



Operational optimisation versus mechanical retrofit in non-domestic buildings: An SRI-informed life cycle assessment

Mohamed Mustafa^{*}, Yacine Rezgui, Tom Beach^{ID}

School of Engineering, Cardiff University, Queen's Buildings, The Parade, Cardiff CF24 3AA, United Kingdom

ARTICLE INFO

Keywords:

Building smartness
Life cycle assessment
Building retrofit
Operational optimisation
Environmental performance
Non-domestic buildings

ABSTRACT

This study proposes a performance-based framework for building retrofit assessment by integrating the Smart Readiness Indicator (SRI) within a scenario-based Life Cycle Assessment (LCA). Using empirical indoor environmental monitoring data and EnergyPlus simulations, three operational strategies were evaluated for a UK non-domestic social space: a conventional baseline, a mechanical retrofit with an Air Source Heat Pump (ASHP), and an operational optimisation scenario based on adjusted heating and cooling setpoints and schedules. Results show that the operational optimisation scenario achieved lower Cumulative Energy Demand (CED) and Particulate Matter Formation (PMF) than the mechanical retrofit, while exhibiting a slightly higher Global Warming Potential (GWP) due to continued natural gas use. Despite a low SRI classification (Class F), indoor thermal comfort and air quality remained within acceptable thresholds across all scenarios. These findings indicate that operational optimisation can be competitive with mechanical retrofit for selected impact categories under the stated boundary conditions. The study demonstrates how SRI-informed operational assumptions can be embedded within an ISO 14040/44-compliant LCA framework to support evidence-based, performance-driven retrofit decision-making.

1. Introduction

In response to mounting environmental challenges and policy commitments, energy systems retrofitting has become a prominent strategy for decarbonising the built environment. The European Green Deal and the Fit for 55 package both highlight the importance of building energy upgrades to achieve climate neutrality [1,2]. Retrofitting existing buildings for energy efficiency is widely regarded as an environmentally beneficial measure, as it reduces operational emissions and enhances occupant comfort [3]. However, this logic becomes less robust in certain contexts, particularly in non-domestic buildings with strong operational performance and adaptive control systems, or where operational performance remains strong despite a low smart-building performance index [4].

Emerging evidence suggests that retrofitting in such cases may not always yield proportional environmental gains [5]. When a building demonstrates efficient energy use, satisfactory Indoor Environmental Quality (IEQ), and a high level of smart control, the embodied carbon from retrofitting may outweigh the marginal operational savings [6]. In such instances, avoiding retrofit may present a more sustainable

pathway [7]. However, taking such decisions requires nuanced methods that quantify operational and embodied trade-offs using performance data, rather than relying on static models [8]. Therefore, evaluating retrofit feasibility requires understanding the relationship between measured building performance and the control capabilities behind it.

Introduced under the Energy Performance of Buildings Directive (EPBD), the Smart Readiness Indicator (SRI) assesses the availability of smart control functions across multiple building technical domains [10]. The SRI assesses the extent to which buildings are equipped with control functions that support energy efficiency, flexibility, and user responsiveness [9]. However, SRI assessment remains largely qualitative and may not reflect real-world performance without empirical substantiation [33]. At the same time, current Life Cycle Assessment (LCA) practices, used to quantify environmental impacts across a building's life cycle, often lack integration with smartness assessments, leading to potential misalignment between environmental modelling and building operational realities [11].

In this study, SRI information is interpreted in conjunction with simulated energy demand to constrain scenario definition to feasible control actions, enabling a performance-based LCA comparison of

^{*} Corresponding author.

E-mail addresses: mustafam2@cardiff.ac.uk (M. Mustafa), BeachTH@cardiff.ac.uk (T. Beach).

operational and mechanical retrofit scenarios. Measured indoor environment comfort data were used to verify indoor comfort thresholds. These comprise 15-minute intervals for indoor environmental monitoring of CO₂ concentration, air temperature, and Volatile Organic Compounds (VOCs) collected over a full calendar year. These scenarios include: (A) a conventional baseline, (B) a retrofit configuration featuring an Air Source Heat Pump (ASHP), and (C) a manual operational optimisation scenario using rule-based HVAC schedule and setpoint adjustments within existing control systems. Indoor sensors supported performance monitoring and comfort verification, but were not used for closed-loop automated control.

This research addresses the following question:

To what extent can optimised operational controls, such as setpoint optimisation, reduce environmental impacts and inform retrofit avoidance in low-SRI non-domestic buildings?

This question is examined through a detailed case study approach rather than statistical generalisation.

This study contributes a replicable, performance-based decision framework that integrates SRI assessment with scenario-based LCA and uncertainty analysis. Rather than treating SRI as a descriptive score, it is used to structure scenario assumptions, operational modelling, and system boundaries within an ISO 14040/44-compliant LCA. The contribution is methodological rather than case-specific, defining a transferable sequence of inputs, decision steps, and outputs for comparing baseline, operational optimisation, and retrofit options under explicit boundary conditions.

2. Literature review

This section reviews existing research across three key domains that underpin the study's methodological approach: (1) LCA practices in the built environment, with emphasis on operational and embodied carbon trade-offs; (2) the environmental rationale for building retrofit and the emerging critiques of its universal applicability; and (3) the SRI framework and its integration, or lack thereof, into LCA-based decision-making. Together, these strands provide the foundation for evaluating schedules and setpoint-based optimisation control as a potential alternative to physical retrofit interventions.

LCA remains the most rigorous and internationally standardised methodology for assessing environmental impacts across a building's life cycle, structured under ISO 14040 and ISO 14044 frameworks [12, 13]. Within the built environment, LCA has been increasingly applied to quantify both operational and embodied emissions. While operational energy has historically accounted for about 60% of total life-cycle emissions in buildings, this balance is shifting as improved energy efficiency reduces operational emissions [14]. Consequently, embodied carbon, associated with construction materials, systems, and retrofit interventions, can account for up to 50% of total life-cycle emissions in high-performance or recently upgraded buildings [15,16].

In this context, retrofit is frequently promoted as a carbon reduction strategy [17]. However, recent research challenges the blanket assumption that retrofit is environmentally beneficial in all cases. For example, [18] show that the embodied carbon emissions from HVAC and glazing retrofits may outweigh operational savings for up to two decades, particularly in moderate climates. Similarly, [19] emphasise that retrofit carbon payback is highly sensitive to existing digital control system efficiency and local energy mixes. These findings indicate the need for evidence-based, building-specific screening criteria, rather than default retrofit prescriptions [20].

In parallel, the SRI has emerged as a policy-driven metric for characterising the availability of digital control functions in buildings [21]. In the literature, SRI is primarily applied as a descriptive indicator of installed smart functionality or digital maturity, often reported alongside energy or comfort outcomes rather than embedded within performance modelling frameworks [22]. As a result, SRI scores are typically interpreted as proxies for potential operational capability, without

explicit linkage to scenario definition, system boundaries, or environmental impact assessment.

Early applications, particularly in educational and office buildings, indicate that high SRI scores correlate with 5–18% reductions in operational energy consumption through digitally enabled systems and adaptive control strategies [23,24]. Despite growing interest in digital indicators, very few LCA studies to date explicitly incorporate SRI scores into system boundaries, functional unit definitions, or retrofit scenarios. This represents a key gap in existing LCA frameworks. The SRI is organised into nine technical domains (including heating, cooling, ventilation, domestic hot water, lighting, dynamic envelope, electricity, electric vehicle charging, and monitoring and control), each subdivided into services that are scored across discrete functionality levels reflecting the degree of automation, control, and user interaction. These domains can be of significant value in informing the LCA outcomes for buildings. Along this direction, recent studies link real-time data from IoT, BMS, and simulations like EnergyPlus to create dynamic Life Cycle Inventory (LCI) models [25]. For example, [26] demonstrates how temporal energy profiles can be used in the Brightway2 software to improve impact resolution [27] propose a similar framework, leveraging smart building data to generate variable LCI flows. Despite this progress, most studies rely on simulated proxies of smartness rather than standardised indicators, such as the SRI assessment [29]. Therefore, current methodologies do not yet incorporate empirical SRI assessments into life cycle system boundaries or use them to guide retrofit decision-making, despite recognised potential synergies [30].

In parallel, applications of Brightway2 and Ecoinvent in building-related LCA highlight the importance of consistent modelling assumptions. The “cut-off by classification” system model remains a standard due to its alignment with attributional LCA logic and compatibility with regulatory frameworks [28]. When process-specific data are unavailable, researchers typically select functionally equivalent proxies, such as central air-handling units or chillers, often regionalised to EU or GLO datasets [26,27]. These choices reflect common practice in case-based LCA models and ensure transparency in foreground–background data integration.

Impact assessment methods, particularly ReCiPe 2016 Midpoint (H), are commonly used to evaluate the environmental consequences of HVAC technologies and retrofit strategies. Four midpoint indicators are widely adopted due to their relevance to building energy performance and regulatory alignment: (1) Global Warming Potential (GWP100), representing climate impact in kgCO₂-eq and used in nearly all carbon accounting frameworks (WorldGBC, 2024); (2) Cumulative Energy Demand (CED), capturing total primary energy input and strongly linked to operational efficiency [34]; (3) Particulate Matter Formation (PMF), used to quantify local air quality and public health effects of fossil combustion (Huijbregts et al., 2023); and (4) Abiotic Depletion Potential – fossil (ADPF), which reflects the depletion of non-renewable fossil resources, increasingly relevant under circular economy policy (Ecoinvent, 2022; Formisano et al., 2023). These indicators collectively enable multi-dimensional evaluation of retrofit and control-based interventions.

