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What Density for Net Zero Energy?: A Simulation-based Multi-objective Optimization of High-rise Residential Precincts in a Tropical Climate

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Abstract

In land-scarce urban contexts like Singapore, achieving on-site net zero energy design is challenging due to limited space for photovoltaic (PV) installation and intense pressure to develop sites to maximize density. This study puts forward methods to identify an optimum (highest possible) density for net zero energy (NZE) residential precincts. A parametric model integrates building energy use and on-site renewable energy generation, with two optimization methods suggesting a gross plot ratio of 2.5 to 2.9 as the maximum viable density for net and near zero energy in Singapore. Results inform city planning for NZE districts, aiding policymakers, planners, developers and architects in identifying target densities and building layouts for energy-efficient urban design.

Introduction

The design of net zero energy (NZE) buildings, especially in developing countries, represents one of the most effective means of achieving urgent building emissions mitigation in the next two decades. The 2022 IPCC report indicates that urban GHG emissions account for a growing share of the global total. While currently measured at 29 GtCO2-eq or 50% of the global emissions, projections indicate that urban emissions will increase to between 34-40 GtCO2e (IPCC, 2022) with an estimated 68% of the global population expected to live in cities by 2050 (UN DESA, 2018). This growing urban population, driven by developing countries, will drive the demand for the construction industry to meet increasing housing needs. The IPCC has indicated that up to 61% of global building emissions can be mitigated by avoiding demand from materials and energy, improving energy efficiency, and renewable energy provision.

NZE buildings are most simply defined as passive or highly energy-efficient buildings where energy consumption is offset by renewable energy generation over a given measurement period. As operational energy consumption accounts for the majority of a building's carbon emissions over its lifespan, achieving NZE buildings has become a high priority for decarbonizing the global building stock. While NZE buildings may offset their energy consumption with on-site or off-site renewable energy, this paper addresses on-site energy generation exclusively. Buildings or districts that generate more renewable energy than they consume are referred to as net positive energy or simply 'net positive' in this paper. Additional definitions of NZE buildings can be found in Marszal et al. (2011).

This paper presents methods of design optimization for NZE housing precincts in a tropical climatic zone. This is a promising research area due to i) its under-representation in current literature and ii) its significant potential for carbon emission reduction. In a survey of over 300 certified Zero Energy Buildings (ZEB) worldwide, Feng et al. (2019) identified only 34 in tropical climatic zones, of which only two were residential buildings. Furthermore, the residential sector accounts for 65% of primary energy consumption globally, according to Harkouss, Fardoun and Biwole, (2018). As many large developing cities fall in tropical climatic zones, and "the largest share of the mitigation potential of new buildings is available in developing countries," (IPCC, 2022), research that elucidates pathways to NZE housing in the tropics is highly relevant to global decarbonization.

Singapore is chosen as the case study for this paper, as a climatic proxy for other developing countries in Southeast Asia (SE Asia) and an example of efficiently planned urbanization. Singapore is a land-scare country with a population of 5+ million residents on 700 km^2, at 1.3 degrees latitude north of the equator in the tropical climatic zone of the Asia-Pacific (data.gov.sg, 2023). Its growing demand for housing is met by the construction of high-rise high-density housing, provided in large part by the national public housing agency, the Housing Development Board (HDB).

Due to the scarcity of available land for development, Singapore's housing is developed at high densities and thus faces significant challenges in balancing energy consumption with on-site renewable energy generation for NZE buildings. While particularly pronounced in Singapore, the challenge of achieving dense NZE housing in the tropics is relevant to cities throughout SE Asia and beyond. Although several research studies have been dedicated to energy-efficient and NZE building design through architectural design optimization, only recently have scholars' interest grown in applying these design optimization methods to achieve energy balance at the urban scale. For instance, Wortmann et al (2020) explored the trade-off between urban density and monthly energy balance, specifically evaluating the net zero energy concept within a hypothetical mixed-use neighborhood in Shanghai, China. In another study, Lan et al (2019) optimized 'H' shaped high-rise residential buildings in Singapore with a focus on thermal and visual comforts, energy efficiency, and Life Cycle Cost. They reported that a 25-storey building with photovoltaic (PV) panels on all its façade could maintain an energy balance up to 19th storey, with 3884 m2 of installed PV area. Taking on a much larger scale, Natanian (2023) developed methods to optimize mixed-use configurations for an urban district to achieve net-zero emissions.

Given the challenges of designing dense NZE housing in the tropics, this paper presents methods to optimize density while balancing energy utilization and energy generation in a model of a residential precinct. Precincts in Singaporean public housing generally includes 400-800 apartments and around 1,500 residents in multiple buildings, referred to as 'blocks' on a single site (Yuen, 2009). The precinct scale is advantageous for finding NZE solutions in comparison to individual building optimization in that it permits wider investigation of site layout parameters and development density. The presented model evaluates energy balance using two metrics: i) site energy use/consumption (kWh), and ii) site renewable energy generation (kWh). Density is measured as Gross Plot Ratio (GPR) which is the ratio of Gross Floor Area (GFA) to the site area.

The study asks if an optimal (highest possible) density for NZE housing precincts can be identified through simultaneous optimization of building energy consumption and on-site renewable energy generation, in a model that integrates prevailing development controls. This question assumes that a limited site area for renewable energy generation will constrain NZE housing development from exceeding certain density levels. The inclusion of Building Integrated Photovoltaics (BIPV) (i.e., cladding the building façade in the model), however, complicates this question as the increasing surface area of the building increases proportionally the total renewable energy produced on-site.

This paper is structured in four sections. The following section provides a detailed overview of the study methodology, including the set-up of the precinct parametric model, building performance simulation, and optimization workflows. Subsequently, the results of two optimization experiments are discussed, along with an examination of study limitations and proposed avenues for future work. The conclusion section summarizes the key conclusions drawn from the study.

Model Setup and Simulation

To achieve net zero (or near zero) energy consumption in high-rise residential buildings while optimizing for density, a parametric model of a residential precinct was developed within the Rhino/Grasshopper software environment (McNeel & Associates, 2019) with a simulation-based design optimization workflow (Figure 1). Two plugins were used, ClimateStudio (Solemma, 2020) and Opossum (Wortmann, 2017), for building performance simulation and optimization workflows, respectively. The three distinct workflows, parametric modelling, building performance simulation, and optimization, are described in separate sections below.

