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# Integrating BIM and life cycle assessment for low-carbon renovation design of existing urban buildings

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**Abstract**

Existing urban buildings require low-carbon renovation strategies that simultaneously address operational energy consumption, embodied carbon, life-cycle environmental impacts, and renovation cost. However, these dimensions are often assessed separately, while effective integration of Building Information Modeling (BIM) and Life Cycle Assessment (LCA) and selection of balanced renovation alternatives remain challenging. This study develops an integrated BIM–LCA framework for assessing and optimizing low-carbon renovation strategies for an existing university office and laboratory building in Tallinn, Estonia. Autodesk Revit 2024 was used to develop the parametric BIM model and extract material quantities, while DesignBuilder/EnergyPlus was employed to simulate baseline and renovation energy performance. The environmental assessment used the ecoinvent life-cycle inventory database and ReCiPe 2016 Midpoint method over a 50-year assessment period. The system boundary included material production, transportation, installation, component replacement, operational energy, and end-of-life stages. Renovation scenarios involving wall and roof insulation, window replacement, heating, ventilation and air-conditioning (HVAC) improvements, envelope renovation, photovoltaic (PV) integration, and combined measures were evaluated. Non-dominated Sorting Genetic Algorithm II (NSGA-II) was applied to identify Pareto-optimal alternatives considering annual operational energy consumption, embodied carbon, operational carbon, and renovation cost. The Pareto-optimal alternatives were then assessed using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), based on the specified criteria and weighting scheme. The selected compromise solution, SOL_040, reduced annual energy consumption from 793.3 to 276.66 MWh/year and Energy Use Intensity (EUI) from 186.22 to 64.94 kWh/m$^2$/year, corresponding to a 65.13% reduction in both indicators, and reduced life-cycle carbon emissions from 11,117.5 to 7,394.40 t $CO_2$e, representing a 33.49% reduction. SOL_040 achieved a recalculated TOPSIS closeness coefficient of 0.6864. The findings demonstrate an integrated BIM, energy simulation, LCA, multi-objective optimization, and multi-criteria decision-making workflow for comparing renovation alternatives and supporting low-carbon renovation planning.

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## 1. Introduction

Urbanization, energy consumption, and the aging of existing buildings have brought about the necessity of sustainable renovation of urban buildings [1]. The high level of energy use and emissions of greenhouse gases by buildings during their life cycle makes existing building renovation an essential factor for achieving low carbon urban development [2]. Renovation, unlike

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building new structures, needs to function within the context of existing structural, architectural, and material limits, while being improved in energy and environmental performance terms [3]. The study integrates building information modeling (BIM), life cycle assessment (LCA), and multi-objective optimization to support sustainable renovation decisions for existing urban buildings. This combination addresses limitations in conventional PE through data-driven movement classification, performance assessment, and adaptive feedback.

The issues related to energy consumption and the environment in existing buildings have to do with the interaction of different physical, technological, and operational variables [4]. Deterioration of the envelope of a building, low efficiency of its insulation and windows, old HVAC systems, and other issues can affect energy use [5]. Changes in occupancy, operating hours, load and climate can also affect energy consumption [6]. Energy-efficient building technologies and improved insulation materials can help reduce energy consumption and greenhouse gas emissions throughout the building's operational life. Renovation towards low carbon is important in enhancing urban sustainability since decisions regarding building renovations affect its performance for long durations [7]. BIM is a digital model of the building structure, materials, components, and system, thus facilitating the extraction of information systematically and scenario development [8]. LCA can allow evaluation of the environmental impact caused by materials, operation, replacement, and various other life cycle phases [9]. Continuous monitoring of building energy performance and environmental conditions can provide valuable information for evaluating renovation effectiveness and identifying opportunities for further energy improvements.

The following research proposes the combination of BIM and LCA to fill out these gaps for the renovation of existing urban buildings. In the first place, a parametric BIM model for existing buildings is created. Afterwards, the process of baseline energy simulation based on Design Builder/Energy Plus is carried out. Then, material quantities, which have been determined through BIM analysis and energy simulation, are inputted into ReCiPe 2016-based LCA. The different types of renovation scenarios including walls, roofs, windows, HVAC, and combinations are created and assessed. NSGA-II is performed to find Pareto-optimal solutions considering energy consumption, carbon emissions throughout life cycle and renovation costs at the same time. TOPSIS is conducted to rank Pareto-optimal solutions and choose the best design. The proposed framework integrates BIM-based modeling, energy simulation, ReCiPe 2016-based life cycle assessment, and NSGA-II optimization to identify cost-effective renovation strategies while minimizing energy consumption and life cycle carbon emissions. Furthermore, evaluating indoor environmental conditions, including temperature, humidity, and air quality, can help ensure that renovation strategies improve building energy efficiency without compromising occupant comfort.

### 1.1 Objectives

- Analysis of baseline energy performance and life-cycle environmental performance of the current urban building using BIM, DesignBuilder/EnergyPlus, and LCA.
- Comparison of different renovation scenarios including walls, roofs, windows, HVAC systems, envelope upgrades, deep renovation, and photovoltaics according to energy efficiency, carbon emissions, environmental impact, and cost performance criteria.
- Optimization of different renovation scenarios using the NSGA-II approach to determine Pareto-optimal renovation scenarios considering energy use, carbon emissions embodied in buildings, operational carbon emissions, and renovation cost.
- Selection of the best low-carbon renovation scenario among Pareto-optimal scenarios using the TOPSIS approach.

### 1.2 Organization of the Paper

The organization of the rest of the paper is as follows. Section 2 provides the literature review and highlights the gap in research. Section 3 gives an outline of the methodology to be used in this study and includes data collection, BIM model creation, energy simulation of baseline and renovation scenarios, LCA, renovation scenario generation, optimization with the NSGA-II algorithm, and decision-making with the use of the TOPSIS technique. Section 4 describes the results of the study and discusses energy, carbon, and environmental issues, optimization.

## 2. Literature Survey

In this section, literature related to BIM, building energy performance assessment, LCA, and BIM-LCA integration is reviewed.

### 2.1 Building Information Modeling for Existing Building Renovation

Yildirim and Polat [10] showed how BIM-based energy modeling could be used to assess energy savings and carbon reductions from different refurbishment options for residential buildings. Their methodology included using Autodesk Revit for developing BIM models, DesignBuilder/EnergyPlus for simulating energy use in the buildings, and ReCiPe 2016 LCA. On the other hand, [11] have developed a BIM-based decision support system named RenoDSS. RenoDSS has been able to reduce the time required to identify renovation scenarios and calculate KPIs by 80% by combining building information, energy simulation and LCA/LCC assessment in IFC format. [12] Investigated the impact of City Information Modeling (CIM) in the creation of digital twins of cities through the integration of BIM, GIS, and IoT data to address the issue of interoperability. This demonstrates the usage of BIM not only for the renovation of buildings but also for creating digital twins of cities. Both studies show how BIM is evolving from being used for buildings to being used for citiesBuilding energy performance is influenced by the thermal properties of construction materials, the efficiency of building systems, and external environmental conditions, all of which must be considered when developing effective low-carbon renovation strategies.

### 2.2 BIM-Based Building Energy Performance Assessment

BIM-ML framework has been proposed by [13] that combines explainable machine learning and multi-objective optimization for better building sustainability. The methodology used DesignBuilder simulation along with a BO LGBM prediction model, explained using SHAP, and optimized using the AGE MOEA algorithm. The results found that BO LGBM yielded $R^2 > 93.4\%$ and MAPE < 2.13%, while having HVAC as the top feature for accuracy of prediction. In an attempt similar to that of [14], a BIM-ML-based decision support framework was developed that improved energy performance assessment of residential buildings. ANN models were found superior to SRM, DTs, and RFs in terms of accuracy of predictions. However, these methodologies are mostly centered around energy prediction. [15] considered the use of BIM 6D to optimize energy efficiency in residential buildings in terms of daylighting and windows. The methodology included construction of 3D models in Autodesk Revit Architecture and energy analysis using Autodesk Insight through application of Building Energy Modeling, Illuminance Analysis, Solar Access and Daylight Autonomy techniques.

