Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Issue 4, October 2025
DOI : https://doi.org/10.33395/sinkron.v9i4.15315
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Hybrid GA–MILP Model for Community Building Retrofit Planning Towards Carbon Neutrality

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Submitted :Sep 6, 2025 | **Accepted** : Oct 14, 2025 | **Published** : Oct 15, 2025

Abstract: Retrofitting community buildings is a key pathway toward carbon neutrality, yet most existing retrofit planning models lack adaptability to the diverse urban contexts of the Global South, where building typologies are heterogeneous and resources limited. Addressing this gap requires approaches that are both computationally efficient and context-sensitive. This study introduces a hybrid optimization framework that integrates Genetic Algorithm (GA) and Mixed-Integer Linear Programming (MILP) to tackle the multidimensional multiple-choice knapsack problem inherent in retrofit planning. The GA explores high-level system configurations, while MILP ensures precise component-level selection under budget and technical constraints. Compared to conventional single-method approaches, the hybrid GA–MILP achieves near-optimal emission reduction with reduced computation time and greater feasibility, offering a balanced trade-off between performance and scalability. Importantly, the framework demonstrates that medium-cost retrofit strategies provide the most cost-effective path to scalable carbon savings, making it highly relevant for resource-constrained urban environments. By situating retrofit planning within the realities of the Global South, this study advances methodological innovation and provides a robust decision-support tool aligned with sustainable development goals for inclusive and low-carbon urban futures.

Keywords: Building retrofit; Genetic algorithm; Emission reduction; Energy planning; Carbon neutrality

INTRODUCTION

The building sector is among the largest contributors to global energy consumption and greenhouse gas (GHG) emissions. According to the International Energy Agency, buildings accounted for approximately 30% of final global energy consumption in 2020, largely from heating, cooling, and lighting systems (International Energy Agency, 2023). Improving the energy performance of existing buildings is therefore central to achieving global carbon neutrality targets.

Global policy frameworks have increasingly emphasized building retrofitting as a strategic pathway to decarbonization. In Europe, the Energy Performance of Buildings Directive (EPBD) mandates long-term renovation strategies aiming at decarbonizing the building stock by 2050 (Energy Performance of Buildings Directive, 2025). Similarly, national initiatives such as France’s National Low Carbon Strategy highlight the role of retrofitting in reducing emissions(Sesana et al., 2021). Efforts to operationalize these directives include the Energy Performance Certificate (EPC) framework (Dell’Anna, 2025; Shakeel et al., 2025) and early-stage decision-support tools at city and territorial scales (Cardoso de Oliveira et al., 2025; Casalicchio et al., 2025; Follador et al., 2024; Golzar et al., 2018).

Despite these advances, research gaps remain evident. First, most studies are Eurocentric, focusing on homogeneous building typologies, specific archetypes, or individual buildings(Aruta et al., 2025; Charles et al., 2025; D’Agostino et al., 2025; Torres-Rivas et al., 2022). Such approaches overlook the spatial heterogeneity and socio-economic diversity characteristic of the Global South. Second, existing optimization models often rely on fixed cost-benefit assumptions, neglecting uncertainties in technology costs, behaviorally driven energy use, and evolving market conditions (Mohseni-Gharyehsafa et al., 2025; Park et al., 2024; Zuhanda et al., 2023). Third,

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there is limited integration of bottom-up urban building energy modeling (UBEM) with rigorous optimization frameworks such as Mixed-Integer Linear Programming (MILP), which are necessary for large-scale, spatially adaptive retrofit planning (Lima & Guirardello, 2025; Seok et al., 2025). These limitations underline the need for methodological innovations capable of capturing heterogeneity, uncertainty, and scalability.

To address these gaps, scholars have begun exploring combined approaches. Fan and Xia (2018) introduced EPC-compliant optimization models that balance regulatory compliance and cost-effectiveness. Cosic et al.(2021) applied MILP to optimize retrofit strategies at community scale, while Cerezo et al.(2017) and Shen and Wang (Shen & Wang, 2024) emphasized archetype characterization and UBEM to capture behavioral and climatic dynamics. At the same time, metaheuristics such as Genetic Algorithms (GA)(Holland, 1992) have demonstrated flexibility in solving nonlinear, multi-constrained optimization problems(Liu et al., 2019; Zuhanda et al., 2024) . However, standalone GA often lacks feasibility guarantees compared to exact methods like MILP.

