

Integrated post-occupancy evaluation and intervention that achieve real-world zero-carbon buildings

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ARTICLE INFO

Keywords:

Post-occupancy evaluation
Zero-carbon building
Data-informed building energy management
Data science
Building simulation
Data analytics
Cost-optimal analysis
Performance gap

ABSTRACT

Many building standards are available worldwide to support sustainable building design. However, most of them only define compliance before occupancy, overlooking the real building usage and its implications for meeting zero-carbon targets. This research proposes a systematic post-occupancy evaluation and intervention (POEI) protocol to analyse real building performance and support cost-effective and zero-carbon upgrading. The novelty lies in integrating novel diagnostic data science techniques to identify performance gaps, advanced physics-driven energy modelling iteratively calibrated with POE data to disaggregate energy use by end-use, and cost-optimal intervention analysis. The POEI protocol has been validated in a university building. The results demonstrated the POEI benefits for the cost-optimal upgrading of in-use building assets based on real needs. By optimising control, reducing demand, increasing efficiency, and implementing renewables, the building can reach the nearly zero-carbon building target with a payback period of 13 years and a 23 % lower life-cycle cost compared to the baseline scenario. Building energy management interventions were identified as the most important actions to reduce the performance gap, reducing energy consumption by 20 % and carbon emissions by 24 %. The results also highlight the critical role of Information and Communication Technologies (ICT), which may represent up to 49 % of energy use in the future zero-carbon building scenario if overlooked.

1. Introduction

This study deals with the problem of how to upgrade in-use building assets towards real-world zero-carbon buildings based on real occupant demands and building needs whilst minimising expenditure.

Zero carbon targets require the complete decarbonisation of the building sector. Over 150 building standards and certification programs are available worldwide to support low-carbon and sustainable building design [1]. Some of the most widely used standards are LEED, BREEAM, Passivhaus, EDGE, HQE or DGNB, in addition to joint harmonisation efforts of building standards at the international level, such as ASHRAE or CEN M/480. However, most of these building standards and certification programmes only provide criteria during the design, construction and/or commissioning stages, leading to uncertainty as to whether these certified buildings save energy during usage. Significant evidence suggests that buildings are not performing as well as expected, generating an important 'performance gap' between expectations and reality [2]. Such uncertainty around real-world benefits can be a significant barrier

to attracting the required finance and investment for building decarbonisation.

Many previous studies have highlighted discrepancies between the expected performance on certified buildings before and after occupancy, identifying inadequate indoor environmental quality [3], higher energy consumption and environmental impact [4,5], and no improvement in occupants' satisfaction in comparison with non-certified buildings [6]. Colclough et al. [7] identified 12 nearly zero-energy homes consuming more than twice the predicted by the energy rating. Zhou et al. [8] analysed 40 certified green buildings. They showed how low professional capabilities, frequently changing technical standards, and lack of supervision mechanisms make it difficult to maintain and improve the designed green performance of the building in the operation stage. Serrano-Jiménez et al. [9] identified large energy consumption variability across various end-users compared to predicted values in energy performance certificates. Lawrence and Keime [10] evaluated two higher-education buildings and identified how the lack of occupants' environmental control promoted general dissatisfaction and potentially higher energy consumption and cost. Deuble and de Dear [11] found

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<https://doi.org/10.1016/j.enbuild.2023.113766>

Received 30 July 2023; Received in revised form 27 October 2023; Accepted 17 November 2023

Available online 19 November 2023

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Nomenclature*Nomenclature and abbreviations*

AC	air conditioning
ACH	air change rate, h ⁻¹
C	CO ₂ concentration, ppm
COP	coefficient of performance
c _p	specific heat, kJ/kg·K
CV-RMSE	coefficient of variation of root mean square error
E	load event
EC	energy consumption
EER	energy efficiency ratio
H	heat transfer
HVAC	heating, ventilation, and air Conditioning
IAQ	indoor air quality
ICT	information and communication technologies
ML	machine learning
NMBE	normalised mean bias error
NV	night ventilation
nZEB	nearly zero-energy building
O	operation
P	power
PIR	passive infrared sensor
POE	post-occupancy evaluation
POEI	post-occupancy evaluation and intervention
PV	photovoltaic
Q	heat flux
q _v	air volume flow, m ³ /h

R ²	coefficient of determination
RH	relative humidity, %
SRF	shading reduction factor
t	time
T	temperature, °C
UK	United Kingdom
V	volume, m ³
VAT	Value Added Tax

Greek letters

ρ	density, kg/m ³
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Subscripts

ap	appliances
bl	baseline
hw	hot water
ind	indoor
inf	infiltration
int	internal
l	lighting
oc	occupancy
op	opaque envelope
out	outdoor
sol	solar gains
tr	transmission
ven	ventilation
w	window

that occupants' satisfaction requirements are less strict when they have an environmental concern, overlooking and forgiving less-than-ideal conditions that promote sustainability. Other studies have commonly identified building faults and incorrect settings that conflict with expected performance, increasing energy waste [12].

Post-occupancy evaluation (POE) has been promoted as a potential solution to overcome this challenge to reduce the performance gap of in-use building assets [13,14]. POE is the process of evaluating the performance of a building after it has been occupied by obtaining and analysing real building performance data and occupants' feedback during use (Fig. 1) [15].

POE can effectively inform specific building faults and needs where interventions should be prioritised for a low-carbon building transition. For example, Han et al. [16] demonstrated how a data-informed building energy management was able to efficiently reduce the energy consumption of heating, cooling, hot water and lighting by 5.4 kWh/m² in a building located in Cambridge (Massachusetts); García-Monge et al. [17] showed how the control of heating, ventilation, and air conditioning (HVAC) systems by CO₂ concentration level could save between

40 % and 70 % of HVAC energy consumption; and Göçer et al. [18] integrated environmental, spatial and user-related data in a spatial database to improve the building data management for effective building performance.

Moreover, POE can help understand occupants' perceptions and satisfaction to ensure a more inclusive built environment. For example, Hou et al. [19] analysed users' satisfaction in a university accommodation and found that the longer the stay of users, the smaller the performance gap; Zallio and Clarkson [20] developed a method to collect data on people's perceptions of inclusion, diversity, equity and accessibility (IDEA method); and Pastore and Andersen [21] identified how temperature and air quality were the most critical factors in occupants' perception of green-rated buildings, with satisfaction rates never more significant than 50 %.

Recent POE studies have also focused on integrating building data flow with Building Information Modelling (BIM) techniques [22]. BIM is a digital representation of the physical and functional characteristics of building assets, widely used for building design and construction stages [23]. Some researchers have proposed the BIM structure in this

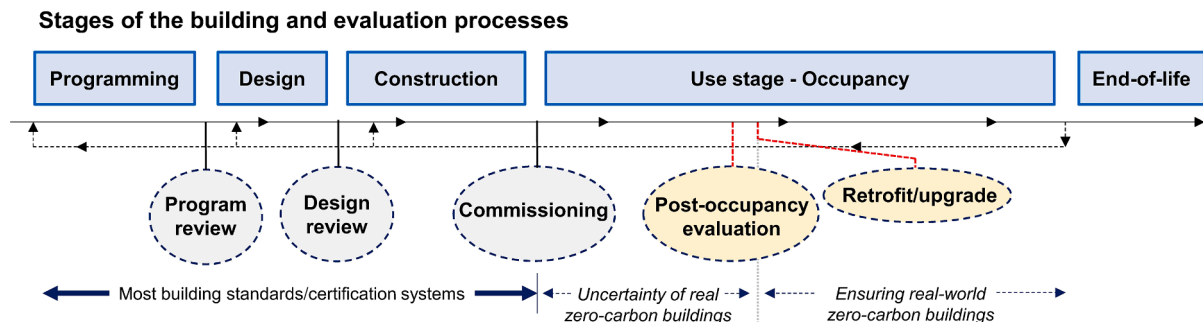


Fig. 1. Building stages and performance evaluation process.

application to store and visualise real-time data to support building operation and maintenance [24].

POE results in a robust strategy not only to identify common performance gaps but also to guide the design of future buildings [25]. However, only a few building certification systems include the measurement of post-occupancy building performance, and the requirement for third-party verification is varied and limited. Some examples are The Living Building Challenge, which implements a final audit after 12 months of occupancy, or the WELL Building Standard, which includes different performance tests during in-use building conditions.

Currently, academic researchers are the main developers and users of the POE framework and criteria [15]. While green building certifications have provided consensus regarding optimal design criteria towards building sustainability worldwide, there still needs to be more certainty regarding the real building usage and occupant needs for a zero-carbon and sustainable building transition [26]. It is vital to ensure that new buildings and retrofitting interventions are completed to expected standards that deliver true carbon savings, minimising capital and operating costs while creating comfortable and healthy environments. With many smart technologies being installed alongside electrification and material changes, it is crucial to guarantee continued optimum operation: users could eventually forget about new tech without ongoing monitoring and engagement. Moreover, POE can separate the contribution of physical building underperformance from user error. This helps correctly target post-occupancy interventions that fix building faults or support users with technology education or troubleshooting.

Even though many POE approaches have been proposed to understand better the performance gap between expectations and reality, most of them have been explicitly focused on the data collection process, visualisation and/or evaluation, with a lack of standardisation, and targeting specific building performance areas individually, such as energy consumption, indoor environmental quality, or occupants' perceptions (*research gap 1*) [27]; only a few of them have focused on the specific needs for climate change adaptation to ensure climate resilience (*research gap 2*) [28,29]; and none of them have completed the main objective beyond evaluation to diagnose and identify the cost-optimal upgrading based on real needs to achieve real-world zero-carbon buildings (*research gap 3*) [26].

This research defines and demonstrates the benefits of a systematic and standardised post-occupancy evaluation and intervention (POE + I) protocol to analyse operational building performance and supports accurate, cost-effective, zero-carbon, and climate-resilient building upgrading. The protocol involves five working steps based on data collection, data analytics, numerical modelling, performance reporting, and cost-optimal analysis. The novelty is based on a holistic analytical approach that combines:

1. systematic and standardised data collection through qualitative methods (occupant survey, interview and walkthrough) and physical measurements (building infrastructures and building operational data).
2. data-based fault detection and diagnosis techniques to deeply understand the real building operation and performance gaps (*addressing research gap 1*).
3. a physics-driven energy model iteratively calibrated with POE data to support further disaggregation of final energy consumption by use; and integrating new building performance indicators related to building passive survivability (discomfort hours, %) and peak energy demand (thermal heating/cooling capacity, kW) with other commonly used metrics such as final energy consumption (FEC, kWh/m²), non-renewable and renewable primary energy consumption (PEC, kWh/m²) and carbon emissions (kgCO_{2eq}) (*addressing research gap 2*).
4. and a cost-optimal analysis of potential interventions towards zero carbon supported by the calibrated physics-driven energy model to

simulate the energy, environmental, and economic performance of potential actions (*addressing research gap 3*).

