Advances in Applied Energy 20 (2025) 100256

Contents lists available at ScienceDirect

Advances in Applied Energy

journal homepage: www.elsevier.com/locate/adapen

Advancing building stock transformation models: An agent-based approach and its application to Germany

Şirin Alibaş [a,b], Songmin Yu [a,*], Mahsa Bagheri [a], Tobias Fleiter [a]

[a] Fraunhofer Institute for Systems and Innovation Research, Breslauer Str. 48, 76139, Karlsruhe, Germany
[b] University of Freiburg, Department of Sustainable Systems Engineering INATECH, Emmy-Noether-Straße 2, 79108, Freiburg im Breisgau, Germany

ARTICLE INFO

Keywords:
Agent-based modeling
Building sector
Decarbonization
Case study
Scenario analysis
Infrastructure
Climate neutrality

ABSTRACT

The building sector is pivotal for achieving climate neutrality, requiring sophisticated modeling tools to guide the energy transition. It is highly heterogeneous with variety in both the built environment and in its decision-makers. While many sectoral models exist, most of them fall short of capturing the barriers and limitations in the energy transition as they lack high spatial resolution and a detailed representation of heterogeneous building characteristics and local infrastructure constraints. To address this gap, we present RENDER-Building, a new agent-based model (ABM) designed for high-resolution analysis of building stock transformation. We validate and apply the model to the German building stock to simulate potential transformation pathways until 2050 under three distinct scenarios. The individual buildings are the agents here with detailed attributes, located in a settlement type in a NUTS3 region. The model explicitly considers the availability of energy infrastructure and simulates agents' decisions about renovation and technology adoption based on bounded rationality. Our case study's results indicate that even with ambitious measures, Germany's building sector may miss its short-term emission targets due to the inertia of the existing stock. A transformation pathway considering realistic challenges could substantially exceed the short- and long-term emission targets, necessitating difficult and potentially costly interventions to get back on track. Our study demonstrates the utility of high-resolution ABMs in providing nuanced, actionable insights for policymakers, helping them to navigate the complexities of the building sector's energy transition.

1. Introduction

Buildings account for 40% of the final energy consumption in the EU and 36% of its greenhouse gas (GHG) emissions [1]. As such, the building sector is a significant part of the energy system and plays a crucial role in the transition to a climate-neutral energy system. Model-based scenario analyses that comprehensively integrate policy measures are essential for projecting transition pathways and supporting effective policymaking. Numerous models have been developed to analyze the building sector with a particular focus on energy use, decarbonization pathways, and policy impacts. These models range from global-scale assessments to national and regional analyses, employing various methodological approaches. Global models have focused on the development of the building stock considering renovation potential [2], household energy use [3,4] and emission targets [5]. European studies have delved deeper into policy options and building stock dynamics [6], and include country-specific analyses for France [7], Italy [8], Switzerland [9], United Kingdom [10] and Germany [11–16]. The energy transition of the building sector is fundamentally characterized by a large number of decision-makers, whose behavior is highly heterogeneous as are the characteristics of their buildings. In the EU, the rate of home ownership varies drastically by member state (47% in Germany up to 94% in Romania), and 23% of the homeowners in Germany have an income below 60% of the median equivalised income [17]. Furthermore, within Germany, not only do the rate of ownership and income level vary by federal state, the building stock itself varies drastically as well in terms of the number of dwellings within a building, dwelling size, construction period, renovation state and the technologies used such as the heating system [18]. Agent-based modeling is particularly suited to representing this highly heterogeneous sector. It enhances the understanding of buildings at the agent or representative building level and model the interactions between buildings and their users within their respective environments. A significant proportion of recent research has utilized agent-based modeling to capture the complex interactions between buildings, their users, and the environment [19–33]. However, local and regional characteristics

* Corresponding author.
E-mail address: songmin.yu@isi.fraunhofer.de (S. Yu).

https://doi.org/10.1016/j.adapen.2025.100256
Received 26 August 2025; Received in revised form 19 November 2025; Accepted 19 November 2025

have been largely overlooked in national or global building sector models. Most critically, the availability of heating infrastructure, such as district heating and gas distribution networks, has often been assessed at an aggregated national level, which tends to simplify the complex regional dependencies of the building stock on the relevant infrastructure. Previous analyses in other fields have demonstrated the importance of detailed spatial considerations in quantitative evaluations [34,35].

Against this background, we developed the RENDER-Building model and integrated novel data sources. RENDER is an agent-based ene**R**gy d**E**ma**N**d mo**D**eling fram**E**wo**R**k developed using two open source Python packages: Melodie[1] and tab2dict.[2] Applying the RENDER framework, RENDER-Building is an agent-based model for the building sector, which captures the heterogeneity among buildings (agents) and bounded rationality in decision-making processes [37]. Leveraging the flexibility of the agent-based framework, RENDER-Building advances modeling the transformation pathways of the building sector through the following contributions:

- Apart from assigning heterogeneous attributes such as building type, construction year, building geometry, and building envelope efficiency, this model also has high spatial resolution. Each building agent is assigned a "location type", which is defined as one of seven settlement types (urban center, dense urban cluster, semi-dense urban cluster, suburban or peri-urban, rural cluster, low-density rural, and very low-density rural), and allocated to a specific NUTS 3 region [38]. The data are the result of aggregating the hectare-level data in the global human settlement layer (GHSL)[3] dataset [39].
- Benefiting from the first point, the development of infrastructure (including district heating, gas distribution, hydrogen distribution networks) is considered at the same spatial resolution to better reflect the potential of the corresponding infrastructure-bound heating technologies, as well as other competing technologies.
- Building agents are assigned living/working units and unit users whose characteristics and behaviors are considered. A discrete choice model is applied to represent bounded rationality in investment decisions for renovations, technology installations and modernizations. The "rebound effect" in heating behavior is also considered [40].

The model is tested and validated by applying it to a case study of the transformation of the German building stock. In the case study, the transition pathways of the German building sector are simulated under three different scenarios – sustainable transformation, challenged transformation, and limited transformation – that were developed using a participatory process in the RokiG2050 project[4] [41]. Data for this process were collected in workshops, extended by literature reviews and then validated again in workshops. The rest of this paper is organized as follows. In Section 2, we review the literature on building stock modeling from both methodological and policy perspectives. Section 3 introduces the RENDER-Building model, including the overall framework, building agent initialization, and simulation processes. Section 4 presents the case study for Germany, explains how the transition scenarios are defined for the German building sector, and how they are quantitatively modeled. The simulation results are presented in Section 5. Finally, discussions and conclusions are provided in Section 6.

2. Literature review

The building sector's transition to climate neutrality has been extensively studied using various modeling approaches. This section reviews building sector models. Table 1 summarizes the literature, comparing the studies' sectoral/spatial scope and resolution, as well as their consideration of infrastructure and decision-maker/occupant characteristics.

There are three important aspects to consider when modeling and analyzing the building sector's transition toward climate neutrality: dynamics of the stock (buildings and technologies), characteristics of the users/occupants, and the building's local environment including infrastructure availability. Sectoral studies not using an agent-based approach (in Table 1) feature a mixed integration of decision-maker/occupant characteristics (7 out of 15 studies), but commonly neglect infrastructure characteristics, except for [14,15]. A few studies, such as [3,16], analyzed the socioeconomic and distributional impacts of a sectoral transition by integrating decision-maker/occupant characteristics without explicitly modeling the life cycle dynamics of technology and building components. Others model these dynamics and integrate decision-maker characteristics without considering the local environment/infrastructure availability [4,7]. Building sector models fall short of understanding the barriers and limitations here if they do not explicitly consider the dynamics of stock and decision-maker/occupant characteristics together with the local environment/infrastructure availability. This is why enhancing the understanding of buildings at the level of an individual or representative building is important to identify levers that can overcome barriers.

Agent-based models (ABMs) characterize physical, social, biological, and economic systems from a bottom-up perspective through the dynamic interactions between agents. They have the advantage of depicting large heterogeneous systems through the actions of the actors involved as well as their interactions with each other and with the environment [42]. As the building sector is highly heterogeneous, this modeling approach is very suitable. Modeling buildings at the level of individual or representative buildings can capture barriers to the energy transition in the sector and ways to overcome them. Insights from previous studies using ABMs show the importance of policies that consider household characteristics and attitudes in decision-making in residential buildings. For example, financial incentives may drive economically-motivated decisions but can fall short if social and psychological factors dominate decision-making [24]. In addition, investment grants are found to be suitable for "pensioners" and low-interest loans for "younger people", and the greatest exploitable potential to reduce CO_2 emissions can be approximately half the technical potential due to barriers such as lack of financing options, information deficits, and unwillingness to renovate [27]. Policy mixes should address the diverse needs of consumer groups to be more effective [33] and the right information should be provided to households at the right time [23], all of which are possible to capture in ABMs.

However, agent-based building sector models on a national or global scale do not allow the depiction of the building stock's local and regional characteristics such as locally available resources. Most critically, the availability of heating infrastructure, such as district heating and gas distribution networks, has either not been considered (5 out of 12 studies in Table 1) or often been considered at an aggregated national level (5 out of 12 studies in Table 1), which tends to simplify the complex regional dynamics of the building stock and the relevant infrastructure. Even when household characteristics are considered representatively at the municipal level, such as in the case of [27],

[1] Melodie is an open source general framework for agent-based modeling in Python [36], available at: https://github.com/ABM4ALL/Melodie.

[2] tab2dict is a data management tool designed for model development in Python, especially for developing agent-based models. The package is open source at https://github.com/ABM4ALL/tab2dict.

[3] The Global Human Settlement Layer (GHSL) project is supported by the European Commission, Joint Research Centre and Directorate-General for Regional and Urban Policy. The GHSL produces new global spatial information, evidence-based analytics, and data describing the human presence on the planet. Website: https://human-settlement.emergency.copernicus.eu/.

[4] Roadmap for a climate-neutral building stock (RokiG2050) under the Accompanying Scientific Research Energiewendebauen (BF2020) — Module Buildings. Project details can be found at https://www.ebc.eonerc.rwth-aachen.de/go/id/qfkxc/lidx/1.

Table 1
Overview of existing studies in the field and their methodological approach.

	Reference	Sector	Spatial scope, resolution & characteristics	Infrastructure characteristics	Decision-maker/occupant characteristics
Building sector studies not using ABMs	Zhang et al. [2]	Res. & NRes.	Global, continental or national, –	–	–
	Daioglou et al. [3]	Res.	Five developing world regions, 26 world regions, urban & rural	–	Income quintile
	Daioglou et al. [4]	Res.	Global, 26 world regions, urban & rural	–	Income quintile
	Camasara et al. [5]	Res. & NRes.	Global, continental or national/sub-national climate zones, –	–	–
	Uihlein & Eder [6]	Res.	EU27, national	–	–
	Charlier & Risch [7]	Res.	France, national, –	–	Size, income quintile, tenure, disposable income, saving rate, borrowing power
	Bianco & Marmori [8]	Res.	Italy, national, –	–	–
	Streicher et al. [9]	Res.	Switzerland, 26 cantons, urban & suburban & rural	–	–
	Li et al. [10]	Res.	United Kingdom, national, –	National	Existing technology, number of bedrooms
	McKenna et al. [11]	Res.	Germany, 2 sub-national regions (old & new federal states), –	–	Number of households
	Henkel [12]	Res.	Germany, national, small village & others	–	Income, preference for space requirement
	Elsland [13]	Res.	Germany, national, –	–	–
	Bauermann et al. [14,15]	Res.	Germany, national, –	National	–
	Hornykewycz et al. [16]	Res.	Germany, national, –	–	Income
Building sector studies using ABMs	Zhao et al. [19,20]	NRes.	Midwest (US), building-specific, –	–[a]	–
	Maya Sopha et al. [21]	Res.	Norway, sub-national regions, 3 location types by density	–	Income, decision strategy, degree of social influence, number of peers
	Sachs et al. [22]	Res.	United Kingdom, national, –	–	GDP per capita/household, age, education level, employment
	Nägeli et al. [25,26]	Res.	Switzerland, national, –	National	Size, discount rate, willingness to pay
	Stengel [27]	Res.	Germany, sub-national, 4–5 location types by population	–	Income, tenure
	Müller [28]	Res. & NRes.	Austria, sub-national (2380 municipalities), settlement areas	Federal state	Income, preference for heating system
	Kranzl et al. [29]	Res. & NRes.	Austria & Lithuania & United Kingdom, national, urban & rural	National, based on location type	Preference for heating system
	Kranzl et al. [30]	Res. & NRes.	EU28, national, –	National	Income, discount rate
	Kranzl et al. [31]	Res. & NRes.	Germany, national, urban & rural	National, based on location type	Same as [32]
	Steinbach [32]	Res. & NRes.	Germany, sub-national (municipality), settlement type	Municipality	Investor type: private landlord, owner-occupier, joint-owner, housing association; decision factors: information awareness, income, age, risk aversion, energy price perception

[a] Considers the electricity network at city/state-scale, not the heating infrastructure.

heat system modernization packages do not consider infrastructure or resource availability with the same spatial resolution. Recognizing the importance of this factor, Steinbach integrated infrastructure availability into his analysis using Invert/EE-Lab, although the most recent data available at that time were from 2011 [32]. In contrast, if ABMs are applied on a much smaller scale, such as in the case of [24], it can be difficult to draw holistic conclusions for a regional entity.