The mathematical formulation of this study aligns with the structure of a Multidimensional Multiple-Choice Knapsack Problem (MMKP), a well-studied combinatorial optimization problem in operations research. Classical foundations of knapsack modeling and solution strategies are extensively discussed in Knapsack Problems: Algorithms and Computer Implementations(Martello & Toth, 1990), which provide essential theoretical underpinnings for addressing resource allocation under multiple constraints. Building upon these principles, this study adapts the knapsack framework to the retrofit planning domain, where budget limitations, system compatibility, and emission reduction objectives must be balanced simultaneously.

Building on these insights, this study proposes a hybrid GA–MILP framework for large-scale retrofit planning of community buildings. The GA explores high-level system configurations (e.g., heating and ventilation), while MILP ensures optimal component-level selection under given configurations. This integration aims to balance solution quality, computational efficiency, and feasibility. Methodologically, the study contributes by demonstrating the synergy of metaheuristic and exact optimization in retrofit planning. Practically, it provides decision-makers—particularly in resource-constrained Global South contexts—with a robust tool to prioritize investments, maximize carbon reductions, and allocate budgets effectively. Ultimately, the proposed model aligns with Sustainable Development Goals (SDG 7 and SDG 11), advancing inclusive, resilient, and low-carbon urban infrastructure.

LITERATURE REVIEW

Problem Description

Summary of recent studies on building retrofit and energy community optimization can be seen in Table 1.

Table 1. Summary of data and parameters

Study	Methodology	Limitations
(Fan & Xia, 2018)	Grouping approach + notch test data with GA	Focused on Energy Performance Certificate (EPC) compliance; limited to whole-building retrofit; less scalable for heterogeneous urban contexts
(Cosic et al., 2021)	MILP framework for Renewable Energy Communities (REC), considering PV and energy storage with full-year optimization horizon	Strong in operational dispatch and tariff modeling; however, computationally expensive and lacks socio-spatial diversity, focused mainly on EU contexts.
(Zwickl-Bernhard & Auer, 2021)	MILP-based optimization of sustainable urban energy portfolios in Vienna	Supports sustainable urban planning but limited in scalability and does not use full-scale yearly optimization.
(Jiang et al., 2023)	Two-stage optimization model for renewable energy sharing in community setups	Provides insight into energy sharing under Time of Use (TOU) tariffs, but assumes uniform prices for all participants and short (24-hour) horizon, limiting realism.
(Perger et al., 2022)	Linear optimization model for energy communities with diverse	Considers willingness-to-pay criteria, but assumes fixed electricity prices and neglects

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	prosumers (apartments, businesses)	uncertainty in tariffs and market dynamics.
This Study (2025)	Hybrid GA–MILP framework for community-level building retrofit, incorporating socio-spatial weights	Bridges heuristic flexibility (GA) and exact precision (MILP); scalable and adaptive to heterogeneous contexts in the Global South; current limitation: requires validation with real-world UBEM and socio-economic data.

The goal of this study is to determine an optimal set of energy-efficient retrofit strategies for a collection of urban community buildings $b \in B$, each composed of various surface elements $s \in S_b$ (such as walls and roofs). For every surface s, there exists a set of retrofit options $r \in R_s$, and each building may adopt a specific heating system $h \in H_b$ and ventilation system $v \in V_b$.

Each decision regarding the implementation of retrofit option r on surface s of building b under heating system h is represented by a binary variable $x_{b,s,r,h} \in \{0,1\}$, where 1 indicates the selection of that option. Similarly, the binary variable $y_{b,v,h} \in \{0,1\}$ denotes whether ventilation system v is chosen under heating system h for building b.

Every retrofit option r is associated with a cost $C_{b,s,r,h}$and an estimated CO₂ emission reduction $E_{b,s,r,h}$. The objective is to minimize total emissions across all buildings while satisfying the following constraints:

1. Total cost must not exceed a predefined budget.
2. Only one retrofit option may be selected per building surface per heating configuration.
3. The choice of heating systems must be consistent across all retrofitted surfaces of a building.
4. At most one ventilation system is selected for each heating option in each building.

