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Review

Agent-based modeling: Insights into consumer behavior, urban dynamics, grid management, and market interactions

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ABSTRACT

A future sustainable energy system is expected to be digital, de-central, de-carbonized, and democratized. As the transition unfolds, new and diverse actors of various sizes will emerge in different segments. Thereby, the future energy system could shift its attention to the actors' behavior than finding an optimum based on the physical system. Agent based modeling tools can reflect decisions from several actors in a decentralized and digital market setting. Then, such tools can enable a sustainable energy transition.

This work sets out to investigate how agent-based models could tackle various challenges in energy transition. This investigation covers four segments of the energy system — consumer, city, microgrid, and market. It starts with the consumer where consumer behavior is modeled. From there, expands to a city level where the dynamic characteristics of a city are simulated. The next step is distributed microgrids, particularly how to optimally plan the grid expansions. The final step in the investigation is simulating an energy market with national and international stakeholders. The selection of models presents how agent-based models can be applied to decision-making processes in the aforementioned segments. Then a novel framework with metrics for characterization is proposed and validated that addresses the challenge — which are the characteristics that make an agent-based model a better fit to tackle a modeling objective? Additionally, the framework identifies the existing knowledge gaps and the scope for further developments.

In summary, this work outlines how far agent-based models have come to tackle energy system challenges to sustain the energy transition. This work specifically highlights the scope, advantages, challenges, and trends of the agent-based models in energy sector applications. Moreover, this study finds that agent-based models reflect what a solution could be more than the traditional modeling practice that focuses on what a solution should be.

Contents

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Nomenclature

ABM	Agent Based Model (s)
MAS	Multi Agent System
CAS	Complex Adaptive System
CRM	Capacity Remuneration Mechanism
EV	Electric Vehicle
LOLE	Loss of Load Expectation
MG	Microgrid
NPV	Net Present Value
RES	Renewable Energy Sources

1. Introduction

In an era marked by rapidly evolving technology and increasing sustainability awareness, energy systems are pivotal interfaces of human progress and environmental stewardship [1]. At their core, energy systems are designed to serve a fundamental purpose: delivering critical energy services to end-users. However, these systems' complexity extends far beyond mere production and distribution [2,3]. As the Intergovernmental Panel on Climate Change (IPCC) underscored [4], energy systems envelop "all components related to the production, conversion, delivery, and use of energy", accentuating their multifaceted nature [5]. Understanding the complexity of energy systems requires a comprehensive view [6,7]. Beyond their intricate matrix of components and technical facets, these systems are emblematic of economic maneuvering, political decision-making [8], and social dynamics [9,10]. While this convergence of elements provides rich opportunities for innovation, it also introduces complexities that complicate the understanding of the system and makes both its analysis and subsequent optimization difficult [11]. Illustratively agent based models are evidently finding new applications in the field of large language models [12], real-time predictions [13], multi-level policies for epidemic management [14], electrical vehicle demand simulation [15], urban growth modeling in Africa [16].

When it comes to analyzing energy systems, the research objective becomes paramount and influences the perspective from which the energy system is viewed [17]. Based on this overarching view, critical system elements can be identified and modeled depending on the specific objective [18]. Given the complexity of energy systems, these models serve as simplifications and essential abstractions that make the system modelable and analyzable [19]. Within this framework, tools like flow network algorithms, including minimal cost flow, find applications [20]. System components can be conceptualized as individual dynamical entities, underscoring the significance of technological modeling rooted in the engineering nuances of particular technologies. As energy systems transform with new technologies and innovative mechanisms, the need for sophisticated modeling grows more pronounced, especially in supporting informed decisions for a sustainable energy future [21]. In this evolving landscape, agent-based modeling (ABM) has emerged as a potent tool, garnering significant attention in recent years [22,23]. ABM is bottom-up approach distinguishes it, allowing for detailed modeling of specific system components and stakeholders. Such granularity offers invaluable insights, especially when navigating novel mechanisms like peer-to-peer trading [23]. By capturing the intricacies of these elements, ABM provides a comprehensive lens to view, analyze, and optimize the ever-adaptive energy system landscape [24,25].