Parametric Modelling

The NZE precinct model comprises three interconnected components: i) a precinct layout algorithm which determines the distribution of residential buildings within the given site, ii) a building generation algorithm that generates residential buildings with geometric and building performance (i.e., energy model) parameters, and iii) a PV layout algorithm which generates on-site solar panels for renewable energy analysis.

Precinct Parameters

In the precinct scale model, three variable parameters are defined, i) gross plot ratio (GPR), ii) building span, and iii) parcel storey scale (PSS).

Gross plot ratio (GPR, defined above) acts as a variable parameter in the model, governing the density of generated housing blocks in aggregate, while accounting for prevailing development controls. Building span is defined as a variable parameter controlling the length of the building floor plan. The model, taking these parameters as inputs, calculates height based on prevailing development controls in Singapore. For example, following Singapore's Urban Redevelopment Authority (URA) guidelines, a GPR of 2.8 allows for a maximum of 36 storeys, while a building span of 130m limits the maximum height at 12 storeys (URA, 2017). Even if a high target GPR is defined for the model, this may not be achieved if, for example, the building span is too large to prevent higher buildings.

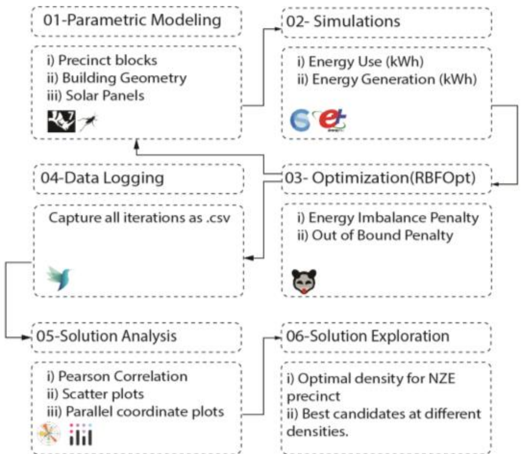

Figure 1 Model framework showing dataflow across modules.

The parcel storey scale (PSS) parameter controls the allocation of storeys among various buildings in the precinct in order to achieve the GPR target. PSS is defined in the model with three discrete values i) lenient, ii) moderate and iii) stringent. A stringent PSS ensures that new buildings are deployed only after the previous building reaches its maximum allowable storeys, whereas a lenient PSS distributes an equal number of storeys to all buildings instantiated in the precinct. The Grid Size and Grid Rotation parameters are constants that control the initial building orientation.

Building Geometry

In the building generation algorithm nine design parameters control building geometry: i) orientation, ii) window to wall ratio (WWR), iii) floor height, iv) design configuration, v) shading type, and vi) shading depth vii) exterior wall thickness (wTk), viii) wall insulation thickness (wInTk), ix) roof thickness (rTk). The building generation algorithm produces an 'H'-shaped footprint, typical of contemporary public housing in Singapore, with the two wings of residential units positioned externally and the service core at its center (Figure 2). The floorplan has a naturally ventilated central corridor and can be extended linearly along the corridor axis. Each residential unit is modelled as a series of simple six-sided cells measuring 6 meters in depth and 3 meters in width. The cells represent the functional spaces of a residential unit, including the living and dining room, kitchen, bedrooms, and bathrooms. The dimensions and arrangement of these cells follow a widely used volumetric construction method in Singapore, known as Prefabricated Prefinished Volumetric Construction (PPVC) (Hwang, Shan and Looi, 2018). Four PPVC cells together create a three-room HDB flat with an area of 72 m^2.

The orientation parameter rotates each building at 15-degree increments. The floor height parameter determines the height of PPVC cells. The WWR parameter controls the glazing ratio over the wall surface of the external facade for all residential units in the precinct. The design configuration parameter translates PPVC horizontally away from the central corridor, resulting in five design configurations shown in Figure 2. Shading type and shading depth parameters control the deployment and depth of shading elements on the block facades. Three façade shading types are studied: absence of façade shading, a simple overhang at each window, and a four-sided projection at each window.

Non-geometric Parameters

The non-geometric model parameters encompass both the building's thermophysical properties as well as its active systems. The three thermo-physical properties included in this study are i) wall solar absorptance (wSA), ii) roof solar absorptance (rSA), and iii) glazing type (Glz). The two model parameters controlling active systems are cooling setpoint (cSp) and cooling coefficient of performance (COP). The value range of each of the non-geometric parameters is given in Table 1.

Solar Panel Generation

The parametric model also generates three types of photovoltaic (PV) panels: i) rooftop PV on each building, ii) Building Integrated Photovoltaics (BIPV) on all façade walls around windows, iii) on-site PV in available areas at ground level. BIPV are modelled as a cladding system applied vertically at the building facade, with the effective BIPV area evaluated as the difference between façade area and window area. On-site rack-mounted solar PV, with access corridors, is generated for all regions within the site boundary except for an offset area from the site boundary and a boundary zone around each building footprint (lavender geometries in Figure 2). While no variable parameters control the generation of the PV panels, their configuration adapts as the site and building models are modified. The efficiency of all PV panels was defines as 16%, in reference to Singapore's Building Construction Authority technology roadmap (BCA, 2018).