### 2.3 Life Cycle Assessment for Building Carbon and Environmental Impact

Integration of AI with BIM and LCA was furthered by [16] for achieving optimum low-carbon architecture designs. This involved three case studies, namely an ML-aided carbon footprint estimation tool, the use of ChatGPT as a virtual assistant to generate design recommendations and BIM – IFC integration combined with carbon footprint analysis in a 3D platform. To complement this, [17] developed a machine learning framework for embodied carbon assessment and created a standard protocol with an average error of 15.71%. However, the former is still based on experimental integration of AI, whereas the latter is data-constrained and needs transportation emission factors as well.[18] Developed an LCA-MLR framework that enhances the prediction of embodied carbon for green certified office buildings in Malaysia. The limitation of the regression-based framework lies in its dependence on specific material hotspots only, which can be influenced by many other parameters, whereas the supervised learning process requires good-quality data.

### 2.4 Integration of BIM and LCA for Sustainable Building Renovation

[19] Studied the application of the BIM-LCA process to assess carbon emissions, water usage, and wastage in renovation projects. The process used Autodesk Revit v2022 for BIM and OneClick LCA for the automated carbon footprint evaluation; the material name and property classification were important in automating impact identification and avoiding redundant impacts in the Revit model. [20] introduced a combined BIM-LCA framework that sought to incorporate sustainability indicators within the initial design process. In their study, four BIM models of equal volume but

differing designs were established in conjunction with LCA databases relevant to their respective countries. What was unique about their study was that it sought to integrate 3D BIM with reinforcement detailing in an nD BIM study, thereby showing how BIM digitization could aid in the development of a smart low-carbon city.

### 2.5 Research Gap

While considerable progress has been made in areas such as BIM-based renovation, energy simulation, and LCA, several limitations in previous research exist. First, prior studies related to BIM have mainly concentrated on the assessment of energy performance and scenarios of renovation without taking into consideration the embodied environmental impacts and renovation costs [21]. The use of BIM-ML has been successful in improving energy prediction and optimization although it has mostly concentrated on operational performance rather than overall environmental assessment of the building [22]. While BIM-LCA allows for material-based assessment of the environment, there are issues of interoperability, data consistency, and automation of BIM information transfer to LCA [23]. Also, previous studies on renovation have not taken into consideration all the factors, including BIM-generated material quantities, dynamic energy simulation, life-cycle carbon assessment, renovation cost, multi-objective optimization, and, finally, multi-criteria decision-making, in one framework.

The integration of BIM, building energy simulation, life-cycle assessment, and optimization for sustainable building design and renovation has received increasing attention. Motalebi et al. [24] integrated 6D BIM, LCA, and mathematical optimization for energy-efficiency retrofit, demonstrating the value of combining environmental and economic assessment with retrofit optimization [24]. Shen and Pan [25] combined BIM-supported DesignBuilder simulation with explainable machine learning and multi-objective optimization for building energy performance assessment [25]. More recent research has expanded multi-objective retrofit optimization by combining building performance simulation, evolutionary optimization, and decision-making methods to balance energy, environmental, economic, and indoor-environment objectives [26]. Similarly, a systematic review of 115 BIM-LCA studies reported that only 21% of the reviewed studies integrated multi-criteria decision analysis or multi-objective optimization, while manual data mapping during life-cycle impact assessment remains a major challenge [27]. Recent renovation research has also highlighted the need to evaluate carbon reduction together with material demand and economic implications rather than considering operational energy alone [28,29]. These developments indicate that BIM, LCA, energy simulation, and optimization are increasingly being connected; however, their coordinated application to existing-building renovation still requires clearer integration of BIM-derived quantities, dynamic energy performance, life-cycle environmental impacts, renovation cost, Pareto-based optimization, and final multi-criteria selection within a single decision-support workflow.

## 3. Methodology

The proposed workflow integrates BIM modeling, dynamic energy simulation, LCA, renovation scenario generation, NSGA-II optimization, and TOPSIS-based decision-making. The methodology develops an integrated BIM-LCA-based framework for evaluating low-carbon renovation strategies for existing urban buildings. It combines building energy simulation, life cycle environmental assessment, and multi-objective optimization to identify renovation solutions that minimize energy consumption, life cycle carbon emissions, and renovation costs while maintaining building performance

The integrated process is shown in Figure 1, starting from the data collection and BIM modelling using Autodesk Revit and ending up with baseline energy simulation (DesignBuilder/EnergyPlus) and life cycle assessment (ReCiPe 2016). Possible renovation scenarios and results of simulations are processed using the Multi-Objective Optimization method (NSGA-II) resulting in Pareto-optimal solutions evaluated by TOPSIS, which helps to choose the optimal building renovation solution and its performance.

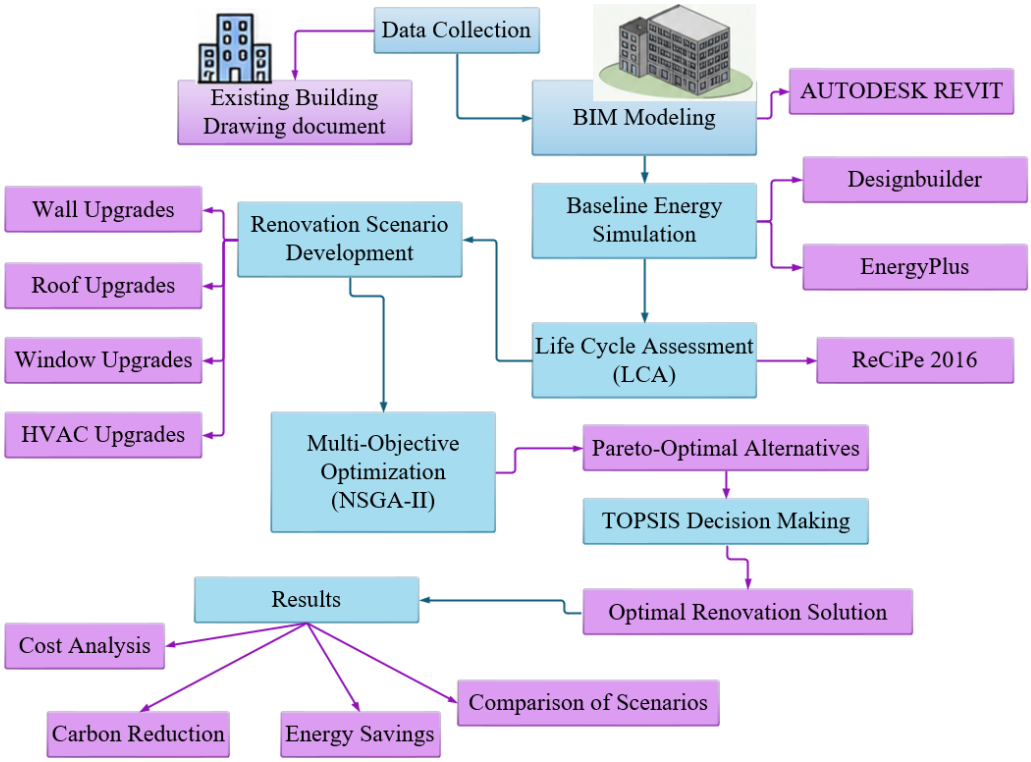



Fig. 1. Integrated BIM–LCA renovation workflow

### 3.1 Data Collection

The building for case study was chosen from the TalTech building database and corresponds to the TalTech Ehituse Maemaja – university office and laboratory building built in 1982. Information on the building was gathered using available drawings, surveys and building documentation, including geometrical dimensions, floor area, number of floors, orientation, room's structure, walls, roofs, windows, materials, occupation and heating ventilation air-conditioning system. The gathered data were used to determine the current state of the building and its baseline characteristics. The conditioned floor area was used as the reference floor area for calculating the EUI in the baseline and renovation energy assessments.

### 3.2 BIM Model Development and Material Quantity Extraction

The collected building data are used to develop a parametric BIM model in Autodesk Revit. The building geometry, including walls, floors, roofs, doors, windows, and ceilings, is modeled based on the existing plans and dimensions. Materials, construction types, and key properties such as thickness, thermal properties, area, and volume are assigned to each element. The resulting BIM model provides accurate building quantities and properties required for energy simulation and LCA. The equation is expressed as Eqn. (1)

- Material Volume

$$V_m = A_m \times t_m \tag{1}$$

where $V_m$ is the material volume ($m^3$), $A_m$ is the surface area of the building element ($m^2$), and $t_m$ is its material thickness (m).

