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Siddique, Muhammad Bilal; Bergaentzlé, Claire; Gunkel, Philipp Andreas

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Fine-tuning energy efficiency subsidies allocation for maximum savings in residential buildings

Muhammad Bilal Siddique *, Claire Bergaentzlé, Philipp Andreas Gunkel

Technical University of Denmark, Department of Technology, Management and Economics, Kgs. Lyngby, Denmark

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ABSTRACT

Energy consumption in buildings accounts for more than a third of European CO_2 emissions. The existing building stock shows the most potential for energy savings but at the expense of costly renovations. Thus, public intervention is decisive in driving transformation in this sector. However, policymakers mostly rely on heat estimates to develop energy-saving policies, limiting the possibility of aligning renovation support policy with environmental gain, slowing down the decarbonization effort. This study explores the benefits of using metered heat demand data with detailed building archetypes for impactful renovation subsidy allocation. We quantify the missed CO_2 emissions due to inaccuracies in heat demand estimates and develop an optimization model to quantify the impact of such inaccuracies on subsidy allocation. For the case study of Lyngby-Taarbæk municipality in Denmark, we find systematic bias in heat demand estimates that attribute higher heat demand to older houses than reality and inversely to newer family houses. Such bias results in the misallocation of 39% of total CO_2 emissions and distortion of 40% of the total subsidy. Ultimately, our results help policymakers identify buildings that should be prioritized for a maximum decarbonization impact.

1. Introduction

Existing building stock accounts for about 40% of total energy consumption in the European Union (EU), producing 36% of its total greenhouse gas (GHG) emissions. To achieve a 55% reduction in GHG emissions by 2030 (compared to 1990), as proposed in the European Green Deal, Europe's energy efficiency targets have been revised and now correspond to a 39% and 36% reduction in primary and final energy use respectively [1]. This brings energy efficiency improvements in building stock into focus. In its "Fit for 55" proposal, the European Commission (EC) reaffirms its intention to prioritize decarbonization of the heating and cooling sector by introducing a compensation mechanism that redistributes part of the revenue raised through carbon-pricing to the most vulnerable consumers to ensure a socially fair transition [2]. At the building or dwelling level, the newly proposed energy efficiency directive almost doubles the annual obligation to save energy from 0.8% to 1.5% of final energy consumption from 2024 to 2030 [1]. The decarbonization strategy introduced by the previous Energy Efficiency Directive (Directive 2006/32/EC) and the Energy Performance in Buildings Directive (Directive 2010/31/EU) tackled energy savings and CO_2 emissions in buildings from two angles: first through the decarbonization of electricity and heat production, and second through support schemes for energy savings like building renovations and the replacement of heating equipment.

Regarding energy savings for households, compliance with the European Commission's directives has led to the implementation of a wide range of incentivizing policy instruments by EU member states, ranging from minimum energy performance standards for new constructions to financial incentives in the form of tax exemptions, low to zero-interest loans or grants and subsidies. Among these, fixed subsidy schemes that cover part of the costs of renovation or replacement of energy equipment are the most widely used financial instruments [3,4].

However, despite the developed policy toolkit, the rate of renovation of Europe's building stock remains low, and ambitious actions achieving deep energy renovations remain largely marginal in the member states. Currently, existing buildings will make up at least 75% of the 2050 building stock [5]. At this pace, it will take EU member states a century to achieve the target of decarbonizing buildings. Furthermore, the Renovation Wave communication for the EU parliament proposes that 35 million buildings in member states should be renovated by 2030 if the EU's net-zero target is to be achieved [6]. These figures raise questions about the causes of the slow progress made in renovation despite

* Corresponding author.
E-mail address: bsikh@dtu.dk (M.B. Siddique).

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the deployment of incentive packages.

The limited effectiveness of financial support schemes, like subsidies, on renovations and the subsequent impact on energy savings is recognized in Ref. [7], and furthermore, most of the literature on these energy renovations focuses on the perspective of homeowners [8], while at the same time a policymaker perspective is lacking. In this study, we take into account policymakers' perspectives to argue that the limited efficiency of existing economic incentives for renovating buildings is partly due to an initial misrepresentation of energy demand. This misrepresentation results in an inefficient allocation of subsidy budgets, as it does not allow households with the greatest energy savings potential to be targeted.

This study refers to estimated heat demand as the demand calculated based on theoretical or empirical models. Therefore, all heat demands calculated outside the scope of this study are referred to here as estimated heat demands. Other studies may refer to these as theoretical or calculated heat demands.

1.1. Literature review

Practical implementation of the above-mentioned policy measures fundamentally depends on estimates of heat consumption that are prone to inaccuracies. The wide-scale legislative push for energy-saving measures has led to the development of heat-estimating tools and national and regional maps or atlases to assess the potential of heat savings for subsequent policy recommendations.

Most of these tools can be classified based on their scope, which varies from the short-term prediction of heat demand [9–14] to identification of the patterns and fundamental relationships that drive heat consumption [15–17]. These models and tools can be classified further into top-down and bottom-up methodologies based on the methodology. Top-down tools or models gauge the systematic relationship between heat consumption in the residential buildings sector and macroeconomic indicators like total heated area, climate conditions and sector activity level. Bottom-up tools start from recording consumption at a small-group or individual level and extrapolate the results to represent the whole sector. Bottom-up models mainly serve to study the impact of technology or similar measures on consumption [18].

All of these tools and models are based on assumptions. Heat atlases or maps are a common tool that builds on bottom-up models. The Danish heating map or atlas is a noteworthy example [19]. The atlas provides estimates of the spatial distribution of heat demand. Similar heating maps are also used in other countries and/or regions [20]: built a heatmap for 27 European countries [21], developed a GIS-based heat map for Shinchi Town in Fukushima and [22] for the USA. These models, heat maps, or atlases not only serve heat-planning, like Euroheat [23], but are also widely used for designing energy policies related to energy savings [24] and district heating [25].

In addition to heat maps and atlases, estimates of heat consumption are often based on the building archetype [26]. developed a table of estimates for all buildings in Denmark based on their use, i.e. the type of building (detached family houses, apartments, etc.) and age. Unlike heat maps and atlases, such estimates enable easier comparison of various buildings based on certain characteristics like the age and type of a building. The primary aim of such estimates is to provide house-owners with an overview of the energy consumption of their houses in comparison to the national average of similar houses to motivate energy renovation investment decisions.

These above-mentioned tools bring insights to aggregated heat consumption nationally or regionally. However, they are limited to chart in detail heat demand in different building types, which merits further investigation as subsidy schemes for renovations target individual households. Therefore, a higher level of detail is needed to improve the effectiveness of the subsidy scheme. Bhattacharyya et al. [27] conducted a comparative study of energy demand models and found that models poorly represent the energy demand difference between rich and poor households, the divide between urban and rural energy, and commercial and non-commercial energy demands [27]. Similarly, in Denmark, Grundahl et al. compare the heat consumption estimates provided in the Danish heat atlas with metered data to validate the accuracy of the estimates and improve heat-sector planning and policymaking. Their results indicate that the accuracy of heat consumption estimates is only observed and validated for single-family houses, while using such data for other categories requires caution [28]. Similarly [29], validated a top-down methodology to estimate local heat demand and found that top-down estimates tend to overestimate the heat demand. They highlight the need for individual data for detailed planning related to heating and cooling.

These works draw attention to the limited reliability of estimates in representing the reality of heating demand in building types, potentially leading to suboptimal and misinformed measures and policies along with a distorted representation of the energy demand of and emissions from buildings. Yet, a fine understanding of heat energy demand and emissions in buildings is crucial to designing efficient policy measures that are capable of addressing the urgent need to decarbonize building stock at the lowest cost for society.

