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A Multi-Objective Optimization Algorithm for Building Systems Retrofits

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ABSTRACT

The building sector accounts for approximately 30-40% of global energy consumption and nearly 40% of Greenhouse Gas (GHG) emissions, making building retrofits essential for achieving significant reductions in energy use and emissions. However, developing effective retrofit strategies requires careful consideration of several critical factors: the economic viability of each retrofit option, local climate, policies, incentives, energy prices, electricity grid emissions intensity, the embodied carbon emissions of materials and processes, and the operational carbon emissions resulting from each retrofit strategy. This study employs a micro-genetic optimization algorithm coupled with the Vertical City Weather Generator (VCWGv1.6.0) urban physics model to identify optimal retrofit strategies for residential buildings in Toronto. The goal is to help homeowners minimize cost, and the associated embodied/operational carbon emissions. The proposed approach offers a framework for sustainable building retrofits that balances energy efficiency, economic viability, and carbon emission reductions simultaneously in the context of evolving policy landscapes.

Keywords: *Building Retrofit, Decarbonization, Economics, Micro-Genetic Alborithm (MGA), Optimization.*

1. INTRODUCTION

As the global community faces the urgent challenge of mitigating climate change, the building sector has emerged as a critical area for intervention. Buildings are responsible for a significant portion of global Greenhouse Gas (GHG) emissions, both through their operational energy use and the embodied carbon in construction materials. Retrofitting existing building systems presents a unique opportunity to reduce emissions and improve energy efficiency, often at a lower cost and with fewer disruptions compared to new construction. Effective retrofits can address aging infrastructure while incorporating modern, low-carbon technologies that significantly enhance sustainability (Aliabadi et al., 2021; Moradi, 2021; Moradi et al., 2021, 2022; Safdari et al., 2024).

In addition to environmental benefits, cost considerations play a vital role in the adoption of retrofit strategies. The economic viability of retrofit measures is often evaluated through Marginal Cost Analysis (MCA), which compares the cost-effectiveness of various strategies for reducing emissions. Cost-effective retrofitting not only reduces operational and embodied carbon but also enhances property values and reduces energy bills, providing a win-win situation for homeowners. Understanding and optimizing these costs is essential to ensure widespread adoption of retrofit solutions (Madadizadeh et al., 2024). Furthermore, a critical aspect of building decarbonization is evaluation of Social Cost of Carbon (SCC) savings achieved through building retrofits. The SCC represents the economic cost of the damages caused by one additional tonne of carbon emissions. By reducing emissions, retrofits contribute to significant SCC savings, which translate into societal benefits.

When considering retrofitting, there are several key aspects to address. The first is carbon emissions savings and the associated environmental benefits, and the second is the cost factor. An effective retrofit strategy should achieve the highest possible emissions savings while minimizing costs or even generating financial returns. To identify the optimal strategy, optimization algorithms are a suitable approach. In particular, Micro-Genetic Algorithm (MGA) is an excellent choice due to its ability to quickly identify quasi-global optimal solutions and their computational efficiency (Aliabadi et al., 2023).

This study investigates the potential of retrofit measures to maximize GHG emissions saving and minimize marginal costs in the residential building sector. Through the application of MGA, we explore optimized retrofit strategies for a typical detached two-storey residential house in Toronto (2020) that balance environmental and economic benefits.

2. METHODOLOGY

2.1. Vertical City Weather Generator (VCWGv1.6.0)

The Vertical City Weather Generator (VCWGv1.6.0) as an urban physics model is used to simulate the performance of residential buildings in Toronto under different retrofit strategies (Fig. 1). VCWGv1.6.0 integrates local weather data, building design parameters, and energy consumption patterns to generate realistic, and high-resolution simulations of building energy use and carbon emissions. The model uses localized climate data for Toronto, accounting for variations in temperature, humidity, wind patterns, and solar radiation over the course of the year 2020. Also, the VCWG model simulates the energy consumption of the building with and without retrofit strategies, considering factors such as thermal insulation, heating and cooling efficiency, and energy consumption patterns. The model calculates both operational carbon (based on energy consumption) and embodied carbon (based on materials used in retrofits) emissions. The total carbon footprint is tracked for each retrofit solution.