- Material Mass

Table 1 summarizes the BIM model configuration, geometric and material parameters, quantity extraction procedure, interoperability with DesignBuilder/EnergyPlus and ecoinvent, and the validation of BIM-derived quantities used in the proposed BIM–LCA framework. The listed parameters define the building geometry, material information, energy simulation inputs, and LCA data required for subsequent renovation scenario analysis.

### 3.3 Baseline Building Energy Modeling and Simulation Using DesignBuilder/EnergyPlus

The BIM model is exported to DesignBuilder/EnergyPlus for baseline energy simulation. Building envelope properties, occupancy, lighting, equipment, HVAC, ventilation, and operating schedules are defined using local TMY weather data for Tallinn, Estonia. Hourly annual simulations estimate electricity and fuel use, heating and cooling demand, peak loads, and monthly energy consumption, providing baseline values for evaluating renovation scenarios. The equations are expressed as Eqns. (2)- (3).

Table 1. BIM model specifications, material properties, quantity extraction, and validation details

| Parameter | Value |
|---|---|
| BIM software | Autodesk Revit 2024 |
| BIM model | Parametric existing-building model |
| Building type | University office and laboratory building |
| Building year | 1982 |
| Building location | Tallinn, Estonia |
| BIM geometry | Walls, floors, roofs, ceilings, doors and windows |
| Exterior wall area | 14,699.72 $m^2$ |
| Roof area | 5,146.59 $m^2$ |
| Window area | 2,043.09 $m^2$ |
| Door area | 1,156.53 $m^2$ |
| Material parameters | Material type, thickness, density, thermal conductivity, specific heat |
| Thermal parameters | U-value and construction-layer thickness |
| Quantity extraction | Revit material schedules |
| Quantity units | $m^2$, $m^3$ and kg |
| DesignBuilder interoperability | BIM geometry/construction data transferred to DesignBuilder/EnergyPlus |
| LCA interoperability | BIM material quantities mapped to ecoinvent LCI datasets |
| Quantity validation | BIM quantities checked against drawings and building documentation |
| Validation deviation | ≤5% |
| Energy simulation | DesignBuilder/EnergyPlus |
| Weather data | Tallinn TMY |
| LCA database | ecoinvent |
| Impact method | ReCiPe 2016 Midpoint |

- Annual Energy Consumption

$$E_{annual} = \sum_{m=1}^{12} E_m \quad (2)$$

where $E_{\text{annual}}$ is the total annual building energy consumption ( kWh/ year), and $E_m$ is the energy consumption during month $m$((kWh/month)).

- Energy Use Intensity

$$EUI = \frac{E_{annual}}{A_f} \quad (3)$$

where $EUI$ is the annual EUI( kWh/$m^2$/ year), $E_{\text{annual}}$ is annual energy consumption (kWh/year), and $\boldsymbol{A_f}$ is the conditioned floor area ( $m^2$ ).

### 3.4 Baseline Life Cycle Assessment Using ReCiPe 2016

A baseline LCA evaluates the building's environmental impacts before renovation. BIM-derived material quantities and baseline energy consumption are assessed using ecoinvent LCI datasets. ReCiPe 2016 Midpoint converts inventory flows into impact scores, distinguishing material and

operational impacts. Climate change is reported as kg $CO_2$-eq, while other categories include particulate matter, acidification, eutrophication, and fossil resource scarcity. The equations are expressed as Eqns. (4)- (6).

- Embodied Carbon

$$EC_{emb} = \sum_{i=1}^{n} Q_i \times EF_i \quad (4)$$

where $EC_{\text{emb}}$ is the embodied carbon $(\text{kgCO}_2 - \text{eq})$, $Q_i$ is the quantity of material $i$ (kg or appropriate functional unit), and $EF_i$ is the corresponding emission factor ( $\text{kgCO}_2$-eq/unit).

- Operational Carbon

$$EC_{op} = \sum_{t=1}^{T} E_t \times EF_{energy} \quad (5)$$

where $EC_{\text{op}}$ is operational carbon ( $\text{kgCO}_2 - \text{eq}$ ), $E_t$ is energy consumption during period $t$(kWh), and $EF_{\text{energy}}$ is the corresponding energy-related climate-change emission factor ( $\text{kgCO}_2$-eq/kWh)..

- Total Life-Cycle Climate-Change Impact

$$LCI_{CC} = EC + OC \quad (6)$$

where $\text{LCI}_{\text{CC}}$ represents the total climate-change impact of the existing building $(\text{kgCO}_2 - \text{eq})$, obtained by combining the material-related embodied climate-change impact and operational climate-change impact over the defined assessment period.

#### *3.4.1 LCA Scope and Assumptions*

The LCA used a 50-year reference period to assess long-term building performance. The functional unit was the entire building over 50 years, with results normalized by conditioned floor area where applicable. The system boundary included material production, transport, replacements, and operational energy. BIM quantities and simulated energy data supported the assessment, using ReCiPe 2016 for consistent comparison of renovation alternatives. Replacement impacts were included within the 50-year reference study period according to the assumed service life of each renovation component. Insulation was assigned a 50-year service life and therefore required no replacement, while windows, HVAC systems, and PV systems were replaced according to their respective service lives. The environmental impacts associated with the production, transportation, installation, and end-of-life treatment of replacement components were included in the LCA.

Table 2 summarizes the LCA methodology, system boundary, life-cycle stages, inventory database, energy inputs, service-life assumptions, replacement cycles, and impact categories adopted in the assessment. The 50-year reference period and whole-building functional unit were applied consistently to evaluate the environmental performance of the renovation scenarios.

### 3.5 Renovation Scenario Generation

Renovation alternatives are developed using the parametric BIM model while preserving building geometry and functionality. Measures include wall and roof insulation, window replacement, HVAC improvements, and combinations thereof, with parameters such as insulation thickness, material type, U-value, and HVAC efficiency varied. Predefined scenarios (S0–S9) provide benchmarks, while NSGA-II explores continuous parameter combinations to optimize energy, carbon, and cost performance. The predefined scenarios S0–S9 represent different renovation configurations, including the existing building condition, wall and roof insulation, window replacement, HVAC improvement, envelope renovation, combined envelope and HVAC renovation, photovoltaic (PV) integration, and deep renovation. These scenarios provide discrete benchmark configurations for comparison, while NSGA-II explores continuous combinations of the corresponding renovation parameters. The equation is expressed as Eqn. (7).

Table 2. LCA scope and assessment assumptions

| LCA parameter | Value |
|---|---|
| LCA method | ReCiPe 2016 Midpoint |
| Reference study period | 50 years |
| Functional unit | Whole building over 50 years |
| Reporting basis | Whole-building and conditioned-floor-area-normalized results |
| System boundary | Product + transport + installation + replacement + operation + end-of-life |
| A1–A3 | Raw material supply, transport to manufacturer and manufacturing |
| A4 | Transport to building site |
| A5 | Renovation/installation |
| B4 | Component replacement |
| B6 | Operational energy |
| C1–C4 | Demolition, transport, waste processing and disposal/recycling |
| Inventory database | ecoinvent |
| Electricity | Tallinn electricity mix/life-cycle inventory factor |
| District heating/fuel | Included according to DesignBuilder/EnergyPlus energy model |
| Transportation | Included for renovation materials |
| Maintenance | Represented through component replacement/service-life assumptions |
| Insulation service life | 50 years |
| Window service life | 30 years |
| HVAC service life | 20 years |
| PV service life | 25 years |
| Replacement cycles | Windows: 1 replacement; HVAC: 2 replacements; PV: 1 replacement |
| Occupancy | Same baseline and renovation schedule |
| Weather | Tallinn TMY |
| Impact categories | Climate change, PM formation, acidification, eutrophication, fossil resource scarcity |

- Renovation scenario representation

$$S_s = \{W_s, R_s, W_{in}, HVAC_s, PV_s, C_s\} \quad (7)$$

where $S_s$ represents renovation scenario $s$; $W_s$ represents the wall intervention; $R_s$ represents the roof intervention; Win $_s$ represents the window intervention; HV AC $_s$ represents the HVAC intervention; $PV_s$ represents the photovoltaic (PV) intervention; and $C_s$ represents the combined renovation configuration.

The decision variables and their evaluated ranges were defined to represent the main envelope, glazing, HVAC, renewable-energy, and airtightness parameters considered in the renovation optimization. Table 3 summarizes the corresponding values obtained for the selected SOL_040 configuration and its resulting renovation performance. The minimum and maximum values in the evaluation range define the search limits used for the continuous NSGA-II decision variables, while the SOL_040 column reports the corresponding selected values.

