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Implementing multi objective genetic algorithm for life cycle carbon footprint and life cycle cost minimisation: A building refurbishment case study

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ABSTRACT

Early design decisions made by architects have been shown to significantly impact the energy performance of buildings. However, designers often lack the resources or knowledge to take informed decisions that might improve building performance. The refurbishment of existing buildings is considered to significantly contribute to the reduction of the life cycle environmental impact of buildings. Building refurbishment is also seen as the most cost-effective way of achieving this goal. In assessing the life cycle impacts of constructing and usage processes of buildings, LCA (life cycle analysis) is often used.

In order to simplify the decision-making process in early design, this study uses MOGA (multi objective genetic algorithms) to find optimal designs for a refurbishment of a residential complex case study, in terms of LCCF (life cycle carbon footprint) and LCC (life cycle cost) over an assumed life span of 60 years.

Results show that utilizing MOGA has the potential to reduce the refurbishment LCCF and LCC. Findings emphasize the life-cycle impacts of insulating thermal bridges and the importance of using different heating systems and fuels. Finally, in comparing LCA with more commonly used performance-based decision-making design procedures, the study highlights that employing these distinctive methods can lead to different design solutions.

1. Introduction

Energy consumption in the built environment accounts for approximately 40% of the total energy consumption in the UK. The global construction industry is also responsible for 40% of global raw aggregates and 25% of wood consumption [1–4]. In the UK, the government has committed to reducing at least 80% of its CO_2 emissions (compared to 1990 baseline figures) by the year 2050 [1].

Energy efficient Refurbishment is considered to be a potential means by which to significantly contribute to the reduction of the environmental impact of buildings and is also widely regarded to be the most cost-effective way of achieving this goal [5,6]. Improving the energy performance of existing buildings, while keeping additional CO_2 emissions and cost to a minimum, has therefore become a key concern and challenge in reducing the life cycle impact of buildings.

Sustainable design metrics and tools are often used for the quantification of sustainability and profitability of a development. LCA (life cycle assessment) is a method that offers a holistic approach for assessing the potential environmental impacts of products and process throughout their life cycle in what is referred to as a 'cradle to grave' approach [7–9]. The outputs of LCA studies are a combination of a range of environmental impacts, however in buildings these impacts are often converted to CO_2e (CO_2 Equivalent) to evaluate the building's GWP (global warming potential). This single value describes the LCCF (life cycle carbon footprint) of the building, which enables the direct evaluation of environmental impacts of alternative solutions. LCC (life cycle cost) examines the whole life economic expenses of using a product or a service. Its main goal is to define a method by which to quantify and measure the level of profitability of a development. As the cost of building materials and the construction process accounts for only a small part of the total expenses throughout the life of a building, LCC takes into account not only expenses for owning and constructing a building, but also those accrued as a result of its operation, maintenance and demolition [10]. Carrying out an LCC can help in the determination of a building's lowest life cycle cost [10].

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In the building sector, energy is used at different stages during a building's life span; during the material extraction process, in the manufacturing of building components and during building construction, usage and demolition [11]. This means that life cycle energy use depends on both decisions taken by the designer (geometry and orientation, choice of materials, window to wall ratios etc.) as well as the fuel sources used for running the building.

Early design decisions have a significant impact on the energy performance of buildings [12]. Ideally, thermal performance analysis should be carried out iteratively throughout the design process; a design should be tested, evaluated, compared with other design solutions and modified accordingly, until an optimal design is found. In practice, however, architects usually lack the necessary resources and technical knowledge to carry out full-performance optimisation studies. Despite the significance of early design decisions on buildings energy performance, easy-to-use decision-making design tools directed towards architects are lacking.

This study therefore examines the applicability of computational efficient search techniques that automatically undertake comparisons between different design alternatives (Multi Objective Genetic Algorithms – MOGA), to allow architects having more informed decisions in early design stages. This will be implemented through the examination of the refurbishment of a residential complex case study with the aim of optimising its refurbishment measures, to minimise its LCCF and LCC. In particular, the study was undertaken with the aim of addressing the following research questions:

- How can computational optimisation methods be utilized in an early design stage to identify the optimal envelope refurbishment measures that minimise LCCF and LCC of a case study?
- What is the impact of using LCCF and LCC to support the design decision-making process as compared to other more commonly used performance-based methods?

To achieve these aims, the following objectives were set:

- Using MOGA, what are the optimal building LCCF and LCC, and what is the balance between the embodied and operational CO_2 emissions throughout the optimal building life cycle?
- How does the life cycle performance of the optimal building compare with that of the original building and with that of the actual refurbishment?

2. Literature review

2.1. Implementing whole life cycle studies in the built environment

MacLeamy [12] showed that a designer ability to easily change a design is most evident at an early design stages and decreases over time. Key design decisions that may impact building energy performance are made at this stage and can include such aspects as building size, orientation, height and materiality which may impact CO_2 emissions due to production of building materials and consumption of energy throughout the building's life.

Energy use in buildings has been extensively researched in recent years, however, building performance analysis often focuses on annual energy consumed in the operation of buildings (kWh/m^2/year), rather than taking into account other life stages such as construction, maintenance or demolition. Life cycle studies in the built environment is a growing research field [13] that gives a wider view of energy consumption in buildings.

LCCF is derived from the analysis of Life Cycle Energy use (LCE). Dixit et. Al (2012) describe the two main sources of LCE consumption in buildings [2]:

- ***The Embodied Component*: EE (embodied energy)** is the sum of energy required for the manufacturing of a product or a service. In buildings, this includes the energy used in the extraction of raw materials, transportation to and from factories and energy required for construction, maintenance, periodic refurbishments and the replacement of various building components once they are worn out [14]. Embodied CO_2 and Embodied Costs are associated parameters, typically calculated by multiplying material ECF (embodied carbon factors) or Embodied Costs by the amount of material used [15]. ECFs can be found in Energy and Carbon Inventories – pre-calculated databases that specify the amount of energy and CO_2 emissions, associated with the production of various building materials. Embodied Costs are calculated by using widely-recognized building component cost guides.
- ***The Operational Component:* OE (operational energy)** is the energy used for maintaining the thermal and environmental conditions within the building – heating, cooling, domestic hot water and lighting [14]. OE is usually calculated by using building performance simulation tools – software that allows the evaluation of building performance. OERC (operational energy-related carbon) and Operational Costs are calculated by multiplying predicted energy consumption values by the CO_2 emissions of the fuel that is used for energy production, and by their costs, respectively. Studies by Gustavsson et al. and Eriksson et al. show that the fuel type used for OE generation has a significant impact on LCA results, as some energy generation technologies are more environmentally-friendly than others [16,17].