Despite these established modelling practices, a critical gap remains: the lack of methodologies that integrate smart readiness assessments, such as SRI assessment, into LCA decision-making [31]. This gap is especially relevant given the growing policy convergence between digitalisation and decarbonisation in the built environment. As regulations increasingly promote smart infrastructure, the role of SRI as a decision gate in LCA becomes both timely and necessary [32]. Embedding SRI assessment into LCA improves goal setting, system boundary definition, and data specificity, key requirements under ISO 14040 and 14044.

In summary, three gaps persist across the literature:

- (1) LCA models rarely incorporate empirical indicators of smart functionality such as the SRI assessment [21].

- (2) Retrofit is often modelled as inherently beneficial, despite evidence that smart systems may render further upgrades environmentally marginal [29,30]
- (3) Lack of existing tools or frameworks enables SRI-informed LCA decision-making [30,33].

In response to these gaps, this study addresses the methodological shortfall in current LCA practice (Gap 1) by incorporating empirical smart readiness data into environmental modelling. It also questions the default assumption of retrofit benefits (Gap 2) by evaluating whether smart-controlled buildings might be justifiably used to inform further upgrades. Finally, it contributes to the development of SRI-informed decision-making frameworks (Gap 3) by applying a scenario-based LCA to the Forum Zone of the Queen's Building at Cardiff University (UK), using full-year IEQ and energy monitoring data.

3. Methodology

To address the research question, this study employs a comparative, scenario-based LCA. Three scenarios are modelled: a conventional baseline, a retrofit intervention featuring ASHP, and a schedule and setpoint-based control optimisation strategy that adjusts HVAC setpoints without physical upgrades. All modelling is conducted in alignment with ISO 14040 and 14044 principles, using empirical performance data and SRI-informed scenario definitions.

The functional unit is defined as one square metre of conditioned floor area over one year of operation ($\text{m}^2\cdot\text{year}$). The conditioned floor area refers to the net conditioned floor area, defined as the usable internal area served by heating and cooling systems. This definition is consistent with operational energy modelling practice and with building LCA standards such as EN 15978, which recommend functional units based on serviced floor area to ensure comparability of operational impacts across studies (BSI, 2011).

The system boundary includes operational energy use for all scenarios. Embodied environmental impacts are included only for Scenario B (mechanical retrofit with ASHP), while the baseline and the control optimisation scenarios exclude embodied impacts, as no physical system modifications are introduced. Embodied impacts associated with the ASHP retrofit were annualised over an assumed service life of 20 years to ensure consistency with the one-year functional unit. Other building systems, structural components, and end-of-life processes were excluded, as they remain unchanged across all scenarios. Annualisation aligns retrofit embodied burdens with the one-year functional unit, but it implies a service-life assumption. Alternative lifetimes (e.g., 15–25 years) would proportionally change Scenario B's annualised embodied impacts and may affect comparative rankings.

3.1. Case study context

The Forum Zone is a mechanically ventilated, mixed-use space within the Queen's Building at Cardiff University, used for student socialising, studying, and events. It represents a typical non-domestic environment with variable occupancy and thermal loads. Despite a low SRI score, the space is equipped with calibrated indoor sensors and offers full-year performance data. This combination of empirical monitoring, multifunctional use, and low digital maturity provides a valid and realistic context for testing whether smart operational strategies alone can justify retrofit avoidance, directly addressing the research question.

Indoor environmental parameters, including CO_2 concentration, air temperature, and VOCs, were recorded at 15-minute intervals over a full calendar year using calibrated in-room sensors. These measurements were used to verify comfort and indoor air quality compliance and to support calibration of the energy simulation models.

3.2. SRI assessment and scenario use

The SRI assessment in this study follows the methodology established under Commission Delegated Regulation (EU) 2020/2155 and applied in the context of the 2024 recast of the EPBD. The assessment was applied at the zone level, consistent with the SRI framework, where scoring reflects the presence, automation, and controllability of technical services within the defined spatial boundary. The assessment focused on the availability and level of automation of relevant technical systems across the nine SRI domains, including heating, cooling, ventilation, domestic hot water, electricity, monitoring and control, dynamic envelope, demand response, and electric vehicle charging. Domain scores reflect system presence and functional capability within the assessed zone only, rather than the wider building.

SRI scoring was undertaken through document review, on-site inspection, and verification against building operation records, supported by operational knowledge of the systems serving the space. The assessment was performed by the authors, informed by formal SRI guidance and prior training in the application of the EC methodology. No deviations from the official scoring rules were introduced.

Domains receiving a score of zero indicate the absence of automated or controllable services within the Forum Zone, rather than data limitations or methodological exclusions. The resulting SRI profile was used to characterise the level of operational control maturity and to inform scenario definition and control assumptions within the subsequent energy simulation and life cycle assessment.

3.3. Energy simulation and operational data

Operational energy for Scenario A (Baseline) was simulated using EnergyPlus v25.1, with parameters representative of the Forum Zone's physical configuration and typical occupancy behaviour. The model included mechanical ventilation, terminal air handling units for cooling, and passive heating via a gas boiler. Lighting and plug loads were also included under occupancy-based control. The total simulated demand was $77.9 \text{ kWh/m}^2/\text{year}$, with subcategories of lighting (39.02), heating (10.22), and cooling (13.34) $\text{kWh/m}^2/\text{year}$, respectively. These results confirmed that observed indoor conditions— CO_2 levels $<1000 \text{ ppm}$, stable thermal comfort, and acceptable IAQ—were achieved within this energy range, supporting the system's functional adequacy without retrofit intervention.

3.4. Life cycle modelling approach

The LCI and impact assessment were conducted using Brightway2, a Python-based LCA framework. The selected impact assessment method is ReCiPe 2016 Midpoint (H), which provides midpoint characterisation factors for multiple environmental categories. All modelling was done locally using open-source environmental data sources, as commercial LCI databases such as Ecoinvent were not accessible. Emission factors for natural gas were sourced from UK DEFRA/BEIS 2024 GHG Conversion Factors, while electricity-related emissions were calculated using a weighted average emission factor derived from the 2024 UK electricity generation mix published by the International Energy Agency (IEA).

Four midpoint indicators were chosen to reflect operational impacts:

- GWP (Global Warming Potential, 100 years) – $\text{kgCO}_2\text{-eq/m}^2/\text{year}$
- CED (Cumulative Energy Demand) – $\text{MJ/m}^2/\text{year}$
- PMF (Particulate Matter Formation) – $\text{g PM}_{2.5}\text{-eq/m}^2/\text{year}$
- ADPf (Abiotic Depletion Potential – fossil) – $\text{MJ/m}^2/\text{year}$

GWP, PMF, and ADPf were characterised using the ReCiPe 2016 Midpoint (H) method, while Cumulative Energy Demand (CED) was calculated using a dedicated CED method implemented within the Brightway2 framework. LCI modelling was performed in Brightway2 using publicly available datasets and emission factors, as access to

commercial databases such as Ecoinvent was unavailable. All modelling followed ISO 14040/44 principles and adopted the “cut-off by classification” system model, consistent with attributional LCA practice [Table 1](#).

Electricity consumption in all three scenarios was modelled using the most recent 2024 UK electricity generation mix, published by the International Energy Agency (IEA, 2024). Emission factors were assigned by energy source and weighted based on national electricity shares. The weighted average electricity emission factor (167.9 gCO₂-eq/kWh), as derived from [Table 2](#), was applied to all scenarios and assumed to be constant throughout the assessment year. This value reflects the relatively low-carbon UK electricity mix in 2024; consequently, the comparative GWP performance of electrification-based Scenario B is conditional on grid carbon intensity and would differ under higher-carbon electricity systems.

Natural gas emissions were calculated using DEFRA 2024 factors (0.184 kgCO₂-eq/kWh), including upstream leakage and combustion-related pollutants. These values were applied to Scenarios A and C, which retained gas-fired systems.

3.5. LCA scenarios

The objective is to assess the comparative environmental performance of mechanical retrofit and smart operational strategies in buildings with differing levels of smart readiness and indoor environmental performance. The analysis compares three scenarios of ASHP Retrofit to both the conventional baseline scenario, where existing systems are retained, and the optimised temperature setpoints scenario. All scenarios are to be simulated in the EnergyPlus 25.1 software version.

3.5.1. Scenario A – baseline

Scenario A retains the existing configuration: a natural gas boiler for heating and a mechanical ventilation system for air handling and limited cooling. No retrofit actions are introduced.

- Boiler efficiency: 85%
- Annual heating demand: ~14,000 kWh/year (based on EnergyPlus simulations calibrated with sensor and utility data).

Table 1
Input boundary conditions used in the energypplus simulation.

