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An agent-based model for energy investment decisions in the residential sector

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ABSTRACT

Energy-related investment decisions in the buildings sector are heterogeneous in that the outcome for each individual varies according to budget, values, and perception of a technology, even if an apparently identical decision task is faced. In particular, the rate of adoption of new energy-efficient technologies is often hard to model and underlines the need for an advanced approach to capture diversity in decision-making, and enable the inclusion of economic, comfort, environmental and social aspects. This paper presents an enhanced agent-based model that captures several characteristics of consumer behaviour that influence investment decisions. Multiple agents with different objectives, search strategies, and decision methods are implemented. A case study is presented which illustrates the benefits of the approach for the residential sector in the UK. The agent-based method shows diversity in investment decisions, without requiring the constraints on uptake needed in many models. This leads to a range of technologies in the market during a transition phase, continuous investment in low capital cost technologies, and eventually the emergence of a low carbon system based on new mass market technologies. The system that emerges is vastly different from one observed when economically rational investment is assumed and uptake constraints are applied.

1. Introduction

Climate change has become increasingly important since it gained global attention in the late 20th century. The implementation of the Paris Agreement to hold the increase in global average temperature to well below 2 °C requires radical change in all energy consuming sectors [1]. Within this context, buildings account for almost a third of final energy consumption globally, and an equally significant amount of CO_2 emissions [2].

While some low-carbon technologies have been shown to be economically competitive, limited understanding of the consumer perspective may block large scale commercialisation [3]. Many barriers such as overseen technical problems and unwillingness to abandon the status-quo also affect the uptake of technologies [4]. It is apparent that the diffusion of technologies and related investment decision-making process is more complex than characterized in many models. Beside several important economic and environmental criteria that people take into consideration when making a decision, investment behaviour is also influenced by social and psychological factors. Hence, behavioural models are needed that include these psychological and social factors along with technical and economic aspects [5].

To account for the consumer behaviour, this paper presents an agent-based model that is integrated within the building sector in the MUSE framework, the ModUlar energy systems Simulation Environment, an integrated assessment model (IAM) developed at Imperial College London. An overview of MUSE is provided in Appendix A.

1.1. Literature review

To build a model of decarbonisation investment behaviour for the building sector, they key elements influencing consumer investment behaviour need to be identified.

1.1.1. Factors affecting the decarbonisation investment behaviour

Several studies [6–10] outline decarbonisation strategies and analyse potential pathways for the decarbonisation of the UK building sector. For example [10], identifies the reduction of the

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carbon intensity of the energy carrier, the reduction of the heat demand, and the development of low carbon heating technologies as key elements to achieve a significant carbon reduction. Similarly [6], highlights the potential of an increase in building performance, re-engineering the heat supply or increasing efficiency of existing technologies. The results of [7] also emphasize the need for a better insulation of all dwellings, alongside a rapid and substantial increase in green energy. In contrast to other works, the study in Ref. [8] integrates one further aspect by examining the role of community or distinct heating schemes alongside building-by-building decarbonisation measures. Following the review of decarbonisation measures above, four main strategies can be identified (i) reduce service demand via behavioural change (e.g. turning off lights or appliances) (ii) increase in building energy efficiency (e.g. daylighting, insulation, controls): (iii) improved or alternative technologies that meet service demand (e.g. lighting, appliances, boilers, heat pumps, etc) (iv) adoption of low carbon supply technologies (e.g. solar PV).

Several factors affecting humans decision making to invest or engage in the decarbonisation options outlined above have been investigated by experimental methods and standardized questionnaires or interviews. In Ref. [11], it is suggested that investments are carried out based on technical and comfort criteria after appliances reach their end of life, or economic incentives draw consumer attention. A similar pattern can be observed in Ref. [12] where installation cost, technical maturity and feasibility are the crucial barriers for adoption followed by communication and interaction between consumers. Similarly to Ref. [12], it is shown in Ref. [13] that social interactions promote energy-relevant investments. The results in Refs. [14,15] indicate that economic factors and product performance are the main criteria with a focus on fuel consumption over capital cost. They further highlight the difficulty of introducing new technologies to the market due to social factors and resistance of social groups. To broaden the scope of the analysis, the study presented in Ref. [16] includes contextual factors and personal factors in addition to economic incentives. They point out the differences in decision making based on age, experience with a technology, and level of education. A categorisation of all the possible factors into five main subsets is presented in Ref. [17]. They identify that households' income has the highest influence on energy-saving technology investment, but emphasize that the expected consequences for and beyond the household are regarded as highly correlated with decision making.

Throughout the reviewed literature three key elements emerge that should be included in a simulation model of energy-relevant decision-making processes:

- Integration of the four key decarbonisation strategies.
- Heterogeneous independent decision makers to capture diversity in how investment decisions are made.
- A combination of economic factors, social factors and investors' personal attitude towards technical problems as criteria for the decision making.

1.1.2. Building sector in IAMs

Integrated assessment modelling is a type of scientific modelling often used in environmental science and environmental policy analysis, characterized by the integration of knowledge from several domains. Apart from MUSE, a variety of IAMs exist, all differing in methodology, level of technical detail, and geographical scope. All of these incorporate a building sector element.

WITCH (World Induced Technical Change Hybrid) is a dynamic global model that includes the most important energy sectors: electricity, transport, and an aggregated non-electric (industry, services and residential) sector [18]. The calculation of technology and fuel switching are based on constant elasticity of substitution functions where energy investments and resources are chosen optimally.

MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental impact) is a commonly used energy system model developed by the IIASA (International Institute for Applied Systems Analysis). It creates scenarios based on minimising total system cost of serving demand using linear programming, where a rich range of technologies are individually characterized [19,20].

Another example is GCAM (Global Change Assessment Model) where the market share of all competing technology options is determined based on a logit-share function on the investment cost without considering additional factors such as the fuel consumption cost, comfort, emissions or similar [21].

NEMS (National Energy Modelling System) is an energy system model representing US energy markets. A 'technology choice' submodule is introduced: For new investments, the choices are determined based on the energy shares derived from surveys and adjusted based on relative life cycle costs. For replacements, fuel switching costs are determined based on the cost and efficiency of each technology, and are used to estimate the percentage of consumers choosing each technology [22,23].

TIMES (The Integrated MARKAL-EFOM System) and TIAM (TIMES Integrated Assessment Model) belong to a family of energy system optimisation models [24,25]. In the building sector, energy investment is optimised, with all consumers having perfect knowledge of all technology options and minimising costs over long time horizons. Constraints are used to attempt to make consumer decisions more realistic. For example, calculated by drivers and consumers' sensitivity to these drivers to render a cost optimal solution. As seen above, in all reviewed energy system models changes in economic factors and macroscopic demographic figures are the main drivers where no homeowners' preferences of end-use technologies are integrated.

In Ref. [26] a heating preference based methodology is embedded in TIMES based on survey data about households' preferences to define fixed constraints on technology switching. Although this study enables the inclusion of consumer preferences and splits the large problem into individual sub-problems, the survey data only guarantees an accurate determination of the preference constraints for the current point in time.

Another study of the residential and transport sector for France, which extends the TIMES framework to include heterogeneity and behaviour, is presented in Ref. [27]. Similar to the study [26] the problem is split up based on survey data to account for 180 household types independently. Each of the defined households then minimizes their overall cost subject to budget constraints, though no non-economic metric is considered.

Recent work with focus on the transport sector in Ref. [28] goes one step further by adding non-monetary and stochastic elements in the objective function to increase the heterogeneity in decision making, yielding the COnsumer CHoice INtegration COCHIN-TIMES model.

All of the above methods create different consumer segments to yield heterogeneity in the consumer choice while keeping the intertemporal optimisation framework of TIMES where the explicit decision-making behaviour is not directly modelled.

The PRIMES (Price-Induced Market Equilibrium System) model is a notable exception in that it shows a first approach to include further behavioural characteristics beside technical and economic metrics in the calculation of investment decisions by calculating a perceived cost including fuel share, which is calculated by a function of fuel costs, households' income and equipment maturity as the basis for investment decisions [29].

1.1.3. Investment behaviour models

Many well-known classic theoretical constructs are concerned with individual motivational factors as determinants of the intention of performing a specific behaviour and thus attempt to predict whether individuals will accept certain new technologies [30]. Some of the influential theories of human behaviour due to their simplicity and proven suitability are the theory of reasoned action (TRA) [31], the theory of planned behaviour (TPB) [32], the decomposed theory of planned behaviour (DTPB), the technology acceptance model (TAM) [33], and the unified theory of acceptance and use of technology (UTAUT) [34]. The determinants for the intention and behaviour differ throughout the models by including perceived behavioural control, ease or difficulty of performing a behaviour [32], underlying belief structure [35], or perceived usefulness and perceived ease of use [36]. Limitations of TRA, TPB, DTPB and TAM are the reliance on the assumption that people are rational and make systematic decisions based on available information, and unconscious motives, affective-cognitive view, personality and demographics are not taken into consideration. UTAUT differs from other approaches in that it simulates individuals' actual behaviour towards certain state-of-art technologies [34]. The behavioural intention in UTAUT is determined based on performance expectancy, effort expectancy and social influence. All aforementioned models are still criticized to be oversimplified and questions remain regarding whether they can be used for explaining human behaviour in dynamic systems [37].

In addition to these approaches, many conceptual frameworks have been established to describe the factors that can affect the households' decision on energy use [38,39]. Apart from concept-only frameworks several studies on individuals' decision-making processes adopt static mathematical methods which ignore the psychological and social influence that could have great impact on the final decision [40–45]. For example, applied simulation or optimisation methods require constraints on the maximum capacity addition of one specific technology at each simulation time step. These methods are highly sensitive to the choice of constraint levels, where an accurate identification of these constraints remains challenging. Similar limitations exist for choice models based on logit or nested logit approaches that can include a large number of parameters that are identified by regression methods. The identification requires the availability of a set of data to yield a reliable parametrisation where the parameters are identified based on selection procedures without basis in the physical system. Another shortcoming on logit models is the independence from irrelevant alternatives axiom [46] stating that the relative odds between any two outcomes are independent of the number and nature of other outcomes being simultaneously considered. Multi-agent simulations can handle a far wider range of nonlinear behaviour than conventional equilibrium models [47] and are thus suitable to model investment decisions in the building sector.