Two research contributions are provided in this study to support a zero-carbon building transition:

- A systematic and standardised POEI protocol integrating novel data science techniques, advanced numerical energy modelling, and cost-optimal analysis. This protocol has been tested and demonstrated in a university building. The data diagnostic code is available on GitHub (https://github.com/lizanafj/POE_techniques).
- Moreover, the case study provides novel insights into building performance, highlighting two essential performance gaps that should be considered as hypotheses in future research to reach a real-world zero-carbon building sector. These gaps are associated with the critical role of building management and control, having higher implications for zero-carbon than efficiency, and the enormous energy demand associated with Information and Communication Technologies (ICT), which need to be more controlled and regulated by building standards.

The paper is structured as follows. First, the description of the case study, and the analytical techniques and methods integrated in the POEI protocol are defined in [section 2](#). Second, the results are presented and discussed in four sections: a descriptive analysis of existing baseline building performance; identification of building faults through diagnostic analytics; cost-optimal analysis of interventions towards a zero-carbon building target; and limitations. Finally, the main conclusions are drawn, highlighting the practical implications of this approach.

2. Materials and methods

This section defines the data and methods integrated and developed for the holistic POEI protocol to evaluate real building design, occupants' satisfaction, energy and water performance, indoor environment quality, and the functionality of facilities. The proposed framework is divided into five stages, as illustrated in [Fig. 2](#): data collection, data analytics, numerical modelling, performance reporting, and analysis of interventions. The case study and data collection mechanisms are detailed in [section 2.1](#). The data-based fault detection and diagnosis methods, physics-driven numerical energy modelling, performance rating, and intervention analysis are described in [section 2.2](#).

The source code and the monitored datasets developed are published under the MIT licence on GitHub (https://github.com/lizanafj/POE_techniques), together with additional documentation and tutorials.

2.1. Materials

2.1.1. Reference case study

A building archetype was selected to test and demonstrate the benefits of the POEI protocol. This case study consists of a university building in Oxford (United Kingdom), illustrated in [Fig. 3](#). The main building details are summarised in [Table 1](#).

The selected building is a university multi-disciplinary hub and co-working space located in a suburban area of Oxford. The building has three floors, with occupancy up to 150 users. It has four main usages associated with offices (shared office space, private offices, meeting rooms, etc.), teaching (two large seminar rooms), laboratories, and common areas (kitchen, canteen, toilets, etc.). The building's fabric consists of concrete blocks with an external insulation system, and the roof is made of a three-layer insulation panel. Occupancy occurs mainly from 8:00 to 17:00 on working days, with sporadic visitors outside this timeframe. It has a total built floor area of 1154 m², with two primary energy sources: natural gas exclusively for heating and electricity for the rest.

The building characteristics and energy systems are better detailed as

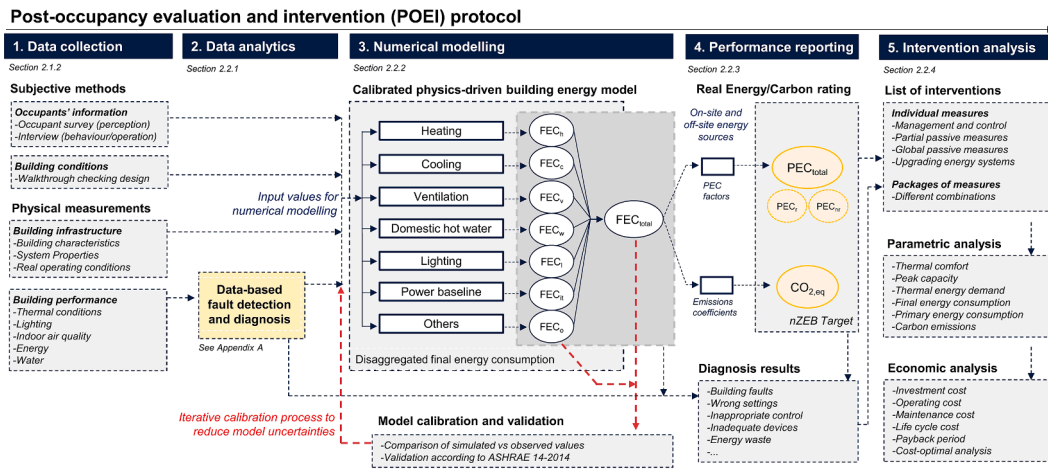


Fig. 2. Diagram of the POEI protocol showing the interrelations between input data, analytical techniques and outputs.



Fig. 3. Pictures of the selected case study: outdoor façade (a) and indoor office space (b).

Table 1
Characteristics of the selected case study.

General characteristics	Case study
Building typology	University building
Main usages	Offices, teaching, laboratories, canteen and common areas
Construction year	1980 (refurbished in 2021)
Total floor area	1154 m ²
Conditioned area	981 m ²
Number of floors	3
Occupancy	150 users

a result of the POE in section 3.1.

2.1.2. Data collection

The data collection procedure is divided into qualitative methods (henceforth subjective methods) and quantitative assessments (onward physical measurements) following the criteria defined by Li et al. [15].

- **Subjective methods** refer to occupant surveys to analyse indoor perception, interviews and group meetings to characterise occupant behaviour and operation, and walkthroughs to check global building design and conditions.
- **Physical measurements** refer to different techniques to characterise building infrastructures (building characteristics, system properties, and real operating conditions) and building performance (specifically indoor thermal comfort, lighting, indoor air quality, occupancy and energy).

The list of equipment used to characterise building infrastructure is defined in Table 2.

The indoor and outdoor monitored variables and sensors to analyse the building performance are summarised in Table 3. These environment variables were collected through an open-source monitoring platform integrated into a Raspberry Pi 4 (model b) running Node-RED for data processing. PostgreSQL with TimescaleDB was used as the database, and Grafana for visualisation and data access. The communication protocols used were MQTT over local Wifi, Modbus TCP/IP, Lora and LoraWan. Real building performance was monitored from October 2022 to March 2023. Additionally, historical energy bill data for electricity and gas was collected from the past two years.

Table 2
Specific equipment to characterise building infrastructure.

Equipment	Purpose
FLUKE Ti10 thermal camera	Identification of thermal bridges and insulation levels
Merlin Lazer Glass Measurement Gauge	Measurement of glass and air-gap thickness (mm)
Laser thermometer	Surface temperatures
Hand meter	Layers/elements thickness and thermal properties
Laser meter	Surface areas

Table 3

Real-time monitoring of the building performance, identifying variables, units, accuracy, frequency and sensors.

Monitored variables	Units	Accuracy	Frequency	Sensor
Power and Energy				
Apparent power	kVA	± 0.005 kVA	1 min	Schneider Electric PowerLogic PM5100
Active power	kW	± 0.005 kW	1 min	Schneider Electric PowerLogic PM5100
Reactive power	kVAR	± 0.005 kVAR	1 min	Schneider Electric PowerLogic PM5100
Cummulative power	Wh	± 0.5 Wh	1 min	Schneider Electric PowerLogic PM5100
Voltage	V	± 0.005 V	1 min	Schneider Electric PowerLogic PM5100
Current	A	± 0.005 A	1 min	Schneider Electric PowerLogic PM5100
Frequency	Hz	± 0.005 Hz	1 min	Schneider Electric PowerLogic PM5100
Active Power	W	± 0.5 mW	1 min	Kasa Smart tp-link KP115
Thermal comfort				
Air temperature	°C	± 0.1 °C	5 min	Sensirion, SHT85
Relative humidity	%	± 1.5 %	5 min	Sensirion, SHT85
Lighting				
Illuminance	lux	± 100 lx	5 min	Light Sensor BH1750
Indoor air quality				
CO ₂ concentrations	ppm	± 50 ppm	5 min	Sensorion, SCD30
Occupancy				
PIR Motion Sensor	pulses	Sensitivity range of 6 m	5 min	Seeed Studio PIR
Local weather conditions				
Outdoor air temperature	°C	± 0.1 °C	15 min	Sensirion, SHT85
Outdoor relative humidity	%	± 1.5 %	15 min	Sensirion, SHT85

PIR: passive infrared sensor.

2.2. Post-occupancy evaluation and intervention framework

2.2.1. Data analytics

A set of data-based fault detection and diagnosis techniques were integrated to identify building faults. The methods are summarised in Table 4 and briefly defined below. They are divided into three action areas, related to building characteristics for indoor environmental quality, energy systems, and occupants' behaviour and perception. The complete mathematical details are included in Appendix A.

a1. Ventilation diagnosis identifies building spaces with inappropriate indoor air quality requiring additional ventilation. It quantifies the percentage of working hours with a CO₂ concentration above 1000 ppm, following recommended indoor air quality guideline levels [30]. See Appendix A1.

a2. Airtightness diagnosis characterises the building's seasonal air

Table 4

Description of diagnostic techniques through data science.

Target audit	Method	Variables used
a. Indoor environmental quality		
a1. Ventilation diagnosis	CO ₂ concentration analysis to identify inappropriate ventilation	CO ₂ concentrations
a2. Airtightness diagnosis (air infiltration)	CO ₂ -based decay method to measure indoor air change rate (ACH, h ⁻¹)	CO ₂ concentrations
b. Energy systems		
b1. Load disaggregation	Non-intrusive load monitoring to disaggregate the consumption of each appliance	Power
b2. Heating Thermostat Control Diagnosis	Temperature analysis to analyse the thermal comfort situation	Indoor and outdoor temperatures
c. Occupants' behaviour and perception		
c1. Lighting system diagnosis	Motion analysis to identify lighting consumption in unoccupied spaces	PIR Motion Sensor and illuminance
c2. Discrepancies between occupancy and HVAC operation	Motion analysis to identify inconsistencies between real building occupancy and HVAC operation	PIR Motion Sensor

change rate (ACH, h⁻¹) related to air infiltration and/or ventilation using the CO₂-based decay method, following the approach defined by López-García et al. [29]. This technique uses large time-series data of indoor CO₂ concentrations to calculate the seasonal ventilation rate of the building, since ventilation is the only significant process for carbon dioxide removal in the indoor environment [31,32]. Here, ventilation refers to all air change alternatives such as air infiltration, natural ventilation, or mechanical ventilation. See Appendix A2.

b1. Load disaggregation. Load disaggregation through non-intrusive load monitoring (NILM) is the process of extracting the consumption of all individual devices in a building from the single aggregated signal measured by a smart meter [33]. Here, two methods are defined according to previous techniques developed by Azizi et al. [33]: one to extract the water consumption from electric water tanks (1), and another one to extract the building's background power consumption (2). See Appendix A3.

b2. Heating thermostat control diagnosis. This analysis focuses on the evaluation of the heating system. It quantifies the percentage of working hours where the indoor temperature is above or below the recommended temperature thresholds, defined between 19 °C and 23 °C. This technique uses indoor and outdoor temperature data. During this monitored period, the thermostat temperature of the heating system was defined at a fixed value of 21 °C. The approach also compares the relationship between the mean hourly indoor temperature and mean hourly outdoor temperature to understand the system operating conditions at full and partial-load operation. See Appendix A4.

c1. Lighting system diagnosis. This analysis quantifies the percentage of working hours in which lighting is on in unoccupied spaces. This technique uses illuminance data to identify lighting on, and PIR motion sensor activity to quantify human occupancy in the monitored areas. See Appendix A5.

c2. Discrepancies between occupancy and HVAC operation. This analysis identifies the percentage of time in which fixed building/HVAC operating schedules do not match with occupancy. Here, the PIR motion sensor activity was statistically analysed to understand the real occupancy patterns of the building in comparison with fixed operating conditions of the HVAC systems. See Appendix A6.

