Multi-objective optimization of building retrofit strategies using staged GHG emission targets

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Abstract

Building energy retrofit plays a crucial role in achieving a GHG emission reduction. However, due to the unique characteristics of existing buildings, it is still challenging to identify the most appropriate retrofitting scenario and its environmental impact and life cycle cost. Hence, this study investigates the impact of the different targets for GHG emissions reduction on the optimal retrofit strategies. A non-dominated sorting genetic algorithm was selected as the optimization algorithm. Annual carbon dioxide emissions and the net present value of each retrofit scenario are defined as objective functions and ensure viable solutions. An office building in Canada was selected as a case study to demonstrate the proposed methodology. The results reveal that the DOAS and chilled beam with a ground source heat pump was the most efficient options for the maximum decarbonizing of the building. Also, a higher value of decarbonizing is feasible without significant variations in LCC.

Introduction

Increasing the energy efficiency of existing buildings can play a key role in achieving the building GHG emissions target by 2030 (ECCC, 2021). Numerous energy efficiency upgrades can improve existing buildings' overall performance. These can be classified into two major categories: recommissioning (RCx) and retrofitting. Recommissioning is a cost-effective method that increases energy performance through improved building operations. On the other hand, retrofitting is the physical change in the building systems, such as building envelopes, lighting systems, and HVAC systems. Natural Resources Canada (NRC) proposed considering RCx as the first step of major energy retrofit projects for commercial and institutional buildings (NRC, 2016).

Energy-saving measures (ESM) are activities designed to enhance energy efficiency or reduce operating costs such as recommissioning, upgrades, or retrofits (Ma et al., 2012). Building performance simulation (BPS) is extensively employed to evaluate various ESM. The Building Energy Software Tools Directory has summarized the abundance of BPS tools. However, these tools evaluate the energy performance with significant uncertainties due to the complex systems simplification and input parameters that users must provide (Beausoleil-Morrison, 2020). Therefore, the inverse energy modelling approach, which employed measured data to identify system structure and parameters, could increase the model's accuracy in representing the actual operating condition. Coakley et al. (2014) reviewed various methods to match simulated data with observed values.

Considering budget and time limitations, optimizing retrofit and operating strategies is vital to reducing GHG emissions, energy usage, and life-cycle costs. Identifying the most appropriate retrofitting scenario and its environmental and economic impact is still challenging due to the unique characteristics of existing buildings. Hence, enormous research has been devoted to building energy retrofit optimization in recent years. Asadi et al. (2012) employed a multi-objective optimization model for decision-making in a retrofit project. They considered energy consumption, retrofit cost, and thermal discomfort hours for training an artificial neural network. Then NSGAII was employed to identify the optimal retrofit strategies. They conclude that the window type and HVAC system were the most influential decision variables. The annual GHG emissions of the building were not considered in this study. A novel optimization model to identify the optimum set of alternative strategies for retrofitting was developed by Li et al. (2021). They considered energy-saving and thermal comfort to select the optimal design solution. Jafari et al. (2017) proposed an optimization framework for the decision-making of energy retrofits. However, they focused only on the economic benefits of retrofitting projects. The developed model was employed to find the optimum retrofitting investment for minimizing the case study's total life cycle cost (LCC). The vast majority of the work in this area has focused mainly on the economic aspects such as Life cycle cost, payback period, and energy saving. Previous research has largely overlooked the impact of the GHG reduction target on the retrofit optimization results.

Moreover, the vast majority of the work in this area has focused on improving envelope specifications and

internal heat gains as retrofit strategies. While selecting the cost-effective and appropriate alternative technologies for replacing the entire HVAC system is challenging in large building retrofitting. Since the limitation of creating energy models for different HVAC systems in retrofit optimization is increasingly apparent. This study proposed a methodology for optimizing building retrofitting by considering various heating, cooling, and ventilation systems technologies. Also, the optimum retrofit scenarios for various decarbonizing goals were investigated, considering life cycle cost and annual GHG emissions.

