Sensitivity of buildings’ carbon footprint to electricity decarbonization: a life cycle–based multi-objective optimization approach

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Abstract

Purpose Life cycle assessment (LCA) is a widely used method for the evaluation of buildings’ environmental impacts, but these analyses contain high levels of uncertainty. Decarbonization of electricity production is key to reach climate goals, influencing all sectors including construction. The objective of this paper is to study the sensitivity of the environmentally optimum building design solution to a changing electricity mix to assist decision-making.

Methods In this paper, multi-objective optimization was applied to minimize the life cycle global warming potential and life cycle costs of a building at the same time, using dynamic energy simulation and LCA. The variables include building envelope parameters such as window ratio, insulation type and thickness in a typical new multi-family apartment building heated with a heat pump. A static, largely fossil-based electricity mix and a dynamic, gradually decarbonizing alternative are considered, as well as two electricity price increase scenarios. New metrics have been introduced to explore the results and describe the Pareto-optimal solutions, for example the improvement potential to contextualize the achievements through the optimization.

Results and discussion The results show that, with the current electricity mix, building envelope optimization can improve the design by 18% on average in terms of the life cycle greenhouse gas emissions compared to typical new designs and by 10% with a dynamic mix in Hungary. With today’s static electricity mix, the optimization proved that the minimum energy efficiency requirements in force are close to cost optimality. However, from an environmental point of view, much higher insulation thicknesses have been shown as justified ($U$-values of less than 0.1 W/m²K).

Conclusions Optimization of building design based on LCA is still not widely applied and the effect of a decarbonizing electricity mix on the optimum has not been studied before. The results of the paper demonstrate the importance of this question. Optimal solutions are different depending on the applied mix but an energy-efficient building envelope remains important: today’s cost-optimal building envelope proves to be both cost- and environmentally optimal in the long run.

Keywords Decarbonization · Electricity · Multi-objective optimization · Life cycle assessment · Life cycle cost · Building

1 Introduction

In 2018, 42% of worldwide CO₂ emissions stemmed from electricity and heat producers (IEA 2021). The reduction potential of power generation is very large with investments into renewable energy and other low-emission sources, such as nuclear power plants and fossil fuel power stations with carbon capture and storage technology (European Commission 2011). Decarbonization of electricity is a key step towards a low-carbon future as it influences the environmental impact of all sectors, including buildings. Besides the electricity consumption of appliances, increasing electrification of space heating and cooling with heat pumps will play a major role (Thomaßen et al. 2021).

There are numerous studies in the literature that evaluate the environmental impacts caused by buildings with the help of the life cycle assessment (LCA) (Nwodo and Anumba 2019). There is also a limited but growing number
of studies that apply optimization algorithms to automatically find building solutions with a minimum life cycle emission (Longo et al. 2019). The reliability of LCA results is highly dependent on how the inherent uncertainty and variability is handled. Uncertainties may relate for example to the construction materials (Hoxha et al. 2017), service lives (Goulouti et al. 2020), modelling options (Häfliger et al. 2017) or user behaviour during the use phase (O’Brien et al. 2020). For the assessment of the operational impacts, the common practice is to convert the final energy consumption into environmental indicators with static, average conversion factors (European Commission-Joint Research Centre-Institute for Environment and Sustainability 2010). With the foreseen decarbonization of electricity, these conversion factors will change dynamically in the near future, yet this effect is seldom considered in building LCA studies (Roux et al. 2016). Decarbonization of electricity will reduce the indirect operational emissions of buildings and shift the balance between the embodied and operational environmental impacts. This will also affect the results of building optimization, as different solutions may prove to be environmentally optimal depending on the conversion factors of the energy source. This question has not been analysed in detail earlier.

This paper aims to investigate the sensitivity of LCA results and the environmentally optimum building design to electricity scenarios with the help of multi-objective optimization. The two objectives are the minimization of life cycle CO₂ emissions expressed in terms of Global Warming Potential (GWP) and the minimization of life cycle costs (LCC). Four distinct electricity scenarios are analysed: a static mix usually applied in life cycle assessment (LCA) studies, a dynamic, gradually decarbonizing mix based on an electricity market model and both combined with two different assumptions for the increase in electricity prices. In addition, the ‘business as usual’ (BAU) new buildings are also assessed using a novel approach to determine the improvement potential achieved by the optimization algorithm. The research is applied to a new residential case study building in Hungary, where the current electricity supply relies heavily on fossil fuels with a GWP above the European average but a significant decarbonization is foreseen in the coming years in line with the European policies.

The paper is organized as follows: Sect. 2 introduces the background and relevant literature on electricity modelling in building life cycle assessment and building optimization studies. Section 3 presents methods for the optimization, energy demand, LCA and LCC calculations and describes the case study building. The optimization results for different electricity scenarios are reported and discussed in Sect. 4. The Pareto front is analysed and new evaluation metrics are introduced for an easier interpretation. The optimal solutions are clustered and visualized and their performance is compared. Finally, Sect. 5 summarizes the conclusions.

2 Background

2.1 Electricity modelling in building LCA

In LCA studies, electricity use in buildings is measured, derived from statistics or calculated with steady-state and dynamic methods. The total annual final electricity demand is then multiplied with life cycle–based emission factors to obtain the impact assessment results. The current approach in building LCA is to apply a static, average national electricity mix. There are only few studies on the effect of electricity modelling on building LCA. For example, in a survey of the Nordic building industry, stakeholders named emission factors for energy sources and electricity as an important knowledge gap in building LCA (Schlanbusch et al. 2016).