Meta-analysis studies show that EE (Embodied Energy) accounts for between 2 and 38% of the life cycle energy use in conventional buildings, and 9–46% in low-energy buildings (as the later consume less energy during their operational phase, and their construction is usually more carbon-intensive) [9,10,18–21].

2.2. Building performance and optimisation

Life Cycle studies are iterative comparative processes – the performance of one design solution should be compared with that of other designs and the better option should then be selected. This type of parametric simulation is often used for improving the performance of buildings [22], however, this procedure is considered to be time and resource consuming [23], especially when a large number of alternatives are examined. To address this, advanced computational search methods are used to help find optimal design solutions more efficiently. Optimisation, in this case, refers to the task of finding the best out of all feasible solutions in a given system [24].

Various studies have used optimisation methods for such aspects as load distribution, building systems, construction materials and building form to improve building performance [25–28]. While some studies focused on optimising designs to improve modelled energy performance in buildings [29,30], others employed optimisation methods for reducing LCC [31–33]. Notably, relatively few examined building performance optimisation in terms of LCA or LCCF [18,34].

While Wang et al. (2005) [35] used an optimisation algorithms to minimize both LCA and LCC, the study focused on the design of new buildings. Ostermeyer et al. [36] used multi-criteria optimisation for finding optimal refurbishment designs, in terms of cost and environmental impacts. Their study, however, used PHPP (PassivHaus Planning Package – a static thermal simulation tool) for operational energy calculation instead of a dynamic simulation tool which enable more flexibility in evaluating energy consumption [37]. Furthermore, instead of using the most widely used CO_2 Equivalent measurement for LCA environmental impact, the study

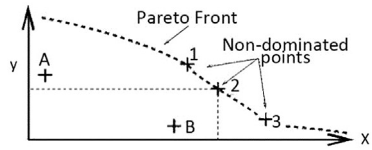


Fig. 1. Pareto front. Source: Poli et al., 2008 [40], (adapted from Langdon, 1998).

Table 1
CO_2 emissions and energy cost per kWh. Data based on [51–53,55].

Energy type	CO_2 emissions (kgCO_2/kWh)	Cost (£/kWh)
Electricity	0.529	0.160
Waste combustion district heating	0.057	0.045
Natural gas	0.210	0.045

used ‘ReCiPe Ecological Indicator’ – a closed credit system that translates a number of ecological impacts into a weightless credits. Chantrelle et al. [29] used GA for finding optimal refurbishment measures of a school building, however, it is not clear from the published study whether all steps in the life cycle of the building were taken into account. Aspects such as transportation, construction, maintenance and demolition are not mentioned in the study, furthermore neither the heating system nor the fuel used in the study is indicated. Nguyen et al. [23] show that GA (genetic algorithms) is the most widely used optimisation method in building performance analysis.

3. Methodology

To identify a set of design solutions with the minimal LCCF and LCC, this study aims to apply efficient computational search techniques that automatically perform comparisons between different design alternatives for the refurbishment of a case study and find the optimal ones. To achieve this, production processes are defined and optimised, and the balance between embodied and operational CO_2 emissions and costs is found.

3.1. Overview of analysis approach

Since this study involves more than one objective for optimisation (both LCCF and LCC), a MOGA (multi objective genetic algorithms) was used. Zhang [38] shows that Non-dominated Sorting Genetic Algorithm (NSGA2) is the most widely used MOGA in research of the built environment. It is also claimed that NSGA2 is less prone to local optimums than other optimisation algorithms [39].

NSGA2 is based on the principle of Pareto Dominancy; this denotes that when a set of objectives is given, one solution (often referred to as ‘individual’) Pareto dominates another when it has as good solutions as the second one for all objectives, and at least one solution where it is better [40]. Fig. 1 shows a two-dimensional Pareto optimal front, where individual ‘B’ is better than ‘A’ along the x axis and individual ‘A’ is better than ‘B’ along the y axis. They dominate each other on different objectives. Individual ‘2’, however, is better than ‘B’ in both axes. No other individual dominates ‘2’ in both axes. NSGA2 finds a set of solutions which are not dominated by any others [40].

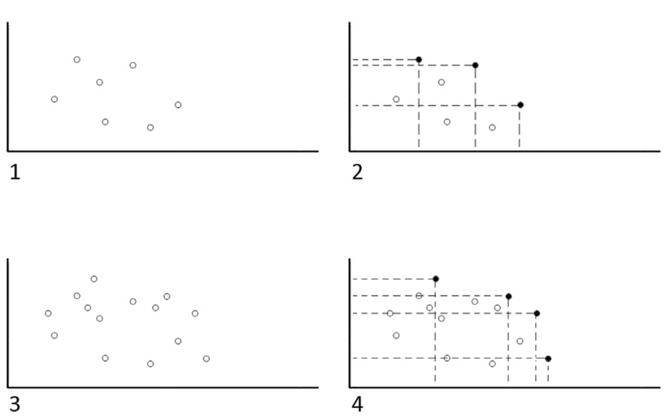


Fig. 2. NSGA2 steps.

The description of the NSGA2 code is shown in Fig. 2. NSGA2 starts with a random population of solutions and plots them on a graph (1). It then identifies the Pareto non-dominated solutions (2), breeds, mutates and crosses-over some of their genes and produces a new set (generation) of solutions. Statistically, this new set of solutions should perform better than the previous generation (3). The code finally goes back to the second step, where it identifies the new Pareto non-dominated individuals. This process is repeated until a maximum number of generations is reached.

3.2. The case study building

The case study building examined in this paper is a recently refurbished “Grade II listed building[1]” council housing complex. While a listed building in general presents specific restrictions (extensions are not allowed and changes in general are more limited), findings of this work are also applicable to non-listed buildings.

The complex was built in the late 1950s in Sheffield, England. In its early years of occupation the complex gained success, however, during the 1980s it slowly deteriorated until all tenants left. Due to its unique design, the complex was designated as a “Grade II listed building” in the late 1990s, and a design competition for its refurbishment was launched shortly thereafter. The first phase of refurbishment was recently completed, and the design of the refurbishment of the second phase was ongoing at the time of writing. Waste Combustion District Heating (WCDH) – a very efficient and low emissions heating technique – was used for the complex's space and water heating. As noted in Table 1, the system emits 0.057 kgCO_2/kWh compared to 0.21 kgCO_2/kWh in the case of natural gas).

This study focuses on a specific section of the complex comprised of two similar blocks with different orientations (Fig. 3) -a north building (A) and a south building (B) As different orientations can lead to differences in OE (operational energy) consumption, the study set out to examine the performance of the refurbishment of both buildings separately, and to determine how orientation impacts building LCCF.