2.2. Micro-Genetic Algorithm (MGA)

The Micro-Genetic Algorithm (MGA) is employed to search for optimal retrofit solutions. MGA is a computationally efficient version of traditional genetic algorithms, designed to solve problems involving multiple conflicting objectives. The algorithm operates by evolving a population of potential solutions (5) (representing different retrofit strategies) over a series of generations (5), selecting the best individuals based on the lowest fitness according to the defined objective functions.

The primary goal of this study is to identify retrofit strategies that maximize operational carbon saving ($\text{GHG}_{o,s}$) over $N = 20$ years, embodied carbon emission (GHG_e) over $N = 20$ years, and

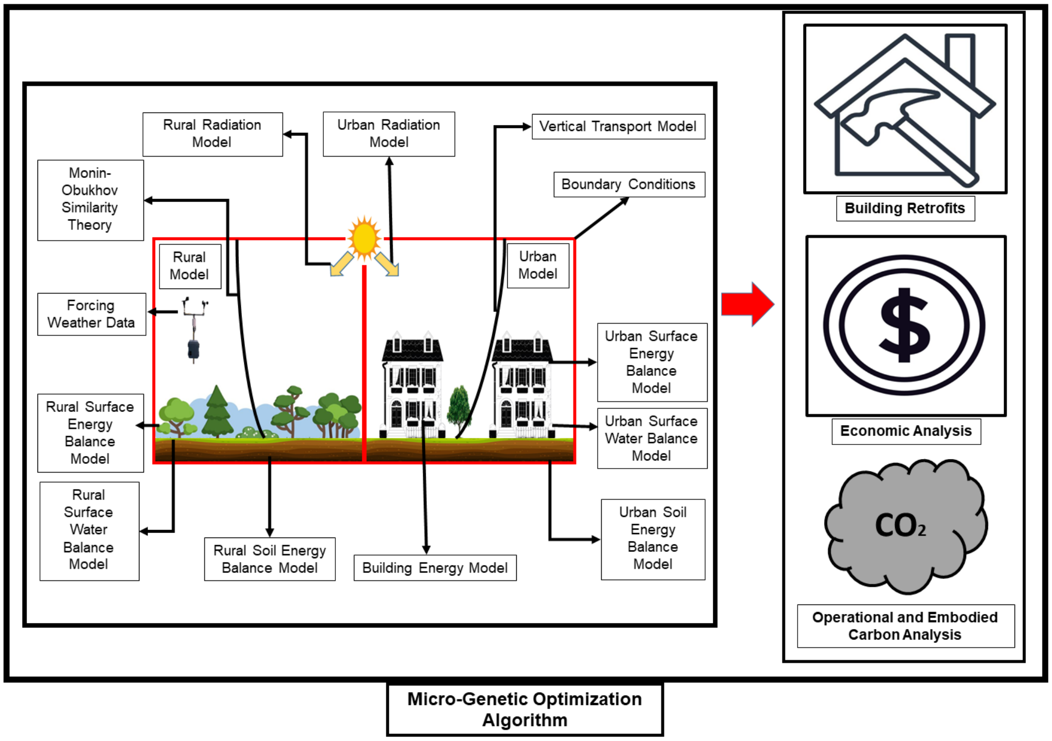


Figure 1. Vertical City Weather Generator (VCWGv1.4.6) and the associated sub-models.

the annualized marginal cost saving (C_s) of each retrofit strategy (Eq. 1). These objectives are considered simultaneously in the optimization process using weighted sum, which is to be minimized:

$$F = -w_{o,s}\frac{\mathrm{GHG}_{o,s}}{\mathrm{GHG}_{0o,s}} + w_e\frac{\mathrm{GHG}_e}{\mathrm{GHG}_{0e}} - w_{C_s}\frac{C_s}{C_{0s}} \tag{1}$$

Since all three objectives are equally important for our analysis, we assign the same weights to each, such that $w_{o,s} = w_e = w_{C,s} = \frac{1}{3}$. $\mathrm{GHG}_{o,s}$ [kg-CO_2], GHG_e [kg-CO_2], and C_{0s} [$] represent the operational carbon savings, embodied carbon emissions, and marginal annualized cost savings, respectively. These values are derived from the solution of the first iteration of the optimization process. The optimization itself is conducted over a set of retrofit parameters with predefined discrete ranges and intervals, as listed in Table 1.