Methodology

Figure 1 represents this study's main methodology for retrofit analysis. First, the process was started by obtaining the base model data, such as hourly utility data and local weather files, and creating the geometry model. Note that all information about the internal heat gains, surrounding shading, building orientation, and thermal zoning was considered in this step. Next, the model was calibrated using an optimization algorithm. Finally, multi-objective optimization of retrofit strategies was conducted for different decarbonizing targets.

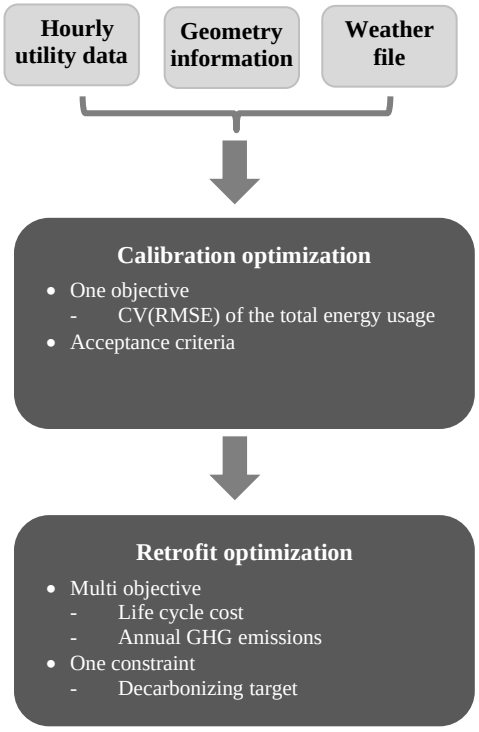

Figure 1: The main methodology for retrofit analysis

This study employed an open-source Python framework for energy model optimization. The main advantage of this framework is that it dramatically reduces the computational processing time by automatically assigning various HVAC system configurations and creating a database to prevent repeated simulation in the optimization process. Furthermore, this workflow integrated Modelkit, EnergyPlus, and a python library for optimization (Platypus) to create an energy model, evaluate the whole building's performance, and run the optimization algorithm. Figure 2 represents this study's methodology for calibration and retrofit optimization.