Future energy mix scenarios are occasionally explored in a sensitivity analysis in building LCA, but this is still not common practice (Vilches et al. 2016). Among the relevant precedents in the literature, De Wolf et al. (2017) showed that four industry experts out of 12 took grid decarbonization into account when calculating the carbon dioxide equivalent of buildings. Another attempt concerned the present and future Swedish mix for 2035 for electricity and heating when analysing rebuilding vs. new construction of a multifamily house (Erlandsson and Levin 2005). Blom et al. (2011) studied the effect of policy-based and theoretical electricity mix scenarios in a sensitivity analysis of a Dutch apartment dwelling and concluded that changing the environmental impact of the electricity supply may be more effective than changing user habits. In an Austrian residential case study, the impact of future energy scenarios was used among many options to identify the refurbishment scenario with the lowest environmental impact (Passer et al. 2016). It was shown that the environmental benefit of applying photovoltaics will be reduced in the long term with the shift towards renewables in the mix. Rasmussen et al. (2013) took into account the average of the Danish grid mix between 2010 and 2060 in a sensitivity analysis of an office building. In a dynamic LCA study incorporating time-dependent factors, 3 single family houses were analysed with a pessimistic and a very optimistic future energy mix scenario (Fouquet et al. 2015). In the latter scenario, a technological breakthrough is assumed where oil power plants are replaced by gas and coal technologies with Carbon Capture and Storage (CCS). Roux et al. (2016) developed an hourly model to include the long-term evolution of the electricity mix and the effect of climate change on the demand. The results showed a high variation depending on
the long-term scenarios, and the energy mix evolution had a greater influence on the results than climate change showing the relevance of this topic. Vuarnoz et al. (2020) also came to the conclusion that the use of hourly conversion factors has a significant influence on the LCA results.

### 2.2 Environmental optimization of buildings

In mathematical optimization, one or more objective functions are minimized or maximized with respect to some variables. Optimization techniques are increasingly applied to building design, for example to minimize costs and energy demand or maximize thermal comfort (Evins 2013; Kheiri 2018) or the performance of building elements (Nagy 2019). There are studies on the environmental optimization based on LCA but still in a limited number (Longo et al. 2019). In these studies, energy calculation is linked to existing or self-developed LCA modules to find the design options with the lowest environmental impact, usually with a focus on greenhouse gas emissions. The optimal design will be different depending on whether only the operational performance is assessed or also the trade-off between embodied and operational impacts (Pal et al. 2017). In some cases, life cycle costs are also selected as an objective function to find both environmental and cost optima (Sharif and Hammad 2019a; Schmidt and Crawford 2018).

Both new buildings and retrofit designs have been assessed (Hollberg and Ruth 2016; Sharif and Hammad 2019b). For example, Amani and Kiaee (2020) combined energy simulation with DesignBuilder and LCA in SimaPro to rank internal insulation systems for the retrofit of existing buildings with maximum energy saving and minimum environmental impact. Besides residential buildings, non-residential buildings have also been optimized (Azari et al. 2016; Sharif and Hammad 2019a). A new approach is to connect environmental optimization with Building Information Modelling (BIM) (Najjar et al. 2017; Najjar et al. 2019; Shadram and Mukkavaara 2018; Tushar et al. 2021; Abbasi and Noorzai 2020).

Commonly evaluated variables include the insulation material and thickness, glazing and window type, window-to-wall ratio, heating system, heat recovery and lighting system. Mayer et al. (2020) also considered different hybrid renewable energy systems and their components. In rare cases, the building shape is also a variable, for example to maximize solar radiation incidents on the building envelope with a parametric design approach (Lobaccaro et al. 2018; Monteiro et al. 2021).

As seen from the literature review, most LCA studies still apply static, current electricity emissions factors but an increasing number assess the sensitivity of the results to future scenarios as well. LCA-based building optimization is still scarce but gaining in popularity. To the best of the authors’ knowledge, no studies analysed the effect of a decarbonizing electricity mix on the building design optimum considering both life cycle environmental impacts and costs.

### 3 Methodology

The assessment is carried out in an optimization framework developed earlier and described in detail in (Szalay and Kiss 2019; Kiss and Szalay 2020). This framework has been further developed to enable dynamic energy simulation as well as life cycle cost calculations and time-dependent modelling of the environmental impacts of electricity. The electricity scenarios will be tested on a multi-storey representative apartment building, heated with a heat pump.

#### 3.1 Optimization framework

The framework is capable of minimizing the life cycle environmental impact of a building design through automated optimization (Fig. 1). The workflow can be described in three
major steps. (1) Setup: first, an initial simulation model is developed with additional information (construction material names) linked to cost and environmental impact datasets. Design parameters are defined to serve as optimization variables and background data is prepared about the information that is not included in the initial model (environmental data, cost data and material physical data). (2) Optimization: the parametric model definition accumulates the initial model and the design parameters so that the model can be recreated with different parameter values (including geometrical aspects, materials and constructions or heating, ventilation and air conditioning (HVAC) systems). Calculations use this model and the previously linked background data to perform energy demand calculation, extract the bill of quantities and calculate the environmental impact along with the life cycle cost. The result (single-objective) or results (multi-objective case) are used by the optimization module as objectives to define a new set of parameter values (optimization variables). The model is recreated with the new parameters and the loop is continued until a certain stop criterion (e.g. maximum number of loops) is met. (3) Evaluation: in the last step, the optimization results are analysed using different models and data visualizations with regard to the objectives as well as the optimal values of the design parameters. The framework is developed in a modular manner so individual modules can be easily replaced. For example, energy demand can be calculated with a steady-state method or a dynamic simulation and different optimization algorithms can be connected. The framework has been implemented in the Python programming language, combining self-developed components with existing tools (DesignBuilder, EnergyPlus and OpenLCA).

3.2 Case study building

The case study building is a schematic model of a typical multi-storey apartment building located in Hungary. Similar models have been applied by other researchers (for example see (Lavagna et al. 2018; BPIE 2011)). The four-storey building has a total net heated floor area of 768 m² with a ceiling height of 3 m, a central (heated) staircase and no basement. It has a slab-on-ground and a flat roof and the mass is simplified to a rectangular shape (Fig. 2). The reference study period is 50 years for both LCA and LCC, considering the product stage, construction process, the use stage as well as the end-of-life stage.

3.2.1 Materials and constructions

The main composition of the building elements is fixed (Table A1 in the Annex), assuming ceramic block walls with an external thermal insulation composite system (ETICS). Internal slabs and the flat roof have a monolithic reinforced concrete structure. Opaque material properties are summarized in Table A2 (Annex). The internal partition walls are considered as a fixed mass of wall constructions as thermal storage. Other elements not influencing the operational energy demand (e.g. foundation) are not modelled, as these represent a constant impact and hence do

Fig. 2 Illustration of the building model
not influence the optimization results. Windows have two options for glazing (triple or double), and two options for frame material (wooden, plastic) (Table A3 in the Annex). A moveable horizontal aluminium blind is considered as an option for each window, on each façade as separate a variable.