Category	Parameter	Distribution	Unit/ Format
Zone	Zone area	Total floor area	350 m ²
	Zone height	Total height of the zone	6 m
Thermal properties	Wall U-value	Heat transfer coefficient of the wall	0.30 W/m ² K
	Roof U-value	Heat transfer coefficient of the roof	0.26 W/m ² K
	Window U-value	Heat transfer coefficient of the window glazing	0.55 W/m ² K
	Infiltration rate	Air leakage through the building envelope	1.8 ACH
Schedules	Occupancy schedules	Time-dependent schedules	Fraction (0-1)
	Lighting schedule	Occupancy-based lighting sensors	Fraction (0-1)
	Lighting power density	Lighting power density per floor area	3.5 W/m ²
	Equipment schedules	Time-dependent schedules	Fraction (0-1)
	Equipment power density	Equipment power per floor area	5.0 W/m ²
	HVAC operation schedule	Terminal AHU control	VRF terminal control
	Heating setpoint/ Setback	Setpoint - setback	19°C -14°C
	Cooling setpoint/ Setback	Setpoint - setback	20°C - 24°C
Air flow rate	Air supply per occupant	8 L/s/person	

Table 2
UK electricity generation mix and emission factors (IEA, 2024).

Source	Share (%) (gCO ₂ /kWh)	Emission Factor (gCO ₂ -eq/kWh)	Weighted Contribution
Natural Gas	31	450	139.5
Wind	30	11	3.3
Nuclear	15	12	1.8
Biomass & Waste	9	40	3.6
Solar	5	30	1.5
Net Imports	10	180	18.2
Total Weighted Avg.	100	—	167.9

- Cooling demand: minimal; handled by existing air handling units and modelled in EnergyPlus.
- All operational energy and emissions are derived from EnergyPlus outputs. Emissions from natural gas are calculated using DEFRA 2024 factors (0.184 kgCO₂-eq/kWh). As no materials are added or replaced, embodied emissions are excluded.

3.5.2. Scenario B: retrofit

Embodied emissions from the ASHP system and its distribution infrastructure were modelled using publicly available LCI proxies in Brightway2. Since Ecoinvent access was unavailable, the modelling relied on datasets from the open-source PSILCA and AGRIBALYSE databases, complemented by values from ICE v3.0 (University of Bath, 2019) and Carbon Leadership Forum (2022) component-level inventories. The following proxies were applied:

- ASHP unit (8.5 kW): modelled using a proxy for an air-cooled packaged heat pump system with aluminium-copper heat exchangers and hermetic compressor assemblies (ICE v3.0; CLF, 2022).
- Refrigerant R32: included based on IPCC AR6 Global Warming Potential values (GWP100 = 771), assuming 3% annual leakage and 5 kg total charge (EN 378 standard).
- Ductwork and piping: embodied emissions modelled using galvanised steel ducts (ICE v3.0: 1.9 kgCO₂-eq/kg) and copper piping (CLF: 4.0 kgCO₂-eq/kg).
- Control systems: represented as a proxy mix of printed circuit board (PCB) electronics and sensors, referencing values from the Carbon Leadership Forum’s 2022 electronics module.
- Although the ASHP system electrifies space heating entirely, domestic hot water (DHW) remains supplied by an existing gas-fired system. As such, minor gas consumption is retained in Scenario B for DHW purposes and is reflected in the operational energy modelling.

The total embodied environmental impacts of the ASHP system were annualised over a 20-year assumed service life and allocated to the functional unit defined in [Section 3](#).

3.5.3. Scenario C – schedule and setpoint-based control optimisation

Scenario C introduces no physical system changes but reduces operational demand through advanced control strategies: adaptive zoning, optimised HVAC scheduling, and dynamic setpoint management.

- Same physical HVAC systems as in Scenario A
- Annual heating demand: reduced by ~20% to ~11,200 kWh/year based on simulation with updated control logic
- Cooling and ventilation loads are similarly reduced by narrowing occupancy hours and tolerances, following recent literature benchmarks (WRAP 2022; Carbon Trust 2020)

- Simulations confirm that indoor CO₂, temperature, and IAQ remain compliant despite reduced operational schedules, affirming the functional adequacy of this scenario.

Electricity use is calculated from EnergyPlus simulation, with emissions calculated using the weighted average UK electricity emission factor derived from the 2024 IEA generation mix.

3.5.4. Foreground life cycle inventory definition

Foreground life cycle inventories were defined at the scenario level and implemented in Brightway2 using aggregated energy and material flows. Scenarios A and C include operational electricity and natural gas consumption for space conditioning, ventilation, lighting, and equipment, with identical system configurations and fuel pathways. Scenario B additionally includes embodied inventories associated with the ASHP retrofit, comprising the heat pump unit, refrigerant charge and leakage, distribution components, and control electronics. Embodied impacts were annualised over an assumed 20-year service life and allocated to the one-year functional unit. Quantified operational demands are reported in Section 4.

3.6. Life cycle impact assessment

LCI Assessment was performed using the ReCiPe 2016 Midpoint (H) method within the Brightway2 platform. This method is widely adopted in building LCA due to its ability to capture a broad range of environmental impacts while maintaining interpretability at the midpoint level (Huijbregts et al., 2017). The midpoint (H) version provides characterisation factors for 18 environmental indicators, enabling systematic comparison of operational and embodied interventions. In this study, four midpoint indicators were selected based on their relevance to HVAC retrofitting, operational phase energy use, and building systems, as can be seen in Table 3.

The selected indicators reflect a representative cross-section of climate, energy, resource, and health-related impacts, aligned with best practices in European and UK building LCA frameworks (e.g., EN 15978; LETI, 2023). All scenarios were modelled using attributional LCA principles under the “cut-off by classification” system model, capturing upstream emissions from material extraction and manufacturing while excluding downstream reuse or recycling benefits, in accordance with ISO 14040/44. Calculations were conducted using Brightway2, combining custom inventory structures (e.g., ASHP components, operational flows) with public emission factors from ICE v3.0, PSILCA, DEFRA, and SAP 10.2. Electricity-related emissions were based on the 2024 UK grid mix (IEA, 2024), with a weighted average of 167.9 gCO₂-eq/kWh.

Due to limited access to commercial databases such as Ecoinvent, proxy datasets were used for specialised components, including ASHP units and R32 refrigerant, selected for material and functional

Table 3
Selected life cycle impact categories, functional units, and justification for inclusion in the LCA.

Impact Category	Unit	Justification
GWP	kgCO ₂ -eq/m ² /year	Most commonly reported climate metric in building LCA. Measures radiative forcing over 100 years (IPCC, 2021).
CED	MJ/m ² /year	Captures total primary energy use, both renewable and non-renewable, across material and operational stages (Frischknecht et al., 2020).
PMF	g PM _{2.5} -eq/m ² /year	Reflects health impacts from airborne pollutants, notably from combustion-based heating (Sharma et al., 2022).
ADPF	MJ/m ² /year	Accounts for fossil fuel resource depletion, sensitive to fuel type and energy efficiency (Milić et al., 2021).

equivalence. Their accuracy was cross-validated against published benchmarks (±15%). While this approach may reduce component-level granularity, it preserves methodological consistency and supports transparent, replicable comparisons across scenarios.

To address uncertainty and seasonal variability in energy demand, a Monte Carlo simulation with 1,000 iterations was applied to each scenario. Triangular distributions (±10%) were assigned to operational energy inputs based on empirical full-year sensor and simulation data. Results were presented as mean values and 90% confidence intervals across all four impact categories, enabling robust and reproducible assessment.

3.7. Modelling framework, representativeness, and data transparency

To ensure reproducibility and methodological transparency, all life cycle modelling was conducted using the Brightway2 framework (version 2.5.3) implemented in Python 3.11. A local modelling environment was configured under Windows 11, with all packages managed via virtual environments and tracked through Git-based version control. Custom Python scripts were developed to automate scenario modelling, run ReCiPe 2016 midpoint evaluations, and conduct Monte Carlo simulations (1,000 iterations per scenario). These scripts are fully documented and available for review, ensuring traceability of every modelling assumption in line with ISO 14040 and 14044 standards.

Geographically, the case study and all foreground inputs are specific to the UK context, based on sensor data and energy simulations from Cardiff University. The 2024 UK electricity mix was adopted from International Energy Agency (IEA, 2024) statistics, and all emission factors and thermal conversion assumptions were based on UK government datasets (DEFRA/BEIS, SAP 10.2, and LETI). Temporal representativeness is focused on the 2023–2024 operational year, aligning with the most recent available grid intensities and measured indoor conditions.

System boundaries apply attributional logic and adopt the “cut-off by classification” model in Brightway2, wherein upstream emissions (material extraction, manufacturing, and transport) are included, while downstream benefits from recycling or reuse are excluded. This system model is widely recognised in academic and regulatory LCA applications due to its clarity and alignment with decision-oriented analysis. No allocation rules were required, as all systems analysed are mono-functional, and material flows were fully attributed to each scenario.

To address parameter uncertainty in the LCI, a Monte Carlo simulation was implemented using custom Python scripts, sampling 1,000 iterations per scenario. Triangular distributions (±10%) were applied to operational energy inputs and embodied material flows. KDE-based visualisation of these distributions is presented in the results section, capturing both central tendency and tails across all impact categories.