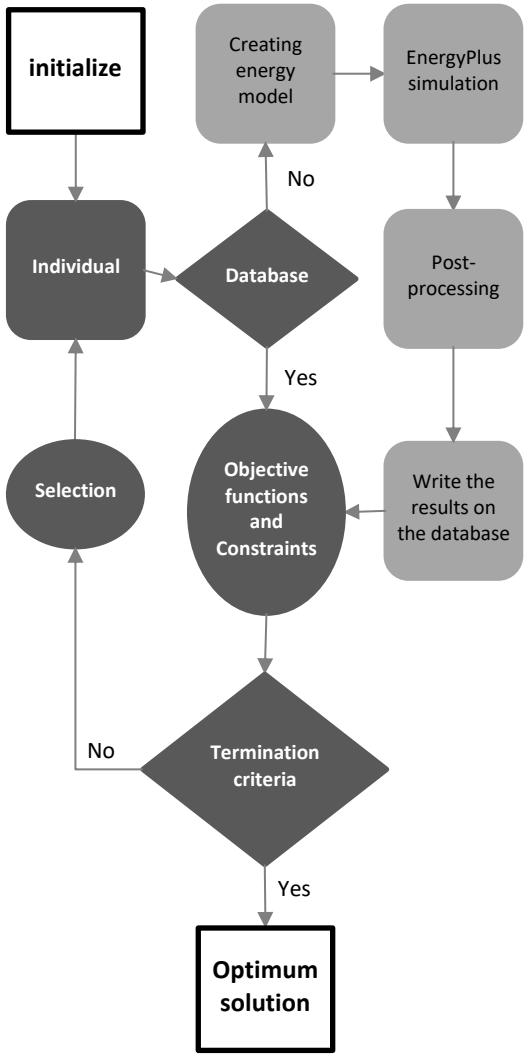

Figure 2:Optimization workflow

First, a random population of individuals was created from the input variable ranges. Then, to prevent repeated simulation, each individual's existence was checked in the database. Note that SQLite was utilized to create a database. The objective functions and constraints values were read from the database if the simulation results were available. Otherwise, a new energy model based on each input parameter value was created using Modelkit. Due to integrating templates and scripting, Modelkit is a highly-efficient and flexible workflow for creating energy models (Ellis, 2015). Note that Modelkit has about 16 templates for different HVAC systems, such as variable air volume (VAV) system or variable refrigerant flow (VRF) system. After assigning the proper HVAC configuration, the EnergyPlus was called

to run the simulation. Next, a Python script was run to calculate several measures such as net present value and annual GHG emissions and write the results on the database. Finally, each individual's values of objective functions and constraints were read from the database, and the following population of individuals was selected based on the mutation and crossover. The process is stopped when the number of generations reaches the set value. Moreover, various optimization algorithms and objectives could be selected for optimization. As mentioned before, this paper applied the optimization workflow for energy model calibration and retrofit analysis.

Calibration Optimization

The base model energy consumption can play a crucial role in calculating the annual GHG emissions reduction after applying each retrofit scenario. Hence, energy model calibration was conducted prior to the retrofit analysis to increase the model's accuracy.

The genetic algorithm, a widespread optimization algorithm for calibration (Asadi et al., 2014; Ramos, Ruiz et al., 2016), was applied to determine the optimal value of the unknown parameters in the reference energy model. This algorithm determines a potential solution to a specific problem by evolving a population (combining the parameters' values). In this step, the objective function was set to the coefficient of variation of root means squared error (CV(RMSE)) of the total energy usage. ASHRAE Guideline 14 (2014) proposed the acceptance criteria for calibrated model based on the two error functions: the coefficient of variation of root mean squared error (CV(RMSE)) and the normalized mean bias error (NMBE). For hourly calibration, CV(RMSE) and MBE must be less than 30% and 10%, respectively. Equations 1 and 2 indicate the calculation method for these two error functions.

$$CV(\mathrm{RMSE}) = \frac{\sqrt{\sum_{i=1}^{N}(M_i - S_i)^2}/N}{\bar{M}} \quad (1)$$

$$\mathrm{NMBE} = \frac{\sum_{i=1}^{N}(M_i - S_i)}{\sum_{1}^{N}(M_i)} \quad (2)$$

where M is the measured energy data point during the time interval; S is the simulated energy data point during the same time interval; N is the number of the time interval; $\bar{M}$ is the mean of measured values. Note that the objective function in this step was CV(RMSE) of the total energy consumption. ASHRAE Guideline 14 was used as the acceptance criteria (ASHRAE, 2014).

Retrofit optimizing

The non-dominated sorting genetic algorithm (NSGA-II) from the evolutionary algorithm family was used for multi-objective optimization of retrofit scenarios considering different decarbonization targets. As mentioned before, each energy-saving measure's environmental and economic impacts were considered in this study. Hence, Two objective functions were defined for the optimization algorithm: life cycle cost (LCC) and annual GHG emissions. Also, the GHG reduction goal was considered as a constraint.

Life cycle cost

The first objective function was defined as the difference between life cycle cost (LCC) before and after applying any ESM (Equation 3) to determine the most cost-effective retrofit strategies.

$$\mathrm{Obj_1} = \mathrm{LCC_{reference}} - \mathrm{LCC_{retrofit}} \quad (3)$$

The LCC or present value of all costs or benefits was calculated using Equation LCC = $\mathrm{NPV_{Investments}}$ + $\mathrm{NPV_{Energy}}$ + $\mathrm{NPV_{Replacement}} - \mathrm{NPV_{Salvage}} - \mathrm{NPV_{Income}}$ (.

$$\mathrm{LCC} = \mathrm{NPV_{Investments}} + \mathrm{NPV_{Energy}} + \mathrm{NPV_{Replacement}} - \mathrm{NPV_{Salvage}} - \mathrm{NPV_{Income}} \quad (4)$$