2.2.2. Numerical modelling

A calibrated physics-driven building energy model is integrated using all the input data and diagnosis results. This model targets three different contributions to support the POEI protocol: the disaggregation of final energy consumption by use; a detailed breakdown of the real energy and carbon performance rating of the building using different indicators; and the analysis of the energy, environmental and economic performance of potential interventions.

The numerical energy model follows the approach defined by Lizana J et al. [34] to develop an hourly dynamic simulation using Excel environment. The model simulates heating, cooling, ventilation, domestic hot water, lighting and other energy uses following a coherent set of assumptions and procedures concerning boundary conditions of educational buildings, derived from their modular basis, typical building configuration, and space uses.

The model requires hourly meteorological data of dry-bulb temperature, relative humidity, wind speed, and solar radiation (global horizontal, direct normal, and diffuse), which can be obtained from Typical Meteorological Years (TMY) weather files (for example, from the “Climate.OneBuilding.Org” database [35], an online repository of free weather data for energy modelling), or specifically for the year under post-occupancy analysis (for example, from official weather stations, in this case, from the Met Office MIDAS database [36] in the UK).

The heating and cooling demand model is based on the “Simplified hourly method” detailed in ISO 13790:2008 [37]. This method consists of explicit hourly operating schedules and explicit hourly climate data. The mathematical procedure integrates five resistances and one capacitance model (5R-1C). The model considers heat transfer by ventilation and infiltration ($H_{\text{ven-inf}}$), transmission heat transfer (H_{tr}) through opaque envelope area ($H_{\text{tr,op}}$) and the window area ($H_{\text{tr,w}}$), heat gains through internal loads (Φ_{int}), such as occupants ($\Phi_{\text{int,oc}}$), appliances ($\Phi_{\text{int,ap}}$) and lighting ($\Phi_{\text{int,l}}$), and solar gains (Φ_{sol}) through the opaque envelope ($\Phi_{\text{sol,op}}$) and windows ($\Phi_{\text{sol,w}}$). It enables its use for thermal comfort checks and increases accuracy by considering the radiative and convective parts of solar, lighting, and internal heat gains. Furthermore, it uses an hourly time step, and all building and system input data can be modified per hour. As a final step, the method calculates the final energy consumption for heating and cooling based on the thermal demand and the specific equipment characteristics, such as load conditions, environmental conditions, and equipment control strategies, following design data, energy standards, and manuals [38,39], according to the procedure defined by Lizana J et al. [34].

Ventilation consumption is calculated according to Eq. (1). It is characterised by a daily constant consumption profile per building area throughout the year according to the total power of ventilation unit/s and operating hours per day.

$$EC_{\text{ventilation}} = P \cdot O_{\text{hours}} \quad (1)$$

where:

$EC_{\text{ventilation}}$: energy consumption of ventilation in simulated building area (kWh/day).

P : total ventilation power installed (kW).

O_{hours} : Operating hours.

The hot water demand is calculated according to Eq. (2). It is characterised by a daily constant consumption profile through the year, the temperature of hot water consumption, and the average annual temperature of the water supply. Annual FEC of hot water is calculated considering annual building operating days and using the seasonal performance factors of existing thermal production systems.

$$D_{\text{water}} = \rho \cdot c_p \cdot Q_{\text{SHW}} \cdot (T_{\text{ref}} - T_{\text{ws}}) \cdot \frac{1}{3600} \quad (2)$$

where:

D_{water} : energy demand for hot water production per day (kWh/day).

ρ : water density (kg/litre).

c_p : specific heat capacity of water (4.18 kJ/kg·K).

Q_{SHW} : water consumption per day at reference temperature (l/day).

T_{ref} : reference temperature of hot water (60 °C).

T_{ws} : average water supply temperature (°C).

The lighting consumption is calculated according to Eq. (3). It is characterised by a daily constant consumption profile per building area throughout the year according to the total power of lighting fixtures, total operating hours per day, and a simultaneity factor. Total lighting power is calculated according to the technology of the lamp (tubular fluorescent, compact fluorescent, halogen, LED, metal halide, incandescent or sodium vapour), the power per lamp, the number of lamps per fixture, the type of ballast, and the number of luminaires per zone.

$$EC_{\text{lighting}} = P \cdot O_{\text{hours}} \cdot SF \quad (3)$$

where:

EC_{lighting} : energy consumption of lighting in simulated building area (kWh/day).

P : total lighting power installed per building area (kW).

O_{hours} : Operating hours.

SF : Simultaneity factor.

Other energy uses can be integrated into the numerical model, whose estimated energy consumption (function or static value) can be introduced on a monthly basis.

Moreover, the numerical modelling integrates an iterative calibration process based on the real building performance data obtained from the POE to reduce model uncertainties and match measured and simulated observations, achieving high final accuracy. After each simulation, the model compares the measured data with simulated values, automatically calculating statistical indices for model calibration and validation, following the criteria defined by ASHRAE Guideline 14–2014 [40]. For the case study under analysis, the final energy results of this iterative calibration and validation process are illustrated in Fig. 4, highlighting the good match between simulated and measured energy data for gas and electricity. In addition to these annual and monthly validations, it should be noted that the model also integrates the individual calibration of specific energy uses, such as hot water and background load, whose energy consumption was disaggregated from the monitored data following the techniques defined in Section 2.2.1 (see b1), and further characterised in Appendix A3. It should be noted that the calibration and validation were performed without subdivision by building usage since there are no subdivisions in existing building systems and associated data.

The results of the standard statistical indices used for model validation are summarised in Table 5. They are the Normalized Mean Bias Error (NMBE), the Coefficient of Variation of the Root Mean Square Error (CV-RMSE) and the Coefficient of determination (R^2). The validated model fulfils the ASHRAE Guideline, which recommends that the simulation model should have an NMBE lower than $\pm 5\%$ and a CV-RMSE lower than 15 % for good monthly reliability. Additionally, a minimum R^2 value of 0.75 is recommended.

2.2.3. Performance reporting

The building performance is quantified through key performance indicators to characterise the passive building survivability (or heat resilience), thermal energy demand, energy consumption, and environmental impact. They are listed and briefly explained below:

-Percentage of discomfort hours in summer (DH, %). Percentage of time with temperature $> 26\text{ °C}$ in the absence of air conditioning (AC).

-Peak thermal capacity of the cooling system ($Q_{\text{C,peak}}$, kW). Peak cooling capacity is measured through the 99th percentile of hourly thermal cooling demand required in the building.

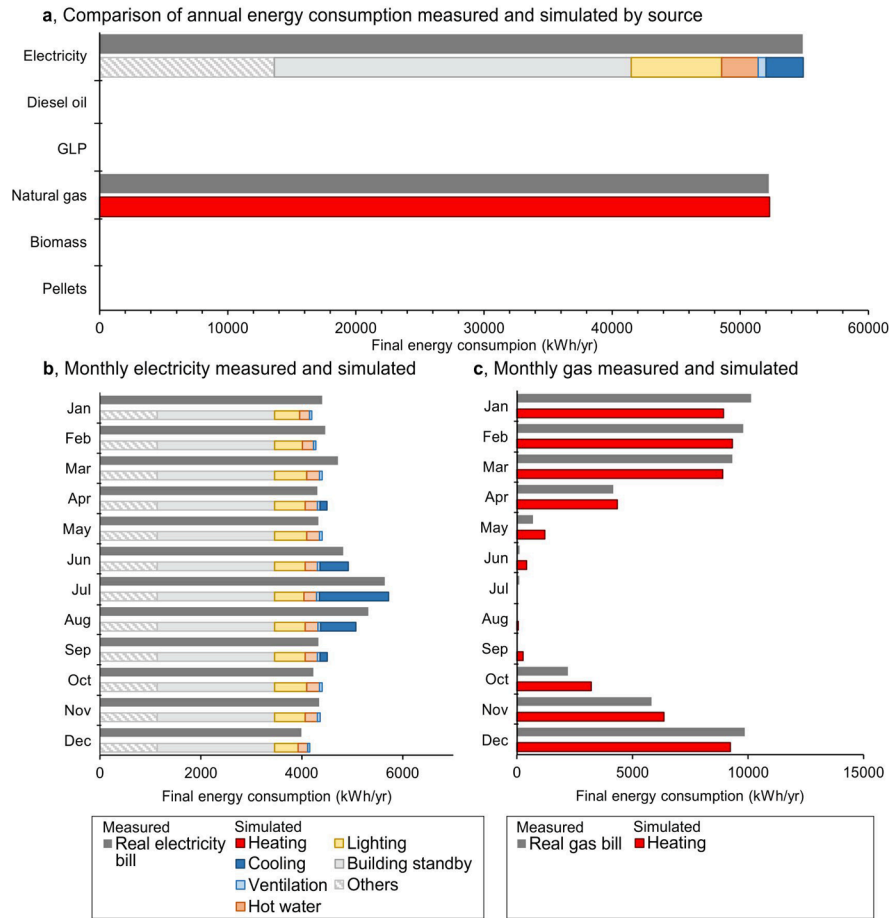


Fig. 4. Final results of model validation of the selected case study during the POEI protocol by energy source (a) and monthly final energy consumption (b).

Table 5

Validation results between monthly measured and simulated values according to ASHRAE Guideline 14–2014.

Indicator	Monthly criteria	Monthly electricity test	Monthly gas test
NMBE	±5	−0.1 %	−0.1 %
CV(RMSE)	15	4.1 %	13.9 %
R ²	>0.75	0.85	0.99

NMBE: Normalised Mean Bias Error; CV-RMSE: Coefficient of Variation of the Root Mean Square Error; R²: Coefficient of determination

-**Peak thermal capacity of the heating system** ($Q_{H,peak}$, kW). Peak heating capacity is measured through the 99th percentile of hourly thermal heating demand required in the building.

-**Thermal energy demand for heating and cooling** ($Q_{HC,nd}$, kWh/m²). Total annual thermal energy demand required in the building to meet the defined thermal comfort criteria.

-**Final energy consumption** (FEC, kWh/m²). Annual FEC of the building considering all energy uses (heating, cooling, ventilation, hot water, lighting, background power consumption (mainly from ICT), and others).

-**Renewable primary energy consumption** (PEC_r, kWh/m²). This refers to the annual PEC based on renewable energy considering all energy uses. This was calculated according to the specific primary energy factor defined in the region per energy source.

-**Non-renewable primary energy consumption** (PEC_{nr}, kWh/m²). This consists of the annual PEC based on non-renewable energy considering all energy uses.

-**CO₂ equivalent emissions** (Kg CO₂eq/m²). Total annual CO₂ equivalent emissions related to the building operation and considering all energy uses and energy sources. It was obtained according to the CO₂eq emissions coefficient derived from consumed energy sources.

The specific primary energy factors and CO₂eq emission coefficients per energy source used are detailed in Table 6.

2.2.4. Interventions analysis

Once the real building baseline is characterised and diagnosis results are analysed, the calibrated physics-driven building energy model also supports the energy, environmental and economic analysis of different interventions to identify cost-optimal solutions. This final analysis is

Table 6

Primary energy factors and carbon emission coefficients for the United Kingdom (UK) according to [34,41–43].