### 3.6 Renovation Energy Simulation and Performance Assessment

Each renovation scenario is evaluated using DesignBuilder/EnergyPlus to determine its impact on building energy performance. Renovated walls, roofs, windows, HVAC systems, and combined measures are simulated using the same climate, occupancy, internal loads, and operating conditions as the baseline. Annual simulations provide energy consumption, heating and cooling demand, electricity use, and energy savings for each renovation scenario. The equations are expressed as Eqns. (8)- (9).

Table 3. Decision variables, evaluation ranges, and selected SOL_040 values

| Decision variable | Range evaluated | SOL_040 value |
|---|---|---|
| Wall insulation thickness | 0–200 mm | 160 mm |
| Wall insulation | Mineral wool | Mineral wool |
| Wall U-value | 0.15–0.60 W/m$^2$K | 0.21 W/m$^2$K |
| Roof insulation thickness | 0–250 mm | 200 mm |
| Roof insulation | Mineral wool | Mineral wool |
| Roof U-value | 0.10–0.45 W/m$^2$K | 0.16 W/m$^2$K |
| Window type | Double/triple glazing | Triple glazing |
| Window U-value | 0.70–2.00 W/m$^2$K | 0.85 W/m$^2$K |
| Window SHGC | 0.30–0.65 | 0.42 |
| HVAC system | Heat pump/efficient HVAC | Air-source heat pump |
| Heating COP | 2.5–4.5 | 3.6 |
| Cooling COP/EER | 2.5–4.5 | 3.2 |
| Heat-recovery efficiency | 50–85% | 75% |
| PV capacity | 0–200 kWp | 120 kWp |
| PV efficiency | 15–23% | 20.10% |
| Envelope airtightness | 0.5–1.5 ACH | 0.70 ACH |
| Renovation configuration | Combined/deep renovation | SOL_040 |
| Renovation cost | — | € 6,78,325.31 |
| Annual energy | — | 276.66 MWh/year |
| Life-cycle carbon | — | 7,394.40 $tCO_2e$ |

- Energy savings

$$ES_s = E_{base} - E_s \tag{8}$$

where $ES_s$ is the energy saving achieved by renovation scenario $s$ (kWh/year), $E_{\text{base}}$ is baseline annual energy consumption, and $E_s$ is the annual energy consumption after renovation.

- Energy reduction percentage

$$ER_s = \frac{E_{base} - E_s}{E_{base}} \times 100 \tag{9}$$

where $ER_s$ is the percentage reduction in annual energy consumption.

### 3.7 BIM-Based Life Cycle Assessment of Renovation Scenarios

LCA is performed for each renovation alternative using updated BIM material quantities and simulated energy results. New, replaced, and removed materials for walls, roofs, windows, HVAC systems, and combined interventions are quantified. Component service lives are considered for replacement impacts over the study period. ReCiPe 2016 then evaluates material, replacement, and operational environmental impacts for each renovation scenario. The equations are expressed as Eqns. (10)- (11).

- Operational Carbon

$$EC_{op,s} = \sum_{t=1}^{T} E_{s,t} \times EF_{energy} \tag{10}$$

where $E_{s,t}$ is the energy consumed by scenario $s$ during period $t$, and $EF_{\text{energy}}$ is the corresponding energy emission factor.

- Total Life-Cycle Carbon

$$EC_{total,s} = EC_{emb,s} + EC_{rep,s} + EC_{op,s} \tag{11}$$

where $EC_{\text{total, }s}$ represents the total life-cycle carbon impact of renovation scenario $s$.

### 3.8 Comparative Energy, Carbon, Environmental Assessment

The baseline and renovation scenarios are systematically compared using annual energy consumption, energy savings, and embodied, operational, and life-cycle carbon emissions. ReCiPe 2016 midpoint indicators provide additional environmental insights. The comparison identifies the environmental and energy benefits of each intervention and supplies key energy, carbon, and environmental indicators for NSGA-II optimization, while ReCiPe indicators remain non-optimization criteria. The equation is expressed as Eqn. (12).

- Carbon Reduction

$$CR_s = \frac{EC_{total,base} - EC_{total,s}}{C_{total,\ base}} \times 100 \tag{12}$$

where $CR_s$ is the total life-cycle carbon reduction (%), $EC_{total,base}$ is the total life-cycle carbon of the baseline building, and $EC_{total,s}$ is the total life-cycle carbon of renovation scenario $s$.

### 3.9 NSGA-II-Based Multi-Objective Optimization

NSGA-II simultaneously optimizes renovation alternatives using four objectives: annual energy consumption, embodied carbon, operational carbon, and renovation cost. Candidate solutions are evaluated and ranked through non-dominated sorting, while crowding distance maintains solution diversity. The optimization generates Pareto-optimal renovation solutions, representing balanced trade-offs were improving one objective would negatively affect another. The equations are expressed as Eqns. (13)- (17).

$$minF(X) = \{f_1(X), f_2(X), f_3(X), f_4(X)\} \tag{13}$$

Where, $X$ represents the renovation decision variables, $F(X)$ overall multi-objective function, $f_1(X)$ annual operational energy consumption., $f_2(X)$ embodied carbon, $f_3(X)$ operational carbon, $f_4(X)$ renovation cost.

$$minf_1(X) = E_{op}(X) \tag{14}$$

Where, $f_1(X)$annual operational energy objective, $E_{op}(X)$ annual operational energy consumption obtained from DesignBuilder/EnergyPlus, X renovation decision variables.

$$minf_2(X) = C_{emb}(X) = \sum Q_i(X) \times EF_{emb,i} \tag{15}$$

Where, $f_2(X)$ embodied-carbon objective, $C_{emb}(X)$ total embodied carbon associated with the renovation, $Q_i(X)$ quantity of renovation material i, $EF_{emb,i}$ embodied-carbon emission factor of renovation material i, i index representing each renovation material., X renovation decision variables.

$$minf_3(X) = C_{op}(X) = \sum E_e(X) \times EF_e \tag{16}$$

Where, $C_{op}$ is operational carbon, $E_e$ is the consumption of energy source $e$, and $EF_e$ is the corresponding energy-related emission factor.

$$minf_4(X) = C_{cost}(X) = \sum Q_i(X) \times UC_i \tag{17}$$

Where $C_{cost}$ is renovation cost, $Q_i$ is the quantity of renovation material/measure $i$, and $UC_i$ is its unit cost. Total life-cycle carbon represents the combined embodied carbon and cumulative operational carbon over the 50-year assessment period. It is used as a life-cycle assessment indicator and is not treated as a separate fifth NSGA-II optimization objective. Renovation cost was calculated based on the quantities of the selected renovation materials or measures and their corresponding unit costs. The total cost represents the initial renovation expenditure associated with the selected intervention package. The cost calculation does not include financing costs, energy-price escalation, maintenance expenditure, residual value, or other future life-cycle economic effects.

Algorithm 1. NSGA-II-Based renovation optimization

$Input$:
$Baseline\ BIM\ model\ B$
$Decision-variable\ bounds\ Xmin\ and\ Xmax$
$Population\ size\ N$
$Maximum\ number\ of\ generations\ Gmax$
$Objective\ functions\ \{E, ECemb, COp, Cost\}$

$Output$:
$Pareto-optimal\ renovation\ solutions\ P*$

$Initialize\ population\ P0\ within\ [Xmin, Xmax]$
$Evaluate\ E(X), ECemb(X), COp(X), and\ Cost(X) for\ each\ X \in P0$
$Set\ generation\ \boldsymbol{g} \leftarrow 0$

$while\ g\ <\ Gmax\ do$

$Perform\ non-dominated\ sorting\ on\ Pg$
$Calculate\ crowding\ distance\ for\ each\ solution\ in\ Pg$

$Select\ parent\ solutions\ using\ tournament\ selection$
$Apply\ crossover\ to\ generate\ offspring$
$Apply\ mutation\ to\ offspring$
$Repair\ infeasible\ solutions\ according\ to\ decision-variable\ constraints$

$Evaluate\ E(X), ECemb(X), COp(X), and\ Cost(X) for\ each\ offspring\ solution\ Combine\ pa-rent\ and\ offspring\ populations$:

$Rg \leftarrow Pg \cup Qg$

$Perform\ non-dominated\ sorting\ on\ Rg$
$Calculate\ crowding\ distance\ within\ each\ non-dominated\ front$

$Select\ the\ best\ N\ solutions\ from\ Rg\ based\ on$:

1. $Non-dominated\ rank$
2. $Crowding\ distance$

$Set\ Pg+1\ \leftarrow\ selected\ solutions$
$g \leftarrow g\ +\ 1$
$end\ while$
$Extract\ the\ non-dominated\ solutions\ from\ Pg$
$Return\ Pareto-optimal\ set\ P*$

The NSGA-II based renovation optimization algorithm is described in Algorithm 1, where the renovation solutions are created by varying decision variables within certain limits and then ranked by evaluating annual energy consumption, embodied carbon, operational carbon, and cost of renovation. Solution selection is done based on non-domination and crowding distance, whereas crossover and mutation operators create new solutions till the stopping criteria is met. The obtained non-dominated solutions constitute the Pareto optimal front.

