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Towards agent-based building stock modeling: Bottom-up modeling of long-term stock dynamics affecting the energy and climate impact of building stocks

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A B S T R A C T

Buildings are responsible for a large share of the energy demand and greenhouse gas (GHG) emissions in Europe and Switzerland. Bottom-up building stock models (BSMs) can be used to assess policy measures and strategies based on a quantitative assessment of energy demand and GHG emissions in the building stock over time. Recent developments in BSM-related research have focused on modeling the status quo of the stock and comparatively little focus has been given to improving the modeling methods in terms of stock dynamics. This paper presents a BSM based on an agent-based modeling approach (ABBSM) that models stock development in terms of new construction, retrofit and replacement by modeling individual decisions on the building level. The model was implemented for the residential building stock of Switzerland and results show that it can effectively reproduce the past development of the stock from 2000 to 2017 based on the changes in policy, energy prices, and costs. ABBSM improves on current modeling practice by accounting for heterogeneity in the building stock and its effect on uptake of retrofit and renewable heating systems and by incorporating both regulatory or financial policy measures as well as other driving and restricting factors (costs, energy prices).

1. Introduction

In the EU and in Switzerland, residential and commercial buildings together are responsible for about 40 and 30% of the energy demand and emitted greenhouse gases (GHG), respectively [1,2]. A large share of these buildings has been erected before minimum energy efficiency standards were implemented and accordingly are not very energy efficient and mainly equipped with fossil-based heating systems. Therefore, buildings offer a large potential for energy efficiency and a resulting GHG emission reduction compared to the status quo.

In order to make use of this potential at a scale, targeted policy measures and strategies are needed. Such strategies are ideally based on a quantitative assessment of the building stock and a respective quantification of effects. Both can be generated through bottom-up building stock models (BSMs) [3,4]. BSMs forecast energy demand and GHG emissions of the building stock by modeling the changes of the stock through new construction, building retrofits and demolition of existing buildings as well as through the change in building technologies. They have the advantage of being technology-specific and can consider conflicts and synergies between the different implemented measures.

Bottom-up BSMs typically estimate the energy demand of representative archetype buildings in the stock and aggregate the results to the stock level [3]. They have been applied at a transnational to national scale [5–7] as well as a urban [8,9] or district scale [10,11], using data from various sources with different levels of disaggregation. Depending on the model purpose, BSMs can be used to study policy scenarios [6,12,13], support energy planning [14–16] or evaluate retrofit strategies [10].

Recent developments in bottom-up BSM-related research have focused on data input, energy modeling techniques, and validation of results for the status quo of the building stock, typically at the urban scale [14]. This development has been driven by a wider access to building-specific data and increasing computational capabilities. Comparatively little focus has been given to improving the modeling methods in terms of stock dynamics to forecast changes in the stock. Most BSMs either focus on the analysis of the status quo or forecast changes in the stock primarily through assumed rates of building retrofit, technology diffusion, demolition and new

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construction [17]. These rates are generally defined exogenously - typically based on historic rates or expert judgment [17]. Such approaches do not explicitly consider the effect of economic, environmental or policy factors, such as for example energy prices, resource availability and labor costs, on building ownerś decision to renovate or adopt a certain technology.

Not considering these important influencing factors limits the reliability of the results. Moreover, it limits their output, as the interaction between model results and these influencing factors cannot be described, which limits the applicability of BSMs in terms of policy advice. Models that do consider these factors are rare. For example, models such as [18–21] use a combination of turnover rates or lifetimes in combination with discrete-choice approaches to model changes in market shares and the subsequent transition of building archetypes based on the changing technology costs and policy interventions. These models highlight the usefulness of endogenous modeling of stock dynamics and technology adoption, but often work on a higher level of aggregation and do not consider the full heterogeneity of the building stock in terms of different building types, sizes and states. One way to address these shortcomings and advance modeling practices is through evolving BSM by exchanging the established practices with an agent-based modeling (ABM) approach to model stock dynamics that allows to model the interaction between building ownerś decision making and relevant influencing factors as well as different building states based on individual building agents.

This paper first introduces the theoretical background and context of the agent-based building stock model developed in this paper and the decision model applied therein (Section 2). The paper then describes the operationalization of the developed model for the residential building stock of Switzerland (Section 3). In Section 4 the model results are presented and are compared to and validated against statistical data across different dimensions. Finally, in Section 5, we discuss the methodology and results and their implications as well as present our conclusions in Section 6.

2. Theoretical background

2.1. Agent-based modeling

Building stock modeling has so far focused on modeling technological aspects of the development of energy use in the stock and neglect complex interactions between technology, economics and policy when modeling the development as outlined in Section 1. Agent-based modeling (ABM) has been shown to be an ideal tool to model such complex interactions bottom-up by representing different actors in a system as autonomous agents, which can have different attributes, decision processes, the ability to learn, and to interact with each other and their environment [22]. This makes ABM especially useful when modeling complex, multilevel problems with heterogenous populations by describing overarching patterns through micro-level processes [22].

ABM has already been widely used to model energy efficiency technology adoption in different realms [23,24] as well as in the building sector in specific [25–29]. These studies show, how ABM can be used to model technology adoption in the building sector focusing on different aspects such as the importance of decision processes [25,26], spatial aspects [26,30] and interactions between actors [27,31] in the diffusion of building technologies.

As such these studies focus on the heterogeneity of, and interaction among decision makers when modeling technology adoption in the building sector. But even though they account for a heterogeneity in adopters, the large variation of buildings as well as how the building specific attributes such as size, age, installed heating systems, etc. might affect the ownerś decision is so far not considered. Moreover, these studies only look at adoption behavior and do not investigate the effect these technologies have on lowering GHG emissions and energy demand of the building stock.

By linking ABM with a BSM these issues can be addressed. The BSM is technology explicit and describes the building in detail. Based on the available building level information, the effect to adopt a certain technology can be evaluated. This can be used to assess the feasibility and utility to adopt a certain technology for a given building and, therefore, give the basis on which the building ownerś choice can be modeled. As technological changes are tracked on the building level through a BSM, the interaction of technologies can be assessed both in terms of the overall energy demand of the building but also how previous technological choices for a certain building might affect later decisions (e.g. how the decision to retrofit the building envelope might affect the choice in heating system later on). Moreover, the effect on energy demand and GHG emissions can also be assessed after the adoption to track the effect of the diffusion of certain technologies on the overall demand. By doing so, an ABBSM will be able to model both the effect of policy on the diffusion of technology in terms of the rate of adoption as well as to quantify the effect in terms of energy or emissions saved.

2.2. Modeling building owner's adoption decisions

A key advantage of implementing ABM into BSM is to enable modeling of building owner decisions to adopt certain technologies. There are many different approaches to modeling adoption decisions in ABMs, ranging from simple decision rules to sophisticated psychological and economic models [23,24]. In the context of buildings, only a few studies forecast the diffusion of technologies in the stock through ABM [26–28,31]. These studies mainly focus on a single technology or technology group and do not model the overall stock development in terms on new construction, retrofit and replacement. Moreover, they mainly focus on single-family house owners [27,28,31]. As such these studies give focus on interaction between house owners but only rudimentary model the buildingś effect on the choice. In order to do so, economic approaches to decision modeling such as a discrete choice approach seem most appropriate as also showcased by Müller [21].

Beyond ABMs, there are numerous other studies, that address building ownerś energy efficiency technology adoption decisions, ranging from renovation to the choice of heating system, most of which focusing on private homeowners in particular [27,28,32–36]. Many of these studies focus on finding determinates for technology adoption decisions employing methods such as regression and discrete choice models [32,34,36,37]. A common finding between these studies is that building ownerś choice both in heating systems as well as renovation decisions is affected by more than just costs and the technological attributes, but that the choice context [32,37], network and interaction effects [27,28] and owner characteristics [34,37] also may have a significant impact on the decision. This shows, that it is crucial to not just take technological and economic attributes but also situational and individual aspects in the decision process into account when modeling technology adoption in BSMs using an ABM approach. Taking restrictions on the side of the decision maker into account is in line with the concept of bounded rationality [38].

2.3. Bounded rationality

The concept bounded rationality addresses the fact that human decision making is limited by both access to information and information processing ability [38]. Therefore, human decision making is characterized by heuristics and biases to simplify the choice task. In the case of building owners, research suggest, that one such heuristic lies in reducing the number of options that are considered. For example, results from Lehmann et al. [35,39] suggest, that in the case of heating system substitution decisions, building owners often do not even consider any or only a few alternatives when replacing their existing system (i.e.,. they have a strong status-quo bias [39]). This is consistent with findings in other studies, suggesting a two-stage decision process when operationalizing this aspect of bounded rationality in modeling [40,41]. Namely, a first screening stage in which the alternatives to be considered are collected based on simple rules, followed by the actual evaluation of the preselected alternatives. Mueller and de Haan [42] show how such an approach can per implemented in ABMs by screening alternatives based on their market share in combination with a discrete choice model for the detailed evaluation of alternatives.

3. Agent-based building stock model

The following section describes the agent-based building stock model developed for this paper and its application for the residential building stock of Switzerland. The description partially follows the structure of the ODD (Overview, Design concepts, and Details) protocol for the description of ABM [43]. A more complete description of the model can be found in the supporting information. The model was implemented in Python using the libraries Pandas [44], Numpy [45] and mesa [46].

