Incorporating sociodemographic constraints in multi-objective building stock retrofit optimization

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Abstract

Buildings have a significant role in the total carbon emissions in the UK. Retrofitting the existing building stock can be an effective solution to reduce GHG emissions. Large scale retrofit interventions, however, can drastically affect the social and economic balance of communities. The objective of this study is to investigate how incorporating sociodemographic derived limitations in the cost-effective retrofit optimization of energy efficiency measures (EEM) distribution, across a building stock, can alter the ability of communities to achieve their emissions reduction targets, as well as the distribution of those EEM across the stock.

The English Housing Survey (EHS) was used to populate a parametric model using Grasshopper for Rhino and Energy Plus as a dynamic simulation engine. The behaviour of 36 representative building archetypes, for the East Midlands, was simulated when EEM were applied. The entire stock was then optimized using the NSGA-II genetic algorithm, incorporating new constraints to tackle the risk of fuel-poverty.

Results show that adding these constraints to the optimization led to a 40% loss in the carbon emission reduction potential for the building stock. Also, EEM distribution changes accordingly to the introduced constraints: uptake frequency of more expensive measures, such as multi-glazed windows and solid walls insulation, is reduced. Lastly, some dwellings are excluded from the optimal solutions when the difference between their household income and their baseline heating operational costs was to low.

This study provides policymakers and local authorities with a novel science-based approach to social-sustainability analyses when dealing with large-scale retrofit policies.

Introduction

In the UK, the built environment significantly contributes to carbon emissions. (UK CCC, 2019) This impact can reach 30%, with half of it directly deriving from residential buildings (BEIS, 2018b). One reason is that the existing building stock is outdated and energetically not efficient. According to a report by (Ministry of Housing Communities & Local Government, 2018), 70% of the residential buildings that will exist after 2050 will be older than 50 years. In a recent report (IET & NTU, 2018) claim that retrofitting the existing building stock in the UK is the only valid option to achieve GHG reduction goals. However, interventions of such a scale could affect the social and economic aspects of the context in which they are applied. According to (Campbell, 2016), policymakers whose strategies aim to reduce carbon emissions, cannot avoid considering the wider implications of their policies, to develop a balanced and successful planning scheme. Therefore, the sociodemographic context associated with the building stock to be retrofitted cannot be ignored.

Previous research has found that households' sociodemographic characteristics have an impact on the uptaking rate of EEM in the UK. Specifically, (Pelenur and Cruickshank, 2012) showed that cost is the main barrier preventing from adopting energy efficiency measures (EEM) and (Hamilton et al., 2014) showed that investment cost barrier and affordability do not only affect low-income households but prevent high-income households from retrofit their homes. Although this, and the fact that sociodemographics has an impact also on dwellings' energy consumption (Eckartz and Grave, 2015) (Aragon et al., 2019), these aspects are hardly analytically considered in combined-approach policies.

As an example, the currently active ECO3 Scheme (BEIS, 2018a) allows UK households to retrofit their houses, obligating energy companies to reduce the emissions derived from their customers, retrofitting their homes. Although this scheme addresses the fuel-poverty issue with a system that prioritizes low-income households and benefit-recipients, it does not contain any indication about the relationship between the involved households' sociodemographic conditions and the EEM to be installed in their houses. To understand what could be the ideal cost-effective distribution of a set of possible EEM across a building stock, multi-objective optimization can be performed. Cost and emission reduction are competing objectives since more expensive EEM usually lead to higher emission reductions. The analysis of the Pareto front of optimal solutions can help policymakers and local authorities to better address the investments and the choice of a strategy. An example of an application of this approach can be found in (He et al., 2015).