1.2. Contribution

This study compares the accuracy of state-of-the-art heat estimates with the accuracy of metered heat-demand data obtained from a municipality, similar to Refs. [27,28]. Furthermore, this study assesses and analyses how discrepancies between estimated heat consumption and metered data lead to an inaccurate representation of and accountability for CO_2 emissions in buildings, as well as to inefficient allocations of subsidies promoting energy efficiency, using the city of Lyngby-Taarbæk in Denmark as a case study. We develop an optimization model that optimally allocates the state budget for subsidies between building types to reach the highest energy savings at the least cost, thereby quantifying the impact of inaccuracies in heat consumption estimates on subsidy allocations. The model takes into account the exponential relationship between energy saving spending and achieved energy savings [30,31]. Finally, in our case study we test three scenarios of subsidy scheme allocation, including the current Danish allocation methodology, across building types to quantify the extent of missed CO_2 emissions and to advise policymakers on what buildings should be targeted as a priority.

This article is organized as follows: Section 2 introduces the case study and methodology used in calculating and comparing heat consumption and subsequent CO_2 emissions resulting from two different heat consumption datasets mentioned in section 3. Section 4 gives a description of the optimization model. The results are presented in section 5, followed by a discussion in section 6. Finally, section 7 concludes the study.

2. Case study

This study compares the accuracy of selected heat-demand estimates [26] for different building archetypes with real/metered data from a municipality. This section presents the chosen heat-demand estimates and the municipality as case studies.

2.1. Danish heat-demand estimates for heat consumption: state of the art

The state-of-the-art heat estimates considered in this study are the result of a project collaboration between the Danish District Heating Association (Dansk Fjernvarme), Green Energy (Grøn Energi) and Aalborg University [26]. This project was designed for district heating utilities to assess future expansion plans. These state-of-the-art estimates serve an important purpose in providing Danish house owners with an overview of their energy consumption compared to similar houses in Denmark. Our study adds further weight to these estimates by highlighting some important cautions when using them in local decision-making. Therefore, the results of this study add value to these estimates rather than criticizing them.

Table 1 is the state-of-the-art heat-estimate table that will serve as a baseline for this study. The table divides Danish buildings based on their year of construction and the code, which represents the purposes of particular buildings, such as detached and semi-detached family houses, apartments, dormitories, and so on. It indicates the average heat consumption in kWh/m2 in a year for each building category of use code and construction year. A closer look at Table 1 shows a steady decline in the heat consumption of buildings based on their age or year of construction, with newer buildings consuming less energy than older ones.

2.2. Case study of the Danish municipality of Lyngby-Taarbæk

In Denmark, the residential building stock alone accounts for 25% of total energy consumption, with an emissions share of 16% [32]. The Danish government has set forth to completely decarbonize residential energy consumption by 2035, as mentioned in the Climate Agreement of 2020, highlighting such a political priority [33]. The government set out a budget of 60 million EUR to support energy efficiency renovations in buildings and another 11 million EUR for the conversion of individual oil and gas boilers until 2030. The main economic incentive implemented by the authorities is a fixed subsidy scheme. Lyngby-Taarbæk is a suburban municipality with a population of 55,000 located in eastern Denmark that targets 25% of CO_2 emissions reduction, compared to the 2015 level, by 2025 in its local strategic energy plan [34]. This plan further stipulates an emissions reduction of about 4–6% from heat-saving measures in buildings.

The municipality directly provided metered heat-consumption data for Lyngby-Taarbæk, as utilities in a particular municipality collect data on heat consumption. The metered data on the municipality's heat consumption contains 113,380 data points corresponding to 26,089 unique houses/addresses. After cleaning and filtering, 39,763 data points that correspond to 11,529 unique houses/addresses were left for analysis. Appendix A.1 represents the filtering flow chart. After cleaning the metered heat consumption data, this is linked with building characteristics like heated floor area, year of construction and type of building to make it comparable with Table 1. In Denmark, these building stock characteristics are provided by the Danish Ministry of Housing, Urban, and Rural Affairs in its central Register for Buildings and Dwellings (BBR). The BBR datasets contain information about the characteristics of each building in Denmark, including the number of rooms, floor area, number of windows, etc. More information on this dataset can be found here [35].

The metered heat consumption data were cross-referenced with the relevant BBR data. Those categories with fewer than 10 data points were removed from the analysis to comply with EU GDPR requirements on data privacy. Accordingly, only residential buildings with the use codes 120, 130, 140 and 150, corresponding to detached and semi-detached family houses and apartments and dormitory buildings, were included in the analysis. The final total number of unique addresses/buildings left in the datasets is shown in Table 2.

Ultimately, about 11,500 households are represented in the study, 64.7% of which covered their heat demand with natural gas boilers, 25.8% with heat pumps, 7.8% with oil boilers and the residual 1.7% with the local district heating system (Fig. 1).

3. Methodology

This section discusses the underlying methodology for comparing the accuracies of state-of-the-art heat-consumption estimates, metered heat consumption and calculations of subsequent CO_2 emissions.

3.1. Calculation of average yearly heat consumption for the building stock in Lyngby-Taarbæk

After cross-checking household demand with building characteristics and heating sources, the metered heat consumption data, or heat delivered *Hd*, is used to calculate the yearly average of useful heat consumption *Hu* per m^2, given in equation (1).

$$Hu_{jk} = \frac{\sum_i \left(\frac{Hd_{i\ jk} * \varepsilon_i}{A_{i\ jk} * D_{i\ jk}} * 365 \right)}{\sum_i i_{jk}} \quad (1)$$

where i is the number of buildings or measurements in the dataset belonging to a particular building category of use code classification j and construction year classification k. D refers to the duration of heat consumption measurement, which varies between 360 and 370 days, so that a multiplication factor of 365 ensures the normalization of heat consumption to a year. A is the heated area in m^2 of a particular building i. ε_i represents the technological efficiency of the heating system installed in each house i. The Coefficient of Performance (COP) replaces the technological efficiency of heat pumps, and for district heating a technological efficiency of 1 is assumed, thereby ignoring distributional losses. Table 4 represents various estimates of efficiencies ε_i.

The average heat consumption calculated from the metered data validates the estimate in the baseline (Table 1) in the results section.

3.2. Calculation of CO_2 emissions of the building stock in Lyngby-Taarbæk

The gap between measured and estimated heat consumption is quantified by calculating the average annual CO_2 emissions generated by heat consumption in residential buildings. To calculate the CO_2 emissions due to baseline/state-of-the-art consumption estimates, total annual CO_2 emissions E_e_{jk} are calculated from the average heat consumption per m_2 per year *Hg*, given in Table 1. Since CO_2 emissions values are dependent on fuels, the supply mix of the case-study municipality, calculated from the metered heat consumption, is considered. Finally, the total CO_2 emissions resulting from the heating demand of residential buildings in a year are calculated by multiplying the total heated area of buildings belonging to each building category $j\,k$ by average emissions per m^2, as in equation (2).

$$E\_e_{jk} = Hg_{jk} * \sum_f \left(S_f * \partial_f \right)_{jk} * \sum_u A_{u\ ,\ jk} \quad (2)$$

where u is the number of unique buildings in each building category of use code classification j and construction year classification k, which are

Table 1
State-of-the-art (baseline) estimates of average heat consumption in Danish buildings in kWh/m^2/year [26].

Use Code	Year of Construction								
	<1850	1850–1930	1931–1950	1951–1960	1961–1972	1973–1978	1979–1998	1999–2006	>2006
120 = **detached single-family house**	152	185	197	163	123	110	97	82	65
130 = **semi-detached family house (vertical separation between the units).**	170	180	192	172	130	112	80	69	67
140 = **housing in a multi-storey building (apartments)**	143	139	144	148	117	116	84	76	68
150 = **dormitory housing**	182	177	164	141	128	180	122	111	86

Table 2
Number of unique addresses or buildings in Lyngby-Taarbæk with metered energy consumption data used in this study.