Energy source	PEC/kWh of FEC	PECnr/kWh of FEC	kg CO ₂ eq/kWh of FEC
UK. Electricity	1.501	1.135	0.136 ^a
UK. Diesel oil	1.273	1.268	0.311
UK. GLP	1.168	1.166	0.254
UK. Natural gas	1.161	1.159	0.239
UK. Biomass	1.037	0.034	0.018
UK. Biomass (pellets)	1.542	0.082	0.044

^a Annual emission factors for the UK grid electricity 2020–2024 defined for the National Calculation Methodologies for Energy Rating of Dwellings (SAP/RdSAP), which may differ from historical values.

divided into three areas: determination of the interventions, parametric analysis of energy and environment performance, and economic analysis.

Determination of interventions. Based on the baseline results extracted from the POE, a list of interventions is proposed and divided into five action groups according to the time, complexity, efforts, and costs required for their implementation:

- **Group 1-Control:** Measures to improve building energy management. It consists of all interventions to improve energy and environmental management to reduce the building's energy demand, such as thermostat control, lighting control, operating schedules, free-cooling, smart control, or energy waste from unused devices.
- **Group 2-Partial:** Partial passive measures to reduce energy demand. It involves all minor interventions to improve the building characteristics and mitigate building faults, such as pipe insulation, thermal bridges or solar protection to reduce the energy demand of the building.
- **Group 3-Global:** Global passive measures to reduce energy demand. This group consists of major retrofitting interventions to improve the global building envelope and reduce energy demand.
- **Group 4-Systems:** This group involves all large-scale technological upgrades in the building to increase energy efficiency and maximise the use of renewable energy.
- **Group 5-Packages (combination of measures):** This last group involves the successive combinations of previous groups of individual measures to improve the building's energy and environmental performance.

Parametric analysis of energy and environment performance. Once the list of measures and intervention packages have been defined, a

parametric study using the calibrated physics-driven building energy model is developed to quantify the energy and environment performance of each proposed intervention and combination.

The economic analysis characterises each intervention's investment, maintenance, and operating costs to evaluate its financial profitability. Different economic indicators are calculated: the payback period (PBP, years) and the life cycle cost (LCC, £). An annual increase in energy price of 4.5 % was considered following the criteria defined by previous studies [9]. The LCC is calculated assuming 20 years of operation, and PBP was obtained considering a discount rate of 1.5 %.

The detailed list of interventions is presented in Table 7 for the specific case study under analysis.

3. Results and discussions

3.1. Descriptive analysis of the real building energy performance

The POEI protocol can characterise the baseline performance of the building in detail before any intervention. The main building characteristics and energy systems of the case study are summarised in Table 8.

The analysis shows a partially insulated building, with a U-value ranging from 0.9 to 1.3 W/m² K, with two condensing boilers for heating, fifteen split air-conditioning units for cooling, one air handling unit for ventilation and heat recovery, LED lighting technology, and nine hot water tanks with immersion heaters of 15L (one per bathroom/kitchen).

During the data collection, the physical measurements of building infrastructures identified vulnerabilities and building faults. They are summarised in Fig. 5 and are related to the lack of insulated surfaces on the ground floor, window frames without thermal breaks, and specific thermal bridges in the roof and the contact between the roof and walls.

Fig. 6 illustrates the detailed breakdown of the real baseline building

Table 7

Breakdown of the proposed interventions for the specific case study under analysis (individual measures and packages).

ID	Solution	Investment cost (£)	Investment cost per unit	Cost unit
Group 1-Control: Measures to improve building energy management and control				
S1.1	Heating. Reduce winter set-point temperature by 1 °C	0	–	
S1.2	Heating. Match heating times to building occupancy	0	–	
S1.3	Heating. Smart Thermostatic Radiator Valves (TRV)	11,000	418–462	£/unit
S1.4	Cooling. Increase of summer set-point temperature by 1 °C	0	–	
S1.5	Cooling. Summer night natural ventilation for heat dissipation	0	–	
S1.6	Hot water. Smart control of hot water charging using smart plugs	775	74–81	£/unit
S1.7	Lighting. Smart control through illuminance sensors	500	95–105	£/unit
S1.8	ICT. Reduce ICT background load - switch off appliances not in use using smart plugs	300	48–53	£/unit
Group 2-Partial: Partial passive measures to reduce energy demand				
S2.1	Heating. Insulate boiler room pipework	350	83–92	£/lm
S2.2	Heating/Cooling. Reduce of thermal bridges (in the roof)	2,325	44–49	£/m ²
S2.3	Cooling. Movable external shading devices for windows	8,000	380–420	£/window
Group 3-Global: Global passive measures to reduce global energy demand				
S3.1	Roof insulation (target U-value: 0.3 W/m ² K)	21,600	34–38	£/m ²
S3.2	External wall insulation (target U-value: 0.5 W/m ² K)	39,000	120–133	£/m ²
Group 4-Systems: Upgrading energy systems, increasing efficiency and renewables				
S4.1	Heating/Hot water. Air-to-water heat pump	64,500	638–705	£/kW
S4.2	Ventilation. Smart mechanical ventilation with heat recovery	2,000	1,583–1,750	£/kW
S4.3	Add solar PV panels	77,500	1,990–2,199	£/kW
S4.4	Install ceiling fans	2,500	198–219	£/unit
Group 5-Packages: Combination of individual measures				
S5.1	Package A (Group (1))	11,984	–	
S5.2	Package B (Groups (1) + 2)	22,125	–	
S5.3	Package C (Groups (1) + 2 + 3)	79,695	–	
S5.4	Package D (Groups (1) + 2 + 3 + 4)	195,370	–	
S5.5	Package Z (Groups (1) + 2 + 3 + 4) - without optimal sequencing and integration a	230,370	–	

^aIn this scenario, the investment cost of HVAC technologies is not reduced due to the lower thermal peak capacity of the building after the interventions defined in groups 1, 2 and 3.

Table 8

Summary of characteristics of the building and systems (baseline before intervention).

Building envelope	Characterisation
Opaque envelope	
Ground (U-value, W/m ² K)	1.3 (average)
Roof (U-value, W/m ² K)	0.8 (average)
Facade (U-value, W/m ² K)	0.9 (average)
Openings	
Windows (U-value, W/m ² K)	1.4
Window (%) [frame factor]	20 %
Energy systems	
Heating	
Energy source	Condensing boiler (x2)
Total nominal capacity (kW)	Natural gas
Seasonal efficiency	96
	1.030
Cooling	
Energy source	Heat Pump (x15)
Total nominal capacity (kW)	Electricity
EER	96
	2.80 (average)
Ventilation	
Mechanical ventilation (m ³ /h m ²)	10.0
Power installed (kW)	1.20
Lighting	
	LED technology
Power installed (W)	4400
Total power rate (kW/m ²)	4.5
Hot water	
	Electric boilers (x10)
Efficiency	1
Water demand (l/day)	215

performance obtained through the POEI protocol. The annual primary energy consumption (PEC kWh/m²) of the building compared with reference standards is shown in Fig. 6a. The building has a PEC ratio of 146 kWh/m², much higher than the recommended nearly zero-energy building (nZEB) threshold defined by the European guidelines (ranging from 80 to 100 kWh/m² with 30–60 kWh/m² covered by renewable energy according to the region) [44], and more than twice the Passivhaus (Classic) standard (60 kWh/m² with 45 kWh/m² covered by renewable energy).

The baseline of final energy consumption per energy use is detailed in Fig. 6b, with heating the largest consumption sector responsible for 48.8 % of energy needs, followed by building standby (or background power consumption) at 26.0 % and lighting at 6.6 %. The high background power consumption of the building, with a flat constant power consumption of approximately 3.5 kW, is mainly from ICT, an energy use often overlooked by building standards.

Electricity and natural gas were the two main energy sources in the building, responsible for 51 % and 49 % of the annual final energy consumption, respectively (Fig. 6c). However, the cost distribution was not equally distributed, with electricity responsible for 78 % (Fig. 6d), mainly because the higher energy cost, taxes and levies of electricity in comparison with gas within the UK [45]. During this annual period, the electricity rate was 0.22925 £/kWh while natural gas was 0.0907 £/kWh; levies were 14 % for electricity and 3 % for gas; and the Value Added Tax (VAT) rate of electricity was 20 % and just 5 % for gas. These discrepancies clearly show the comparative financial disadvantage of electricity compared with natural gas in the UK, which is a barrier to decarbonising the building sector [45].

3.2. Identification of building faults

A set of data-based fault detection and diagnosis techniques was developed to analyse and extract information from the monitored building data to identify potential building faults, wrong settings, inappropriate control, inadequate devices or energy waste, among others. Fig. 7 summarises the results obtained from these techniques, providing additional insights regarding building characteristics for indoor environmental quality (Fig. 7a and b), energy uses (Fig. 7c and d), and real building operations according to occupants' behaviour and perception (Fig. 7e and f).

The building ventilation diagnosis is provided in Fig. 7a, which shows the histogram of CO₂ concentrations during working hours. CO₂ concentrations above 1000 ppm were found to be 10.5 % of the time, evidencing inadequate ventilation rates according to recommended indoor air quality guidelines [30].

The airtightness diagnosis is shown in Fig. 7b, which summarises the results of the CO₂-based decay method to measure indoor air change rates (ACH, h⁻¹). The results showed an adequate mean ACH of 0.13 h⁻¹ (or ACH₅₀ at 50 Pa of 2.6 h⁻¹) compared to the recommended thresholds. As reference values, ASHRAE [46] reports how the most ACH values in new buildings may range from 0.25 to 0.75 h⁻¹; and the Passivhaus Standard requires an ACH₅₀ value below 0.6 h⁻¹ obtained through a blower door test. However, under inadequate ventilation in summer, this low ACH value may lead to extreme indoor overheating.

The disaggregation of power consumption through NILM techniques extracted the electrical consumption patterns related to background power (or building standby mainly from ICT) and hot water. The detailed results are shown in Table 9 and summarised in Fig. 7c. Background power consumption was responsible for 53.0 % of mean electricity consumption, and hot water for 5.7 % during the monitored period. Background power consumption was mainly from ICT equipment, according to the average consumption values measured using tp-link K115 smart plugs. ICT involved local research servers (average consumption of 200 W each), building security and network (wifi) infrastructure (500 W each rack-mounted server), teaching audiovisual equipment (100–500 W each) and other standby consumption such as fire alarm or cooling specific to ICT load.

These disaggregated energy uses also helped to reduce the uncertainty in the numerical model by calibrating these energy consumption sectors individually, as indicated in section 2.2.2.

The diagnosis of the heating thermostat control (from October 2022 to March 2023) shows how the indoor temperature was higher than 23 °C during 42.2 % of working hours (Fig. 7d). The heating system seems to provide the expected thermal criteria configured in the thermostat (temperature of 21 °C) only during the coldest days when the system works at full capacity. When the system is in partial operating conditions, it tends to overheat the indoor space more than required, wasting heat and energy. Additionally, a few working hours were found below 18 °C, to a period when the boiler was not working.