This study proposes a methodology to analytically incorporate sociodemographic derived constraints in a multiobjective building stock optimization. Different factors can be considered to assess the social

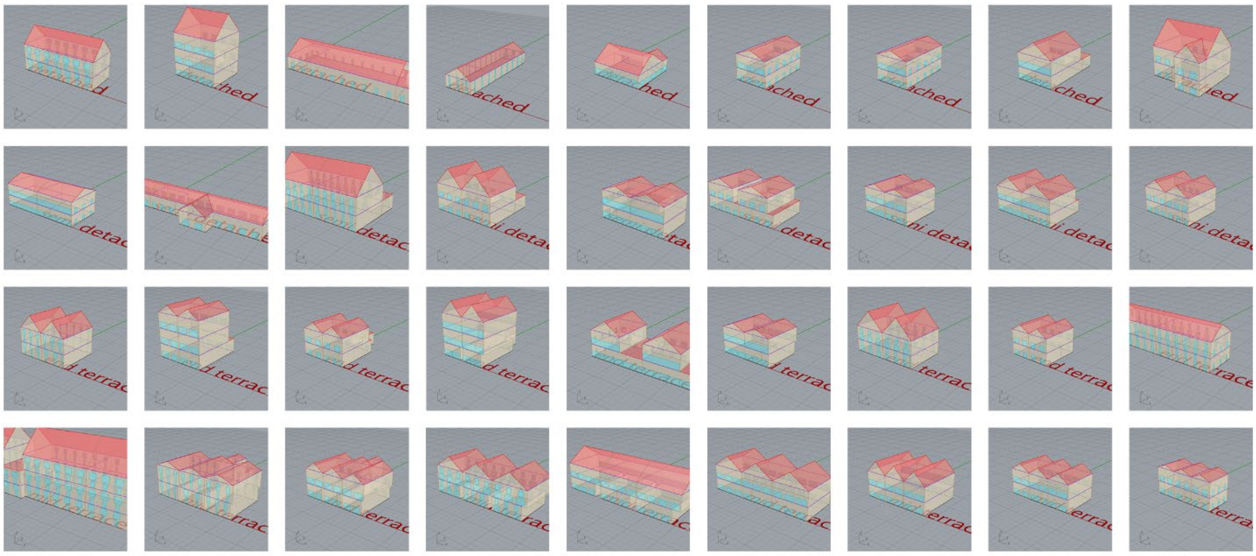

Figure 1: Automatically generated archetype geometries

sustainability of an energy policy; among them, fuel-poverty is a well-defined concept and can be analytically measured, as well. (Department of Business Energy & Industrial Strategy, 2019) In a first attempt to incorporate sociodemographic variables in the optimization problem, this study focuses on the "Before Housing Costs" household income (i.e., the total income after deductions for income tax, National Insurance and pension contributions, council tax, and maintenance payments) and uses it for a simplified evaluation of fuel-poverty. That conceptual approach is then implemented in an actual constraint for the optimization problem, as further discussed. Lastly, a publicly available dataset such as the English Housing Survey, already provide income information with a high-resolution level of detail: this was another reason why this specific sociodemographic variable was selected.

Methodology

Base-case model

The English Housing Survey (EHS) (Ministry of Housing Communities & Local Government, 2018) dataset was used to populate a parametric model.

The dataset is based on a continuous survey commissioned on a national scale by the UK Ministry of Housing, Communities and Local Government. This dataset is publicly available via the UK Data Service and contains a list of weighted archetypes, representing a larger number of houses, with the relative information about physical and sociodemographic characteristics. However, the type of accessible data was changed over the last years; specifically, starting from 2013 only general information about the buildings have been released, excluding high-resolution details about the archetypes' geometry and the household composition. Consequently, due to the high level of detail required for this study, data from 2013 datasets have been used.

Starting from the complete dataset, this study focused on the analysis of the East Midlands region. Firstly, among the archetypes belonging to this region, a selection was made to identify the ones that did not miss any physical or sociodemographic required data. Secondly, flats and commercial dwellings were excluded because of the additional complexity deriving from addressing costs, benefits and income attributes in such cases. Lastly, 36 archetypes were selected picking the most frequent ones across nine different available age bands and four different dwelling types: semi-detached, end-terraced, mid-terraced, and detached houses.

Grasshopper for Rhino (Robert McNeel & Associates, 2020) was used to automatically build a geometrical model of the selected archetypes, including characteristics like the shape of the building, the orientation, the living room position and size, the roof slope and the window-to-wall ratio. Figure 1 shows all the 36 automatically generated geometries based on the EHS dataset.