We developed RENDER-Building to address the research gap concerning this trade-off between local, detailed representation and system-level implications. With this study, we intend to address the following research questions: (1) How can building stock transformation be effectively modeled through the simulation of building stock dynamics while integrating regional and decision-maker/occupant characteristics and novel data sources? (2) What conclusions can be drawn about the building stock of large entities like countries or sub-national regions such an integrated modeling approach?

3. Methodology

Section 3.1 introduces the model framework, followed by the details about the building agent initialization (Section 3.2) and the simulation processes (Section 3.3).

3.1. Model framework

RENDER-Building is implemented with Melodie [36], an open-source general framework for agent-based modeling in Python. There are five main components in ABMs developed with Melodie. First is "Model", which encompasses the following four: (1) "Environment", which coordinates the agents' decision-making processes and interactions; (2) "AgentList", which saves the data and logic of individual agents; (3) "Scenario", which imports input data into the model and can be accessed by the environment and each agent; (4) "DataCollector",

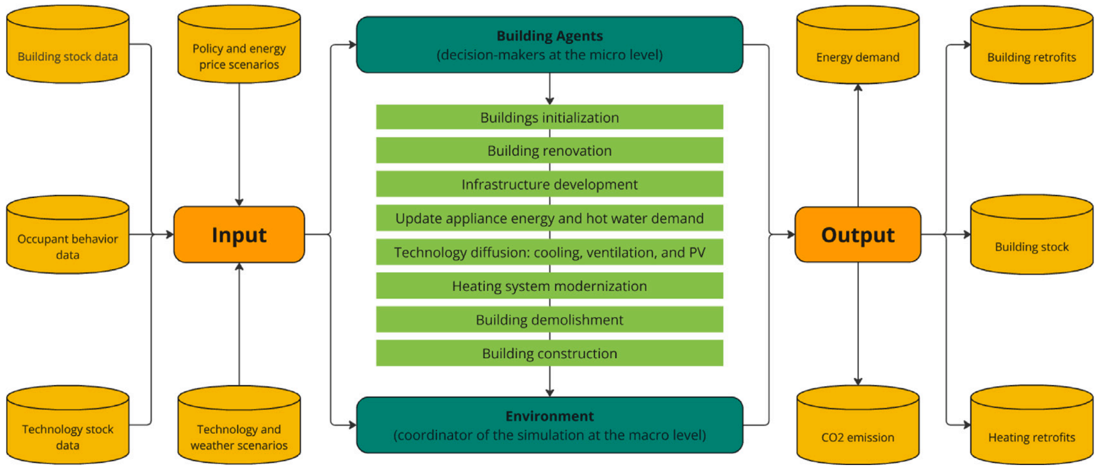

Fig. 1. Workflow of the RENDER-Building model.

which collects the model's micro- and macro-level results. In addition, Melodie also provides two optional components: (1) "Calibrator", which can calibrate multiple macro-level parameters of an ABM by minimizing the distance between model output and a pre-defined target; (2) "Trainer", which can train the behavioral parameters of agents using a genetic algorithm [42]. Unlike the popular ABM framework Mesa [43], which organizes the simulation logic around the "step()" function of individual agents, Melodie organizes the simulation workflow with the environment object. The workflow of RENDER-Building is shown in Fig. 1.

As shown, the model takes five categories of input data.

1. *Building stock data*: number of buildings by region, sector and type; share of buildings by construction period and settlement type; number of apartments and floor area by building type; building envelope U-values and lifetime of building components.
2. *Occupant behavior data*: population, socio-demographic structure, number of households by household size, number of employees by sector, demand profiles of appliances and hot water.
3. *Technology stock data*: shares of heating systems and technologies in the building stock, penetration rates of other technologies including cooling, ventilation, and solar PV, and efficiency coefficients of technologies.
4. *Policy and energy price scenarios*: taxes and subsidies, efficiency classes and minimum energy performance standards for building components, technology bans, energy carrier prices, and CO_2 prices.
5. *Technology and weather scenarios*: availability of infrastructure (district heating, gas grid, hydrogen grid), costs and efficiency of heating technologies, penetration pathways of other technologies (cooling, ventilation, and solar PV), technology standards for new buildings, projection of ambient temperature and radiation profiles for future years.

Based on the input data, the "environment" coordinates the "building agents" through a series of processes in each simulation year. After initialization, the building agents update their renovation status, infrastructure availability, energy demand for appliances and hot water, adoption of other technologies, and their heating systems. Then, old buildings are demolished, and new buildings are constructed according to the socio-demographic development. Finally, based on all the data from the building agents and the environment, output files are produced, including final energy demand by carrier and end-use, CO_2 emissions, historical retrofits of buildings and their heating systems, as well as the detailed information of each building agent in each simulation year.

3.2. Building agent initialization (step 0)

Leveraging the flexibility of ABM, the building agents in RENDER-Building are initialized in detail as shown in Fig. 2. First, we defined four basic IDs that are assigned to each agent and then used for further initialization to organize the data from different sources for initializing the building stock. Each combination of the four basic IDs corresponds to one segment of the building stock, for which we estimated the number of buildings (N_{real}).

1. **id_region**: the geographic region where the modeled buildings are located.
2. **id_sector**: residential (Res.) and non-residential (NRes.) sectors.
3. **id_subsector**: residential sector and 16 non-residential sectors A-S according to NACE, rev. 2 [44].
4. **id_building_type**: 5 residential building types according to total number of dwellings in the building, and 11 non-residential building types such as office buildings, educational buildings, etc.

Second, for each building segment, we define a coverage rate λ and use $N_{model} = \lambda N_{real}$ agents for representation. These building agents are further assigned the heterogeneous properties and data below. In our previous paper [45], we described how the data from different sources are harmonized to initialize the building stock in Germany with detailed technological information at high spatial resolution.

5. **id_building_construction_period**: from "before 1900" to "after 2011" at ten-year intervals.
6. **id_building_location**: seven settlement types defined by GHSL [39], including urban center, dense urban cluster, semi-dense urban cluster, suburban or peri-urban, rural cluster, low density rural, very low density rural.
7. **id_building_height**: height (number of floors) is assigned to buildings based on GHSL data.
8. Building components: four components are considered for each building agent in the model: roof, wall, window, and basement. Their U-values are assigned according to the building type and construction period. Then, by assuming a set temperature of 20 °C, the heating and cooling demand are calculated for the building in hourly resolution following the 5R1C approach (DIN ISO 13790). According to the calculated heating demand, **id_building_efficiency_class** is then assigned to the building and used to update the real set temperature for the building to reflect the "rebound effect", i.e., more efficient buildings have a higher set temperature [40].

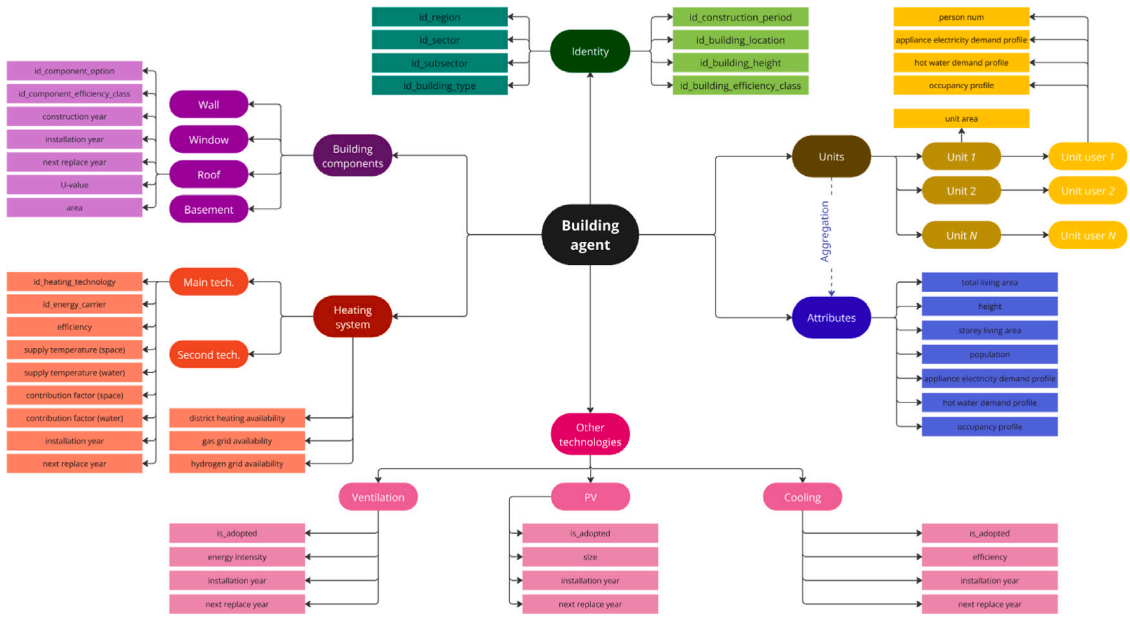

Fig. 2. Data structure of building agents.

9. Heating system: Four types of heating system are considered in the model: district heating, central/block heating, dwelling/floor unit heating, and single-room heating. These heating system types encompass 23 heating technologies, including heat pumps with different heat sources, as well as boilers with different energy carriers. Finally, the model considers the availability of infrastructure, e.g., district heating, gas grid, and hydrogen grid.
10. Other technologies: For a more comprehensive coverage of end-uses, the model also accepts exogenous input for the penetration pathways of ventilation, solar PV, and cooling technologies. Their energy demand or generation are calculated accordingly, e.g., electricity generation from solar PV is calculated according to the roof size of the building.
11. Units: Based on building type, we assign the number of living/working units to the building and then the type of unit user to the unit. For residential buildings, the unit users are five types of household: single-person, couple without resident child(ren), couple with resident child(ren), single parent with resident child(ren), and other households (e.g., shared apartment). For non-residential buildings, the unit users are companies/entities from specific sectors. Then, all unit users are assigned a number of persons and profiles of appliance energy demand, hot water demand, and building occupancy. The profiles are further aggregated to the building level.

After initialization, the building agents go through a series of processes, as described in Section 3.3.

3.3. Simulation processes

3.3.1. Building renovation (step 1)

The model defines each building agent as having four components: roof, wall, window, and basement. Renovation is modeled at the level of building components, i.e., when one component reaches its end-of-life, it will be replaced, and the U-value of this component is adjusted. The heating and cooling demand of the building agent is updated immediately after renovation. For each building component, we consider 12 efficiency classes with different U-values from A+++ to "very poor" (see Table 2).

To model efficiency improvements and regulation policies, we compile a table with the efficiency class options available on the market each year. We also distinguish the availability of options for "conventional renovation", "serial renovation" and "construction" activities, so that (1) newly constructed buildings can have higher efficiency standards than the renovation options for existing buildings, and (2) the difference between "conventional renovation" and "serial renovation" can also be captured. This table starts from 1900 to cover old buildings constructed and renovated before the simulation's starting year, i.e., when initializing the building stock in the starting year, we consider historical building construction and renovation, and the corresponding years are documented. Two attributes are defined for each building component in each building to track its life cycle: "installation_year" and "next_replace_year". The difference between the two attributes is the lifetime of the building component, drawn from a predefined interval based on [46].

Table 2
U-values of building components in different efficiency classes.