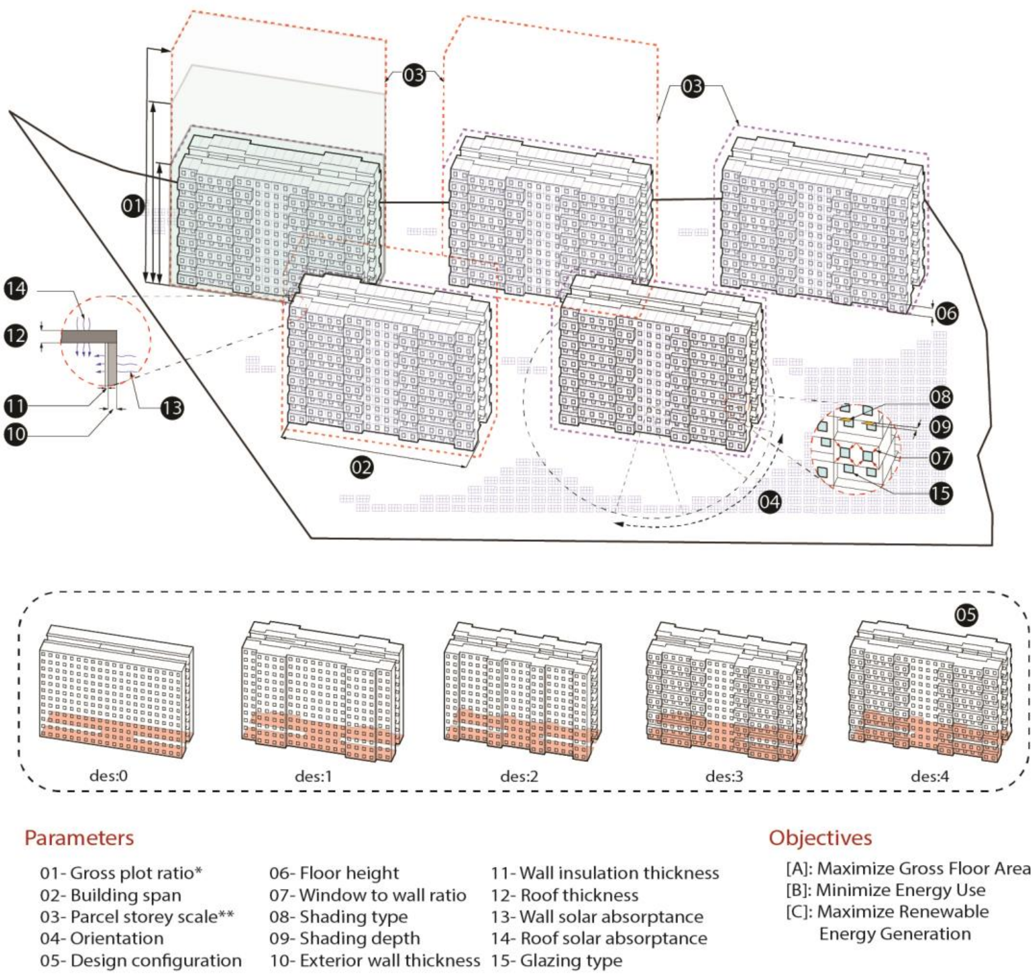

Figure 2: Diagram of model parameters and objectives.

Table 1 List of input parameters and their value ranges

Category	Parameters		Variable/Constant	Value Range
Site	P01	Gross Plot Ratio (GPR)	Continuous float	1.4 to 5
	P02	Building Span (Num Block)	Continuous	36m to 120m [3 to 10]
	P03	Parcel Storey Scale (PSS)	Discrete	[0, 1, 2]
	P04	Grid Rotation	Constant	160
	P05	Grid Size	Constant	5
Building	P06	Orientation	Discrete	[0, 15, 30 … 150,165]
Geometry	P07	Design configuration	Discrete	[0, 1, 2, 3, 4]
	P08	Floor height	Continuous float	2.8 To 3.6
	P09	Window to Wall Ratio (WWR)	Discrete	[30%, 40%.... 70%]
	P10	Shading type	Discrete	0 & 1
	P11	Shading depth	Continuous float	0.0 to 1.0
	P12	Exterior Wall Thickness (wTk)	Discrete	[0.2, 0.25, 0.3]
	P13	Wall Insulation Thickness (wInTk)	Discrete	[0, 0.025, 0.5]
	P14	Roof Thickness (rTk)	Discrete	[0.2, 0.25, 0.3]
Non-geometric	P15	Wall Solar Absorptance (wSA)	Discrete	[30%, 50%, 70%]
	P16	Roof Solar Absorptance (rSA)	Discrete	[30%, 50%, 70%]
	P17	Glazing type (Glz)	Discrete	[0,1,2,3,4]
	P18	Cooling Setpoint (cSp)	Constant	26
	P19	Cooling Coefficient of Performance (COP)	Constant	3.58

Simulation

A multi-zone thermal model is generated for all housing blocks and analyzed for its energy performance utilizing EnergyPlus within ClimateStudio. Each residential unit is defined as a separate thermal zone, controlled by a single cooling, lighting, equipment and occupancy schedule, as illustrated in Figure 3. The walls between the thermal zones were not designated as adiabatic. Each floor has only one core thermal zone, which takes a separate non-conditioned zone template. These core zones contribute to the lighting and equipment loads. Furthermore, open balcony-style corridors are defined as shading elements instead of thermal zones. Model-generated buildings were not explicitly designated as shading elements within the energy simulation due to software limitations. Impact on the study results due to changes in these shading rules should be small to negligible as comparative testing showed difference to be less than ± 0.05 kWh/m^2/a. Simulation is conducted for a 4.6-hectare residential plot in Singapore near Bedok Reservoir. A predefined EPW weather file for Singapore is used to set the weather conditions. Additional simulation setup values are detailed in Table 2. Site energy use (measured in kWh) is the primary metric evaluated for the model.

Table 2 Simulation Setup

Parameters	**Values**		
People Density [P/m2]	0.0556		
Metabolic Rate [Met]	1.2		
Equipment Power Density [W/m2]	6.6700		
Lighting Power Density [W/m2]	6.4583		
Heating, Hot water, Mechanical ventilation	OFF		
Min Cool Supply Air Temp [°C]	18		
Min & Max Humidity	20% & 80%		
Glazing Types	**U-value**	**SHGC**	**tVis**
0. Single pane: Clear	5.82	0.818	0.865
1. Double pane: Clear pane	2.69	0.703	0.774
2. Double pane: Atlantica Solarban 90 (Argon)	1.33	0.29	0.381
3. TripleLoE	0.785	0.764	0.661
4. Triple Pane: Solarban 90 (2) - Solarban 90 (4) - Clear (Krypton)	0.58	0.163	0.291

Renewable energy generation (kWh) was simulated utilizing EnergyPlus in ClimateStudio. The three types of PV panels included in the model were used as inputs for simulation. All buildings in the precinct were treated as shading elements. To reduce model complexity, several simplifications were implemented. For instance, all coplanar PV panels were merged into a single surface. Similarly, BIPV around windows, were simplified by simulating the entire façade wall and excluding the window area from the effective PV panel area. Preliminary PV simulation tests revealed that both the detailed and simplified versions of the model produced nearly identical results, with a marginal difference of ±1%.