Grasshopper is a Visual Programming Language environment with high versatility that allowed a direct implementation of the model, its parametric variation when retrofit strategies were applied, and its connection with the simulation engine. Furthermore, using the Ladybug Tools suite (Ladybug Tools LLC, 2020), the geometrical model was enriched with construction properties and thermal loads. Construction properties of the geometry surfaces were directly derived from the EHS, combining the dataset information with the CIBSE indications (CIBSE, 2019). Typical materials were considered for assigned EHS construction types.

Thermal loads and occupancy schedules were based on BREDEM indications (Henderson and Hart, 2015). A different schedule was assigned to the living room (7:00-19:00, 16:00-23:00 for the weekdays and 7:00-23:00 for the weekend) and the rest of the dwelling (0:00-9:00, 18:00-24:00 for the weekdays and 0:00-9:00, 14:00-24:00

for the weekend). A setpoint temperature of 17 °C was applied to the living room and 20°C to the rest of the house.

The loft was differently modelled depending on the given EHS classification; when a "room-in-roof" was present, space was set accordingly. Finally, information about the heating system type and age were retrieved from the EHS; the efficiency parameters were obtained combining those information and BREDEM indications. All the buildings are heated using radiators with, however, different fuel sources.

Table 1 summarizes the main modelling features, the dataset sources and the assumption references.

Table 1: Model features

Model section	Features	Data source - assumptions
Geometry	Dwelling shape	EHS
	Number of storeys	
	Roof slope	
	Window-to-Wall ratio	
	Living room dimensions	
	Orientation	
Fabric	Construction type	EHS - CIBSE
	Insulation level	
Loads	Infiltration rate	BREDEM - ASHRAE
	People per area	
Occupancy	Heating setpoints	BREDEM
	Occupancy schedule	
Systems	Type of heating systems: 30 gas boilers, 4 heating oil boilers, 2 electric radiators	EHS - BREDEM
	Efficiency coefficients: 0,7-0,9 for gas boilers 0,66-0,92 for heating oil boilers 1 for electric radiators	

Energy Plus (Drury et al., 2000) via OpenStudio was used as a simulation engine. This piece of software was selected because it is largely used in the field and validated on different occasions. Heating demand was simulated, considering ideal air loads for an analysis period of a year.

As a preliminary validation of the results, simulated heating energy demand was compared with the energy demand relative to each dwelling found in the EHS, evaluated using the UK Standard Assessment Procedure (SAP). As shown in Figure 2, the discrepancy between the two sets of data is overall acceptable. A Normalized Mean Bias Error (NMBE) index of 1,93 was calculated. Although the cross-model comparison is not the scope of this work, this evaluation gives an idea of the reliability of the model.

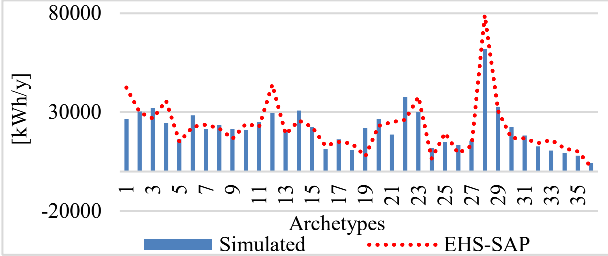

Figure 2: Model-SAP comparison

Energy Efficiency Measures

This study investigated the application of passive EEM. That means interventions to improve the insulation efficiency of the building envelope. Specifically, three main retrofit strategies were applied: wall insulation, loft insulation and window glazings.

The archetypes were characterized by four main external wall types: uninsulated solid walls, insulated solid walls, uninsulated cavity walls and insulated cavity walls. When the insulation was not present, according to the EHS, insulation was applied to solid and cavity walls. Specifically, internal insulation was applied to solid walls. Analysed dwellings had a variable percentage of single and double-glazed windows surface. In case of single-glazed windows, retrofit consisted of an upgrade to double or triple-glazed windows; double-glazed windows were, instead, retrofitted to triple-glazed windows. Loft surfaces had a larger variety of configurations, with many different ranges of insulation. For this study, however, two main retrofit strategies were applied, with the intent to top-up or fully insulate every loft to 270 mm, depending on the initial condition. Also, loft zones were divided into conditioned and not-conditioned ones. Conditioned zones were modelled when a "room-in-roof" occurred in the EHS; in that case, insulation was only applied to the roof surface. In case of a not-conditioned attic, instead, insulation was also applied to the floor of the zone.