Efficiency class	Unit	Wall	Window	Roof	Basement
A+++	W/m² K	0.1	0.6	0.1	0.1
A++	W/m² K	0.15	0.7	0.15	0.2
A+	W/m² K	0.2	1.0	0.18	0.25
A+	W/m² K	0.25	1.2	0.2	0.3
B	W/m² K	0.3	1.4	0.25	0.35
C	W/m² K	0.5	1.6	0.3	0.45
D	W/m² K	0.65	1.8	0.4	0.55
E	W/m² K	0.8	2.0	0.5	0.65
F	W/m² K	1.0	2.5	0.6	0.75
G	W/m² K	1.2	3.0	0.9	0.85
H	W/m² K	1.6	4.0	1.0	1.0
Very poor	W/m² K	2.0	5.0	2.0	2.0

When an agent is triggered to consider the renovation of one building component because this has reached its end-of-life, the agent will first go to the market and find the available options. Then, the levelized cost of each available option i and renovation type j (conventional or serial) ($LC_{i,j}$) is calculated based on (1) interest rate (r), (2) unit investment expenditure ($IEU_{i,j}$), (3) the area of the component (A), (4) expected lifetime of the building component (LT), and (5) the energy cost saving due to renovation ($EC_0 - EC_i$) — EC_0 refers to the energy cost before renovation and EC_i refers to the energy cost if option i is installed (Eq. (1)). The investment expenditure is calculated based on material costs (MC_i), labor demand ($LBD_{i,j}$), labor costs ($LBC_{i,j}$), and the subsidy rate ($sub_{i,j}$) (Eq. (2)). As indicated by Eqs. (1) and (2), the type of renovation impacts material and labor costs, but not the

U-values and lifetime of the components. Finally, according to $LC_{i,j}$ of all available options and renovation types, the building agent will select one of them following Eq. (3), i.e., higher cost ($LC_{i,j}$) means a lower probability ($P_{i,j}$) of selection. This probabilistic form of discrete-choice modeling reflects the bounded rationality [37] of the building agents in the model.[5]

$$LC_{i,j} = \frac{r \times IEU_{i,j} \times A}{1-(1+r)^{-LT}} - (EC_0 - EC_i) \tag{1}$$

$$IEU_{i,j} = (MC_{i,j} + LBD_{i,j} \times LBC_{i,j}) \times (1 - sub_{i,j}) \tag{2}$$

$$P_{i,j} = \frac{e^{-\beta LC_{i,j}}}{\sum_{i,j} e^{-\beta LC_{i,j}}} \tag{3}$$

Once the final decision has been made, the building's heating and cooling demand are updated based on the U-value of the new component. The "installation_year" and "next_replace_year" of this component are also updated. In addition, the model collects the information about the renovation and saves it in the "Building retrofits" output file (Fig. 1) for further analysis. This includes the costs of the selected option, as well as the heating and cooling demand of the building before and after the renovation.

3.3.2. Infrastructure development (step 2)

RENDER-Building considers three types of infrastructure: district heating, gas grid, and hydrogen grid. The availability of these three types of infrastructure is defined as exogenous scenario input. To achieve adequate spatial resolution, the availability ratio is based on two IDs: **id_region** and **id_building_location**. In each simulation year, it is checked whether the building agents have these three infrastructures available. If not, a probability is calculated based on the availability ratio in the previous and the current year, given the building's **id_region** and **id_building_location**. Then, according to this probability, we update the corresponding attributes of the building's heating system: "district heating availability", "gas grid availability", "hydrogen grid availability" (see Fig. 2). The availability of infrastructure is the prerequisite for a building agent selecting the corresponding technology when possible (see Section 3.3.5).

3.3.3. Update appliance energy and hot water demand (step 3)

As shown in Fig. 2, each building agent contains a number of working/living units. For residential buildings, the number of living units depends on the building type. For non-residential buildings, we assume there is only one working unit, and for simplicity, we do not consider that a non-residential building is occupied by firms from multiple sectors.

We assign the number of persons to each living/working unit. Each person has a specific energy demand for appliances and hot water. Note that the energy demand for appliances refers to final energy demand, while that for hot water refers to useful energy demand, because the final energy demand for hot water is calculated endogenously together with the heating system. RENDER-Building does not model the appliance technology stock endogenously but takes exogenous scenario input from other models. The same applies to the useful energy demand for hot water. In every simulation year, we update the values of the two end-uses according to the scenario input.

In addition, for hourly temporal resolution, we consider the profiles of the energy demand for appliances and hot water, i.e., the annual demand is allocated to 8760 h in the year according to predefined profiles based on the HOTMAPS project.[6] The profiles are also updated in this simulation process.

[5] Sensitivity runs for the discrete-choice parameter, β, are presented in Appendix.

[6] HOTMAPS is an EU-funded project aiming to develop a toolbox that supports local, regional and national heating and cooling planning processes. The project also developed generic electricity load and hot water demand profiles for different sectors. The results can be found at: www.hotmaps-project.eu.

3.3.4. Technology diffusion: cooling, ventilation, and PV (step 4)

For complete coverage of the end uses in the building sector, RENDER-Building uses simplified modeling for the diffusion of cooling, ventilation, and PV technologies. Using exogenous penetration rates as input, the building agents are coordinated by the environment in each simulation year to check whether they have adopted these technologies. Then, if not, an adoption probability is calculated based on the penetration rate in the previous and current year, given the building's **id_region**, **id_sector**, and **id_subsector**. We consider seven efficiency classes for cooling and ventilation technologies, from which building agents choose one following the discrete-choice approach. The size of the cooling system required depends on the peak cooling demand calculated using the 5R1C approach. The size of the ventilation system required depends on the total living area in the building. Furthermore, the size of the PV system depends on the building's roof area.

3.3.5. Heating system modernization (step 5)

In RENDER-Building, a building agent's heating system is modeled as a combination of a "main" technology and an optional "second" technology. The model considers four types of heating system (district heating, central/block heating, dwelling/floor unit heating, and single-room heating), 23 main technologies distinguished by type of energy carrier, and two second technologies (solar thermal and electric heater). If there is a second heating technology, space and water heating are shared by the two technologies, as indicated by the two attributes in Fig. 2: "contribution factor (space)" and "contribution factor (water)". Every building agent is assigned a main heating technology and some are assigned a second heating technology in the initialization process. Then, a building agent is triggered to replace the heating technology as soon as its end-of-life is reached. For simplicity and due to the lack of data, we only consider agents replacing the main heating technologies. In this process, the impact of infrastructure availability and technology ban policies are modeled. **Each building agent** goes through the steps shown in Fig. 3.

- First, the building agent checks the available heating technologies on the market in the current simulation year. These technologies are added to the option list. To model regulatory restrictions in technology choice, we developed a scenario table informing the model which heating technologies are available in which simulation years.
- Second, the agent checks infrastructure availability: district heating, gas grid, and hydrogen grid. If a specific infrastructure is not available, the agent removes the corresponding technologies from the option list.
- Third, for each technology n in the option list, as shown in Eq. (4), the agent calculates the levelized cost (LC_n). This is based on (1) interest rate (r); (2) initial expenditure for each unit of capacity invested (IEU_n), considering both material and labor costs and distinguishing three cases: new installation, replacement with the same type of system, and replacement with a different type of system; (3) capacity of the heating technology (CAP), determined as the 90th percentile of the 8760 hourly heat demand (the sum of space and water heating) values over the year, to avoid unrealistic oversizing due to peak hours; (4) expected lifetime of the heating technology (LT_n); (5) subsidy rate (sub_n); (6) energy cost (EC_n), depending on the efficiency of the heating technology and the price of the corresponding energy carrier, including taxes and CO_2 emission price; and (7) operation and maintenance cost (OMC_n).

$$LC_n = \frac{r \times IEU_n \times CAP}{1-(1+r)^{-LT_n}} \times (1 - sub_n) + EC_n + OMC_n \tag{4}$$

- Finally, the agent calculates the selection probability ($P_n = e^{-\beta LC_n} / \sum_n e^{-\beta LC_n}$) of the available heating technologies, with this probability-based discrete-choice approach representing its

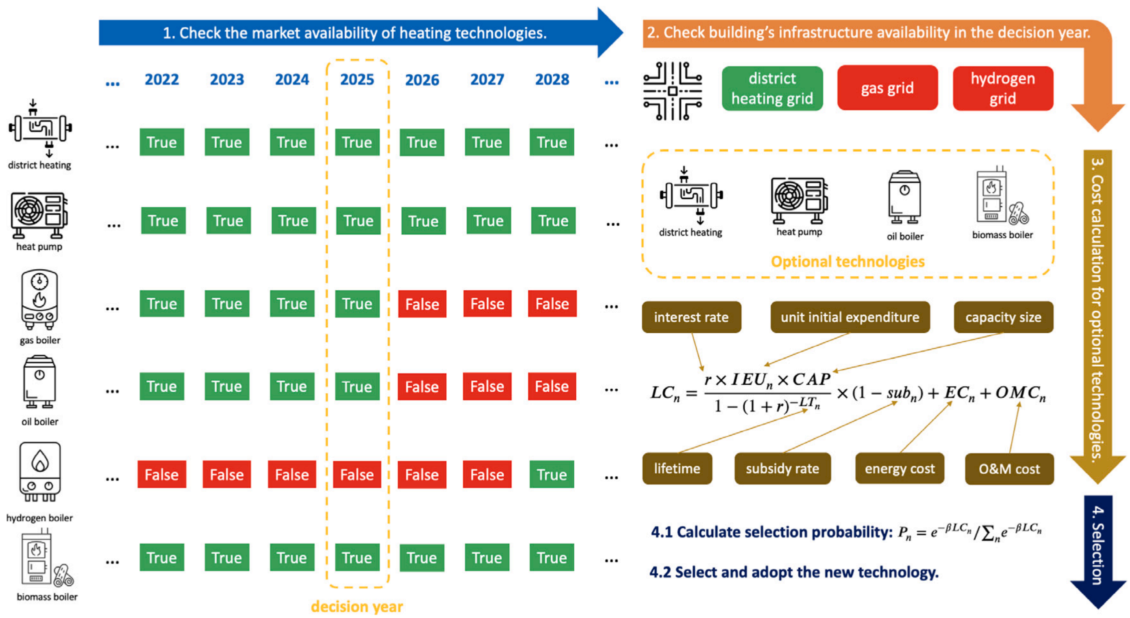

Fig. 3. Illustration of the decision-making process for replacing the heating technology with exemplary assumptions.

"bounded rationality".[7] Then, after installing the technology, the agent updates the **id_heating_technology** and **id_energy_carrier** of its heating technology, as well as the attributes "efficiency", "installation year", and "next replace year" (Fig. 2).

All the actions of heating system modernization are collected by the model and saved in the "Heating Retrofits" output file (Fig. 1) for further analysis. This includes the costs of the selected heating technology, as well as the components of the replacement cost.

3.3.6. Building demolition and construction (steps 6 & 7)

When initializing the building stock in the starting year of the simulation, we assigned each building agent two attributes: "construction year" and "demolition year". Once a building reaches its end-of-life, it is demolished.

For non-residential buildings, we assume the number of new buildings matches the number of demolished ones, with all their properties unchanged except for efficiency standards. For residential buildings, the model calculates the number of remaining dwellings after the demolition process, then calculates the number of new residential buildings that need to be constructed. The demand for dwellings is calculated by considering socio-demographic changes, for example, a rise in the proportion of single-person households will require a larger number of dwellings. We also define the percentages of different residential building types that are planned to be constructed each year in the scenario input. Finally, the newly constructed residential buildings will have different efficiency standards based on the efficiency classes of different building components assumed to be available in that year.

4. Case study: Germany

The building sector in Germany accounts for 16% of GHG emissions, as outlined in the Federal Climate Action Act (KSG) [47]. With over 70% of heating dependent on fossil fuels, this sector plays a crucial role in Germany's transition to green energy. The KSG established sector-specific emission reduction targets for 2030, aiming to decrease GHG emissions in the building sector to 67 $MtCO_{2eq}$, which is nearly half that of recent levels. Although the targets are not binding for individual sectors but rather for overall cross-sectoral emissions, substantial sectoral transformation is needed to achieve this target. We recognize the necessity of exploring scenarios that consider challenges, such as supply chain disruptions, societal trends and opposition, regulatory compliance, and financial obstacles. Our goal is to illustrate the range of uncertainty influencing sectoral emission pathways while accounting for these factors.

In our case study, we apply the RENDER-Building model to Germany and validate it. Applying the model enables us to achieve our above-mentioned goal, as the heterogeneity of the building stock and its actors are captured at high spatial resolution. We chose a coverage rate of $\lambda = 5\%$ (see Section 3.2)[8] and RENDER-Building covers around 1.1 M agents to represent the residential and non-residential building stock of Germany at NUTS3 resolution. Multiple data sources are harmonized to initialize the building stock, including the TABULA database [48,49], Census 2022 and 2011 [18,50], GHSL [39], and public reports [51–54]. The availability of gas and district heating networks is based on the hectare-level census data for the base year, then assumed for future years under different scenarios. The key economic parameters used to calculate investment expenditures are based on prior research [13,55]. The simulation begins in 2010 and runs with an annual timestep. Section 4.1 presents the validation of our model, Section 4.2 introduces the scenarios analyzed in the case study, and Section 5 presents the results.

4.1. Model validation

To validate the model, we compared the model's results with publicly available statistics (or statistically representative data) for different year ranges between 2010 and 2023. Renovation rates (total and specific to building components) and the stock's energetic performance are shown for the validation of residential buildings, while final energy demand at national and federal state levels is used for the validation of the entire building stock.

[7] Sensitivity runs for the discrete-choice parameter, β, are presented in Appendix.

[8] We initialized the model five times with $\lambda = 5\%$ and computed the relative deviation of the entire building stock's useful heating demand in the base year; the deviation was 0.056%, indicating that $\lambda = 5\%$ is sufficient to ensure model stability.

Table 3
Overall and component-specific renovation rates between 2010 and 2015.