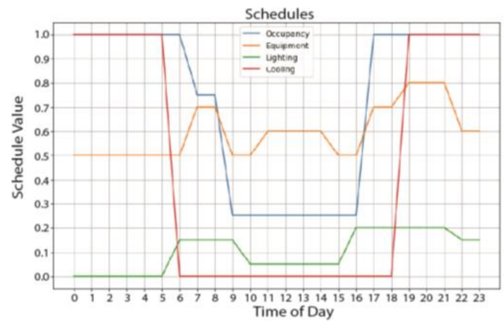

Figure 3 Schedules implemented for energy simulation.

Additional simplifications permitted fast simulations for improving the optimization process. Initial tests for a single iteration involving annual energy and PV simulations for the precinct-scale building energy model with 400-500 thermal zones required an average of 9 minutes and 30 minutes per simulation. This presented a challenge for the optimization methodology which required many hundreds of simulations. As a workaround, a series of daily simulations were tested as a proxy for an annual study. A methodology using the one-day energy balance estimation for a typical summer day in hotter climates was previously published by Natanian (2023). For the purposes of this study a single reference day, August 22, was assigned for all simulations. This assumption builds from Singapore's equatorial climate which has limited variation in temperature and sun path over the course of the year. For the referenced day (August 22), the mean air temperature was 27.8°C, with a mean relative humidity of 82.5% and solar radiation of 189.3 kWh. Maximum values reached 30.2°C, 94%, and 625 kWh, respectively.

All data points for the two simulations were gathered in a single comma-separated value (CSV) file which was passed on to the optimization solver (See Figure 1). The generated data points from the PV simulation included total site PV power generation, Renewable Energy Production Intensity (REPI) in kWh/m^2, daily PV yield at rooftop (kWh), daily BIPV (façade) yield (kWh) and daily site PV yield (kWh), along with effective PV area (m^2) of total installed PV panel. The data points generated from the building energy simulation included total site energy use (kWh), lighting energy demand (kWh), cooling energy demand (kWh), and energy use intensity (EUI) (kWh/m^2).

Optimization

The presented methodology implements multi-objective optimization (MOO) to search for best solutions from model generation and simulation. To identify optimal densities for NZE high-rise residential precincts, three objectives are defined for the model: i) minimize daily site energy use (or energy consumption); ii) maximize renewable energy generation; and iii) maximize achieved GFA.

The MOO problem defined by the three objectives listed above is converted to a scalarized single objective optimization (SOO) by assigning a weight factor to each objective function and then minimizing the weighted sum. Each objective function is first converted to a minimization function before scalarization (see Equations 2-4). The fitness function for the experiment is defined in Equation 1, below.

$$ff = 0.4 * eff + 0.4 * dff + 0.2 * rff + penalty \tag{1}$$

In Equation 1, *ff* is the fitness function, while *eff*, *dff*, and *rff* are the fitness scores for the objectives of energy use, density, and renewable energy generation respectively. The three objective functions are weighted to first prioritize energy reduction and achieving desired density, followed by renewable energy generation.

$$eff = \frac{EUse}{maxEUse} \tag{2}$$

$$dff = \frac{maxGFA - AcheivedGFA}{maxGFA} \tag{3}$$

$$rff = \frac{maxRGen - RGen}{maxRGen} \tag{4}$$

In Equations 2-4, the abbreviated terms *EUse* and *RGen* represent the energy use and renewable energy generation values calculated during building performance simulation. Density is measured by *AchievedGFA*: the ratio of gross development floor area over site area.

The implementation of a penalty function was necessary to prevent the optimization from converging exclusively towards low-density energy-positive precincts. As the research goal is to identify efficient densities for net-zero development, the penalty function prevents the selection of results which diverge too extensively from energy balance.

Two penalty functions for the optimization are tested in this study, resulting in two separate sets of experimental results. The two penalty functions are defined in detail below and given the titles: i) Energy Imbalance Penalty (Ei-Penalty) and ii) Out of Bounds Penalty (OB-Penalty). The Ei-Penalty scores solutions in proportion to the difference between energy consumption and generation if the value is greater than zero. As no penalty is applied if energy generation exceeds consumption, this penalty is expected to prioritize net-positive solutions at optimal densities.

$$\text{If EUse – RGen > 0:} \tag{5}$$

$$penalty = abs\left(\frac{EUse - RGen}{maxEUse - maxRGen}\right) \tag{6}$$

The OB-Penalty function impacts solutions when the absolute value of the difference between energy consumption and generation exceeds a tolerance of 2500 kWh. This constrains the optimization to converge toward near-zero solutions with net positive and negative energy balances.

$$\text{If abs (EUse – RGen) > 2500:} \tag{7}$$

$$penalty = abs\left(\frac{EUse - RGen}{maxEUse - maxRGen}\right) \tag{8}$$

Model optimization was implemented with the Opossum solver (Wortmann, 2017), using a radial basis function optimization called RBFOpt. RBFOpt is a surrogate-based optimization method that converges with fewer iterations than common metaheuristics like genetic algorithms (Holmström et al.2008; Costa & Nannicini 2018; Wortmann & Nannicini 2016). Faster convergence makes this optimization method well-suited for time-intensive simulation-based optimization methodologies like the building energy simulations required in this study.

Two separate optimization experiments were run, implementing the two penalty functions presented above. We conducted 1000 iterations for each experiment, using the number of iterations as the sole termination criterion.

Results and Discussion

This section presents the results from the two NZE precinct optimization experiments with discussion of their significance. Results are presented with i) optimization time first followed by ii) correlation of parameters and objectives, iii) presentation of optimal and selected near-optimal results relative to energy balance, and iv) discussion of best parameter ranges and result types for NZE precinct design. Optimal NZE precinct density values identified in the two experiments range from a GPR of 2.5 for a net-positive solution (using Ei-Penalty) to a GPR of 2.9 for a near-zero solution (using OB-Penalty). Discussion of the difference between the two optima is followed by reflection on the limitations of the study and areas of future work.