Use code*	Year of construction								
	<1850	1850–1930	1931–1950	1951–1960	1961–1972	1973–1978	1979–1998	1999–2006	>2006
120	14	292	692	785	1279	537	899	443	702
130		78	1097	1038	404	174	411	115	146
140		120	878	461	323	49	429	71	25
150							17	50	

120 = detached single-family house; 130 = semi-detached family house (vertical separation between the units); 140 = housing in a multi-storey building (apartments); 150 = dormitory housing.

Table 3
Total heated area in the studied buildings in Lyngby-Taarbæk in m.[2].

Use code[a]	Year of Construction								
	<1850	1850–1930	1931–1950	1951–1960	1961–1972	1973–1978	1979–1998	1999–2006	>2006
120	2247	45,624	95,126	104,265	199,029	88,243	143,485	75,376	128,160
130		9974	105,945	118,109	52,058	21,736	48,224	14,349	19,349
140	116	10,784	62,083	37,067	25,427	4414	35,182	7385	2661
150							562	2091	

[a] **120 = detached single-family house; 130 = semi-detached family house (vertical separation between the units); 140 = housing in a multi-storey building (apartments); 150 = dormitory housing**.

Table 4
Efficiencies and carbon coefficients of different heating technologies and corresponding fuel used.

Heating technology	Fuel	Technological efficiency %	Carbon coefficient (kg/kWh)
Natural gas boilers	Natural gas	92 [36]	0.2020 [37]
Heating oil boilers	Heating oil	84 [36]	0.2786 [37]
Heat pumps	Electricity	3.15* [38]	0.2910 [39]
District heating	National fuel mix	100	0.0935 [39]

*Represents Coefficient of Performance (COP) of residential heat pumps in Denmark.

the same as in Table 2. The total heated area of unique buildings ($\sum_u A_{u\,,\,jk}$) is presented in Table 3. Similarly, S_f is the share of technology (i.e. Fig. 1) using fuel f, and ∂_f is the carbon coefficient of that fuel as shown in Table 4, where for district heating, the carbon intensity of the district heating fuel mix at a national average is used. This analysis only considers the current carbon intensity of electricity and district heating in Denmark. With the continuous replacement of fossil fuels-based generation technologies by low carbon technologies, the carbon footprint of each building type is expected to decrease. However, future decarbonization of electricity and district heating is beyond the scope of this study.

The calculation of CO_2 emissions from the metered data uses a bottom-up approach to account for the granularity in the data. Total yearly CO_2 emissions resulting from the metered heat consumption Hd for each household is calculated from the fuel f of the installed heating

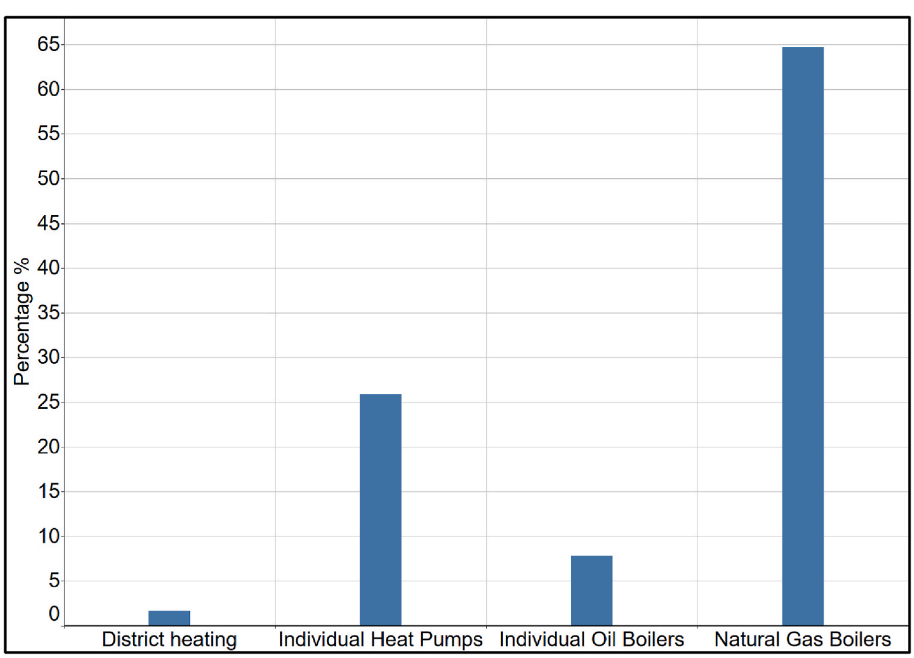

Fig. 1. Heat generation technology mix of the studied buildings in Lyngby-Taarbæk municipality.

system, followed by averaging total yearly emissions for each house u with more than one heat consumption measurement i. Averaged yearly CO_2 emissions per unique house u are finally summed together according to the classification of use code j and construction year k. Equation (3) gives the formula of the yearly total CO_2 emissions E_r_{jk} calculation.

$$E\_r_{jk} = \sum_u \frac{\sum_i \left(Hd * \partial_f\right)_{i\ u\ jk}}{\sum_i i} \tag{3}$$

4. Allocation of energy efficiency subsidies: an optimization model

In this section, the developed optimization model is presented to quantify the impact of the identified gaps between state-of-the-art (baseline) heat-consumption estimates and real metered consumption data on the design of a subsidy scheme for energy efficiency improvements (energy renovations).

This model optimally allocates or distributes the overall subsidy budget among different categories of buildings based on their heat consumption, taking into account the exponential relationship between investments in energy-efficient renovations and the resulting heat savings. This model maximizes the total energy savings by allocating more resources or subsidies to building categories that consume relatively more and thus have a high potential for energy savings. As a consequence of energy savings, CO_2 emissions are also deemed to decline, given the municipality's heat-supply mix (Fig. 1). It shows how subsidies would be distributed among building categories in the scenario of estimated data and metered data, and compares the results with the allocation methodology used in the current subsidy scheme in Denmark [40].

4.1. Mathematical formulations of the optimization model

The optimization model takes into account heat consumption and the exponential relationship between investment in energy-efficient improvement measures (or energy renovations) and the resulting energy savings. This exponential relationship has been extensively discussed in the literature and used for policy recommendations. The exponential relationship basically models the increasing difficulty of saving another unit of energy after each unit [31]. uses microeconomic concepts for end-use energy-savings to improve understanding for policymakers [31]. identifies the effect of crucial factors like user behavior and technological improvements on energy efficiency. The microeconomics analysis assumes an exponential relationship between investment in energy-savings and the resulting savings. Similarly, another study [30] collected the exponential cost curves for investment in energy-efficient improvement measures and the resulting savings to identify the full potential of energy savings in heterogeneous Danish residential buildings and to evaluate the cost-effectiveness of investments in energy savings in areas connected to district heating.

In the present study, we expand the field of application of the exponential relationship from the perspective of policymakers and apply it to optimize the allocation of subsidy schemes at the aggregate level of the municipality *based on different heat consumption estimates*. The optimization model maximizes the effectiveness of the subsidy scheme. This optimization model considers the constraint of limited public spending (total subsidy budget), and furthermore it models the exponential relationship between investment in energy renovation and energy savings. It is implemented in GAMS.

This non-linear optimization model is implemented in the case-study municipality of Lyngby-Taarbæk to design a subsidy scheme with maximum energy savings based on the heat consumption data discussed in previous sections.

