text{district\_mode}}}^{\text{Vector Representation}}\text{”} \tag{4}$$

The identifiers shown in the representation are linked to the building parameters using the primary key from the simulation database. Since there are seven buildings, there are seven unique databases where energy simulation results are stored. The district mode variable represents which combination of technologies were utilized as described in Section 3.3. Results from community simulations are stored in a separate database.

Figure 6 shows the community EA with data synchronization from the islanded building EAs. First, data is synchronized from building EA islands. The population is initialized by randomly generating building representations from the synchronized database. Individual building designs are randomly selected from the database using building indices. Only the buildings with performance evaluated within building EAs are considered in the community EA. These individuals become the parent population entering the evolutionary cycle. Parent are selected from community representations for variation operators such as recombination and mutations. The fitness of new individuals are evaluated using the average community power load performance indicator as described in equation 2. This loop is repeated for 50 iterations to ensure convergence before synchronizing back with building EA populations.

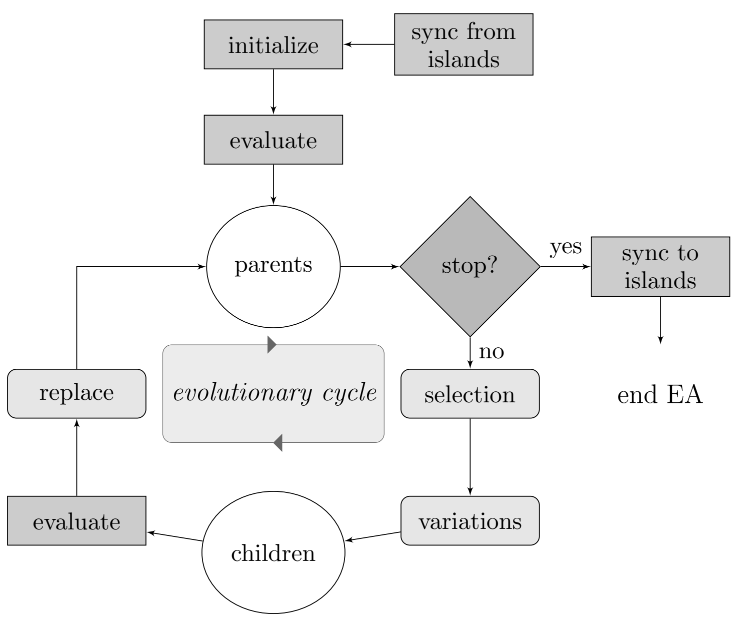

Figure 6: Community Evolutionary Algorithm with Data Synchronization

After completion, the scaling factors were updated and then populations of buildings are migrated back to islanded EA nodes. Scaling factors ensured that poor performing buildings at the community node are less likely to be reselected within the following generations at the building EA nodes. Since community permutations with low average power were desirable, the EUIs of corresponding representations were scaled with a factor of one. Poorly performing buildings in community permutations have EUIs scaled up by a factor of 5. In other words, building permutations in high performing communities continue to use unscaled EUIs whereas poorly performing buildings have performance indicators that are penalized. The selection of the upper-limit for scaling factors is arbitrary and depends on how one wishes to penalize poor community performance. All other intermediary building EUIs have scaling factors which are a linear interpolation between the upper and lower limits. Building EUIs are scaled starting from the poorest performance community permutations and finishing on the best performance permutation so that the best performing solutions are preferred. Also note, buildings that have not been evaluated in the community EA are assigned an arbitrarily high fitness level so they are not selected to survive in later generations unless they are proven to perform well within a community permutation.

Table 4 highlights key configuration parameters of the community EA configuration used in the case-study.