### 3.2.2 Variables

Variables are specific design parameters that are changed by the optimization algorithm. The variables can be classified into three categories: **building envelope** (wall, floor and roof insulation type and thickness, window areas); **fixtures** (shading, glazing type, window frame type) and **HVAC and equipment** (Table 1). Variables in an optimization may be continuous or discrete but, in this case, the continuous design parameters are discretized by defining a sufficiently small step size (1% for fenestration ratio and 1 cm for insulation thickness). The ranges are determined considering physical and engineering limits extended to extreme values (e.g. 80 cm of insulation) to cover theoretical optima too.

In addition to the optimization runs, a Monte Carlo simulation was also performed to define the business as usual (BAU) for new buildings. This will be used to quantify the improvement potential that can be achieved by the optimization algorithm. The parametric building definition is the same as for the optimization case, but the parameter values are characteristic for the current practice. The values have been identified based on Zöld et al. (2012) and are summarized in Table 1. The insulation material thicknesses were defined so that any possible envelope constructions satisfy the current requirements for the $U$-values.

### 3.2.3 HVAC system

The end-uses of space heating, cooling and lighting were considered. Energy use of domestic hot water and appliances is a user-dependent parameter, therefore excluded from the optimization (Zöld and Szalay 2007; Lützkendorf et al. 2015). Lighting is also user-dependent, but it was included since window size is also an optimization variable affecting the lighting energy demand.

The building has a central heating and cooling system with a heat pump with a seasonal efficiency of 3.33 for space heating and 2.8 for space cooling. The modelling of the system is simplified, the energy calculation module calculates the net demand of the systems and the gross demand is calculated from the seasonal efficiency values. Auxiliary power (electricity) is calculated as a percentage of the net demand. Distribution and storage losses are omitted in the model. No mechanical ventilation is used in the building.

### Table 1 Design parameters used as variables of the optimization with their limits and the values representing the BAU case

| Design parameter | Value limits / options | Business As Usual (BAU) values |
|------------------|------------------------|-------------------------------|
| Fenestration ratio | N, W, S, E | 1 - 80 % | 13 - 24 %, 23 - 34 %, 33 - 44 %, 23 - 34 % |
| Glazing type | double / triple | double / triple |
| Shading | yes / no | yes / no |
| Frame type | plastic / wooden | plastic / wooden |
| Roof insulation material thickness | EPS white / EPS graphite / PUR / rock wool | EPS white / EPS graphite / PUR / rock wool |
| Wall insulation material thickness | EPS white / EPS graphite / PUR / rock wool / wood wool / ICB | EPS white / EPS graphite / rock wool |
| Floor insulation material thickness | 1 - 80 cm | 4 - 10 cm |
3.3 Energy demand calculation

The energy demand (heating, cooling, lights) is calculated with dynamic energy simulation based on EnergyPlus v8.9.0 (National Renewable Energy Laboratory 2018) and DesignBuilder v6.1.0 (DesignBuilder Software Ltd. 2019). Each storey is modelled as one zone, as multi-zone modelling would significantly increase the optimization time. This is a simplification, but as the goal is to determine the energy demand of the whole building and not of individual spaces and the setpoint temperatures are the same in the rooms and they are supplied by the same service systems, this is acceptable (Klimczak et al. 2018; EN ISO 52016 2017; EnergyPlus Documentation 2018). Thermal mass is modelled accurately as internal slabs and the mass of internal walls was included in the model.

The simulation was made for the Budapest climate. The climate file was downloaded from the TMY tool of the PVGIS system with the following parameters: Latitude: 47.43; longitude: 19.182; period: 2007–2016 (Huld et al. 2012). Thermal bridges were omitted in the calculation because of the simplified simulation model. No external shading obstacles were assumed.

Fixed simulation parameters and schedules are summarized in Table A4 (Annex) for each HVAC system and activity. User behaviour was out of the scope of this study, and default DesignBuilder profiles were applied harmonized with the ‘standard user’ according to the Hungarian energy regulation (TNM 2006). This means a fixed rate of internal gains of 4.7 W/m², and a minimum continuous air change rate of 0.5 l/h. In the summer, when natural cooling is possible (during night), a higher, 4.0 l/h air change rate was assumed for cross-ventilation of the building.

3.4 Life cycle assessment (LCA) calculation

The environmental impacts are calculated with the standardized Life Cycle Assessment methodology according to the general standards (ISO 14040 2006) and the standard for buildings (EN 15978 2011). The functional equivalent is the apartment building for a study period of 50 years.

In LCA studies of buildings, environmental data for materials and products taken from generic databases or Environmental Product Declarations (EPD) are aggregated to calculate the embodied impacts (EN 15978 2011). In this study, the widely used and renowned database, ecoinvent v3.6, was applied to generate the required LCIA data (Wernet et al. 2016). The generic datasets contained in ecoinvent are location-specific, which means they are valid only in a specific region/country. In order to create localized datasets, a localization process is used for the products primarily produced in Hungary. This localization is achieved by changing the electricity and gas providers in the product system from the original location to a specific for the new location (see Table A5 in the Annex for the localized GWP value of the applied materials).

The following life cycle stages are considered: product stages (A1–3), transport and construction process (A4–5), use stage (B2–B4 and B6 operational energy use) and end-of-life (C2–C4). Other modules are not considered either because they are expected to have little impact on the final environmental performance or data availability is low. The optional Module D was not considered. To account for transport from the factory to the construction site, building materials were classified into four transport categories based on the number and location of the factories in Hungary, and standard distances were applied in the background database. For the construction phase, very little information is available; hence, only the cutting of waste was accounted for (Kellenberger and Althaus 2009). Reference service life data is used to calculate regular maintenance and replacements of building components (EN 15978 2011; BBS 2009); see Table A6 in the Annex. In the case that a material has lower estimated service life (ESL) than the reference study period (RSP) of the building, the materials need to be replaced. The number of replacements is calculated with the floor division of ESL/RSP for each material and system (EN 15978 2011). The values were modified in some cases depending on the position of the material in the building element, for example underground bitumen membranes were not exchanged. In the end-of-life phase, the most probable scenario for reuse/recycling/disposal was taken into account. The basic assumptions were that wood and plastics are incinerated, minerals are landfilled and metals are recycled. The transportation of waste (C2) was calculated using a standard distance of 30 km.