The objective function is expressed in equation (4), which maximizes the energy savings ΔES by optimally distributing the overall subsidy budget, $\sum \Delta C\_inv$, among buildings belonging to different categories. The overall state budget for subsidies is limited and is introduced in the model as a constraint (equation (5)). The optimization problem is formulated as follows:

$$Max\ \Delta ES = \sum_{jk} w_{jk} \frac{\left(\ln\left(b^{ES_1\ jk} + \Delta C\_inv_{\ jk}\right) - \ln\left(b^{ES_1\ jk}\right)\right)}{\ln b} \tag{4}$$

subjected to

$$\sum_{jk} \Delta C\_inv_{\ jk} \le 100 \tag{5}$$

$$0 \le \Delta ES_{jk} \le C\_x_{\ jk} \tag{6}$$

ES_1 is the initial energy saving achieved from some initial investment $C_{inv\ 1}$, invested some time before the start of the present subsidy scheme. Essentially ES_1 represents the state of buildings before implementation of the present subsidy scheme. This ES_1 is calculated from average heat consumption (C_x) before the model is run and is set out in equation (7).

$$ES_{1\ jk} = \left(\max\left(H\_x_{jk}\right) - H\_x_{jk}\right) \tag{7}$$

where H_x is the average heat consumption per m^2 in a year for a building belonging to category jk. This H_x is replaced by either baseline estimates or metered consumption, depending on the scenario. Equation (7) ensures that building categories with relatively higher heat consumption are located at a relatively lower segment of the exponential curve. In Fig. 2, this is represented by the example of two houses H_1 and H_2, where average consumption, H_x, of H_1 is higher than of H_2. Thus, house H_1 has a greater potential for heat savings with a given investment in energy renovations as compared to H_2. Therefore, equation (7) places H_1 in the lower portion of the exponential curve than H_2. Furthermore, the choice of max (H_x) is to ensure 1) relative placement of buildings on the exponential curves based on their heat consumption and 2) making sure that all the buildings are in the first quadrant of the graph avoiding negative values, depicted in Fig. 2.

The weighting factor, w_{jk}, is added to account for the relative distribution of total heated area among different categories. It is calculated as a share of the heated area belonging to each building category of jk out of the total heated area; see Table 3.

The upper bound for the overall state budget available for the subsidy scheme is kept at 100 units. This choice is intended to make subsequent discussion simpler by directly talking about percentages and avoiding further conversion. Furthermore, the objective is to study the relative distribution of resources under different scenarios and their impact on energy savings. Thus, a simple choice of 100 not only simplifies our discussion but also preserves the objective. Finally, the slope of the exponential curve is 1.03 (b = 1.03), which is based on the slope of the marginal cost curve for energy renovations in residential buildings in Denmark. This cost curve is reported in Ref. [30].

4.2. Scenarios for subsidy allocation in Lyngby-Taarbæk

We model three scenarios for subsidy allocation, which are defined as follows:

a) The *Baseline estimates scenario* optimally redistributes the subsidy budget based on baseline heat consumption estimates ($H\_x_{jk} = Hg_{jk}$ in equation (7)).
b) The *Metered consumption scenario* shows the optimal redistribution of subsidy budget based on metered heat consumption using the observed data ($H\_x_{jk} = Hu_{jk}$ in equation (7)).
c) The *Current scheme scenario* shows the allocation of the current Danish subsidy scheme. This scheme has been found to allocate a similar subsidy amount for renovations to each building category

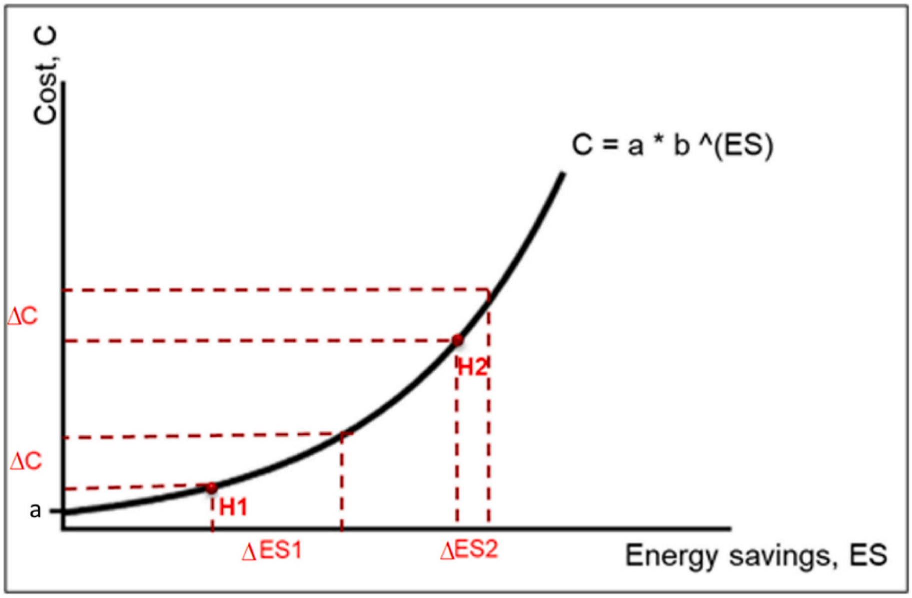

Fig. 2. Exponential cost curve for energy savings, representing exponential relationship between investment in energy-efficient improvements and resulting energy savings achieved. H_1 represents a house with higher consumption and subsequent higher potential for energy saving, while H_2 represents a house with lower consumption. "a" is a constant and scales the exponential curve along the y-axis. Its value is equal to 1 in this study.

irrespective of building categories (this is found by using the tools published on the subsidy scheme website, available at [41]). Therefore, to take into account the subsidy allocation under this scenario, the total subsidy budget is manually divided among different building categories based on their share of the total heated floor area, as in Table 3. Even though the optimization model is not used for this scenario, the allocation of subsidy achieved under the current Danish subsidy scheme scenario merits discussion in the light of the two scenarios mentioned above.

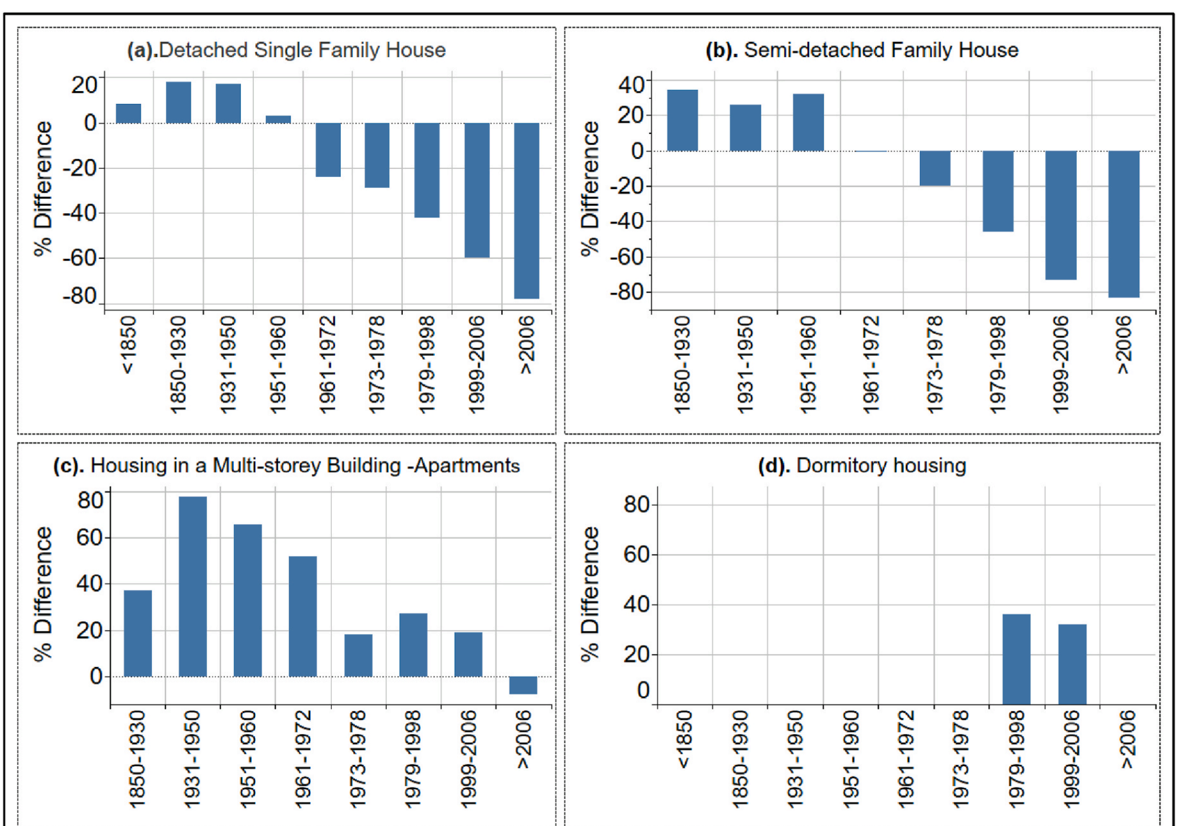

Fig. 3. Percentage difference in baseline estimates from metered heat consumption.