	Unit	Overall	Wall	Window	Roof	Basement
Model results	%	1.04	0.85	1.68	1.60	0.43
Reference data [51]	%	1.06 ± 0.08	0.87 ± 0.07	1.88 ± 0.11	1.60 ± 0.10	0.39 ± 0.04

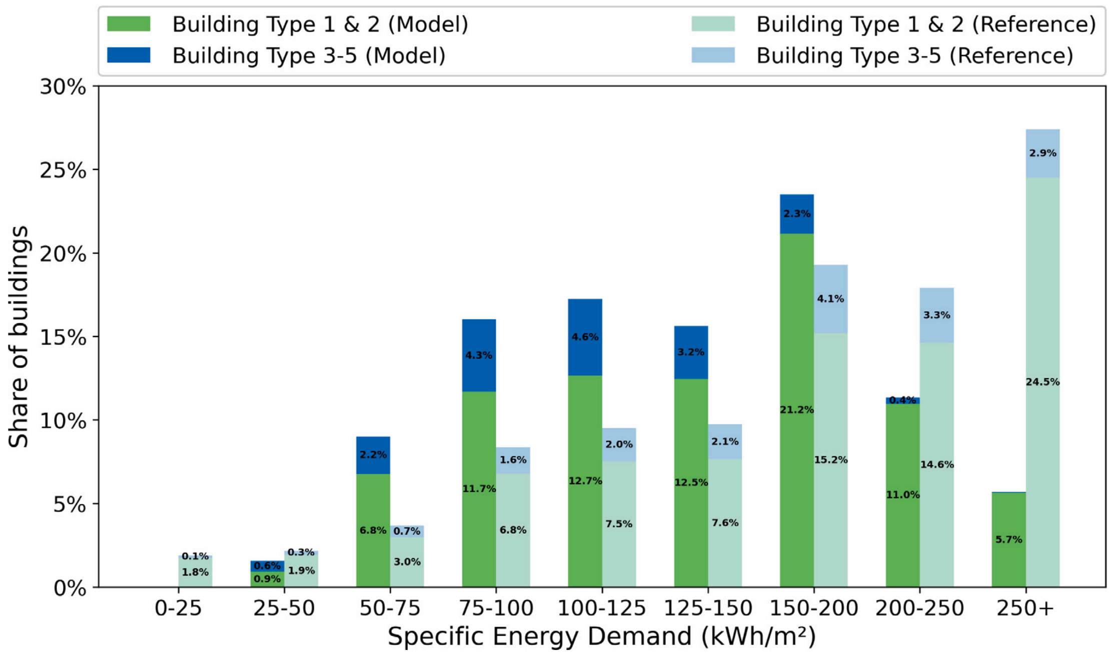

Fig. 4. Distribution of buildings by theoretical specific energy demand intervals: model (left) and reference (right) [53].

4.1.1. Renovation rates and the energetic performance of residential buildings

The renovation rates for a specific period can be derived from the renovation activities of buildings in the model. Table 3 shows the overall and component-specific renovation rates for the period 2010 to 2015. We followed the definition of renovation rate published by IWU [51]. The overall and component-specific renovation rates in the model approximate the values in the reference data. This demonstrates the strength of the model in simulating the renovation activities.

A building's specific energy demand for space heating is an indication of its energetic performance. Fig. 4 shows the distribution of buildings in the stock by specific energy demand intervals, alongside the reference distribution published by dena for the year 2014 [53]. We only show the distribution of residential buildings, as non-residential buildings are very heterogeneous and there are insufficient data available for comparison. The comparison for residential buildings reveals that there are fewer buildings that belong to the two highest and two lowest specific energy demand intervals in the model. However, as buildings with a specific energy demand up to 50 kWh/m^2 make up a smaller share of the stock, the difference between the modeled stock and the reference data in these intervals is negligible. Moreover, in reality, buildings with a theoretical specific energy demand for heating of more than 200 kWh/m^2 consume approximately 30% less energy for heating [53]. This phenomenon is tackled later in the model calculation by calibrating the consumption behavior of residents who live in these "inefficient" houses, as explained in 3.2. This approach means the modeled building stock converges to the real building stock in terms of its final energy demand by capturing consumption behavior.

4.1.2. Final energy demand

The final energy demand of the modeled building stock is compared with national statistics. Due to data availability, we used the numbers published by the German Federal Ministry for Economic Affairs and Energy for the years 2010 to 2020 [56], and the values from AGEB for the years 2021 to 2023 [57,58]. The relative difference is calculated as the ratio of $(Demand_{model} - Demand_{ref})/Demand_{ref}$ and shown in Fig. 5. Positive values indicate the model overestimates and negative values that the model underestimates compared to the reference figures.

Since the years before 2015 are initialization years in the model, we focused on the years from 2015 to 2023. During these years, the model overestimated the final energy demand of residential buildings by 10% on average and underestimated that of non-residential buildings by 3% on average. The final energy demand for appliances and water heating is calibrated top-down, so it remains within a 10% deviation. However, the space heating demand is estimated using the vintage stock model, and showed an average deviation of 14% for residential buildings and −11% for non-residential buildings. When looking at the breakdown by energy carrier, most deviations for individual energy carriers are within 20%. Fig. 6 shows the significance of energy demand by end-use and energy carrier in 2020 for both residential and non-residential sectors, respectively. The deviations are also presented as percentages, supplementing the time series perspective in Fig. 5.

Within space heating, electricity exhibited the highest average deviation in both residential and non-residential sectors (Fig. 6). This could be caused by the approximated assumption on the contribution factor of electricity when it is the secondary heating system. In reality, this is highly dependent on the system configuration. However, given the fact that electricity only accounts for 1 to 5% of final space heating demand and main heating technologies such as heat pumps are not affected by electricity as an auxiliary energy carrier, the observed deviation is not expected to influence the robustness of the final energy demand projections from the model. Nevertheless, this assumption could be revisited and backed up by more evidence in the future. In contrast, although other energy carriers remained within ±15% for the residential sector, natural gas and district heating were notable outliers in the non-residential sector. The input data for heating systems

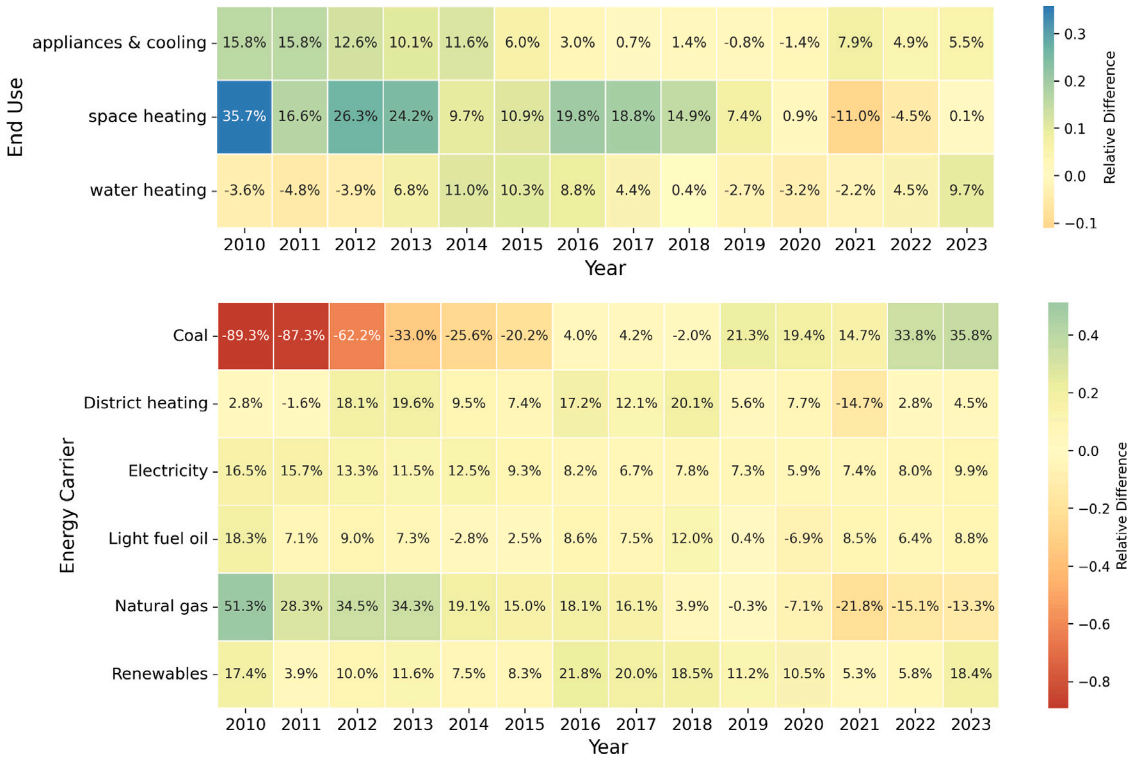

Fig. 5. Relative difference of final energy demand by end use (top) and energy carrier (bottom) from 2010 to 2023.

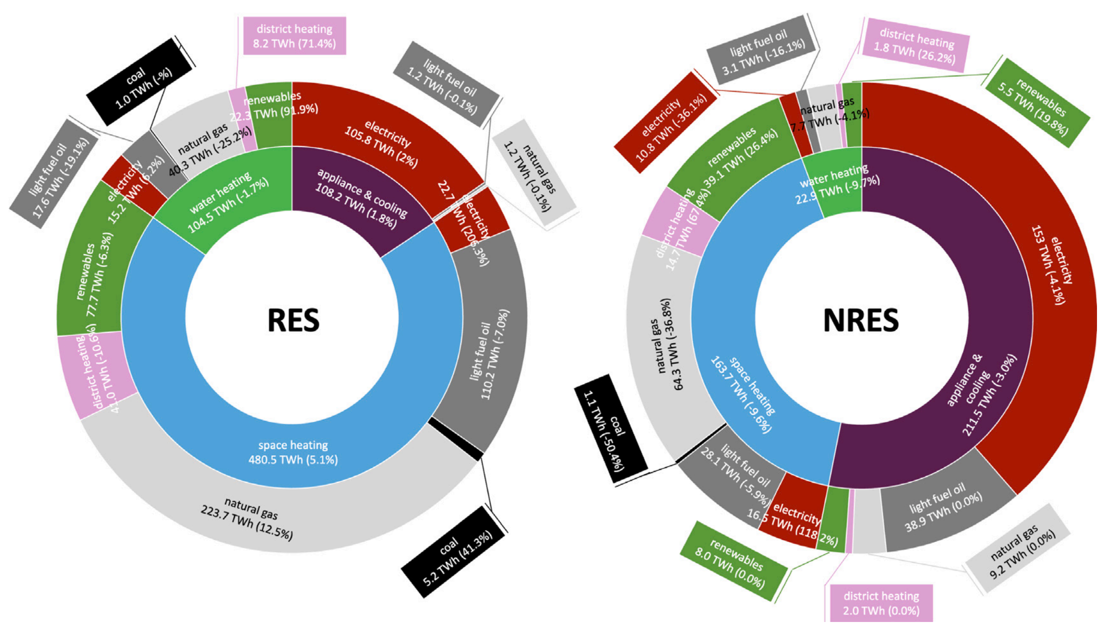

Fig. 6. Final energy demand and relative differences for the residential (RES) and non-residential (NRES) sectors in 2020.

were derived from hectare-level statistics for residential buildings, but such detailed data were not available for non-residential buildings. As a result, the infrastructure availability for the non-residential sector was based on that of the residential sector, which helps to explain the larger deviations observed for natural gas and district heating in non-residential buildings. Nevertheless, it is important to note that the relative deviation of each energy carrier share in the model from that in the reference in each sector is within 25%. Here, "energy carrier share" denotes the energy carrier's proportion of the respective final energy demand (model or reference).