3.1. Model purpose

The model is designed to support the study of the development of building stocks in terms of their energy demand and GHG emissions and in particular how building ownerś decisions to retrofit the building envelope and replace heating systems under different policy interventions affects this development. It is developed for the residential building stock of Switzerland and calibrated to model the past development in the stock from 2000 to 2017.

3.2. Model entities

Currently, the ABBSM includes two main entities: buildings and the model environment. Building agents combine general building properties including the various building components together with building owner and location properties. The model environment holds attributes on the climatic, economic, technological and policy framework conditions. More agent types (e.g. tenants/households) could be added in future applications.

3.2.1. Building

Next to general building characteristics such as building type, age, etc., each building agent is made up of different building components (such as roofs, walls, floors and windows), and HVAC systems (heating system, hot water system, solar system and ventilation system (if applicable) and one to many dwellings (see Fig. 1). Building agents are initialized based on the method to construct synthetic building stocks described in [47] (see Section 3.3.1). The method synthetically reconstructs a representative sample building stock, where each of the generated synthetic buildings is representative of a part of the stock and includes all data needed to run a building energy demand simulation using the calculation engine developed in [47]. The building agents' properties are built up based on the same structure and extended for the purpose of the ABBSM.

Next to the building properties to run a building energy demand simulation, the building definition covers also building owner and building location specific properties such as the decision parameters of the decision model used as well as building specific framework conditions such as the availability of which energy resources are available for a building (e.g. is it possible to use a ground-source heat pump). The heating system choice of a building will be constrained according to this criterion. In case of the grid-bound energy sources (gas and district heating), these properties might be changed over the model period based on the shares defined in the model environment that define how the availability of these energy sources change over time. Lastly, based on the other characteristics, the model calculates the building agent's energy use differentiated according to different energy services (space heating, hot water, ventilation, lighting, appliances and auxiliary) as well as the resulting primary energy demand, GHG emissions and energy costs (see Section 3.3.3).

3.2.2. Model environment

The model environment holds all other climatic, economic, technological and policy framework data needed to run the simulation. This includes (1) climate data to run the energy calculation, (2) the market environment, i.e., economic and technological characteristics of the technologies modeled for retrofits and new buildings (e.g. costs, efficiencies and lifetimes of building components and HVAC systems)), market availability and energy prices, (3) the policy environment, i.e.. the policy framework data such as the building standard, the development of restrictions of technologies to building agents and subsidy levels as well as (4) other data such as socio-demographic data (e.g.. population development). A detailed description of the data and its sources is included in the supporting information.

3.3. Model overview

The structure of the ABBSM is shown in Fig. 2. After the model is initialized (see Section 3.3.1), the stock dynamics is modeled through the processes of new construction, demolition as well as retrofit and replacement in existing buildings (Section 3.3.2). The general decision model applied in these processes to model agents' choices is described in Section"General decision model", with subsequent section describing the individual processes. The effect of the changes in the building stock in terms of energy and GHG emissions is tracked using an integrated energy demand simulation and impact assessment module (Section 3.3.3). Results are used to calibrate and validate the model based on the historical development (see Section 4.1).

3.3.1. Building stock initialization

The status quo is initialized by synthetically generating a representative sample stock of the building stock of Switzerland for the year 2000 based on the method described in [47]. The initial stock size is set to 50′000 building agents at the model start. Each of these synthetically created buildings is representative of a number of buildings in the actual stock, which is represented by a scaling factor and representative floor area in the model (cf. Fig. 1), which is used to scale results to the stock level. The structure of the stock is based on data of the 2000 census [48], which is complemented with building archetype data to generate the synthetic buildings and complement them with the attributes needed to assess the energy demand of the building (see supporting information for a detailed description).

Additionally, each building is given a location specific attribute, which states which energy resources are available for a building, defining whether gas, district heating as well as ground or groundwater source heat pumps are available or allowed for a given agent. The share of buildings with such restriction is based on data from Lehmann et al. [35] for district heating and heat pumps as well as from VSG [49] for gas.

Building	
Building type	Multi-Dwelling Building
Climate zone	Switzerland
Construction year	1926
Scaling factor	109
Representative floor area	27721 m^2
Number of floors	2
Number of basement floors	1
Roof type	Pitched
Number of dwellings	2
Residential floor area	211 m^2
Heated floor area	253 m^2
Footprint area	126 m^2
Height floor	2.9 m
Perimeter	19.0 m
Volume	761 m^3
Ventilation rate infiltration	86 m^3/h
Electricity auxiliary	1066 kWh/a
Heat capacity	234 kJ/K m^2

Opaque Components	
Component Type	Roof
Year	1979
Surface Area	152 m^2
U-Value	0.53 W/m^2 K
Insulation thickness	75 mm
Orientation	139°/319°
Angle	20°

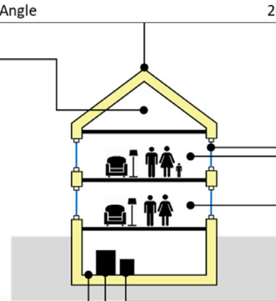
Transparent Components	
Component type	Window
Year	1987
Surface area	20.7 m^2
U-value	1.7 W/m^2 K
g-value	0.69
Shading factor	0.71
Frame ratio	0.12
Orientation	144°
Angle	90°

Dwellings	
Dwelling area	105 m^2
Number of rooms	5
Number of occupants	2
Occupancy time	15 h/pers. Day
Indoor temperature	20.9 °C
Consumption hot water	32 m^3/pers. Day
Electricity lighting	407 kWh/a
Electricity appliances	2231 kWh/a

Building Location	
Gas access	False
District heating access	False
HP groundwater allowed	False
HP ground allowed	True

Building Owner	
Discount rate	2%
Weight investment cost	-0.6
Weight maintenance cost	-0.1
Weight energy cost	-0.1
Weight WTP	0.6
Weight market share	350

Building Energy Use	
Useful energy	135 kWh/m^2 a
Final energy	197 kWh/m^2 a
Primary energy	327 kWh/m^2 a
GHG emissions	62 kgCO$_2$/m^2 a
Energy costs	15 CHF/m^2 a



Ventilation	
Ventilation type	Natural
Year	-
Central	False
Ventilation rate	296 m^3/h
Efficiency heat recovery	0%
Specific fan power	0 W/m^3 h
Maintenance costs	0 CHF/a

Heating System	
System type	Oil Boiler
Year	1991
Central	True
Power	20 kW
Efficiency	80 %
Energy carrier	Oil
Maintenance costs	680 CHF/a

Hot Water System	
System type	Electric water heater
Year	1991
Central	False
Volume	200 l / day
Efficiency	66 %
Energy carrier	Electricity
Maintenance costs	386 CHF/a

Solar System	
System type	Solar Collector
Year	1991
Central	False
Area	10 m^2
Efficiency	90%
Energy carrier	Solar Heat
Maintenance costs	121 CHF/a

Fig. 1. Example representation of a building agent including its building components, systems, usage and other characteristics. Adapted and extended from FOS [47].

3.3.2. Building stock dynamics

Once the model is initiated, the model simulates the development of the stock in time steps of one year. Each time steps starts with updating the model environment, after which the existing building agents are updated individually. For each building agent the scaling factor and representative floor area is adjusted based on the age of the building in order to account for demolition. The model then checks whether a building envelope component needs to be refurbished or the heating system replaced by checking if the component has reached the end of its assigned lifetime. If so, the respective decision process is carried out and the building updated accordingly. After the existing buildings have been updated, the model calculates the demand for new construction based on the population development and new agents are added to represent the newly constructed buildings. The model initializes each of these new building agents and chooses what heating system to install based on the new heating system decision.

General decision model: The model applies a general decision model (GDM), which is adapted for the different modeled decision processes such as for the envelope retrofit, heating system replacement as well as the heating system choice for new buildings. The GDM is operationalized by combining different conceptual models such as the model for strategic decision processes by Mintzberg et al. [50] and the theory of innovation [51] to structure the decision process. The model is structured after the model for strategic decision process by Mintzberg et al. [50], who structure the decision process in three main steps: (1) Identification, (2) Development and (3) Selection (see Fig. 3). Within these steps the model applies the concept of bounded rationality (in the development step) and a discrete choice approach (in the selection step) as outlined in Section 2.

First, the building agent identifies the need to make a decision. The ABBSM differentiates between three different decision types: (1) new building heating system, (2) heating system replacement and (3) building envelope retrofit. The new building heating system decision is triggered by a new agent being created, while the two latter decision types are triggered by a component reaching the end of its assigned lifetime. The lifetime for each building component is assigned randomly based on a Weibull distribution (see Section "Aging building components and demolition").