The original building envelope was considered to have a poor thermal performance due to an exposed access passage to the flats every third floor (illustrated in Fig. 4), this large surface area increases the potential for heat losses. Moreover, as exposed concrete frames were one of the main architectural features of the original design, a high priority for the refurbishment was to retain them. These were therefore kept exposed (and un-insulated). The refurbishment hence included the complete disassembly of the building envelope, retaining the original exposed concrete structure and recladding the building with a higher performance facade. While this approach maintained the original appearance of the building, it can

[1] Listed Building – in the UK, a building with a special Architectural or Historical interest. Listed buildings should be preserved. They should not be demolished or extended without a permission by the local authority [62].

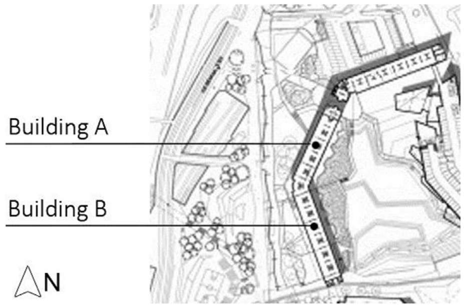


Fig. 3. Site plan.

also lead to an increased risk of thermal bridges, which has been shown to be associated with high energy consumption and the formation of mold on interior surfaces [41,42].

Since the main architectural intervention was the new envelope design – this study explored the life cycle properties of the different envelope components and focused on optimising their build-ups, window-to-wall ratio and thermal bridge insulation.

3.3. Implementation

This study is based on a small-scale pilot study [43], which was conducted for the testing, refining and developing of the methodological approach before using it in a larger scale analysis. This initial analysis was limited in scope and only examined limited design variations. Based on this, the implementation of the research design for this study involved the utilization of four main tools (Fig. 5, Table 2):

a . Building geometry was first modelled in Sketchup and then exported to an EnergyPlus.idf (Input Data File) using the Legacy Open Studio plug-in for Sketchup.
b . Model thermal properties (weather file data, HVAC system, occupancy rates etc.) were defined in EnergyPlus.
c . Genes to be optimised were defined in jEPlus [44]– An EnergyPlus parametric simulation manager that allows the control of a batch simulation. jEPlus was responsible on the generation of new individuals (new models, based on a combination of different design parameters as seen in Table 3) and for sending them for simulation.
d . GA objectives, mutation, number of generations and crossover rates were set in jEPlus + EA – a platform that allows the performance of GA optimisation studies. Once a maximum number of generations had been reached– the optimisation was stopped.

The building components that the NSGA2 code could manipulate are highlighted in Fig. 4. Table 3 shows the GA genes and their possible values. Overall, a total of 55,296 possible models could potentially be generated.

The CIBSE "UK–Manchester.TRY" [45] weather-file was used for the thermal simulations as this is the closest and more reliable available weather data. 10 optimisation scenarios were implemented, as described in Table 4, all were simulated on a cloud simulation service.

3.4. LCA analysis

Based on earlier methods, the ISO (International Organization Standardization) published its latest sets of LCA standards in 2006, known as ISO 14040:2006 (Environmental Management–Life Cycle Assessment -Principles and Framework), and include ISO 14040 to ISO 14045. The LCA methodology used for this study, is based on the ISO1 4040 methodology, which involves the following steps:

3.4.1. -Goal and scope

As described in Section 1, the main goal of this study was to identify the optimal measures for the refurbishment of the case study building, in terms of LCCF and LCC. The study took into account all stages from "cradle to grave" and calculated LCCF and LCC by using a mixture of calculated and assumed coefficients based on a number of studies [13,16,46–48], as shown in Table 5. As the building is situated in the UK, this study followed the BRE (building research establishment) guidelines indicates that 60 years should be considered as the expected building life span for reporting purposes [49]. The functional unit for each building was 1 m^2 floor area. As the focus of this study is the performance of the building fabric – it is assumed that the efficiency of the HVAC systems is constant.

3.4.2. -LCI (life cycle inventory)

Based on the architectural drawings and specifications, an inventory of the building materials under use and their environmental impacts and costs was established. These were based on various assumptions:

Embodied component – The total quantity of each material used in each simulation was multiplied by the relevant ECF (embodied carbon factors) and costs, using Bath ICE (inventory of carbon and energy) [11] and Spon's Guide for Architects [50], as shown in Tables 5 and 6.

Operational component – OE consumption was calculated in EnergyPlus. Outputs were multiplied by NCM (National Calculation Methodology) CO_2 conversion factors to get OERC [51] and by UK

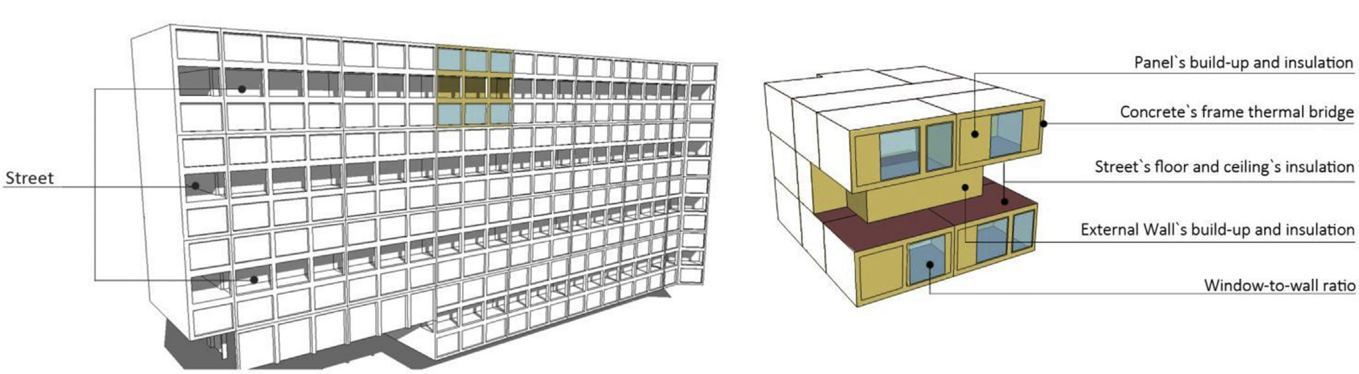


Fig. 4. Building "B" (left) and the elements for the GA optimisation (right).