2.3. Economic analysis

The equations in this section are adapted from Aliabadi et al. (2023). For calculating the annualized cost of residential building retrofits, the following equation is used,

$$C = C_I + C_F + C_E + C_{OM} + L - C_S, \tag{2}$$

Table 1. Optimization variables with minimum value, maximum value, and variation interval: Building Integrated Thermal Energy Storage (BITES), Solar Thermal (ST), Wind Turbine (WT), PhotoVoltaic (PV)

Variables	Minimum	Maximum	Interval
Volume of BITES (V_{bites}) [$m^3 m^{-2}$]	0.01	0.20	0.01
Roof Albedo (α_R)	0.1	0.7	0.05
Working Fluid Flow Rate for ST ($\dot{m}_{\text{st,f}}$) [kg $s^{-1} m^{-2}$]	0.0001	0.002	0.0001
Collector Area for ST (A_{st}) [$m^2 m^{-2}$]	0.2	0.6	0.05
Roof Thermal Resistance (R_{roof}) [m^2K W^{-1}]	5.46	11.5	0.5
Infiltration Rate (V_{inf}) [ACH]	0.5	3.5	0.5
Wall Thermal Resistance (R_{wall}) [m^2K W^{-1}]	3.6	7	0.5
Ventilation Rate (V_{vent}) [L $s^{-1} m^{-2}$]	0.3	0.4	0.05
Glazing Ratio (GR)	0.1	0.4	0.05
Air Flow Rate for ST ($\dot{m}_{\text{he,st}}$) [kg $s^{-1} m^{-2}$]	0.001	0.02	0.001
Swept Area of WT (A_{wt}) [$m^2 m^{-2}$]	0.05	0.2	0.05
Solar Heat Gain Coefficient (SHGC)	0.1	0.7	0.1
Collector Area for PV (A_{pv}) [$m^2 m^{-2}$]	0.1	0.6	0.1

where C_I is the annualized initial investment, C_F is the annual fossil fuel cost, C_E is the annualized grid electricity consumption cost, C_{OM} is the annualized operation and maintenance cost, L is the annualized loan cost, C_S is the annualized income from alternative energy system salvage all in [$]. The annualized cost saving is given by:

$$C_s = C_{\text{Base}} - C_{\text{Retrofit}} + SCC_{saving}, \tag{3}$$

where C_{Base} [$] is annualized marginal cost for the base case without any retrofit, C_{Retrofit} [$] is annualized marginal cost for each retrofit strategy, and SCC_{saving} is annualized social cost of carbon saving.

2.4. Environmental analysis

The environmental analysis involves the calculation of potential operational GHG emissions savings ($\text{GHG}_{o,s}$) and embodied carbon emission GHG_e through various building retrofit strategies. The embodied carbon emission is the summation of carbon emission of each retrofit strategy as shown in Eq 4:

$$\begin{aligned}\text{GHG}_e = & A_{\text{pv}}\text{ECF}_{\text{pv}} + A_{\text{wt}}\text{ECF}_{\text{st}} + V_{\text{BITES}}\text{ECF}_{\text{BITES}} \\ & + A_{\text{st}}\text{ECF}_{\text{st}} + R_{\text{wall}}A_{\text{wall}}\text{ECF}_{\text{Insulation}} \\ & + R_{\text{roof}}A_{\text{roof}}\text{ECF}_{\text{Insulation}} + \alpha_R\text{ECF}_{\text{CoolRoof}}\end{aligned} \tag{4}$$

where embodied carbon factor (ECF) for PV systems (ECF_{pv}) is 50 kg CO_2e m^{-2}), for wind turbines (ECF_{wt}) is 100 kg CO_2e m^{-2}), for the BITES system ($\text{ECF}_{\text{BITES}}$) is 30 kg CO_2e m^{-3}), and for solar thermal systems (ECF_{st}) is 40 kg CO_2e m^{-2}). Additionally, the embodied carbon factor for insulation materials ($\text{ECF}_{\text{Insulation}}$) is 10 kg CO_2e m^{-2}) and for the cool roof ($\text{ECF}_{\text{CoolRoof}}$) is 5 kg CO_2e m^{-2}).