Where: NPV is the net present value. The calculation method for the net present value of each term is indicated by Equation 5.

$$NPV = \sum_{t=0}^{N} \frac{R_t}{(1+i)^t} \quad (5)$$

where: R_t is the net of the cash flow at each timestep, i shows the market interest rate, and N is the number of years. A period of 25 years was considered for a life-cycle cost analysis. Also, the market interest rate can be calculated as follow:

$$i = f + a + (f \times a) \quad (6)$$

Where: f is the annual inflation rate, a is the actual interest rate. This study assumed the annual inflation is equal to the Bank of Canada target for inflation (2%) (Bank of Canada 2019). In addition, the actual interest rate was set equal to the average yield of the government of Canada marketable bonds for more than ten years (3.08%) (Bank of Canada 2022).

In addition, the retrofit investments were estimated based on Equation (7).

$$\mathrm{I} = \mathrm{MaterialCost} + \mathrm{LightingCost} + \mathrm{AirtightnessCost} + \mathrm{HVACCost} \quad (7)$$

The material cost is the total pricing of any changes to the building envelope, including raw material and labour costs. Table 1 displays the cost per area and properties of the different window replacement alternatives. The total cost for replacing the windows equals the total window area multiplied by the cost per area for each scenario. Note that the unit cost data for all retrofit scenarios were sourced from RSMeans 2022 data (RSMeans, 2022).

Table 1: Cost and properties of the different window replacement alternatives

Description	U-Value (W/m^2K)	SHGC (%)	Cost ($/m^2$)
Double glazing without thermal break air-filled clear glass	3.2	65	714.4
Double glazing without thermal break argon-filled) clear glass	2.8	65	794.2
Double glazing without thermal break argon-filled) tinted glass	2.8	45	832.5
Double glazing with thermal break argon-filled filled- clear glass	2.2	65	849.3
Double glazing with thermal break argon-filled filled-tinted glass	2.2	45	869.7
Triple glazing without thermal break air-filled-clear glass	1.6	65	895.4
Triple glazing without thermal break air-filled-tinted glass	1.6	45	905.5
Triple glazing with thermal break argon-filled - clear glass	1.1	65	950.9
Triple glazing with thermal break argon-filled - tinted glass	1.1	45	979.5

Table 2 shows two scenarios for the minimum and maximum decrease in lighting power density (LPD) compared to the reference model and their cost. The existing lighting system was assumed to be at the end of its lifespan and must be replaced in the current year. The pricing of lighting upgrade with any other reduction value in LPD was estimated based on the linear interpolation. For example, the cost of upgrading the lighting system to decrease LPD by about 3 W/m^2 was assumed to be equal to 235.5 $\$/m^2$.

Table 2: Replacing scenarios for the lighting system

Description	Reduction in LPD compared to the reference (W/m^2)	Cost ($/m^2$)
Florescent	0	198
Upgrading entire of the system to LED	6	273

The reference model's infiltration rate was assumed to be the maximum possible rate for airtightness without any cost. The minimum achievable infiltration rate was set to one-third of this value by spending 31.5 $\$/m^2$. Then, linear interpolation was employed to estimate the cost of airtightness improvement for other values of envelope airtightness. The replacement period of different materials is summarized in Table 3. In addition, the salvage cost of each material was evaluated based on the linear depreciation method and its lifespan.

Table 3: Replacement period of materials[1]

Material	Replacement period (years)
Windows	25
Fluorescent lamps	2
LED lamps	8
HVAC system	25

Finally, the cost of several HVAC systems was assessed based on their unit cost per total building area. Table 4 shows the six replacement options and their unit cost for HVAC systems.