Mathematical Model

Sets and Indices:
B: Set of buildings
S_b: Set of building surfaces (e.g., walls, roofs) for building b
R_s: Set of available retrofit options for surface s
H_b: Set of heating system options for building b
V_b: Set of ventilation system options for building b

Decision Variables:
$x_{b,s,r,h} \in \{0,1\}$:1 if retrofit option r is selected for surface s of building b with heating system h, 0 otherwise.
$y_{b,v,h} \in \{0,1\}$: 1 if ventilation system v is selected for building b under heating option h, 0 otherwise.
Parameters:
$C_{b,s,r,h}$: Cost of implementing retrofit r on surface s of building b with heating option h
$E_{b,s,r,h}$: Expected emission reduction from retrofit r
$BUDGET$: Maximum allowable total retrofit cost
Objective Function:

$$\min \sum_{b \in B} \sum_{s \in S_b} \sum_{r \in R_s} \sum_{h \in H_b} x_{b,s,r,h} \cdot E_{b,s,r,h} \tag{1}$$

Subject to:

$$\sum_{b \in B} \sum_{s \in S_b} \sum_{r \in R_s} \sum_{h \in H_b} x_{b,s,r,h} \cdot C_{b,s,r,h} \leq BUDGET \tag{2}$$

$$\sum_{r \in R_s} x_{b,s,r,h} \leq 1 \quad \forall b \in B, s \in S_b, h \in H_b \tag{3}$$

$$\sum_{r \in R_{s1}} x_{b,s1,r,h} = \sum_{r \in R_{s2}} x_{b,s2,r,h} \quad \forall b \in B, s1, s2 \in S_b, h \in H_b \tag{4}$$

$$\sum_{v \in V_b} y_{b,v,h} \leq 1 \quad \forall b \in B, h \in H_b \tag{5}$$

$$x_{b,s,r,h}, y_{b,v,h} \in \{0,1\} \tag{6}$$

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The mathematical formulation of this study is designed to identify the optimal set of retrofit strategies that minimize total emissions resulting from energy renovation actions in community buildings. Equation (1) shows the objective function, which seeks to minimize the aggregated emissions from selected retrofit options across all buildings, surfaces, and system configurations. This objective is subject to several constraints that ensure practical feasibility.

Equation (2) restricts the total implementation cost to remain within the allocated retrofit budget. Equation (3) ensures that only one retrofit option can be chosen for each building surface under a given heating configuration. To maintain consistency among selected options, Equation (4) enforces that all retrofitted surfaces within the same building share a coherent heating system configuration. Equation (5) limits each building to selecting only one ventilation system per heating option. Finally, Equation (6) declares all decision variables as binary, indicating that retrofit and ventilation options are either selected or not. This formulation aligns with the structure of a Multidimensional Multiple-Choice Knapsack Problem (MMKP), enabling scenario-based decision-making in energy retrofit planning while considering environmental, economic, and technical constraints

METHOD

In the context of large-scale energy retrofitting, particularly for community buildings in the Global South, the decision-making process must address numerous constraints including budget limitations, heterogeneous building typologies, spatial diversity, and varying retrofit options. Traditional optimization approaches such as Mixed-Integer Linear Programming (MILP) provide precise solutions but struggle with scalability and computational tractability as the complexity of the model increases. Conversely, Genetic Algorithms (GA) are capable of exploring vast and nonlinear search spaces effectively but may produce suboptimal or infeasible solutions when strict constraints must be satisfied.

To reconcile the strengths and limitations of these two approaches, this research proposes a hybrid GA-MILP framework. The central idea is to divide the decision-making process into two hierarchical levels: strategic-level decisions regarding system configurations are handled using GA, while operational-level decisions involving selection of retrofit actions for each building surface are delegated to MILP solvers. This decomposition allows for efficient search and fine-grained optimization while adhering to real-world constraints such as budget caps and system compatibility. The stages of the research methodology are illustrated in Figure 1.