1.1.4. Agent-based modelling

ABM finds its application in various fields to model the dynamics of complex systems on a micro-level where macro system characteristics emerge from the aggregation of the behaviour of individuals; the decisions of individual agents, their heterogeneity, and interactions with each other and their environment can be approached with limited knowledge about the larger complex system [47,48]. At the macro level, the approach arguably results in outcomes that have a higher probability of actually occurring. The core of the methodology is the definition of different heterogenous agents rather than treating them as a single entity that follows a single decision method. Each agent is defined by its own goal, attributes and methodology to solve a specific problem. Although agents can be defined in various ways and there is no necessary agreement on a general approach, several characteristics are believed to be essential [48]:

- An agent is considered as a self-contained and identifiable individual, with a boundary that enables determination of unique attributes.
- An agent is autonomous, able to interact with other agents and is able to get access to information within the environment they live in.
- An agent's behaviour is goal-oriented. An agent needs to react to the pre-defined goals and adjust its decision making to achieve them.

The agent-based method (ABM) can provide an understanding of the emergent properties of many interacting considerations in complex circumstances where intuition fails [47].

In Ref. [49], an ABM based on the Power Distance of Hofstede's national culture model, measures of extroversion, social status, social responsibility, agreeableness and openness, as well as a five-factor model of personality is used to model investment decisions in the transport sector. The work in Ref. [50] focuses on the investment behaviour according to certain brands and their characteristics based on cost, quality, advertisement, and social influence. A novelty in this work is the integration of the decoy effect, which models the change in behaviour if new technologies enter the market. However, both methods assume a common decision and search behaviour for all agents where the only heterogeneity lies in the different objective weightings.

Several ABMs can be found to simulate the land use in the agricultural sector. One widely used method is presented in Ref. [51] where an ABM is combined with a cellular automata to integrate spatial aspects. Sequences of linear programming problems are autonomously solved for each agent based on the same objective but different cost factors. Adoption constraints are introduced in form of network-threshold values that reflect the cumulative effects of experience and observation of peers' experiences.

Multi-agent models can not only include different decision criteria but also enable definition of a bounded rationality for each agent in which the investment decision is carried out [52]. In this approach several agents with different goals and rationality types are defined which leads to different search rules and decision methods. Although this method presents a good approach in modelling energy investment behaviour, the agents definition is only carried out for one specific city, technology types available are limited, there is no distinction between retrofit and new buildings, and there is no foresight about future energy demand and which technologies will be decommissioned over time.

Overall ABM help to overcome limitations of conventional investment models since they enable the integration of a more realistic consumer behaviour towards technological change by using several objectives to mimic the versatile investment behaviour of different decision-makers in a population.

1.2. Main contributions

The focus of this work lies in the development of an advanced building sector model using an ABM to realistically depict investment behaviour and subsequent energy consumption, within the framework of an IAM. In particular, the combination of ABM and techno-economic investment models presents a promising approach to overcome current limitations and thus to avoid arguably idealistic representations of energy system change. It takes the heterogeneity of decision makers into account by the use of several socio-demographic factors and subjective criteria (e.g. comfort) to determine preferences for energy technologies. The proposed model structure enables the investigation of the technology adoption in more detail by e.g. examining the influence of the information gathering and decision making independently. The in depth analysis further facilitates the identification of target groups that are more likely to take up specific technologies. The main contributions of this paper can be summarized as follows:

- An enhanced building sector model using an agent-based method to represent the real-world decision making via ability of people to gather information, evaluate the options, and make decisions.
- A methodology to model the limits, barriers and speed of consumer adoption of technologies, avoiding sensitive constraints on the technology capacity addition or similar.
- The development of a suitable modelling framework which is adaptive to several geographical regions to account for customer needs and cultural differences.
- The distinction between investments required in new buildings and retrofits of existing building, which has been neglected in many studies.
- The analysis of the energy transitions of the residential building sector in the United Kingdom under limited foresight to integrate the uncertainties on future energy demand and price while simultaneously presenting an adequate investment behaviour.

The paper is organised as follows. In section two, a descriptions of the agent-based method, including agent definition and investment strategy, is given. The parametrisation of the agents is outlined in section three. In section four, a case study for the United Kingdom is used to illustrate the advantages of the proposed approach. Section five gives a conclusion.

2. Methodology

This section presents how the incorporation of ABM within the residential building sector module (RBSM) in MUSE provides a richer depiction of future energy demand and technology choice, by taking demographic and socio-economic heterogeneity as well as individual beliefs into account.

There are four potential pathways for decarbonisation of the residential building sector as identified in section 1.1.1. The current version of the RBSM focuses on the last two aspects (adaption of improved, alternative and low carbon technologies) and the former two points are aspects of future work (behavioural change and increase in building efficiency) and are therefore only indirectly considered in this paper. The effect of measures reducing energy demand (e.g. insulation) and behaviour changes in technology usage are investigated via a sensitivity on the service demand projections.

2.1. Residential building sector module (RBSM)

Within the MUSE framework, RBSM aims to simulate future final energy consumption based on an investment decisions representing real consumers' behaviour in the market, disaggregated into 28 global regions and temporally resolved into 30 timeslices per year. In order to take people 's attitude towards technologies and technological changes into account, the RBSM applies a bottom-up approach to technology characterisation, based on unit technology cost, efficiencies, lifetime and emissions. It includes 64 different technologies to provide lighting, cooling, space heating, space cooling, appliances, and water heating. The RBSM is implemented as a two-step simulation approach. First, the service demand is dynamically calculated for each end-use using macro-economic drivers. Then the agent-based investment algorithm is used to determine the technology market share, and, consequently the fuel mix.

2.2. Investment algorithm

The modelling concept can be describe by four main steps and is schematically illustrated in Fig. 1.

In the first step, the end-use demand of each agent is determined. Dependent on the definition of each agent, a set of possible technologies, the so-called search space, is created. Technology choice for each agent is then calculated based on the agent-specific objectives and the defined decision strategy. The last step is given by an update of the agent technology stock. Similar to Ref. [52] the algorithm uses different search spaces, decision strategies, and objectives for each agent to produce realistic macroscopic sectoral results.

2.2.1. Definition of agents

The fundamental principle of agent classification used within this paper is bounded rationality theory [53], which assumes individuals to have distinct ability to deal with information from the energy market and to make investments based on their own decision-making routes and heuristics.

To describe the investment behaviour of the population of a region, several representative agents are defined and equipped with a certain set of attributes

$$A = \{\mathrm{Obj}, \mathrm{SR}, \mathrm{DS}, \mathrm{TP}, \mathrm{B}, \mathrm{MT}, \mathrm{TS}, \mathrm{TO}, \mathrm{PP}\}, \tag{1}$$

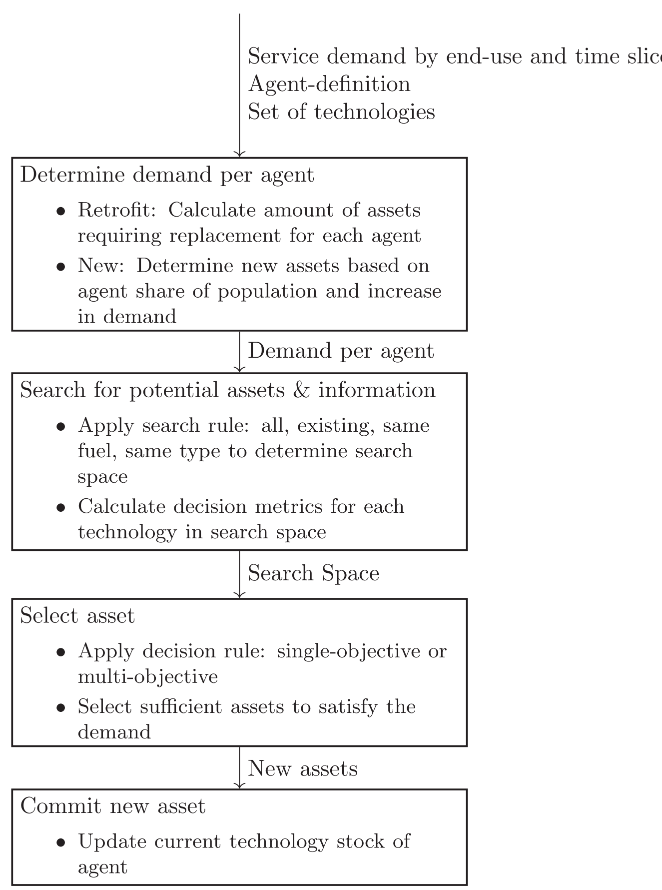


Fig. 1. Schematic representation of agent based investment algorithm.

with one or multiple objectives Obj, search rule SR, decision strategy DS, new or retrofit type TP, budget B, maturity threshold MT, technology stock TS, technology ownership TO, and the percentage of the population PP represented by the agent.

2.2.2. Objectives

The decision criterion for each agent defines their investment goals. These are a combination of economic, environmental, technology dependent aspects and personal factors. Important economic metrics are the investment cost, the payback period, the net present value, and operational costs. Environmental factors are CO_2-emissions, total energy consumption, and integration of renewable energy. In addition, less tangible factors such as comfort play an important role. The choice of objectives can be associated with different investment planning strategies:

- Short-term planning: The main focus lies on the immediate expenses taking only the required investment for an asset, the capital cost, into account.
- Long-term planning: All costs emerging over the lifetime of the asset are taken into consideration. Important decision metrics are the Net Present Value (NPV) or the equivalent annual cost (EAC).
- Energy-saving: The main aim is the reduction of the energy consumption where the fuel consumption or efficiency are the key decision criteria to identify low-energy technologies.
- Environment: CO_2-emissions reduction is the primary criteria.
- Comfort: Individual perception, e.g. thermal comfort or frequency of maintenance.

To date there is no universal standard of assessment for comfort. A research report from the Department of Energy & Climate Change (DECC) provides the most commonly referenced criteria by household owners in the UK [54]. Approximately 30% of household owners focus on the frequency of maintenance and cleaning of technologies, around 30% pay attention to users' experience, and another 30% take the space occupied indoor and outdoor into consideration. The remaining 10% pay heed to the installation time, noise made by equipment, whether it needs the delivery of combustion fuel, etc.