The LCIA data for each stage of materials or systems can be expressed on a per kg, m², m³ or piece basis. Within the calculation, the unitized impact is always multiplied with the amount depending on the available LCIA data, calculated from the building model automatically. For example, for the production stage:

\[
I_p = \bar{I}_m \cdot a_m
\]

where

- \(I_p\) is the production impact of the material or system,
- \(\bar{I}_m\) is the unit impact of the material or system included in the LCIA database,
- \(a_m\) is the weight/area/volume/number of the material or system used in the model.

Apart from the electricity in the dynamic scenarios, impact data was assumed to be constant during the lifetime of the
building. The impact assessment method of CML 2001, Climate Change—Global Warming Potential (GWP 100a) was applied. While this paper focuses only on a single issue, in a previous study, other environmental indicators were also analysed (Kiss and Szalay 2020). This study showed that not all environmental impact categories are conflicting; hence, it is acceptable to focus on a limited number of categories. GWP and cost proved to be conflicting in a preliminary analysis, hence suitable for multi-objective optimization.

### 3.5 Life cycle cost (LCC) calculation

Life cycle cost calculations are carried out in line with the European calculation procedures (EN 15459 2017; EU 2012). The structure and methodology of the LCC calculation are very similar to the LCA calculation. Life cycle cost, also referred to as global costs, is the sum of the costs during the life cycle of the building (initial investment costs, running costs, replacement costs and disposal costs if applicable), referred to the starting year and expressed as present value:

\[
C_g(\tau) = C_I + \sum_j \left[ \sum_{i=1}^{T} (C_a(j) \cdot R_d(i)) - V_{f,j}(\tau) \right]
\]

where
- \(\tau\) is the calculation period;
- \(C_I\) initial investment costs for measure or set of measures \(j\);
- \(C_a(j)\) annual cost during year \(i\) for measure or set of measures \(j\);
- \(V_{f,j}(\tau)\) residual value of measure or set of measures \(j\) at the end of the calculation period (discounted to the starting year);
- \(R_d(i)\) discount factor for year \(i\) based on discount rate \(r\).

Since construction costs are very dependent on the actual economic situation, the best option is to rely on up-to-date statistical data. Therefore, the cost data was collected from an annually published database of manufacturer-specific and average construction costs (HUNGINVEST 2019). For materials that were not available, manufacturer and market values were compiled. Installation costs are based on standard hourly wages in the construction sector specific to different worker types, and the standard installation time is extracted from the online construction budgeting platform TERC (TERC 2020). Energy prices are based on EUROSTAT statistics for electricity (EUROSTAT 2020). All prices are consumer prices and include local VAT (27% in the Hungarian context), and are expressed in EUR, with an exchange rate of 330 HUF/EUR. The background data on cost can be found in Table A6 (Annex). A discount rate of 3% is applied for all cost items (EU 2012).

### 3.6 Optimization

Heuristic techniques prove to be a good option for building optimization that utilize many different steps during the calculation of the objective function (Longo et al. 2019). The major advantage of these techniques is that nothing other than the numeric value of the objectives is needed for the evaluation of the solution and any type of numeric parameter (continuous or discrete) can be optimized. This makes them appropriate for such “black-box” optimizations as presented in this paper where the evaluation of a solution includes a simulation. Also, Nguyen et al. (2014) identified that stochastic population-based algorithms (evolutionary algorithms, genetic algorithms, particle swarm optimization and hybrid algorithms) are the most frequently used for building performance optimizations. One disadvantage of such “black-box” techniques is that the variables cannot be directly explained in the fitness function, and consequences can be derived only implicitly. Another disadvantage of these techniques is that the entire solution space is not evaluated; therefore, a global optimum is not guaranteed. However, if the purpose of the optimization is to support decision-making and to improve building design, this is not a problem if a “good enough” solution or a range of such solutions can be determined by the algorithm. Also, if the optimized variables are meaningful from the engineering perspective, they can be directly adopted in design solutions. Based on the above considerations, the NSGA-II (Deb et al. 2002) genetic algorithm was used in this research for the optimization of the building design. Since NSGA-II is a multi-objective optimization algorithm, its fitness function takes the objective values (in this case the GWP and LCC) as arguments to derive the fitness. One of the advantages of NSGA-II is that the Pareto-optimal solutions are well distributed along the Pareto front thanks to the consideration of the so-called “crowding distance” within the fitness function (Deb et al. 2002). The settings of the algorithm are summarized in Table 2. An important feature of the above-defined model is that any combination of the variables (within the defined ranges in Table 1) corresponds to a valid design, so no other constraints need to be set to the optimization.

| Setting                          | Single-objective | Multi-objective |
|---------------------------------|------------------|-----------------|
| Population size                 | 100              | 100             |
| Max population number           | 30               | 50              |
| Crossover probability           | 0.6              | 0.6             |
| Mutation probability            | 0.2              | 0.2             |
| Number of evaluations           | 6000             | 10000           |
3.7 Electricity scenarios

For the assessment of decarbonization, two different electricity scenarios were used:

- The default Hungarian low-voltage electricity mix contained in the ecoinvent database v3.6 (Wernet et al. 2016), which relies on statistical data and does not change over time (the same GWP value is assumed during the whole reference study period (RSP)). This scenario represents the usual practice in LCA and is referred to as static in the following.

- The “Decarbon” scenario targets an emission reduction of 94% for 2050—compared to 1990 emission levels—in line with the long-term indicative EU emission reduction goals for the electricity sector as a whole (European Commission 2011). This scenario was developed in the South East Europe Electricity Roadmap (SEERMAP) project (Szabó et al. 2017). The projection was carried out by the interaction of the European Electricity Market Model (EEMM) and the Green-X model (Capros et al. 2014; Mezősi and Szabó 2016), and life cycle–based emission factors were calculated until 2050 (Kiss et al. 2020). No further changes are assumed after 2050 (until the end of the RSP). This scenario is referenced as dynamic in the following.

Figure 3 compares the evolution of the GWP of 1 kWh grid electricity in the two scenarios. There is a significant difference in GWP already at the beginning of the analysis period because of the different data sources for the share of each technology. The ecoinvent dataset is based on statistics from the year 2016, while the modelled period in the EEMM starts in 2018 and there are significant improvements until 2020. Moreover, there is a major decrease in the GWP in the dynamic scenario due to the fulfilment of the emission reduction goals by 2050.