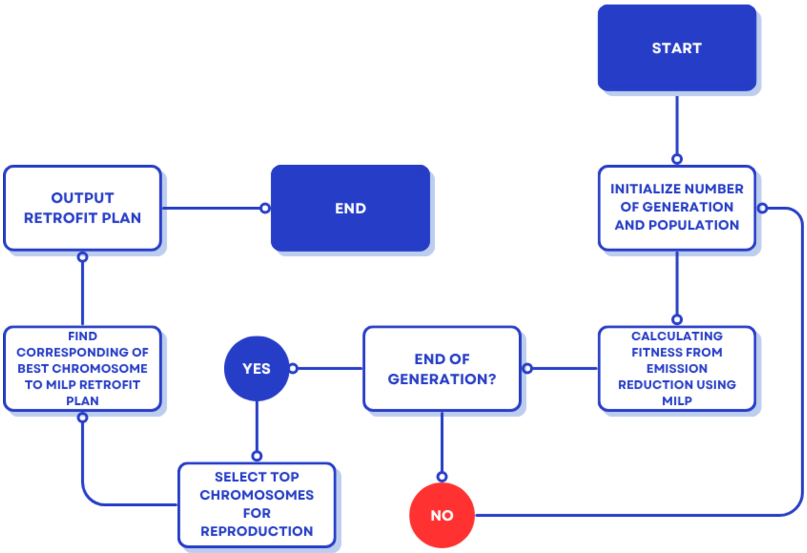

Figure 1. Average retrofit cost by option

The retrofit planning problem formulated in this study exhibits characteristics typical of Multidimensional Multiple-Choice Knapsack Problems (MMKP), where each building can be assigned multiple retrofit options per surface, subject to budget and system constraints. Solving such problems exactly with MILP becomes computationally intensive as the number of buildings and options increase, especially when multi-objective or scenario-based decision-making is required. Algorithm 1 describes a hybrid optimization procedure that combines Genetic Algorithm (GA) to explore system-level configurations and Mixed-Integer Linear Programming (MILP) to determine optimal retrofit actions for each building, aiming to maximize emission reduction under budget constraints.