2.2.3. Search rule

The search rules present the first step of the decision process, the collection of information about available technologies and processing abilities of the decision makers. They are defined based on an agent's basic status such as educational level, age, profession and financial lucidity as well as attitudes shown towards innovations and the inherent level of risk. The search rules lead to the search space of each agent which includes a subset of all defined possible technologies in the residential sector. The search space belonging to one agent changes over time depending on the maturity of each technology, cost, the current technology in use, efficiencies, and emission characteristics. To capture the different information gathering strategies, as well as attitudes towards new technologies, four main search rules are defined:

- Same type: Investors are assumed to rely on mature technologies and are likely to repeat past decisions by installing a similar technology which has proven to be reliable.
- Same fuel: Investors are assumed to favour established technologies that consumes the same fuel as the one that needs to be replaced to avoid additional costs and intrusive installation.
- Conventional: Investors are assumed to gather more information to make their decision including different technology types and fuel sources but focus remains on established technologies.
- All: Investors are assumed to be sophisticated, open to innovations and risk, and able to gather information on all available technologies.

In addition to characteristic search rules, individual agents use maturity-thresholds for new technologies that reflect the cumulative effects of experience and observation of peers' investments as per [51]. This enables the model to capture time lags for adapting new technologies as they appear in an increased number of agents' search spaces with increasing market share.

2.2.4. Decision strategies

The choice between possible energy technologies and fuel alternatives for each agent is limited by behavioural constraints [51] within the decision making process. To capture the heterogeneity, different decision strategies are implemented:

- Single-objective: This decision strategy uses a merit-order approach, the technologies are ranked according to the main objective of the agent and the technology with the lowest/highest objective is chosen. In case the capacity of one technology is limited and if it is not enough to cover the demand, the next technology is added, and so on.
- Multi-objective: Usually more than one objective is considered during the decision process. To include this in the simulation model, three possible multi-objective approaches are implemented within the RBSM in MUSE.

The first of the multi-objective methods is given by the *Weighted Sum* that transforms the set of objectives into a single-objective obj_{WS} by multiplying each objective with a pre-defined weight w_i with $i \in 1, \ldots, n$

$$obj_{\mathrm{WS}} = \sum_{i=1}^{n} w_\mathrm{i} obj_{\mathrm{norm,i}}, \tag{2}$$

with $\sum_{i=1}^{n} w_\mathrm{i} = 1$ and normalized objectives $obj_{\mathrm{norm,i}}$ to eliminate the effect of magnitude. Hence, a good performance in one aspect compensates for a poor performance in another, allowing agents to select the technology with the best overall rating. The normalized objective of a technology is calculated by

$$obj_{\mathrm{norm,i}} = \frac{obj_\mathrm{i} - obj_{\mathrm{worst,i}}}{obj_{\mathrm{best,i}} - obj_{\mathrm{worst,i}}} \tag{3}$$

with the objective values of the best $obj_{\mathrm{best,i}}$ and worst $obj_{\mathrm{worst,i}}$ performing technology. Due to the nature of the problem, the metrics could be interdependent, as for example NPV includes the present value of the cost of fuel consumption. Another method for the reformulation of the objective function is given by the *Epsilon-Constraint* method [55]. The investment decision is carried out based on one specific objective where all the other objectives are constrained within pre-specified values ε_2, ε_3 and can be formulated as

$$\begin{array}{l} \min \quad obj_1 \\ \text{subject to} \\ obj_2 \leq \varepsilon_2 \\ obj_3 \leq \varepsilon_3 \end{array} \tag{4}$$

All technologies that have a good performance regarding one objective but show a poor performance for the other criteria are eliminated.

The third option represents the *Lexicographic* method [55]. The method consists of a sequence of single-objective minimisations, where additional constraints are added after every iteration, as per

(4). It selects the alternative with the best performance on the most important aspect. If more than one alternatives show a good performance for the first criteria, filtering will continue to select the best option with regards to the second priority. This is achieved by the use of constraints that are determined using the optimal values of the objectives from the previous iterations. The first iteration considers the minimisation/maximisation without constraints. The formulation of the second iteration would therefore be given by

$$\begin{aligned} &\min \quad obj_2 \\ &\text{subject to} \\ &obj_1 \leq \delta_1 obj_1^* / obj_1 \geq \delta_1 obj_1^*, \end{aligned} \tag{5}$$

with the optimal value of the first objective obj_1^* and the sub-optimality factor δ_1, which defines the confidence interval. The amount of technologies selected in each step depends on the defined confidence interval around the preceding objectives.

2.2.5. Technology stock

Each agent owns a set of technologies, referred to as technology stock TS, which they subsequently update following the decision-making process introduced earlier. The initialization of the technology stock of each agent is carried out using additional agent attributes such as the agent type, technology ownership, and the percentage of the population that each agent represents.

First, the agent type, TP, separates the agents in two overarching categories corresponding to the type of investment: new and retrofit. This separation requires the linkage of each new agent to one retrofit agent to transfer its stock to a retrofit agent for the later renewal of the assets. The use of two separate agents for new and retrofit investment is based on the influence of the installed infrastructure, housing type, and experience with using technology in the retrofit decision. The technology ownership TO is a vector containing the percentage of each technology that is owned by a retrofit agent in the base year. All available technologies in the market are split between the retrofit agents based on these values.

The new type agent iteratively builds up its own technology stock by making investments in new technologies to guarantee that the demand is always satisfied. The demand for a certain service to be supplied by each new type agent is assigned in proportion to the total demand based on the percentage of the population PP represented by that agent.

The overall algorithm for making investment decisions is embedded within the RBSM framework and implemented as shown in Algorithm 1.

Algorithm 1. ABM Methodology.

```
for agent_i ∀i ∈ V do
  Initialisation;
    Determine demand_i for each end-use, technologyset_i;
    Determine search space SP_k ∀  technology_k ∈ technologyset_i;
    Calculate Obj_{i,m} ∀  technologySP_m ∈ SP_k;
  for technology_k ∈ technologyset_i do
      Apply DS_i to further select and re-rank all technologySP_m ∈ SP_k ;
      Obtain an ordered list of alternatives;
      Select sufficient assets to satisfy the demand for all timeslices;
  end
  Update TS_i
end
```

3. Parametrisation of agents

The modelling concept furthermore includes the aggregation of available technology characteristics and relevant geographic information, as well as socio-economic data to define representative agents, their number and attributes, for one specific country or region. To establish a consistent parameterisation approach of all agents, socio-economic and macro-economic information is used to reflect agents' social status, age, income and is matched with the social milieu classification which represents the agent's life attitudes and beliefs.

3.1. Social milieus

In this work, the definition of the different agents is informed by the SINUS-Milieu-Typology [56]. The SINUS-Milieus link up demographic criteria such as education, occupation, or income with the actual life worlds of the people, i.e. with their everyday-life, their fundamental values, attitudes towards work, family, leisure, money and consumption to provide an insightful real-life image of socio-cultural diversity. Normally, nine categories could be specified in terms of individuals' class and basic values, which are respectively high achievers, enlightened educational elites, transnational trendsetters, adaptive pragmatics, escapists, middle class, precarious, established conservatives and traditionalists [56]. These definitions are used to define objectives Obj, search rules SR, and decision rules DS.

3.2. Macroeconomic data

Beside the use of social milieus, the agent parameterisation is based on data combining households and demographic information to provide a specific agents' classification:

- Households' infrastructure information to determine the possible available technologies and relevant energy fuel: Information such as building type, construction period, number of people living in a household and location.
- Demographic and socio-economic information to make specific classifications and corresponding definition of agents: Information such as GDP per capita/household, education level, age, and employment.

The gathered socio-economic data is further linked to the SINUS-Milieus to determine the share of the population PP represented by one agent, the type TP, the technology share TS and their budget B. Household infrastructure also influences the choice of search rules SR.

4. Case study and sensitivity analysis

The following study is designed to demonstrate the functionality of the algorithm, highlight its benefits and its suitability to model the building sector in energy system simulation tools. A case study was carried out for the United Kingdom (UK) to test the feasibility and the sensitivity of the model. The reader should note that the RBSM has been developed as part of the global version of MUSE. The complexity of such global IAMs, which cover the whole energy system, leads to a consequential need for simplification of the individual sector modules. The RBSM in its current version is designed to capture the most relevant aspects that drive consumer technology choice on a regional scale, with some additional detail added to support the single-country application presented in this article. Key points of future work to enrich these characterisations are the inclusion of dwelling type, tenure, and more detailed treatment of measures that reduce the energy service demand that must be met by energy-consuming technologies. The simulation was conducted to capture the diffusion situation for the technologies of heating, lighting and cooking fuel for a multi-agent and a single-objective method. The reader should note that no capacity constraints on technology additions are integrated in this approach and the technology uptake is thus only limited by the choices of the agents. Addressing the problem of unavoidable subjective interpretations, two sensitivity tests on the agent parametrisation are carried out: 1) Maturity level, 2) Search rule, objectives and decision rule.

4.1. Agent classification for UK households

The SINUS-Milieus specialized for the UK are obtained from Ref. [57] for the classification and attributes assignment of agents. The basic descriptions of different agents' stereotypes are gathered and used as the reference for attributes assignment according to the explanation from several literature sources [57–61]. According to the methodology introduced above, socio-economic survey data of household representative persons (HRP) [62] can be adopted to allocate households into social groups. The basic classification is based on a 2-dimensional socio-economic categorisation of HRP in the UK from July 2012 to June 2014 including income and occupation. The segments of the HRP data are grouped to match the SINUS-Milieus agent groups, using the share of the population and classification data as illustrated in Table 1.

To link these results with information about age, the Annual Population Survey, including the number of employees within six age ranges for 370 professions, is manually grouped into nine categories aligning with the HRP classifications given in Table 1 and can be found in Appendix C. For a simplification, the age groups are merged into three (e.g. 16–34, 35–54, 55+) instead of six groups. This three dimensional social-economic-age classification is finally linked with data on projection of the housing market [63], household expenditure and new constructions in the UK to identify the investment type. The overall agent definition based on the correlation of the different socio-economic drivers is given in Table 2.

The data indicates that several age groups within an agent classification carry out retrofits instead of investing in new buildings, resulting in three retrofit categories. For a simplification in this study, the retrofit groups are further aggregated. Agent attributes are assigned based on the description provided in SINUS-Milieus [57]. The description comprises the information in three aspects: the ability to get access to information, wealth level, and the personality description with regards to making investment decisions. Correspondingly, an agent 's search rule, maturity threshold, and decision-making method are assigned. The budget limit is determined based on an agent 's average income alongside the average expenditure on maintenance and repair of the dwelling. The percentage of income, which presents the limit on the budget for making investments in different end-use technologies, is increased if the ratio of the annual expenditures on maintenance and repair to the income is higher than the average ratio. Thirteen representative agents are defined to model the investment behaviour for people in the UK, given in Table 3.