Therefore, for every dwelling, 24 configurations were virtually possible, for a total amount of 864. However, given the base-case condition of the stock and the fact that not every EEM could be applied to each dwelling, the resulting number of configurations was 380, unevenly distributed among the dwellings. Finally, all the 380 configurations were simulated with Energy Plus.

For every different configuration, the relative CO_2 equivalent emissions load (E_a) was calculated for each archetype a. As shown in (1), the annual energy demand (W_a) was multiplied by the UK Government conversion factors (G_a) (BEIS 2019), according to the main fuel type used by each archetype, based on what specified in the EHS.

$$E_a = W_a G_a \tag{1}$$

Cost analysis

The general cost for retrofit (C_a) interventions can be a complex factor to evaluate since different factors affect it. Therefore it is necessary to define the initial assumptions of this study. In general, total retrofit costs were represented by the sum of investment costs (C_{Ca}) and operational costs(C_{Oa}), as shown in (2).

$$C_a = C_{Ca} + C_{Oa} \tag{2}$$

To evaluate the investment costs, firstly, for every possible retrofit options combination, the mere capital cost (K_a) was evaluated for each archetype, according to Table 2.

Table 2: Retrofit measures costs

Retrofit options	Cost	Source
Loft insulation (complete insulation)	395 £ (detached houses)	(EST, 2019)
	300 £ (semi-detached/end-terrace)	
	289 £ (mid-terrace)	
Loft insulation (top-up to 270mm)	265 £ (detached houses)	
	220 £ (semi-detached/end-terrace)	
	215 £ (mid-terrace)	
Cavity wall insulation	720 £ (detached houses)	
	475 £ (semi-detached/end-terrace)	
	370 £ (mid-terrace)	
Solid walls insulation	87 £/m2	
Double glazing	261 £/m2	(Sweett, 2014)
Triple glazing	567 £/m2	

The policy scenario hypothesized for this study does not involve the government or any other local authority as an active part distributing funds for a retrofit plan. The focus, instead, is on understanding how a certain building stock might keep up with carbon emissions reduction targets, relying solely on its financial strength. Therefore, the assumption made is that households would access a loan, to annualize the investment costs. The other reason for this approach is that, according to what showed in (SHAP, 2018), loans are commonly adopted strategies for financing retrofit and can be accessed more easily, without regional limitations (differently from regional and local funding plans).

According to the same report, a term of 8 years (y) at 10% (i) of fixed annual interest was assumed for the annualization, as an average of the most common retrofit-purpose loan schemes. The annual payment is then calculated on a monthly base. Therefore, the general formula for investment costs is (3).

$$C_{Ca} = K_a \frac{\frac{i}{12}\left(1+\frac{i}{12}\right)^{12y}}{\left(1+\frac{i}{12}\right)^{12y} - 1} 12 \tag{3}$$

Operational costs, on the other hand, were evaluated multiplying the simulated heating energy demand (W_a) by the average regional energy prices (P_a) officially published in the "Quarterly Energy prices" Government bulletin (BEIS 2020). Specifically, 0,068 £/kWh for gas, 0,068 £/kWh for heating oil and 0,1437 £/kwh for electricity. Given their impact on the energy bills (Osmon 2018), standing charges (SC) of 155 £ per year were also added to (4) for the total operational cost C_{Oa}.

$$C_{Oa} = W_a P_a + SC \tag{4}$$

Costs and emissions evaluation can be considered as a stand-alone problem for a given community, however, the optimization of this problem including all the possible retrofit combination alternatives increases its complexity.

Optimization

The objective of the optimization process was to identify the best cost-effective distribution of EEM across the investigated stock, minimizing the GHG emissions, as well. For this study, the Pymoo (Blank, 2018) package for Python was used to implement the Non-dominated Sorting Genetic Algorithm II (NSGA-II) proposed by (Deb, Pratap, Agarwal, Meyarivan, 2002). The optimizations ran for 500.000 generations, each one of them composed of 300 solutions, for a total amount of $1{,}5\times10^{8}$ solutions evaluated.