Second, during the development step, the building agent constructs the choice set for a given decision. Based on a universal choice set for each of the decision types, which includes all possible options, the actual consideration choice set is constructed. In the case of the retrofit decision, the choice set is directly formed from the universal choice set, while for heating systems, the model first filters out any unfeasible and inapplicable solutions for a given building agent (see Fig. 3) to filter out any options that are not relevant (e.g. unavailability of district heating). Based on the remaining options, the model narrows down the options further to account for the fact that not all options might be considered by the building owner according to the concept of bounded rationality (see Section 2.3). For this purpose, first the consideration choice set size is defined based on a gamma distribution after the approach taken by de Haan et al. [52], see Eq. (1). The parameters of the gamma function are set to $\alpha = 3$ and $\theta = 2.5$, which yields a distribution with an average choice set size of 7.

$$p(n, \alpha, \theta) = \frac{1}{\Gamma(\alpha)\theta^{\alpha}} e^{-\frac{n}{\theta}} n^{\alpha-1} \tag{1}$$

p probability of choice set size nn number of choices in the choice setα shape parameterθ scale parameter

The choice set composition is then chosen through weighted randomly sampling of the remaining options. The probability is defined for each choice set based on the market share of the technologies in a given option as well as the current state of the building (e.g. in the case of existing buildings, the currently installed system is always included except if it is no longer available due to policy measures), see Eq. (2). The market share of the different technologies is based on the aggregated decision behavior of building agents of the previous time step in order to take changing preferences and interactions with the market into account.

$$P_{ni} = \frac{e^{\sum w_{mn} MS_{mi}}}{\sum_j^S e^{\sum w_{mn} MS_{mj}}} \tag{2}$$

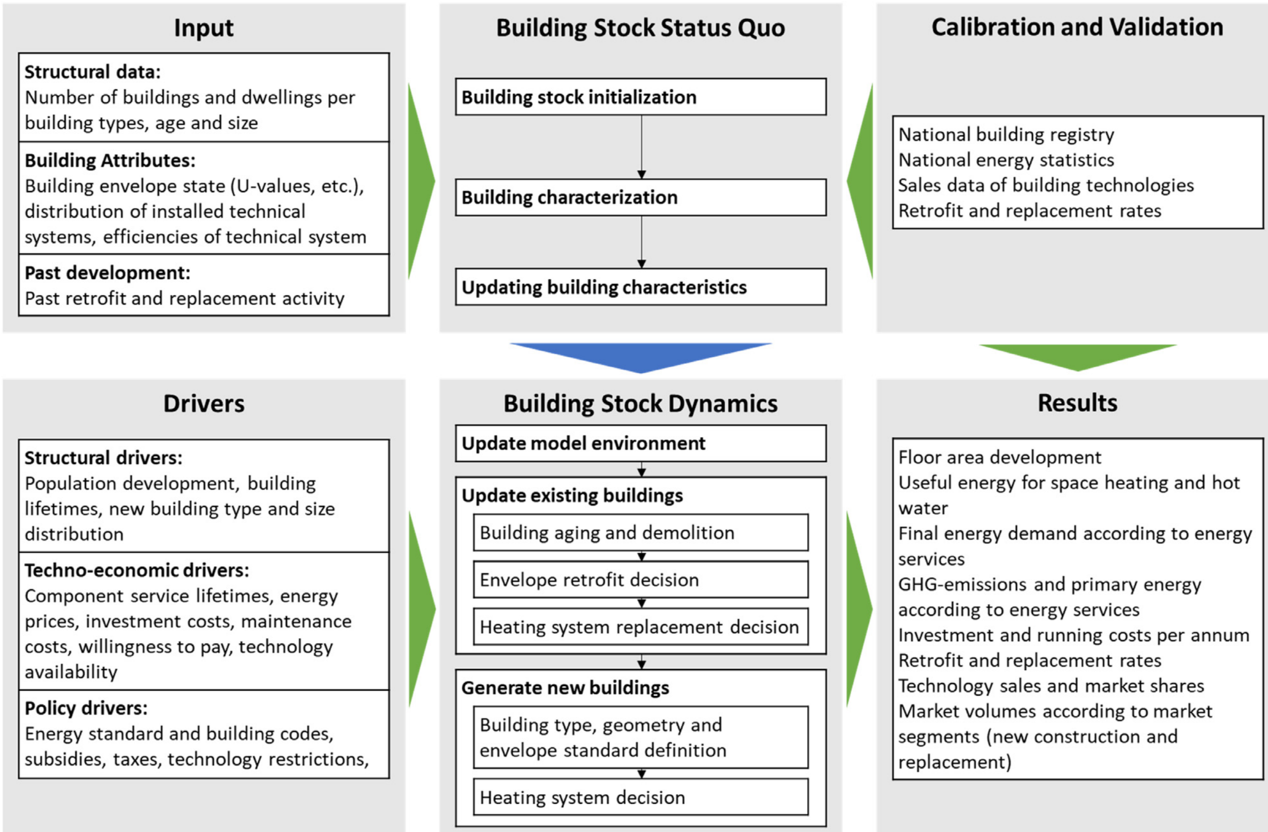


Fig. 2. Overview of the structure of the agent-based building stock model. Green arrows represent data flow, blue arrows the model flow.

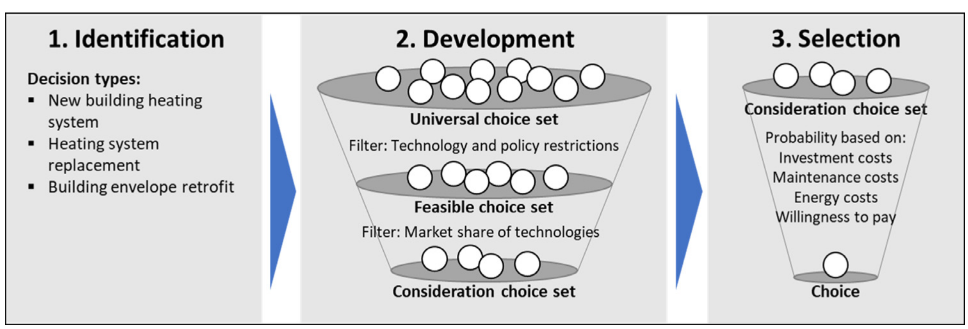


Fig. 3. Structure of the general decision model.

P_{ni}: Probability of option i being included in consideration choice set of decision maker nw_{mn}: Weight of technology m for decision maker nMS_{mi}: Market share of technology m which is part of option i

In the third step, the building agent evaluates each option in the consideration choice set and finally decides which option to choose from. In order to model the selection process, the model applies a discrete choice modeling (DCM) approach in order to simulate the agentś decision-making process. The DCM model is based on microeconomic utility theory and calculates the choice probability of a certain option based on the utility of that option in relation to the utility of the other options in the choice-set (Eq. (3)). The option is then randomly selected based on the calculated probability P_i of each of the options in the choice set.

$$P_i = \frac{e^{V_i}}{\sum_j^S e^{V_j}} \tag{3}$$

The utility of a given option i is calculated based on an assessment of the total costs of the option (see Eq. (4)). In order to reduce unwanted scale effects in the calculated probability between building agents of different sizes (i.e., distortion of the probability according to the logit function purely due to the size of the building, rather than the economic viability of the alternative) and to be able to use the same utility function regardless of building size the costs are converted to specific cost per m^2 floor area. However, scale effects on the costs of the different measures arising from both the building size and the energy-efficiency of the buildings are considered through the cost factors of different measures and technologies (e.g., cost factors for different heating systems depend on the required nominal heating power). Moreover, to make investment costs comparable to recurring costs such as energy or maintenance and operation costs, the investment costs are converted to specific equivalent annual costs. using the annuity formula Subsidies for different technologies and retrofit options are considered as a reduction in the investment costs. The effects of CO_2-tax are accounted for by changes in the energy price which together with the final energy demand affects the energy costs of each of the options. The willingness to pay (WTP) factor is calculated based on a percentage of the annualized investment costs and reflects additional attributes of a technology not covered by the other factors (e.g. increased comfort through new windows). The WTP factors are defined technology specific based on literature assessing the willingness to pay for different retrofit and renewable heating systems [34,53]. A more detailed differentiation of the WTP factors according to agents was not possible due to a lack of data. A detailed description of the utility function can be found in the supporting information.

$$V_i = \beta_{AC} EAC_{I,i} + \beta_{MC} C_{M,i} + \beta_{EC} C_{E,i} + \beta_{WTP} WTP_i \quad (4)$$

$EAC_{I,i}$: Specific equivalent annual investment costs of option i in CHF/year $m^2$$C_{M,i}$: Specific operation and maintenance costs of option i in CHF/year $m^2$$C_{E,i}$: Specific energy costs of option i in CHF/year $m^2$$WTP_i$: Willingness to pay for option iβ_n Weighting factor for decision criteria n

Update model environment: Each time step starts by updating the model environment. This involves the adjustment of framework parameters such as energy prices, technology efficiencies, cost factors, new building and retrofit standards as well as the availability of technologies based on input data. Moreover, the location-based availability of grid-bound energy systems (i.e. gas and district heating) of buildings is updated. Meaning, the availability of gas and district heating for randomly selected buildings is adjusted depending on whether the grid is extended or shrunk.

Aging building components and demolition: The aging of building agents over the model period has two effects. Firstly, the aging of the building components triggers the retrofit and replacement decisions in existing buildings and, secondly, it drives the demolition of buildings.