Table 4: Summary EA Configuration for Community Node

Algorithm Parameter	Setting
Representation	Vector with database indices
Solution Space Size	6.76×10^{154} unique designs
Objective 1	Community average power with standard deviation (kW_{eq}), see equation 2
Population Size	10
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	Tournament Selection
Elitism?	Yes
No. of Children	10
Survivor Selection	Best parents and children, $(\mu + \lambda)$
Diversity Control	Yes, increased probability of mutation occurring, see [20]

4. Results and Discussion

4.1. Algorithm Convergence Characteristics

Figure 7 shows the convergence characteristics of repeated community optimization runs. This figure shows that the community fitness function did repeatedly converge for each of the optimization trials. Each community optimization study required 80 hours, or 1.6 hours per community iteration, for convergence to occur. This required simultaneously solving seven building optimization problems and one community optimization problem, by combining results from distributed islands. To achieve convergence, roughly 50 iterations between building EA nodes and the community EA were required. The main time limitation originates from the energy simulation requirements of the largest buildings in the community. Figure 7 also shows the impact of co-optimizing building and district energy systems on average community power. A box-whisker plot shows the limits, quantiles and average fitness function for five repeated optimization runs. Superimposed on the box-whisker is a convergence or bean plot which shows the relative frequencies of a particular community energy system's performance. Displayed in the convergence plot are the pre-convergence artifacts originating from running repeated community iterations before synchronizing with islands. This occurred because globally optimal solutions were not identifiable until building EUI was sufficiently reduced to lower the community average power.

Conducting repeated optimization runs is necessary to claim that consistent convergence to global optimums was achieved. Figure 7 shows that globally optimal solutions were identified for each of the five optimization runs conducted. A statistical power test suggests, with a high degree of confidence, that an optimal

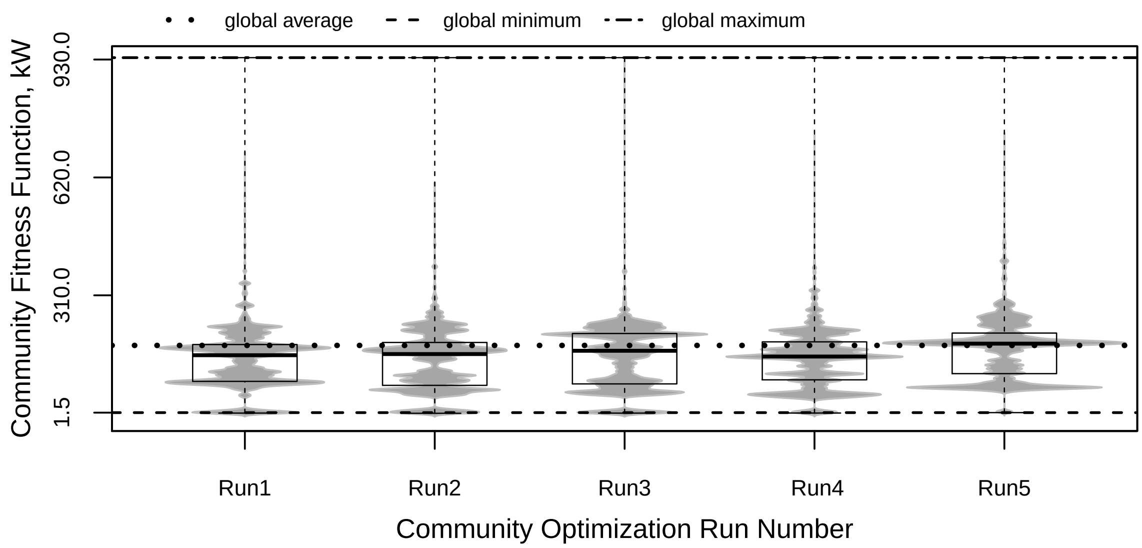

Figure 7: Comparison of five optimization runs and combined convergence characteristics

solution can be reached on repeat searches. Using effective storage and controls, the average community power was reduced to nearly zero for every community optimization run.

The community optimization algorithm identifies different solutions from a building optimization study conducted in isolation. Figure 8 compares results of two different optimization studies: the office building using EUI as a performance indicator and the other being the office building as part of the community energy system. Figure 8 shows that the results of optimizing a building in isolation (black dotted line) differs from how the building interacts as a load in the community (blue solid line) during integrated optimization studies. As shown, the community integrated optimization run for the office building converges to a sub-optimal 'building only' solution compared to the community-integrated optimization run. This result implies that building performance could differ by as much as 25 kWh/m^2 between sub-optimized and globally optimized community solutions for a particular building.