Agent-based modeling (ABM) has become a crucial tool in energy research, enabling the simulation of complex systems with interacting agents, such as consumers, firms, and policymakers. The use of ABM in energy systems dates back to the 1990s, when early models began to explore consumer behavior and market dynamics in electricity systems [26]. In the mid-1990s, ABM's potential for modeling decentralized systems and decision-making processes in energy markets became more widely recognized, with studies such as Tesfatsion in [27] demonstrating its capacity to simulate electricity markets and pricing mechanisms. By the early 2000s, ABM expanded to incorporate more complex scenarios, including renewable energy integration and environmental policy impacts in [28]. In the 2010s, ABM became essential for studying the dynamic transitions of energy systems, as it was increasingly used to model energy transitions, renewable energy adoption, and consumer behavior in response to climate policies [29]. More recently, ABM has been leveraged to simulate the interactions between diverse energy technologies, policy incentives, and societal behavior, providing insights into how small-scale decisions can affect large-scale system transformations [30]. These historical developments highlight the growing sophistication and applicability of ABM in understanding and managing energy systems.

One of the very first ABMs created showed that in a simulated neighborhood where the inhabitants had a slight preference for similar neighbors to oneself will generate total segregation [31]. Here, the model showed that even though none of the individual agents had a wish or desire for segregation, this was the macro-level outcome. This is one of the main functions of ABMs; to model the behavior of individual agents and observe macro-level outcomes. As ABM relies on the codification of individual behavior, it is therefore deeply connected to the behavioral sciences [32].

Generally, codifying agents' behavior can be separated into two categories. In the first category, agents act according to rational decision-making. Here, agents perform a certain action when they are financially beneficial, or when the benefits outweigh the risks [33]. This type of modeling gives better predictions, but the validity is often questioned, as humans are not purely rational decision-makers. In the second category, agents act according to existing behavioral research. Here, agents do not typically act rationally, but in accordance with their values, motivations, barriers, mental shortcomings, and decision-making strategies [34]. For the purpose of this paper, we dub it psychological-behavioral systems. The aforementioned factors can be based on the modeler's own research or existing behavioral theory. This type of modeling is less precise but could be argued to be more valid.

Although the knowledge gained from decision-making research is starting to be integrated into energy system modeling, the process is slow. Huckebrink and Bertsch Huckebrink and Bertsch [35] state in their recent review of the literature that "developing more sophisticated ways for integrating behavioral aspects in energy system optimization or simulation models is of utmost importance in order to allow for behavioral realism of the output from energy system models". Translating behavioral research to model code is difficult, but vital to the validity of energy system models.

Agent-based modeling is a modeling approach that has been developed that focuses on capturing the behaviors of real-world actors as computational agents. It is a tool that ought to be considered when working on the transition to sustainable energy [30].

The future energy system is decarbonized meaning low-emission or, at best, carbon-neutral. The transition to a sustainable energy future aims to achieve a better balance by adjusting both supply and demand sides [36]. A better balance could be achieved by actively engaging stakeholders at various levels, essentially democratizing the energy sector. Rapid digitalization is underway to accelerate the process. As the transition unfolds the system is expected to be decentralized where several pockets of distributed generations, consumers, and prosumers will maintain the supply–demand balance. The European Union in its 'Fit for 55' package seeks to increase the flexibility in the energy system by active engagement of consumers [37]. NODES in Norway aims to increase flexible power consumption through the NorFlex project [38]. Through this project, a local flexibility market is operated to achieve a better balance by deferring consumption, and investments and securing network operations. This project illustrates that the future energy system is expected to be decarbonized, digital, decentral, and democratized [39–43].

The transition is then reflected in the policies and models that drive the decision-making process. Existing policies are expected to be revised to cater to a consumer-centric approach. In terms of models, the attention is shifting towards behavioral-based predictions from an often non-attainable theoretical global optimum from the technology perspective. Reflecting the behavior of various actors in the system is often a challenge due to the layers of complexity as opposed to rule-based decision-making. Then it is paramount to better understand the motivations and responses of the agents in the energy system.

An agent-based model (ABM) can be understood as a model with a defined environment, an autonomous decision-making entity with feedback loops as the entity interacts with the environment [44]. Intelligent agents have been described as software, hardware, or computer-based entities that are autonomous, proactive in a goal-oriented manner, react in a timely manner by perceiving their environment, and have the ability to communicate and coordinate with other agents in the environment or human beings [45]. A Multi-agent system (MAS) can be understood as a collection of such agents, forming a hive that could simulate real-world scenarios. ABM has the feature to integrate various types of models or methods for decision-making. For instance, mathematical functions, statistical models, machine learning, network analysis, optimization models, and game theory. A MAS could link one or more types of methods through utility functions or rule-based mechanisms to approximate a system behavior with many heterogeneous agents. Rai and Henry [29] explain the fundamental and applied aspects of ABM to model consumer energy choices. Melliger and Chappin [46] used an ABM approach to investigate the investment preferences considering renewable energy support schemes. How agent-based models can be used to simulate the occupant behaviors in a building is proposed by Lee and Malkawi [47]. This illustrates that ABM tools can be utilized to render decisions on investment planning as long as consumer behaviors.