Finally, the energy balances of federal states were taken from the official reports of each state and put together for validation at the federal level. Fig. 7 the relative differences for each state in 2020. City states such as Berlin, characterized by high population density, are systematically underestimated, with deviations ranging from −19% to −25%. In contrast, states with low population density, such as Brandenburg and Mecklenburg-Western Pomerania, are systematically overestimated, showing deviations between 5% and 30%. The average floor area of a dwelling is given as input to the model at the national level, differentiated by building type and construction period. Similarly, the average total floor area for non-residential building types,

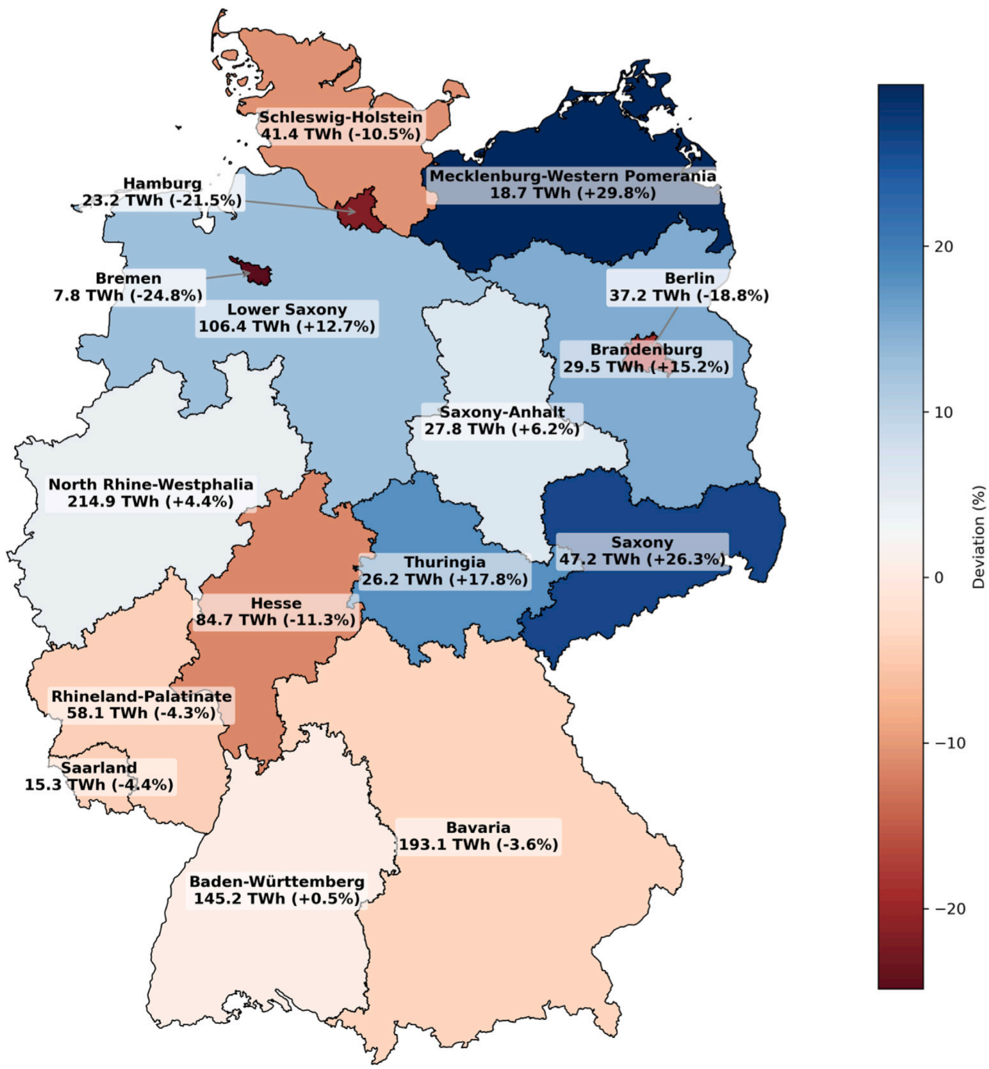

Fig. 7. Relative differences between modeled energy demand and reference energy consumption by federal state.

along with the allocation of building types to sub-sectors in the non-residential sector, are also inputs at the national level. However, these averages vary between federal states, influenced by factors such as population density and the predominance of specific activity types in the non-residential sector. The total floor area of the generated building stock in the model is validated only at the national level and found to deviate from the reference figures by approximately −1%. Moreover, it is important to note the uncertainty associated with the references used for validation. The total of the final energy demands reported by federal states does not match the total national demand reported by the federal ministry. This discrepancy between the two statistical sources varies, with individual energy carriers exhibiting a difference of approximately ±20%.

4.1.3. Summary

RENDER-Building is a bottom-up building stock model that uses spatially detailed statistical data as input where available. Given the inherent uncertainties regarding the statistics used for validation and the real availability of the technical options modeled, the model is precise enough to understand the dynamics of energy demand in buildings at the national level. It is particularly suitable for the analysis in this study, as this aims to illuminate different transformation pathways for a nation. There is potential to improve the calibration in the distribution of the residential stock in terms of efficiency level, estimation of space heating demand, contribution of electricity to space heating as an auxiliary energy carrier, and the heating system stock of non-residential buildings. Moreover, the regional deviations stem from assumptions made at the national level. By focusing on improving and integrating more detailed input data at regional level, the model could also provide robust results at this geographical level.

4.2. Scenarios

As described in Section 1, we analyzed the long-term evolution of the building sector in Germany under three scenarios developed in the RokiG2050 project. The narratives of the three scenarios are described below and the qualitative scenario factors are summarized in five categories in Table 4.

1. The *sustainable transformation scenario (STS)* outlines an optimistic vision of the German building sector in 2030, in which comprehensive measures have been taken to make the building stock more sustainable. This concerns implementing technologies and regulations as well as economic and social aspects. This scenario fully exploits the potential for increasing the efficiency of buildings and this positive development continues until 2045.
2. The *challenged transformation scenario (CTS)* is characterized by some challenges and limited progress. This scenario is a hybrid variant of the two extreme scenarios and assumes a medium development pathway for most of the scenario aspects. Due

Table 4
Description of scenarios according to categories.

Categories	STS	CTS	LTS
Category 1: Energy-efficient building refurbishment as a core component of the energy transition	• Serial renovation is widely adopted from 2030. • Low-temperature district heating is widely used. • Digitalization of timetables for the entire building. • Buildings as prosumers.	• Serial renovation is widely adopted from 2045. • Low-temperature district heating is partly used. • Digitalization of timetables for specific components. • Buildings prefer HPs.	• Serial renovation only starts to take shape in 2045. • Low-temperature district heating is not used. • No digitalization of timetables. • Buildings prefer fossils.
Category 2: Integration of the individual building into the overall system	• DSM technologies adopted by most large electricity consumers. • Smart meters are widely adopted.	• No flexibility from buildings, only from large central storage facilities. • Smart meters are partially adopted in new buildings.	• No flexibility. • Smart meters are not adopted even in new buildings.
Category 3: New construction as a driver of innovation	• High efficiency increase in technological progress. • Climate-neutral operation is obligatory for new buildings and partly implemented in existing buildings. • Solar obligation for all new buildings (80% of roof area).	• Medium efficiency increase in technological progress. • Climate-neutral operation is obligatory for new buildings. • Solar obligation for all new buildings (60% of roof area).	• Low efficiency increase in technological progress. • Climate-neutral operation is not mandatory. • Solar obligation not enforced.
Category 4: Regulatory framework	• Well-distributed funding for the promotion of climate-neutral construction and heat generators. • Minimum 80% RE in every newly installed heating system. • KfW EH 100 requirements.	• Funding is not well distributed and lacks long-term orientation. • Minimum 65% RE in every newly installed heating system. • KfW EH 75 requirements.	• Funding is limited and only for specific objectives. • No tightening of the current RE requirements. • No requirements for building efficiency.
Category 5: Society and Economy	• Sufficient supply of skilled workers. • Supply chain well managed. • Inequality reduced and subsidies granted to the right target groups. • The idea of communal living becomes popular.	• Supply of skilled workers does not achieve target level. • Supply chain partly managed. • Inequality has not decreased. • The number of old households increases, while the other households remain stable.	• Clear shortage of skilled workers. • Supply chain not well managed. • Inequality is clearly greater. • Single-person households increase, resulting in higher demand for living space.

to the challenges to implementing technologies or regulations, the potential for increasing the efficiency of buildings is only partially exploited in this scenario.

3. The *limited transformation scenario (LTS)* is almost a continuation of the status quo and outlines a pessimistic vision of the German building stock with only limited or no improvement in building efficiency until 2030. This scenario considers difficulties due to the shortage of skilled workers and disruptions in the global supply chain. In addition, technological potentials remain untapped due to low investment readiness in the sector.

As shown, the three scenarios range from optimistic to pessimistic: two envision extreme developments – one positive (STS) and one negative (LTS) – and the third (CTS) represents a middle-of-the-road approach between the other two. As a result, twelve scenario factors were selected and quantified using different parameters in the RENDER-Building model as shown in Table 5. Then, we investigated the sectoral decarbonization potential in the defined scenarios and identified the critical bottlenecks to achieving climate neutrality. We analyzed the system costs and costs for individual end-users comparatively in alternative pathways.

5. Results and discussion of the case study

Fig. 8 presents the modeled pathways of final energy demand and direct CO_2 emissions (excluding indirect emissions from electricity and DH) for Germany's building sector from 2020 to 2050, disaggregated by end uses across three policy scenarios (STS, CTS, LTS). Fig. 9 provides more detailed results for space and water heating by energy carrier, modeled using a vintage stock approach. As shown, by 2045, the total final energy demand in the three scenarios is 540 TWh, 580 TWh, and 640 TWh, respectively. The final energy demand for space and water heating drops to around 220 TWh in STS, The CTS and LTS scenarios both have a substantial demand for fossil fuels of approximately 150 TWh and 230 TWh, respectively. Although absolute electricity demand decreases across all scenarios, its relative importance grows significantly, with its share in total final energy demand reaching 53% in STS, 50% in CTS, and 43% in LTS.

Regarding CO_2 emissions, despite being the most ambitious pathway, the STS scenario falls short of meeting the 2030 KSG target (67 $MtCO_2$) by 13 $MtCO_2$. The emissions in this scenario include approximately 60 $MtCO_2$ from space heating, 10 $MtCO_2$ from water heating, and 10 $MtCO_2$ from appliances, as shown in Fig. 8. This progress is driven by aggressive policy measures, including a 65% minimum renewable energy requirement for new heating systems implemented from 2025, and substantial subsidies of up to 60% for renewable heating technologies. Despite these improvements, the 2030 KSG target is not met due to strong inertia in the modernization of the building stock. Moreover, the decarbonization of non-heating end-uses, especially in non-residential buildings, has to take place simultaneously. More ambitious policy instruments are needed to substantially increase the rate of heating system replacement and building refurbishment. However, when looking further into the future, the STS scenario demonstrates strong long-term potential, achieving 95% CO_2 emission reduction by 2045 and approaching climate neutrality. Thus, the assumed pace of decarbonization in the STS scenario could be a guideline for the transition to a climate-neutral building sector in Germany in the long term.

Compared with STS, the CTS scenario faces more significant challenges in meeting climate targets and misses the 2030 KSG target by 30 $MtCO_2$. By 2045, there are still 40 $MtCO_2$ direct emissions, suggesting that delayed implementation of the renewable energy requirements (starting in 2035) and reduced subsidy allocations for renovation and modernization could cause even the long-term emission targets to be missed. To explore potential improvements to this scenario, we added an enhanced scenario CTS*, which incorporates a gradual transition to 100% biogas by 2045. However, even this variation still misses the 2030 KSG target. By 2045, it comes closer than CTS to eliminating the emissions, but there are still 25 $MtCO_2$ of direct emissions remaining.

Table 5
Overview of scenario factors, corresponding categories and quantitative assumptions.

Category	Scenario factor	STS	CTS	LTS	Model parameter
1	Serial renovation cost	10% lower	5% higher	20% higher	Total costs in relation to conventional renovation after 2030
1	Efficiency gains	High (40)	Medium (25)	Low (15)	Efficiency improvements (%) in appliances by 2050 (on average compared to 2020)
2	Own consumption of solar PV	50	30	15	Self-consumption rate (%) of electricity from solar PV
3, 4	Solar PV adoption in new buildings	Mandatory after 2025	Mandatory after 2025	No obligation	Installation requirements of solar PV
4	Emission Trading System II (ETS II)	230	175	115	CO_2 price by 2050 (EUR/tCO_2)
4	Minimum requirements for building renovation from 2025	Only low U-value	Low to medium U-value	Low to medium-high U-value	Market availability of insulation measures according to their thermal transmittance (U-value)
4	Solar PV adoption in existing buildings	80	50	20	Penetration rate (%) of PV by 2050
4	Regulatory restrictions on new heating system installations	65% (2025)	65% (2035)	65% (2045)	Minimum renewable energy percentage requirement for the heating system (year of effect)
4, 5	District heating infrastructure expansion	30% expansion	20% expansion	10% expansion	District heating infrastructure availability (by 2045)
4, 5	Subsidy for building renovation	Up to 75%	Up to 50%	Up to 30%	Share of subsidies in initial investment expenditure on renovation measures
4, 5	Subsidy for heating system modernization	Up to 60%	Up to 45%	Up to 30%	Share of subsidies in initial investment expenditure on renewable heating technologies
5	Household size	25% decrease	Stays the same	12% increase	Share of single-person households in 2050 compared to 2020

Fig. 8. Final energy demand and CO_2 emissions by end use in the three scenarios.

An in-depth analysis of the CTS scenario results reveals important insights into the transformation of the building sector, especially if the currently targeted progress faces the realistic challenges assumed. In terms of renovation activities, the scenario achieves approximately 1.45 million renovations annually, with steady growth of roughly 12,000 activities per year. These efforts result in an average specific heat demand reduction of 25 kWh/m^2 over two decades (Fig. 10). The heating system modernization progresses at a rate of 830,000 new installations annually, with renewable energy technologies becoming increasingly dominant. As a result, the share of fossil fuel heating systems in the building stock decreases to approximately 20% by 2045 (Fig. 11).