4.2. Results and discussion

The model is now applied to compare the ABM algorithm with that of a single-objective model, and to draw insights on sector decarbonisation. The single-objective model applied for this purpose assumes all investors only use EAC as the decision metric, with growth constraints of 5% per year applied for each technology. The case study selected for this comparison is the UK, with exogenous CO_2 and energy prices drawn from Ref. [64]. The case study does not directly account for the changing carbon intensity of electricity, but rather considers the influence of the carbon price on the electricity price as a proxy. The inclusion of the carbon intensity of the power sector may have an impact on agent decisions where those agents are driven by environmental performance, and given that electricity emission factors in Ref. [64] indicate a steady decline to 2050. To capture the transition of the power sector future work concerns the investigation of scenarios of the full MUSE model including all sectors. For each model, outputs are produced for cases with and without a CO_2 price. Results presented below cover space and water heating technology. Further results for cooking and lighting along with corresponding discussion are included in Appendix B.

Table 1
HRP agent classification in UK and percentage corresponding sinus milieus.

Employment	Less than £20,000	£20,000 but < £85,000	£85,000 but < £200,000	£200,000 but < £300,000	£300,000 but < £500,000	£500,000 but < £1 MM	£1 MM or more
Large employers and higher managerial	0.20	0.70	1.393	1.00	1.69	2.49	2.59
Higher professional	0.76	2.08	3.03	1.89	3.41	4.35	3.41
Lower managerial and professional	1.29	2.10	2.75	1.94	2.91	3.39	1.78
Intermediate occupations	0.61	1.02	1.02	0.75	1.16	1.36	0.82
Small employers and account workers	0.61	1.00	1.11	0.72	0.83	0.94	0.28
Lower supervisory and technical	2.23	2.48	2.23	1.49	1.73	1.61	0.62
Semi-routine occupations	2.35	2.25	1.94	1.23	1.23	0.92	0.31
Routine occupations	2.78	1.39	0.83	0.49	0.63	0.42	0.42
Never worked/long term unemployed	2.22	1.83	1.83	1.18	1.96	2.22	1.83

modern performer 8.87%
post materialist 11.01%
ground breakers 6.84%
pleasure seekers 14.04%
quiet peaceful britain 18.63%
precarious 11.31%
established 10.16%
traditional 19.13%

Table 2
Summary of HRP agent group classification. The retrofit groups are further divided based on the age ranges.

Agent	New [%]	Retro 1 [%]	Retro 2 [%]	Retro 3 [%]
modern performers	0.76 (age:35+)	5.70 (age:35+)	2.41 (age:35-)	0
post materialist	2.61 (age:35+)	5.65 (age:35+)	2.76 (age:35-)	0
ground breakers	1.12 (age:35+)	4.07 (age:35+)	1.67 (age:35-)	0
pleasure seekers	1.59 (age:35+)	8.07 (age:35+)	4.38 (age:35-)	0
quiet peaceful Britain	1.78 (age:35+)	10.93 (age:35+)	5.91 (age:35-)	0
precarious	0	3.93 (age: 16–34)	3.11 (age: 35–54)	4.27 (age:55+)
established	0	2.97 (age: 16–34)	3.90 (age: 35–54)	3.29 (age:55+)
traditional	0	6.48 (age: 16–34)	5.78 (age: 35–54)	6.87 (age:55+)

Table 3
Definition of representative agents for the UK.

Agent	Objective 1	Objective 2	Objective 3	Decision Strategy	Search Space	Type
modern performers1	emissions	efficiency	comfort	all	Epsilon Con.	New
modern performers2	emissions	efficiency	comfort	all	Epsilon Con.	Retrofit
post materialist1	NPV	emissions	efficiency	all	Weighted Sum	New
post materialist2	NPV	emissions	efficiency	all	Weighted Sum	Retrofit
ground breakers1	emission costs	NPV	comfort	all	Epsilon Con.	New
ground breakers2	emission costs	NPV	comfort	all	Epsilon Con.	Retrofit
pleasure seekers1	capital costs	efficiency	comfort	all	Epsilon Con.	New
pleasure seekers2	capital costs	efficiency	comfort	similar	Epsilon Con.	Retrofit
quiet peaceful britain1	capital costs	emissions	comfort	all	Weighted Sum	New
quiet peaceful britain2	capital costs	emissions	comfort	similar	Weighted Sum	Retrofit
precarious1	capital costs	efficiency	comfort	similar	Epsilon Con.	Retrofit
established1	capital costs	emissions costs	comfort	fuel	Weighted Sum	Retrofit
traditional1	capital costs	NPV	comfort	existing	Lexicographic	Retrofit

modern performers - multi-optional; efficiency-oriented top performers, avantgarde when considering consumption and style; very IT minded and risk taking post materialist - liberal and intelligent individuals; adopt a post-material and liberal outlook of the world ground breakers - high level of geographic and cultural mobility; nonconformist exploring new field pleasure seekers - modern young individuals with pragmatic outlook on life; fun and entertainment oriented; ambitious and flexible; strong sense of social responsibility quiet peaceful britain - mainstream of the society; willing to adapt into the new trends; seek for a harmonious lifestyle; fear of social demotion precarious - lower class; seeking for social belongings; strive to keep up with the standards with the main stream; social disadvantages make them receive a sense of exclusion from the middle class established - achieve established social responsibility, ethic, the aspirations of leadership; a growing desire for balance traditional - older generations; ever-greater sense of lagging behind the main stream [56].

4.3. Space and water heating

Fig. 2 presents the results for the ABM, with and without the CO_2 price. In contrast with this, corresponding results from the single-objective model are presented in Fig. 3. Comparison between the models for the case without the CO_2 price shows a broadly similar result in that natural gas boilers remain the dominant heating technology due to the fact that they are a reliable, cheap and trusted technology. This result is nuanced by the fact that the ABM selects a more diverse range of heating systems, reflecting the diversity of agents. For the case with a CO_2 price, results between the two models differ much more markedly. The single-objective model

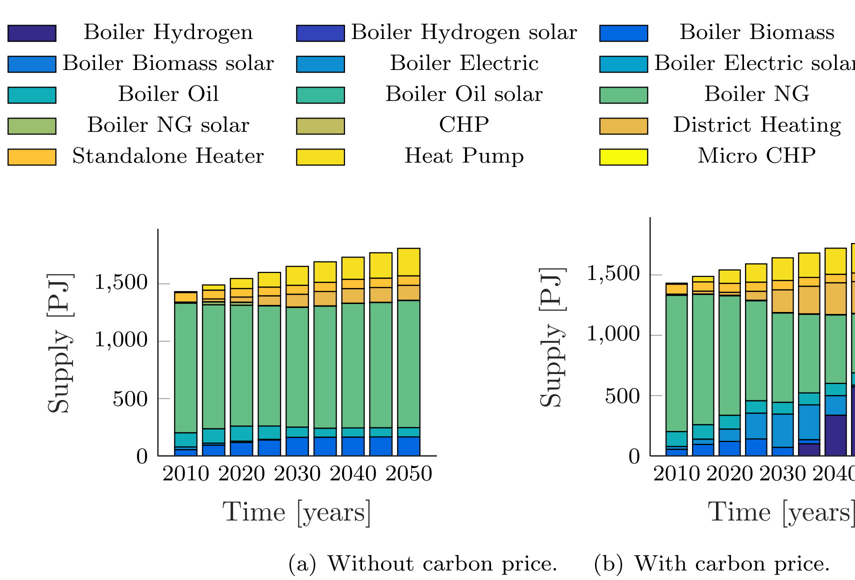


Fig. 2. Comparison of diffusion of heating technologies for two carbon scenarios using the agent-based approach.

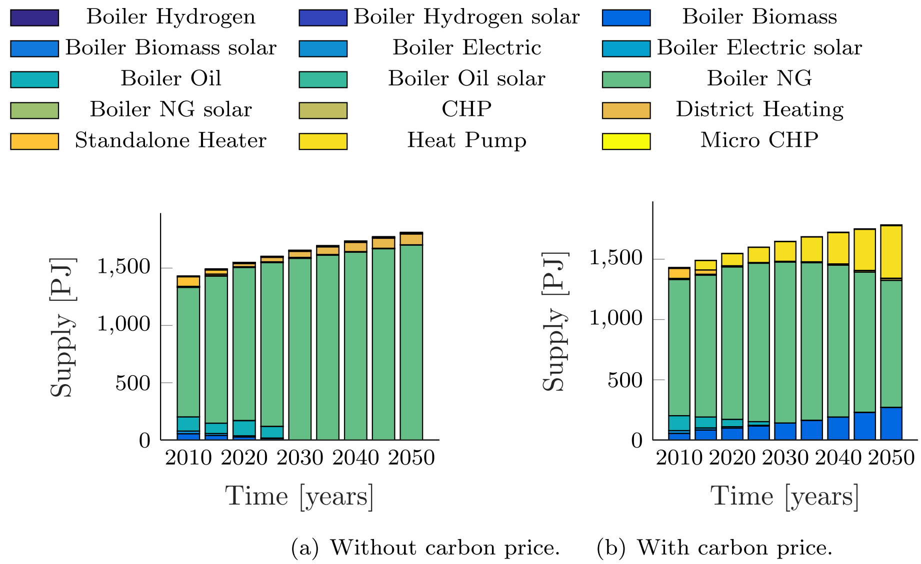


Fig. 3. Comparison of diffusion of heating technologies for two carbon scenarios using the single-objective method.

adopts heat pumps as fast as possible (up to the growth constraint), with biomass boilers fulfilling the remaining demand. The ABM on the other hand shows a distinct transition period in the 2030s where a mix of technologies compete for market share, before hydrogen boilers eventually become a trusted technology, enter the search space of the mass market, and become pervasive towards 2050. The final technology mix produced by the ABM is vastly different to that of the single-objective model.

The difference in outcomes between the two models is emphasised by Fig. 4, which presents sector final energy consumption and CO_2 emissions over time. The first contrast between approaches to note is the difference in the sector CO_2 emissions reduction achieved, with the ABM achieving much greater progress. This is in contrast with the single-objective model, while heat pump technology enters the market at the maximum rate possible, their cost characteristics prevent them from becoming dominant, and ultimately leads to disappointing emissions reduction. However, it should be noted that if the growth rate constraint in the single-objective model is relaxed to 7.5% (instead of the base case 5%), much more significant emissions reductions are achieved. This demonstrates the sensitivity of single-objective approaches to uptake constraints, which is not present in the ABM approach. Furthermore it highlights the importance of empirically-grounded modelling strategies. The presented ABM framework enables a detailed representation of the investors based on empirical data, e.g. household surveys, and thus manages to overcome some limitations of other models.