The lighting system diagnosis shows the lighting was on with no occupancy for almost 26 % of working hours in the office space, happening with higher frequency in the afternoons (35 %, see Fig. 7e).

The building operating schedule diagnosis also shows discrepancies between occupancy and HVAC operation. The occupancy rate was found to be below 20 % in the afternoons (Fig. 7f), with the heating system still working at full capacity. Here, we highlight how centralised thermal systems often heat or cool empty spaces. An important opportunity exists to reduce energy demand by combining lower centralised thermal requirements with individual environmental control systems for user adaptability according to different personal needs [47].

3.3. Cost-optimal analysis of interventions for a nearly zero-carbon building

The cost-optimal analysis of interventions to achieve a zero-carbon

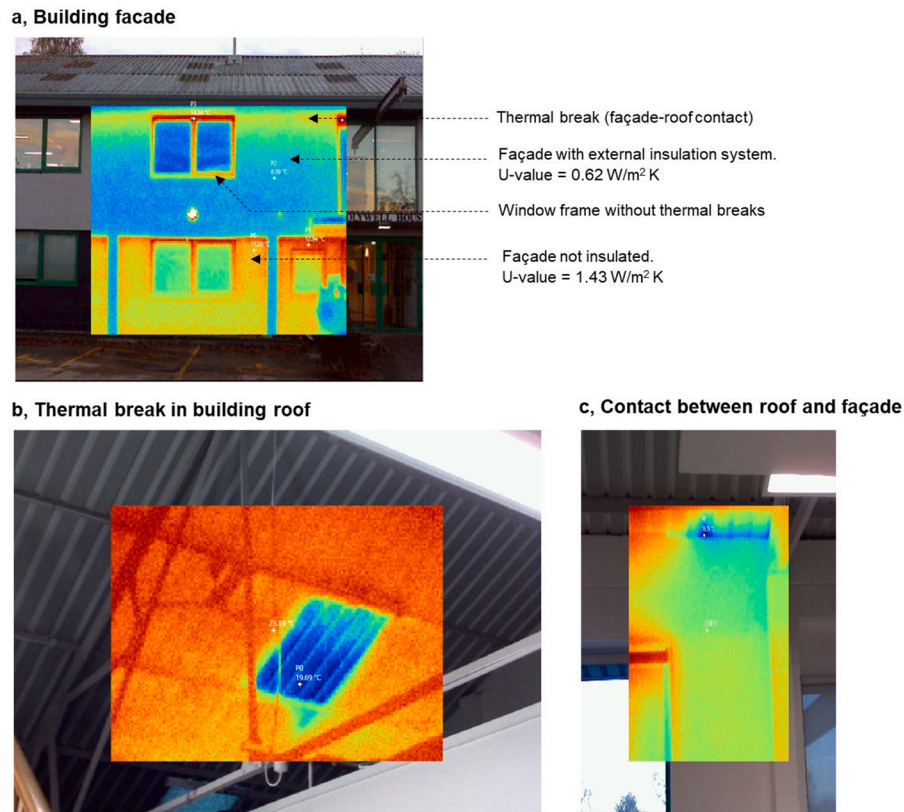


Fig. 5. Infrared images identifying building thermal bridges in main building façade (a), building roof (b), and roof-wall contact (c).

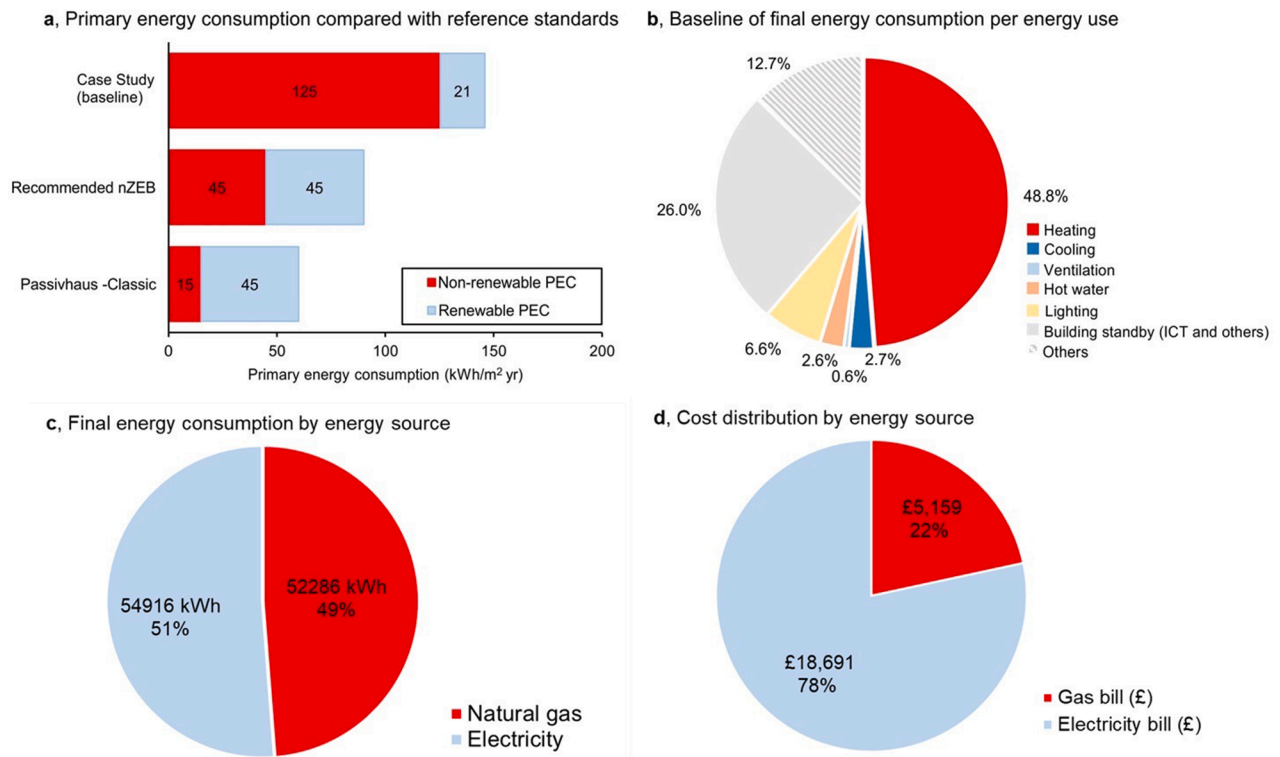


Fig. 6. Detailed breakdown of the baseline building performance obtained through the POEI framework. a, Primary energy consumption compared with reference standards. b, Baseline of the final energy consumption of the building by use. c, Baseline of the final energy consumption of the building by energy source. d, Cost distribution of the building by energy source.

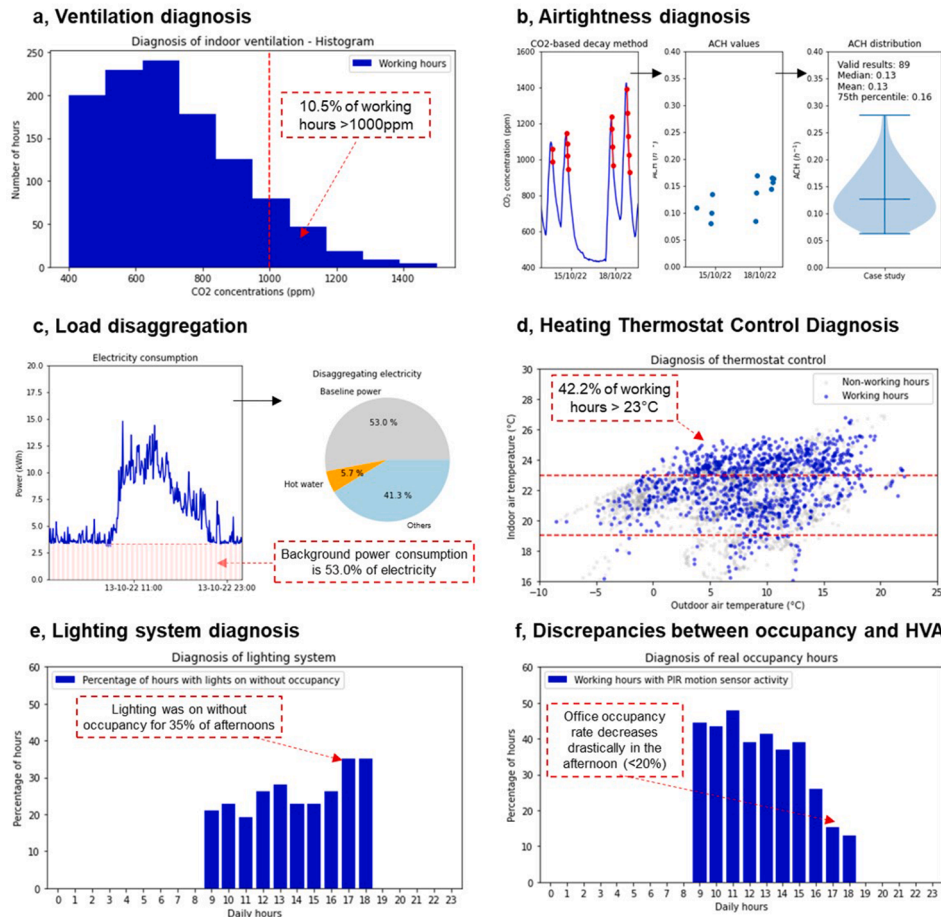


Fig. 7. Summary of diagnostic techniques applied in the case study for ventilation (a), airtightness (b), load disaggregation (c), heating thermostat control (d), lighting system (e), and occupancy and HVAC operation (f).

Table 9

Results of the load disaggregation techniques to extract electrical consumption patterns by energy use.

Month	Background power consumption (kWh)	Hot water electricity consumption (kWh)
October	2324.0	249.9
November	2249.7	245.3
December	2350.2	245.5
January	2318.4	255.5
February	2103.4	240.6
March	2324.0	269.0
Average	2278.3	251.0

building is summarised in Fig. 8, where Fig. 8a shows the payback periods of all individual and combined interventions, Fig. 8b provides the life-cycle cost analysis for a timeframe of 20 years by comparing the life cycle cost (LCC in £/m²) and the expected annual non-renewable primary energy consumption (PEC_{nr} in kWh/m²); and Fig. 8c shows the reduction of primary energy consumption per package of measures (Group 5).

Firstly, the payback periods of interventions can be compared in Fig. 8a. The results are provided individually by intervention, and interventions are grouped into the five action groups as described in section 2.2.5 (groups from 1 to 5: control, partial, global, systems, and packages). The results highlight the importance of data-based fault detection techniques to optimise building control (Group 1-Control), in which most of the measures achieved a payback period below 2 years. Considering only individual interventions (Groups 1–4), only five

actions have a payback period higher than 10 years: the implementation of smart thermostatic radiator valves (S1.3: 11 years), movable external shading devices for windows (S2.3: 15 years), the global insulation of the roof and building façade (S3.1: 18 years; and S3.2: 28 years), and the electrification of the heating and hot water sector through a heat pump (S4.1: 31 years).