Algoritm 1 Hybrid GA-MILP for Community Building Retrofit Planning

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Input: Set of buildings $B$, retrofit options $R$, surfaces $S$, budget $C_{max}$
Initialize: Population $P$ with random chromosomes encoding $(H_b, V_b)$ for each $b \epsilon B$
for generation $g = 1$ to $G$ do
    for each chromosome $c$ in $P$ do
        Extract heating $H_b$ and ventilation $V_b$ assignments from $c$
        Solve MILP with fixed $H_b$, $V_b$, to select $x_{b,s,r}$ that maximizes emission reduction
        Record MILP objective value as fitness of $c$
    end for
    Select top $k$ chromosomes for reproduction
    for each new chromosome $c'$ do
        Apply crossover and mutation to generate $c'$
        Add $c'$ to new population $P'$
    end for
    $P \leftarrow P'$
end for
Output: Best chromosome $c^*$ and its corresponding MILP retrofit plan
```

GA offers a way to intelligently guide the search through higher-level configurations by rapidly evaluating and evolving combinations of heating and ventilation system assignments across buildings. However, GA alone lacks the granularity to assess cost-emission trade-offs at the component level, especially under strict constraints.
The hybrid GA-MILP strategy hence facilitates:

1. Using GA to navigate high-level design space across buildings.
2. Using MILP to optimize component-level choices based on GA-derived configurations.

In this study, synthetic data were employed, carefully designed to be representative of real community building conditions. The use of synthetic data was chosen because actual retrofit data are often difficult to obtain in a complete and integrated form, while synthetic data provide flexibility to design various scenarios and enable sensitivity analysis under controlled parameters. Moreover, synthetic data enhance transparency and replicability, allowing other researchers to reproduce and extend the methodological approach. Nevertheless, future validation of the proposed model will be conducted using real-world data through case studies on selected community buildings with comprehensive technical, cost, and energy consumption records. This validation will compare the model's predicted outcomes—both in terms of costs and emission reduction potential—against observed field data to ensure reliability and practical relevance of the model for urban retrofit planning.

RESULT

The experimental model relies on synthetic but representative data inputs to simulate realistic urban retrofit scenarios. Data were structured at the building-component level, incorporating spatial, technical, and economic attributes. Table 2 summarizes the key data components and parameters used in the model.

Table 2. Summary of data and parameters

Component	Description
Building Set (B)	10 community buildings
Surface Types (S_b)	Each building has two surfaces: wall and roof
Retrofit Options (R_s)	R1: Minimal insulation R2: Standard retrofit R3: High-performance reflective envelope
Heating Systems (H_b)	H1: Gas boiler H2: Heat pump
Ventilation Systems (V_b)	V1: Natural ventilation V2: Mechanical ventilation with heat recovery
Cost Range (C)	IDR 15–80 million per retrofit option depending on type and configuration
Emission Reduction (E)	200–1200 kg CO_2/year per component, based on EPC and retrofit type
Budget Constraint	IDR 500 million (baseline), varied during scenario testing
Socio-Spatial Weights	Values from 0.5 to 1.5 based on density and income vulnerability indices

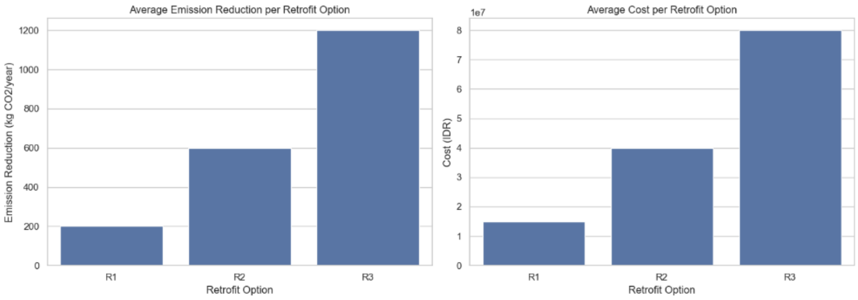

Figure 2. Average retrofit cost by option

Figure 2. Average Retrofit Cost by Option illustrates the cost comparison among the three retrofit strategies: R1, R2, and R3. The visualization clearly shows that R1 is the most economical option, with an average cost of IDR 15 million; R2 represents a mid-range solution at around IDR 40 million; while R3 is the most expensive, costing up to IDR 80 million. This trend highlights a direct relationship between investment level and the effectiveness of energy efficiency improvements. In essence, higher-cost retrofit options tend to offer greater potential for carbon emission reductions, although they limit the number of units that can be implemented under a fixed budget.

Table 3. Sensitivity Analysis

Budget (IDR)	Retrofit Option	Max Units	Total Emission Saved (kg CO2/year)
200000000	R1	13	2600
200000000	R2	5	3000
200000000	R3	2	2400
300000000	R1	20	4000
300000000	R2	7	4200
300000000	R3	3	3600
400000000	R1	26	5200
400000000	R2	10	6000
400000000	R3	5	6000
500000000	R1	33	6600
500000000	R2	12	7200
500000000	R3	6	7200
600000000	R1	40	8000
600000000	R2	15	9000
600000000	R3	7	8400