Fig. 1 summarises the methodological sequence, combining energy modelling, embodied carbon data, and Brightway2-based LCA to assess operational and embodied impacts across retrofit scenarios. The inclusion of three operational scenarios, baseline, ASHP retrofit, and control setpoint optimisation, enables comparative assessment under consistent boundary conditions. Ultimately, Monte Carlo uncertainty analysis facilitates a robust interpretation of results and informs scenario-specific retrofit recommendations.

Based on these outlined comparable impact profiles, the following results section presents these findings, evaluating whether operational smartness alone can reduce environmental burdens to a level that justifies avoiding retrofit, thus directly answering the research question.

4. Results

This section presents the integrated findings of the SRI assessment, energy simulation, and scenario-based LCA. Scenario C (Schedule and setpoint-based control optimisation) achieved lower impacts than the baseline and comparable or lower impacts than the retrofit scenario across multiple environmental indicators, without incurring embodied

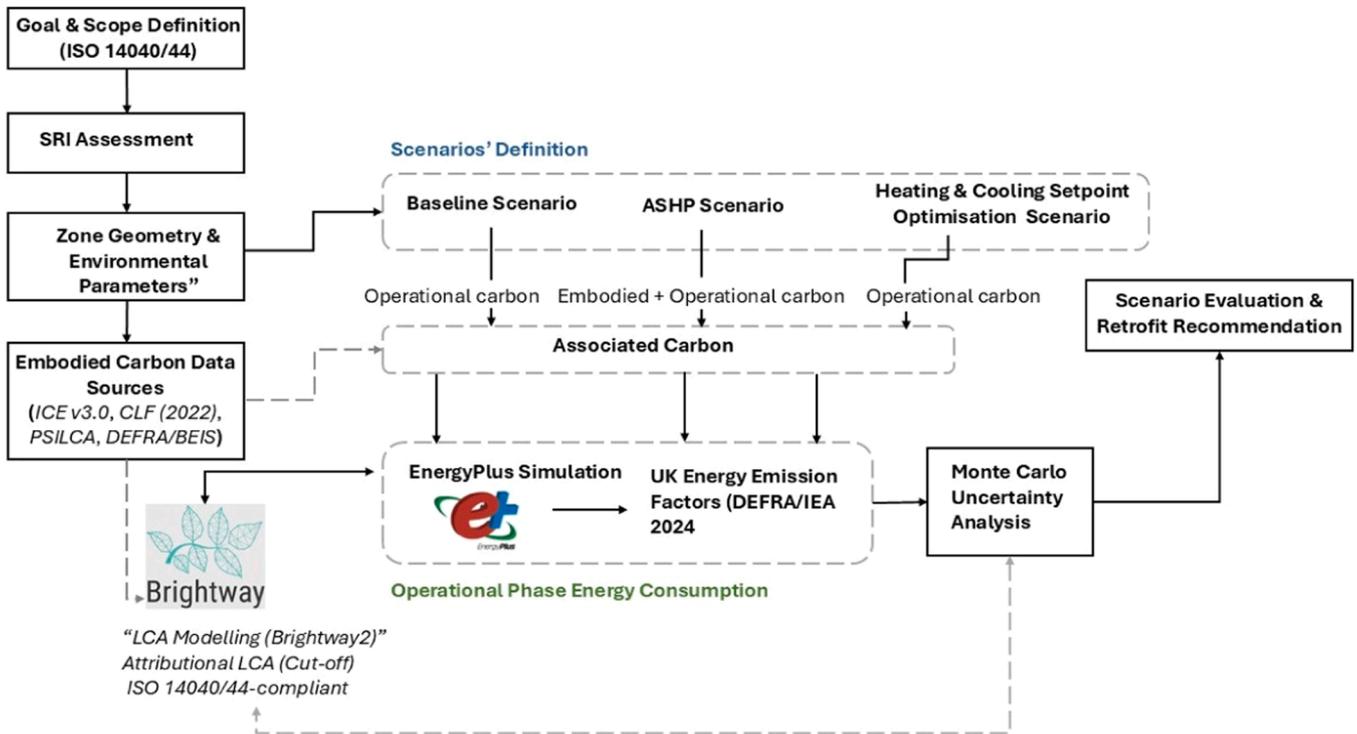


Fig. 1. Methodological workflow integrating SRI, energy simulation, and scenario-based LCA.

emissions. Results are structured around digital readiness evaluation, operational energy breakdown, environmental impact modelling, and uncertainty analysis.

4.1. Smart readiness and indoor environmental performance

The SRI assessment for the Forum Zone, conducted using the

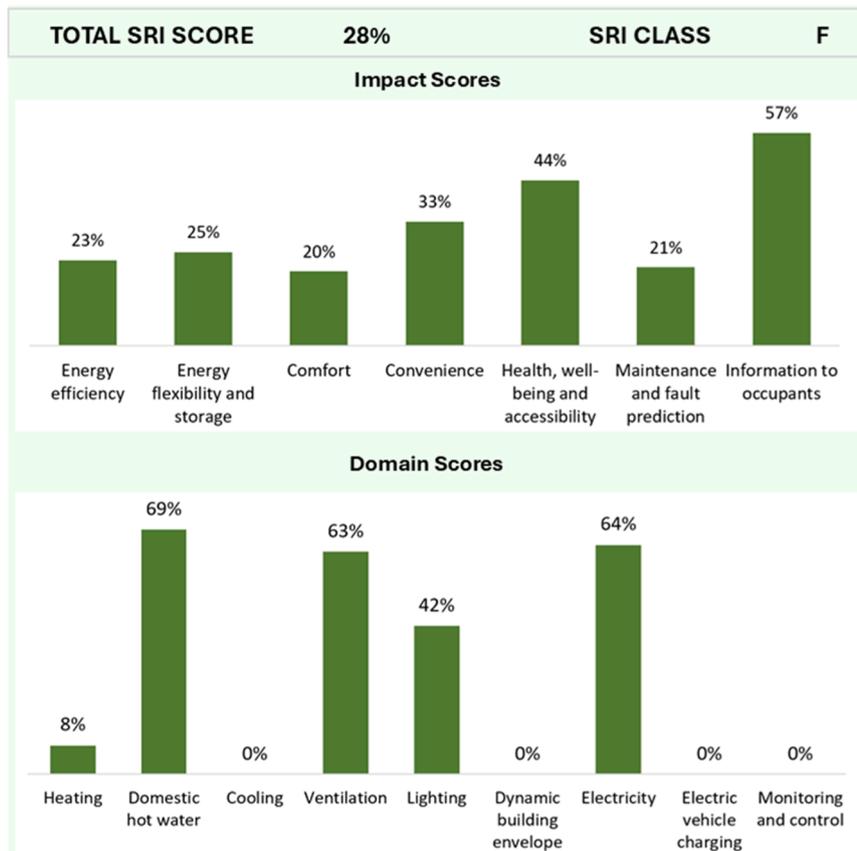


Fig. 2. SRI domain scores for the Forum Zone.

European Commission’s v4.4 methodology, yielded a total score of 27.97%, corresponding to SRI Class F.

Fig. 2 presents the SRI domain scores across nine technical systems. Ventilation (63%), Electricity (64%), and Domestic Hot Water (69%) scored moderately, while Cooling, Dynamic Envelope, and Monitoring & Control scored 0%, indicating no automation in those areas.

Environmental performance was assessed using calibrated indoor sensors over a full calendar year. Key results showed that, despite a low level of smart readiness, the building is still performing within acceptable levels of indoor environmental comfort. These explicitly shows that:

- CO₂ concentrations remained below 1000 ppm during all occupied hours.
- Indoor temperatures remained within ±1.5 °C of setpoints for nearly 50% of the year.
- VOC levels were consistently under 300 ppb.

Fig. 3 compares SRI functional coverage with simulated energy demand across building domains. SRI reflects digital capability rather than energy use. In this case study, the zero SRI score for the cooling domain reflects the absence of automated control functions rather than poor functional performance. Simulated cooling demand remained low, and comfort thresholds were met through passive and manually managed operation, indicating that additional cooling automation was not environmentally justified under the assessed conditions. In contrast, Lighting exhibits moderate SRI coverage yet high energy use, as the occupancy-based sensor lighting system is frequently triggered in this highly active social space.

Fig. 3, therefore, indicates that SRI domain scores describe the presence of actionable control capability rather than operational energy intensity, framing the relationship between available control functions and observed energy outcomes. This distinction motivates the subsequent comparison of annual end-use energy demand across scenarios, where the extent to which available control capability translates into energy reduction under maintained comfort conditions is examined quantitatively.

4.2. Annual end-use energy

Fig. 4 illustrates the simulated annual energy demand by end-use category:

- Scenario A: The baseline scenario used 77.9 kWh/m²/year, primarily gas-based.

- Scenario B: Electrification via ASHP eliminated fossil fuel use but increased electricity consumption to 81.6 kWh/m²/year.
- Scenario C: Schedule- and setpoint-based control optimisation reduced energy use to 63.4 kWh/m²/year, achieving a 19% total demand reduction vs Scenario B.

Lighting and plug load demands remain constant across scenarios due to identical occupancy assumptions. For Scenario B, residual natural gas consumption associated with domestic hot water provision is included in the LCA calculations but omitted from the end-use energy figure for visual clarity.