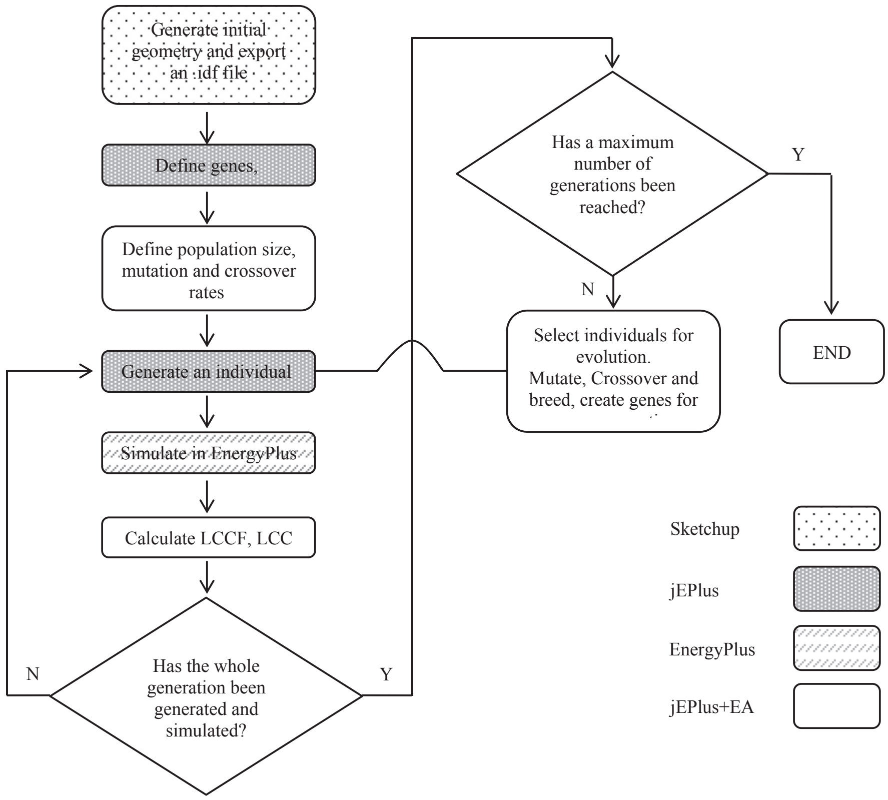


Fig. 5. Research design. Based on [31].

Table 2
Tools used in the study.

Tool	Description
Google Sketchup 8.0	A Popular 3D modelling tool. Widely used in architecture and design studios.
EnergyPlus	A Platform that allows whole building thermal simulation. EnergyPlus was developed by the U.S Department of energy and is widely used by the research community worldwide due to its flexibility.
jEPlus	A java-based parametric simulation manager, developed at De Montfort university, Leicester, and designed for EnergyPlus users. jEPlus allows the control of a batch simulation.
jEPlus + EA	A Platform that allows an easy manipulation of a batch simulation and the performance of GA optimisation studies by using the NSGA2 algorithm.

government Energy Price Statistics – energy costs [52] to get life cycle OE expenses.

Heating supply system –WCDH has a significantly lower environmental impact when compared to more common fuel types (as seen in Table 1). As WCDH is not very common in the UK this study conducted LCA optimisations both for the original heating system and for a gas fuelled condensing boiler – a more common heating system in use in the UK. While the two systems vary in OERC (operational energy-related carbon) emissions, the cost of energy both system use is the same [53].

3.4.3. -LCIA (life cycle impact assessment)

In order to minimise their LCCF and LCC, the MOGA code was required to calculate both values for each and every model generated. The calculations were split into two parts, where the first summed up the EC (embodied carbon) and cost and the second calculated the OERC and cost.

LCCF was calculated using the following Eq. (1):

$$LCCf = \sum_{i=0}^{ni}\left(Ki \times Ti \times Di \times (1+Mi) \times \left(\sum_{j}^{mj} Ai,j\right)\right) + Y(((S+W) \times EH) + (E \times EE)) \quad (1)$$

Where:
i = Number of material.
Ki = Material's embodied CO_2 ($kgCO_2/kg$).
Ti = Material's thickness (m).
Di = Material's density (kg/m^3).
Mi = Material's waste, transport, construction, maintenance and demolition CO_2 coefficient.
Ai = Material's area (m^2).
j = Number of surfaces of the i'th material.
Y = Number of years.
S = Space heating energy (kWh).
W = Water heating energy (kWh).
EH = CO_2 emissions due to heating fuel ($kgCO_2/kWh$).
E = Electricity energy (kWh).
EE = CO_2 emissions due to electricity fuel ($kgCO_2/kWh$).

Similarly, LCC was calculated using the following Eq. (2):

$$LCC = \sum_{i=0}^{ni}\left(Ci \times (1+Li) \times \left(\sum_{j}^{mj} Ai,j\right)\right) + Y(((S+W) \times CH) + (E \times CE)) \quad (2)$$

Where:
i = Number of material.
Ci = Material's cost (£/m^2).
Li = Material's waste and transport and maintenance cost coefficient.
Ai = Material's area (m^2).
j = Number of surfaces of the i'th material.
Y = Number of years.
S = Space heating energy (kWh).
W = Water heating energy (kWh).
CH = Cost of heating energy (£/kWh).
E = Electricity energy (kWh).
CE = Cost of electricity (£/kWh).

Table 3
Genes and possible values.

Gene number	Name	Possible values
1	Panel insulation, Street insulation	50, 100, 150 [mm]
2	Exterior insulation	50, 100, 150 [mm]
3	Bricks	0, 100 [mm]
4	Thermal bridges insulation	0,50,100 [mm]
5	Window (Top floor, West)	25, 50, 75, 100 [%]
6	Window (Mid floor, West)	25, 50, 75, 100 [%]
7	Window (Bottom floor, West)	25, 50, 75, 100 [%]
8	Window (Top floor, East)	25, 50, 75, 100 [%]
9	Window (Bottom floor,East)	25, 50, 75, 100 [%]
Total Number of combinations		55,296

Table 4
Scenarios examined in this study.

Scenario number	Objective	Heating system	Buildings
1-2	Embodied CO_2/Operational CO_2	WCDH	A, B
3-4	LCCF/LCC	WCDH	A,B
5-6	Embodied CO_2/Operational CO_2	Natural Gas	A, B
7-8	LCCF/LCC	Natural Gas	A, B
9	LCCF/LCC	Natural Gas	B[a]
10	Annual energy consumption/annual energy spending	Natural gas	B[a]

[a] B = Scenarios 9 and 10 examined the optimisation result difference of a fully south oriented building B, when the optimisation objectives varied (LCCF/LCC versus Annual energy consumption/annual cost).

Table 5
LCI summary. Data based on [13,16,46,47,48].

Boundary factors	LCCF	LCC	Data source
Building Materials Including waste	√	√	Sketchup model, Architectural drawings and Bath ICE
Transport	√	√	3%[a]
Construction (labour)	√	–	7%[a]
Energy in use	√	√	EnergyPlus
Demolition	√	–	2%[a]
Maintenance	√	√	See Table 6

[a] Percentages refer to the total building EC- regarded as 100% of “Building Materials including Waste”.

Table 6
Material waste rates and maintenance – life expectancy [51,54].