### 3.10 TOPSIS-Based Final Renovation Selection

TOPSIS ranks the Pareto-optimal renovation alternatives to identify the most balanced low-carbon solution. Four criteria—annual energy consumption, embodied carbon, operational carbon, and renovation cost—are assigned equal weights of 0.25. The decision matrix is normalized, weighted, and used to determine positive and negative ideal solutions. Alternatives are ranked using their Euclidean distances and TOPSIS closeness coefficients. The equation is expressed as Eqn. (18).

- TOPSIS Closeness Coefficient

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (18)$$

The alternative with the largest closeness coefficient $CC_i$ receives the highest TOPSIS ranking. TOPSIS criteria and their assigned weights, with life-cycle carbon receiving the highest weight (0.35), followed by annual energy consumption (0.30), renovation cost (0.20), and environmental impact (GWP) (0.15).

Table 4. TOPSIS decision matrix and criterion weights

| Solution | Annual Energy (MWh/yr) | Life-cycle Carbon ($tCO_2e$) | Cost (€) |
|---|---|---|---|
| SOL_012 | 301.8 | 7,610.20 | 418,500 |
| SOL_029 | 287.4 | 7,485.60 | 512,800 |
| SOL_040 | 276.66 | 7,394.40 | 678,325.31 |
| SOL_043 | 282.9 | 7,430.50 | 590,600 |
| SOL_047 | 294.2 | 7,520.30 | 465,900 |

Table 4 presents the decision matrix of the evaluated renovation solutions based on annual energy consumption, life-cycle carbon, renovation cost, and environmental impact. The corresponding criterion weights used in the TOPSIS analysis are also provided.

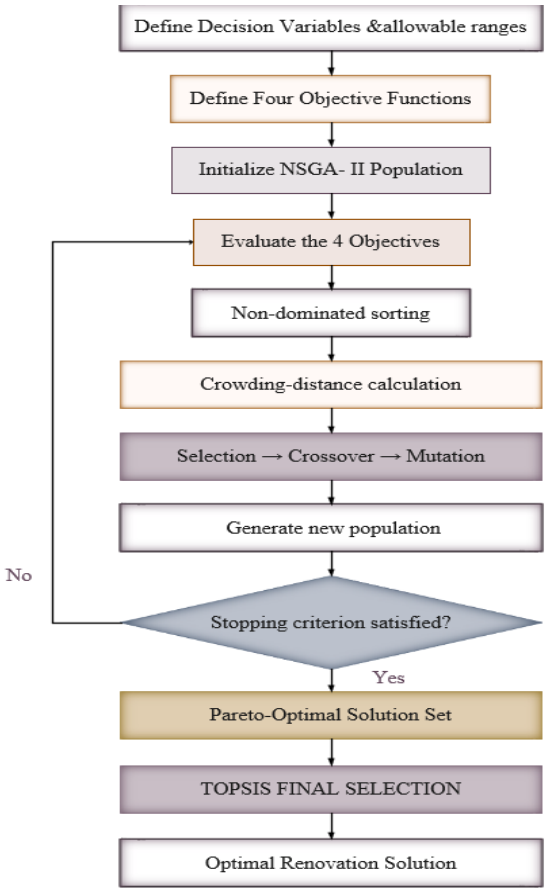



Fig. 2. NSGA-II–pareto–TOPSIS optimization

Table 5. TOPSIS normalization, closeness coefficients, and final ranking

| Solution | R(Energy) | R(Carbon) | R(Cost) | R(Environment) | $D^+$ | $D^-$ | $CC_i$ | Rank |
|---|---|---|---|---|---|---|---|---|
| SOL_040 | 0.4558 | 0.4479 | 0.5965 | 0.4479 | 0.0681 | 0.1490 | 0.6864 | 1 |
| SOL_043 | 0.4661 | 0.4501 | 0.5194 | 0.4501 | 0.0747 | 0.1384 | 0.6495 | 2 |
| SOL_029 | 0.4738 | 0.4534 | 0.4510 | 0.4534 | 0.0848 | 0.1262 | 0.5980 | 3 |
| SOL_047 | 0.4850 | 0.4555 | 0.4098 | 0.4555 | 0.0946 | 0.1163 | 0.5514 | 4 |
| SOL_012 | 0.4975 | 0.4609 | 0.3682 | 0.4609 | 0.1060 | 0.1050 | 0.4976 | 5 |

Table 5 presents the normalized and weighted decision values, separation measures, closeness coefficients, and final ranking of the evaluated renovation solutions. The ranking identifies SOL_040 as the TOPSIS-selected compromise solution.

Optimization process and the selection process are illustrated in Figure 2, starting with decision variables, the acceptable range, and four objective functions, followed by NSGA-II population initialization, evaluation of objectives, non-domination sorting, calculation of crowding distance, genetic operators, and repeating the process until the stopping criteria are satisfied, followed by the application of TOPSIS to choose an optimal renovation solution.

## 4. Results

Proposed SOL_040 renovation resulted in reduction of annual energy consumption by 65.13%. and EUI by 65.13%, compared to the baseline building.

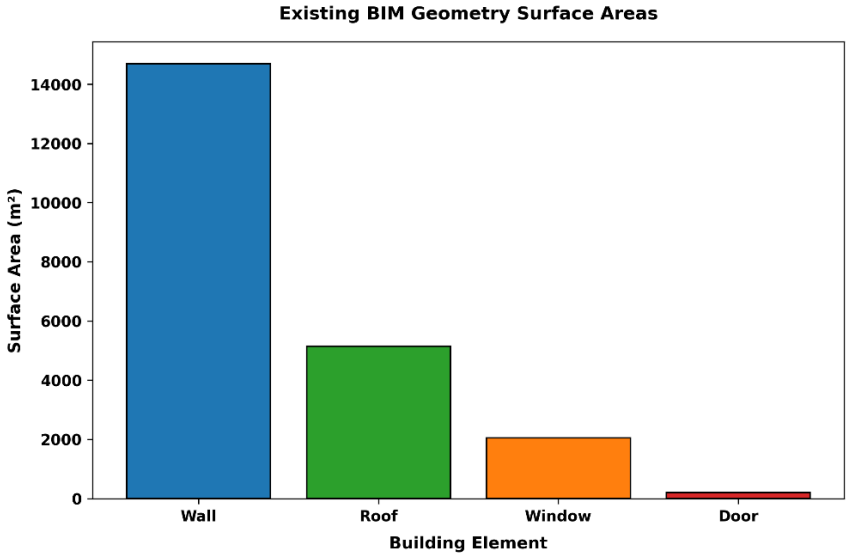



Fig. 3. Existing BIM geometry surface areas

This can be seen in Figure 3 showing the areas of the main components of the building derived from the BIM model. The exterior wall has an area of 14,699.72 $m^2$, while the roof is 5,146.59 $m^2$, windows have an area of 2,043.09 $m^2$, and the doors are 1,156.53 $m^2$.