Fig. 5 shows more detail on the uptake of heat pumps and district heating in the ABM, driven by innovative individuals preferring these technologies.

Heat pumps are chosen by some agents for new buildings initially, but over time their increasing maturity makes them attractive for more agents. Ground source heat pumps are eventually favoured over air source even though they have higher capital cost. Their higher efficiency, and the more appealing principle of renewable ‘heat from the ground’, and stable year-round operation (i.e. comfort) [54] are important in this regard. Variation in the fuel source for district heating between the carbon price scenarios can also be explained in similar terms. Without a CO_2 price, natural gas is preferred, due to the trusted nature of this fuel

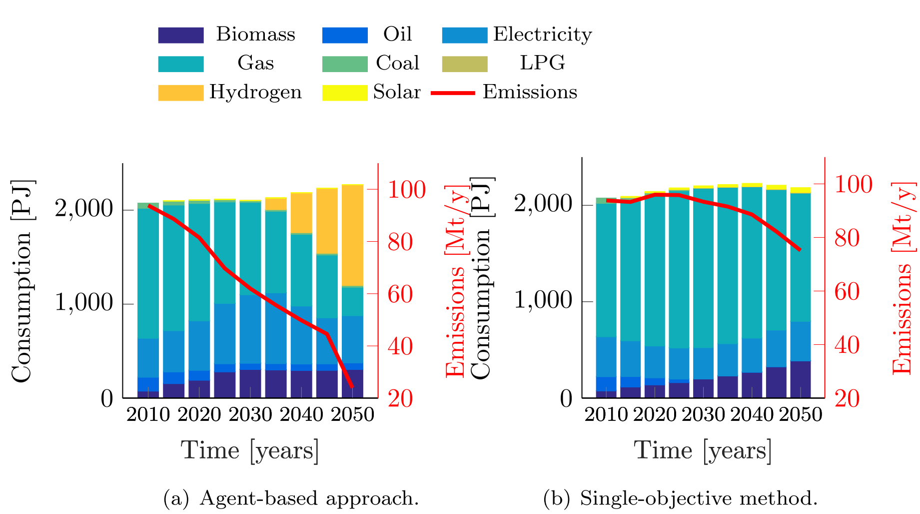


Figure 4. Comparison of final energy consumption for two carbon scenarios using the multi-agent approach and the single-objective method.

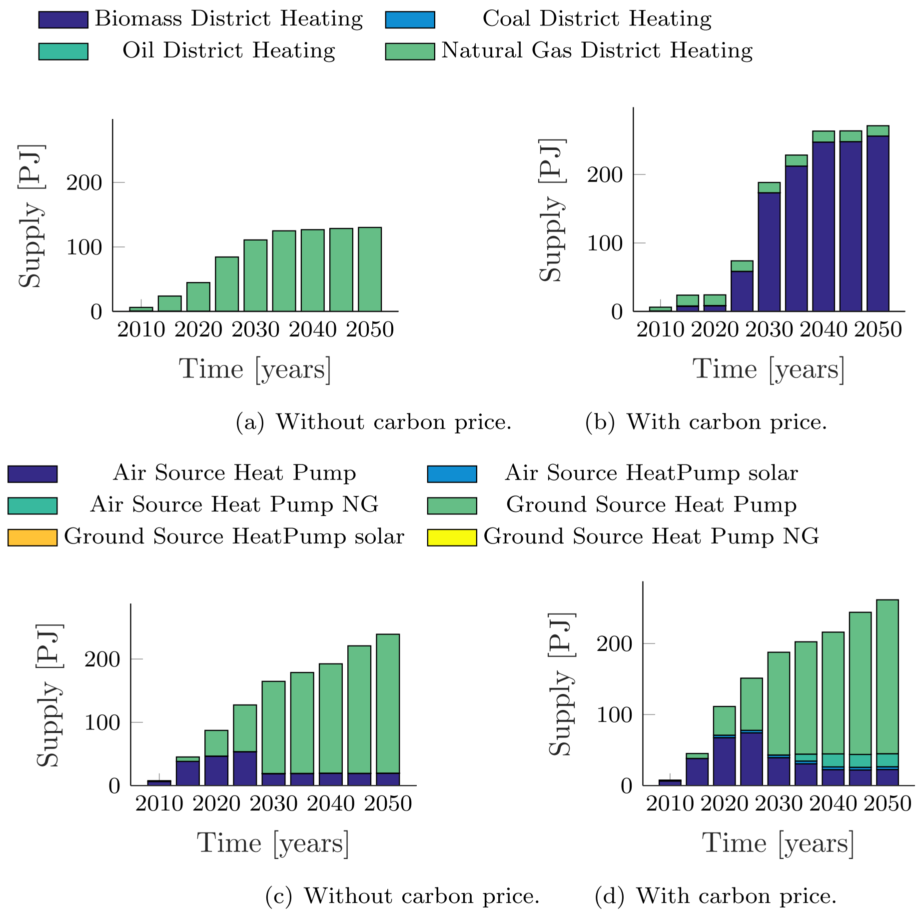


Fig. 5. Comparison of diffusion of heat pumps and DHS for two carbon scenarios using the agent-based approach.

in the UK and relatively low fuel price. With a CO_2 price, biomass-based district heating is preferred due to perceived environmental credentials. According to Ref. [54], people consider biomass as a suitable and environmentally friendly heating fuel option. Thus initially there is an increase in biomass based boilers (see Fig. 4) followed by a shift to district heating fuelled by biomass. This is further driven by evidence that communal heat supply is appealing, whereas individual biomass boilers are seen as bulky and unattractive [54].

A decision to adopt a technology is triggered when either new demand is created (e.g. population growth and new building construction) or an existing technology requires replacement at the end of its lifetime. Once a decision is required, the agents consider their search space and apply their decision rules to make that decision. Both search space and input variables to calculate decision metrics are dynamic across the model time horizon. With regard to decision rules, changes in fuel price (or carbon price), capital cost, efficiency or environmental performance can lead to a change in the ranking of technologies over time. With regard to search space, different technologies can also enter an agent ‘s search space when that technology reaches a specified market share. Overall this leads to dynamic rates of penetration observed in the Figures.

A uniform definition of objectives, as in most energy systems models, corresponds reasonably well to homogeneous actors and thus potentially leads to sudden switches towards one technology. To avoid abrupt changes in favour of one specific technology, models often implement capacity growth constraints to limit the uptake and thus to guarantee a mix of technologies in the market. The ABM method presented overcomes this problem by the inclusion of individual decision makers with distinct objectives. Overall the presented methodology is a more nuanced framework to model the decision making process in the residential building sector and thus is more useful for decision makers considering ways to influence agents to achieve aims such as deep decarbonisation.

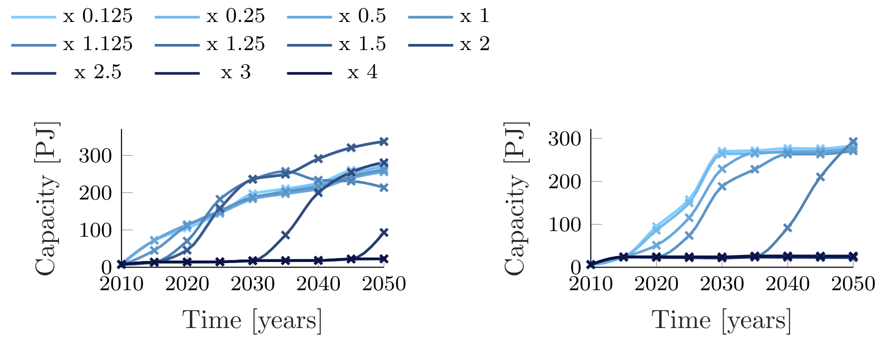
4.4. Sensitivity analysis

To examine the change in the results towards changes in the agent parametrisation and technology cost, a sensitivity analysis is carried out. The maturity threshold, the search rule, objectives and decision rules are varied. Different capital costs for heat pumps, CHP and district heating were also investigated but show a low sensitivity, e.g. change in 2% of capacity for change in cost of 75%, due to definition of the agents and the implementation of the maturity thresholds and thus is not the focus of the analysis here.

4.4.1. Sensitivity towards maturity threshold

The maturity level indicates the market share a certain technology needs to have before it appears in the search space of an agent. This value varies according to agent definition to capture heterogeneity and openness towards new technologies. The main effect of the maturity threshold on the results can be seen in Fig. 6 and Fig. 7.

The key factors driving the investments are the objectives assigned to an agent. However, direct investments are often prevented by the maturity threshold until a technology reaches a certain market share. If the threshold is scaled down or up, the



(a) Uptake of heat pumps for different maturity thresholds.

(b) Uptake of DHS for different maturity thresholds.

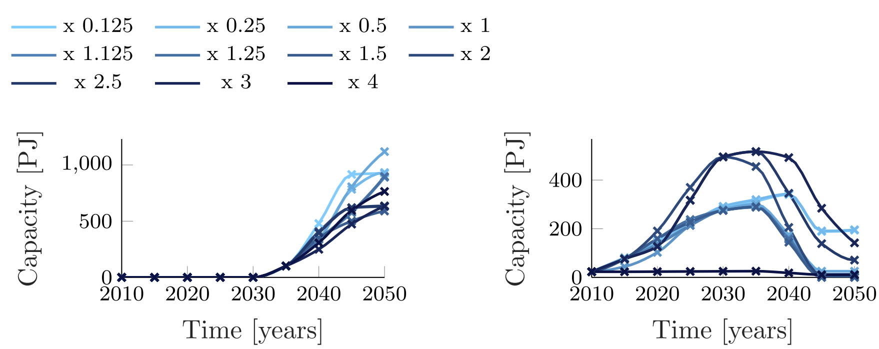
Fig. 6. Analysis of the sensitivity to different maturity threshold levels scaled from 0.125 up to 4 times of the original value for heat pumps and district heating.

point in time when the technology grows or deceases more quickly in the market is shifted, and consequently the maximum uptake is also shifted. But the overall diffusion for the long term remains similar provided that the constraints are not chosen too conservatively, which may prevent technologies entering the market. For example, if the threshold values are scaled by a factor of 2.5, leading to a minimum threshold for the adoption of retrofits of 1.25% for the modern performers, 2.5% for pleasure seekers and a large increase to 6.25% for quiet peaceful britain and up to 75% for traditional agents, the ultimate capacity of heat pumps is significantly influenced. An interesting effect for gas boilers in 2050 is apparent where the final capacity value for different maturity thresholds is aggregated into three clusters. The number of clusters can be related to the number of agents investing in a certain technology. With decreasing maturity threshold more and more agents switch away from gas boilers to alternative sources. Such a cluster point is reached when one agent constantly replaces its stock with the same technologies.