Material	Waste rate (%)	Life span (years)
Insulation	15.0	Lifetime
Aluminium cladding	5.0	30
Fibre cement	3.0	Lifetime
Timber	15.0	30
Plaster	22.5	Lifetime
Windows	5.0	30
Paint	0.0	10
Steel	15.0	Lifetime
Brick	15.0	Lifetime

4. Results and discussion

The first part of this section discusses the MOGA results for the case study buildings for both scenarios (WCDH and Gas as primary fuel types). Later, a comparison between the original (un-refurbished) building, the original refurbishment and the optimal refurbishment is carried out. A CO_2 payback time calculation is then undertaken and the impact of building orientation on LCCF and LCC is examined. Lastly, a comparison between the results of LCCF and annual thermal performance is conducted.

Ten optimisation projects were simulated using the JESS (jEPlus simulation server) – DMU (De Montfort University) cloud simulation service. Each project took around 6 h to simulate, compared with 10 h on an i7 Intel processor with 6.0 GB installed memory.

4.1. Optimisation results

4.1.1. LCCF/LCC

Fig. 6 shows the LCCF and LCC analysis that MOGA generated and tested. Fig. 6a and b examined the WCDH scenario while Fig. 6c and d examine that of the gas boiler. MOGA successfully found a single optimal model for the former, and several optimal models for the later.

Four groups of individuals are clearly seen on the graphs – individuals with and without additional brick layer and individuals with and without thermal-bridge insulation. The importance of using insulation is clearly shown by the results. All optimal individuals had the thickest available insulation, and insulating the thermal bridge brought to a reduction of between 10 and 20% in the LCCF and LCC. Results also show that individuals with a brick layer have lower operational energy consumption than individuals without it; however, it seems that this layer embodies more CO_2 than it saves throughout the buildings life.

Fig. 6 shows that Building B emits less CO_2 and costs less to build and run per m^2 throughout its life. This is assumed to be due to its favourable orientation and spatial arrangement which increases its exposure to solar gains and set better conditions for passive heating than that of building A. Interestingly, the optimal individuals in both buildings in the WCDH scenario had small south-facing windows. This means that even a fully glazed south-facing façade – i.e. a facade that allows maximum passive solar radiation heat gains (which might potentially lead to a decrease in energy use and CO_2 emissions for heating) – embodies more CO_2 than it saves due to solar gains.

Fig. 6a and b illustrate different relationships between their LCCF and LCC results, compared to Fig. 6c and d. This can be attributed to the different fuel types used in the operational phase in each scenario: The case study's LCC was substantially affected by the building's Embodied Cost. As the WCDH scenario has a prominent Embodied component (since WCDH Operational CO_2 emissions are relatively low, compared to that of the gas boiler), the relation between its LCCF and LCC is stronger.

4.1.2. Embodied CO_2/operational CO_2

Fig. 7 examines the embodied and operational CO_2 emissions results for both buildings. Fig. 7a and b show the case of the WCDH, and Fig. 7c and d show the case of using gas as the fuel for space and water heating. Each dot on the graphs represents a model with a specific set of properties (genes), where the red dots are the “Pareto Front”.

Results show that for all cases, the embodied energy of the refurbishment was between 210 and 310 $kgCO_2/m^2$. In the case of a very efficient heating energy source (WCDH) – the EC is between

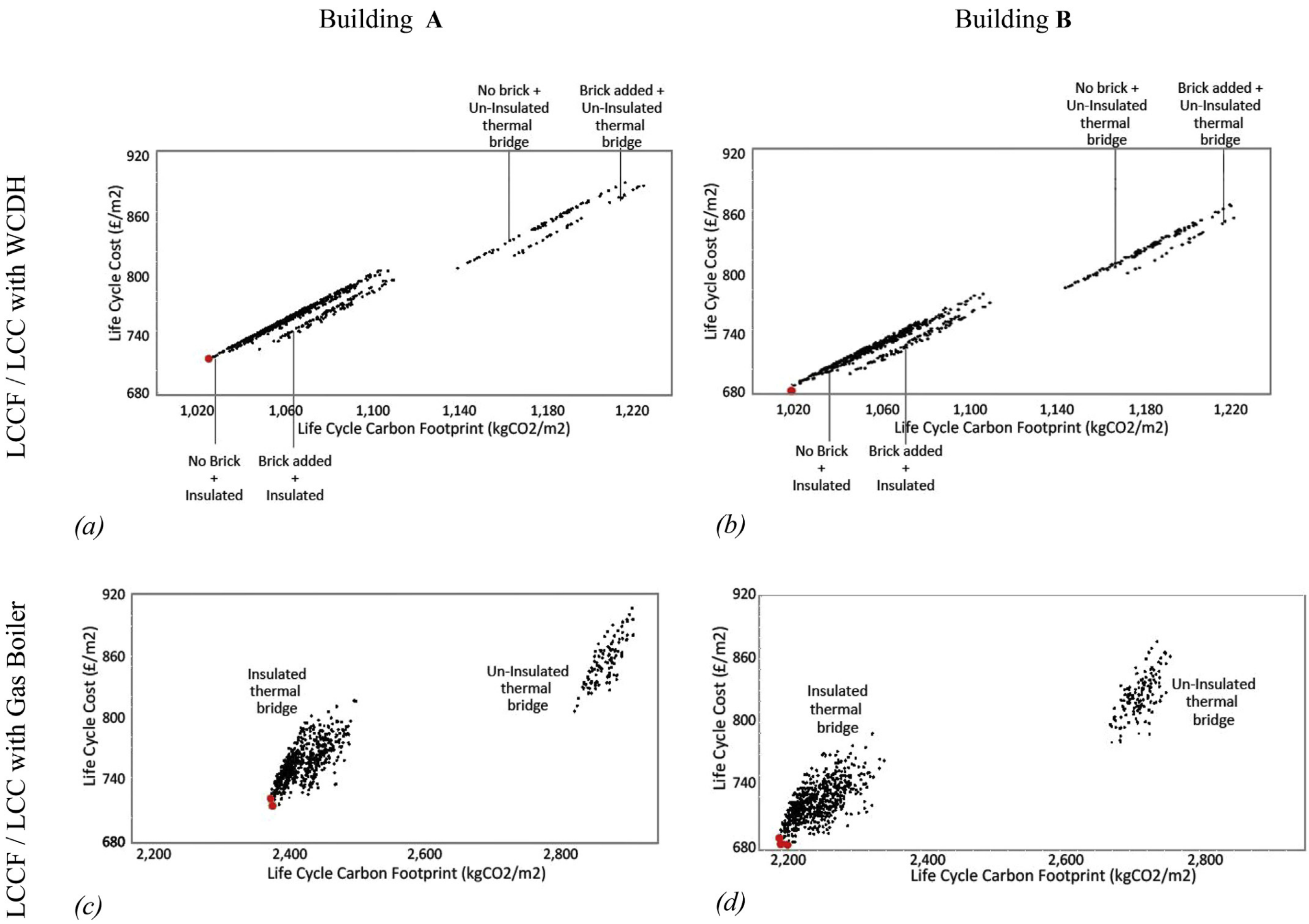


Fig. 6. Natural gas heating system, embodied/operational CO_2 (a, b) LCCF/LCC (c, d).