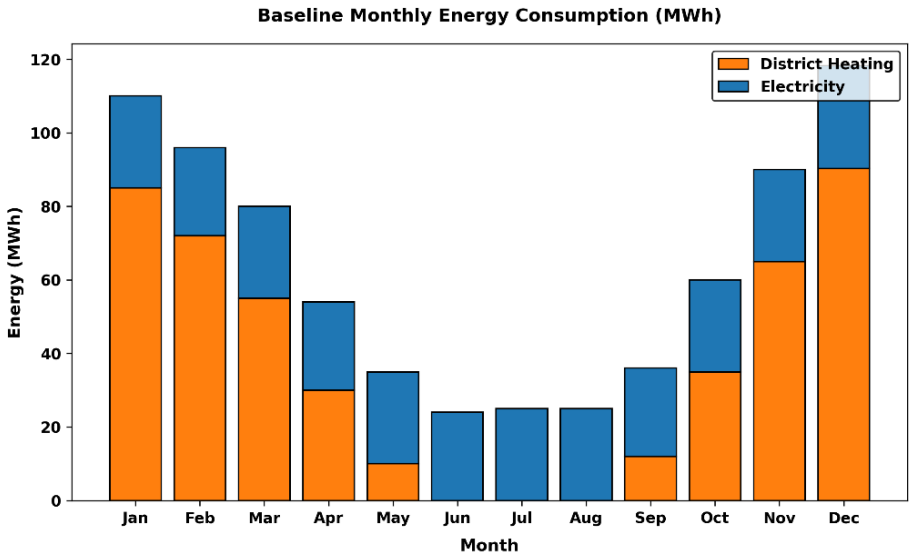



Fig. 4. Baseline monthly energy consumption

Figure 4 presents the monthly energy demand of the building broken down into heating needs and electricity demands. Peak values are reached during the months of January (about 115 MWh) and

December (about 110 MWh), which is caused mainly by the heating need, whereas the lowest values are observed in June-August (about 45-50 MWh).

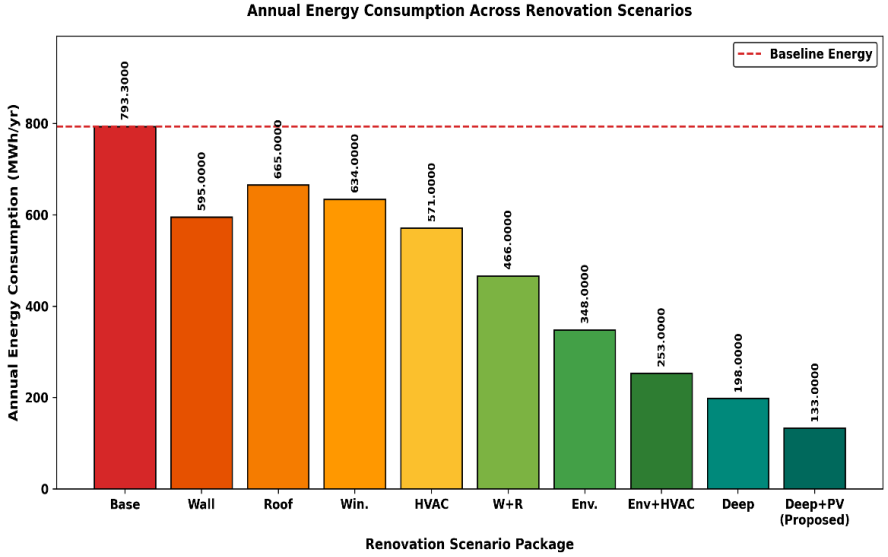



Fig. 5. Annual energy consumption across renovation scenarios

Figure 5 shows the annual energy consumption for different types of renovation scenarios. It is apparent that energy consumption declines as the renovation progresses from the Base scenario to the Deep renovation scenario. Base is the highest value of energy consumption at 793.30 MWh/yr and serves as the reference point indicated with the red dashed line.

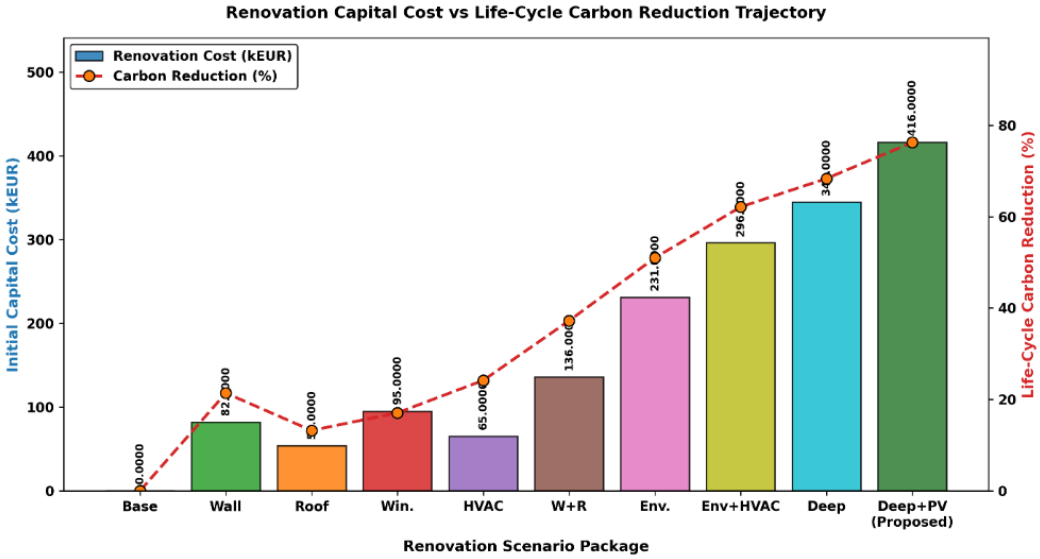



Fig. 6. Renovation capital cost vs life-cycle carbon reduction trajectory

Figure 6 illustrates the correlation between the cost of renovation investment and long-term carbon reduction. For the base scenario S0, where there is zero cost for renovation investment, the renovation cost is taken to be 0 kEUR. The other more thorough renovation designs - Wall+Roof (136.00 kEUR, 37.22%), Envelope (231.00 kEUR, 50.98%), and Envelope+HVAC (296.00 kEUR, 62.13%) - demonstrate better results.

A three-dimensional projection of the Pareto-optimal solutions for the four-objective NSGA-II approach is illustrated in Figure 7. The axes represent annual energy consumption, operational carbon, and renovation costs, respectively. Embodied carbon constitutes the fourth optimization objective, which is used for evaluating Pareto dominance.

Figure 8 shows the ranking of Pareto-optimal solutions to renovation through the closeness score ($C_i$) of the TOPSIS technique. The new solution R1 (SOL_040) obtains the highest value of 0.6855,

then comes the second-ranked R2 (SOL_029 = 0.6940) and third ranked R3 (SOL_012 = 0.6930). Some other solutions like R4 (SOL_043 = 0.6925) and R5 (SOL_047 = 0.6919).