The original size of the research space of the problem was $2{,}34\times10^{33}$, given by the possible combination of 380 alternatives, unevenly distributed across the 36 archetypes composing the stock. However, the space size was reduced by applying a double-stage optimization approach. In the first stage, every set of retrofit alternatives for each dwelling was optimized, minimizing the cost and the emissions, and only the Pareto-optimal alternatives were selected. The optimal alternatives were then used for stock-scale optimization, reducing the search space to $5{,}62\times10^{28}$ and 265 alternatives.

In the second stage, the general optimization problem, for the 36 archetypes, was defined by the two objective functions (5) and (6).

$$\min C_{stock} = \sum_{a=1}^{36} C_{Ca} + C_{Oa} \tag{5}$$

$$\min E_{stock} = \sum_{a=1}^{36} W_a G_a \tag{6}$$

After running the first optimization, a second one was performed limiting the annualized cost to be less than 10% of the households annual income (I_a), as described in (7), further reducing the research space to 3,26×10[20] and 164 alternatives.

$$C_a \leq 0.1 I_a \tag{7}$$

The rationale behind the choice of this constraint is to avoid a specific household to become fuel poor when EEM are applied, including the annual investment cost for retrofit as a factual part of the energy expenses. The 10%-income indicator was introduced by (Okushima 2017) and it is now used by the UK Government combined with the new multidimensional Low Income – High Cost (LIHC) indicator (Department of Business Energy & Industrial Strategy 2019) to assess fuel poverty. Although the operational cost to evaluate fuel poverty usually includes expenses for lighting, cooking and utilities, the approach of this study that only focuses on the expenses for heating, is cautionary. Including other expenses would further reduce the affordability of certain retrofit configurations, given a lower difference between the operational cost and the 10%-income cap. Figure 3 shows the relationship between the heating operational cost for the simulated energy demand and 10%-income cap, for the base-case of the investigated stock.

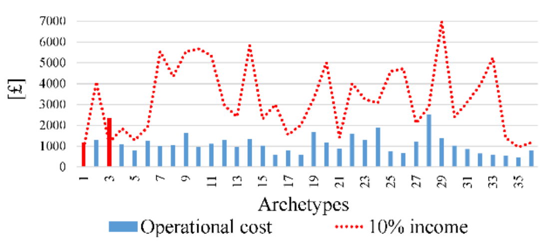

Figure 3: Base-case operational costs

Finally, the differences between constrained and unconstrained optimizations were evaluated.

Results and discussion

The set of non-dominated solutions for the last generation of each optimization run is plotted in the research space in Figure 4, representing the trade-off between the total cost and carbon emissions. In both cases, all 300 solutions were found to be optimal.

In the base-case scenario, when no intervention is applied, the total amount of annual carbon emissions for the stock is about 151 ton CO_2e, and the relative operational cost for the stock is about 40.000£/y.

The first difference between the two sets of optimal solutions is that unconstrained solutions allowed a minimum emission load of about 103 ton CO_2e, costing to the stock 144.000£/y, with a potential 32% reduction compared to the base-case. On the other hand, constrained solutions only reached a minimum load of about 123 ton CO_2e, for a general cost of 80.000£/y for 19% less carbon emission than the base-case. That means that implementing income constraints in the optimization process, led to a loss of 40% in emission reduction potential, for this particular building stock.

The second main difference is in the morphology of the two distributions. Given the cap that the introduced constraint put on cost, the genetic algorithm was forced to look for less expensive solutions; this is noticeable looking at the 'tails' of the trade-offs. The cheapest among the constrained solutions are closer to the base-case option than the unconstrained ones. Furthermore, although the evident shift of the constrained front towards the high-emissions part of the research space, both the sets of solutions show one kneepoint and a slope variation. The reason behind that can be explained through the analysis of how different measures are distributed across the solutions.

To analyse the distribution of EEM, the total number of installations was counted for every solution of each optimal front.