5. Results

This section first presents the overall differences between the estimated heat demand and the metered/real heat demand based on our datasets. Then, the resulting differences in CO_2 emissions are quantified and illustrated to visualize the shortcomings of the traditional approach to targeting buildings with large potentials for CO_2 reductions. Lastly, the subsidies are reallocated using the optimization model presented.

5.1. Differences between the state-of-the-art approach and measured data in Lyngby-Taarbæk

The average heat consumption per m^2 calculated from the metered heat consumption data using equation (1) is compared with the baseline estimates in Table 1. To make subsequent comparisons easier, the percentage difference between the baseline estimate and metered consumption (Appendix A.2) is calculated and presented in Fig. 3. A positive percentage indicates that the baseline estimates a higher consumption compared to metered consumption, which are also referred to as overestimates. A negative percentage indicates an underestimate in the baseline as compared to observed consumption.

The results in Fig. 3 provide an overall overestimate of heat consumption by baseline estimates in detached and semi-detached family houses constructed before 1960 at the aggregated municipality level. An opposite deviation is observed for the same category of buildings constructed after 1960, where the baseline estimates a lower heat consumption than what is observed (). The results indicate that the rate of deviation/difference between metered and baseline estimated data for these two building types built from the 1960s is 45.6%, against a deviation rate of 19.7% overestimated for the same building types built in the previous periods. About 77% of the single-family houses are underrepresented by the baseline estimates, and the remaining single-family houses are overrepresented. Similarly, about 42% of the semi-detached family houses are underrepresented, while the remaining semi-detached family houses are overrepresented by the baseline estimates. A similar trend was observed in this study [42].

For multistorey buildings or apartments and student dormitories (), the baseline usually overestimates heat consumption. Over the entire building stock of apartments, the average difference is about 36%.

Since the majority of the houses in the study belong to the category of detached and semi-detached family houses (Table 2), it can be concluded that a bias exists in baseline estimates which tends to overestimate heat consumption in older buildings and underestimate it in newer buildings in Lyngby-Taarbæk.

5.2. From deviations in heat demand to misrepresented CO_2 emissions

The average yearly CO_2 emissions associated with heat consumption are calculated with reference to both baseline heat consumption estimates and metered heat consumption data, using equations (2) and (3) respectively. The absolute values of total CO_2 emissions are shown in Appendix A.3. However, these results have been reproduced in Fig. 4 to visualize better the CO_2 emissions wrongfully allocated by baseline estimates to different building categories. This is done by first summing the absolute values of differences between emissions resulting from baseline and metered consumption for all building categories, then a percentage share of each category is calculated from this total of misrepresented CO_2 emissions (the detailed calculations are shown in Appendix A.3).

The positive bars in Fig. 4 indicate that baseline estimates assign a higher CO_2 emissions level than reality (metered consumption), and negative bars indicate CO_2 emissions missed by the baseline estimate data compared to metered consumption. The height or magnitude of each bar represents the relative share out of the total misrepresented emissions generated by the given building type. Thus, the higher the bar, the higher the CO_2 emissions wrongfully assigned by baseline estimates in comparison to metered data.

The comparison of the overall CO_2 emissions shows that baseline estimates result in 11% higher emissions than what is emitted and wrongfully assign about 40% of the overall CO_2 emissions (Appendix A.3).

As can be noted in Fig. 4, baseline estimates over-represent emissions from semi-detached family houses, apartments and, to a lesser extent, detached single family houses constructed between 1930 and 1960. This accounts for about 50% of the total misrepresented CO_2 emissions (or 20% of the overall emissions). Similarly, about 12% of the overall CO_2 emissions (or 40% of total misrepresented CO_2 emissions) from detached single-family houses constructed after the 1960s are misrepresented by

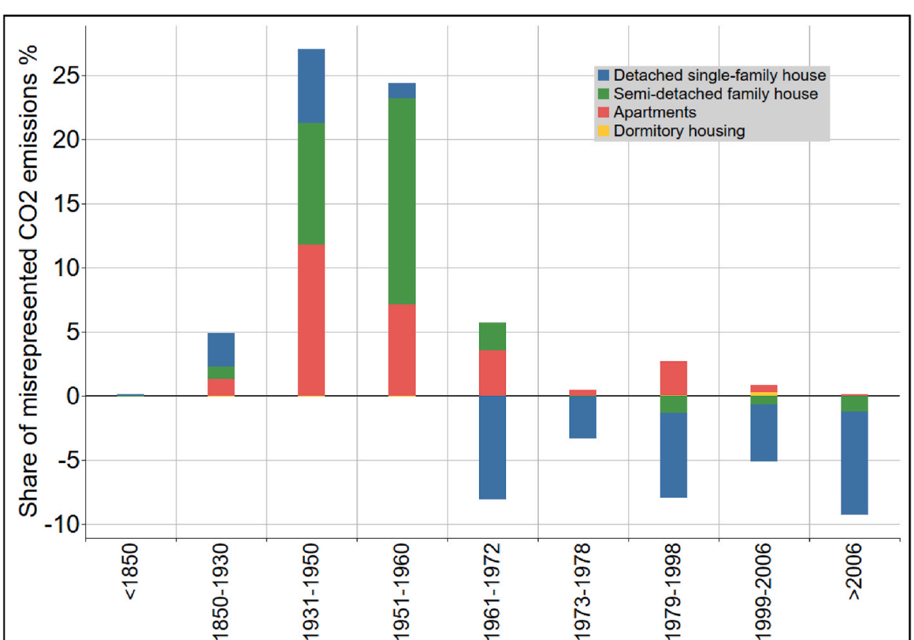

Fig. 4. Relative share of misrepresented CO_2 emissions (for each category) of total misrepresented emissions.

the baseline estimates.

5.3. Towards an optimal allocation of economic incentives for energy efficiency

The results of the optimization problem indicate the share of the total subsidy budget allocated for each building type and construction year in the three scenarios. Detailed calculations and results are shown in Appendix A.4 and Appendix A.3 respectively. Optimal allocation is reached under the metered data scenario. Misallocations of subsidy budget in the baseline estimates scenario and the current Danish subsidy scenarios are represented in Fig. 5a and b respectively as the relative difference in allocations in these two scenarios with that in the metered scenario. Positive bars indicate over-allocations of the subsidy budget for the given building type and age of construction compared to optimal allocation, and negative bars indicate under allocations.

The baseline scenario distorts about 60% of the overall subsidy budget. A deeper dive into different categories shows that about 26% of the subsidy budget is over-allocated in the baseline scenario for detached and semi-detached family houses and, to a less significant extent, apartments constructed between 1931 and 1960. The detached single-family houses constructed from 1973 receive an under-allocation of subsidy, accounting for about 27% of the overall subsidy budget.