Each of the building components has an assigned maximum lifetime after which it either needs to be reinstated, retrofitted or replaced. The maximum lifetime of each component is assigned randomly based on a Weibull distribution, which is calibrated based on data from Agethen et al. [54,55]. Once a component reaches the end of its lifetime, the respective retrofit or replacement decision is triggered.

Demolition is modeled by adjusting the scaling factor and the representative floor area of each building agent in the stock, simulating the share of the buildings represented by an agent being demolished each year. This adjustment is modeled by the change in the survival function deepening on the building agents´age from one timestep to the next and does not depend on the demand for new construction. The model uses a loglogistic survival function, which is fitted based on survival data from Aksözen et al. [56,57].

Envelope retrofit: A building envelope retrofit is triggered by a building component reaching the end of its assigned lifetime. The choice set consists of a reinstatement option (i.e. keeping the current level of energy efficiency) as well as three retrofit options with an increasing level of energy efficiency (e.g. three different insulation thicknesses in case of a wall retrofit) based on the retrofit standard of that time step. The level of energy efficiency (i.e. insulation thickness, U-values of windows) is increased over the modeling period to reflect the increasing standards in line with increasing standards for new construction due to technological progress and a tightening of codes and standards. For each of the options in the choice set the utility-based choice probability is calculated and one option randomly selected based on the GDM.

Heating system replacement: Similar to the envelope retrofit, the heating system replacement is triggered by the heating system reaching the end of its lifetime. To simplify implementation, the system is always replaced as a whole, including a potential separate hot water system or connected solar collectors. The universal choice set for the replacement is constructed from all possible combinations of heating system, hot water systems and including additional solar collectors (see supporting information for a full list of technologies). The choice set is then adjusted to exclude unfeasible and inapplicable solutions based on the current system (e.g. buildings with central heating do not switch to a decentral system), location restrictions (e.g. district heating not available for that building) or policy restrictions (e.g. central electrical heating is not allowed to be newly installed). Based on the remaining feasible choice set, the consideration set is formed based on the market share of the technologies using the bounded rationality approach outlined in Section "General decision model". However, the current heating system option is always included in the choice set, except if it is no longer available to that building due to policy restrictions (e.g. ban of central electric heating). The heating system to be installed is then randomly chosen based on the calculated choice probability.

New construction: For each time step, the new construction demand in terms of new dwellings being added is calculated as a function of population growth. The function is calibrated based on the actual population development and building stock growth over the modeling period (see supporting information for details). Based on the demand for new dwellings, the number of new buildings and new building agents is calculated based on the average scaling factor in the existing stock. Afterwards, each of the new agents is initialized and characterized individually. The characterization method mirrors the approach used to generate the initial synthetic buildings based on [47]. First, the building type and size in terms of dwelling size, number of dwelling and floors are defined based on the statistical data from that year. Afterwards, the building geometry is defined based on a shoebox model (see supporting information for details) and the efficiency standard of the envelope chosen based on the currently applicable building standard. The ventilation system is defined by technology shares based on [58]. Lastly, the heating system is chosen based on the new building heating system decision process. The process mirrors the heating system replacement decision. The differences lie in the choice restrictions (different policy restrictions apply) there is no currently installed system, which is included in the choice set and investment costs may differ. Moreover, the market share relevant to the construction of the consideration choice set is tracked separately for new construction choice affecting the composition of the consideration choice set.

3.3.3. Energy demand and impact assessment

The individual building agentś energy demand and the related GHG emissions are assessed using an integrated energy demand model. The model is described in the supporting information and is based on a monthly steady-state energy balance for space heating demand according to ISO EN 52,016-1 [59] (or the Swiss equivalent SIA 380/1 [60]). The model is extended with a method to account for the performance gap and the fact that, in general, the indoor temperature is notably lower in inefficient buildings than in newer energy-efficient buildings, which affects their energy consumption [61]. Based on the calculated final energy demand the model then calculates the related primary energy and GHG emissions using emission and primary energy factors of the different energy carriers based on [62].

3.4. Scenario

The modeled scenario is aimed to reflect the historic development of the Swiss residential building stock between 2000 and 2017. Scenario drivers are, therefore, defined based on historical data. The population development driving the demand for new construction is defined based on [63]. The resulting new construction and the distribution in terms of building types, number of floors, dwellings, dwelling size is defined based on the distribution of newly added building to the national building and dwelling registry during that time [64]. The energy standard of new buildings is defined based on the evolution of the Swiss building model code [65–67]. The same codes also define restrictions on the installation of heating systems (e.g. banning central direct electrical heating), as well as giving requirements on the use of renewable energy sources (RES) for new buildings. These restrictions are, however, not introduced in all states (cantons) of Switzerland simultaneously. Accordingly, the restriction is introduced stepwise based on the percentage of the population living in regions with this regulation in place according to ([68], including previous editions of the same report). The development of the availability of grid based energy sources is based on data from [49,69–71].

Key drivers impacting the decision for retrofit and heating system replacement are the costs of the different options and the costs of energy. Cost factors for retrofit options and heating systems are based on [72–76]. The different cost factors are adjusted over time based on labor and material cost development in the construction industry [77–79]. Additionally, technological learning is assumed for newer technologies such as heat pumps based on [80] and updated sales volumes for heat pumps based on [81]. Additionally, subsidies for building retrofits and renewable heating technologies are included based on the development of the "harmonized subsidy model" [82–85]. The energy price development is taken from [86], with updated prices for wood based on [87]. The prices also include a CO_2-tax on fossil energy carriers since 2008 of 12 CHF/tCO_2 (11 EUR/tCO_2), which has since been increased stepwise to currently 96 CHF/tCO_2 (85 EUR/tCO_2).

3.5. Calibration

The calibration of the decision model for the building envelope retrofit and the heating system replacement and new construction has been carried out using empirical data on the aggregate retrofit activity between 2000 and 2010 [88] and heating system structure in the stock in 2017 [89] as benchmarks. Furthermore, the structural change in the stock as well as the development of the residential energy demand are used to validate the model behavior as well (see Section 4.1). The calibration of the model was carried out in two steps. First the initial parameterization of the decision model was set manually to arrive at reasonable parameter ranges for the different parameters of the decision model (i.e. weighing factor of the utility function, discount rate) as well as setting the parameters of the gamma function to estimate the choice set size (Eq. (1)) and market share weights (Eq. (2)). Second, the model calibration was fine-tuned by running multiple model runs using different combinations of parameter settings for the parameters of the utility function. The different parameter settings are assessed by calculating the root mean square deviation to the reference data in terms of the share of retrofitted building components on the one hand as well as the resulting heating system structure in the stock on the other hand, see Eq. (5). The parameter setting with the lowest average RMSD between the two was selected. The results of the different model runs and the selected parameters are shown in Table 1.

$$RMSD = \sqrt{\frac{\sum_n^N \left(\hat{y}_n - y_n\right)^2}{N}} \tag{5}$$

RMSD: Root mean square deviationN: Number of observationsy: Observed and predicted values

4. Results and validation

In this section, the results of the ABBSM for the residential building stock of Switzerland are described. First, the model results are validated against reference data and statistics from the model period of 2000–2017. Subsequently, the results of the stock development in terms of energy and GHG emissions are further assessed.

4.1. Validation of model results

Fig. 4 shows the structure of the modeled building stock as well as the reference statistics of the Swiss building and dwelling registry [48,64] for the year 2000 and 2017. As the building stock in 2000 is initialized using data from FOS [48], the structure of the modeled stock matches the reference statistics. In the year 2017, the structure of the modeled stock deviates slightly in some aspects from the reference statistics. Overall, there are less buildings in the modeled stock compared to the reference statistics, this is mainly due to a mismatch in the number of buildings for the building periods before 1945 between the two reference years. For these building periods the number of building increases from 2000 to 2017 in the reference statistics, even though it could have been expected to decrease due to demolition. Potential explanations for this are conversion of buildings and/or an update of the statistical basis. Overall, the model slightly overestimates the new construction activity in terms of number of buildings. This may be partially be explained that, compared to the reference statistics, the model shows slightly higher shares of small buildings with one dwelling compared to larger multi-dwelling buildings.

The modeled retrofit activity of the building envelope components is compared to survey results from Jakob et al. [88] and is shown in Fig. 5. As can be seen from this figure, the model has a tendency to underestimate the retrofit activity (i.e. energy efficiency improvement of the components) and overestimate the pure reinstatement of the component compared to the reference data from Jakob et al. [88]. This is most notable in the case of windows, where especially the share of retrofitted windows in multi-dwelling buildings is underestimated.

The resulting distribution of heating and hot water systems in the modeled building stock is calibrated with reference statistics of the Swiss census [48] for the year 2000 and validated against a survey from the office for statistics [89] for 2017 (see Fig. 6). Results from the period between is not available as the information on space heating and hot water systems in the Swiss building registry is not updated consistently for existing buildings and is therefore unreliable. The results show slight deviations between the modeled stock and the reference data already for 2000 due to random sampling when initializing the stock as well as differences arising from mapping the information in the statistics to the space heating and hot water system definition in the ABBSM (see supporting information for details). In 2017, the distribution of space heating systems in the modeled stock matches rather well with the statistics. There is, however, a slight underestimation in the share of oil and gas boilers, with an overestimation of the increase in heat pumps. Moreover, the share of direct electric heating is overestimated both in the initial year 2000 as well as in 2017.