4.3. Hourly and cumulative load profiles

Fig. 5 presents simulated hourly load profiles for a representative winter weekday, selected to illustrate typical heating and electricity demand patterns across the scenarios. The profiles are derived directly from EnergyPlus time-series outputs using the same weather file and occupancy schedules across all scenarios. Scenario differences reflect changes in heating technology (gas boiler versus ASHP) and control logic, including setpoint schedules and operating hours, rather than differences in climatic or occupancy inputs.

The hourly load profiles across a typical winter day showed:

- Scenario A: Early-morning and evening gas-driven heating peaks associated with static temperature setpoints.
- Scenario B: Morning and midday electricity peaks driven by ASHP operation.
- Scenario C: Flattened load curves with reduced peak intensity and duration due to adaptive control.

These patterns confirm the responsiveness of the control optimisation to real-time conditions and occupancy variability. This is further confirmed by the cumulative trends in electricity and gas use, as shown in Fig. 6, where:

- Scenario C achieved a 26% reduction in gas use compared to the baseline, while keeping electricity use relatively stable.
- Scenario B, though fully electrified for space heating, still shows minor gas consumption due to domestic hot water provision, which remains served by a separate gas system.

These cumulative profiles highlight the operational efficiency of Scenario C and the energy shift associated with Scenario B’s electrification pathway.

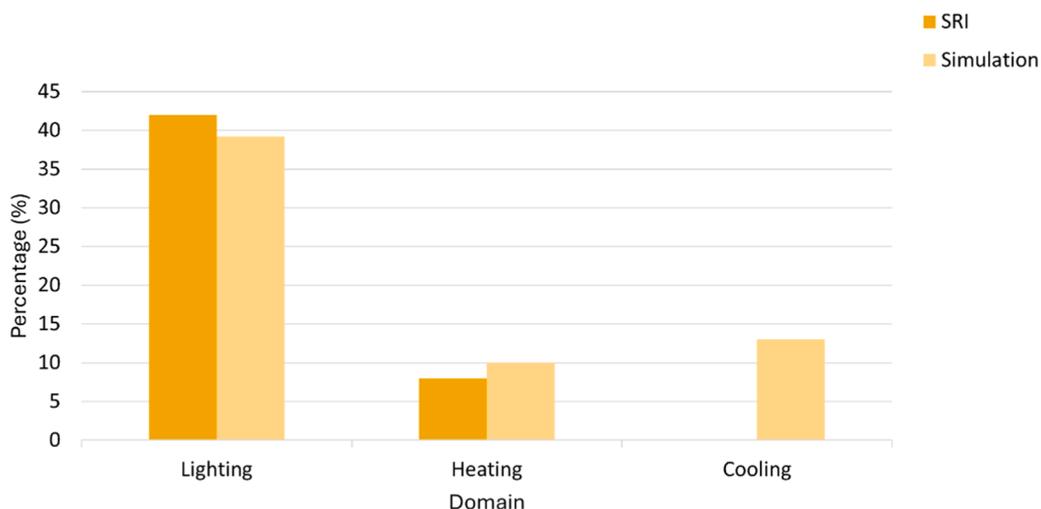
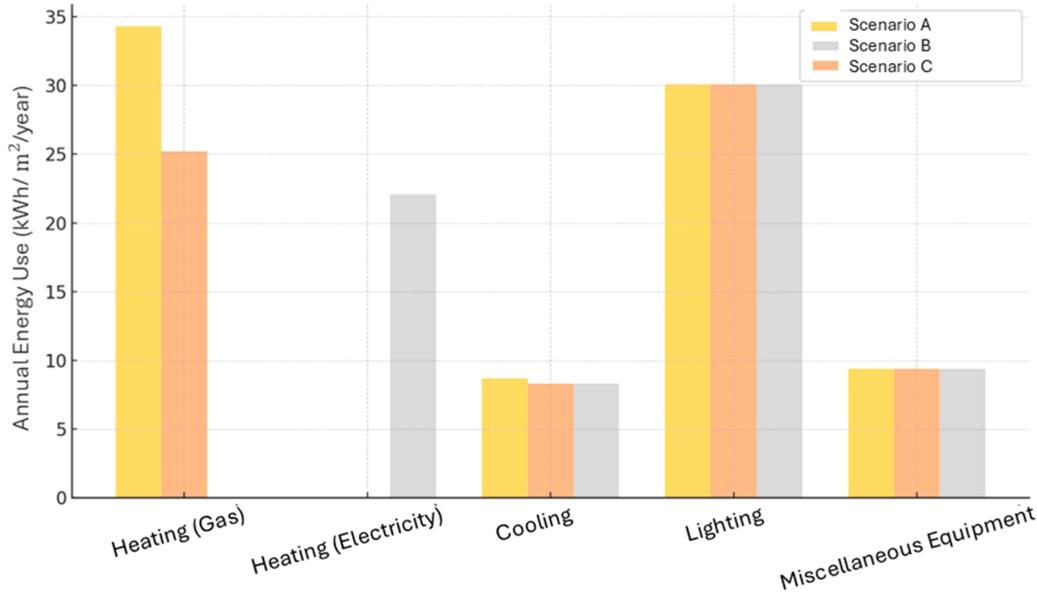


Fig. 3. Comparison of SRI domain scores and simulated annual operational energy demand by domain.



4. Simulated annual operational energy demand by end-use for Scenarios A (baseline), B (ASHP retrofit), and C (Schedule and setpoint-based control optimisation).

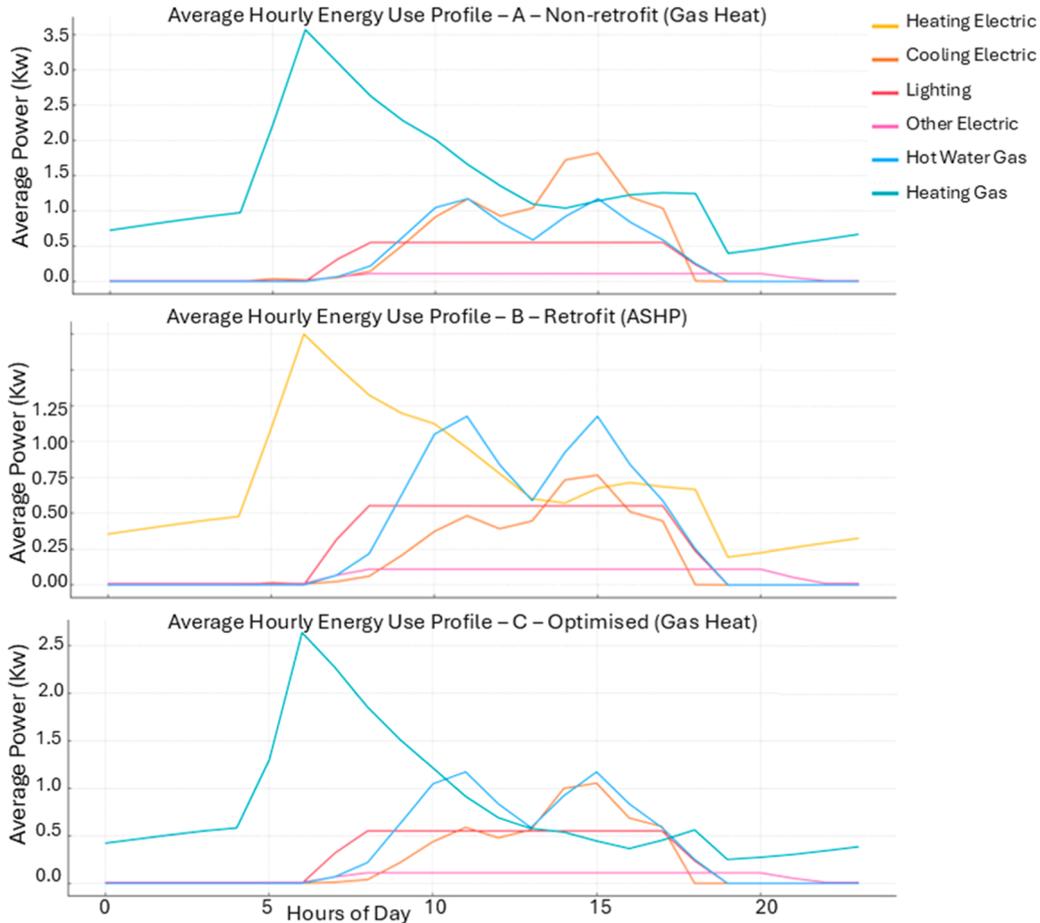


Fig. 5. Simulated hourly heating and electricity load profiles for a representative winter day across the three scenarios.

4.4. Life cycle impact assessment

Environmental impacts were evaluated using the ReCiPe 2016 Midpoint (H) method in the Brightway2 platform. Four midpoint indicators were selected to reflect the most policy-relevant and HVAC-

sensitive environmental dimensions in building LCA.