Focusing on the heating system stock reveals significant opportunities and challenges in accelerating decarbonization. Fig. 12 shows the age distribution of heating technologies in 2040. Approximately 5 million fossil fuel boilers will be older than 10 years by then, and 3 million of these are gas boilers. Fossil fuel boilers have low upfront investment costs and, when modernizing the heating system, agents tend to choose a new system based on the initial expenditure together with the fuel costs in recent years. Therefore, even though the prices

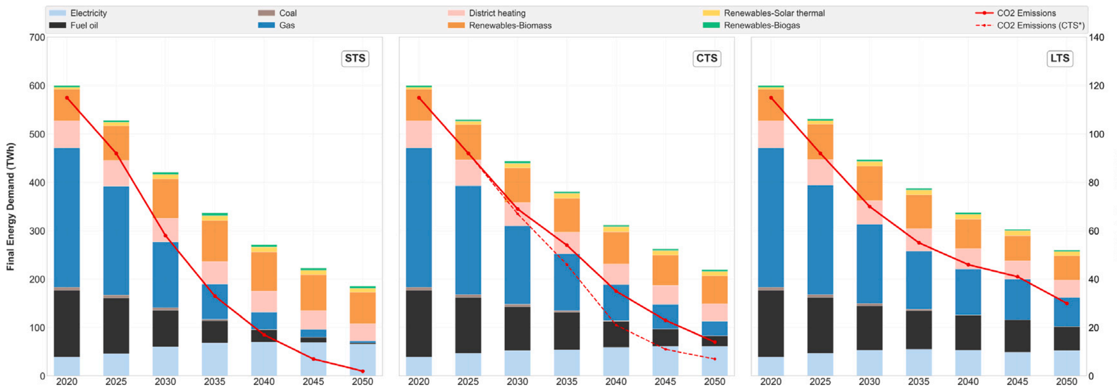

Fig. 9. Final energy demand and direct CO_2 emissions from space and water heating by energy carrier in the three scenarios.

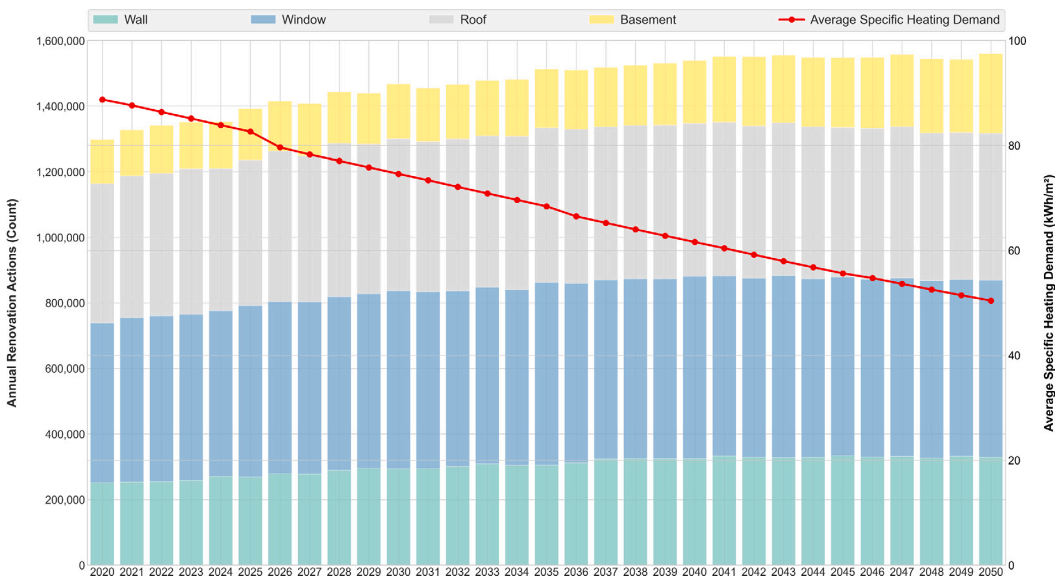

Fig. 10. Annual renovation activities and the average specific heating demand of the building stock (CTS).

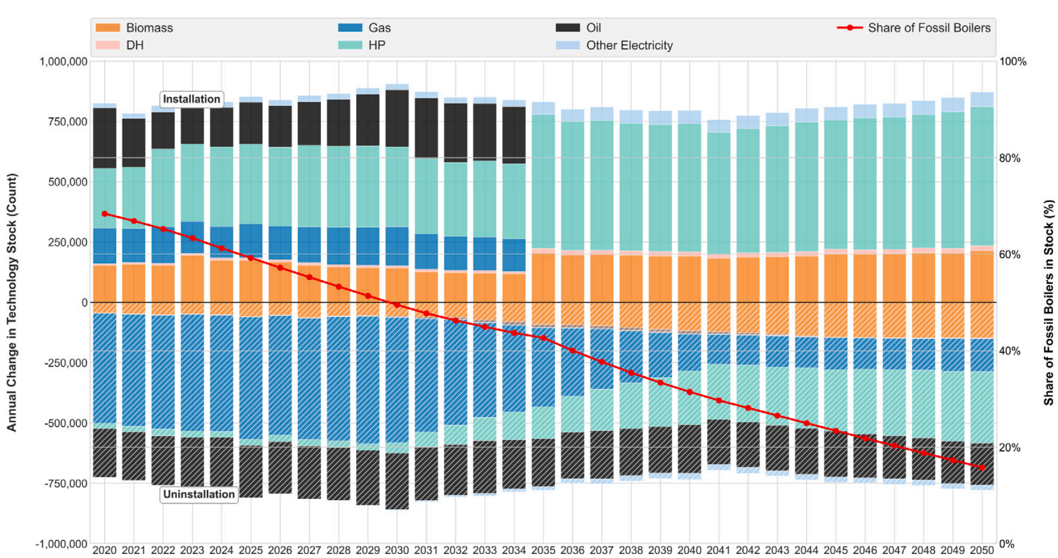

Fig. 11. Annual change in heating technology stock and share of fossil boilers in stock (CTS).

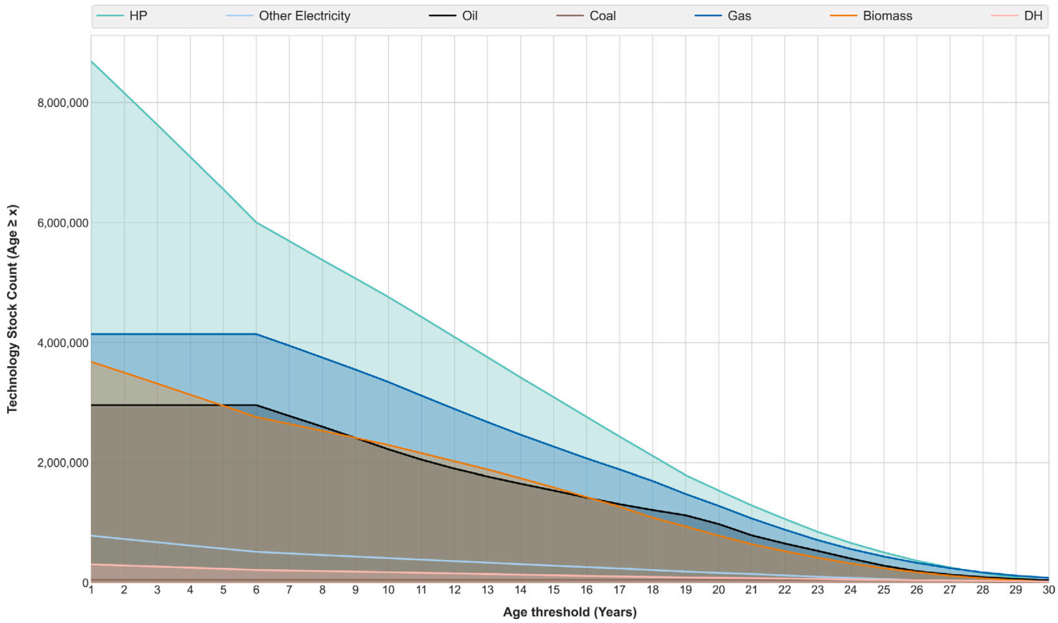

Fig. 12. Distribution of the heating technology stock by age in 2040 (CTS).

for fossil fuels are expected to be much higher in the future, the agents cannot base their decisions on this and may continue to invest in fossil fuel boilers until the system configuration does not meet the minimum requirements for the share of renewable energy. The aging of this boiler stock is a critical decision point, as these systems face substantially higher operating costs by 2045, primarily due to the projected doubling of fuel costs (between 2040 and 2045) driven by the transition to climate-neutral gas supplies and rising grid fees [59,60]. This implies that a comparative economic analysis between the continued operation of gas boilers with biogas (CTS*) and their early replacement would be crucial and highly relevant.

The estimated total investment required for early replacement of the remaining gas boilers ranges from €6 to 28 billion, contingent upon the availability of alternative renewable energy sources and infrastructure. While this represents a significant upfront cost, our analysis of the potential cost savings (CS)[9] due to early replacement reveals compelling economic benefits. The benefits are particularly pronounced for buildings with high specific heating demand (exceeding 150 kWh/m^2), where the switch to heat pumps could generate the highest cost savings (see Fig. 13). Among the alternative technologies evaluated, both heat pumps and district heating demonstrate the most favorable economics for early replacement across a broad range of building types. These technologies could bring about cumulated cost savings of between €9 and 17 billion. In contrast, biomass boilers show a limited cost-saving potential (€1 billion cumulated), suggesting they may be better suited for specific use cases rather than widespread adoption. This age-based analysis of the heating technology stock not only highlights the urgency of addressing aging fossil fuel systems but also provides valuable insights into strategically targeting replacement for the greatest economic and environmental benefits.

$$CS_n = \sum_{t=2040}^{2045} EC_{g,t} - \sum_{t=2040}^{2045} AIE_{n,t} + EC_{n,t} \tag{5}$$

Our findings underline the immense scale and complexity of the challenge ahead. The scenario analysis reveals a critical insight: even under the optimistic scenario (STS), with aggressive policy support and widespread technological adoption, Germany's building sector is projected to miss the 2030 emissions reduction target. While climate neutrality by 2045 appears achievable in this scenario, the short-term gap highlights the inertia of the existing stock and the time lags inherent in large-scale transitions. It is also worth noting that, for a developed country such as Germany, higher renovation rates could lead to less floor area constructed [2]. In our current model, however, renovations are endogenously triggered by building components reaching their end-of-life, which results in similar renovation rates across scenarios. Policies that proactively trigger renovations could therefore further accelerate decarbonization. Furthermore, the challenged scenario (CTS) reveals that a less ambitious approach results in a substantial emissions gap, necessitating difficult and potentially costly interventions, such as operating millions of gas-based heating systems with biogas or their early replacement to get back on track.

The strategic implications for policymakers are clear. Achieving a climate-neutral building stock is not a matter of finding a single solution, but rather of orchestrating a portfolio of robust, sustained, and adaptive policies. Our results demonstrate that a combination of regulatory standards, substantial financial incentives, and coordinated infrastructure development is essential. In particular, the analysis of the CTS pathway and its variant goes beyond abstract targets to quantify the concrete economic trade-off between options that are still capable of achieving emission reduction targets when short-term ambition is lacking. This highlights the need for policies that not only encourage the fast adoption of renewable technologies but can also manage the economic and social consequences of retiring existing assets.

In summary, by using the agent-based RENDER-Building model, our research offers policymakers crucial guidance and orientation for designing effective and robust decarbonization strategies, by assessing full policy mixes, translating sector targets into concrete measures, informing system-level infrastructure and budgeting, comparing differentiated subsidies (by building type, settlement, and decision-maker) to optimize resources, evaluating infrastructure rollout timing and sequencing, and testing targeted policies (e.g., technology mandates for specific vintages, income-based incentives). It also provides end users clear insights to help navigate the transition. The model and analysis can benefit from integrating more regionally detailed input data, as well as quantitative research on the real-life characteristics of renovation and technical systems, decision-making of building agents

[9] CS is calculated in Eq. (5) as the difference in cumulated energy cost, EC, between continued operation of the gas boiler (g) until the end of 2045 (with biogas as in CTS*) and its early replacement with renewable heating technology (n) including the annualized initial expenditure of investment, AIE.