20 and 30% of the overall LCCF, while in the case of gas boiler it only accounts for around 10%. These results echo previous studies [46,56].

Also, the graphs indicate that insulating the thermal bridge and external walls can achieve a reduction of around 15% OERC values, as a great majority of optimal individuals selected the thickest available insulation for both. None of the optimal individuals used any brick, which suggests that its embodied CO_2 and relatively little contribution to the performance of the buildings did not make it beneficial from a life cycle point of view. As expected, all optimal individuals combined the thickest available insulation with the smallest north-facing windows.

4.2. Original, refurbished and optimal performance

4.2.1. Lifetime use of OERC emissions

The OERC emissions over a period of 60 years of the original non-refurbished building, were compared to the emissions of the original refurbishment and that of the optimal design (Fig. 8). In this section, only the original WCDH was considered as the space and water heating energy source.

The ‘Optimal Refurbishment’ bar in Fig. 8 shows the mean operational-energy related CO_2 emissions of all optimal designs (and not the range of their spread) for clarity reasons: the other 2 bars (‘Non-Refurbished' and 'Original Refurbishment’) do not have any sample as they are singular models.

Results show that the original refurbishment achieves a 13% reduction in operational energy consumption throughout its life compared to the non-refurbished building, while the optimal refurbishment option achieves a reduction of around 29%.

4.2.2. LCCF

Fig. 9 shows the LCCF of the non-refurbished, the original refurbishment and the optimal refurbishment for both buildings. Results show that the original refurbishments emit 20% (or around 200 $kgCO_2/m^2$) more CO_2 than the non-refurbished building. As previous LCCF studies show that EC values of new buildings are between 300 and 700 $kgCO_2/m^2$ [16,57,58], this suggests that the act of refurbishing the building did save a significant amount of CO_2, compared to the option of re-building the blocks. The refurbishment managed to significantly improve the living conditions for occupants, while having minimal CO_2 investments.

Still, the optimal alternative shows that the building could have been refurbished with even lower LCCF – similar values to that of the un-refurbished building.

4.2.3. LCCF breakdown

A breakdown of the LCCF to its different components is shown in Fig. 10. It was assumed that lighting and water heating demands are similar in all cases. Results illustrate that the optimal design for

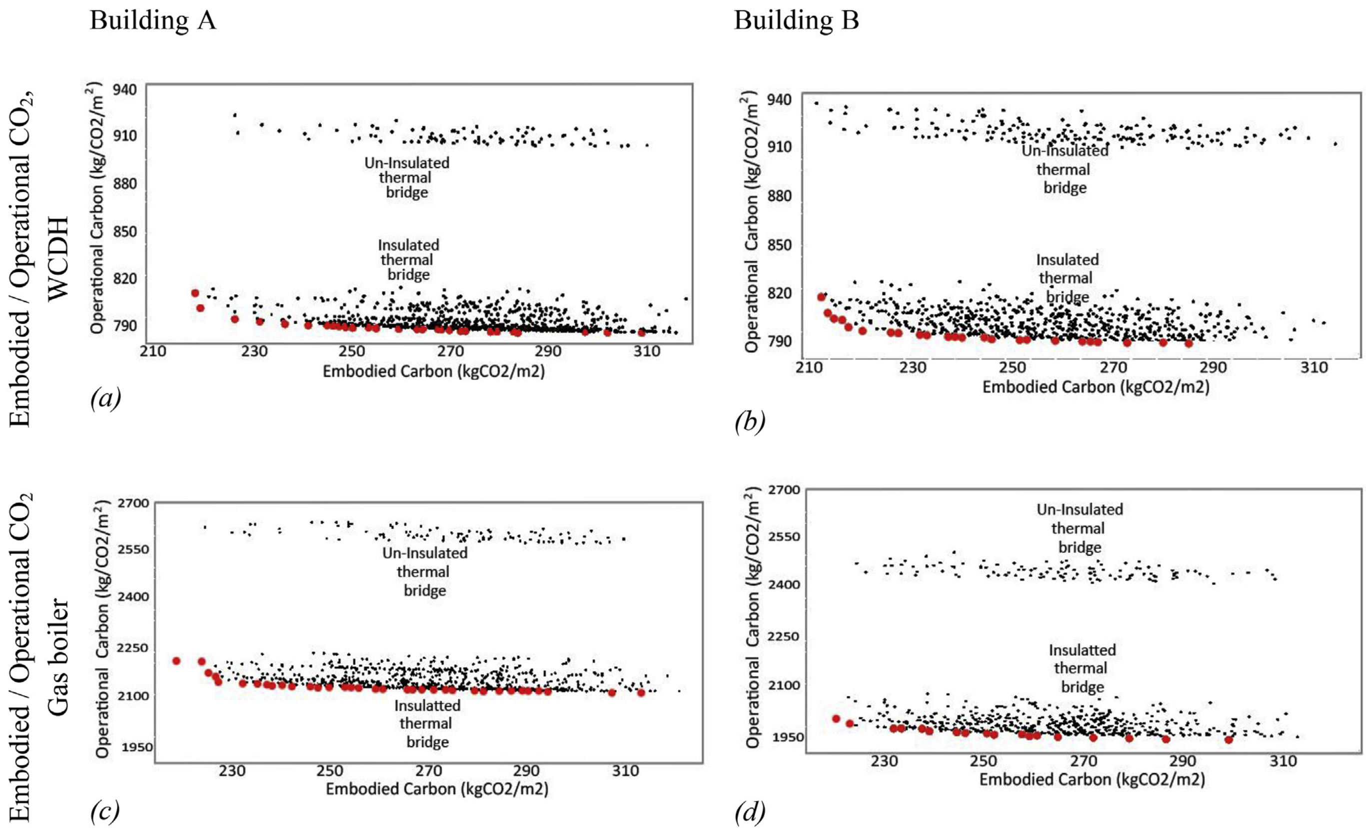


Fig. 7. Waste combustion district heating, embodied/operational CO_2 (a, b) LCCF/LCC (c,d).

both buildings achieves maximum OERC savings with the least additional EC.

Also, results show that energy consumption for space heating in Building A is 16% higher than that of building B. This is due to the fact that Building B is more exposed to solar gains than Building A, which enables solar radiation to passively heat its spaces. As the two buildings have a different mix of spaces facing south (bedrooms/living rooms/corridors etc.), and while the Building A south façade is the windowless "street" floor (every third story), the entire Building B south façade has habitable spaces with windows (bedrooms or living rooms only). This means that spaces behind it gain more solar energy and therefore consume less energy for heating.