Model optimization was lengthy due to the high number of iterations (1000) specified by the research protocol and the time required per simulation. On a 13th Gen Intel Core i9-13900KF 3.00GHz CPU, the first optimization, Energy-Imbalance Penalty (Ei-Penalty), ran for a total of 126 hours and 59 minutes, averaging approximately 7.5 minutes per iteration. The second optimization, Out of Bounds Penalty (OB-Penalty), took about 252 hours and 49 minutes, with an average of approximately 15.16 minutes per iteration. Each iteration regenerated the precinct model followed by completing both the energy use and PV simulations. The longer time required for the OB-Penalty optimization was expected as this model allowed for the exploration of higher densities, with a proportional increase in the number of simulated elements. The convergence graph for each optimization experiment is visualized in Figure 4, which plots the improvement of the fitness function against the iteration number. The optimum was identified at the 245th iteration for the Ei-Penalty and the 962nd iteration for the OB-Penalty, with model fitness plateauing at ~200 and ~400 iterations respectively. While further improvements are always possible with a heuristic solver, the methods applied here are consistent with other published use of RBFOpt to identify optimal model solutions.

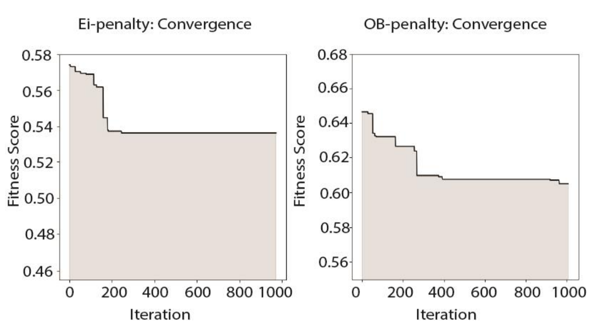

Figure 4 Optimization Convergence graph for Ei-Penalty (left) and OB-penalty (right).

Correlation of model objectives and parameters

Pearson Correlation analysis of all objectives and model parameters is presented in Figure 5. The right side of Figure 5 highlights the model objectives with moderate to high correlations by excluding weakly correlated features. An inverse correlation (-1.00) is measured between the density objective (*dff*) and the energy use objective (*eff*). This indicates that the goal of maximizing density shows a strong tradeoff with the goal of minimizing energy consumption (all objectives in the model are formulated as minimization problems). The renewable energy generation objective (*rff*) shows a strong tradeoff of (-0.75) with the energy use reduction objective (*eff*), i.e., results that produce more renewable energy are not the best in minimizing energy use. Finally, the renewable energy objective (*rff*) and density objective (*dff*) show a strong positive correlation (0.77): as the model becomes denser more renewable energy is being produced due to higher areas of BIPV.

The positive correlation between density and renewable energy generation is complicated by the fact that renewable energy generation in the model combines three quantities: i) on-site PV array yield, ii) façade-integrated BIPV yield, and iii) rooftop PV array yields. The correlation of on-site photovoltaics production (SiteArray_Yield) versus GFA shows a noteworthy tradeoff of -0.57. This result reflects the fact that on-site arrays become increasingly small and overshadowed in the highest-density model solutions. The tradeoff between on-site PV yield and density is masked in the correlations for *'rff'* and overall renewable energy yield (RGen) by the strong positive correlation of BIPV (BIPV_Yield) with GFA (0.90).

In the results presented in the next section, it is noted that achieving energy balance in the model is no longer possible above densities of ~2.5 gross plot ratio (GPR). Thus, the tradeoff between development density and renewable energy generation becomes increasingly negative at the highest sampled densities. Nonetheless, the strong contribution of façade integrated BIPV to the correlation of density and renewable energy underscores the role this technology would play in achieving a high-rise high-density NZE precinct.

The correlations among the model objectives are observable in Figure 9 which plots all solutions according to the three objectives (center), and each pair of objectives (below, left and right.) Pareto solutions shown in Figure 9 are derived by extracting the individual fitness function values from each solution and identifying those which are non-dominated in all three objectives. While a large percentage of the solutions are pareto-efficient across the three objectives, as the optimizations employed a scalarized SOO with penalty function, a single best result has nonetheless been obtained for each experiment.

A strong negative correlation between the building span parameter (bSpn) and energy balance (eBal) is observed (-0.66). This finding suggests that long and low building typologies may not be as suitable for achieving energy balance in Singapore in comparison with taller 'tower' type massings. Building span (bSpn) is also negatively correlated with development area (GFA), and energy use (EUse). These tradeoffs are expected as the model incorporates a constraint based on development controls that restrict their height, as described above.