For the electricity price increase, two scenarios are established as well (Fig. 4):

- Three percent yearly price increase. This is a moderate assumption considering no radical change in the energy sector. Applying the 3% discounting rate together with the price increase results in a constant discounted price over the analysis period.

- Zero percent price increase. This is an extreme assumption considering that the production of renewable energy is very cheap (after the initial investment is made).

The decarbonization and the price increase options are combined to produce four distinct scenarios:

- Static mix, 3% price electricity increase
- Dynamic mix, 3% electricity price increase
- Static mix, 0% electricity price increase
- Dynamic mix, 0% electricity price increase

4 Results and discussion

The objective of the optimization is to minimize both life cycle global warming potential and life cycle costs. Four electricity scenarios were considered with static or dynamic mix and 3% or 0% electricity price increase for heat pump space heating and cooling.

For all options, three optimization runs were initiated: one multi-objective with a limit of 10,000 function evaluations and two single-objective runs, with a limit of 6000 function evaluations each. In addition, a Monte Carlo simulation was conducted for the BAU case with a limit of 5000 evaluations.
4.1 Analysis of the Pareto front

The optimization results in a set of non-dominated Pareto-optimal solutions. However, in engineering problems, some of the dominated solutions located near the Pareto front may also be interesting as their performance is only slightly lower than that of the optimal solutions (Hester et al. 2018). These near-optimum solutions were also included based on an approx. 1% relative limit in impact and cost. In other words, solutions that have 1% higher GWP or LCC than those of the Pareto front are also considered. This way, the number of admissible solutions increases from 1–2000 to around 9000. The term ‘optimal’ will henceforth include both the non-dominated and the near-optimal solutions.

Figure 5 shows the results of the four cases in the objective space. An average reduction of 25–26% can be observed in GWP when dynamic electricity mix is compared to the static mix. On the other hand, a relatively low, 1.5–3% difference occurs in the LCC of the optimal solutions if the price increase rate changes from 3 to 0% because running costs are relatively low in the whole life cycle. As expected, the cost-optimal solutions deliver the same LCC as their pairs with the same energy price increase rate because the electricity mix decarbonization only affects the GWP objective. The same situation applies vice versa, there is no difference between the GWP-optimal solutions with the same electricity mix scenario.

To better describe the optimal solutions, some new metrics have been introduced (Table 3). The improvement potential (IP) describes the improvement in the objective values compared to a reference. The reference is defined here as the mean of the BAU new building set calculated with a Monte Carlo simulation. The relative improvement potential (rIP) is expressed in a percentage of the reference (mean of the BAU). The maximum relative improvement potential (rIPmax) in terms of GWP is higher (18%) if the static mix is used and lower (10%) in the case of dynamic mix because the mean GWP of the BAU case is also significantly reduced when the dynamic mix is applied. The absolute improvement potential corresponds to 127
Table 3 Indicators describing the Pareto front

|                          | Static, 3% | Static, 0% | Dynamic, 3% | Dynamic, 0% |
|--------------------------|------------|------------|-------------|-------------|
|                         | GWP        | LCC        | GWP         | LCC         | GWP         | LCC         | GWP         | LCC         |
| Maximum improvement potential | rIP_{max}  | 18%        | 13%         | 10%         | 13%         | 10%         | 13%         |
| Minimum improvement potential | rIP_{min}  | 10%        | −11%        | 8%          | 6%          | 7%          | 5%          |
| Absolute improvement potential | IP_{max}   | 127,333 kg CO2-eq | 114,446 EUR | 127,241 kg CO2-eq | 110,950 EUR | 46,615 kg CO2-eq | 114,432 EUR | 46,640 kg CO2-eq | 110,950 EUR |
| Improvement potential of the trade-off solution | rIP_{DI_{min}} | 15%        | 12%         | 9%          | 12%         | 9%          | 12%         |
| Minimum distance to ideal point | DI_{min}   | 0.20       | 0.23        | 0.09        | 0.11        |

The preference between the objectives. Adapting the naming convention used by Vallet et al. (2018) and Luukkanen et al. (2012), these shall be called ‘synergy’ variables. For numerical variables <5% in standard deviation and for categorical variables >80% in occurrence within the near-optimal solutions, the standard deviation in the case of numeric variables and the most often occurring value for categorical variables. Variables whose optimal values depend on the preference between the objectives will be called ‘trade-off’ variables (yellow background in Table 4). Finally, variables that do not have an effect on the optimal results will be called ‘neutral’ variables (white background in Table 4).

4.2 Optimal solutions

After describing the Pareto front in general, the optimal solutions are evaluated in more detail. Some variables take similar values within all optimal solutions, regardless of the preference between the objectives. Adapting the naming convention used by Vallet et al. (2018) and Luukkanen et al. (2012), these shall be called ‘synergy’ variables. For numerical variables <5% in standard deviation and for categorical variables >80% in occurrence within the near-optimal solutions, the standard deviation in the case of numeric variables and the most often occurring value for categorical variables. Variables whose optimal values depend on the preference between the objectives will be called ‘trade-off’ variables (yellow background in Table 4). Finally, variables that do not have an effect on the optimal results will be called ‘neutral’ variables (white background in Table 4).

Fenestration ratio on the South façade depends on the preference between LCC and GWP for a static mix but is a synergy variable in the case of a dynamic mix, with values of 23 ± 3% and 22 ± 4% in case of 3% or 0% energy price increase, respectively. In the static scenarios, triple glazing is preferred on the South façade, while in the dynamic scenarios, it is double glazing. In most of the optimal solutions, no shading is required. Within the optimized solutions, the windows are minimized on the North, West, and East façades; therefore, variables regarding glazing type and shading on these façades are neutral.