Embodied emissions were included only in Scenario B and modelled using open-access proxies, as outlined in the Methodology (Section 3.3). These components include:

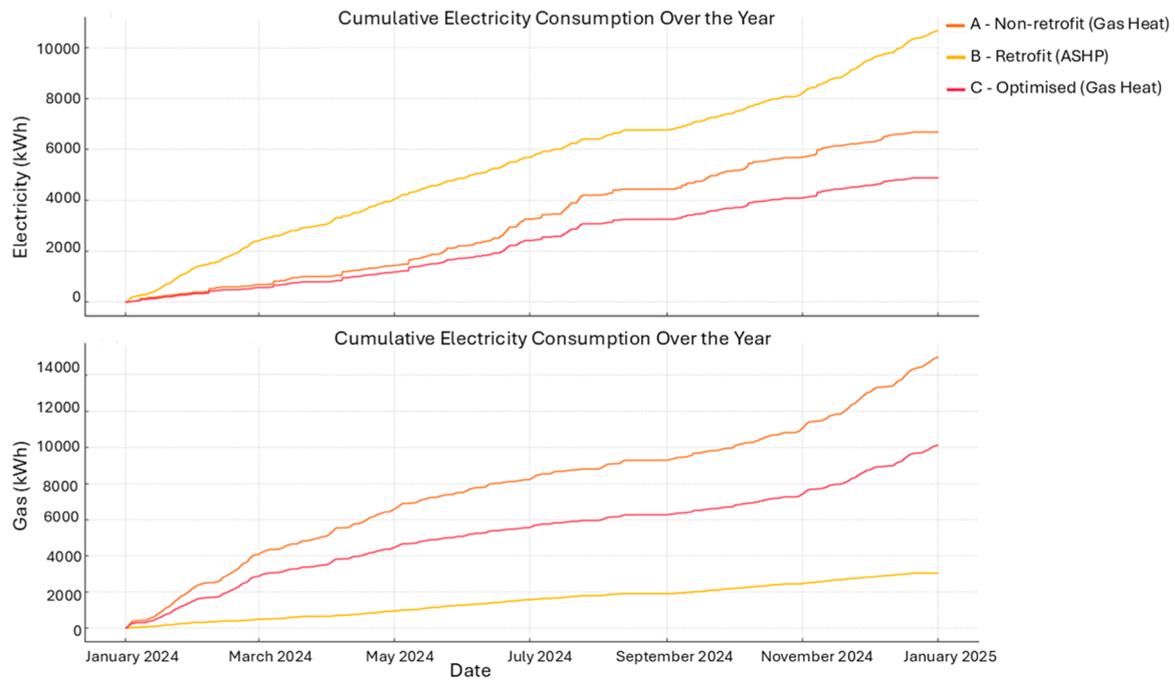


Fig. 6. Cumulative annual electricity and natural gas consumption across scenarios.

- ASHP unit (8.5 kW).
- Refrigerant charge and leakage (R-32, 5 kg, 3%/year).
- Ductwork (galvanised steel) and piping (copper).
- Control electronics (PCBs and sensors).

Fig. 7 presents normalised midpoint impacts across the four LCA indicators. Results are scaled relative to the worst-performing scenario in each category (100%).

Table 4 reports the exact normalised values underlying the radar chart in Fig. 7, provided to support numerical interpretation of relative scenario performance across impact categories.

Table 4

Normalised midpoint values corresponding to Fig. 7.

Scenario	GWP	CED	PMF	ADPf
Scenario A (Baseline)	100	100	100	100
Scenario B (ASHP retrofit)	70.1	89.7	75.6	73.9
Scenario C (Schedule and setpoint-based control optimisation)	73.6	76.2	66.7	52.2

Scenario A (Baseline) shows the highest impacts across all categories, driven by static operation and full gas dependency. Scenario B, although

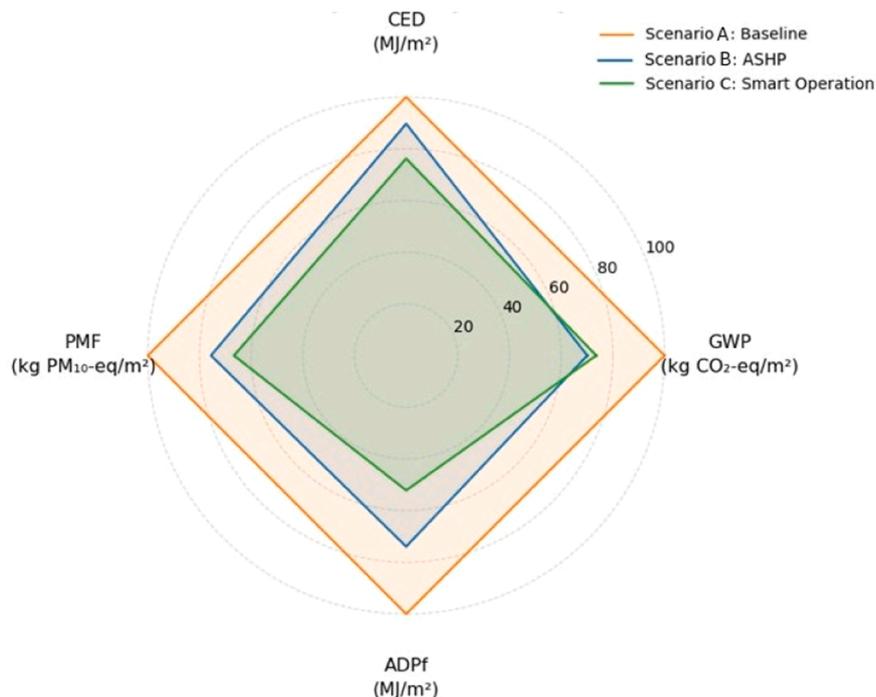


Fig. 7. Normalised midpoint environmental impacts for the three scenarios, scaled to the highest-impact case (100%) for each indicator.

burdened by embodied emissions from heat pump retrofit, benefits from full space heating electrification and the lower carbon intensity of the UK grid (167.9 gCO₂/kWh), a condition that underpins its relative GWP advantage under the stated grid assumptions.

Scenario C (Optimised operational control) shows the lowest relative impacts for CED, PMF, and ADP_f, forming the smallest area on the radar chart overall. However, it exhibits a slightly higher GWP than Scenario B (ASHP retrofit) due to continued natural gas use for both space heating and domestic hot water. This highlights that operational optimisation primarily reduces energy demand and pollutant-related impacts, while full climate mitigation (GWP reduction) remains contingent on complete fuel switching.

For reference, the absolute annualised GWP value ranges obtained from the Monte Carlo analysis were approximately 35–42 kg CO₂-eq/m²-year for the baseline (Scenario A), 49–60 kg CO₂-eq/m²-year for the ASHP retrofit (Scenario B), and 36–44 kg CO₂-eq/m²-year for the operational optimisation scenario (Scenario C). These values provide contextual magnitude for the normalised results. The absolute GWP ranges (~35–60 kg CO₂-eq/m²-year across scenarios) indicate that observed differences reflect substantive environmental magnitudes rather than graphical scaling effects.

These results highlight that operational optimisation (Scenario C) can significantly reduce multiple environmental burdens even without full equipment retrofit, while relative GWP performance remains conditional on fuel mix and electricity grid carbon intensity.

4.5. Uncertainty analysis

A Monte Carlo sensitivity analysis was performed using 1000 iterations per scenario to assess the robustness of midpoint impact results across the four selected categories: (GWP), (CED), (PMF), and (ADP_f). Distributions were generated by randomly varying input parameters related to energy use, material emissions, and background datasets, using triangular probability distributions with ±10% variation around baseline values, across 1,000 Monte Carlo iterations per scenario. Although triangular distributions were used for parameter sampling, results are presented as kernel density estimates to illustrate distribution shape and overlap. Fig. 8 presents the resulting probability density

distributions for each impact category.

The resulting probability density distributions for each impact category can be seen as:

- GWP: Scenarios B and C show overlapping but distinct distributions. Scenario B exhibits a lower operational GWP contribution due to full electrification of space heating; however, when annualised embodied impacts are included, its total GWP distribution remains higher than Scenario C, with values extending above 55 kgCO₂-eq/m². Scenario C shows a slightly higher GWP than Scenario B on an operational basis due to the continued use of the gas heating.
- CED: Scenario C consistently outperforms A and B, with the lowest cumulative demand (~68–75 MJ/m²) across nearly the entire range. Scenario B shows moderate overlap with Scenario A but shifts left due to ASHP efficiency gains.
- PMF: The tightest and lowest distribution belongs to Scenario C, followed by Scenario A. Scenario B is significantly shifted to the right, indicating high sensitivity to operational inefficiency.
- ADP_f: Scenario C again shows the lowest values, while Scenario A shows the highest fossil resource depletion. Scenario B occupies an intermediate position, reflecting the trade-off between embodied emissions and grid dependence.

Across all indicators, Scenario C demonstrates the narrowest and most favourable distributions, reinforcing its environmental advantage even under uncertainty. Scenario A consistently ranks as the least favourable, with minimal overlap with other scenarios, affirming the robustness of its comparatively higher impact.