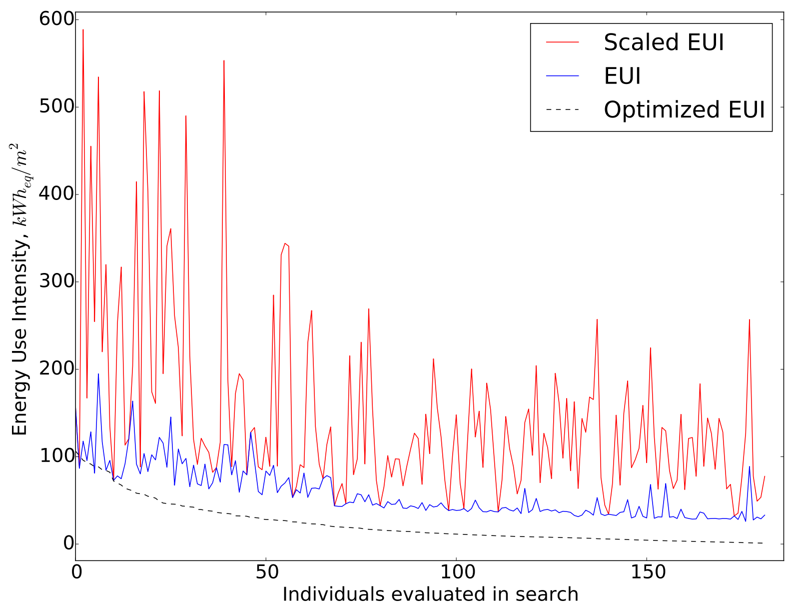

Figure 8: Comparison of Optimization Results for Commercial Office: Isolated Optimization versus Community Integrated Optimization

The search algorithm discovered several interesting community design strategies. First, building orientations were diversified, deviating from an exact south facing orientation as suggested by single building optimization solution sets. This aided in diversifying both heating/cooling loads and when BIPV peak generation occurred. For district infrastructure and control, both modes 4 and 5 were dominant in optimized community-integrated solutions, implying that battery storage is an essential piece in balancing loads between buildings. Clearly, electrical storage, whether in the form of stand-alone batteries or electric vehicles, plays a pivotal role in balancing community load profiles. Thermal storage mode 3 offered several scenarios that reduced the community fitness function to a minimum of 15 kW_{eq} representing a low-cost solution to balancing loads without using more costly battery storage.

5. Conclusion and Future Work

This paper proposed a distributed evolutionary algorithm which helps communities achieve NZE while mitigating peaks using a district energy system. A key outcome of the paper is recommending technological solutions which aid in flattening and reducing district loads to a near net-zero point for a cold-climate case-study. This is a departure from previous research where design changes in a building were not of consequence to district system design.

The contribution of this paper is a methodology that demonstrates how building and district energy systems can be coevolved using an islanded and master-slave model dEA. Several important decisions that made this problem solvable were: (i) using energy use intensity as an objective function for buildings, (ii) proposal of a community fitness function based on sub-hourly profiles using average power plus one standard deviation of signal, and (iii) evaluating shared mechanical, generation and storage technologies between buildings. The results suggest that building energy saving measures and district systems can significantly reduce consumption while better managing peak loads.

This complex building optimization problem was solved using sub-population sizes of 10 (for each of the seven buildings) and island population sizes of 10. A small population size is necessary as each fitness evaluation requires 20 minutes per individual. This raises the question as to how this large and complex problem is solvable in the first place? We suggest that this is most likely due to building optimization problems strongly relying on sparse matrices to solve energy balances between surfaces over sub-hourly timesteps [21]. Although the problem is non-linear at its root, having quasi-linear properties likely aids in yielding solutions using small population sizes. Future work will determine how the algorithm scales with additional buildings being added to the community energy balance.

Additional future work can be summarized as follows: (i) add life-cycle cost as an additional objective function, (ii) conduct an uncertainty and sensitivity analyses on the energy model to identify significant model parameters, (iii) add additional district system configurations such as geothermal borehole storage and ice-storage, (iv) consider the proximity of buildings to district resources, (v) incorporate measured weather data to evaluate the robustness of proposed community solutions, (vi) utilize the proposed optimization methodology to develop community design archetypes and (vii) additional implementation of predictive control strategies.

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