4.2.4. CO_2 payback times

CO_2 Payback times have been calculated for the original refurbishments and for the optimized individuals, for both Buildings A and B, under both primary energy source scenarios. Table 7 shows that the payback times for the optimised solutions are much shorter than those of the original refurbishment – around half the time. This verifies that using computational optimisation methods can result with more efficient buildings and significantly reduce the overall environmental impact and costs of buildings.

Additionally, Table 7 implies that the refurbishment of buildings that use WCDH might not be worth the investment, in terms of LCCF, as the payback time in this scenario is very long.

4.3. Examining the impact of orientation on LCCF + LCC

Since results from previous sections have shown that Building B (the one with more south-facing windows and a better potential for passive heating) had lower OERC emissions, a further study was performed to examine the performance of a fully south-facing building.

As south-facing windows allow more solar radiation, it was expected that the LCCF/LCC optimisation would choose individuals

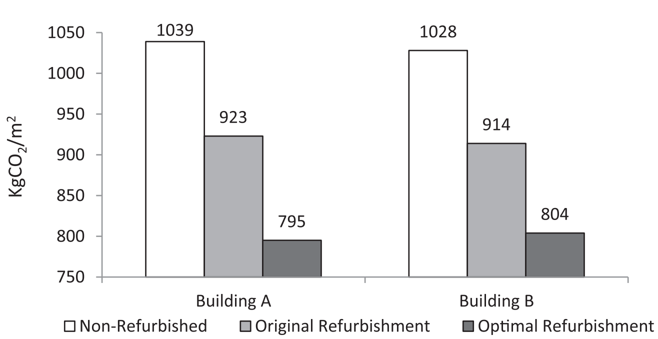


Fig. 8. Comparison of non-refurbished, refurbished and optimal building options: 60-year operational-energy related CO_2 emissions.

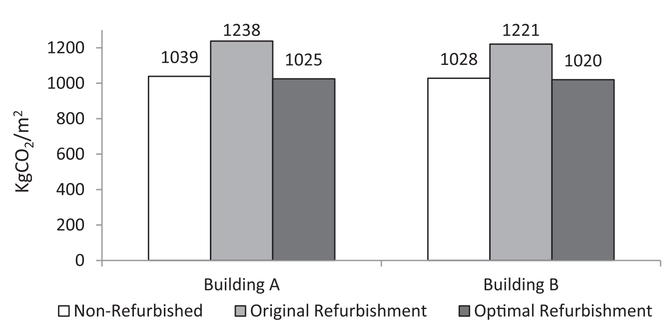


Fig. 9. Non-refurbished, refurbished and optimal buildings – 60 years LCCF.

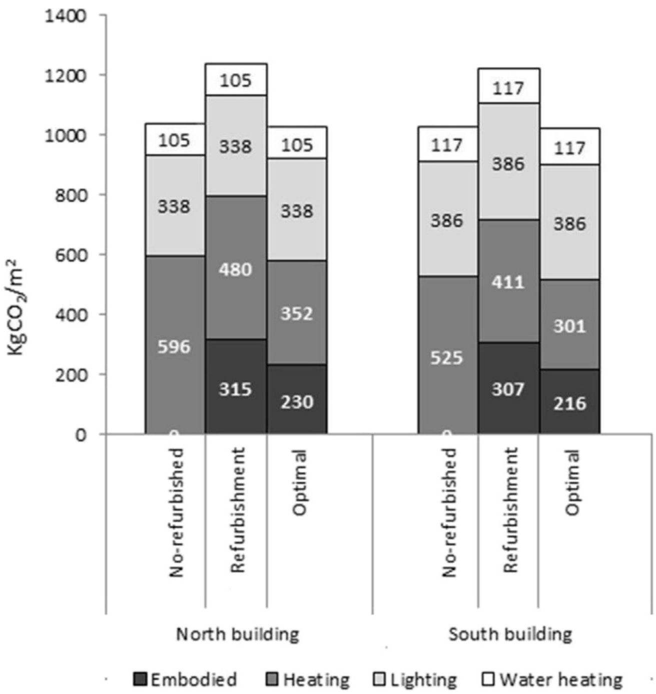


Fig. 10. Non-refurbished, refurbished and optimal buildings – 60 years LCCF breakdown.

with big south-facing windows which will allow solar radiation to get into the building and reduce heating demands, in opposed to that of the previous, non-fully south-facing model. The simulation used natural gas as its primary energy source.

Although a full southern orientation did result in some reduction of both LCCF and LCC compared with the original building's orientation (as shown in Fig. 11a), the optimal individuals still had the smallest available windows (or, minimal EC). This means that the windows EC is still greater than the OERC they can save by letting solar radiation penetrate the building. Windows in buildings are used not only for enabling passive heating in buildings but also for answering other occupants comfort criteria and needs. For example – window can allow occupants a view outside or supply natural daylight to the different spaces in the building, which is considered to contribute to occupant's visual performance and psychological needs [59]. Operable windows can also contribute to occupant's thermal satisfaction and sense of control, as they enables occupants to actively change their environment – allow breeze to cool the building or prevent heat from escaping out [60]. While these are important aspects in façade and window design, this study focused on the potential impact of window-to-wall-ratio on the LCCF and LCC of the examined case study buildings.

Table 7
Original and Optimised solutions CO_2 payback times.

		Optimal solutions		Original refurbishment	
		Building A	Building B	Building A	Building B
Annual energy savings ($kWh/m^2/y$)		70	67	33	32
Waste combustion district heating	Operational related CO_2 savings ($kgCO_2/m^2/y$)	4.1	3.7	1.93	1.9
	payback time (years)	56	58	163	161
Natural gas-based heating system	Operational related CO_2 savings ($kgCO_2/m^2/y$)	14.5	13.6	6.6	6.5
	payback time (years)	15.5	16.0	47	45

4.4. Comparing annual energy consumption with LCCF

As annual energy consumption (kWh/m^2/year) is considered to be the primary goal of current legislation PART L [61], rather than a more comprehensive analysis, such as LCA, a comparison between the optimal design solutions according to the two objectives was carried. For this, a fully southern oriented building (using gas boiler for heating) was simulated, once to minimise LCCF/LCC and once to minimise annual energy consumption and costs ($kWh/m^2/y$ and £/m^2/y).

As expected when using operational energy and running costs as the fitness criteria MOGA selected the individual with the biggest south-facing windows (as passive solar radiation resulted with reduce operational energy and costs), while the LCCF/LCC optimisation selected individuals with the smallest windows for all facades (Fig. 11, Table 8). Also, the optimal building in the case of annual energy consumption used a brick layer, while the LCCF/LCC optimal buildings did not.