Table 4: The different scenarios and the cost of upgrading the HVAC system

Upgrading option	Description	Cost ($/m^2$)
Op1	Replacing the fans[2]	91.5
Op2	Replacing the fans and upgrading the ventilation system	91.5
Op3	Replacing the entire system with DOAS and chilled beam	183.9
Op4	Replacing the entire system with DOAS and chilled beam and upgrading the plant system to a low-temperature district system (LTDH)	203.3
Op5	Replacing the entire system with DOAS and chilled beam with ground source heat pump (GSHP)	389.8
Op6	Replacing the entire system with a variable refrigerant flow (VRF) system	440.5

Moreover, the electricity cost was computed based on the total electricity consumption and peak demand. The flat electricity rate and peak demand cost were assumed to be 0.09 $/kWh and 13.1917 $/kW, respectively. Also, the natural gas cost rate was $0.199 for each cubic meter (Ontario Energy Board, 2022).

Annual GHG emissions

The annual GHG emissions were considered the second objective function for the retrofit optimization. Although the emission factor for electricity varies over time (St-Jacques et al. 2020), annual GHG emissions were calculated based on the emission factors' published values for different fuel types. Considering the location

[1] The lamp lifetime was calculated based on 12 hour per day for all days (Michalski and Druzik, 2020)
[2] The existing fans was assumed to be at the end of lifetime and must be replaced.

of the building, the emission factor for electricity and natural gas was specified as 0.031 $kgCO_2e/kWh$ and 0.180 $kgCO_2e/kWh$, respectively (EPA, 2013; TAF, 2019). In this case, the boilers are natural gas-fired, and the chillers use electricity.

Case study

An office building located in Ontario was modeled as a case study. The total floor area is approximately 20,000 m^2. A district heating and cooling system provide steam and chilled water for all HVAC and hot water needs. After meetings with the building's operator and a detailed audit, some basic information about the geometry and operating parameters was obtained. The geometry inputs for a building energy model were created manually in SketchUp using Euclid (a free, open-source extension). Figure 3 represents the case study model with the surrounding structures (indicated by purple-colored surfaces).

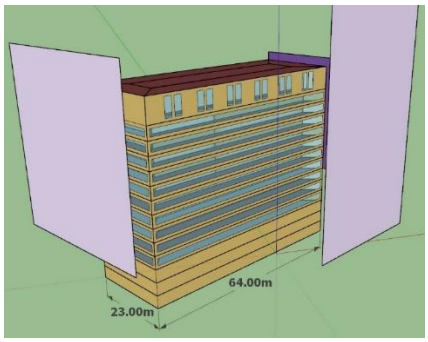

Figure 3: The initial model, including neighboring buildings that shade it

The base model infiltration rate was calculated based on the above-grade exterior surface area flow rate. Also, the windows were modeled based on the simple performance parameters (thermal transmittance of windows and solar heat gain coefficient).

Table 5 summarizes the information used to create the base model. In this case study, drawings or detailed information about structural and insulating materials were unavailable. Hence, material properties of surfaces such as exterior walls and roof for the base model were specified based on the engineering judgment, observations from the site, and discussion with the building operator.

Moreover, the hourly consumption of electricity, heating, and cooling energy loads in 2016 was collected. Due to the gas-fired boiler providing steam for heating, heating energy consumption was the primary source of GHG emissions.

Table 6. These parameters were selected based on the global sensitivity analysis conducted in the previous study (Derakhti et al., 2021). The optimal values of most calibration parameters vary considerably compared to the base model assumption. For example, the infiltration

Two types of weather files were employed to evaluate the energy performance of the building. First, the actual meteorological year (AMY) file related to the building location for 2016 was used in the calibration process. This file has been created from weather station data White Box Technologies (2021) for the local airport, which is 13 km away from the case study building. Next, the retrofit analysis process used the Canadian weather year for energy calculation (CWEC), a typical meteorological year (TMY). The impact of different types of weather data was conducted in the past, and it is not the purpose of this study (Bhandari et al., 2012).