The operational GHG emissions saving is the summation of GHG saving through a reduction of electricity and fossil fuel consumption. The fuel usage reduction is computed as

$$G_{\text{save}} = [G_{hB} + G_{whB} - (G_h + G_{wh})]A_{bld}N, \tag{5}$$

where G_{hB}, G_{whB}, G_h and G_{wh} [$\mathrm{m}^3\ \mathrm{m}^{-2}$] are the natural gas usage for the base and retrofitted buildings for space and water heating, respectively. Then, the operational GHG emissions reduction potential in CO_2e associated with gas saving is estimated by,

$$GHG_{G_{\text{save}}} = G_{\text{save}} \rho_G \frac{MW_{\text{CO2}}}{MW_G}, \tag{6}$$

where $\rho_G = 0.669\ \mathrm{kg}_G\ \mathrm{m}^{-3}$ is the density of natural gas, $MW_{\mathrm{CO_2}} = 44\ \mathrm{g}_{\mathrm{CO_2}}\ \mathrm{mole}^{-1}$ is the molecular weight of CO_2, and $MW_G = 16\ \mathrm{g}_G\ \mathrm{mole}^{-1}$ is the molecular weights of natural gas. The electricity usage reduction is computed by,

$$E_{\text{save}} = [E_{cB} + E_{dB} - (E_c + E_h + E_d - E_{pv} - E_{wt})]A_{bld}N, \tag{7}$$

where E_{cB}, E_{dB}, E_c, E_h, and E_d [$\mathrm{kW\text{-}hr\ m}^{-2}$] are the electricity usage for space cooling/heating and domestic appliance in base/retrofitted buildings, and E_{pv} and E_{wt} [$\mathrm{kW\text{-}hr\ m}^{-2}$] are electricity generated by PV and WT, respectively, in the retrofitted building. Then, the GHG emissions reduction potential in CO_2e associated with electricity saving is found as,

$$GHG_{E_{\text{save}}} = E_{\text{save}} EI_E, \tag{8}$$

where $EI_E = 25\ \mathrm{kg}_{\mathrm{CO_2}}\ \mathrm{kW\text{-}hr}^{-1}$ is the electricity grid GHG emissions intensity in Toronto in 2020.

3. RESULTS AND DISCUSSION

Fig. 2 illustrates the normalized overall objective function for three runs ((F-min)/(max-min)). It demonstrates that, for all runs, the objective function consistently decreases with each iteration. After more than 30 iterations, the function reaches a stable minimum value, indicating that the optimization process has made progress. This behavior highlights the efficiency of the MGA optimization algorithm in reaching an quasi-optimal solution.

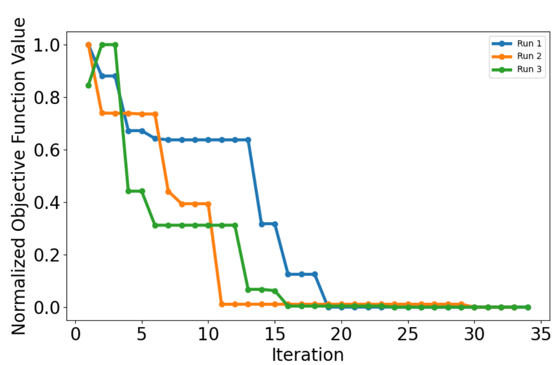


Figure 2. Normalized Best Overall Objective Function.

Table 2 shows best solution values of selected variables for optimization. The comparison between the initial setup of optimization variables (Table 1) and the optimized solutions (Table 2) reveals several key insights into effective retrofit strategies for Toronto. Some variables were maximized. The maximization of photovoltaic collector area (A_{pv}) suggests that integrating solar panels is a highly beneficial strategy for reducing operational carbon emissions, supporting the transition towards sustainable energy. Some variables were minimized, such as ventilation rate (V_{vent}), swept area of wind turbine A_{wt}. Other variables found an optimized value in the middle of their ranges (e.g. solar thermal collector area A_{st}, roof albedo (α_R), the infiltration rate (V_{inf}), Solar Heat Gain Coefficient (SHGC), Glazing Ratio (GR), and volume of BITES). Note that some optimization runs produced values in the entire range for some varaibles (e.g. infiltration rate).