The resulting development in the modeled stock in terms of final energy demand can be validated against the energy statistics [90]. For this purpose, the modeled space heating demand is weather adjusted according to factors from Prognos [86] to make it comparable. The model overestimates the overall energy demand in 2000 by 1.9%. Over the modeling period until 2017 the deviation between model and statistics fluctuates between −1.3% and 2.9% (in 2017), which may also reflect uncertainties in the energy statistics.

The breakdown and comparison of the energy statistics and model results according to energy carriers is shown in Fig. 7. The modeled results are weather adjusted based on [86]. Compared to the overall demand, the demand per energy carrier deviates more significantly. Over the whole modeling period, demand for wood

Table 1
Parameter settings and room mean square deviation of model results compare to calibration data of [88,89]. The different model runs are ranked according to the decreasing value of the average RMSD.

Input parameter					RMSD			Rank
Discount Rate	Weighting Factor Invest Cost	Weighting Factor WTP	Weighting Factor O&M Cost	Weighting Factor Energy Cost	Retrofit Activity	Heating Systems	Average	
0.02	−0.5	0.5	−0.1	−0.1	0.036	0.016	0.0259	16
0.04	−0.5	0.5	−0.1	−0.1	0.037	0.011	0.0238	3
0.06	−0.5	0.5	−0.1	−0.1	0.040	0.010	0.0245	5
0.02	−0.6	0.6	−0.1	−0.1	0.036	0.010	0.0233	1
0.04	−0.6	0.6	−0.1	−0.1	0.039	0.011	0.0247	8
0.06	−0.6	0.6	−0.1	−0.1	0.042	0.012	0.0274	21
0.02	−0.7	0.7	−0.1	−0.1	0.039	0.011	0.0247	7
0.04	−0.7	0.7	−0.1	−0.1	0.042	0.012	0.0273	20
0.06	−0.7	0.7	−0.1	−0.1	0.045	0.017	0.0310	26
0.02	−0.5	0.5	−0.15	−0.15	0.036	0.022	0.0291	24
0.04	−0.5	0.5	−0.15	−0.15	0.036	0.015	0.0254	9
0.06	−0.5	0.5	−0.15	−0.15	0.039	0.010	0.0246	6
0.02	−0.6	0.6	−0.15	−0.15	0.037	0.014	0.0257	12
0.04	−0.6	0.6	−0.15	−0.15	0.039	0.010	0.0245	4
0.06	−0.6	0.6	−0.15	−0.15	0.042	0.010	0.0258	14
0.02	−0.7	0.7	−0.15	−0.15	0.037	0.010	0.0237	2
0.04	−0.7	0.7	−0.15	−0.15	0.041	0.010	0.0257	13
0.06	−0.7	0.7	−0.15	−0.15	0.046	0.013	0.0293	25
0.02	−0.5	0.5	−0.2	−0.2	0.036	0.027	0.0315	27
0.04	−0.5	0.5	−0.2	−0.2	0.037	0.020	0.0284	22
0.06	−0.5	0.5	−0.2	−0.2	0.038	0.015	0.0265	18
0.02	−0.6	0.6	−0.2	−0.2	0.037	0.020	0.0286	23
0.04	−0.6	0.6	−0.2	−0.2	0.038	0.014	0.0259	15
0.06	−0.6	0.6	−0.2	−0.2	0.041	0.011	0.0259	17
0.02	−0.7	0.7	−0.2	−0.2	0.037	0.014	0.0255	10
0.04	−0.7	0.7	−0.2	−0.2	0.041	0.010	0.0255	11
0.06	−0.7	0.7	−0.2	−0.2	0.044	0.010	0.0272	19

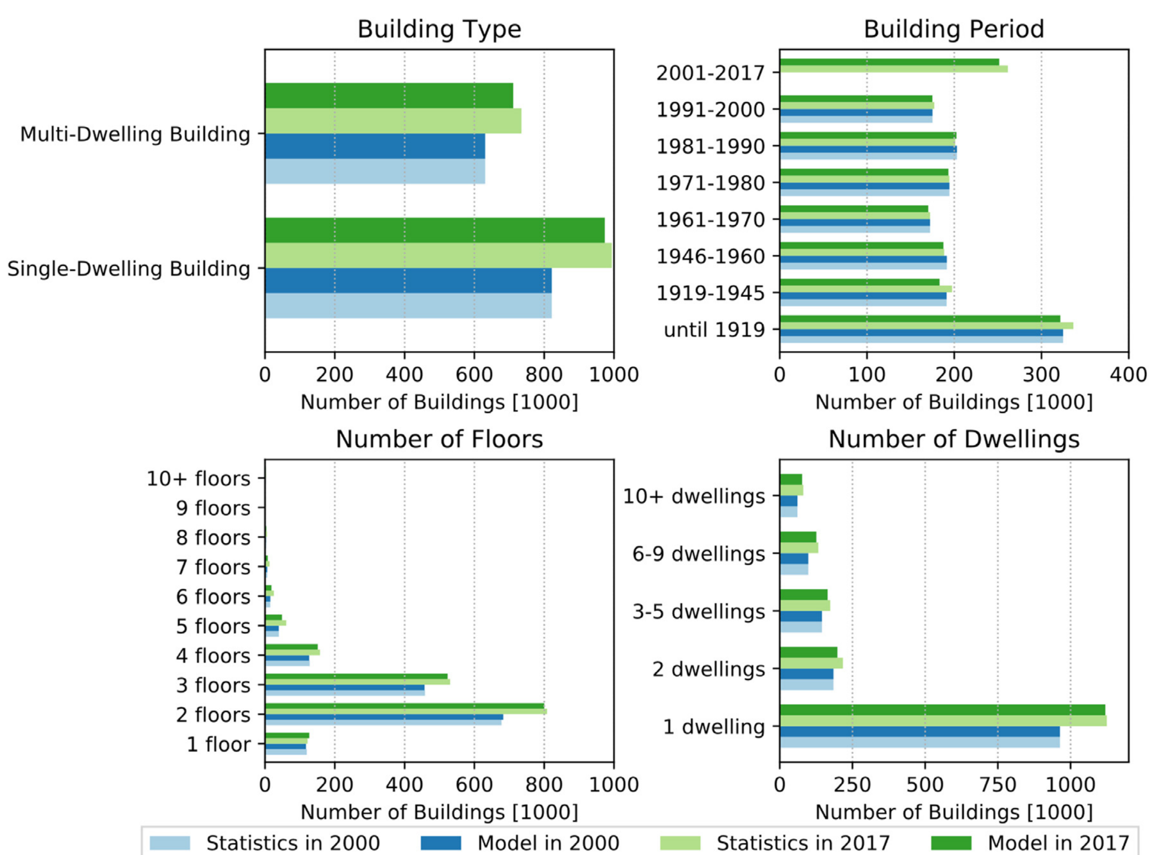


Fig. 4. Structure of the building stock for the year 2000 and 2017 based on model results and statistics [48,64].

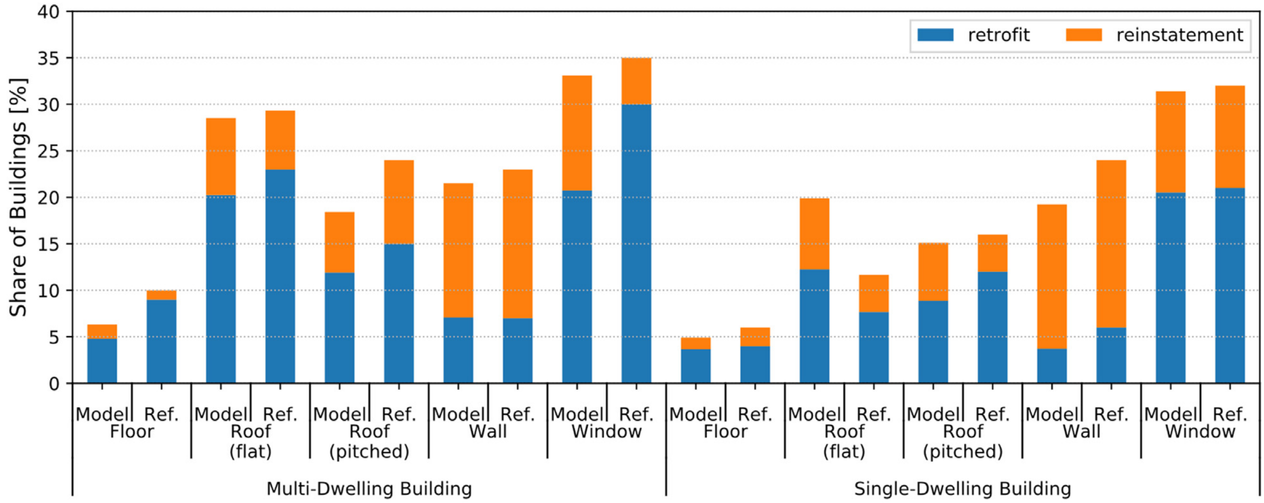


Fig. 5. Share of retrofitted and reinstated building components in the modeled building stock as well as based on reference data (Ref.) from [88]. Share represent carried out retrofits and reinstatements per building component in the stock built before 1990 from 2000 to 2010.