5. Discussion

The following discussion, critically evaluates the LCA results, drawing on established literature and contextualising the environmental implications of each intervention scenario. Particular emphasis is placed on the interplay between operational and embodied impacts, the methodological integration of the SRI, and the implications of uncertainty in input parameters. The findings are further examined regarding current retrofit practices and policy frameworks relevant to building

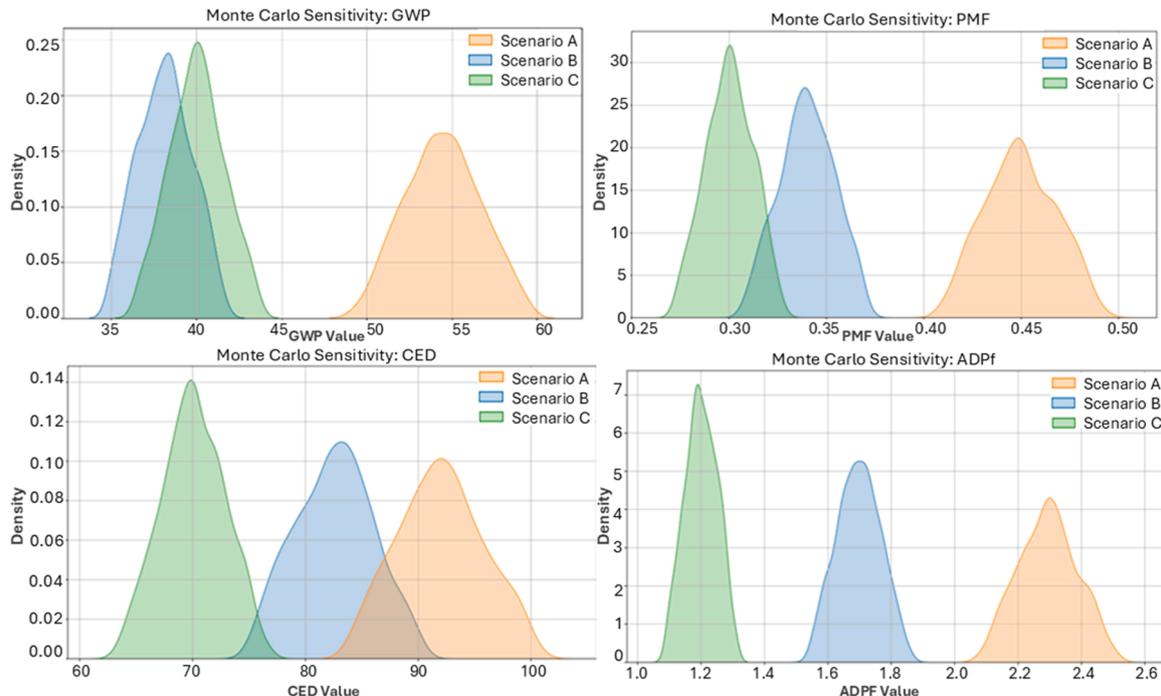


Fig. 8. Monte Carlo uncertainty distributions for selected midpoint impact categories.

decarbonisation.

5.1. Interpreting environmental performance across scenarios

The results demonstrate clear variation in environmental impact across the three modelled scenarios. Scenario C, which applied manual optimisation of control schedules and temperature setpoints, achieved the lowest impact in three of the four midpoint categories: CED, PMF, and ADPf. Scenario B, which replaced the heating system with an ASHP, recorded the lowest GWP due to full electrification of space heating. Scenario A, representing the unmodified baseline, consistently resulted in the highest impacts across all categories.

These outcomes highlight the distinct environmental trade-offs between operational and embodied interventions. While Scenario B delivered the greatest reduction in GWP, this was offset by higher CED and material-related burdens. In contrast, Scenario C reduced environmental loads across most categories without introducing additional equipment or embodied emissions. This suggests that targeted operational improvements can yield significant environmental benefits, particularly in buildings where baseline conditions already meet thermal comfort and air quality standards.

The observed difference in GWP between Scenarios B and C can be attributed to fuel mix and system configuration. Scenario B's full electrification leveraged a relatively low-carbon grid, while Scenario C continued to rely on natural gas for both space heating and domestic hot water. Despite this, Scenario C's manual optimisation reduced overall energy use, partially narrowing the GWP gap between the two approaches. However, the relative GWP advantage of Scenario B is contingent on the assumed electricity carbon intensity. While a single average UK grid factor was applied to ensure consistency with the monitored year, future grid decarbonisation trajectories or higher-carbon electricity contexts would alter the relative ranking between electrification and operational optimisation strategies. Under lower-carbon grids, electrification benefits would strengthen, whereas in higher-carbon or slower-decarbonising contexts, demand-reduction strategies such as operational optimisation may remain comparatively favourable. In practical terms, this means that retrofit decisions should not rely on GWP alone, but should weigh climate benefits against CED, PMF, ADPf, and the embodied burden of system replacement.

5.2. Role of embodied impacts in retrofit decision-making

Scenario B incurred substantial embodied impacts due to the manufacture, transportation, and installation of new heating equipment, refrigerants, and associated infrastructure. These embodied emissions accounted for a significant proportion of total GWP, delaying the environmental payback of the retrofit. The findings confirm that even environmentally efficient technologies may carry considerable upfront burdens, which must be weighed against their long-term operational benefits.

In contrast, Scenario C required no additional physical components. The operational improvements were achieved solely through reprogramming of existing control systems. As such, it incurred no embodied emissions, offering an environmentally efficient intervention with minimal physical modification. In contexts where systems are already functional and thermal demand is moderate, such interventions may offer the greatest environmental return on investment.

Moreover, indoor environmental quality was maintained across all zones in Scenario C, as evidenced by empirical monitoring data. Despite its low classification under the SRI, the system achieved compliance with CO₂ and VOC thresholds, indicating that acceptable performance can be achieved without technological upgrades, provided operational strategies are sufficiently refined.

5.3. Integration of smartness and LCA: a methodological contribution

A key methodological contribution of this study is the explicit integration of operational control, through optimised schedules and temperature setpoints, as a defining parameter within the LCA system boundaries. Scenario C did not rely on smart automation, yet its manually optimised schedules resulted in clear environmental advantages. This underscores the importance of including operational behaviour and system tuning as active variables in environmental modelling.

From a methodological perspective, the novelty lies in treating operational control capability as an LCA-defining parameter rather than a background assumption. In existing smart building LCA studies, control strategies are typically simulated without reference to standardised smartness indicators. As mentioned, the SRI domain coverage, when coupled with energy simulation, is used to delimit which control actions are feasible, ensuring consistency between assessed smart readiness and modelled operation. This coupling is empirically supported by the observed distinction between domain-level control capability and its simulated energy demand. In this way, SRI functions as a constraint on scenario definition rather than as a predictor of energy performance, moving it from a descriptive assessment tool to an active decision variable within environmental modelling.

While SRI classifications typically reflect the presence of smart infrastructure, they do not necessarily capture how systems are actually used. In this study, low-cost, low-tech operational adjustments were sufficient to achieve measurable reductions in impact, highlighting a disconnect between feature-based readiness scores and real-world environmental performance.

This study positions the SRI not merely as a feature checklist but as a contextual input that bounds operational choices within scenario-based LCA, even in buildings classified with low digital readiness. By informing which operational control capabilities may be realistically deployed or emulated, the SRI helps shape system boundaries and operational assumptions in environmental modelling. The modelling approach also demonstrates the feasibility of conducting robust scenario-based LCA using transparent, open-access tools and datasets. Despite the absence of commercial LCI databases, the results were consistent and replicable. This approach provides a useful reference model for assessing retrofit options in constrained data environments and for integrating simulation outputs with environmental evaluation.

5.4. Integrated decision-making framework

The findings suggest that not all buildings require physical retrofit to achieve environmental improvement. Where systems already deliver acceptable indoor conditions, operational refinement may offer a competitive alternative to mechanical retrofit for selected impact categories. Scenario C demonstrated that energy savings and environmental benefits can be achieved through simple control adjustments, without the need for equipment replacement or construction works.

This supports a rethinking of retrofit priorities, particularly in the context of building stock with moderate demand and functioning systems. A performance-based hierarchy of interventions may be more effective than one based on technical classifications alone. In such a framework, manual or semi-automated operational improvements would be prioritised before more resource-intensive mechanical upgrades.

From a policy perspective, this calls for a more nuanced interpretation of SRI scores. A low SRI classification does not necessarily imply poor performance or retrofit urgency. As demonstrated in this study, buildings with low feature availability may still perform well in practice if managed effectively. Incentive schemes and regulatory frameworks should therefore consider both installed capability and measured performance when determining retrofit pathways or funding eligibility.

5.5. From analytical findings to decision guidance

This subsection synthesises the analytical findings into a decision-oriented interpretation, bridging the Discussion and the Conclusions by translating scenario-based results into practical and policy-relevant guidance. Accordingly, the proposed framework is designed to be replicable across sites through a defined sequence of steps.

(1) empirical verification of indoor environmental performance and baseline energy use, (2) SRI assessment to identify domains with feasible operational control, (3) scenario definition covering baseline operation, control optimisation, and mechanical retrofit, (4) attributional LCA of operational and embodied impacts using consistent functional units, and (5) uncertainty-informed comparison using Monte Carlo simulation outputs includes relative impact rankings, confidence ranges, and a performance-based recommendation on whether retrofit intervention is environmentally justified.