Variables relating to insulation material and thickness are mostly trade-off variables with the static mix, but the insulation thicknesses are very homogenous if a dynamic mix is used. In conclusion, if the electricity mix is decarbonized, optimal insulation thicknesses can be established (17 ± 3 cm and 18 ± 3 cm on flat roof, 14 ± 3 cm and 15 ± 4 cm on wall and 4 ± 2 cm and 3 ± 2 cm on the floor to ground) regardless of the preference between GWP an LCC, for 3% and 0% electricity price increase, respectively. Please note that insulation thickness is shown in this section for an easier visualization of the results, but as the thermal conductivity of materials varies, U-values are also calculated in Sect. 4.2.5.
Those categorical trade-off variables that cause a significant shift along the Pareto front are called ‘distinguishing’ categorical variables (red borders in Table 4). These are used to group the optimal solutions into clusters in the objective space. Within these clusters, the trade-off variables show little variation, so we can express the properties of the cluster with the average variable values. The separation of clusters can be easily justified visually in the objective space.

In the static scenarios, almost all variables that influence the energy performance of the envelope need to be used as a distinguishing variable. On the other hand, in the case of a dynamic mix, only the insulation and window frame materials are responsible for the position on the Pareto front. In other words, the design question is simplified to a trade-off between the cost and GWP values of some materials. In the following sections, the clusters are analysed in the four scenarios.

### 4.2.1 Static electricity mix, 3% electricity price increase

Table 5 summarizes the characteristics of the established clusters in the first scenario. The tendency is that moving towards the GWP-optimal end requires additional insulation thickness (up to an extreme of 47 cm on the wall and 32 cm on the roof) and a change to a less impacting material (wood wool on the wall). In terms of the best fenestration ratio, an increase up to 63% is observed. The increasing glazed area implies the application of shading to avoid unnecessary cooling demand. Also, the less impacting wooden frame tends to be applied. On the cost-optimal end, double glazed and smaller windows (20%) are applied without any shading and with a plastic frame. The table also shows the share of the embodied and operational impacts. Although the assessment does not include all building elements, this indicator shows how the ratio is changing when moving from LCC-optimal solutions towards GWP-optimal solutions, and when expressed in GWP or LCC. While the share of operational GWP as well as operational LCC decreases towards the GWP-optimal solutions (as a result of the increased energy performance of the envelope), the savings in GWP are much more significant than in LCC. This illustrates the observation that an increased energy performance shifts the emphasis from the operational to the embodied GWP and LCC. However, an extreme level is only beneficial from the environmental point of view (GWP), because the potential savings in operational impact share a more significant portion in the life cycle than for LCC. This effect is one of the keys in understanding the trade-off between GWP and LCC within the optimized solutions.

### 4.2.2 Static electricity mix, 0% electricity price increase

Table 6 shows the characteristics of the clusters for the static mix and 0% electricity price increase. The tendencies are similar to the first case. The insulation thickness values are somewhat higher in some groups than in the 3% case but mostly because other materials with higher thermal conductivity are preferred (wood wool at the GWP-optimal end and EPS white).
The reduction of the energy price increase to 0% results in an even lower energy efficiency at the LCC-optimal solutions than in the previous case (double glazing, white EPS insulation, 14 cm on the roof, 9 cm on the wall and 2 cm on the floor). Consequently, the net heating energy demand increases from about 24 kWh/m²/year to 29 kWh/m²/year. This increase in the operational energy use is responsible for the higher share of operational GWP, as well as a lower \( rIP\) (7% instead of 11%) in GWP in the LCC-optimal solutions. Although more energy is used during the operation of the

### Table 5: Characteristics of the clusters in the static electricity mix, 3% electricity price increase scenario

| Graphical representation | Parameters | Pareto position | GWP share and improvement potential | LCC share and improvement potential |
|--------------------------|------------|----------------|-------------------------------------|------------------------------------|
| Roof                     | 32 ± 2 cm  | EPS graphite (99%) | ![Diagram](image1)                  | ![Diagram](image2)                 |
| Wall                     | 47 ± 3 cm  | wood wool (100%)   | ![Diagram](image3)                  | ![Diagram](image4)                 |
| Floor                    | 17 ± 2 cm  | EPS graphite (55%) | ![Diagram](image5)                  | ![Diagram](image6)                 |
| Fenestration             | 63 ± 2 %   | wooden frame       | ![Diagram](image7)                  | ![Diagram](image8)                 |
| Glazing                  | triple     | shaded             | ![Diagram](image9)                  | ![Diagram](image10)                |

| Roof                     | 27 ± 1 cm  | EPS graphite (90%) | ![Diagram](image11)                  | ![Diagram](image12)                 |
| Wall                     | 23 ± 2 cm  | EPS graphite (99%) | ![Diagram](image13)                  | ![Diagram](image14)                 |
| Floor                    | 10 ± 4 cm  | EPS white (61%)    | ![Diagram](image15)                  | ![Diagram](image16)                 |
| Fenestration             | 39 ± 2 %   | wooden frame       | ![Diagram](image17)                  | ![Diagram](image18)                 |
| Glazing                  | triple     | shaded             | ![Diagram](image19)                  | ![Diagram](image20)                 |

| Roof                     | 26 ± 2 cm  | EPS white (52%)    | ![Diagram](image21)                  | ![Diagram](image22)                 |
| Wall                     | 22 ± 3 cm  | EPS graphite (86%) | ![Diagram](image23)                  | ![Diagram](image24)                 |
| Floor                    | 11 ± 4 cm  | EPS white (76%)    | ![Diagram](image25)                  | ![Diagram](image26)                 |
| Fenestration             | 32 ± 3 %   | wooden frame       | ![Diagram](image27)                  | ![Diagram](image28)                 |
| Glazing                  | triple     | not shaded         | ![Diagram](image29)                  | ![Diagram](image30)                 |

| Roof                     | 25 ± 2 cm  | EPS white (81%)    | ![Diagram](image31)                  | ![Diagram](image32)                 |
| Wall                     | 19 ± 4 cm  | EPS graphite (82%) | ![Diagram](image33)                  | ![Diagram](image34)                 |
| Floor                    | 8 ± 4 cm   | EPS white (79%)    | ![Diagram](image35)                  | ![Diagram](image36)                 |
| Fenestration             | 30 ± 3 %   | plastic frame      | ![Diagram](image37)                  | ![Diagram](image38)                 |
| Glazing                  | triple     | not shaded         | ![Diagram](image39)                  | ![Diagram](image40)                 |

| Roof                     | 20 ± 3 cm  | EPS white (92%)    | ![Diagram](image41)                  | ![Diagram](image42)                 |
| Wall                     | 15 ± 3 cm  | EPS white (87%)    | ![Diagram](image43)                  | ![Diagram](image44)                 |
| Floor                    | 3 ± 1 cm   | EPS white (92%)    | ![Diagram](image45)                  | ![Diagram](image46)                 |
| Fenestration             | 20 ± 4 %   | plastic frame      | ![Diagram](image47)                  | ![Diagram](image48)                 |
| Glazing                  | double     | not shaded         | ![Diagram](image49)                  | ![Diagram](image50)                 |

The graphical representations show the distribution of energy use and environmental impacts across the different materials and configurations. The Pareto position diagrams illustrate the trade-offs between LCC and GWP, highlighting the optimal trade-offs for different scenarios.
building, the share of operational costs is lower than with higher energy prices.