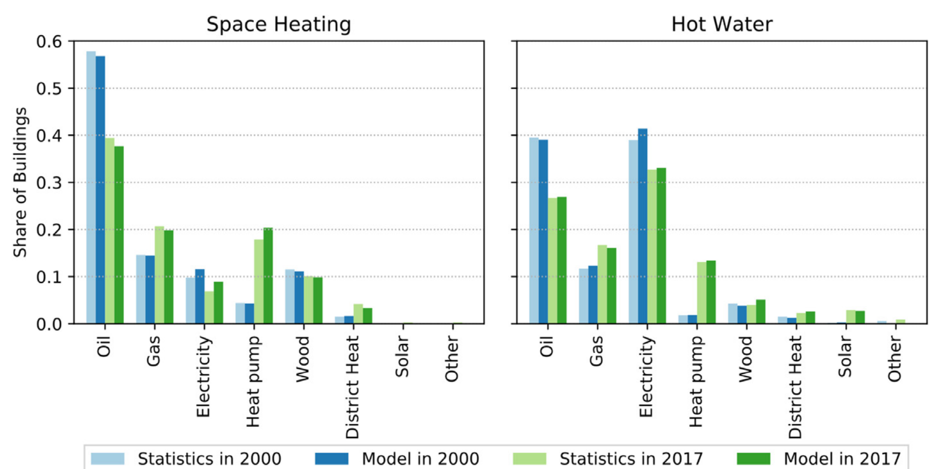


Fig. 6. Distribution of heating systems and hot water systems in the building stock for the year 2000 and 2016 based on model results and statistics [48,89].

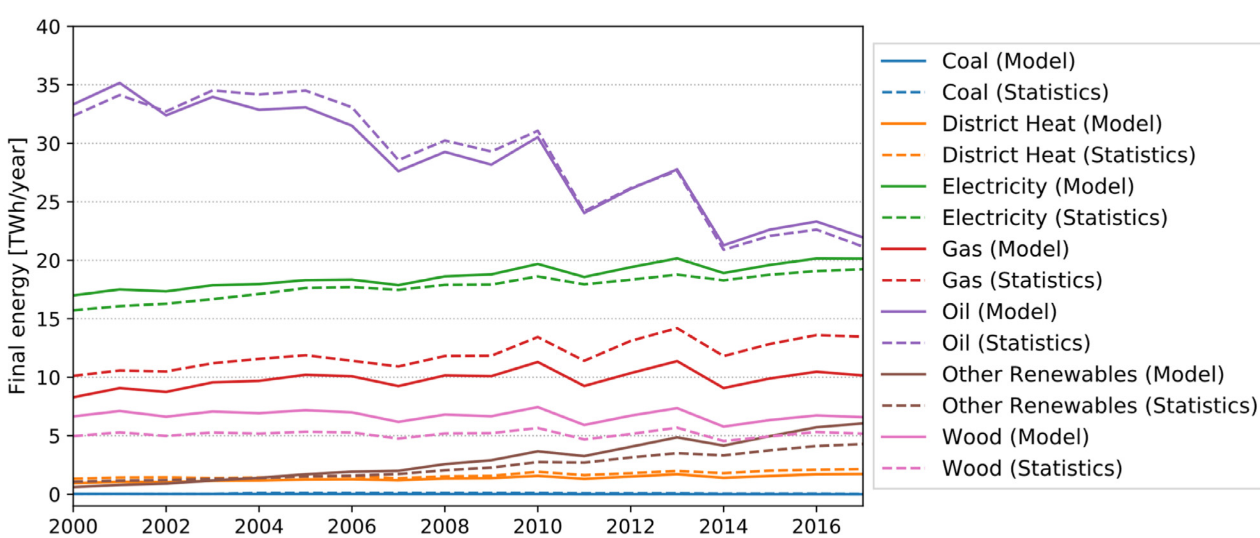


Fig. 7. Development of the final energy demand of the residential building stock according to model results (weather adjusted based on [86]) and household energy statistics [90].

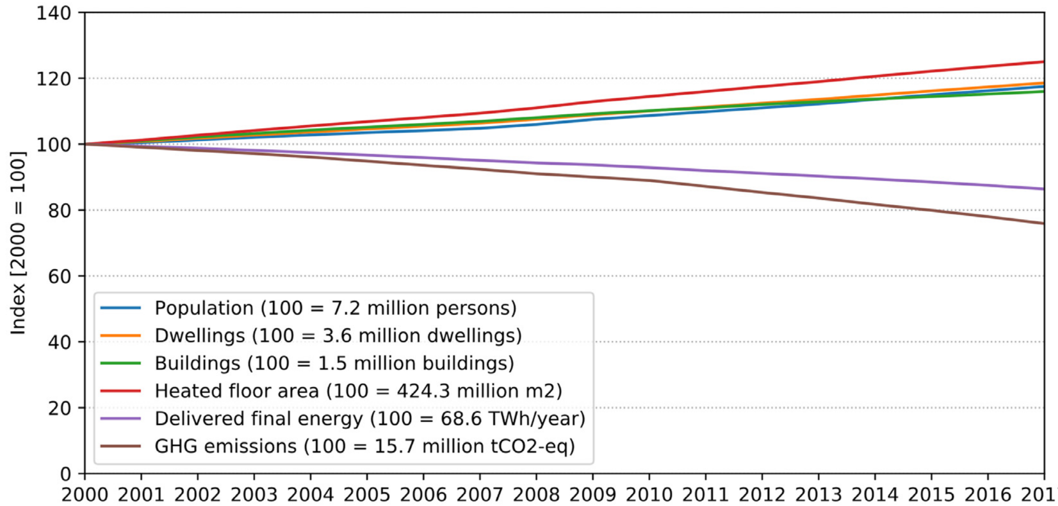


Fig. 8. Index of the aggregated stock development in terms of structural parameters (population, dwellings, buildings and floor area) and the resulting energy and GHG emissions. Delivered final energy (and the related GHG emissions) is shown excluding electricity for household appliances and lighting and excluding energy from ambient and solar heat. Starting values in 2000 correspond to index of 100.

is overestimated, while the demand for gas is underestimated. To some degree these differences may be explained due to structural differences in the distribution of heating systems in the stock between the synthetic stock and reality. For example, gas might me more frequently used in larger buildings found in urban areas, while wood-based systems (e.g. wood stoves) are might be more common in smaller buildings, which would lead to the under- and over estimation of the energy demand of these energy carriers respectively. The overestimation of wood may also be attributed to the fact that many wood-based heating systems (e.g. stoves) must be operated manually (which is not reflected in the model), resulting in underheating of buildings as they are not used to the same degree as thermostat operated heating systems. Moreover, such buildings may have a secondary heating system (e.g. electric heaters) covering part of the space heating demand. The underestimation of gas may also be partially due to additional gas consumption for cooking, which is not included in this model. Moreover, the deviation between model and statistics in terms of gas demand may also stem from uncertainties as to the degree of deployment of condensing boilers before 2000 and during the modeling period and the effect this has on the efficiencies defined in the input data [58,73,86,91,92].

4.2. Energy and GHG emission development

The development of aggregate indicators of the modeled building stock from 2000 to 2017 such as delivered final energy demand and GHG emissions as well as related structural parameters (number of dwellings, buildings and total heated floor area) are shown in Fig. 9. Compared to the overall final energy demand, the delivered final energy demand does not include on-site production and, therefore, excludes energy from ambient and solar heat (which in Fig. 8 is included under the category “Other Renewables”). Moreover, both delivered final energy and the related GHG emissions are not including electricity for household appliances and lighting.

The building stock increases over the whole modeling period. The number of buildings grows slower compared to the number of dwellings in the second half of the modeling period as the share of multi-dwelling building increases in new construction. The growing stock does not translate into an increasing energy demand as the demand from new construction is more than compensated by energy efficiency retrofits as well as demolition of existing buildings. This leads to decreasing energy demand over the entire modeling period. The energy demand reduction is sped up from 2008 when the new building code takes effect in most cantons, increasing the energy efficiency standard for new building, resulting in an overall energy demand reduction of 9.3 TWh/year (−14%) in 2017. The GHG emission are reduced more significantly compared to the delivered final energy demand due to the decreasing use of oil for space heating and hot water to more and more use of heat pumps as well as to a lesser degree district heating (cf. Figs. 6 and 7).

This development is also reflected in the development of the delivered final energy demand and GHG emission intensities in the stock (see Fig. 9). In 2000, the majority of the stock still consumed more than 100 kWh/m^2 year. However, this share is steadily decreasing until 2017, where only about 60% of the floor area still consume more than 100 kWh/m^2 year. This development comes from new buildings being added to the stock, the demolition of existing buildings as well as building retrofits and heating system replacements contribute to lowering demand intensities in the existing stock. A similar development can be seen in terms of GHG emission intensities in the stock, where buildings with a GHG intensity of below 10 kgCO2-eq/m^2 year make up only 10% of the stock in 2000, which increases to 38% in 2017. However, the underestimation of gas use as shown in Fig. 7 may lead to an underestimation of the share of buildings with a high GHG emission intensity.