Although the findings are based on a single non-residential UK building, the methodological approach is designed for replication across other building types and climatic contexts. The use of standardised LCA structure, scenario logic, and performance thresholds supports broader applicability. However, sensitivity to local climate (especially for ASHP performance) and baseline indoor environment conditions should be considered when adapting the framework elsewhere. Future applications should recalibrate control optimisation and energy modelling parameters accordingly.

Based on the findings of this study, a performance-based retrofit decision-making framework is proposed that integrates SRI assessment with scenario-based LCA and uncertainty evaluation. Fig. 9 presents the framework, synthesising methodological insights and practical outcomes into a structured decision pathway. The framework links SRI-derived status and indoor comfort thresholds with operational energy modelling to define baseline, control optimisation, and retrofit scenarios. These scenarios are evaluated through LCI modelling of embodied and operational energy flows, followed by Monte Carlo-based

life cycle impact assessment using the ReCiPe 2016 midpoint method. The results interpretation stage acts as a decision node for scenario comparison and uncertainty-informed ranking. As indicated by the dashed feedback loop, SRI level and indoor environmental performance function as both initial conditions and evaluation criteria, informing retrofit decisions where performance shortfalls justify the associated environmental impacts.

Overall, this framework demonstrates a methodologically coherent and data-driven approach for assessing the carbon trade-off against indoor environmental performance. The decision logic and operational-first intervention hierarchy are transferable across non-domestic buildings, as they rely on measurable operational performance, control capability, and life-cycle structure. Numerical scenario rankings, particularly for GWP, remain context-dependent and reflect local climatic conditions, fuel use, and electricity grid carbon intensity. While the framework enables performance-based retrofit decisions, its application and interpretation are therefore subject to the following methodological constraints.

5.6. Limitations

A Monte Carlo simulation was used to evaluate the robustness of the results under input variability. Across 1,000 iterations per scenario, the relative ranking of scenarios remained consistent in all categories. Scenario C maintained the lowest impacts in CED, PMF, and ADPF, while Scenario B retained the lowest GWP due to full electrification of space heating.

These results confirm that relative scenario rankings are not sensitive to minor fluctuations in input assumptions. The separation of distributions, especially in GWP and ADPF, supports the statistical significance of Scenario C's environmental benefits under uncertainty.

Accordingly, several limitations can be summarised as:

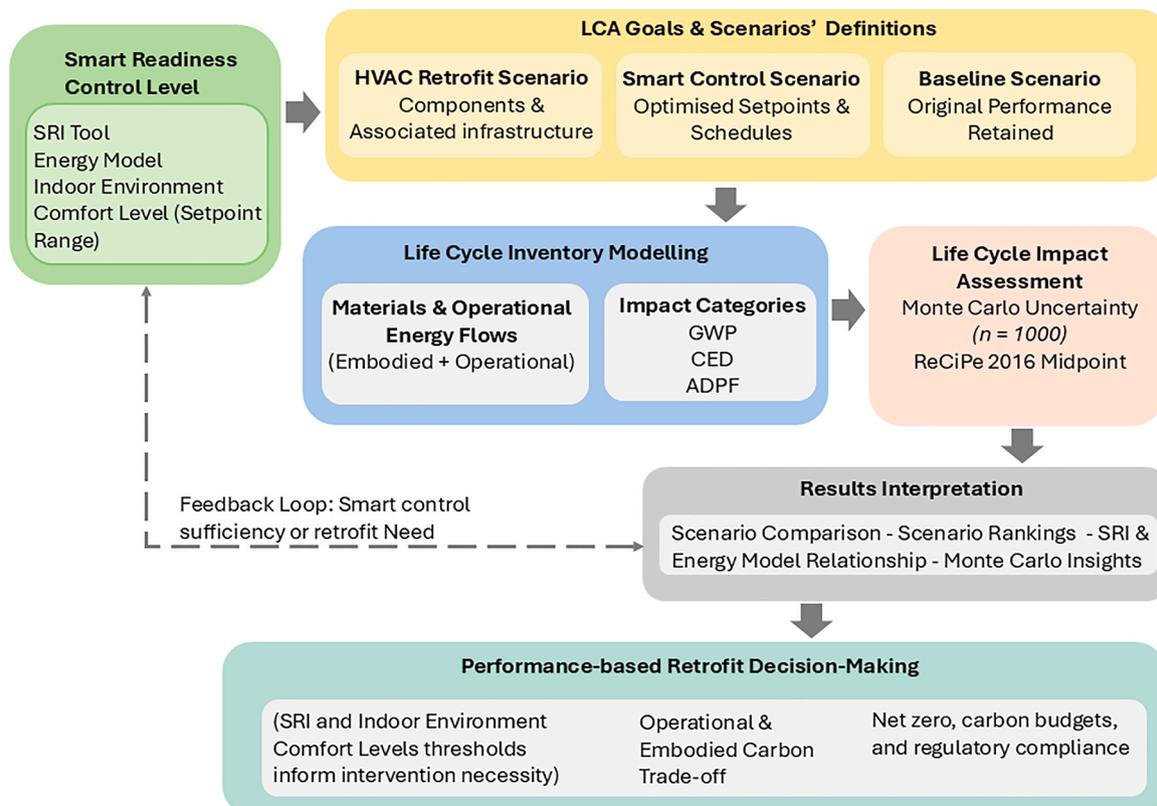


Fig. 9. SRI-based conceptual framework for performance-based retrofit decision-making and life-cycle impact interpretation.

- Simplified embodied modelling: Emissions for Scenario B were based on proxy datasets. While functionally appropriate, this introduces uncertainty in absolute values.
- Fixed emission factor: Electricity-related emissions were calculated using a single weighted value (167.9 gCO₂/kWh), aligned with the monitored year. Grid intensity fluctuations were not modelled seasonally.
- Constrained uncertainty bandwidth: The Monte Carlo simulation applied ±10% triangular variation based on expert judgement and sensor data. Computational resources constrained a broader sensitivity analysis.
- While this study demonstrates that low SRI scores can coexist with acceptable operational performance, particularly in manually optimised buildings, the generalisability of this finding remains context-dependent. The proposed interpretation framework highlights the value of validating SRI classifications against empirical indoor environmental and energy data. Further application across varied building types and control regimes is needed to assess whether such discrepancies are systemic or case-specific.
- Lifetime sensitivity (annualisation): Embodied impacts for Scenario B were annualised assuming a 20-year ASHP service life; shorter or longer lifetimes (e.g., 15 vs 25 years) would shift the annualised retrofit burden and could alter Scenario B's relative position where operational differences are marginal.
- Grid carbon intensity: Electricity-related emissions were modelled using a single 2024 UK average emission factor. In regions with higher-carbon electricity mixes, the GWP advantage of the electrification scenario (Scenario B) would diminish or potentially reverse relative scenario rankings.
- Scenario-level GWP rankings are sensitive to assumed electricity carbon intensity and may differ under alternative grid decarbonisation pathways.

6. Conclusion

This study demonstrates that integrating empirical operational performance, SRI assessment, and scenario-based LCA provides a robust and transparent basis for retrofit decision-making. Manual optimisation of HVAC control schedules and temperature setpoints (Scenario C) substantially reduces environmental impacts across several midpoint indicators without introducing embodied emissions. Under the stated boundary conditions, these operational strategies were competitive with mechanical retrofit for selected impact categories, while full electrification (Scenario B) achieved the lowest Global Warming Potential. In this context, the SRI adds value by constraining scenario definition to feasible control capabilities, enabling performance-based comparison beyond what measured energy and indoor environmental data alone can support.

The proposed framework and conclusions are most applicable to non-domestic buildings with moderate thermal demand, stable indoor environmental performance, and existing HVAC systems that permit schedule and setpoint adjustment, under temperate climatic conditions. Relative scenario rankings, particularly for GWP, remain conditional on electricity grid carbon intensity and control system maturity. Accordingly, the primary transferable contribution of this study lies in the decision-making framework and intervention hierarchy, rather than in the direct transfer of scenario-specific impact magnitudes.

These findings support a performance-based retrofit hierarchy in which low-impact operational interventions are evaluated and prioritised before resource-intensive mechanical upgrades. Overall, the framework provides a transferable and replicable methodological alternative to default retrofit-first strategies by embedding operational performance constraints and scenario-based life cycle assessment, including uncertainty analysis, directly into retrofit decision-making.

Future work should extend the framework to include cost and carbon payback analysis, maintenance and end-of-life stages, and application

across diverse building typologies and climatic contexts. Further development of standardised methods for representing operational responsiveness within LCA workflows would support closer integration of building digitalisation and decarbonisation strategies.

Data Access Statement

The data underpinning this study are available in the Zenodo repository at <https://doi.org/10.5281/zenodo.19095372>. The dataset includes processed and aggregated outputs from life cycle assessment and simulation modelling. Access to raw building operational data is restricted due to data sensitivity and institutional constraints.

CRedit authorship contribution statement

Mohamed Mustafa: Writing – review & editing. **Yacine Rezgui:** Supervision. **Tom Beach:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to acknowledge the financial support of the Engineering and Physical Sciences Research Council (EPSRC) in the UK, for the research under grant agreement (EP/T019514/1; INTER/UKRI/19/14106247).

Data availability

Data will be made available on request.

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