These results are consistent with earlier results in Figs. 4 and 3. A policy intervention based on baseline estimates could lead to a non-optimal allocation of the subsidy scheme where detached and semi-detached family houses, along with apartments constructed between 1931 and 1960, are allocated more support than optimal while neglecting the support needed by detached family houses constructed after 1973.

Similarly, Fig. 5b represents the distortion in subsidy allocation resulting from current Danish subsidy scenarios. In total, about 40% of the overall subsidy budget is distorted, which is lower than the baseline estimates scenario. Here most of the distortion is centered around detached and semi-detached houses and apartments constructed between 1931 and 1998, which also form a major portion of the residential buildings in Lyngby-Taarbæk. Mostly, the apartments are allocated more subsidies than optimal, while detached family houses are under-allocated. Thus, the current Danish subsidy scheme tends to over-allocate subsidies to apartments while at the same time under-allocating subsidies to detached family houses.

The total heat savings achieved by the subsidy distribution in the three scenarios in Lyngby-Taarbæk are calculated. Since the total subsidy budget is hypothetically selected, the absolute values of energy savings are irrelevant. Therefore, relative energy savings are calculated by benchmarking the savings resulting from the subsidy distribution (Fig. 5 & Appendix A.4) for the three scenarios against the average metered consumption (Appendix A.2). The metered consumption scenario leads to about 12% and 11% more savings as compared to the baseline and present scheme scenarios respectively. The detailed energy savings resulting from the subsidy re-distribution of three scenarios are shown in Appendix A.5.

6. Discussion

The heating sector is usually localized, mostly influenced by local and/or municipal laws and actions. Similarly, there is an increasing focus on local energy planning to enable the active engagement of citizens, communities and local businesses in achieving a carbon-neutral society. A project run by the Danish government in 2014 saw 96 out of 98 municipalities in Denmark actively engage in developing strategic energy plans based on local resources, needs and aspirations. Such a local dimension of the heating sector and the increasing need for local energy planning, along with a focus on the decarbonization of energy

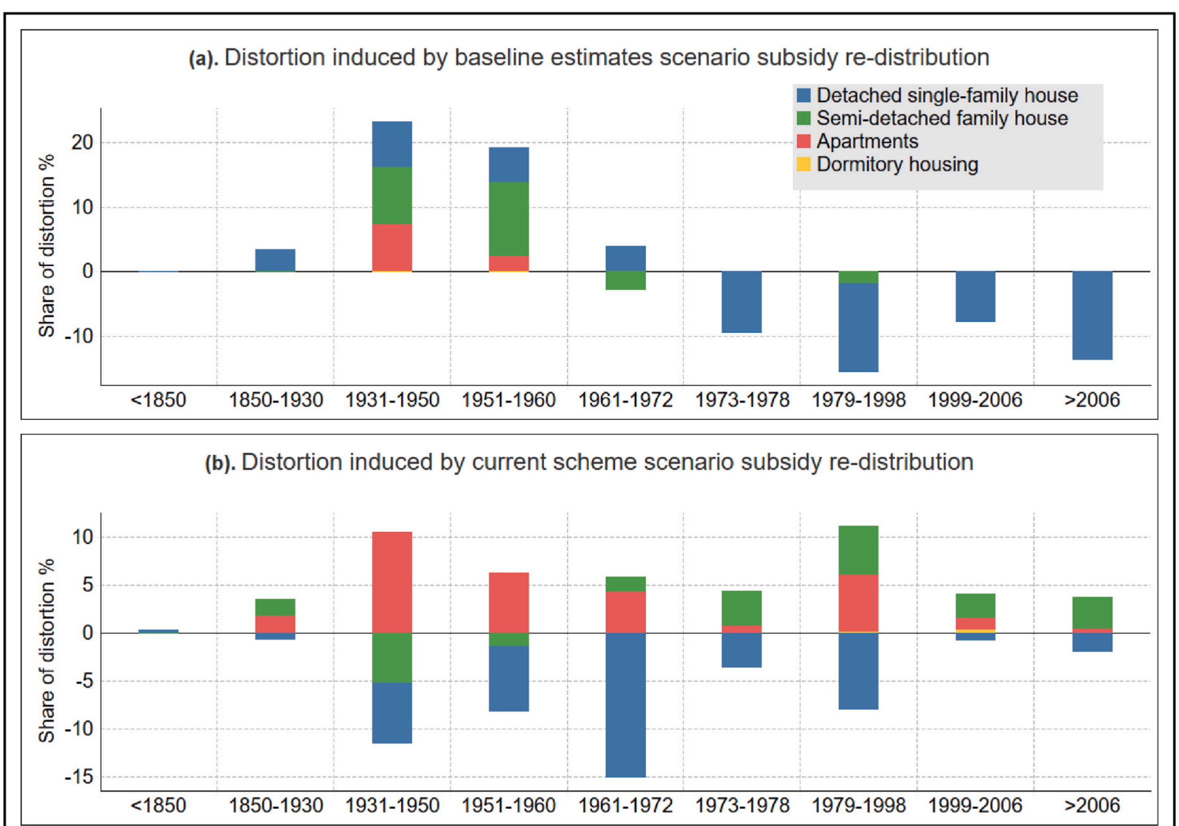

Fig. 5. Subsidy re-distribution distortion induced by (a) baseline estimates scenario and (b) current Danish subsidy scheme scenario as compared to metered scenario. Positive bars indicate over-allocation as compared to optimal (metered scenario), and negative bars indicate under-allocation.

consumption in building stock, requires adapted tools to support high-impact policy actions. While subsidy schemes, in Denmark, are designed, implemented and managed nationally, municipalities' strategic energy plans nudge homeowners towards energy renovations through local actions such as free energy audits [43]. However, the role of local authorities in Denmark will expand further in the future, as already shown in Ref. [44]. Similarly, in some other countries, if local authorities are designing and implementing subsidies, that will further strengthen the need for the tools adapted to the challenges faced by local policymakers.

The analysis highlights the consequence of using estimates for local energy-planning purposes. To the best of the authors' knowledge, no tool exists today from the perspective of local decision-making for local heat-planning, despite municipalities' direct influence in this sector. With more access to the heat consumption data of smart meters, current, widely used top-down methodologies may be complemented and adapted to improve consideration of this finer representation of actual heat demand by building type. This study quantifies the subsidy scheme's effectiveness resulting from the use of local data. Due to higher energy prices and the security of supply issues faced by the EU [45], energy saving measures to limit energy consumption is one of the central EU strategies as highlighted in the REPowerEU plan [46]. Therefore, improving the effectiveness of subsidy schemes for energy savings is of great importance.

Better transparency in terms of data availability could ensure effective policies with maximum impact and make the information more reliable in terms of public trust. As mentioned before, the current Danish subsidy scheme for energy renovation, SparEnergi, provides a tool to calculate the energy and cost savings resulting from energy renovation. Although the use of this tool is cautioned on its website, no information on the methodology for such calculations is provided. Furthermore, this tool has been found to overestimate the energy savings achieved by proposed renovations. For some buildings in the Lyngby-Taarbæk municipality, the estimated energy savings calculated with this tool exceed the metered/actual consumption. Although for privacy reasons, this article cannot disclose the details of such buildings, it is still important to emphasize that such wrong or overly optimistic estimates are likely to result in sub-optimal renovation projects and emissions reductions. As local utilities are responsible for collecting heat-demand data, and as the Danish authorities make web-based calculation tools for energy renovation subsidies publicly available, the implementation of real data for each house should require limited effort.