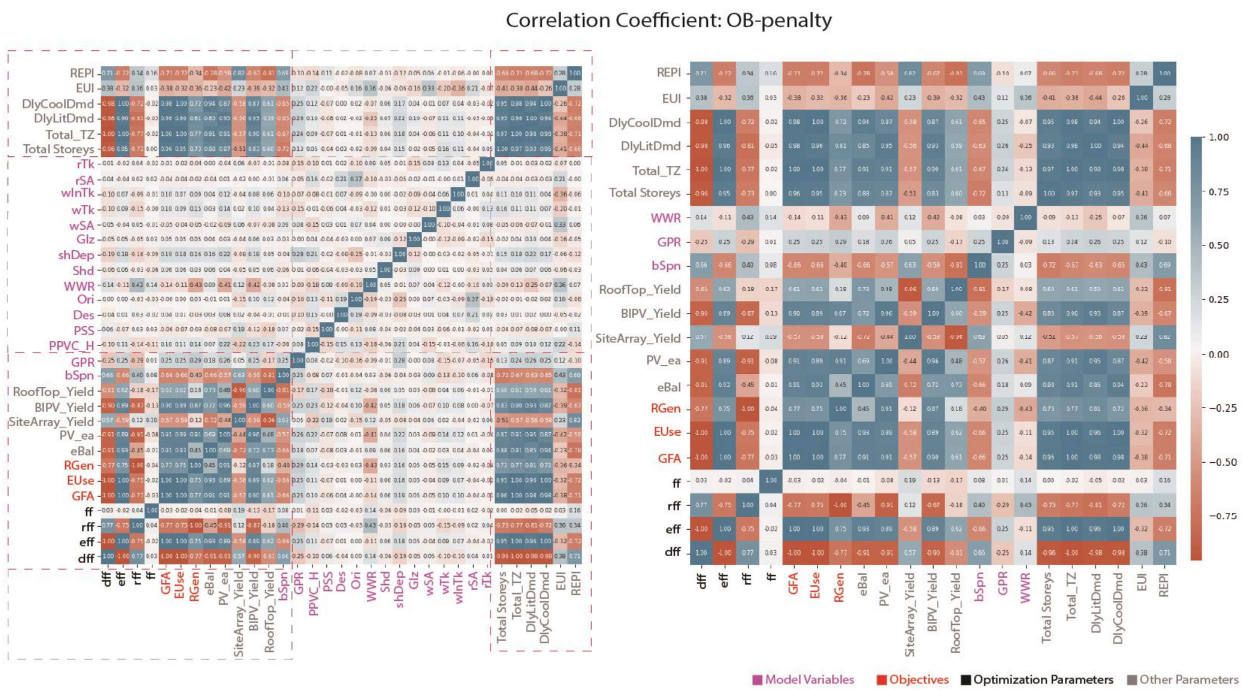

Figure 5 Correlation of model objectives and parameters, (OB-Penalty).

Optimization Results

Energy balance for all results from both optimization experiments are presented in Figure 6. The optimum value in each chart is marked with a red X. All solutions generated are plotted based on their simulated energy use (horizontal axis) and renewable energy generation (vertical axis.) Solution density, measured in hectares of development area, is indicated by the color scale. Square plot points represent solutions with building spans greater than 60 meters, and circular plot plots represent those with spans less than 60 meters. The energy balance line, where generation equals consumption, is marked by a dashed grey line.

The OB-Penalty optimization, in comparison with Ei-Penalty, has identified a greater number of high-density solutions (12.8 ha development area and above.) This difference is attributable to the penalty function definition: while Ei-penalty penalizes all the solutions that exceed net-zero energy, the OB-penalty accepts a range of solutions with +/-2500 kWh of energy balance. The difference extends to the best values identified by each experiment: the optimal solution for Ei-penalty has a lower development area of 11.6 ha (GPR 2.5) in comparison with 13.5 ha (GPR 2.9) for OB-Penalty. The difference of 19,000 m^2 (0.4 GPR) between the two optima is the equivalent of 184 additional residential flats. However, while the optimum identified by Ei-penalty is net positive, contributing ~240 kWh per day to the grid, the OB-penalty optimum is net negative, drawing ~250 kWh per day from the grid.

Figure 7 extracts and visualizes the best solutions at six density ranges for both optimization experiments. It is accompanied by a scatter plot of all solutions charting the deviation from energy balance (vertical axis) as density increases (horizontal axis). Solutions below the energy balance axis produce more renewable energy than they consume. The +/- 2500 kWh penalty range for OB-penalty is shown as two additional dashed horizontal lines. A line is drawn connecting the optimal solutions at each density. The point where this line intersects the energy balance line provides an additional indication of the optimal precinct density at which net zero is attainable. For the 4.6 ha plot simulated in these experiments, a development area of ~116,000 m^2 (11.6 ha) GFA or 2.5 GPR, is the highest possible density for achieving net zero identified through the Ei-Penalty optimization experiment. This result required on-site PV installation area of 48,800 m^2 or ~42% of the development area (including roof-top, BIPV and on-site PV).

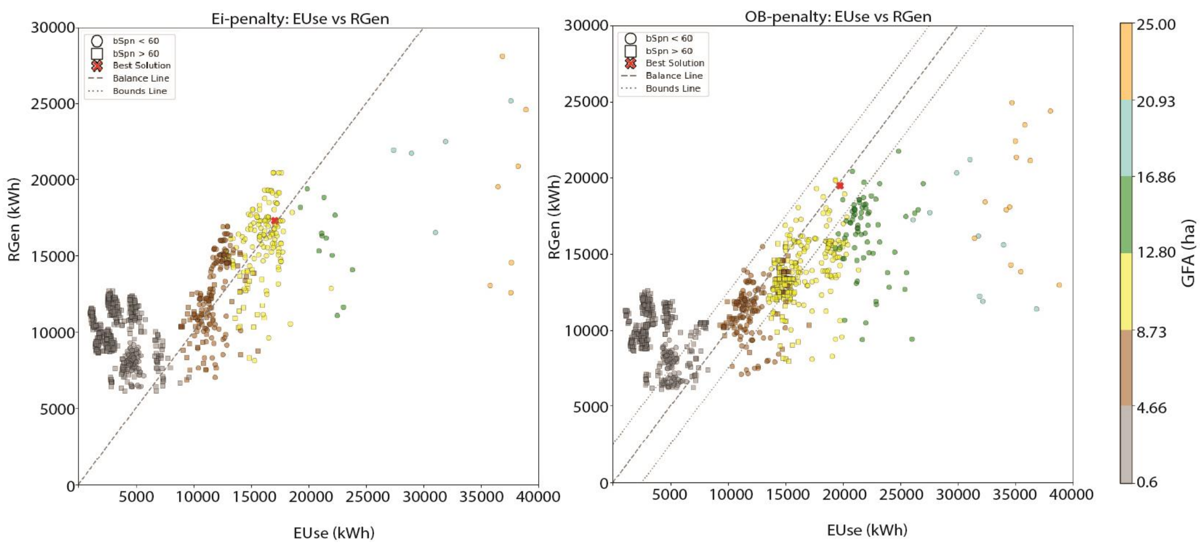

Figure 6 Optimization results plotted by site energy use (kWh) and on-site renewable energy generated (kWh). The dashed line indicates 'energy balance' where energy use and generation are equal.