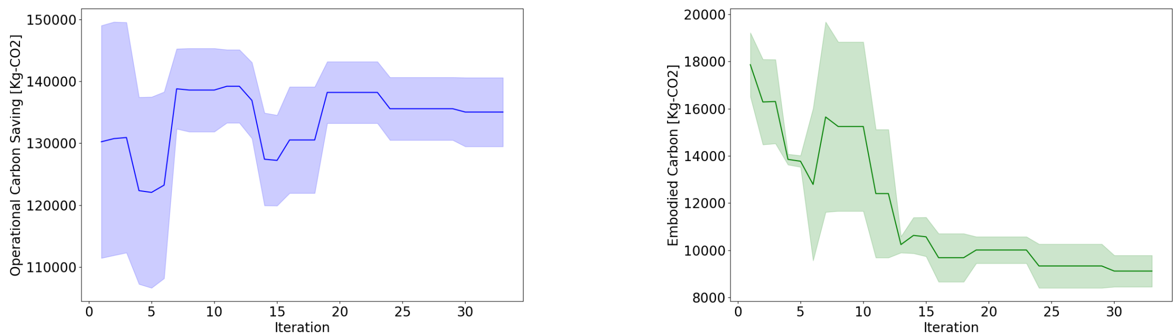
Table 2. Optimized variables for each run

Variable	Run 1	Run 2	Run 3
V_{bites} [$m^3 m^{-2}$]	5.00e-02	6.00e-02	5.00e-02
α_R	5.00e-01	5.50e-01	4.50e-01
$\dot{m}_{st,f}$ [kg $s^{-1} m^{-2}$]	5.00e-04	4.00e-04	6.00e-04
A_{st} [$m^2 m^{-2}$]	2.00e-01	5.00e-01	4.00e-01
R_{roof} [m^2K W^{-1}]	1.146e+01	1.096e+01	6.96e+00
V_{inf} [ACH]	1.50e+00	5.00e-01	3.00e+00
R_{wall} [m^2K W^{-1}]	5.10e+00	5.10e+00	4.60e+00
V_{vent} [L $s^{-1} m^{-2}$]	3.00e-01	3.50e-01	3.00e-01
GR	2.50e-01	4.00e-01	1.50e-01
$\dot{m}_{he,st}$ [kg $s^{-1} m^{-2}$]	8.00e-03	2.00e-03	1.10e-02
A_{wt} [$m^2 m^{-2}$]	5.00e-02	5.00e-02	5.00e-02
SHGC	2.00e-01	2.00e-01	1.00e-01
A_{pv} [$m^2 m^{-2}$]	6.00e-01	6.00e-01	6.00e-01

Fig. 3a demonstrates the process of optimizing operational carbon emissions savings through retrofitting strategies, showcasing the potential benefits for homeowners. Initially, the carbon emissions savings are inconsistent, fluctuating between approximately 120,000 and 130,000 kg-CO_2, indicating instability in the sub-objective function. However, as the optimization progresses, the savings increase and stabilize around 135,000 to 140,000 Kg-$CO-2$ on average, with reduced variability, reflecting greater reliability and consistency in the solution. For homeowners, this translates into significant carbon emissions reductions, potentially saving an additional 10,000 to 20,000 Kg-CO_2 compared to the sub-optimal initial solution.

Fig. 3b illustrates the embodied carbon emissions associated with retrofit strategies over an optimization process. At the beginning, embodied carbon emission levels are notably high, approximately 18,000 Kg-CO_2. As the optimization progresses, significant reductions are noted, with embodied carbon emissions stabilizing around 9,000 to 10,000 Kg-CO_2. For homeowners, achieving this reduction means cutting embodied carbon emissions by nearly 50% compared to the initial solution.