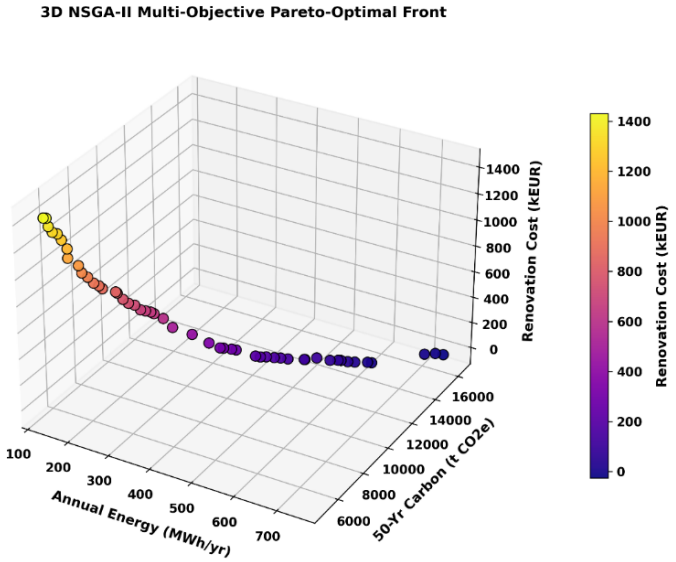



Fig. 7. 3D NSGA-II multi-objective pareto-optimal front

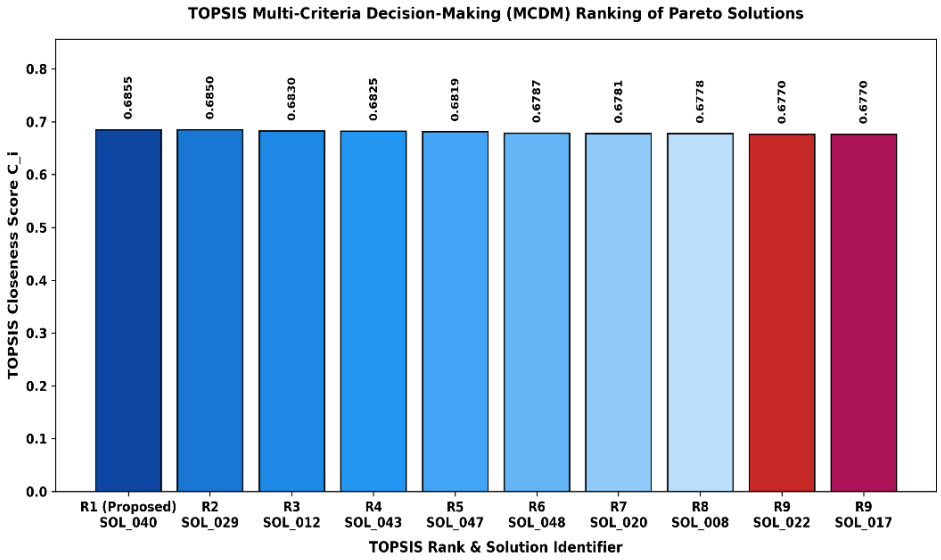



Fig. 8. TOPSIS ranking of pareto solutions

Table 6. Pareto-optimal renovation solutions

| Solution | Annual Energy (MWh/yr) | Embodied Carbon ($tCO_2e$) | Operational Carbon ($tCO_2e$) | Renovation Cost (€) | Pareto status |
|---|---|---|---|---|---|
| SOL_012 | 301.8 | 2,240.50 | 5,369.70 | 4,18,500 | Non-dominated |
| SOL_029 | 287.4 | 2,180.60 | 5,305.00 | 5,12,800 | Non-dominated |
| SOL_040 | 276.66 | 2,315.40 | 5,079.00 | 6,78,325.31 | Non-dominated |
| SOL_043 | 282.9 | 2,260.10 | 5,170.40 | 5,90,600 | Non-dominated |
| SOL_047 | 294.2 | 2,205.70 | 5,314.60 | 4,65,900 | Non-dominated |

Table 6 presents the annual energy consumption, embodied carbon, operational carbon, renovation cost, and Pareto status of the non-dominated renovation solutions obtained from NSGA-II. These solutions represent the non-dominated alternatives considered for subsequent TOPSIS-based selection.

Table 7. Comparison of renovation scenarios

| Scenario | Cost (€) | Annual Energy (MWh/yr) | Energy Reduction | Life-cycle Carbon ($tCO_2e$) | Carbon Reduction |
|---|---|---|---|---|---|
| Baseline | 0 | 793.3 | 0% | 11,117.50 | 0% |
| Wall+Roof | 1,36,000 | 520.1 | 34.44% | 6,979.40 | 37.22% |
| Envelope | 2,31,000 | 388.9 | 50.98% | 5,449.10 | 50.98% |
| Envelope+HVAC | 2,96,000 | 300.4 | 62.13% | 4,210.30 | 62.13% |
| SOL_040 | 6,78,325.31 | 276.66 | 65.15% | 7,394.40 | 33.48% |

Table 7 compares the renovation scenarios in terms of renovation cost, annual energy consumption, energy reduction, life-cycle carbon, and carbon reduction relative to the baseline building. SOL_040 achieves the lowest annual energy consumption among the compared scenarios, while its higher renovation cost reflects the combined measures selected through the multi-objective optimization and TOPSIS-based decision process.

Table 8. Final TOPSIS ranking of the pareto-optimal renovation solutions

| Rank | Solution | TOPSIS closeness coefficient |
|---|---|---|
| 1 | SOL_040 | 0.6864 |
| 2 | SOL_043 | 0.6495 |
| 3 | SOL_029 | 0.598 |
| 4 | SOL_047 | 0.5514 |
| 5 | SOL_012 | 0.4976 |

Table 8 presents the final ranking of the Pareto-optimal renovation solutions based on their TOPSIS closeness coefficients. Higher closeness coefficients indicate greater relative proximity to the defined ideal solution under the selected TOPSIS criteria.

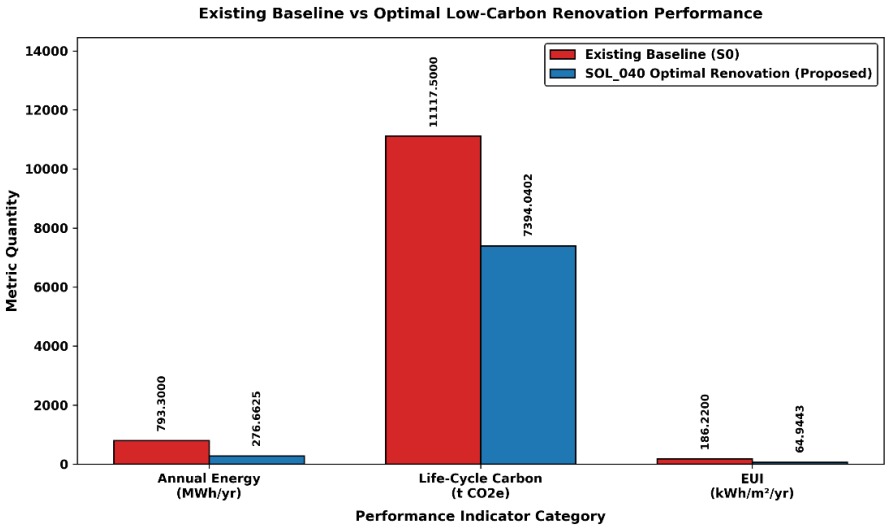



Fig. 9. Existing baseline vs optimal low-carbon renovation performance

The differences between the baseline (S0) scenario and the best renovation approach (SOL_040) can be observed using three performance metrics illustrated in Figure 9 below. The total annual energy consumption is reduced from 793.3 MWh/yr to 276.66 MWh/yr, whereas the life cycle carbon emissions are decreased from 11,117.5 t $CO_2$e to 7,394.04 t.

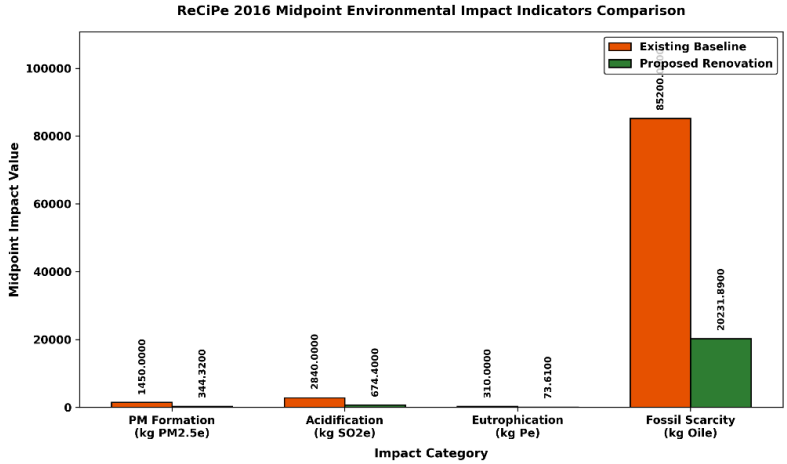



Fig. 10. ReCiPe 2016 midpoint environmental impact indicators comparison

Environmental impact assessments have been compared in Figure 10 below using four criteria between the baseline and proposed renovations. The baseline shows the following higher figures for the environmental impact assessment: PM Formation is 1450 kg PM2.5e, Acidification 2840 kg SO2e, Eutrophication 310 kg Pe, and Fossil Scarcity 85,200 kg Oile. On the other hand, the proposed renovation will reduce environmental impacts to the following levels: PM Formation 344.22 kg PM2.5e, Acidification 674.40 kg SO2e, Eutrophication 73.61 kg Pe, and Fossil Scarcity 20,721.39 kg Oile.

Table 9. ReCiPe 2016 midpoint environmental impact results

| Impact category | Baseline | SOL_040 | Absolute reduction | Reduction (%) |
|---|---|---|---|---|
| Particulate matter formation | 1,450.00 kg $PM_{2.5}e$ | 344.22 kg $PM_{2.5}e$ | 1,105.78 | 76.26% |
| Acidification | 2,840.00 kg $SO_2e$ | 674.40 kg $SO_2e$ | 2,165.60 | 76.25% |
| Eutrophication | 310.00 kg Pe | 73.61 kg Pe | 236.39 | 76.25% |
| Fossil resource scarcity | 85,200.00 kg Oile | 20,721.39 kg Oile | 64,478.61 | 75.68% |

Table 9 presents the environmental impacts of the baseline building and SOL_040 across four ReCiPe 2016 Midpoint impact categories. The results show the absolute and percentage reductions achieved by the SOL_040 renovation scenario.