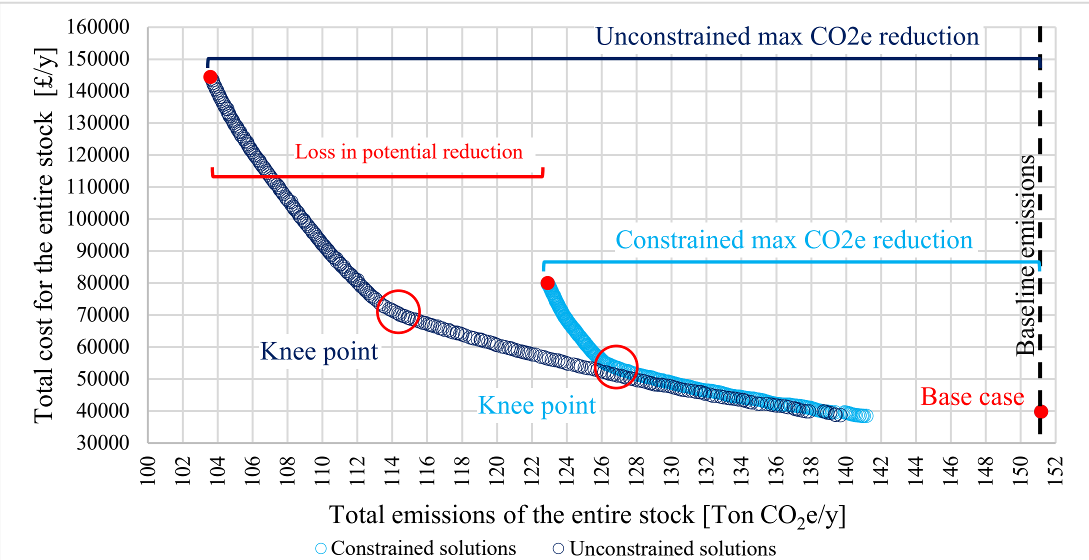

Figure 4: Optimal solutions and research space

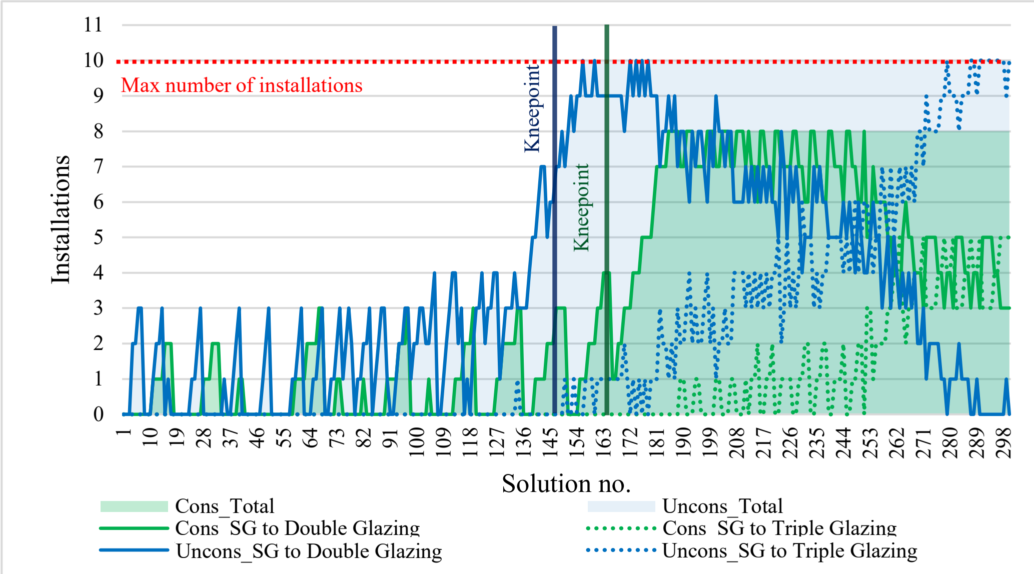

Figure 5: Uptake of single-glazed windows retrofit

Figure 5 shows the uptaking rate of retrofit strategies that consider the substitution of single glazed windows with double and triple glazed ones. Solutions are ranked from the one that has the highest emissions to one with the lowest CO_2e load. In the analyzed stock, 10 dwellings had retrofittable single glazed windows. As noticeable, kneepoints correspond to the increasing uptake of expensive measures like more efficient windows, but with two main differences between constrained and unconstrained solutions. Firstly, the uptake of triple glazing increases constantly in the unconstrained solutions, while double glazing decreases to 0. On the other hand, constrained solutions are less likely to consider triple glazing as a possibility and the less polluting options include almost even dissemination of double and triple glazing. Secondly, although the unconstrained solutions suggest to completely retrofit every possible single-glazed dwelling, constrained solutions exclude 2 out of 10 archetypes from the uptaking.

Retrofitting double-glazed windows to triple-glazed ones was excluded, as an option, by the optimization process. This is reasonable because that is an expensive strategy that does not have a comparable impact in terms of emissions reduction. By contrast, loft insulations dominate the first part of the solutions, before the kneepoints, since