Fig. 4 shows the marginal annual cost savings achieved through optimized retrofit strategies. For the initial solution, homeowners are subject to significant negative savings (or positive expenses), with losses exceeding $2,500 annually. However, as the optimization process progresses, the annual cost savings improve significantly, eventually stabilizing at approximately $500 per year. This indicates that implementing the optimal retrofit strategies can result in substantial financial benefits, allowing homeowners to save up to $500 annually on operational costs, while enhancing



(a) Operational Carbon Saving **(b)** Embodied Carbon

Figure 3. Comparison of Operational and Embodied Carbon Savings.

energy efficiency and reducing carbon emissions.

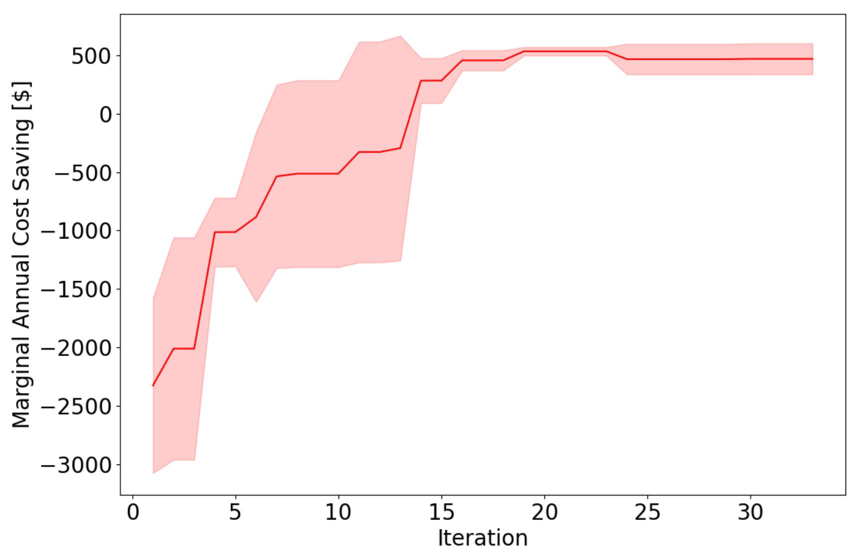


Figure 4. Marginal Annualized Cost Saving.

In addition to optimizing environmental and economic performance, this study also evaluates the savings associated with the SCC for each retrofit strategy. The SCC represents the societal cost of carbon emissions, encompassing the damages caused by climate change, such as extreme weather events, health impacts, and ecosystem destruction. By reducing carbon emissions through retrofits, this study calculates the annualized SCC savings, offering a valuable measure of the broader societal benefits. The reduction in carbon emissions for each retrofit strategy is calculated by comparing the operational and embodied carbon before and after the retrofit. The SCC is derived from existing studies and models that estimate the economic cost per tonne of GHG emissions avoided. Results show that the annualized SCC savings, calculated over 30 iterations, fluctuate between

$1,100 and $1,350. This amount of savings is of great importance as it highlights the potential for reducing the economic impact of emissions on society. The SCC savings underscore the long-term financial and environmental benefits of pursuing greener homes. By finding the optimal retrofit strategy, not only can we reduce emissions and mitigate climate change, but we can also see a financial return on these investments. Such strategies contribute to a more sustainable, resilient society, making the case for sustainable building practices both economically and environmentally beneficial.

4. CONCLUSIONS

The findings highlight the potential of MGA optimization for achieving comprehensive and sustainable building retrofit solutions. By balancing trade-offs between operational carbon emissions savings, embodied carbon emissions caused by retrofitting, and annualized cost savings, the proposed approach demonstrates a practical pathway for reducing upfront environmental impacts while ensuring long-term carbon benefits. Using the VCWG v1.6.0 urban physics model combined with economic analysis tools, the study optimizes retrofit strategies to maximize environmental and financial gains. Results show that retrofitting residential buildings in Toronto can lead to significant carbon emission reductions, up to 140 tonnes over 20 years, while generating annual cost savings of approximately $500. This outcome underscores the dual benefits of reducing carbon emissions and achieving financial savings, replacing high energy expenditures on electricity and gas consumption with sustainable and cost-effective solutions.

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