4.3. Retrofit and heating system market shares

The achieved annual retrofit rates per building component are shown in Fig. 10, showing the share of building components that are retrofitted each year. Floor and wall retrofits are implemented on average at a low rate of below 0.5%/year, while window and flat roof retrofits are implemented at considerably higher rates, mainly driven by shorter component lifetimes (case flat roofs) and higher utility from replacement due to comfort increase (case of windows). The retrofit rate of both pitched and flat roofs shows a slight increase over the modeling period, while all other rates remain more or less constant. The slight fluctuations in the rates are mainly due to the stochastic nature of the decision model.

The realized market shares of different heating systems for replacement and new construction according to the model results

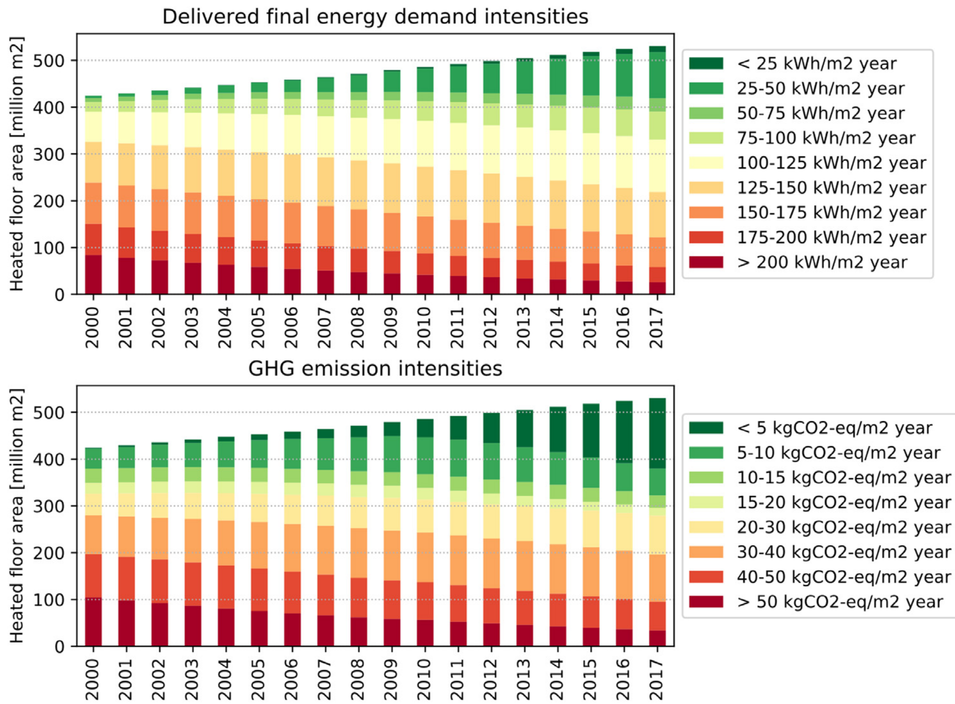


Fig. 9. Development of the delivered final energy demand and GHG intensities in the building stock based on the share of total heated floor area.

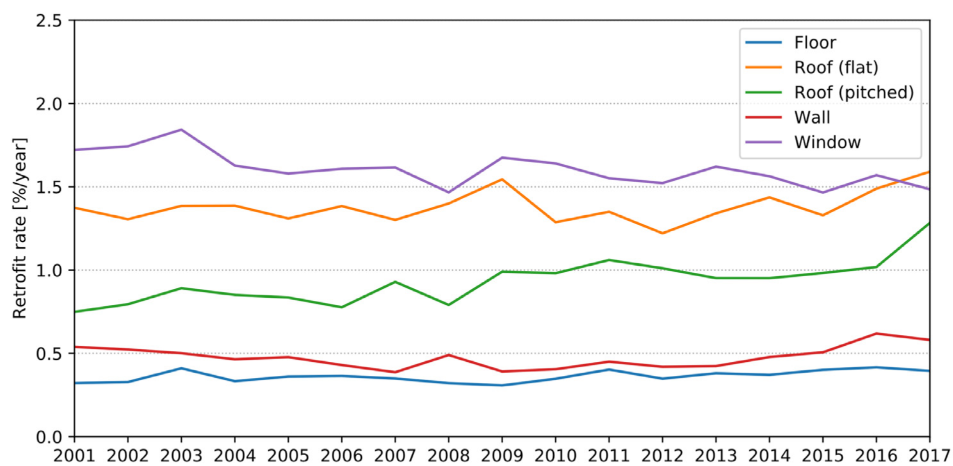


Fig. 10. Development of the retrofit rate per building component.

are shown in Fig. 11. The market shares in the replacement market show that fossil-based heating systems have the highest share, even though it is decreasing over the entire model period. In contrast, they decrease significantly in new construction and are almost phased out by 2008. In new construction, oil and gas-based heating is mainly replaced by heat pumps and to a lesser degree by an increase in district heating. Direct electric heating, while still making up a small share of the replacement market, is decreasing towards the end of the model period.

4.4. Detailed stock breakdown

Fig. 12 shows the distribution of key parameters in the stock according to construction period and shows how their distribution evolved over the model period from 2000 (blue) to 2017 (red). The results show the shift in the distribution of U-values, with the median U-value (horizontal lines) shifting significantly especially for roofs and windows, which are retrofitted at a higher rate than walls and floors. The results also show that the distribution is not even and that the retrofitted building components form a secondary peak in the distribution of the U-values.

The resulting distribution of final energy demand and GHG emissions in the stock shifts also to lower intensities. Clear secondary peaks are formed in the existing stock, reflecting mainly the increasing share of buildings with heat pumps. The more pronounced peak in the case of GHG emissions comes from the share of wood-heated buildings, which also results in a low GHG intensity. The distribution of heating systems for 2000 and 2017 in Fig. 12 shows the shift from mainly oil based heating to gas as well as (to a lesser degree) heat pumps and district heating in the existing stock. In the building period after 2000 the dominance of the heat pump is clearly visible as well as the reemergence of wood-based heating.

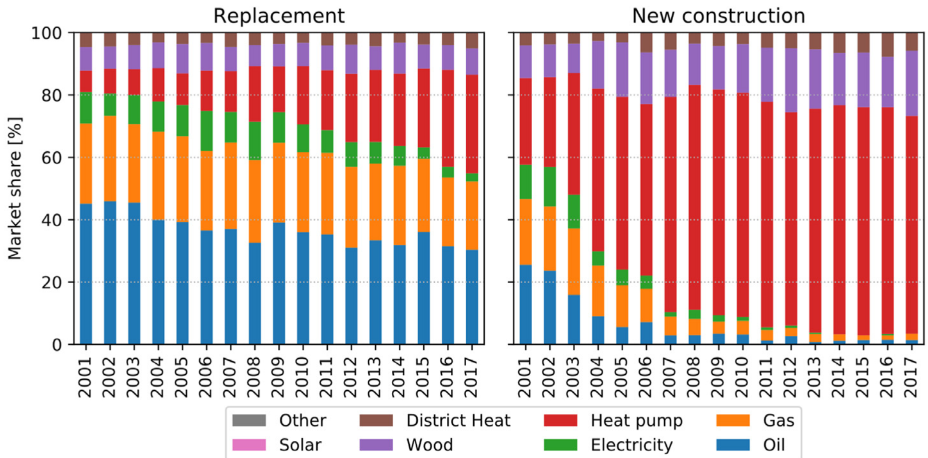


Fig. 11. Market shares per heating systems for replacement and new construction according to the classification of [48,89].