4.4.2. Sensitivity towards search rule, objective and decision rule

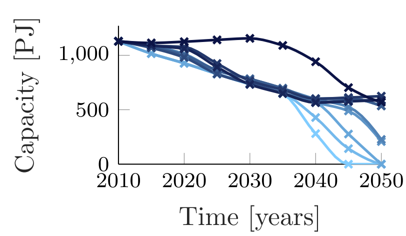
In a next step, the agent search rules, objective and decision methods are changed, with the results are shown in Fig. 8 and Fig. 9. A higher sensitivity can be observed by assuming that even technology-driven people with a high budget restrain their retrofit decisions to the same fuel feedstock, to limit additional cost, or the same technology type. If the retrofit decisions aim to keep the same technology type, heat pumps and DHS remain at a low level since their initial market share is low and overall retrofits dominate over investments in new equipment. Similarly, if people are reluctant to change fuel type, the market share of heat pumps increases but does not reach a significant share due to the limited initial use of electricity for heating. The diffusion of boilers is not affected by changes in the search rules and results still shows an uptake of hydrogen boilers since hydrogen and natural gas fall under the fuel type category gas.

Next, the sensitivity to the agents' objectives is investigated. This is done by replacing the capital cost with EAC and vice-versa as well



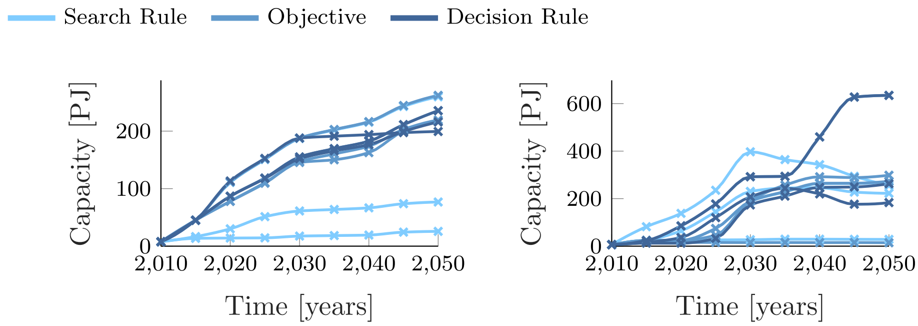
(a) Uptake of hydrogen boilers for different maturity thresholds.

(b) Uptake of electric boilers for different maturity thresholds.



(c) Uptake of natural gas boilers for different maturity thresholds.

Fig. 7. Analysis of the sensitivity to different maturity threshold levels scaled from 0.125 up to 4 times of the original value for boilers.



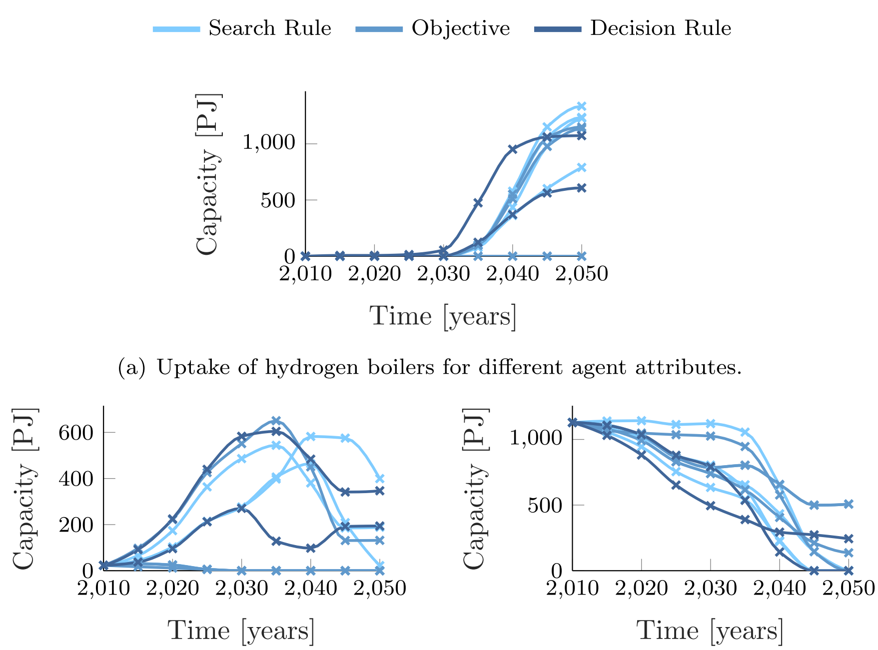
(a) Uptake of heat pumps. (b) Uptake of DHS.

Fig. 8. Analysis of the sensitivity to changes in the search rule, decision rule or objectives of agents.

as the replacement of the emissions consideration by fuel cost. The replacement of one objective by another makes the decision making more uniform since more agents share the same objective. The use of capital cost as decision metric leads to a lower share of DHS where more boilers remain in the market as less people switch from boilers to district heating solutions. Conversely, if the capital cost objective is replaced by the EAC, the market share of boilers goes down in favour of DHS and heat pumps. It is interesting to note that the uptake of heat pumps is not affected by the change from EAC to capital cost. This results from the fact that heat pumps are largely installed by people concerned about fuel consumption or emissions where costs have less influence. It needs to be pointed out that for a change of the objectives from emissions to fuel consumption no hydrogen boilers enter the market since more efficient technologies are chosen. The overall share of boilers decreases significantly and shows a mix of electric and natural gas boilers.

The lowest sensitivity of the results for the variation in the agent definition can be observed for a change in the decision rules. The diffusion of the technologies only marginally changes for a switch of epsilon constraint method to lexicographic or weighted sum. However, as noted above, a switch to “single objective” has a marked influence on results.

The presented analysis shows that a wide spectrum of technologies can be found in the market to reduce CO_2 emissions as no one single solution exists that is attractive for all people. The sensitivity analysis highlights the importance of considering uncertainty in definition of agents, which has a higher influence on the result than changes in the component costs. Although, the changes in maturity level, search strategy or objectives have an influence on the outcome, they show a common trend of the diffusion of technologies which aligns with the presented carbon price scenario above.



(a) Uptake of hydrogen boilers for different agent attributes.

(b) Uptake of electric boilers for different agent attributes. (c) Uptake of natural gas boilers for different agent attributes.

Fig. 9. Analysis of the sensitivity to changes in the search rule, decision rule or objectives of agents.

5. Conclusion and future research

This paper presents an effective modelling framework for the assessment of the technology diffusion in the residential building sector for heating, cooking, cooling, lighting and appliances. It sets out an agent-based method for modelling of the investment decision making processes of heterogeneous decision makers. The integration of several decision making steps including information gathering, the assessment of the performance of each option as well as the final selection enables more intuitive representation of energy system change, and more tangible links with what does and what does not work with regard to affecting energy system transition. The modelling framework includes most key elements of an ideal model of decarbonisation investment behaviours for the residential sector by including multiple independent decision makers, a combination of economic and non-monetary objectives as well as one of the finest detail in terms of number of decarbonisation options, which will be extended in future work to cover all four decarbonisation strategies identified in section 1.1.1.

Where optimisation and simulation models require difficult-to-specify constraints to limit uptake, the proposed agent-based approach overcomes this problem by the inclusion of multiple individual decision-makers with distinct objectives and methods, and limited foresight of future demand and cost. The definition of the agents attributes enables a direct prametrisation of the agents from survey data, subject to availability, whereas several parameters of the logit model would need to be identified through selection procedures. This allows more nuanced modelling of consumer behaviour and enables model users to consider the factors that influence where, when and why certain approaches to energy system change may or may not be successful. It also addresses the fact that several models neglect the differences in the available budget of households and thus potentially overestimate the market share of such capital intensive technologies.

The method developed has been illustrated using a case study of technology diffusion in the residential sector in the UK between 2010 and 2050. The results show a range of technologies entering the market over time, with one technology eventually becoming dominant even though it is not the least cost option. The key observations are the uptake of certain amount of energy efficient technologies (e.g. heat pumps) takes place regardless of a carbon price, the switch from biomass boilers to biomass powered district heating after 2030, and the uptake of hydrogen boilers in middle-low classes eventually leading to this technology dominating a large part of the market. In particular in largely populated urban areas, district heating present a promising option since it is a relatively low cost solution and the concept of a communal heat supply is generally appealing. For new buildings, mostly in urban areas, heat pumps are a preferred option for people with sufficient capital, but the uptake is otherwise limited due to the high initial costs.

Notwithstanding these results, it should be noted that a large database, including macroeconomic data linked with peoples, consumption behaviour, values and preferences, is needed for an accurate parametrisation of the agents, which is certainly challenging on a global scale. Parallel research underway is gathering empirical data to improve the parametrisation and increase the granularity of the agent definition, by separating agents by type of dwelling and tenure. This will enable a distinction between users, purchasers and builders. To capture all decarbonisation strategies, the framework will be extended to include measures for efficiency improvements and behavioural change to capture their effect on energy service demand. Furthermore, the search rules are a simplified representation of the agents information gathering and could be replaced by more sophisticated approaches. Thus, future research priorities will focus on the extension of the method to other European counties where the decision-making methodology will be partially revised.

A key aspect of the future work concerns the improvement of the calibration and validation of the model using empirical data. To overcome the issue of data availability, a country wide survey of the UK has been designed to gather empirical information about technology stock, housing type, consumption, socio-economics, behavioural data (e.g. values, energy literacy, environmental awareness) on a household level. This data will be thoroughly analysed and used to calibrate and validate further studies.