Table 10. Contribution of renovation measures to environmental impact reductions

| Measure | PM formation reduction contribution | Acidification contribution | Eutrophication contribution | Fossil scarcity contribution |
|---|---|---|---|---|
| Wall insulation | 17.80% | 18.50% | 16.90% | 17.10% |
| Roof insulation | 12.60% | 13.10% | 12.00% | 12.40% |
| Triple-glazed windows | 9.80% | 10.20% | 9.50% | 9.70% |
| HVAC improvement | 31.40% | 30.80% | 32.10% | 30.50% |
| PV integration | 28.40% | 27.40% | 29.50% | 30.30% |
| Total | 100% | 100% | 100% | 100% |

Table 10 presents the percentage contribution of each renovation measure to the reduction of the four environmental impact categories. The contributions of all measures sum to 100% for each impact category.

Table 11. Sensitivity analysis of key parameters

| Parameter | Base value | Sensitivity range | Effect on annual energy | Effect on life-cycle carbon | Effect on TOPSIS CC |
|---|---|---|---|---|---|
| Material quantities | 100% | ±10% | ±0.0% | ±2.1% | ±0.012 |
| Electricity emission factor | Base | ±20% | ±0.0% | ±6.4% | ±0.028 |
| Energy price | Base | ±20% | ±0.0% | ±0.0% | ±0.021 |
| Occupancy | 100% | ±10% | ±4.8% | ±3.7% | ±0.018 |
| Weather conditions | TMY | ±10% | ±5.6% | ±4.9% | ±0.023 |
| HVAC efficiency | 100% | ±10% | ±6.2% | ±5.8% | ±0.031 |
| Insulation service life | 50 yr | ±20% | ±0.0% | ±1.7% | ±0.009 |
| Window replacement cycle | 30 yr | ±20% | ±0.0% | ±1.2% | ±0.007 |
| HVAC replacement cycle | 20 yr | ±20% | ±0.0% | ±2.8% | ±0.015 |
| LCA inventory dataset | Base ecoinvent | Alternative dataset | ±0.0% | ±4.6% | ±0.024 |

Table 11 reports the sensitivity ranges applied to the major model parameters and their effects on annual energy, life-cycle carbon, and TOPSIS closeness coefficient. The analysis covers material quantities, emission factors, energy prices, occupancy, weather, HVAC efficiency, service life, replacement cycles, and LCA inventory data.

Table 12. Uncertainty assessment of key model inputs

| Source of uncertainty | Base assumption | Uncertainty interval | Importance |
|---|---|---|---|
| BIM material quantities | BIM schedules | ±5% | Medium |
| Energy price | Base tariff | ±20% | High |
| Electricity emission factor | Base factor | ±20% | High |
| Occupancy | Design occupancy | ±10% | Medium |
| Weather | Tallinn TMY | ±10% | High |
| HVAC efficiency | Nominal efficiency | ±10% | High |
| Material service life | Component-specific | ±20% | Medium |
| Replacement cycle | Component-specific | ±20% | Medium |
| LCA inventory | ecoinvent | Alternative datasets | Medium–High |

Table 12 summarizes the major sources of uncertainty, their assumed uncertainty intervals, and their relative importance in the assessment. The assessment covers BIM quantities, energy prices, emission factors, occupancy, weather, HVAC efficiency, service life, replacement cycles, and LCA inventory data.

### 4.1 Discussions

The integrated BIM, energy simulation, LCA, NSGA-II, and TOPSIS framework effectively supports low-carbon renovation assessment. SOL_040 reduces annual energy use by 65.13%, EUI by

65.13%, and 50-year life-cycle carbon by 33.49%, achieving the highest TOPSIS coefficient (0.6855). ReCiPe 2016 also indicates reduced environmental impacts. The proposed renovation framework emphasizes energy-efficient building components and sustainable material selection to reduce operational energy consumption and life cycle environmental impacts. The integration of BIM and LCA facilitates comprehensive evaluation of renovation alternatives while supporting informed decision-making for low-carbon urban building development. They enable continuous, non-invasive data acquisition during daily activities.

## 5. Conclusions

This study developed an integrated BIM–LCA framework for low-carbon renovation assessment of existing urban buildings by combining BIM-based material quantification, DesignBuilder/EnergyPlus energy simulation, ReCiPe 2016 Midpoint life-cycle impact assessment, NSGA-II multi-objective optimization, and TOPSIS-based decision-making. The proposed framework demonstrates the effectiveness of integrating Building Information Modeling (BIM), Life Cycle Assessment (LCA), and multi-objective optimization for identifying sustainable and cost-effective renovation strategies for existing urban buildings. Its integration of autoencoder feature extraction, EBSO optimization, and DNN classification supports adaptive feedback and individualized exercise guidance. BIM was used to develop the existing-building model and extract material quantities, while DesignBuilder/EnergyPlus was used to evaluate building energy performance. The LCA stage incorporated a 50-year assessment period and ReCiPe 2016 Midpoint environmental impact assessment, providing a broader basis for evaluating renovation alternatives beyond operational energy consumption alone.

The optimization results demonstrated that renovation planning involves trade-offs among annual energy consumption, embodied carbon, operational carbon, and renovation cost. NSGA-II generated a set of Pareto-optimal renovation alternatives representing different combinations of these competing objectives. The subsequent TOPSIS procedure was used to evaluate the non-dominated alternatives according to the defined decision criteria and weighting scheme. Based on the recalculated TOPSIS closeness coefficients, SOL_040 was identified as the TOPSIS-selected compromise solution, with a closeness coefficient of 0.6864, followed by SOL_043 (0.6495), SOL_029 (0.5980), SOL_047 (0.5514), and SOL_012 (0.4976). Thus, SOL_040 represents a compromise among the considered decision criteria rather than a solution that independently minimizes every individual objective.

For SOL_040, annual energy consumption decreased from 793.30 to 276.66 MWh/year, corresponding to a 65.13% reduction, while EUI decreased from 186.22 to 64.94 kWh/$m^2$/year, also representing a 65.13% reduction. The 50-year life-cycle carbon decreased from 11,117.50 to 7,394.40 $tCO_2e$, corresponding to approximately a 33.49% reduction. The environmental assessment also showed reductions in particulate matter formation, acidification, eutrophication, and fossil resource scarcity. These results demonstrate the value of evaluating operational, embodied, and environmental effects together when assessing renovation strategies.

The main methodological contribution is the integration of BIM, building energy simulation, LCA, NSGA-II, and TOPSIS into a coordinated renovation assessment workflow. The framework links detailed building information with quantitative energy and environmental assessment, identifies non-dominated renovation alternatives through multi-objective optimization, and subsequently supports the selection of a compromise solution through multi-criteria decision-making. From a practical perspective, this approach can support building owners, designers, and renovation planners in comparing alternative retrofit strategies using consistent quantitative indicators. The results also demonstrate how BIM-enabled information exchange can support more systematic low-carbon renovation planning for existing urban buildings.

### 5.1 Limitations and Future work

The study has several limitations. Results may vary with building geometry, climate, materials, occupancy, and energy systems. LCA accuracy depends on inventory data, emission factors, service-life assumptions, and replacement schedules, while energy simulations depend on occupancy,

HVAC operation, and weather conditions. Optimization results are also influenced by the selected renovation scenarios and objective functions.

The study is based on a single building in Tallinn, Estonia, so the results may vary for different building types, locations, and climate conditions. The LCA results also depend on the selected ecoinvent data, emission factors, service-life assumptions, and replacement schedules. Future studies should evaluate multiple buildings and climate conditions using updated and region-specific LCA data. Future electricity decarbonization, occupant behavior, and PV degradation may also affect long-term results and should be considered in future assessments. Further research should also examine different renovation scenarios and TOPSIS weighting schemes to improve the generalizability of the proposed framework.

The economic assessment is limited to the initial renovation cost considered in the optimization. A comprehensive life-cycle cost analysis, including maintenance, replacement, energy-price escalation, financing effects, residual value, and payback period, was not performed. Future work can incorporate these economic factors to provide a more comprehensive assessment of the long-term financial performance of the renovation alternatives.

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