Considering future research, an important limitation of the proposed optimization model is that it does not consider additional investment in energy renovations resulting from subsidies, as usually subsidies or grants only cover a part of the total of energy-efficient investments. Therefore, the total investment in energy-efficient improvements or renovations surpasses the overall subsidy budget. However, this can easily be taken into account in this study, as usually subsidy schemes indicate the percentage of energy renovations covered by the subsidy grant. This model does not consider the rebound effect when calculating the energy savings resulting from a given investment in energy renovations (equation (4)). However, the metered data do implicitly take into account the rebound effect of past renovations, which may partly explain why we observe a higher heat demand in the newly built buildings. While the authors acknowledge that this hypothesis is plausible, it would go beyond the scope of the present study to try to decouple the relative share of the heat demand mismatch that may be due to the rebound effect or misestimating. Finally, this model can be used to ensure socially just policy measures by incorporating the socio-economic characteristics of families living in the different building types.

This article does not consider the deviations in heat demand due to the behavioral patterns of dwellings and variations in the efficiency of similar heating systems. The energy system's efficiency could deviate because of the different maintenance practices of homeowners. However, in our study, a constant efficiency value is considered for a similar heating system (Table 4) due to a lack of data on heating systems in individual houses. Furthermore, since in Denmark homeowners are recommended to get their heating system certified every two years [47], we assume no large deviation in efficiency among similar heating systems. However, if efficiencies do vary a lot, then a potential substantial decrease in the heating system's efficiency would make energy renovations more suitable. Similar, outcome can also results from increases energy prices.

Behavioral patterns are an important estimator of variations in the heat demand of particular households. A Dutch study calculated that occupant behavior can be responsible for about 50% of a household's variation in heat demand [48]. However, in this study, averaging is done over multiple data points, which tends to decrease the effect of such individual variations. Nonetheless, if specific behavior is consistent in a particular category of buildings/households, this may distort the effectiveness of the design of subsidy scheme proposed in this study. Such heat demand variations due to behavioral patterns and lack of data on past renovations can also distort the allocation of different building categories on the exponential curve of Fig. 2.

Finally, subsidies in building retrofitting are often based on several beneficial outcomes, such as energy-saving gains and comfort. However, considering the present state of emergency in light of the latest IPCC communication [49], consumers are being urged to limit their energy consumption and subsequent GHG emissions. Therefore, policymakers are encouraged to give GHG reduction metrics/goals the same level of importance as the other "traditional" outcomes. In response to this new reality, Italy has already decided that no air conditioning should be set below 25° [50]. Future energy policies should invent such practices which aim at striking a more sustainable balance between level and comfort, energy-saving and GHG emissions reductions.

7. Conclusion

Residential heating demand constitutes a quarter of total energy consumption in Denmark, and decarbonization of the heat sector is vital for the decarbonization of the whole society. For our case study, data comparison unambiguously shows an overshoot of the assumed heat demand in older dwellings constructed before 1960, while the newest homes appear to be less energy-hungry than they actually are. This limitation of baseline estimates allocates about 39% of total CO_2 emissions to the wrong building categories in our test case. Such a bias in baseline estimates is likely to limit the impact of energy efficiency policy, as about 40% of the overall subsidy budget may be wrongfully allocated. Using metered heat data as a basis for subsidy design results in about 12% additional energy savings compared to baseline estimates. Essentially, for Lyngby-Taarbæk municipality, measures to improve energy efficiency, such as subsidies or the facilitation of audits, should prioritize detached and semi-detached family houses. Instead of a sole focus on old houses, such energy renovation policies should not neglect newly constructed houses.

In general, optimally distributing the (hypothetical) subsidy budget to maximize energy gains, the present article allows a comparison of different subsidy allocations based on initial assumptions regarding heat consumption. This model can therefore be used to guide subsidy scheme design adapted to any type of building in a city, provided that data on building archetypes and metered heat demand are available. Therefore, our results should advise policymakers on subsidy allocations and contribute to the improvement of existing decision-making data and tools to accelerate decarbonization. Considering a more local and bottom-up dimension seems unavoidable if we are to improve the efficiency and effectiveness of local energy planning and energy-saving policies, strike the best balance between public spending and carbon emissions reductions and support a faster energy transition that is also cheaper for society.

Authors' contributions

Muhammad Bilal Siddique: Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft writing, reviewing and editing. **Claire Bergaentzlé**: Conceptualization, Supervision, writing, reviewing and editing. **Philipp Andreas Gunkel**: Conceptualization, Methodology, writing, reviewing and editing.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.

Acknowledgments

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Appendix A.1Pre-processing steps

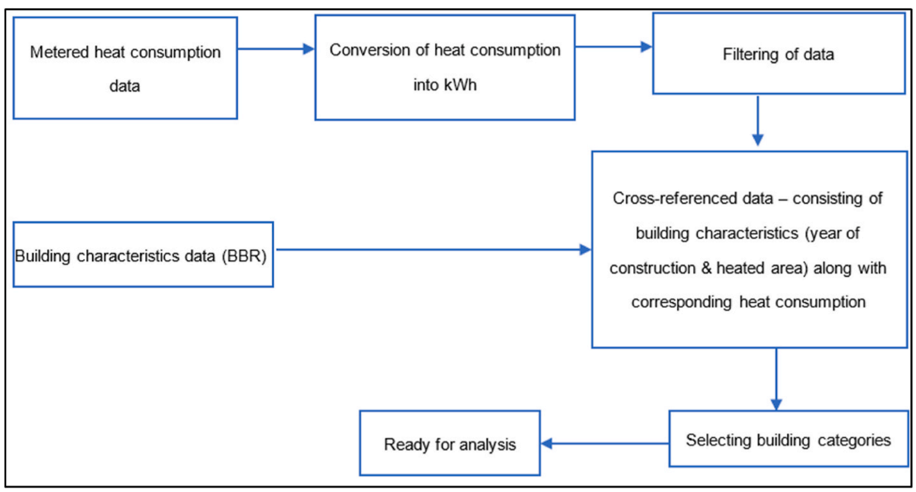

Figure A.1Overview of pre-processing steps and cross referring two datasets

The metered heat consumption dataset for buildings in Lyngby-Taarbæk contains two main information: the heat consumption of each building and the type of supply or fuel used for heating such as natural gas or oil boilers. The different types of heat supplies/fuel were converted into a common unit, kWh, based on their calorific values using 10.7 kWh/l for heating oil and 11.015 kWh/m3 for natural gas [34]. Data filtering included the removal of all negative values for consumption in the dataset as well as outliers representing very low or very high consumption considered as with 1% of the highest and 1% of the lowest consumption data points. All metered data points showing faulty time intervals of heat consumption measurement, defined as less than 360 days or more than 370 days, were removed. Finally, datasets also contain electricity consumption data which is only kept for those households where no other heating consumption data (natural gas, heating oil, or district heating consumption data) is available. Thereby, assuming that such households are heated by individual electric heat pumps whose share is about 83% of total electricity consumption [35].

Table A.1
Overview of data points removed, and data points left for analysis during the different pre-processing steps

Pre-processing steps	Number of data points …		Number of residential buildings …	
	Removed	Left for analysis	Removed	Left for analysis
1 Consumption is zero or less than zero	0	119,380	0	26,089
2 Removing outliers (1% of the lowest & 1% of the highest values)	6923	112,457	12,891	13,198
3 Duration of meter reading less than 260 days or more than 270 days	61,145	51,312	1226	11,972
4 Electricity heating redundancy	11,514	39,798	429	11,543
5 Category selection	35	39,763	14	11,529
Total available data points for analysis	39,763		11,529	

Table A.2
Average metered heat consumption per m2 per year

Use Code	Year of construction								
	<1850	1850–1930	1931–1950	1951–1960	1961–1972	1973–1978	1979–1998	1999–2006	>2006
120	139.8	151	163	159	153	142	137	132	116
130		120	142	117	131	135	117	119	122
140		88	31	50	57	95	62	62	73
150							78	76	

Table A.3
CO2 emissions and calculation of misplaced emissions by baseline scenario.