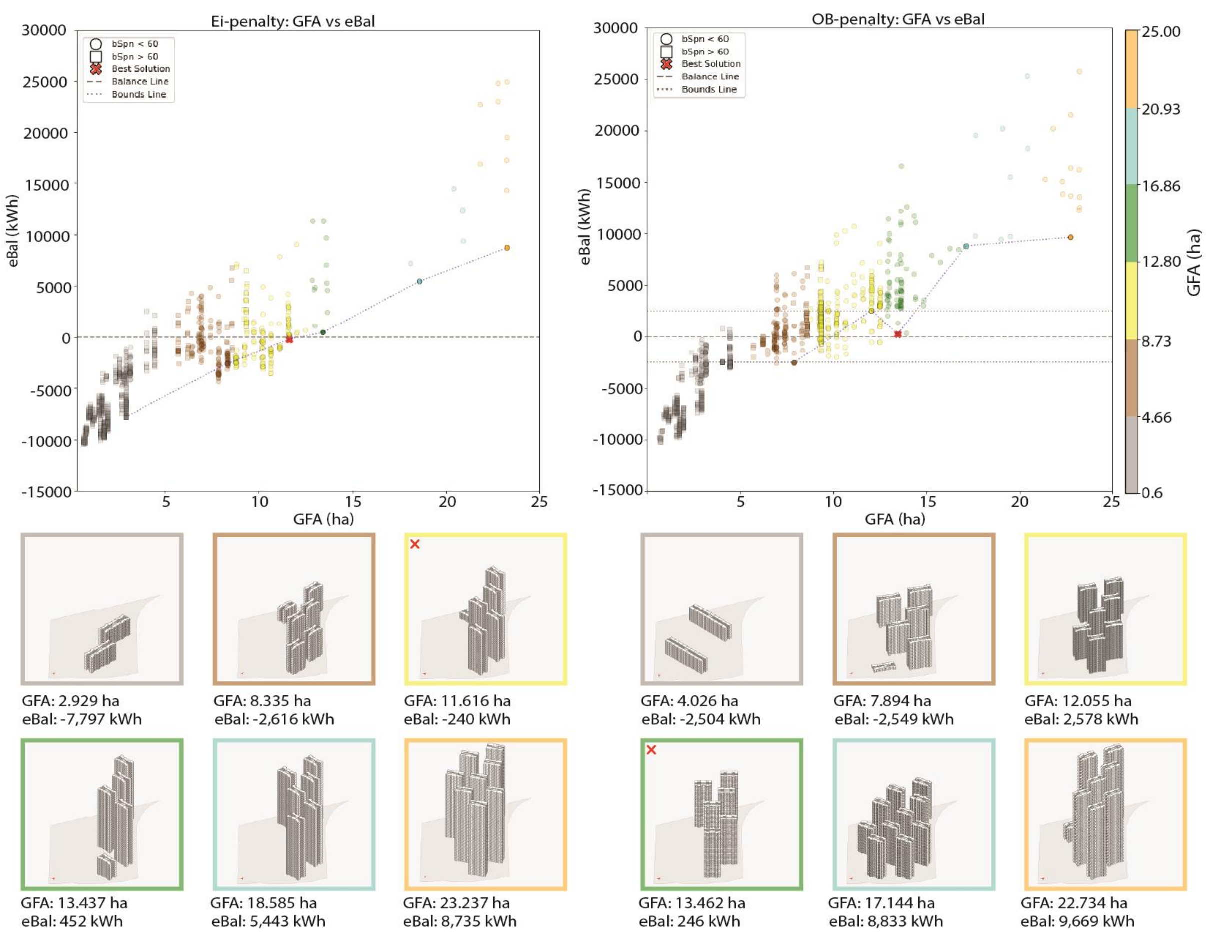

Figure 7: Above: Solutions for each optimization experiment plotted for development density (GFA) against energy balance (eBal.) Below: Best solutions extracted from each of the six density ranges. Global optimum is indicated by a red X.

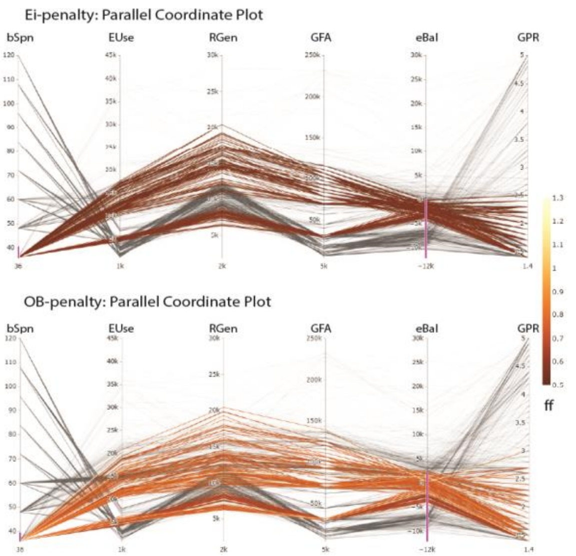

Figure 8 Parallel coordinate plot of model parameters and objectives for both optimization experiments.

The best-performing parameter ranges for both optimization experiments are shown in parallel coordinate plots in Figure 8. Solutions with the lowest (best) fitness scores are indicated by colors approaching red/brown. Building span (bSpn) converges to a very narrow range of solutions (bSpan $\leq$ 36) representing tower-type buildings as the optimization approaches the lowest fitness values. This trend can also be observed in Figures 7 & 8, where long building span solutions, marked by a square plot point, do not achieve densities higher than 10 ha (yellow color scale in Figures 6 and 7). The inability of these 'slab' type buildings to produce adequate renewable energy even at moderate densities further supports the finding that this building type is unlikely to permit achieving dense NZE developments.