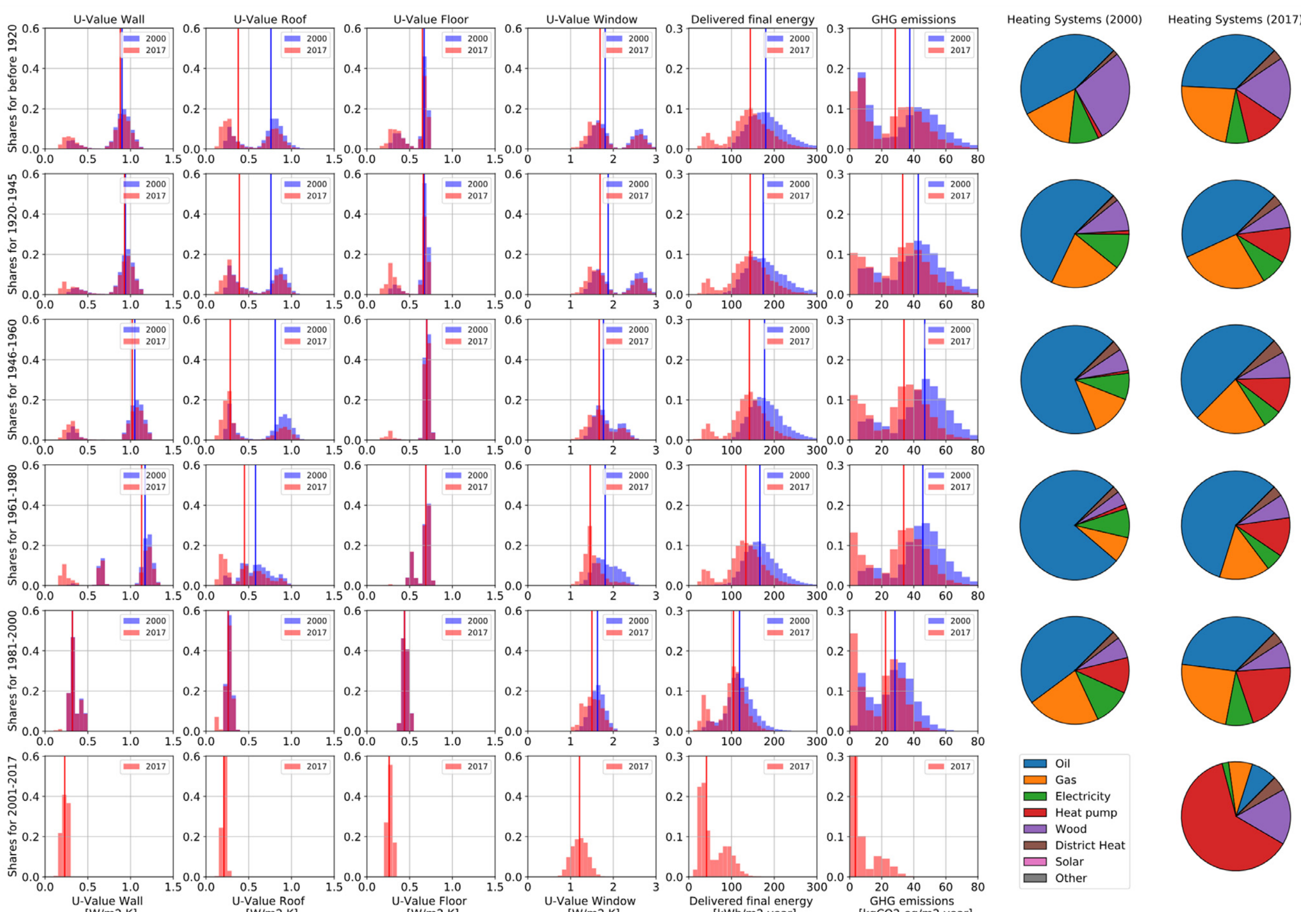


Fig. 12. Overview of the distribution of key parameters as well as the share of heating systems in the building stock according to the different building periods for the year 2000 and 2017. Blue: stock in 2000, red: stock in 2017. Vertical lines indicate the median value for this stock segment. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Discussion

5.1. Discussion of the methodology

The agent-based building stock model presented in this paper improves on the general building stock modeling practices in numerous ways. The main improvement comes from moving away from modeling stock dynamics through exogenously defined rats (e.g. diffusion, renovation or new construction rates) to modeling individual decisions of building owners. Modeling retrofit and replacement decisions on the building level makes it possible to consider the effect of drivers on the decision such as costs, energy prices, technology availability as well as policy measures such as subsides or renewable energy requirements. This allows for a more detailed description of stock dynamics over time and makes the analysis of detailed and complex policy measures possible (e.g. such as the requirements for renewable energy according to [66]).

Modeling decisions on the building level enables the model to consider nonlinearities of interactions within the building as well as in the stock in the diffusion of retrofit and heating system decisions. E.g. as the economics of energy efficiency measures are assessed on the building level, the sequence in which decisions on heating system and retrofit are made by a building agent affects the final outcome. Moreover, as the choice of heating system depends among other things on the market share of the different technology, the diffusion of technologies is accelerated as they gain in market share. Therefore, both the influence of building level attributes as well as higher level diffusion dynamics (such as the "popularity" of technologies in the market) are accounted for in the decision model for heating systems and retrofits.

The model not just accounts for a heterogeneity in the building stock in terms of buildings, but also differentiates between different decision frames and their effect on the diffusion of technologies in the case of heating systems. By differentiating the decision model between replacement and new construction the model takes into account not just the different requirements but also the difference in market share and costs of technologies between the two as well as status quo bias in replacement. This makes it possible to model the different diffusion dynamics between the replacement and new construction market.

The agent-based building stock modeling approach shown in this paper has some limitations. First and foremost, building agents are mainly characterized from a building energy demand simulation perspective and less detailed on the building owner attributes. A more detailed description of different owner types as well as their decision-making processes and criteria would greatly improve the model. However, lack of a comprehensive overview as well as data on the processes and criteria of different owner types led to the development of this more simplified approach at this stage.

Missing or incomplete data on the stock development in terms of building retrofit and HVAC systems increases the difficulty in the calibration and validation of the model behavior. The current model conceptualized based on established theory of decision-making of building owner and is calibrated and validated across different aggregate dimensions (e.g. aggregate stock development and retrofit rates). However, more detailed validation based on actual choice data or detailed longitudinal dataset tracking buildings over time could help improve the model further by improving the decision model as well as the underlying datasets (e.g. component lifetime distributions).

5.2. Discussion of model results

The results show the historic development of the Swiss residential stock between 2000 and 2017. Despite growing floor area, which increases by 26%, the total delivered final energy demand of the stock decreases by 12% and GHG emissions even by 18%. This shows, that the decarbonization of the Swiss residential stock is progressing and the policies introduced to curb GHG emissions are taking effect. Especially the introduction of the RES requirement for new buildings helped make renewable based heating systems such as heat pumps the dominating technology in new construction. In contrast, while the share of renewable energy heating system in the existing stock are growing as well, there is still a large share of fossil heating systems as many buildings are still staying with oil and gas or are switching from oil to gas rather than to a renewable heating system.

Over the model period, retrofit rates of the different building components remain more or less stable as costs remained fairly stable and subsidies increased only incrementally. It is, however, unclear how the latest, more significant, increase in subsidies [85] will affect retrofit rate in the future.

The model results show the phase out of oil- and gas-based heating in new construction due to the implementation of RES requirements in the building code. The phase out according to model results is almost complete, making heat pumps the dominant technology in new construction. Only few buildings are built with fossil-based heating systems after 2008, at which point the restriction for RES is implemented in the majority of cantons. The possibility to use fossil-based heating in case of an increased efficiency standard of the envelope according to the regulation [66] is not modeled as the choice of heating system is only modeled after the definition of the efficiency level of the building envelope. This exemption leads to a still slightly larger share of buildings being built with fossil-based heating systems than the model results suggest compared to reference statistics [93].

In the existing building stock, the model shows decreasing shares of oil-based heating, which are replaced by gas to a large extend, but also a significant share of heat pumps in building of all building periods. The large share of buildings with direct electric heating, especially from the 1970s and 1980s are decreasing as well, being replaced by other systems as the restriction on installing and replacing direct electric heating systems takes effect.

6. Conclusion

The agent-based building stock model presented in this paper was designed to support the study of the development of building stocks in terms of their energy demand and GHG emissions and in particular how building ownerś decisions to retrofit the building envelope and replace heating systems affects this development. The model was implemented and validated for the residential building stock of Switzerland based on the past development in the stock from 2000 to 2017. The results show that the model can effectively reproduce the historic development of the stock based on the development in policy, energy prices, and costs during that time, showcasing the effect of these policies on the energy and GHG emissions of the stock.

The agent-based building stock modeling approach improves on the current BSM modeling practice and is a useful tool to evaluate policies that influence the building stock development and aimed at lowering its energy and GHG emissions due to the following reasons:

- The use of disaggregate representative building agents compared to common building archetypes makes it possible to assess results not just aggregated per building stock segment, but to analyze distribution of key parameters and results in the stock as well as track their development over time.
- The model accounts for heterogeneity in the building stock and decision frames, differentiating between new construction and retrofit/replacement, in the diffusion of retrofit measures and renewable heating systems including building related as well as external driving and restricting factors such as costs, energy prices, policy instruments, etc.
- The model can incorporate a diverse set of policy measures from regulatory (e.g. building codes, RES-requirements) to financial (e.g. subsidies, taxes) instruments and assess their impact on the adoption of energy efficiency measures and renewable energy technologies as well as the resulting development of the energy demand and GHG emissions of the building stock.

The developed ABBSM may be extended in numerous ways and lays the groundwork for future development of the agent-based building stock modeling approach. A logical next step is the application of the model in forecasting future scenarios, which will be tackled in future publications. In addition to that, the agent-based approach to BSM could be further developed both in terms of the description of (building) agents as well as their interactions both between each other as well as with their environment. For example, the model could be expanded to differentiate between building owner types and to refine the model for decision making processes in terms of decision criteria and preferences of these different types (e.g. differentiate between owner-occupiers and landlords, etc.) as well as further differentiating decision triggers (e.g. building purchase as a trigger for renovation). Moreover, additional agents such as households or actors from the building supply chain (installers, architects/engineers) could be added to more accurately describe interactions such as between the owner and tenants, building and user or owner and supply chain actors at point of sale. Another possible development would be to spatially distribute building agents to differentiate building locations based on region (e.g., cantons in Switzerland), municipality, or hectare raster level depending on the scale of the application in order to account for geographical differences more accurately (e.g., energy prices or costs). Furthermore, other building types could be added to the model framework to represent the complete building stock. Moreover, a comprehensively study of the sensitivities and uncertainties of the model, similar to [94,95] is also planned for future publications as part of the ongoing work in IEA-EBC Annex 70.

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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.enbuild.2020.109763.

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