Table 5: base model information

Parameter name	Unit	Value
Above-grade floor area	m^2	16000
Floor height (slab to slab)	m	3.5
Number of floors (including 3 below grade)	-	14
Layout	-	Rectangular
Shading	-	Surrounding buildings
Window to wall ratio	%	50
Fan schedule	-	Always on
Supply air temperature in summer	^oC	14
Supply air temperature in winter	^oC	18
Air distribution units	-	VAV
Perimeter heating	-	Hydronic radiators
Supply fans power	HP	20
Return fans power	HP	10
Maximum capacity of fans	l/s	7000
Occupancy density	people/m^2	0.04

Results

This section explains the results of the described methodology in the case study.

Optimization calibration

The base model's CV(RMSE) hourly data for annual energy usage was approximately 68% which illustrated a considerable gap between the prediction of the base model and metered data. As mentioned before, the value of unknown parameters that the user must be provided for the simulation engine is the primary source of uncertainty. Hence, optimization calibration was employed to evaluate the optimal value of unknown parameters to increase the model's accuracy.

The calibration parameters ranges, and their optimal value are displayed in

rate value in the calibrated model is almost double the value of the initial model, which could significantly alter the heating consumption during winter.

Table 6: Calibration parameters, their ranges, and their optimal values

No.	Parameter name (short form)	Unit	Base value	Min	Max	Calibrated
1	Lighting power density (LPD)	W/m^2	8.5	4	14	10.5
2	Infiltration rate (INF)	$L/s\text{-}m^2$	0.35	0.1	0.9	0.68
3	Thermal transmittance of windows (UWIN)	W/m^2K	3.5	2	5.5	3.78
4	Window solar heat gain coefficient (SHGC)	%	50	30	70	43
5	Heating setback (HSB)	^oC	18	16	24	20
6	Cooling setback (CSB)	^oC	30	22	30	24
7	Outdoor air flow rate (OAF)	$L/s\text{-}m^2$	0.5	0.1	1.5	0.3

Also, the heating setback after calibration has been increased by 2˚C, which considerably affects the after-hours energy consumption. The calibrated model represents the actual operating condition much better than the base model. CV(RMSE) of the sum of all energy loads dramatically dropped to 21%. Also, NMBE for the total energy usage after hourly calibration was approximately 8%. Hence, according to the two error function values, the model has been calibrated based on the acceptance criteria of ASHRAE Guideline 14.

Retrofit analysis

Before applying various retrofit strategies to the calibrated model, some RCx were considered, such as changing the ventilation rate based on the occupant number (9.44 L/S-person). Also, the heating and cooling setback were switched to 18 and 28, respectively. It was assumed that the RCx was applied at the first stage prior to all retrofit strategies. These adjustments diminished almost 22% of annual CO_2 emissions. Next, Different measures were considered to evaluate the optimal strategies for achieving the decarbonizing targets with minimum cost. Accordingly, the GHG emissions reduction goal was defined as between 25% and 95% with a 10% interval as a constraint in the retrofit optimization process. Then the optimum solution for each bound was sorted according to the LCC.

The optimal retrofit strategies for the various percentage of decrease in annual production of CO_2 are represented in Table 7. According to the results, replacing the lighting system with LED should consider all decarbonizing targets significantly increased cost savings. However, to achieve around a 60% reduction in GHG emissions, changing approximately half of the lamps to LED is the optimum solution. Also, the entire HVAC system replacement and the lower value for SHGC should be deemed for all GHG reduction targets,