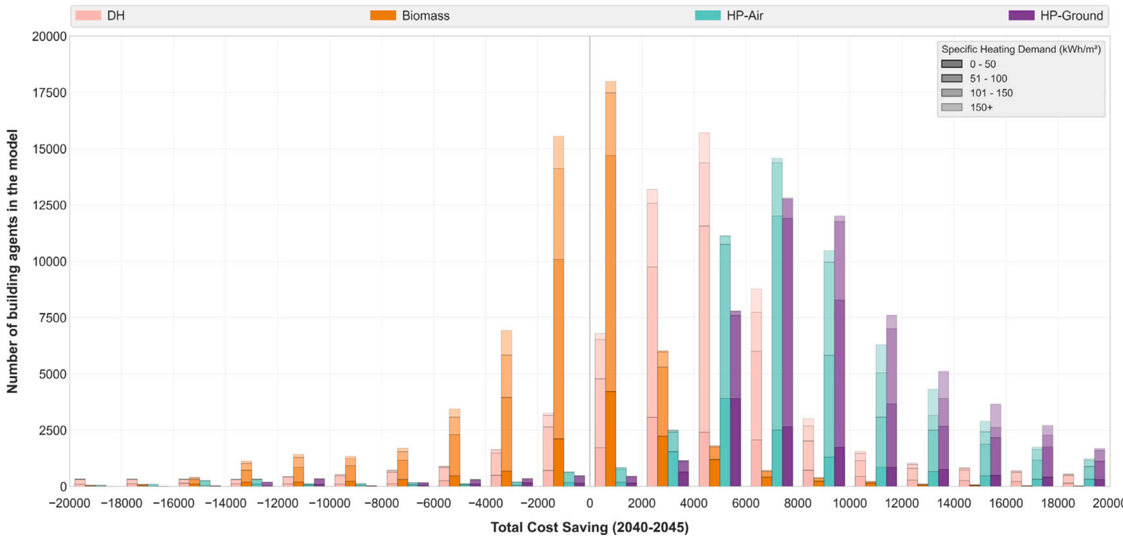

Fig. 13. Potential cost savings due to early replacement of natural gas boiler by alternative RE technology for agents clustered by specific heating demand.

(e.g., estimating the β discrete-choice parameter using empirical survey data), social influences on technology choice, and supply chain bottlenecks of skilled labor and materials. Related aspects also include the feasibility of decentralized heat pumps, generation mix of individual district heating networks, and the transformation of individual gas distribution grids. A systematic consideration of these aspects would enable a more robust assessment of the transition pathways.

6. Conclusions

In this study, RENDER-Building, an agent-based building stock model with high spatial resolution, was developed and tested to explore the transformation of the German building sector. We analyzed three scenarios with detailed policy mixes and compared their decarbonization pathways with Germany's targets. The findings reveal a critical gap: even in an optimistic scenario with aggressive policy support, the building sector is projected to miss its 2030 emissions reduction target, highlighting the significant inertia of the existing building stock and the time lags inherent in large-scale transitions. Furthermore, we highlight the potential costs and savings for buildings of realigning a challenged sectoral pathway to achieving climate neutrality. From a methodological perspective, our research underscores the value of agent-based modeling approach for studying the energy system's transformation. By representing the system from the bottom up, RENDER-Building captures granular dynamics that traditional approaches often miss: the heterogeneity of individual buildings, the bounded rationality of millions of decision-makers, and local infrastructure constraints. In particular, it enables flexible use of data at various granularities, offering a solution for approximations if detailed data are not available. The modular framework can be adapted to different regional contexts by adjusting input parameters (building stock characteristics, climate data, policy landscapes), with the acknowledgment that local validation and calibration are essential.

CRediT authorship contribution statement

Şirin Alibaş: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Songmin Yu:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Mahsa Bagheri:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Tobias Fleiter:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this paper the authors used GPT 4o, GPT 5 and Gemini 2.5 Pro to improve its readability and language. The authors then reviewed and edited the content as needed and take full responsibility for the published article.

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.

Acknowledgments

This analysis is based on work conducted within the project "Roadmap für einen klimaneutralen Gebäudebestand RokiG2050" under the Accompanying Scientific Research Energiewendebauen (BF2020) — Module Buildings (project funding number 03EWB002B). The authors would like to thank the project partners, namely E.ON Energy Research Center at RWTH Aachen University, and the Fraunhofer Institute for Building Physics (IBP). The authors also express their gratitude to the student assistants Weijia Yan and Hannah Rickmann for their work on data collection and visualization. The model developed within the scope of this research was supported by the Fraunhofer Institute for Systems and Innovation Research (ISI) through its own research fund given to the SEF Cooperation Project - MELODIE.

Appendix

A.1. Sensitivity analysis of β

Fig. A.1 presents the sensitivity analysis of the final energy demand for different energy carriers to the β parameter, which governs agents' responsiveness to cost differences when making technology and renovation decisions. Higher β values indicate more strongly cost-optimizing behavior. The analysis reveals that the overall energy demand pathways are quite robust to variations in β. As shown, the trajectories for major energy carriers like electricity, heating oil, and natural gas remain tightly clustered, even as β varies from 1 to 3 (around the model's baseline of β = 2), suggesting that structural trends and price signals are dominant drivers.

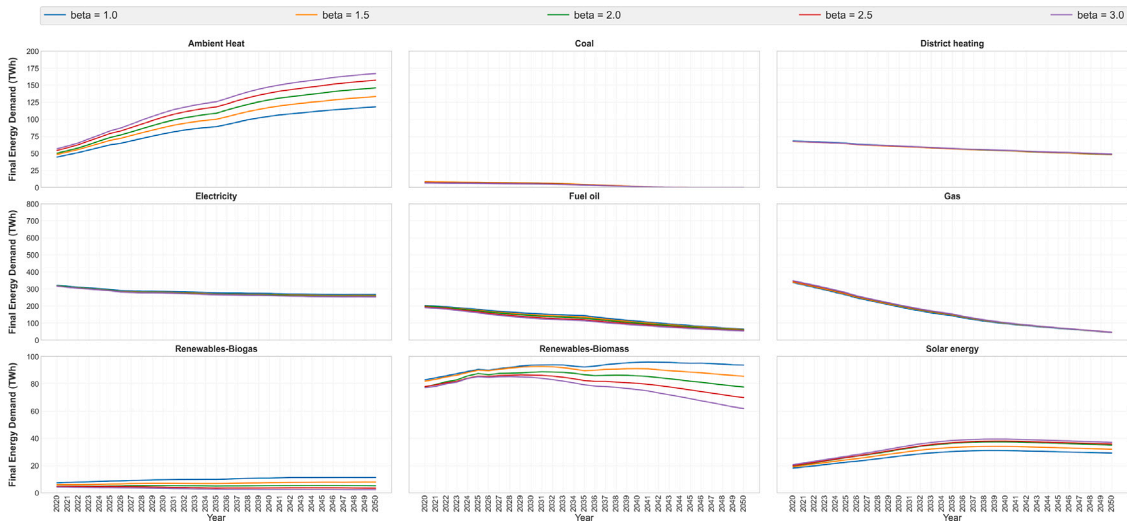

Fig. A.1. β sensitivity of final energy demand by energy carrier.

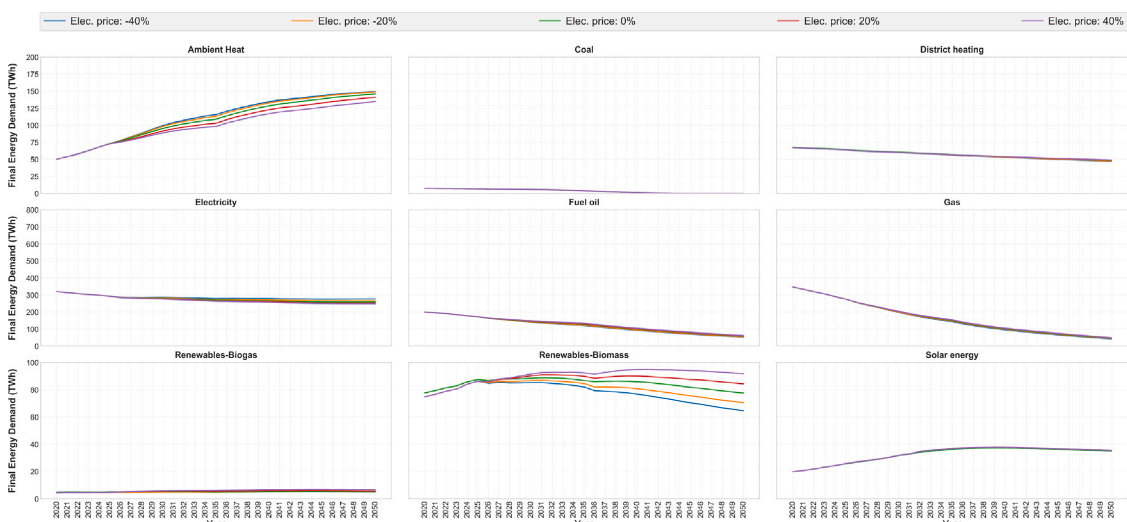

Fig. A.2. Energy price sensitivity of final energy demand by energy carrier.

However, this aggregated stability masks more significant shifts within specific end-uses where technology competition is most direct. When isolating space and water heating, the impact of agent behavior becomes more pronounced as the effects of technology choices accumulate over time. To quantify this, we can examine the coefficient of variation (standard deviation divided by the mean) across the five β scenarios in 2050. This value is approximately 7% for electricity in space and water heating, whereas it is only 2% for natural gas. This indicates that, while the model is broadly stable, uncertainty in agent cost-sensitivity is a material factor in determining the pace of electrified heating, a key lever for decarbonization.

A.2. Sensitivity analysis of the energy price

Relative energy carrier prices are a key determinant of agents' heating technology choices. To test the model's sensitivity to these price signals, we created four additional scenarios based on the CTS, adjusting the electricity price trajectory upward and downward by 20% and 40%. As Fig. A.2 shows, the model exhibits moderate sensitivity at the aggregated level of total final energy demand, particularly for the high-volume carriers of electricity, fuel oil, and natural gas, shown in the second row.

Similar to the sensitivity of β, when isolating the final energy demand for space and water heating, the cumulative effects of technology choices become much more apparent. By 2050, the coefficient of variation across the five price scenarios for electricity demand in heating reaches 14.3%, while it is 7.3% for natural gas. The comparatively lower sensitivity for natural gas is largely explained by the policy constraint in the CTS scenario, which prohibits the installation of new gas boilers after 2035, limiting their long-term market. Consequently, the primary substitution effect of fluctuating electricity prices (which directly influence heat pump economics) occurs between heat pumps and renewable heating options. This is reflected in the high coefficients of variation for biomass solid (14.3%) and biogas (11.6%) demand by 2050.

Data availability

Data will be made available on request.

References

[1] European Parliament, Council of the European Union. Directive (EU) 2024/1275 of the European parliament and of the council of 24 april 2024 on the energy performance of buildings (recast): EPBD. 2024, URL: http://data.europa.eu/eli/dir/2024/1275/oj.

[2] Zhang Shufan, Ma Minda, Zhou Nan, Yan Jinyue, Feng Wei, Yan Ran, You Kairui, Zhang Jingjing, Ke Jing. Estimation of global building stocks by 2070: Unlocking renovation potential. Nexus 2024;1(3):100019. http://dx.doi.org/10.1016/j.ynexs.2024.100019.

[3] Daioglou Vassilis, van Ruijven Bas J, van Vuuren Detlef P. Model projections for household energy use in developing countries. Energy 2012;37(1):601–15. http://dx.doi.org/10.1016/j.energy.2011.10.044.

[4] Daioglou Vassilis, Mikropoulos Efstratios, Gernaat David, van Vuuren Detlef P. Efficiency improvement and technology choice for energy and emission reductions of the residential sector. Energy 2022;243:122994. http://dx.doi.org/10.1016/j.energy.2021.122994.

[5] Camarasa Clara, Mata Érika, Navarro Juan Pablo Jiménez, Reyna Janet, Bezerra Paula, Angelkorte Gerd Brantes, Feng Wei, Filippidou Faidra, Forthuber Sebastian, Harris Chioke, Sandberg Nina Holck, Ignatiadou Sotiria, Kranzl Lukas, Langevin Jared, Liu Xu, Müller Andreas, Soria Rafael, Villamar Daniel, Dias Gabriela Prata, Wanemark Joel, Yaramenka Katarina. A global comparison of building decarbonization scenarios by 2050 towards 1.5-2°C targets. Nat Commun 2022;13(1):3077. http://dx.doi.org/10.1038/s41467-022-29890-5.

[6] Uihlein Andreas, Eder Peter. Policy options towards an energy efficient residential building stock in the EU-27. Energy Build 2010;42(6):791–8. http://dx.doi.org/10.1016/j.enbuild.2009.11.016.

[7] Charlier Dorothée, Risch Anna. Evaluation of the impact of environmental public policy measures on energy consumption and greenhouse gas emissions in the french residential sector. Energy Policy 2012;46:170–84. http://dx.doi.org/10.1016/j.enpol.2012.03.048.

[8] Bianco Vincenzo, Marmori Clara. Modelling the deployment of energy efficiency measures for the residential sector. The case of Italy. Sustain Energy Technol Assessments 2022;49:101777. http://dx.doi.org/10.1016/j.seta.2021.101777.

[9] Streicher Kai Nino, Padey Pierryves, Parra David, Bürer Meinrad C, Schneider Stefan, Patel Martin K. Analysis of space heating demand in the swiss residential building stock: Element-based bottom-up model of archetype buildings. Energy Build 2019;184:300–22. http://dx.doi.org/10.1016/j.enbuild.2018.12.011.

[10] Incorporating homeowners' preferences of heating technologies in the UK TIMES model. Energy 2018;148:716–27. http://dx.doi.org/10.1016/j.energy.2018.01.150.