Acknowledgments

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Appendix A. MUSE - ModUlar energy systems Simulation Environment

MUSE is a bottom-up technology-rich model of the whole energy system (i.e. including demand, transformation/conversion and supply sectors), on a global scale, with a geographical disaggregation into 28 regions and a time slice disaggregation into a number of yearly sub-intervals which varies depending on the sector, illustrated in Fig. A.10. MUSE follows a simulation approach coupled with an imperfect foresight to model the real-world decision making of investors as realistically as possible. This framework allows sector-specific modelling and thus the use of the most appropriate methodology for each energy sectors. The main focus lies on an accurate description of the investment and operational decision making in each sector, where a variety of methods are implemented ranging from merit-order simulation methods to agent-based modelling. This is distinct in that most models either use a central planning approach to suggest optimal energy system changes, or use a single investment metric across the economy. The focus on the investors view within the modelling results in an arguably more realistic presentation of the energy market transition compared with the normative pathways from optimisation models. Beside giving a new perspective on the energy system transitions, MUSE is designed to enable transparent and flexible analysis of all sectors of the energy market as a whole or separately. It includes all sources of CO_2 emissions and shows the complex relationships within the energy system among technology, economics, and impact on the environment. The energy equilibrium of MUSE is given by the market clearing algorithm (MCA) which connects all parts of the model and is responsible for the information flow between all sectors. The solution algorithm of MUSE is given by an inner loop for each time period and an outer loop for the simulation horizon (e.g. 2050 or 2100). The MCA iterates between all sector modules until a system equilibrium on price and quantity for each energy commodity in each region and time period is achieved. The work in this paper focuses on the Residential Building Sector module (RBSM) which is one of the end-use sector modules.

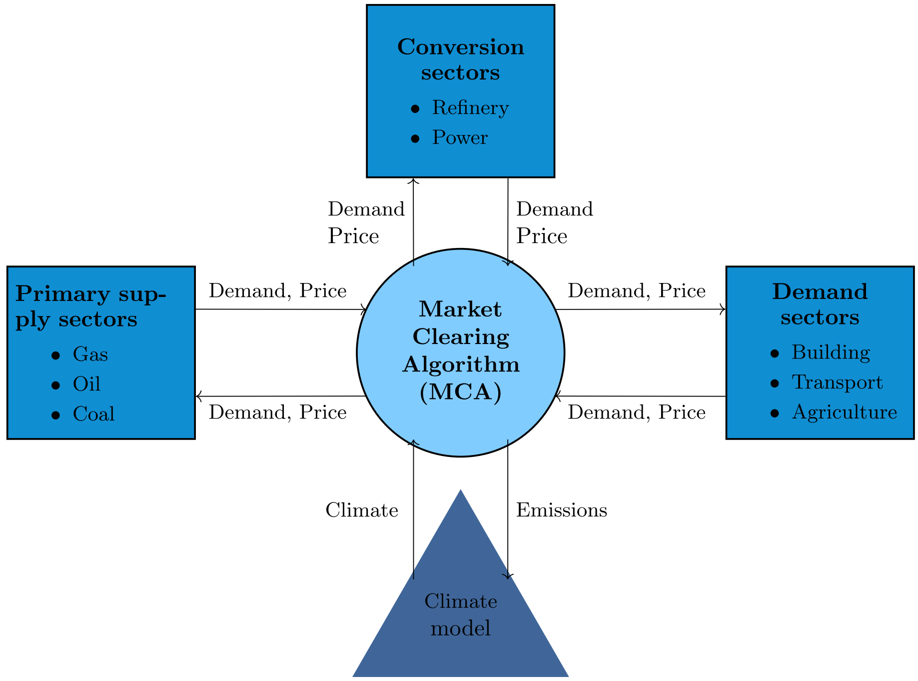


Fig. A.10. Schematic representation of the MUSE Framework.

The RBSM module dynamically exchanges a set of variables with the MCA of MUSE to determine the fuel demand in every modelled region per time period and timeslice. A snapshot of the data work flow for a generic iteration in a generic time period, timeslice and region is shown in Fig. A.11.

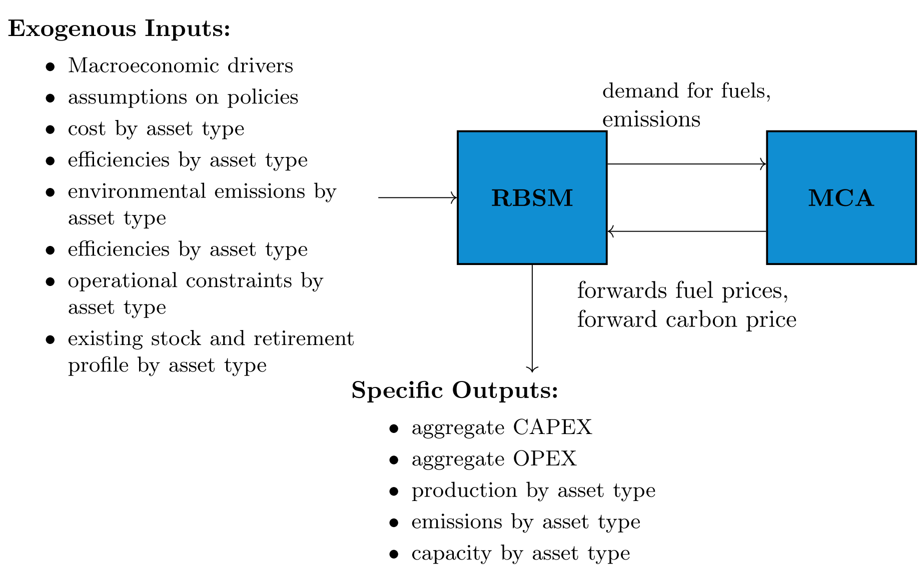


Fig. A.11. Integration of RBSM into MUSE and interaction with Market Clearing Algorithm (MCA).

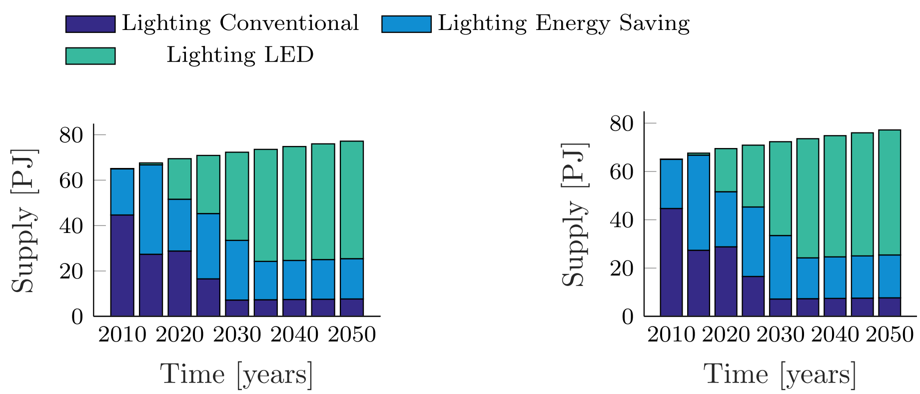
The module uploads exogenous parameters for the techno-economic and environmental characterisation of each technology type per region in the base year as well as projected improvements in the next simulation periods.

Appendix B. Diffusion of Cooking and Lighting Technologies

The presented results are an extension of the case study of section 4 and use the same agent definition and cost trajectories. The use of the same agent definition can be justified by fact that people still follow the same decision-making process and have the same values regardless of the end-use considered but the budget constraints have a lower influence due to the lower initial investment required.

Appendix B.0.1Lighting

Looking at the diffusion of light bulbs Fig. B.12, one notes that an uptake of energy efficient technologies take place regardless of the carbon price.



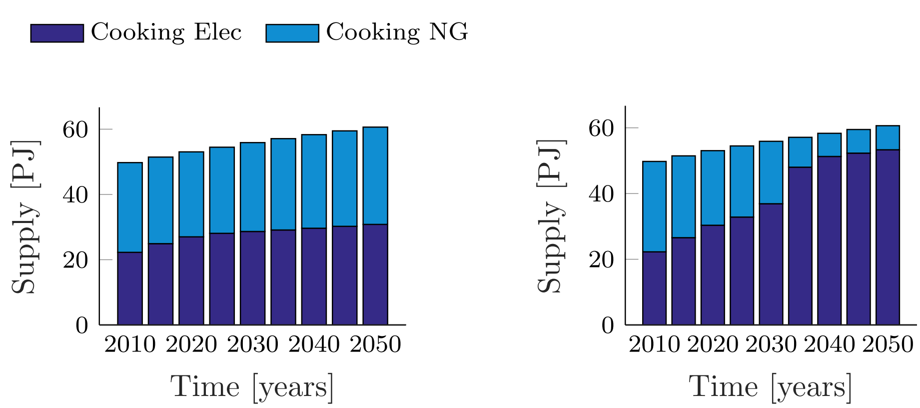
(a) Without carbon price. (b) With carbon price.

Fig. B.12. Comparison of diffusion of lighting technologies for two carbon scenarios using the agent-based approach.

People commonly switch from conventional light bulbs to energy saving ones and from there to LED. This behaviour reflects in the alternating capacity of energy saving bulbs which are more suitable as a transition technology.

Appendix B.0.2. Cooking

Out of all end-use technologies, cooking shows the least changes over time in the no CO_2 price case, with a constant split of the market share between gas and electric systems as illustrated in Fig. B.13.



(a) Without carbon price. (b) With carbon price.

Fig. B.13. Comparison of diffusion of cooking technologies for two carbon scenarios using the agent-based approach.

It is interesting to note, that electric cooking takes over natural gas powered systems and no uptake of hydrogen cooking facilities take place. Although people accept hydrogen as main power source for heating, people favour electric cooking facilities since they are already are well established in the market. However, a reduction in the cost for hydrogen could lead to an uptake of hydrogen for cooking since the low cost makes it more appealing.

Appendix C. Age-occupation linkage

Table C.4
Socio-age classification of HRP.

Employment	16–24	25–34	35–45	45–55	55–65	65^+
Large employers and higher managerial	10.72	10.18	13.68	16.63	15.35	33.49
Higher professional Lower managerial	22.49	27.66	27.50	26.50	25.55	60.56
and professional Intermediate	14.08	39.42	38.71	40.96	23.44	5.85
occupations Small employers and	9.12	17.01	14.52	16.26	9.36	2.18
account workers Lower supervisory	4.79	11.02	11.83	13.50	9.65	4.79
and technical Semi-routine	18.64	16.39	13.39	15.72	17.45	42.91
occupations	23.69	22.31	17.40	20.59	14.95	3.70
Routine occupations	12.96	15.20	12.53	15.71	10.79	2.75
Never worked/long term unemployed	21.02	10.17	8.70	9.66	17.54	64.35

The result of the aggregation of the professions into nine categories and the percentage of people in theses categories within a certain age range is given in Table C.4. The presented data is then, separately for each agent group, mapped to the income-occupation data in Table 1 to obtain a three dimensional age-income-occupation classification.