4.2.3 Dynamic electricity mix, 3% electricity price increase

The results of the scenarios with a dynamic, decarbonized electricity mix show a lower energy efficiency than the previous cases (Table 7). This means an insulation thickness of 17–18 cm on the roof, 13–19 cm on the wall and 3–6 cm on the floor. Some of these values would not fulfill the current requirements of the building energy regulation but they are close to the required values. In all cases, double glazing is used. The main difference between the clusters is the different material usage. On the GWP-optimal end, low-emission materials are preferred (wood
wool and wooden window frame), in contrast to the less costly ones (white EPS and plastic frame) dominating on the LCC-optimal end. There is a slight decrease in the fenestration ratio when moving towards the LCC-optimal end (from 28 to 22%). It is important to mention that, in spite of the absence of shading on the windows, the net cooling energy is kept at a low level (3–4 kWh/m²year) because of the moderate fenestration ratio. A significant reduction can be observed in the share of operational GWP compared to the static case, although the energy efficiency of the envelope is much lower in the dynamic case. This reflects the large difference between the static and the dynamic scenarios in the GWP of the electricity mix. With the reduced GWP of the electricity, the additional energy performance (with additional embodied impact) becomes less beneficial also from the environmental point of view. The share between embodied and operational GWP is much closer to the shares in LCC, which results in less contradiction between GWP and LCC within the optimized solutions.

### 4.2.4 Dynamic electricity mix, 0% electricity price increase

Table 8 summarizes the characteristics of the optimal solutions in the case of dynamic mix, 0% price increase. The difference to the previous scenario is practically negligible. There is a slight decrease in the share of operational cost due to the lack of energy price increase, and the fenestration ratios are smaller by 2–3%.

### 4.2.5 Comparison of energy performance characteristics

Since only minor differences are observed between the different cases in terms of energy price increase, in the following comparison, only the two cases with 3% price increase are included. To compare the two scenarios, only selected solutions are presented from each optimal set. In addition to the **GWP-optimal** and the **LCC-optimal** ones, the solution at **DI_{min}** is also depicted. This can be called the **trade-off solution**, which balances the environmental and economic impacts more closely than the other two solutions.
which represents a balanced choice considering the improvement potential in both objectives. The net energy demand of heating, cooling and lights, as well as the $U$-values, are calculated and presented in Table 9. For the slab-on-ground, along with the $U$-value of the construction, the equivalent $U$-value is depicted which includes the effect of ground, calculated according to EN ISO 13370.

Since the electricity mix decarbonization affects the GWP only, the **LCC-optimal solutions** are the same in both cases. The insulation thickness and the $U$-values are closer to current regulations (0.20 W/m$^2$K on the roof, 0.19 W/m$^2$K on the wall and 0.30 W/m$^2$K-eq. on the floor); however, the roof is not compliant with the current regulation (0.17 W/m$^2$K) (TNM 2006).

The **GWP-optimal solutions** are similar regarding material use (wood wool insulation on the wall, graphite EPS elsewhere and wooden window frame) but differ significantly in the energy efficiency levels. While in the static scenario $U$-values are much lower (0.09 W/m$^2$K on the flat roof, 0.08 W/m$^2$K on the wall and 0.13 W/m$^2$K-eq. on the floor) and the insulation thicknesses are extreme, in the dynamic scenario, the thicknesses are more compatible with the usual values (0.17 W/m$^2$K on the flat roof, 0.13 W/m$^2$K on the wall and 0.29 W/m$^2$K-eq. on the floor). This aspect is also reflected in the net heating energy demand. In the dynamic scenario, the GWP-optimal solution needs about twice as much energy for heating as in the static scenario (20.25 kWh/m$^2$year vs 11.92 kWh/m$^2$year).

Even though the **trade-off solutions** are closer to each other in terms of variables, a similar trend can be observed (lower insulation level and higher energy demand for a dynamic mix). The $U$-values are 0.19 W/m$^2$K, 0.18 W/m$^2$K and 0.17 W/m$^2$K-eq. on the flat roof, wall and floor, respectively, and the corresponding net heating energy demand is
23.3 kWh/m²/year in the dynamic scenario. In the static scenario, white EPS and triple glazing is preferred, but in the dynamic scenario, graphite EPS and double glazing is used instead. Both cases result in a wooden frame in the trade-off solution. The relative improvement potentials of the trade-off solutions are not much less than the achievable maximum (the single-objective optima) in both cases. In the dynamic case, less than 1% needs to be sacrificed from the \( rI_P^\text{max} \) in both objectives to arrive at a feasible trade-off solution. In all cases, the net cooling and lighting energy demand is relatively low and is less influenced by the variables.

In the analysis of Hester et al. (2018), similar thermal transmittance values (0.1–0.16 W/m²K for the wall and 0.09–0.23 W/m²K for the roof) were found in the quasi-optimal range in a life cycle impacts and costs optimization for Chicago. They also showed that the window-to-wall ratio was one of the critical factors.

The results are in line with the findings of Landuyt et al. (2021) who also concluded that the optimal insulation thickness is very much affected by the choice of the energy mix and the thickness reduces when an electricity mix with a lower environmental impact is considered for Belgium. The choice of the heating energy source may be more significant than the envelope performance in some cases (Galimshina et al. 2021).

### 4.3 Investment strategies

Although electricity mix decarbonization cannot be influenced by the building owner or investor, viewing this aspect from the policy-making perspective raises the question to what extent it is better to improve the energy performance of buildings or to invest more into the decarbonization of the electricity production in order to achieve a low-carbon building sector. To elaborate on this question, the results of the BAU case can be compared with a decarbonized mix and the optimized solutions with the static mix (Fig. 6). Without decarbonization, the maximum reduction of GWP is 18%, albeit with an increased life cycle cost. However, even at the LCC-optimal end, GWP can still be significantly reduced (with at least 10%) and at the same time, LCC can be reduced by up to 13%.