they are cheap and highly effective. No considerable differences between constrained and unconstrained solutions were registered. The same can be assessed for cavity wall insulations: where affordable, they were constantly an option for uninsulated cavity walls, across the 300 solutions, in both the constrained and unconstrained scenarios.

Solid walls insulation, instead, was highly affected by the introduction of the income constraint.

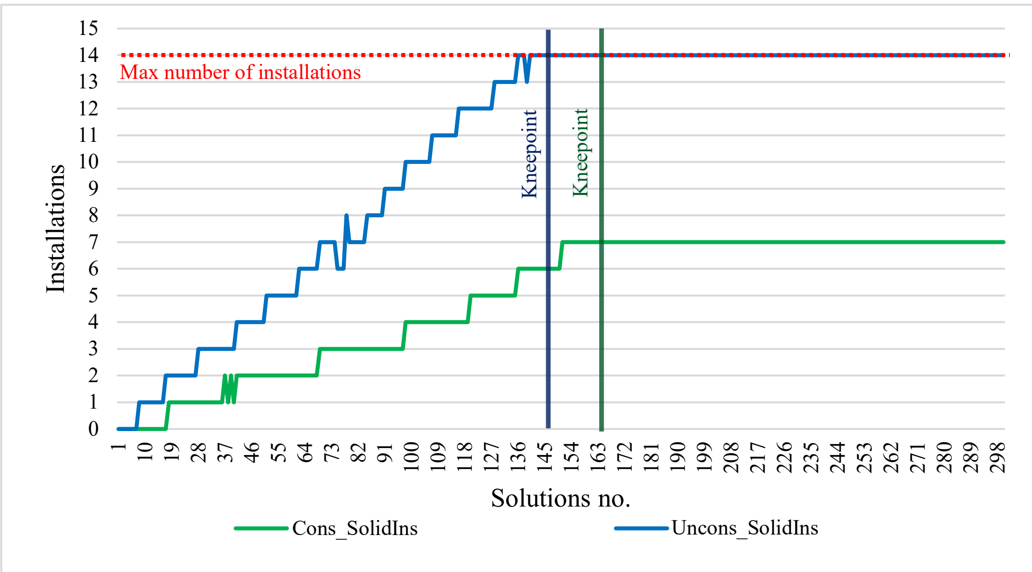

Figure 6: Uptake of solid walls retrofit

Figure 6 shows how, although the increasing rate is constant in both the scenarios, unconstrained solutions entirely fulfil the possible uninsulated solid walls retrofit options. On the other hand, constrained solutions exclude 50% of the possible interventions.

It is then useful to understand how this difference is distributed across the stock.

The uptake of solid walls insulations across the stock is plotted in Figure 7. Solutions are ranked in the same way as in Figure 5 and Figure 6, and the y-axis represents the 36 archetypes. The graph shows how 7 out of 14 archetypes are excluded from the optimal distributions when new constraints are introduced. Comparing this figure with Figure 3 it is evident that excluded archetype are the ones with the lower differences between the operational cost and the 10%-income threshold.

Lastly, the uptake of this specific retrofit measure is affected also for the other archetypes: the uptaking frequency is significantly reduced in the constrained solutions before the kneepoint.