References

[1] IPCC. Climate change 2014: synthesis report. contribution of working groups i, ii and iii to the fith assessment report of the intergovernmental panel on climate change. Tech. rep., IPCC; 2014.
[2] IEA. Technology roadmap energy-efficient buildings: heating and cooling equipment, Tech. rep.. International Energy Agency; 2011.
[3] Pachauri S. An energy analysis of household consumption. Changing patterns of direct and indirect use in India. Berlin: Springer-Verlag; 2007.
[4] Sopha BM, Klöckner CA, Hertwich EG. Adopters and non-adopters of wood pellet heating in Norwegian households. Biomass Bioenergy 2011;35(1):652–62.
[5] Lutzenhiser L. Social and behavioral aspects of energy use. Annu Rev Energy Environ 1993;18(1):247–89.
[6] Lowe R. Technical options and strategies for decarbonizing UK housing. Build Res Inf 2007;35(4):412–25.
[7] Europe H. Household projections for england and local authority districts, Tech. rep. The European Federation for Public, Cooperative and Social Housing; 2018.
[8] Element energy, Decarbonising heat in buildings: 2030–2050, Tech. rep. The Committee on Climate Change; 2012.
[9] Ekins P, Strachan N, Keppo I, Usher W, andGabrial Anandarajah JS. The UK energy system in 2050: comparing low-carbon, resilient scenarios, Tech. rep.. UK Energy Research Centre; 2013.
[10] Chaudry M, Abeysekera M, Hosseini SHR, Jenkins N, Wu J. Uncertainties in decarbonising heat in the UK. Energy Pol 2015;87:623–40.
[11] Achtnicht M, Madlener R. Factors influencing German house owners' preferences on energy retrofits. Energy Pol 2014;68:254–63.
[12] Sopha BM, Klöckner CA, Skjevrak G, Hertwich EG. Norwegian households' perception of wood pellet stove compared to air-to-air heat pump and electric heating. Energy Pol 2010;38(7):3744–54 [large-scale wind power in electricity markets with Regular Papers].
[13] Shove E. Comfort, cleanliness and convenience: the social organization of normality (new technologies/new cultures. Berg Publishers; 2004.
[14] Mahapatra K, Gustavsson L. An adopter-centric approach to analyze the diffusion patterns of innovative residential heating systems in Sweden. Energy Pol 2008;36(2):577–90.
[15] Kinnear DGLTC. Exploring the consumer decision process in the adoption of solar energy systems. J Consum Res 1981;8(3):271–8.
[16] Nair G, Gustavsson L, Mahapatra K. Factors influencing energy efficiency investments in existing Swedish residential buildings. Energy Pol 2010;38(6):2956–63.
[17] Kastner I, Stern PC. Examining the decision-making processes behind household energy investments: a review. Energy Res Social Sci 2015;10:72–89.
[18] Bosetti V, Carraro C, Galeotti M, Massetti E, Tavoni M. Witch a world induced technical change hybrid model. Energy J 2006;27:13–37. http://www.jstor.org/stable/23297044.
[19] IIASA. Energy modeling framework: model for energy supply strategy alternatives and their general environmental impact (message), Tech. rep.. International Institute for Applied Systems Analysis; 2009.
[20] Messner S, Strubegger M. User's guide for message iii, Tech. rep.. International Institute for Applied Systems Analysis; 1995.
[21] JGCRI. The global change assesment model (gcam). 2016. http://jgcri.github.io/gcam-doc/index.html.
[22] EIA. Residential demand module of the national energy modeling system: model documentation, Tech. rep.. U.S. Energy Information Administration; 2014.
[23] Wilkerson JT, Cullenward D, Davidian D, Weyant JP. End use technology choice in the national energy modeling system (nems): an analysis of the residential and commercial building sectors. Energy Econ 2013;40:773–84.
[24] R. Loulou, U. Remme, A. Kanudia, A. Lehtila, Goldstein, Documentation for the times model part ii. energy technology systems analysis programme, ETSAP.
[25] Loulou R, Labriet M. Etsap-tiam: the times integrated assessment model part i: model structure. Comput Manag Sci 2008;5(1):7–40.
[26] Li P-H, Keppo I, Strachan N. Incorporating homeowners' preferences of heating technologies in the UK times model. Energy 2018;148:716–27.
[27] Cayla J-M, Maïzi N. Integrating household behavior and heterogeneity into the times-households model. Appl Energy 2015;139:56–67.
[28] Ramea K, Bunch DS, Yang C, Yeh S, Ogden JM. Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models. Energy Econ 2018;74:663–76.
[29] E3MLab. Primes model - detailed model description, Tech. rep.. E3MLab/ICCS at National Technical University of Athens; 2014.
[30] Dillon A. User acceptance of information technology. London: Taylor and Francis; 2001.
[31] Hale JL, Householder BJ, Greene KL. The persuasion handbook: developments in theory and practice, Chapter 14: the theory of reasoned action. SAGE Publications Ltd; 2002.
[32] Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process 1991;50(2):179–211.
[33] Legris P, Ingham J, Collerette P. Why do people use information technology? a critical review of the technology acceptance model. Inf Manag 2003;40(3):191–204.
[34] Howard R, Restrepo L, Chang C-Y. Addressing individual perceptions: an application of the unified theory of acceptance and use of technology to building information modelling. Int J Proj Manag 2017;35(2):107–20.
[35] Taylor S, Todd P. Decomposition and crossover effects in the theory of planned behavior: a study of consumer adoption intentions. Int J Res Market 1995;12(2):137–55.
[36] M.N., G.A.. An energy analysis of household consumption. changing patterns of direct and indirect use in India. Heidelberg: Univ Access Inf Soc, Springer-Verlag; 2015.
[37] Davis Jr FD. A technology acceptance model for empirically testing new end-user information systems: theory and results. PhD Thesis. Massachusetts Institute of Technology; 1985.
[38] Kowsari R, Zerriffi H. Three dimensional energy profile:: a conceptual framework for assessing household energy use. Energy Pol. 2011;39(12):7505–17.
[39] Stephenson J, Barton B, Carrington G, Gnoth D, Lawson R, Thorsnes P. Energy cultures: a framework for understanding energy behaviours. Energy Pol 2010;38(10):6120–9.
[40] Cantono S, Silverberg G. A percolation model of eco-innovation diffusion: the relationship between diffusion, learning economies and subsidies. Technol Forecast Soc Change 2009;76(4):487–96.
[41] Eggers F, Eggers F. Where have all the flowers gone? forecasting green trends in the automobile industry with a choice-based conjoint adoption model. Technol Forecast Soc Change 2011;78(1):51–62.
[42] Islam T. Household level innovation diffusion model of photo-voltaic (pv) solar cells from stated preference data. Energy Policy 2014;65:340–50.
[43] Berry ST. Estimating discrete-choice models of product differentiation. Rand J Econ 1994:242–62.
[44] Hui SC, Lee R. Development of energy labels for residential buildings in Hong Kong. In: The 10th Asia Pacific conference on the built environment: green energy for Environment,Kaohsiung, Taiwan; 2009. p. 1–8.
[45] Banfi S, Farsi M, Filippini M, Jakob M. Willingness to pay for energy-saving measures in residential buildings. Energy Econ 2008;30(2):503–16.
[46] Kucharavy D, Guio RD. Logistic substitution model and technological forecasting. Procedia Engineering 2011;9:402–16 [proceeding of the ETRIA World TRIZ Future Conference].
[47] Farmer JD, Foley D. The economy needs agent-based modelling. Nature 2009;460(7256):685–6.
[48] Bonabeau E. Agent-based modeling: methods and techniques for simulating human systems. Proc Natl Acad Sci Unit States Am 2002;99(suppl 3):7280–7.
[49] Roozmand O, Ghasem-Aghaee N, Hofstede GJ, Nematbakhsh MA, Baraani A, Verwaart T. Agent-based modeling of consumer decision making process based on power distance and personality. Knowl Base Syst 2011;24(7):1075–95.
[50] Zhang T, Zhang D. Agent-based simulation of consumer purchase decision-making and the decoy effect. J Bus Res 2007;60(8):912–22.
[51] Berger T. Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agric Econ 2001;25(2–3):245–60.
[52] T. Wittmann, R. I. Morrison, T. Bruckner, A bounded rationality model of private energy investment decisions, Available at: SSRN 922020.
[53] Kahneman D. Maps of bounded rationality: psychology for behavioral economics. Am Econ Rev 2003;93(5):1449–75.
[54] of Energy D, Change C. Homeowners' willingness to take up more efficient heating systems, Tech. rep.. Department of Business, Energy and Industrial Strategy; 2013.
[55] Papageorgiou M. Optimierung: statische, dynamische, stochastische Verfahren. Springer-Verlag; 2012.
[56] Sinus sociovision, informationen zu den sinus-milieus, http://www.sinus-institut.de/sinus-loesungen/sinus-meta-milieus-weltweit/, accessed: 2017-01-15.
[57] Bertram B, Berthold BF. Was sind sinus-milieus®? Berlin, Heidelberg: Springer Berlin Heidelberg; 2012.
[58] Karin Markvica NH, Millonig A. Using milieu-based communication strategies for changing mobility behaviour towards low energy modes. In: 4th European conference on behaviour and energy efficiency, coimbra, Portugal; 2016. p. 1–8.
[59] Schwarz N, Ernst A. Agent-based modeling of the diffusion of environmental innovations — an empirical approach. Technol Forecast Soc Change 2009;76(4):497–511 [evolutionary Methodologies for Analyzing Environmental Innovations and the Implications for Environmental Policy].
[60] Barr S, Gilg AW, Ford N. The household energy gap: examining the divide between habitual- and purchase-related conservation behaviours. Energy Pol 2005;33(11):1425–44.

[61] Palmer J, Sorda G, Madlener R. Modeling the diffusion of residential photovoltaic systems in Italy: an agent-based simulation. Technol Forecast Soc Change 2015;99:106–31.
[62] Chamberlain E. Wealth in great britain, july 2012 to june 2014, Tech. rep. Office for National Statistics; 2014.
[63] Ministry of Housing CLG. Decarbonisation of the building stock: a two-front battle, Tech. rep.. UK Government; 2014.
[64] MORI I. The Energy Saving Trust, Green book supplementary guidance: valuation of energy use and greenhouse gas emissions for appraisal, Tech. rep.. Department for Business, Energy & Industrial Strategy; 2018.