On the other hand, if the decarbonization of the electricity mix is fulfilled but the building envelope is not optimized, then the reduction in GWP is 30% in average, with no change in LCC. If building optimization is carried out in

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**Table 9** Net heating, cooling and lighting energy demand and \( U \)-values of the GWP-optimal, trade-off and LCC-optimal solutions for the static and dynamic mix, 3% price increase scenarios \((U_{\text{floor}}^* = \text{equivalent } U\text{-value according to EN ISO 13370})\)

| Static mix, 3% price increase | Dynamic mix, 3% price increase |
|-------------------------------|---------------------------------|
| Q heating \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q heating \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 11.92 | 20.25 |
| Q cooling \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q cooling \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 4.44 | 4.42 |
| Q lighting \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q lighting \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 2.68 | 3.14 |
| \( rI_P^{\text{GWP}} \) \% | \( rI_P^{\text{GWP}} \) \% |
| 18.5% | 9.7% |
| \( rI_P^{\text{LCC}} \) \% | \( rI_P^{\text{LCC}} \) \% |
| -10.3% | 6.6% |

| Trade-off | LCC-optimal |
|-----------|-------------|
| Q heating \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q heating \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 17.91 | 24.76 |
| Q cooling \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q cooling \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 3.69 | 3.05 |
| Q lighting \( k\text{W} / \text{m}^2 \cdot \text{yr} \) | Q lighting \( k\text{W} / \text{m}^2 \cdot \text{yr} \) |
| 3.17 | 3.43 |
| \( rI_P^{\text{GWP}} \) \% | \( rI_P^{\text{GWP}} \) \% |
| 15.3% | 10.7% |
| \( rI_P^{\text{LCC}} \) \% | \( rI_P^{\text{LCC}} \) \% |
| 11.5% | 12.9% |

**Fig. 6** Energy performance of the optimal solutions for the static and dynamic mix. The results of the trade-off solutions are shown in the middle, with the GWP-optimal on the left and the LCC-optimal on the right.
addition to the decarbonization, the maximum reduction is up to 37% in GWP (with a reduced LCC of at least 6%). As seen in the previous sections, the optimized building parameters are significantly different and much closer to the BAU today case if the decarbonization plan is fulfilled.

The results show that the decarbonization of the electricity mix is a key aspect to achieve a low-carbon building sector, and it is a very relevant condition when defining the GWP-optimal building design. It is important to mention that these findings apply if a heat pump is used to heat the building, which is increasingly used in new buildings.

4.4 Limitations of the study

An important limitation of this study is that only one case study building is used in one location, which currently has a fossil-based electricity mix, though with high decarbonization potential. The results might be different if the size or the usage of the building is different. The application of local solar energy utilization is not analysed. The sole focus is on the environmental impact and the cost of the building, without considering other architectural, aesthetical and technical parameters that are influencing a real building design. Also, other environmental indicators might highlight different aspects of sustainability, and would result in other optimal solutions. In this study, a genetic algorithm was applied to find the optimum solutions. Due to the nature of the algorithm, finding the global optimum is not guaranteed. However, the algorithm achieved a great improvement compared to the typical designs and a range of good enough solutions could be found, which are also relevant in engineering problems.

Fig. 6 Optimization results for the static and dynamic 3% electricity price increase scenarios, showing the current BAU and BAU with decarbonized electricity
5 Conclusions

In this paper, the sensitivity of environmental building optimization to the electricity mix scenario was evaluated, with a heat pump used for space heating and cooling. The influence of electricity price changes has also been examined. For the analysis, a multi-objective optimization framework has been developed that integrates parametric building model generation, environmental and cost databases, dynamic energy simulation, life cycle assessment calculation and optimization algorithms into one platform. The framework provides an efficient and automatic mechanism to search for building design solutions with the lowest environmental impact and cost.

The results demonstrate that the electricity mix turns out to be a major factor in the environmental impacts and significantly influences the environmentally optimal building design. Using a dynamic, gradually decarbonizing electricity mix, the whole life cycle GWP was on average 25% lower in the optimized building solutions compared to the current Hungarian static mix. With today’s static electricity mix, the optimization proved that the minimum energy efficiency requirements in force are close to cost optimality, in line with the EU regulation. However, from an environmental point of view, much higher insulation thicknesses have been shown as justified (U-values of less than 0.1 W/m²K).

With a decarbonizing electricity mix, energy efficiency still remained important, but GWP and LCC turned out to be much less conflicting and today’s cost-optimal requirements proved to be both cost- and environmentally optimal.

The paper also introduced new evaluation metrics for the description of the Pareto front, which could be of interest to other researchers focusing on building optimization. The improvement potential was defined as the difference in the total emissions/costs between the optimized and the reference building sample, with the reference defined as business-as-usual new building designs calculated with a Monte Carlo simulation based on typical building parameters. The optimization algorithm achieved 18% (127 t) CO₂-eq. improvement potential for a static mix and 10% (46 t) if a dynamic mix was applied. As the performance of the BAU design also improves with decarbonization, building design optimization is more important if the current, high emission mix is applied than with the future mix. Building optimization not only reduces the GWP but in most cases the life cycle costs too, indicating cost-efficiency. However, the reduction in operational impacts is much more attributed to the reduced GWP of the electricity in the case of the dynamic mix than to the increased energy performance. This not only avoids the extreme insulation level of the envelope but also decreases the trade-off between GWP and LCC in an optimal design.

Although the results are specific to the present case study, it has implications for other locations with a heavy reliance on fossil fuels that is expected to give way to substantial decarbonization, for example Poland or Germany. Further research is needed to widen the scope to more building types and geographical areas, while assessing the sensitivity of the results to other parameters.

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Data availability The datasets generated and analysed during the current study are available from the corresponding author on reasonable request. Some of the data that support the findings of this study are available from ecoinvent but restrictions apply to the availability of these data, which were used under licence for the current study, and so are not publicly available.

Declarations

Conflict of interest The authors declare no competing interests.

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