Secondly, the relationship between the LCC of the building during the next 20 years (£/m²) concerning annual non-renewable primary energy consumption (kWh/m²) is illustrated in Fig. 8b. The current building baseline scenario is shown as a grey square dot, showing the baseline cost situation where no interventions are applied to the building. This baseline scenario has an LCC of 763 £/m², where the cost is only associated with the operation and maintenance of the existing building (mainly energy bills). All the individual measures and packages of interventions are also illustrated as different dots, showing the economic profitability and environmental efficiency of each solution or package to mitigate the use of fossil fuels. Here, the investment cost of intervention is added to the operation and maintenance cost in the cash flow to calculate the LCC for all these scenarios in a 20-year timeframe. The results highlight the cost-optimal performance of solar PV panels (S4.3), reducing non-renewable PEC_{nr} and LCC by 19 % and 16 %, respectively. Also, the good performance of all control strategies is highlighted (combined in package S5.1), reducing PEC_{nr} by 20 % and LCC by 11 %.

The combination of all these interventions implemented in the right order (from S5.1 to S5.4: optimising control, reducing demand, increasing efficiency and integrating renewables) demonstrates how even despite the high investment cost of some interventions, the LCC of

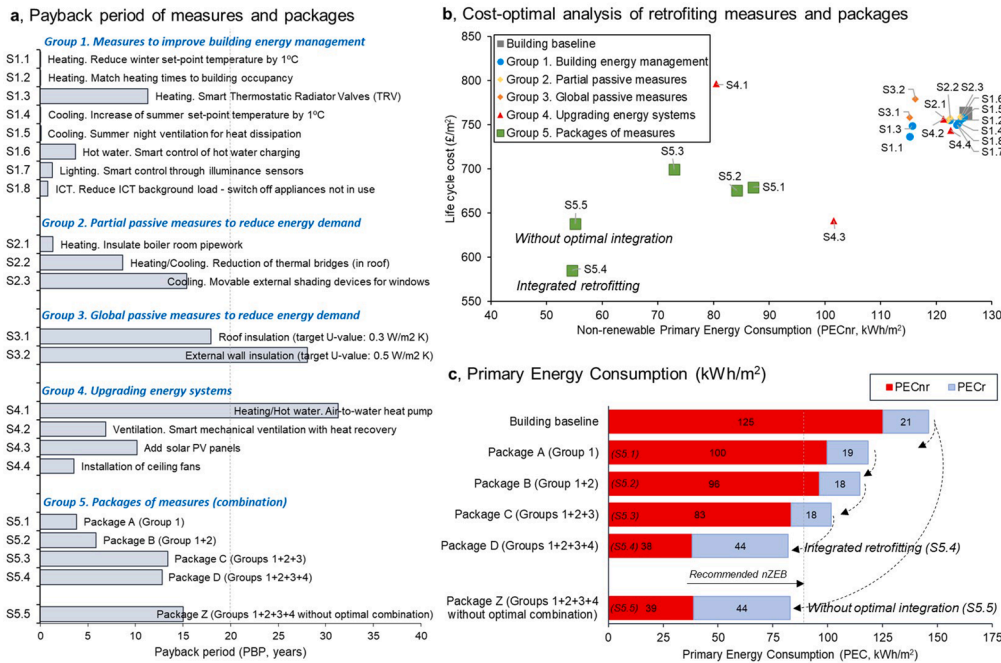


Fig. 8. Energy, environmental and economic analysis of retrofitting measures and packages toward a zero-carbon building. a, Payback period (PBP, years) of individual measures (from S1.1 to S4.4) and packages (from S5.1 to S5.5). b, Cost-optimal analysis of retrofitting measures and packages. c, Primary energy consumption of the package of measures (from S5.1 to S5.5).

the building can be reduced by 23 % (from 763 to 585 £/m²). This is only possible due to reduced investment costs for technological upgrading and decarbonisation. The control optimisation (interventions listed in Group 1-Control) and the reduction of thermal energy demand (Group 2-Partial + Group 3-Global) could mitigate the thermal peak capacity for heating and cooling by 33 % and 54 %, respectively, reducing the required peak capacity and investment cost for heating electrification (from 98 kW to 65 kW) and PV generation. This also eliminates the need to extend or upgrade indoor radiators since existing units would have enough heat transfer surface/capacity for the reduced thermal demand.

The results also show a possible scenario S5.5, where the building decarbonisation is addressed without an integrated design (without following the right steps). This scenario shows a 9 % higher LCC (from 584 to 638 £/m²) mainly due to the higher capital cost for heating electrification and PV generation, even with slightly higher non-renewable primary energy consumption due to the inappropriate sizing of thermal systems.

Thirdly, from the point of view of primary energy consumption,

Fig. 8c illustrates the PEC reduction after each package of measures (Group 5, from S5.1 to S5.5), showing how the two most important packages were related to optimising the building energy management (Group 1-Control) and the technological upgrading to increase the efficiency and renewable energy sources (Group 4-Systems). Group 1-Control mitigated final energy consumption by 20 % (22.2 kWh/m²) and carbon emissions by 24 % (4.8 kgCO_{2eq}/m²); and Group 4-Systems reduced final energy consumption by 17 % (18.3 kWh/m²) and carbon emissions by 38 % (7.7 kgCO_{2eq}/m²).

After implementing all proposed solutions in the correct order (S5.4), the building would reach an estimated primary energy consumption of 82.0 kWh/m², with 43.8 kWh/m² (53 %) covered by renewable energy, fulfilling the recommended criteria for a nZEB (80–100 kWh/m² with 30–60 kWh/m² covered by renewable energy) [44]. If the control optimisation and thermal energy demand reductions are not implemented before upgrading the energy systems (S5.5), the primary energy consumption will be higher (83.0 kWh/m²).

The results demonstrate how an integrated zero-carbon retrofitting,

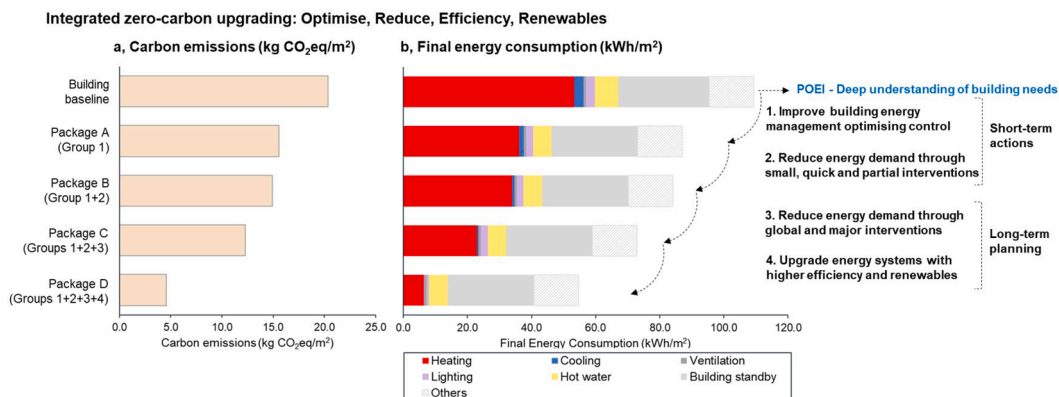


Fig. 9. Net-zero carbon retrofitting following the right steps in the right order (optimise, reduce, efficiency and renewables). a, Carbon emissions by the package of measures (from S5.1 to S5.4). b, Final energy consumption by the package of measures (from S5.1 to S5.4). The initial building baseline is also provided as a reference value.

implementing steps in the right order (optimising control, reducing demand, increasing efficiency and maximising renewables), can provide quick benefits in the short term and create synergies for a future low-carbon energy transition. Fig. 9 shows the benefits of the different packages of measures (Group 5, from S5.1 to S5.4) from the point of view of carbon reductions (Fig. 9a) and mitigation of final energy consumption (Fig. 9b). The different packages are based on the combination of previous individual interventions:

- Package A (S5.1): all interventions listed in Group 1-Control;
- Package B (S5.2): Group 1-Control + Group 2-Partial;
- Package C (S5.3): Group 1-Control + Group 2-Partial + Group 3-Global;
- Package D (S5.4): Group 1-Control + Group 2-Partial + Group 3-Global + Group 4-Systems.

Group 1-Control and Group 2-Partial involve immediate actions to improve energy management (Package A – S5.1) and reduce energy demand with small, quick and localised interventions (Package B – S5.2). These sets of interventions can be implemented quickly and can acutely reduce carbon emissions by 27 % (from 20.4 to 14.9 kgCO₂eq/m²) and final energy consumption by 23 % (from 109.3 to 84.1 kWh/m²). Group 3-Global + Group 4-Systems involve major interventions in reducing building energy demand through global actions (Package C – S5.3) and increasing the efficiency of energy systems while integrating renewable energy sources (Package D – S5.4). These two groups of actions require long-term planning for implementation, and if well integrated with previous localised interventions, the final investment cost can be drastically reduced by downscaling systems' capacity needs, specifically for heating, cooling, and PV generation. These two additional packages reduce total carbon emissions by 77 % (from 20.4 to 4.6 kg CO₂eq/m²) and final energy consumption by 50 % (from 109.3 to 54.6 kWh/m²).

It should also be noted that ICT consumption plays a critical role in the final zero-carbon building scenario (Package D – S5.4), where the background power consumption (mainly from ICT) is responsible for 49 % of final energy consumption (27.0 out of 54.6 kWh/m²). This crucial energy use shouldn't be overlooked in the future low-carbon building sector, where smart control linked to occupancy alongside improved standards and regulations may be required to guarantee minimum power capacity, optimal control, and high efficiency.

3.4. Limitations of the POEI protocol

This study has some limitations. First, the analysis is static, using data and information collected from a specific period and year. So, the reported results may not represent the average energy consumption or impact for a long-term period since climate and operational patterns may change. Second, the method was tested in one building archetype, aiming to demonstrate and validate the potential of the integrated POEI workflow. Thus, the specific conclusions associated with building energy usage (e.g., building energy management or ICT-based energy consumption) should be considered as initial hypotheses to be further studied in future cases. Third, the iterative calibration and validation process was designed to improve the accuracy of the numerical model. However, uncertainty may still remain in those energy uses where different unknown parameters or characteristics influence the final energy consumption and associated environmental impact – even though the final energy consumption matches real observations. Fourth, different assumptions were made to perform the economic analysis, such as the annual increase in energy prices, which introduces a light uncertainty in the final financial profitability of interventions.