The first optimal retrofit strategy (S1) diminishes around 33% of GHG emissions with saving about 17.7 M$ after 25 years. This strategy is the most cost-effective strategy for the decarbonizing goal of less than 33%. It consists of upgrading the entire HVAC system with DOAS and chilled beam without upgrading the plant (Op3), replacing almost half of the lamps with LED, and a 15% reduction in infiltration rate. Once the aim of decreasing the annual GHG emissions compared to the reference model is between 43% and 58%, the third strategy (S3) is the optimum solution. To reach this goal, the low-temperature district heating with DOAS and chilled beam (Op4) and the minimum value for airtightness and lighting power density should be considered. Moreover, when the building must be decarbonized by more than 58%, DOAS and chilled beam with a ground source heat pump (OP5) are optimal for heating, cooling, and ventilation purposes. Note that using this HVAC system and maximum improvement of airtightness and lighting system would reduce 84% of annual GHG emissions, which is only 4% less than the maximum possible drop in annual CO_2 generation. Figure 4 displays the capital expenditure of each optimum scenario for the various decarbonizing targets. For example, approximately 6M$ should be invested to implement the second retrofit strategy (S2). Although applying S4 versus S2 decreases the total GHG emissions significantly, the LCC value for these two scenarios are almost equal. Hence, increasing the GHG emissions reduction could be achieved without considerable changes in LCC. Also, comparing the S3 and S4 reveals that investing in implementing the proper HVAC system instead of changing the windows could diminish a large amount of CO_2 per year. In other words, identifying the most optimal HVAC system to reach GHG emission reduction targets is crucial.

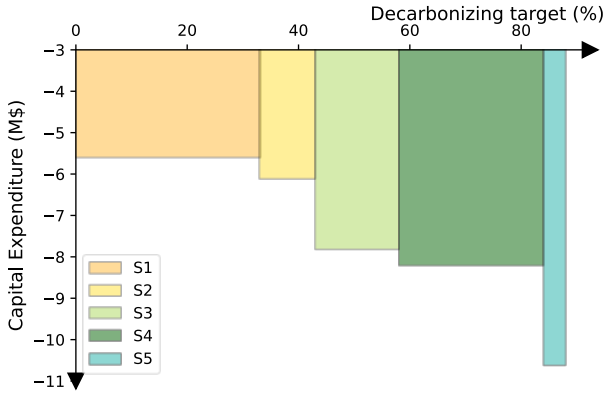

Figure 4: The capital cost of optimal scenarios for the various decarbonizing targets

Table 7: Multi-objective optimization results

Optimal Scenario	RCx		Retrofit upgrades					Objective 1	Objective 2	GHG emissions reduction (%)	Payback period (years)
	HSB (ºC)	CSB (ºC)	LPD (W/m^2)	INF ($L/s\text{-}m^2$)	UWIN (W/m^2K)	SHGC (%)	HVAC System	LCC difference (M$)	Annual CO_2 generation (tonnes)		
Ref	20	24	10.5	0.68	3.78	43	Op1	0	670	0	0
S1	18	28	6.6	0.58	3.78	45	Op3	17.7	450	33	2.3
S2	18	28	4.77	0.36	3.78	45	Op4	17	379	43	2.4
S3	18	28	6.8	0.45	1.1	45	Op4	16.1	280	58	3.2
S4	18	28	4.2	0.41	3.78	45	Op5	15.8	108	84	3.5
S5	18	28	4.1	0.36	1.1	45	Op5	13.2	82	88	5.7