Table 2 displays a sensitivity analysis that examines how different budget levels impact the number of retrofit units that can be implemented and the resulting total CO_2 emission reductions for each retrofit option (R1–R3). As the budget increases from IDR 200 million to IDR 600 million, the number of units that can be installed and the corresponding emission savings increase proportionally for all options. R1 allows for the highest number of installations due to its low cost, but yields the lowest total emission savings per unit. In contrast, R3, while having the highest per-unit impact on emissions, is limited in quantity under tighter budgets. At IDR 400 million and above, R2 and R3 converge in their emission-saving potential (6,000–9,000 kg CO_2/year), making them more attractive in medium-to-high budget scenarios due to their balance between cost and effectiveness. This analysis suggests that for limited budgets, R2 provides the most cost-effective path to maximizing emission reductions.

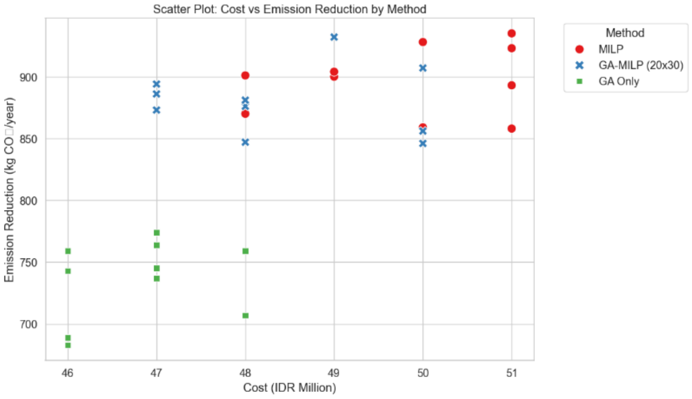

Figure 3. Comparative performance of optimization algorithms for community building retrofits

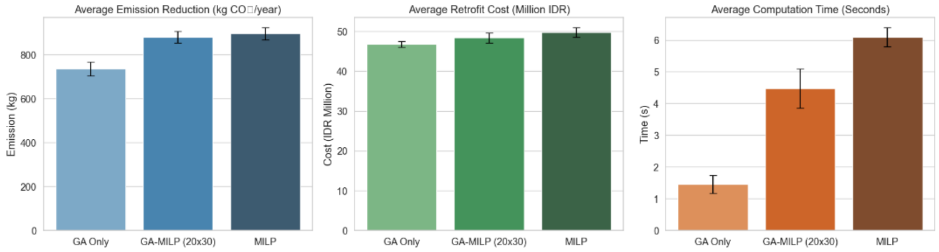

Figure 4. Average emission reduction, retrofit cost, and computation time by optimization method

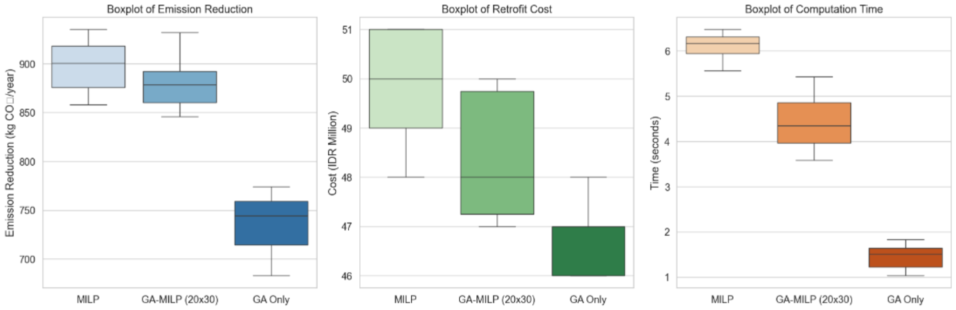

Figure 5. Distribution of Emission Reduction, Retrofit Cost, and Computation Time by Method

Figures 3, 4, and 5 collectively illustrate the comparative performance of the three optimization methods—GA, GA–MILP, and MILP—across key dimensions of emission reduction, retrofit cost, and computation time. MILP consistently achieves the highest average emission reduction (around 897.1 kg CO_2/year) and shows the most stable results, but it requires the longest computation time (6.1 seconds) and incurs the highest cost. The hybrid GA–MILP method delivers nearly identical emission reductions (879.8 kg CO_2/year) while offering lower average costs and shorter computation times (4.47 seconds), making it more efficient for large-scale planning without compromising solution feasibility. Meanwhile, the GA-only method demonstrates the lowest emission reductions (736 kg CO_2/year) yet remains the fastest (1.45 seconds) and most economical, though with greater variability and only partial feasibility. The boxplots and distribution plots highlight that MILP and GA–MILP maintain narrower performance variability compared to GA, reinforcing their reliability. Overall, the figures underscore that while MILP excels in precision, the GA–MILP hybrid strikes the best balance between performance, cost efficiency, and computational practicality, whereas GA alone is most suitable for rapid, exploratory analyses rather than final implementation.

DISCUSSIONS

High-cost retrofit strategies, such as R3 (IDR 80 million), demonstrate the greatest potential for emission reduction, achieving up to 1200 kg CO_2/year. However, their elevated cost intensity imposes significant limitations on scalability, particularly in budget-constrained urban contexts. Conversely, low-cost interventions, exemplified by R1 (IDR 15 million), provide only marginal environmental benefits of approximately 200 kg CO_2/year. The sensitivity analysis underscores that medium-cost strategies, such as R2, can yield emission reductions comparable to R3 under moderate budget allocations (e.g., both achieving 7200 kg CO_2/year at an investment of IDR 500 million), positioning R2 as the most cost-effective option in constrained resource environments.

A comparative evaluation of optimization methods reveals distinct performance profiles. The MILP approach consistently delivers the highest average emission reduction (897.1 kg CO_2/year) but is associated with the longest computational time (6.1 seconds) and the highest average cost. The hybrid GA–MILP method achieves near-identical reductions (879.8 kg CO_2/year) while reducing both average cost and computation time (4.47 seconds), and maintaining full feasibility across all evaluated scenarios. In contrast, the pure GA method, although computationally superior in speed (1.45 seconds), produces lower reductions (736 kg CO_2/year) and meets feasibility constraints in only 60% of cases, limiting its applicability to early-stage solution screening rather than implementation-level decision-making.

The robustness of solution quality further differentiates these methods. MILP and GA–MILP exhibit narrow performance variability, reflecting greater reliability and stability, whereas GA demonstrates wider variability in outcomes, indicative of its heuristic and non-deterministic nature. This stability advantage positions GA–MILP as a particularly valuable tool for urban-scale retrofit planning, where the dual imperatives of solution feasibility and high performance must be met under complex spatial and technical constraints.