[11] McKenna Russell, Merkel Erik, Fehrenbach Daniel, Mehne Stephanie, Fichtner Wolf. Energy efficiency in the german residential sector: A bottom-up building-stock-model-based analysis in the context of energy-political targets. Build Environ 2013;62:77–88. http://dx.doi.org/10.1016/j.buildenv.2013.01.002.

[12] Henkel Johannes. Modelling the diffusion of innovative heating systems in Germany - decision criteria, influence of policy instruments and vintage path dependencies (Ph.D. thesis), Berlin: Fakultät III – Prozesswissenschaften Technische Universität Berlin; 2012.

[13] Elsland Rainer. Development of an integrated modelling concept to capture technological myopia: analysing long-term energy demand in the german residential sector (Ph.D. thesis), Karlsruhe: Fakultät für Wirtschaftswissenschaften, Karlsruher Institut für Technologie; 2015.

[14] Bauermann Klaas, Spiecker Stephan, Weber Christoph. Individual decisions and system development – integrating modelling approaches for the heating market. Appl Energy 2014;116:149–58. http://dx.doi.org/10.1016/j.apenergy.2013.11.046.

[15] Bauermann Klaas, Weber Christoph. Individual choice in a residential building & heating model an application case for Germany. SSRN Electron J 2015. http://dx.doi.org/10.2139/ssrn.2560177.

[16] Hornykewycz Anna, Kapeller Jakob, Weber Jan David, Schütz Bernhard, Cserjan Lukas. Carbon neutrality in the residential sector: A general toolbox and the case of Germany. Npj Clim Action 2025;4(1). http://dx.doi.org/10.1038/s44168-025-00229-2.

[17] Eurostat. Complete energy balances. 2022, URL: https://ec.europa.eu/eurostat/databrowser/product/view/nrg_bal_c?category=nrg.nrg_quant.nrg_quanta.nrg_bal.

[18] Statistische Ämter des Bundes und der Länder. Zensus 2022. 2024, URL: https://www.zensus2022.de/EN/Census_results/_inhalt.html.

[19] Zhao Fei, Wang Jianhui, Koritarov Vladimir, Augenbroe Godfried. Agent-based modeling of interaction between commercial building stocks and power grid. In: 2010 IEEE conference on innovative technologies for an efficient and reliable electricity supply. IEEE; 2010, p. 225–32. http://dx.doi.org/10.1109/CITRES.2010.5619806.

[20] Zhao Fei, Martinez-Moyano Ignacio J, Augenbroe Godfried. Agent-based modeling of commercial building stocks for policy support. In: Proceedings of building simulation 2011:. 2011, p. 2385–92, URL: https://www.researchgate.net/publication/266285050_Agent-based_modeling_of_commercial_building_stocks_for_policy_support.

[21] Maya Sopha Bertha, Klöckner Christian A, Hertwich Edgar G. Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. Energy Policy 2011;39(5):2722–9. http://dx.doi.org/10.1016/j.enpol.2011.02.041.

[22] Sachs Julia, Meng Yiming, Giarola Sara, Hawkes Adam. An agent-based model for energy investment decisions in the residential sector. Energy 2019;172:752–68. http://dx.doi.org/10.1016/j.energy.2019.01.161.

[23] Moglia Magnus, Podkalicka Aneta, McGregor James. An agent-based model of residential energy efficiency adoption. J Artif Soc Soc Simul 2018;21(3). http://dx.doi.org/10.18564/jasss.3729.

[24] Akhatova Ardak, Kranzl Lukas. Agent-based modelling of building retrofit adoption in neighbourhoods. Energy Build 2025;328:115172. http://dx.doi.org/10.1016/j.enbuild.2024.115172.

[25] Nägeli Claudio, Jakob Martin, Catenazzi Giacomo, Ostermeyer York. Towards agent-based building stock modeling: Bottom-up modeling of long-term stock dynamics affecting the energy and climate impact of building stocks. Energy Build 2020;211:109763. http://dx.doi.org/10.1016/j.enbuild.2020.109763.

[26] Nägeli Claudio, Jakob Martin, Catenazzi Giacomo, Ostermeyer York. Policies to decarbonize the swiss residential building stock: An agent-based building stock modeling assessment. Energy Policy 2020;146:111814. http://dx.doi.org/10.1016/j.enpol.2020.111814.

[27] Stengel Julian. Akteursbasierte simulation der energetischen modernisierung des wohngebäudebestands in Deutschland (Ph.D. thesis), Karlsruhe: Fakultät für Wirtschaftswissenschaften, Karlsruher Institut für Technologie; 2014, http://dx.doi.org/10.5445/KSP/1000041854.

[28] Müller Andreas. Energy demand assessment for space conditioning and domestic hot water: a case study for the Austrian building stock (Ph.D. thesis), Wien: Fakultät für Elektrotechnik und Informationstechnik, Technische Universität Wien; 2015.

[29] Kranzl Lukas, Hummel Marcus, Müller Andreas, Steinbach Jan. Renewable heating: Perspectives and the impact of policy instruments. Energy Policy 2013;59:44–58. http://dx.doi.org/10.1016/j.enpol.2013.03.050.

[30] Kranzl Lukas, Aichinger Eric, Büchele Richard, Forthuber Sebastian, Hartner Michael, Müller Andreas, Toleikyte Agne. Are scenarios of energy demand in the building stock in line with Paris targets? Energy Effic 2019;12(1):225–43. http://dx.doi.org/10.1007/s12053-018-9701-1.

[31] Kranzl Lukas, Bürger Veit, Henning Hans-Martin, Hummel Marcus, Kockat Judit, Müller Andreas, Palzer Andreas, Steinbach Jan. Short-term policy strategies and long-term targets: The case of the german building sector. In: Gueorgui Trenev, Bertoldi Paolo, editors. Proceedings of the 7th international conference eEDAL'2013 energy efficiency in domestic appliances and lighting. Luxembourg: Publications Office of the European Union; 2014, p. 1358–72.

[32] Steinbach Jan. Modellbasierte untersuchung von politikinstrumenten zur förderung erneuerbarer energien und energieeffizienz im gebäudebereich (Ph.D. thesis), Karlsruhe: Fakultät für Wirtschaftswissenschaften, Karlsruher Institut für Technologie; 2015.

[33] van der Kam Mart, Lagomarsino Maria, Azar Elie, Hahnel Ulf JJ, Parra David. An empirical agent-based model of consumer co-adoption of low-carbon technologies to inform energy policy. Cell Rep Sustain 2024;1(12):100268. http://dx.doi.org/10.1016/j.crsus.2024.100268.

[34] Möller Bernd, Wiechers Eva, Persson Urban, Grundahl Lars, Connolly David. Heat roadmap europe: Identifying local heat demand and supply areas with a European thermal atlas. Energy 2018;158:281–92. http://dx.doi.org/10.1016/j.energy.2018.06.025.

[35] Manz Pia, Alibaş Şirin, Fleiter Tobias, Billerbeck Anna. Finding an optimal district heating market share in 2050 for EU-27: Comparison of modelling approaches. In: ECEEE summer study proceedings. 2022, p. 177–86.

[36] Yu Songmin, Hou Zhanyi. Melodie: Agent-based modeling in python. J Open Source Softw 2023;8(83):5100. http://dx.doi.org/10.21105/joss.05100.

[37] Simon Herbert A, et al. Theories of bounded rationality. Decis Organ 1972;1(1):161–76.

[38] Eurostat. Statistical regions in the European union and partner countries NUTS and statistical regions 2021 - re-edition 2022. 2022, URL: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-gq-22-010 [Accessed 29 October 2024].

[39] European Commission, Joint Research Centre. Global human settlement layer. 2023, URL: http://ghsl.jrc.ec.europa.eu/ [Accessed 27 October 2024].

[40] Sunikka-Blank Minna, Galvin Ray. Introducing the prebound effect: the gap between performance and actual energy consumption. Build Res Inf 2012;40(3):260–73.

[41] Bagheri Mahsa, Dönitz Ewa, Yu Songmin, Brugger Heike. Exploration of qualitative scenarios towards climate neutrality of the german building sector. In: Lindström Therese, Blume Ylva, Hampus Nina, Hampus Linnea, editors. Eceee summer study proceedings. 2024, p. 1053–63.

[42] Yu Songmin. An agent-based framework for policy simulation: Modeling heterogeneous behaviors with modified sigmoid function and evolutionary training. IEEE Trans Comput Soc Syst 2022;10(4):1901–13.

[43] ter Hoeven Ewout, Kwakkel Jan, Hess Vincent, Pike Thomas, Wang Boyu, Rht, Kazil Jackie. Mesa 3: Agent-based modeling with python in 2025. J Open Source Softw 2025;10(107):7668. http://dx.doi.org/10.21105/joss.07668.

[44] Eurostat. Statistical classification of economic activities in the European community rev. 2. 2024, URL: https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF [Accessed 06 November 2024].

[45] Alibaş Şirin, Yu Songmin. Developing a regionalized representative building stock model for Germany. In: Lindström Therese, Blume Ylva, Hampus Nina, Hampus Linnea, editors. Eceee summer study proceedings. 2024, p. 1107–18.

[46] Goulouti Kyriaki, Favre Didier, Giorgi Morgane, Padey Pierryves, Galimshina Alina, Habert Guillaume, Lasvaux Sébastien. Dataset of service life data for 100 building elements and technical systems including their descriptive statistics and fitting to lognormal distribution. Data Brief 2021;36:107062.

[47] Bundes-klimaschutzgesetz: KSG. 2021, URL: https://www.gesetze-im-internet.de/ksg/.

[48] Loga Tobias, Stein Britta, Diefenbach Nikolaus, Born Rolf. Deutsche Wohngebäudetypologie: Beispielhafte Maßnahmen zur Verbesserung der Energieeffizienz von typischen Wohngebäuden. Darmstadt, Germany: IWU Institut Wohnen und Umwelt / Institute for Housing and Environment; 2015.

[49] Loga Tobias, Müller Kornelia, Reifschläger Kerstin, Stein Britta. Evaluation of the TABULA Database: Comparison of Typical Buildings and Heat Supply Systems 20 European Countries. Darmstadt, Germany: IWU Institut Wohnen und Umwelt / Institute for Housing and Environment; 2015.

[50] Statistische Ämter des Bundes und der Länder. Zensus 2011: Vielfältiges deutschland: Zensus 2011: Endgültige ergebnisse. 2016, URL: https://www.zensus2011.de/DE/Home/home_node.html.

[51] Cischinsky H, Diefenbach N. Datenerhebung wohngebäudebestand 2016: Datenerhebung zu den energetischen merkmalen und modernisierungsraten im deutschen und hessischen wohngebäudebestand. 2018.

[52] Hörner Michael, Cischinsky Holger, Bischof Julian, Schwarz Steffen, Behnisch Martin, Meinel Gotthard, Spars Guido, Busch Roland. Forschungsdatenbank NichtWohnGebäude: Repräsentative primärdatenerhebung zur statistisch validen erfassung und auswertung der struktur und der energetischen qualität des nichtwohngebäudebestands in deutschland. ENOB: dataNWG. 2022.

[53] Deutsche Energie-Agentur GmbH (dena). Dena-gebäudereport 2016: Statistiken und analysen zur energieeffizienz im gebäudebestand. 2016.

[54] Deutsche Energie-Agentur GmbH. DENA-GEBÄUDEREPORT 2023: Zahlen, Daten, Fakten zum Klimaschutz im Gebäudebestand. Berlin: dena; 2022.

[55] Jakob Martin, Madlener Reinhard. Riding down the experience curve for energy-efficient building envelopes: the swiss case for 1970–2020. Int J Energy Technol Policy 2004;2(1/2):153. http://dx.doi.org/10.1504/IJETP.2004.004593.

[56] für Wirtschaft und Klimaschutz Bundesministerium. Zahlen und fakten: Energiedaten. Nationale und internationale entwicklung. 2022, URL: http://www.bmwi.de/Navigation/DE/Themen/energiedaten.html [Accessed on November 2022].

[57] AG Energiebilanzen eV. Anwendungsbilanzen zur energiebilanz deutschland - endenergieverbrauch nach energieträgern und anwendungszwecken. 2023.

[58] AG Energiebilanzen eV. Anwendungsbilanzen zur energiebilanz deutschland - endenergieverbrauch nach energieträgern und anwendungszwecken. 2024.

[59] Frömel Miriam, Sensfuß Frank, Deac Gerda. Langfristszenarien für die Transformation des Energiesystems in Deutschland: Treibhausgasneutrale Orientierungsszenarien - Modul Rahmendaten. Karlsruhe: Fraunhofer ISI and Consentec GmbH and ifeu and Technische Universität Berlin; 2024.

[60] Oberle Stella, Gnann Till, Wayas Louis, Wietschel Martin. Analyzing the regulatory framework gaps for gas distribution networks with decreasing natural gas demand in Germany. Heliyon 2024;10(24):e40800. http://dx.doi.org/10.1016/j.heliyon.2024.e40800.