These results indicate that one of the most common tests conducted in the industry – annual energy consumption – might actually result in higher life cycle CO_2 emissions.

5. Conclusions

As early design decisions are important in terms of life cycle building performance, this study examined the use of optimisation methods to allow Architects taking more informed decisions in early design. This was done by using NSGA II to optimise the refurbishment measures of a case study building in Sheffield, UK. The study focused on optimising envelope properties in order to reduce the building's whole life environmental impact and cost, as this was the primary design intervention. In analysing the results from the work carried out the following conclusions can be made:

Applicability of using the methodology as a decision making tool in early design stages – Though the study successfully resulted with the optimal design solutions, the integration between the different tools was not at all simple. The fact that four different tools had to be used in the process makes a lot of room for mistakes for an inexperienced user. It is therefore concluded that in order for the methodology to be used in practice, a single tool should be developed with a simple user friendly interface.

Furthermore, although running an optimisation scenario took a reasonable length of time in this study, to avoid extremely long simulation times and save valuable computer resources, some basic understanding of thermal simulation, GA and logic behind it is required.

Original refurbishment – The study showed that the original refurbishment OERC resulted in a significant reduction compared to the non-refurbished building, while its total LCCF has increased. In considering that the complex was deserted prior to its refurbishment, the added emissions are still lower than that of the alternative of demolishing and re-building a new complex.

Optimisation results – The study has shown that MOGA successfully found optimal solutions for the different examined scenarios –the optimal models resulted with the lowest LCCF and LCC values and their CO_2 payback times were significantly better than those of the original refurbishment scheme.

The results under all examined scenarios point to the fact that the optimal models include envelope elements that save more OERC or operational cost then they embody. For example, optimal models had the smallest available windows and did not use brick as an insulating layer, as these elements embody more CO_2 and cost

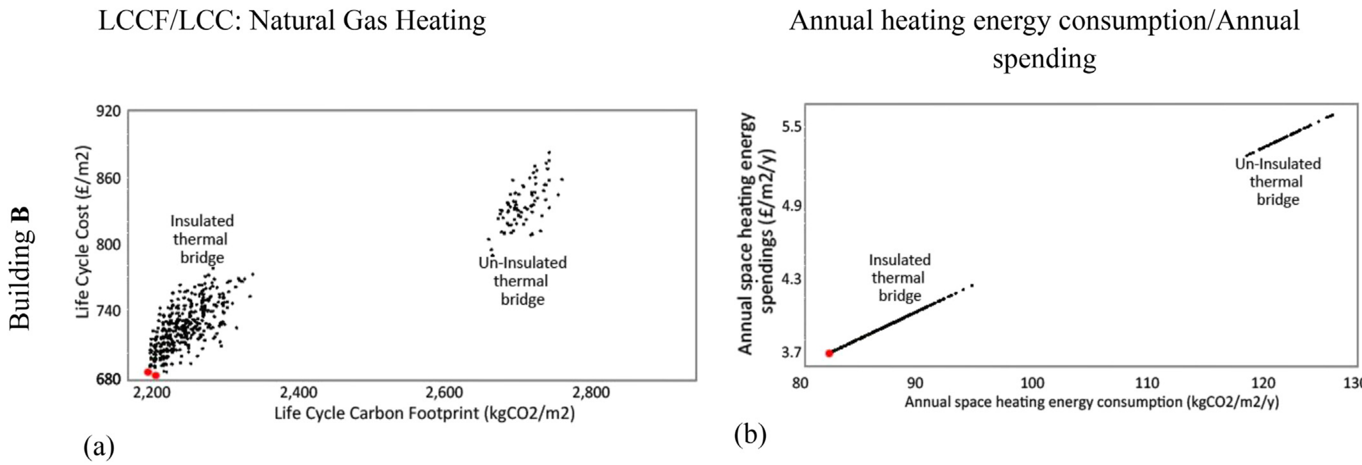
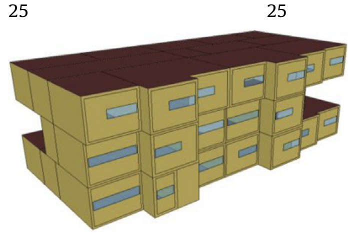
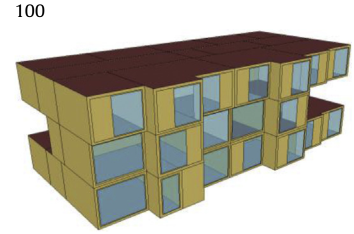
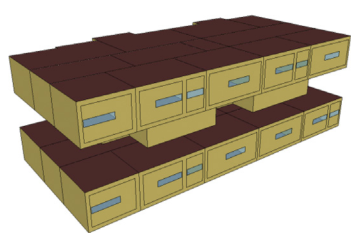
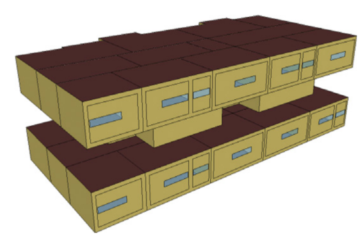


Fig. 11. Fully south-facing building. (a): LCCF/LCC: natural gas heating. (b): Annual heating energy consumption/annual spending.

Table 8
Minimal LCCF and LCC (left) and minimal annual energy consumption (right) optimal buildings.

Building component	LCCF/LCC		Annual heating energy consumption (kWh/m^2/y/£/m^2/y)
	Optimal model A	Optimal model B	Optimal model
Panel + street insulation (cm)	15	15	15
External wall insulation (cm)	15	10	15
Bricks (cm)	0	0	10
Thermal bridges insulation (cm)	10	10	10
North windows (%)	25	25	25
South windows (%)	25	25	100
South façade			
North façade			

more than the OERC or cost they save. The study also examined the impact that primary fuel sources have on LCA, and showed the importance of insulating thermal bridges.

LCCF and Orientation— The study also showed the potential of using the methodology in examining other design aspects. Based on the assumption that a south-facing building with bigger south-facing windows will lead to an increase in the building EC and decrease in its OERC (due to the potential solar gains), the study searched for the optimal design solution of a fully south-facing building.

Results showed, however, that even in the cases of a fully south-facing building with a maximum sun exposure potential, the optimised design had small south-facing windows. This implies that the windows still embody more CO_2 than that they save.

Annual energy consumption vs LCCF Optimisation — The study finally compared the LCA/LCCF optimisation results with other performance-based methods. Results have shown that LCCF analysis led to different design solutions than that of one of the most widely used tests in the industry — that of annual energy consumption: This shows that different analysis methods can lead to different conclusions and effectively have a different impact on the way buildings are designed.

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