4. Conclusions

This research proposes and demonstrates the potential of a holistic

post-occupancy evaluation and intervention (POEI) protocol to upgrade in-use building assets towards real-world zero-carbon buildings whilst minimising expenditure. The novelty lies in the integration of novel data science techniques, advanced numerical energy modelling, and cost-optimal analysis to characterise the real building performance, occupant usage and needs, and support cost-effective zero-carbon transition. The POEI approach results in an integrated multi-intervention strategy to achieve real-world zero-carbon buildings with shorter payback that can be applied to operational buildings. The protocol has been developed and validated in a university building in Oxford (United Kingdom). Based on the results, the following conclusions can be drawn:

There is a significant benefit to taking a holistic and integrated approach to upgrading in-use building assets based on real performance and needs versus considering interventions separately. By optimising control, reducing demand, increasing efficiency, and implementing renewables, the building can reach the nearly zero-carbon building target with a payback period of 13 years and a 23 % lower life-cycle cost compared to the baseline scenario (from 763 to 585 £/m²). The approach identified the optimal pathway to reduce annual primary energy consumption from 146 kWh/m² to 82 kWh/m², with 43.8 kWh/m² (53 %) covered by renewable energy sources. This is only possible due to reduced investment costs for technological upgrading and decarbonisation following a coordinated and integrated implementation. Control optimisation and energy demand reduction could mitigate the thermal peak capacity for heating and cooling by 33 % and 54 %, respectively, drastically downscaling the systems' capital cost for heating electrification and PV generation. If uncoordinated, the payback period and life-cycle cost would increase by more than 15 % and 9 %, respectively.

Building energy management and control interventions are the most important solutions identified to reduce the performance gap, mitigating final energy consumption by 20 % and reducing carbon emissions by 24 % for the case study presented. Data-based diagnosis techniques quickly identified priority actions associated with control faults generating energy waste. This included overheating in winter (42.2 % of working hours at a temperature higher than 23 °C), lighting and hot water operating during times when the building is unoccupied (including closure days), unused Information and Communication Technologies (ICT) devices, and specific high-consumption appliances. The source code of the proposed data analytic techniques to identify building faults is published under the MIT licence on GitHub (https://github.com/POE_techniques).

The results also highlight the impact that background power consumption of the building (mainly from ICT) has on the ability to achieve nearly zero-carbon buildings in real operational environments. In the case study presented, the baseload is responsible for 26 % (28.4 kWh/m²) of final energy consumption. This energy use lacks compliance requirements in existing building energy standards, and if overlooked, it may represent 49 % of energy consumption in the future zero-carbon building scenario. Additional building guidelines for the ICT sector should be defined to guarantee that this energy use is not ignored in zero-carbon targets.

The proposed POEI method is static. Future research will focus on integrating this method into a dynamic POEI protocol to identify, in real-time, (1) best practices to improve the energy and environmental management of the building assets, and (2) the benefits of user-localised interventions.

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.

Data availability

Data will be made available on request.

Acknowledgements

The research was funded by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101023241 and Innovate UK grant ref. 104781—Project LEO. This project is also supported by the Eric and Wendy Schmidt AI in Science Postdoctoral Fellowship, a Schmidt

Futures program. The data supporting this study's findings are available from the corresponding author upon reasonable request. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript (AAM) version arising from this submission. The authors would also like to thank Low Carbon Hub for its advice and technical support.

Appendix A. Detailed description of data-based fault detection and diagnosis techniques

A.1. Ventilation diagnosis.

This technique quantifies the percentage of working hours when CO₂ concentrations are above a recommended threshold. It uses the data collected from indoor CO₂ sensors. Following the recommended indoor air quality guideline levels reported by different European standards, national building regulations and reported long-term health-based guidelines (Table A1) [30], a CO₂ concentration of 1000 ppm was defined as a threshold.

Table A1

Recommended CO₂ concentrations according to different guidelines.

Reference	CO ₂ threshold	Exposure time and observation
EN 13,779 [48]	≤800-1000 ppm	CO ₂ concentration
French regulation [49]	<1000 ppm	Mean concentration during the occupied period. Tolerance up to 1300 ppm.
Portuguese legislation [50,51]	<984 ppm (1800 mg/m ³)	Maximum reference concentration. Tolerance up to ± 10 % according to occupancy rate.
Portuguese legislation [52]	<1250 (2250 mg/m ³)	Mean concentration during the occupied period.
UK regulation [53]	<1000 ppm	Mean concentration during the occupied period with mechanical ventilation. Tolerance up to 1500 over 20 min.

The approach is calculated according to Eq. (A1).

$$CO_2 - stat(t_0, \dots, t_n) = \frac{\sum \text{Working hours with } CO_2 > 1000 \text{ ppm}_i}{\sum \text{Working hours}} \cdot 100 \quad (A1)$$

where:

$CO_2 - stat$: Percentage of time with CO₂ concentrations above the recommended threshold.

t : daily hour.

A.2. Airtightness diagnosis (air infiltration).

Airtightness diagnosis is developed following the approach proposed by López-García et al. [29]. This approach is based on a CO₂-based ventilation analysis, which provides information on the real operating conditions of the building related to air infiltration and ventilation rates. These results can support the decision-making process in identifying additional measures or user behaviour strategies related to air infiltration and ventilation to improve passive building performance.

This method uses large time-series data of indoor CO₂ concentrations in the indoor environment to calculate the seasonal air change rate (ACH, h⁻¹) of the building through the CO₂-based decay method. The mathematical approach is defined in Eq. (A2), which enables the calculation of the seasonal oscillation of ACH in buildings with an accuracy of ±10 % [31].

$$ACH_t = \frac{1}{t} \ln \frac{C_{ind,t=0} - C_{out}}{C_{ind,t} - C_{out}} \quad (A2)$$

where:

ACH : air change rate (h⁻¹) at time t .

$C_{ind,t=0}$: indoor CO₂ concentration (ppm) at time $t = 0$.

$C_{ind,t}$: indoor CO₂ concentration (ppm) at time t .

C_{out} : outdoor CO₂ concentration (400–500 ppm).

Only those CO₂ decay data with a starting point above 1000 ppm and a gradient higher than 50 ppm/h are considered to obtain ACH values in almost empty indoor environments in most cases [29]. These criteria should be adapted according to the building's use.

An example of the procedure is illustrated in Fig. A1, showing the CO₂ concentration profile in blue (Fig. A1a), the selected CO₂ decay curves following the criteria previously defined in red (Fig. A1b), and the obtained ACH values in blue dots (Fig. A1c).

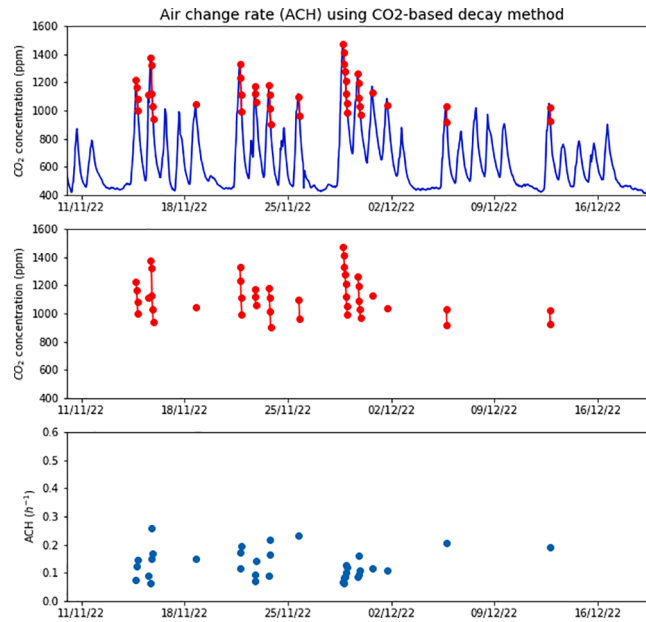


Fig. A1. Analytical steps to calculate ACH values using the CO₂-based decay method.

A.3. Load disaggregation

Unsupervised load disaggregation is developed following the techniques developed by Azizi et al. [33]. Mathematically, building energy consumption can be divided as a set of N devices in the building and their corresponding consumption as $\{1, \dots, N\}$ and $\{P_1, \dots, P_N\}$, respectively. The goal of load disaggregation is to extract $P_i(t)$ from total consumption $P(t)$ as defined in Eq. (A3):

$$P(t) = \sum_{i=0}^N P_i(t) \quad (\text{A3})$$

where:

P : power consumption

t : time.

Two methods were defined in this article to extract the water consumption from electric water tanks and the building's background power consumption. These methods are detailed in the next sub-sections.

A.3.1. Water tank load disaggregation. This building has nine hot water tanks with immersion heaters with a nominal power of 3 kW and a typical ON-duration within their duty cycle of no more than 8 min. To extract the water tank load, we have proposed an event-based method. Generally, in event-based NILM algorithms, a difference between two consecutive samples greater than the pre-defined threshold indicates a mode transition in a device (or multiple devices simultaneously), which is the so-called *event* [54]. Given the total power consumption over the time of the building, the main steps of the proposed algorithm are:

Step 1: calculate the difference between two consecutive samples of $P(t)$ and compare it to the pre-defined threshold (Tr).

$$\Delta P(t) = P(t+1) - P(t) \quad (\text{A4})$$

If $\Delta P(t) > Tr$, a positive event (E_p) happened at $t_p = t$, which can be caused by operating one (or multiple) water tank(s). It should be noted that the Tr is not precisely the nominal power since there is a possibility of simultaneous turning ON/OFF for appliances in the building. Therefore, in this research, we have considered $Tr = 2.75$.

Step 2: Since the ON duration of water tanks is less than 8 samples, in the following 8 samples, compute the difference of two consecutive samples of $P(t)$ as Eq. (A5),

$$\Delta P(i) = P(i+1) - P(i), i = t+1, \dots, t+8 \quad (\text{A5})$$

If $0.8 \times E_p \leq \Delta P(i) \leq 1.2 \times E_p$, then the corresponding negative event (E_n) of turning OFF of the water tank has happened at $t_n = i$. Detected positive and negative events caused by each cycle of a water tank are shown in Fig. A2.

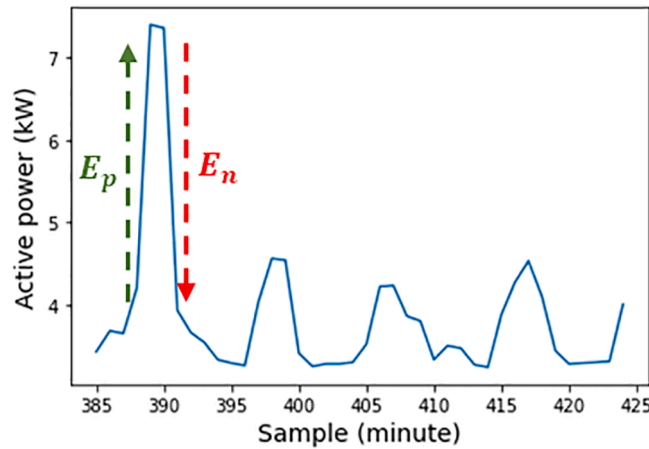


Fig. A2. Total consumption and detected positive and negative events caused by the water tank.

Step 3: To reconstruct each cycle of the water tank profile in each cycle, we have used Eq. (A6).

$$P_{hw}(t_p, \dots, t_n) = \frac{|E_p| + |E_n|}{2} \quad (A6)$$

For computing the daily energy consumption ($E_{hw}(kWh)$) Eq. (A7) is used,

$$E_{hw} = \sum_{i=1}^{C_d} P_{hw}(i) \times \frac{1}{60} \quad (A7)$$

where C_d shows the number of cycles of the water tank per day.