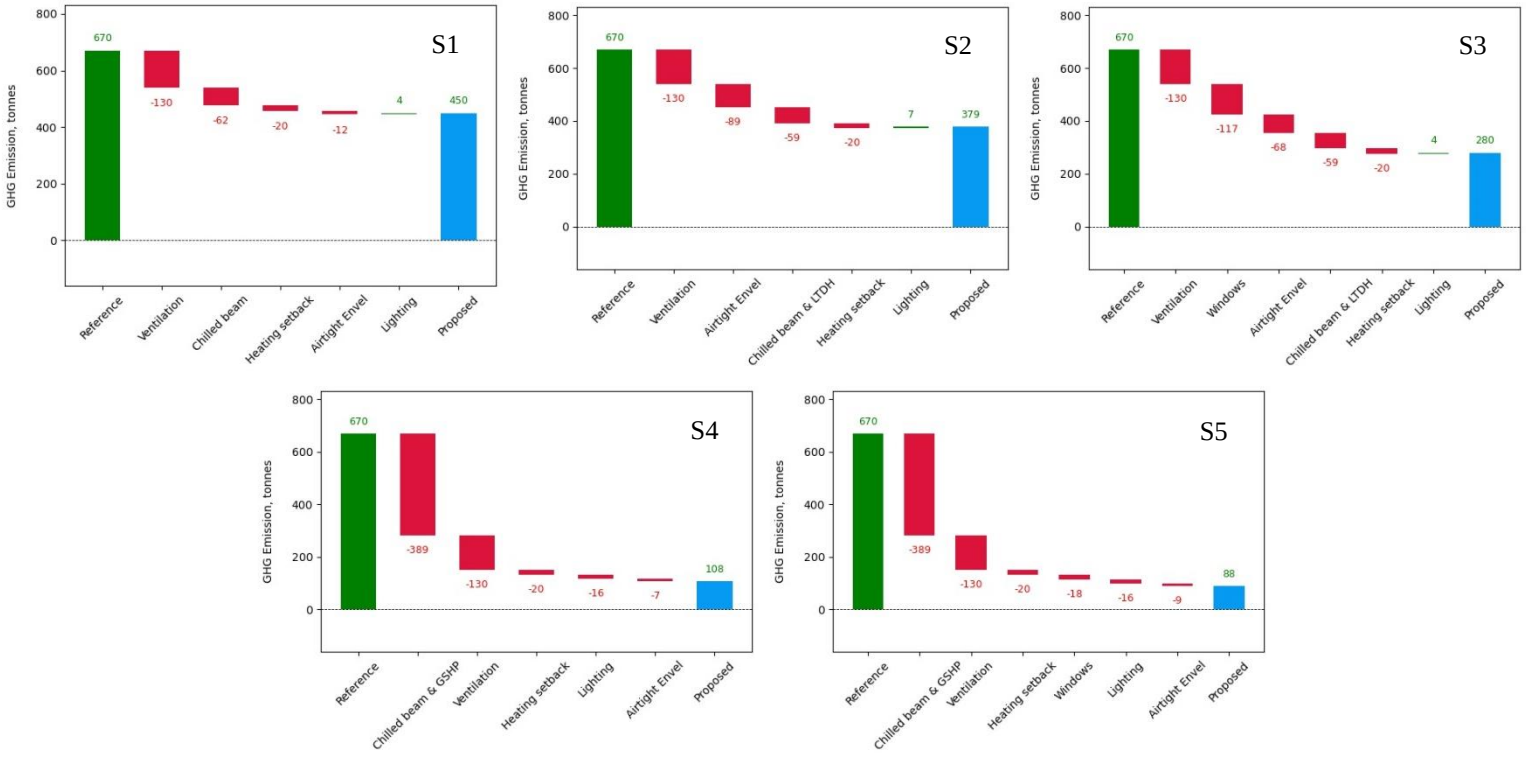

Figure 5: The impact of each upgrade on the different optimum strategies

Figure 5 indicates the influence of each upgrade on the annual GHG emissions in different optimal retrofit strategies. Replacing the HVAC system and upgrading the ventilation system are the dominating options to eliminate around 84% of annual GHG emissions. Note that the upgrades with low decarbonizing impact were chosen due to the large effect on the LCC. Upgrading the lighting system when the heat source is gas, made a negligible increased on the annual CO_2 generation. However, this upgrade could decarbonize once the ground source heat pump was employed to provide heating.

Conclusion

The multi-objective optimization was used for an office building's retrofit analysis. Each retrofit scenario's environmental and economic impacts were set to two objective functions. Note that different decarbonizing targets were defined as a constraint in retrofit optimization. Prior to the retrofit analysis, optimization calibration of the energy model using hourly measured data was conducted to increase the accuracy of the base model. According to the results, the CV(RMSE) of the total energy consumption was reduced to 21% after automated calibration, which is acceptable based on ASHRAE Guideline 14.

Furthermore, according to the results, a 58% decrease in GHG emissions was accessible without upgrading the plant. Also, to decrease about 84% of annual GHG emissions, DOAS and chilled beam with a ground source heat pump were the most efficient system. Moreover, a higher value of GHG emissions reduction is achievable without significant variations in LCC.

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