Use Code	Year of Construction	CO2 emissions baseline scenario [Ton]	CO2 emissions metered scenario [Ton]	Difference in emissions [baseline **scenario** - metered scenario]	% misplaced emissions by baseline scenario
120	<1850	78	64	15	0.1
120	1850–1930	1934	1552	383	2.6
120	1931–1950	4295	3433	862	5.8
120	1951–1960	3895	3714	182	1.2
120	1961–1972	5611	6821	−1210	−8.1
120	1973–1978	2225	2708	−483	−3.2
120	1979–1998	3190	4182	−992	−6.6
120	1999–2006	1417	2083	−666	−4.4
120	>2006	1909	3113	−1204	−8.0
130	<1850	0	0	0	0.0
130	1850–1930	411	266	145	1.0
130	1931–1950	4662	3245	1417	9.5
130	1951–1960	4656	2252	2404	16.1
130	1961–1972	1551	1225	326	2.2
130	1973–1978	558	571	−13	−0.1
130	1979–1998	884	1087	−203	−1.4
130	1999–2006	227	331	−104	−0.7
130	>2006	297	482	−185	−1.2
140	<1850	0	0	0	0.0
140	1850–1930	344	147	197	1.3
140	1931–1950	2049	283	1766	11.8
140	1951–1960	1257	194	1063	7.1
140	1961–1972	682	151	530	3.5
140	1973–1978	117	47	71	0.5
140	1979–1998	677	282	395	2.6
140	1999–2006	129	46	83	0.6
140	>2006	41	24	17	0.1
150	<1850	0	0	0	0.0
150	1850–1930	0	0	0	0.0
150	1931–1950	0	0	0	0.0
150	1951–1960	0	0	0	0.0
150	1961–1972	0	0	0	0.0
150	1973–1978	0	0	0	0.0
150	1979–1998	16	4	12	0.1
150	1999–2006	53	14	39	0.3
150	>2006	0	0	0	0.0
			sum of absolute values of difference	**14,967**	

Table A.4
Subsidy allocation / distribution and calculation of distortion induced by baseline and current scheme scenarios in comparison to metered scenario.

Use Code	Year of Construction	Subsidy allocation - Baseline estimate scenario %	Subsidy allocation - Metered consumption scenario %	Subsidy allocation - Present scheme scenario %	Difference allocation [baseline - metered scenario]	% disortion induced by baseline scenario	Difference allocation [current scheme - metered scenario]	% disortion induced by current scheme scenario
120	<1850	0.0	0.0	0.2	0.0	0.0	0.2	0.4
120	1850–1930	5.8	3.4	3.1	2.4	3.4	−0.3	−0.7
120	1931–1950	14.0	9.1	6.5	4.9	7.1	−2.6	−6.4
120	1951–1960	13.7	9.9	7.1	3.8	5.5	−2.8	−6.9
120	1961–1972	22.5	19.8	13.6	2.7	4.0	−6.1	−15.1
120	1973–1978	0.8	7.5	6.0	−6.7	−9.6	−1.4	−3.6
120	1979–1998	3.4	13.0	9.8	−9.6	−13.9	−3.2	−8.0
120	1999–2006	0.0	5.5	5.2	−5.5	−8.0	−0.3	−0.8
120	>2006	0.0	9.6	8.8	−9.6	−13.8	−0.8	−1.9
130	<1850	0.0	0.0	0.0	0.0	0.0	0.0	0.0

(continued on next page)

Table A.4 (*continued*)

Use Code	Year of Construction	Subsidy allocation - Baseline estimate scenario %	Subsidy allocation - Metered consumption scenario %	Subsidy allocation - Present scheme scenario %	Difference allocation [baseline - metered scenario]	% disortion induced by baseline scenario	Difference allocation [current scheme - metered scenario]	% disortion induced by current scheme scenario
130	1850–1930	0.0	0.0	0.7	0.0	0.0	0.7	1.7
130	1931–1950	15.6	9.4	7.3	6.2	9.0	−2.1	−5.2
130	1951–1960	16.6	8.6	8.1	7.9	11.5	−0.5	−1.3
130	1961–1972	1.0	2.9	3.6	−2.0	−2.9	0.6	1.5
130	1973–1978	0.0	0.0	1.5	0.0	0.0	1.5	3.6
130	1979–1998	0.0	1.2	3.3	−1.2	−1.8	2.1	5.2
130	1999–2006	0.0	0.0	1.0	0.0	0.0	1.0	2.4
130	>2006	0.0	0.0	1.3	0.0	0.0	1.3	3.3
140	<1850	0.0	0.0	0.0	0.0	0.0	0.0	0.0
140	1850–1930	0.0	0.0	0.7	0.0	0.0	0.7	1.8
140	1931–1950	5.0	0.0	4.3	5.0	7.3	4.3	10.5
140	1951–1960	1.6	0.0	2.5	1.6	2.3	2.5	6.3
140	1961–1972	0.0	0.0	1.7	0.0	0.0	1.7	4.3
140	1973–1978	0.0	0.0	0.3	0.0	0.0	0.3	0.7
140	1979–1998	0.0	0.0	2.4	0.0	0.0	2.4	6.0
140	1999–2006	0.0	0.0	0.5	0.0	0.0	0.5	1.3
140	>2006	0.0	0.0	0.2	0.0	0.0	0.2	0.5
150	<1850	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1850–1930	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1931–1950	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1951–1960	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1961–1972	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1973–1978	0.0	0.0	0.0	0.0	0.0	0.0	0.0
150	1979–1998	0.0	0.0	0.0	0.0	0.0	0.0	0.1
150	1999–2006	0.0	0.0	0.1	0.0	0.0	0.1	0.4
150	>2006	0.0	0.0	0.0	0.0	0.0	0.0	0.0
				Sum of absolute values	69.1	Sum of absolute values	40.4	

A.5: Heat-savings resulting from the subsidy distribution in the three scenarios.

Use Code	Year of Construction	Heat savings from Baseline scenario - KWh	Heat savings from Metered data scenario - KWh	Heat savings from current scheme scenario - KWh
120	<1850	–	–	2340
120	1850–1930	1,454,813	1,013,268	949,403
120	1931–1950	5,812,624	4,702,178	3,921,242
120	1951–1960	6,024,073	5,126,103	4,278,344
120	1961–1972	13,371,414	12,630,202	10,602,594
120	1973–1978	495,635	2,842,671	2,467,384
120	1979–1998	2,423,163	6,017,053	5,089,349
120	1999–2006	43	1,627,447	1,554,358
120	>2006	45	3,068,222	2,884,642
130	<1850	–	–	–
130	1850–1930	2	–	26,422
130	1931–1950	5,208,515	3,914,637	3,337,624
130	1951–1960	4,186,437	2,706,706	2,582,463
130	1961–1972	256,194	681,322	796,205
130	1973–1978	21	2211	171,968
130	1979–1998	31	207,912	509,065
130	1999–2006	–	–	53,245
130	>2006	–	–	102,995
140	<1850	–	–	–
140	1850–1930	3	–	13,871
140	1931–1950	119,753	–	101,952
140	1951–1960	37,574	–	59,397
140	1961–1972	–	–	33,638
140	1973–1978	–	–	2783
140	1979–1998	–	–	72,609
140	1999–2006	–	–	3304
140	>2006	–	–	579
150	<1850	–	–	–
150	1850–1930	–	–	–
150	1931–1950	–	–	–
150	1951–1960	–	–	–
150	1961–1972	–	–	–
150	1973–1978	–	–	–
150	1979–1998	–	–	29
150	1999–2006	–	–	381
150	>2006	–	–	–
	Total	**39,390,340**	**44,539,933**	**39,618,186**

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