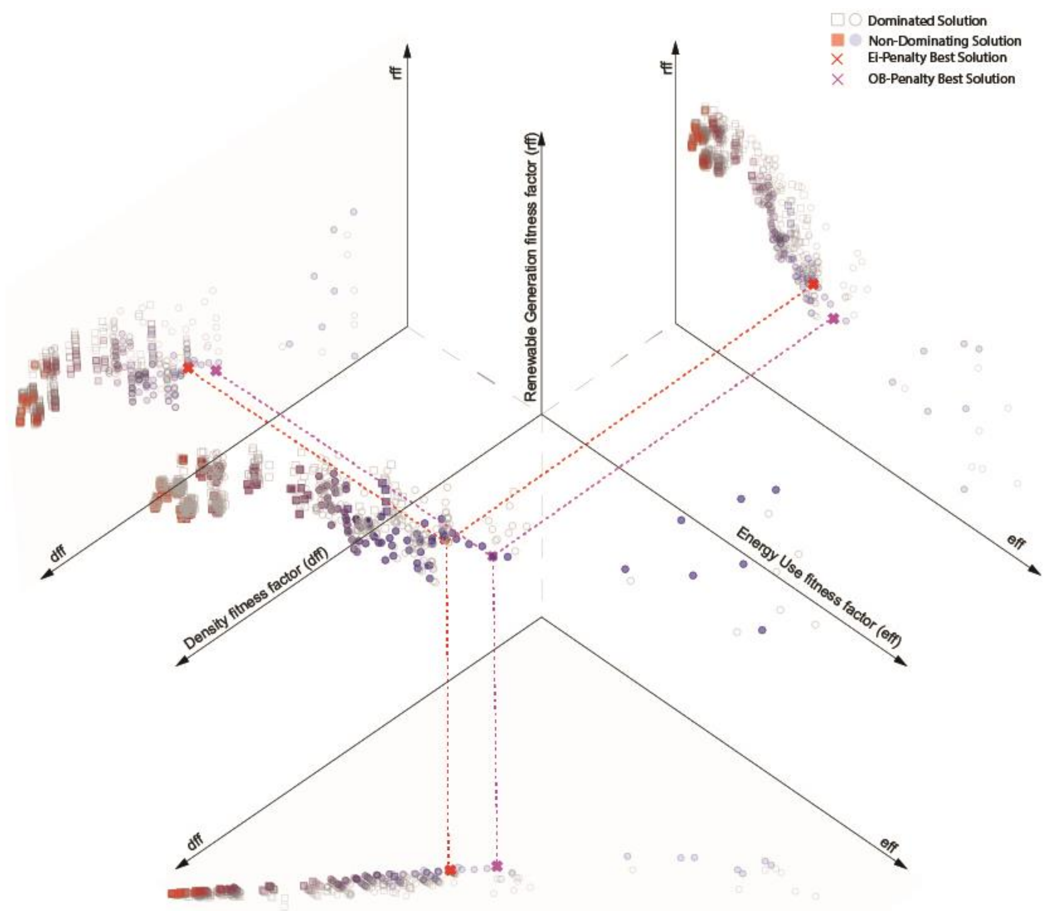

Figure 9 Multi-objective pareto-set of solutions (colored from red to blue) plotted for all three objectives (center), and each pair of objectives (below, left and right.) Overall optimum is marked for Ei-Penalty by a red cross and for OB-Penalty by a magenta cross. Long-span solutions are indicated by a square plot point.

Limitations and future works

Future work on optimization for dense net zero energy urban designs could be expanded to address two limitations of the current study: i) including additional conflicting objectives; ii) testing additional site geometry and climates. Several parameters of the current model converge rapidly to maximal values as no conflicting criteria are included to limit their optimization. Including indoor thermal comfort would provide an important conflicting objective for controlling the cooling schedule in the current model which tends to converge toward the warmest permitted value. Furthermore, a daylighting or natural ventilation objective may provide a limitation on the convergence of the window size to minimal values. Additionally, future work can provide a more accurate assessment of façade area available for BIPV by including a multiplier which reflects the average percentage used in contemporary construction. The current methodology assigns BIPV to the full façade surfaces and is therefore likely to overestimate the area available. Finally, embodied carbon and life cycle cost objectives could provide a check both on development density and photovoltaic deployment.

The introduction of these constraints would be likely to decrease the density at which NZE precincts are attainable. For example, introducing thermal comfort objectives might push the cooling set point lower, consuming more energy per square meter of development, and pushing overall density for NZE solutions lower.

Site geometry and climate zone also affect the optimization result due primarily to their impact on patterns of light and shadow across the site and building facades. Exploring a range of site sizes and geometries will be a meaningful additional test. Though this study addressed the tropical climate of Singapore, future work could also seek to understand if findings are relevant to nearby major cities occupying similar climatic conditions, i.e., Manila, Jakarta, Kuala Lumpur, Bangkok, and Chennai. Finally, to explore running annual simulations instead of one-day simulations further work could develop and test surrogate models for residential precincts.

Conclusion

This study identified the optimum (highest) development density for a net zero energy residential precinct in Singapore. A methodology section described i) the set-up of a parametric model of a residential precinct, ii) simulation for building energy use and renewable energy generation, and iii) optimization using scalarized single-objective optimization. Two penalty functions were tested in separate optimization experiments. The first prioritized solutions which were net zero energy or better (net positive energy) (labelled Ei-penalty) and a second which prioritized solutions within a range above and below energy balance (OB-Penalty).

For each optimization experiment, one best solution was identified: 2.5 GPR for Ei-Penalty and 2.9 GPR for OB-Penalty. The OB-Penalty identified a larger number of high-density solutions, in comparison with Ei-Penalty, over the same number of iterations. Future work to identify NZE urban designs may benefit from an approach similar to the OB-Penalty which permits the optimization to explore near-zero solutions that slightly exceed energy balance. Several limitations of the current study were discussed, which can be implemented in future work, including the introduction of additional conflicting objectives like indoor thermal comfort.

The presented methodology and results will support city planners, developers, and architects as they carry out site planning and early design exercises for net-zero energy districts. For example, the URA's allocated development density for the studied site is 2.8 GPR. The presented methods could support developers seeking a density variance by demonstrating viable NZE solutions at higher densities. The optimal densities identified in this paper improve understanding of the upper limits of development density at which net-zero energy can be achieved. This knowledge can assist planners in allocating land areas and assigning development controls that target net-zero energy outcomes. The presented results will further assist architects and developers in estimating the target maximum gross floor areas for NZE residential developments, as well as the most suitable site layout strategies and building types.

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