A.3.2. Background load disaggregation. Another essential part of the analysis is estimating the background load profile, mainly related to Information and Communication Technologies (ICT) and other almost contact power consumption. We defined background load as the minimum load that would have been consumed during a day. Thus, for each day of the month, the background power and energy are extracted according to Eq. (A8) and Eq. (A9), respectively,

$$P_{bl} = \min\{P(1), \dots, P(1440)\} \quad (A8)$$

$$E_{bl} = P_{bl} \times 24 \quad (A9)$$

Then, the ratio of the background power (P_{bl}) to the total consumption of that day is computed as:

$$R_{P_{bl}} = \frac{P_{bl}}{\sum_{i=1}^{1440} P(i)} \quad (A10)$$

and the average of this ratio per month, $R_{P_{bl}}^m$, is obtained as:

$$R_{P_{bl}}^m = \frac{\sum_{i=1}^{Nd_m} R_{P_{bl}}(i)}{Nd_m} \quad (A11)$$

where Nd_m stands for the number of days per month (m).

A.4. Heating Thermostat Control Diagnosis.

This technique quantifies the percentage of working hours where the indoor temperature is above or below a recommended temperature threshold. It uses the data collected from indoor and outdoor temperature sensors.

Two temperature thresholds are used to compare the number of working hours when the building is overheated (when $T > 23^\circ\text{C}$) and overcooled (when $T < 19^\circ\text{C}$), according to Eq. (A12).

$$T - stat(t_0, \dots, t_n) = \frac{\sum \text{Working hours with the building overheated/overcooled}_i}{\sum \text{Working hours}_i} \cdot 100 \quad (A12)$$

where:

T -stat: Percentage of time with the indoor temperature above/below a recommended threshold.

t : daily hour.

The approach also compares the relationship between the mean hourly indoor temperature and mean hourly outdoor temperature to understand the system operating conditions at full and partial-load operation.

A.5. Lighting system diagnosis.

This technique quantifies the percentage of time with lighting on in unoccupied spaces. It uses the data collected from the PIR motion and illuminance sensors. PIR motion sensor measures the number of movements detected per time, starting from 0 when no motion is detected. Illuminance sensor measures, in lux, the illuminance level of an environment according to natural and artificial lighting.

For a selected timeframe, the method compares the number of hours with lights on without occupancy (lux > 800 ; and PIR sensor < 0.5) per hour

(t), with the number of expected working hours during this period, according to Eq. (A13).

$$Light_on(t_0, \dots, t_n) = \frac{\sum \text{Working hours with lights on without occupancy}_t}{\sum \text{Expected working hours}_t} \cdot 100 \quad (\text{A13})$$

where:

Light-on: Percentage of time with lights on without occupancy.

t: daily hour.

The relationship between these two indicators helps identify constant hours with energy waste for lighting, which can help redesign lighting control.

A.6. Discrepancies between occupancy and HVAC operation

This technique quantifies the percentage of time with real occupancy in the building per working hour. It uses the data collected from the PIR motion sensor, which measures the number of movements detected per time, starting from 0 when no motion is detected.

For a selected timeframe, the method compares the number of hours with real occupancy (PIR sensor >0.5) per hour (t), with the number of expected working hours during this period, as defined by Eq. (A14).

$$Occ(t_0, \dots, t_n) = \frac{\sum \text{Working hours with real occupancy}_t}{\sum \text{Expected working hours}_t} \cdot 100 \quad (\text{A14})$$

where:

Occ: Percentage of occupancy.

t: daily hour.

The relationship between these two indicators helps identify constant hours with a low occupancy rate, which can help redesign the HVAC system operating schedule.

Appendix B. Input data for energy modelling

Appendix B provides most input parameters considered for the physics-driven energy model. The values are divided into building characteristics in Table B1 and energy systems in Table B2.

Table B1
Input data. Characterisation of the building.

Building characteristics			
Building location		Building geometry	
Building name	Case Study	Total floor area (m ²)	1154
City	Oxford	Conditioned area (m ²)	981
Country	UK	Clearance height (m)	2.60
Total building occupancy	150	Window area (%)	29 %
Real mean occupancy	75	Number of floors	3
Thermal properties of the building envelope			
Opaque envelope		Thermal bridges	
Ground (U-value, W/m ² K)	1.37	Façade-ground	Yes
Roof (U-value, W/m ² K)	0.84	Façade-intermediate floor	No
Facade (U-value, W/m ² K)	0.97	Facade-roof	Yes
Openings			
Windows (U-value, W/m ² K)	1.4	Windows (lintels, jambs and sills)	No
Window (%) [frame factor]	20 %	Shading devices (roller blinds)	No
Solar properties			
Opaque envelope		Openings	
Solar absorptance of roof	0.8	Solar factor of windows (g-value)	0.59
Solar absorptance of walls	0.6	Winter SRF	0.80
		Summer SRF	0.75
Internal heat gains		Airtightness (air infiltration)	
Occupants (max, W/m ²)	2.5	Leakage air flow (q _v , m ³ /h m ²)	1.90
Lighting (max, W/m ²)	4.2	ACH of infiltration/leakage (h ⁻¹)	0.32
Appliances (max, W/m ²)	0.5	ACH at n50 (h ⁻¹)	6.37
Thermal capacity		Natural ventilation (summer night ventilation, NV)	
Building heat capacity	Medium	Summer NV (m ³ /h m ²)	0.00
		ACH of summer NV (h ⁻¹)	0
Occupation profile		Average operating conditions	
Opening time (h)	8	Mean set-point temperature in winter	20–22 °C
Closing time (h)	18	Mean set-point temperature in summer	21–23 °C

SRF: Shading reduction factor.

ACH: Air change rate.

Building heat capacity (Very Light, Light, Medium, Heavy, Very heavy).

NV: night ventilation.

Table B2

Input data. Characterisation of energy systems.

Energy systems			
Heating		Cooling	
Heating system		Cooling system	
System type	Condensing boiler	System type	Heat pump
Energy source	Natural gas	Energy source	Electricity
Efficiency or COP	1.030	EER	2.80
Total nominal capacity (kW)	96	Total nominal capacity (kW)	96
Switched on (h)	8	Switched on (h)	10
Switched off (h)	17	Switched off (h)	18
Ventilation		Lighting	
Mechanical ventilation (m ³ /h m ²)	10.0	Power installed (W)	4400
Power installed (kW)	1.20	Total power rate (kW/m ²)	4.5
ACH of mechanical ventilation (h ⁻¹)	–	Zone 1	Ground floor
		Luminary	LED (1x40) + 0
		N° luminaires	55
		Total power installed	2200
		Operating hours per day	9
		Simultaneity factor	0.60
Hot water		N° similar zones	1
System type	Electric boiler	Zone 2	First/second floors
Energy source	Electricity	Luminary	LED (1x40) + 0
Efficiency or COP	1	N° luminaires	55
Water demand (l/day)	215	Total power installed	2200
Reference temperature (°C)	60	Operating hours per day	9
Water supply temp (°C)	16	Simultaneity factor	0.80
		N° similar zones	1

COP: coefficient of performance.

EER: energy efficiency ratio.

ACH: Air change rate.

Appendix C. Detail results of the interventions

Appendix C reports the detailed results from the energy, environmental and economic analysis of the interventions, obtained through the numerical energy model. Table C1 summarises the energy and environmental performance of the solutions, and Table C2 provide the economic performance indicators.

Table C1

Energy and environmental performance of the proposed interventions.

ID	DH (%)	Q _{C,peak} (KW)	Q _{H,peak} (kW)	Q _{HC,nd} (kWh/m ²)	FEC (kWh/m ²)	PEC _{nr} (kWh/m ²)	CO _{2eq} (kgCO _{2eq} /m ²)
S0. Baseline	14 %	51.8	104.6	79.0	109.3	125.3	20.4
Group 1-Control: Measures to improve building energy management and control							
S1.1	14 %	51.8	97.8	70.2	100.6	115.3	18.3
S1.2	14 %	51.8	104.6	79.0	106.7	122.4	19.7
S1.3	14 %	51.8	88.9	79.0	101.0	115.7	18.4
S1.4	14 %	46.8	104.6	77.2	108.1	124.0	20.2
S1.5	11 %	48.2	104.6	78.6	108.9	124.9	20.3
S1.6	14 %	51.8	104.6	79.0	108.6	124.5	20.3
S1.7	14 %	51.8	104.6	79.0	107.9	123.7	20.2
Group 2-Partial: Partial passive measures to reduce energy demand							
S2.1	14 %	51.8	99.4	79.0	106.5	122.1	19.7
S2.2	14 %	50.9	102.2	76.6	106.9	122.5	19.8
S2.3	7 %	38.8	104.6	79.0	108.5	124.4	20.3
Group 3-Global: Global passive measures to reduce global energy demand							
S3.1	15 %	48.6	97.0	71.0	100.6	115.2	18.3
S3.2	15 %	49.1	97.7	71.7	101.5	116.3	18.5
Group 4-Systems: Upgrading energy systems increasing efficiency and renewables							
S4.1	14 %	51.8	104.6	79.0	70.9	80.5	9.6

(continued on next page)

Table C1 (continued)

ID	DH (%)	Q _{C,peak} (KW)	Q _{H,peak} (kW)	Q _{HC,nd} (kWh/m ²)	FEC (kWh/m ²)	PEC _{nr} (kWh/m ²)	CO ₂ eq (kgCO ₂ eq/m ²)
S4.2	15 %	51.7	101.0	75.4	105.8	121.3	19.5
S4.3	14 %	51.8	104.6	79.0	109.3	101.6	17.5
S4.4	14 %	31.9	104.6	73.9	106.9	122.6	20.0
Group 5-Packages: Combination of individual measures							
S5.1	11 %	43.1	83.1	67.6	87.1	99.7	15.6
S5.2	5 %	29.9	80.2	65.3	84.1	96.3	14.9
S5.3	3 %	23.6	70.4	52.1	72.9	83.3	12.3
S5.4	3 %	10.4	65.7	46.9	54.6	38.2	4.6
S5.5	3 %	10.4	65.7	46.9	55.2	38.8	4.7

Table C2

Economic performance of the proposed interventions.

ID	LCC (£)	LCC (£/m ²)	PBP (years)
S0. Baseline	748,200	762.8	
Group 1-Control: Measures to improve building energy management and control			
S1.1	722,792	736.9	0
S1.2	740,741	755.2	0
S1.3	734,758	749.1	11
S1.4	738,096	752.5	0
S1.5	743,935	758.5	0
S1.6	742,645	757.2	4
S1.7	736,070	750.5	1
S1.8	101,707	103.7	0
Group 2-Partial: Partial passive measures to reduce energy demand			
S2.1	740,360	754.8	1
S2.2	743,353	757.9	9
S2.3	744,356	758.9	15
Group 3-Global: Global passive measures to reduce global energy demand			
S3.1	744,086	758.6	18
S3.2	764,265	779.2	28
S3.3			
Group 4-Systems: Upgrading energy systems, increasing efficiency and renewables			
S4.1	781,568	796.8	31
S4.2	742,111	756.6	7
S4.3	629,369	641.7	10
S4.4	729,575	743.8	4
Group 5-Packages: Combination of individual measures			
S5.1	666,051	679.1	4
S5.2	662,598	675.6	6
S5.3	686,085	699.5	13
S5.4	573,566	584.8	13
S5.5	625,949	638.2	15

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