A consistent pattern observed across all methods is the diminishing marginal returns associated with high-cost interventions. Beyond an investment threshold of IDR 400–500 million, strategies such as R3 offer only marginal gains over R2 in terms of cumulative emission reductions. This evidence reinforces the conclusion that the integration of the GA–MILP framework with a medium-cost retrofit strategy, such as R2, constitutes the most strategic and scalable pathway for achieving substantial emission reductions while maintaining financial viability and operational efficiency in urban retrofit programs.

Compared to the works of Fan & Xia (2018) and Cosic et al. (2021), this study offers several distinct advantages. Fan & Xia proposed simplified optimization models for whole-building retrofits by applying grouping techniques and utilizing notch test data to reduce complexity and avoid costly bottom-up audits, with a primary focus on achieving compliance with the Energy Performance Certificate (EPC) standard. Meanwhile, Cosic et al. developed a MILP-based framework for renewable energy communities, emphasizing optimal investment and operational dispatch of distributed energy resources such as PV and storage, with detailed time-of-use tariff structures and full-year optimization horizons. In contrast, the present study introduces a hybrid GA-MILP framework that strategically combines the exploratory capability of Genetic Algorithms at the system-configuration level with the precision of MILP at the component-selection level. This hybridization enables the model to address the multidimensional multiple-choice knapsack problem (MMKP) inherent in large-scale community retrofit planning. As a result, the proposed approach is computationally more efficient and scalable than pure MILP models while offering more robust and feasible solutions than GA alone. Furthermore, unlike previous studies that largely target EPC compliance or operational cost and emission savings, this work explicitly frames retrofit planning in the context of carbon neutrality, with direct emission-reduction metrics. Importantly, it also situates the model within the realities of the Global South, where building typologies are highly heterogeneous, resources are limited, and socio-economic vulnerabilities must be considered.

Nevertheless, several limitations should be acknowledged. First, the evaluation was performed using synthetic datasets, which, while representative, may not capture the full variability of real-world building stocks and behavioral energy-use patterns. Second, the model currently emphasizes energy and emission trade-offs but does not fully incorporate uncertainty in technology costs, long-term policy shifts, or climate-related risks that can significantly affect retrofit outcomes. Third, the framework has yet to be validated at scale with real case studies across diverse urban environments.

These limitations open up promising avenues for future research. Future studies should validate the hybrid GA-MILP approach with empirical data from actual community retrofits to test its robustness under real constraints. Integrating stochastic optimization or scenario-based planning would allow the framework to better handle uncertainties in energy prices, technology adoption rates, and climate variability. Moreover, expanding the model to include social acceptance, financing mechanisms, and behavioral responses could strengthen its applicability for policy and community-level decision-making. Finally, coupling the framework with bottom-up urban building energy modeling (UBEM) and real-time monitoring systems could provide a dynamic decision-support platform that continuously adapts retrofit strategies in pursuit of long-term carbon neutrality goals.

CONCLUSION

In conclusion, this study demonstrates that the hybrid GA–MILP framework is scientifically effective in bridging heuristic flexibility with the rigor of exact methods, enabling scalable and computationally efficient solutions for complex retrofit planning. From a practical perspective, medium-cost retrofit strategies (R2) emerge as the most efficient choice, offering the best balance between emission reduction and budget allocation under resource constraints. Nonetheless, the reliance on synthetic datasets presents a limitation, underscoring the need for validation through real-world case studies. Looking forward, future research should focus on integrating Urban

Building Energy Modeling (UBEM) with real socio-economic data to enhance adaptability, realism, and policy relevance in advancing community-scale carbon neutrality.

ACKNOWLEDGMENT

This research was funded by the Ministry of Higher Education, Science, and Technology based on a contract between the LLDIKTI Region I and Institut Modern Arsitektur dan Teknologi, under Contract Number 56/SPK/LL1/AL.04.03/PL/2025.

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