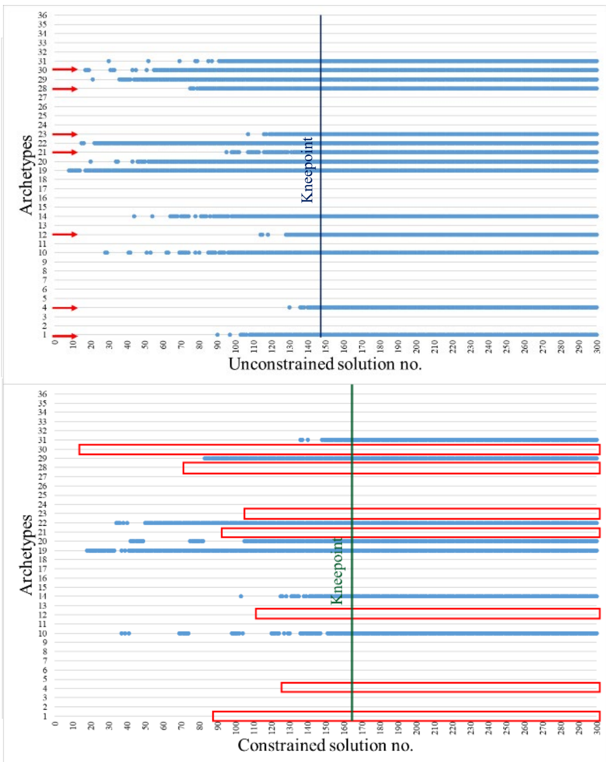

Figure 7: Solid walls retrofit uptake by archetype

Conclusion

This study proposed a novel approach to analytically evaluate the implications of incorporating sociodemographic income constraints in the cost-effectiveness analysis of stock-scale retrofit strategies. Combining parametric design, a genetic evolutionary algorithm and the optimization approach was an effective method to deal with the complexity of this problem.

The 40% decrease in the CO_2e reduction potential, when optimal solutions search was constrained, suggests that planners and policymakers might overestimate the ability of households communities to afford a global retrofit. At the same time, the analysis of the trade-off curves showed that constrained optimizations might advise decision-makers to opt for cheaper EEM. By contrast, this might allow them to suggest the installation of more expensive interventions, being more confident about their affordability.

Furthermore, understanding what the distributive dynamics are, is useful to recognize which dwellings or social categories might be affected by a given policy. As an example, based on what the results showed, a policy aiming to insulate solid walls of the analysed stock as the main objective, would have signified fuel-poverty risk for the 50% of the eligible dwellings and, consequently, a substantial barrier to the uptaking. Considerations of this sort can help legislators to avoid social inequality issues, relying on a direct and clear relationship between a certain retrofit strategy and its impact on a specific social context. Lastly, this methodology can be applied to deliver tailored retrofit solutions for specific case studies since it would be evident which dwelling would be affected the most.

Cost analysis was a sensitive part of the optimization workflow. Therefore, future work will implement a sensitivity analysis of economic parameters like the interest rate and the loan term. The sensitivity of this workflow to costs and energy prices will be also investigated to understand how policy-makers could indirectly take action on improving affordability, intervening on these parameters instead of directly addressing funds.

The reduced number of archetypes is a limitation to the possibility of projecting the problem on a regional scale and finding a clear sociodemographic-related trend in the uptaking rate; however, the scope of this paper was to present a novel approach to be applied to larger archetypes samples. Therefore, further studies will also focus on incrementing the number of archetypes to find possible defined relationships between the implications of constraining the optimization problem and specific types of houses or households.

Lastly, the implementation of only passive EEM in the workflow is a limitation to the evaluation of the GHG reduction potential of the stock. Active measures, i.e., the installation of more efficient heating systems are usually highly effective in reducing carbon emissions but also more expensive. The results of this study are in accord with what assessed in the Net Zero – Technical report (UK CCC, 2019): 75% reduction in buildings carbon emissions is needed and passive strategies can only help to achieve about the 30%. Further work will implement active strategies in the workflow, to understand the distributional impacts and how affordability constraints and fuel poverty barriers can react to more expensive and effective interventions.

Acknowledgements

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