The energy transition towards a carbon-neutral future relies both on the supply and demand side transitions. On the supply side, the transition is focused on switching to low-emission resources such as hydro, wind, and solar. Resources can be further classified into dispatchable and non-dispatchable types. Stored hydropower production is a mostly dispatchable resource while wind and solar are non-dispatchable being reliant on weather conditions; therefore, stochastic. Hydro, wind, and solar resources often come with inherent uncertainties and variability. Adding to that, as the policies and decisions are expected to rely more on consumer behavior, uncertainties in behavior would become a significant part of the decision-making process. For instance, how a consumer responds to electricity prices balancing its desired comfort levels. Such actions are stochastic in nature as their priorities differ from one to another. ABM fits the context of modeling uncertainties and simulates various production scenarios which are partly unpredictable. Ma and Nakamori [44] presents a comparison between three types of optimization models and agent-based models for planning in the energy system. The authors concluded that optimization models can describe "what should be"(normative) and agent-based models explain "what could be" (explorative).

With the growing interest in applying ABMs for simulating and studying the behavior of energy systems and the diversity of agent-based tools that are available, there is a need to analyze and evaluate the relevance of these models and tools. The need for a metric for the classification and characterization of the models has been developed.

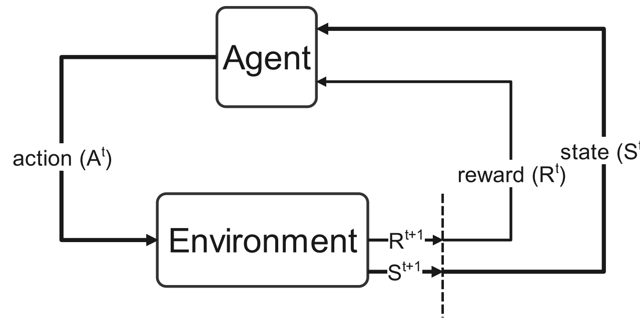


Fig. 1. Structure of an agent.

1.1. Working of an agent-based model

The fundamental working principle of an agent is presented in Fig. 1. An agent is interacting with an environment with three functions — action/re-action, reward, and state. With each time t, the state of the environment S^t is recorded. An agent performs an action A^t seeking reward R^t. Depending on the objective, an agent optimizes the expected reward R^t through action A^t. With each iteration, the agent receives an adjusted reward R^{t+1} and an updated state of the environment R^{t+1}. The objective of the agent is to maximize its reward, with each time step t, through adjusting the action A^t. The key challenge is to design an adequate reward function such that maximum reward can be achieved by the agent through adjusting its actions [48].

The traditional definition of ABM while covering a large part of applications, does not cover pseudo-random events, such as the behavior of consumers. It is although important to be noted that ABM is one of the tools that can still be used to simulate such a dynamic and complex system. Such systems often have a pseudo-random state at their core assumption or starting point. Often highly uncertain and variable systems sit in this category. Instead of being goal-oriented, such models seek to take any feasible state within the set boundary conditions. Consumer behavior in terms of responding to price signals could be mentioned as an example. When the rewards increase the number of random states reduces. For instance, as the number of consumers increases who respond to the signal then the behavior becomes more predictable. ABM are versatile tools that can be used for various perspectives in the context of an electric power system. For instance, ABM can be used to model from the grid owner's perspective to maximize profit or minimize losses, at the same time ABM can be used from a system perspective as in emulating dynamic city-transport dynamics. A reward therefore could be a sufficient attribute but not necessary in the application of ABM in the real world.

A multi-agent system could be understood as a collective of agents through a functional relation to meet a common or central objective.

While ABM primarily focuses on an individual agent's interaction with an environment, a MAS typically emphasizes interactions within the system. For instance, MAS involves the study of coordination mechanisms and multi-criteria decision-making methods. Subsequently, ABM tools are often employed in behavioral studies but MAS is used for intelligent systems with autonomous agents with individual objectives. In terms of methodology, ABM tools utilize a simulation-based approach and are used for observation of the system evolution. MAS covers a broader range of methodologies such as distributed computing, game theory, and coordination mechanisms by mathematical optimization for decision-making. ABM models have been adopted in several recent energy system decision-making challenges such as trading storage [49], strategic bidding in day-ahead energy market [50], integrated energy systems [51], food-energy-water nexus [52] and hybrid ABM-Machine learning prediction of energy consumption [53]. Some relevant protocols for describing ABM that have been proposed in the literature are ODD, ODD+, Mr. Potatoehead [54–56].

1.2. Scope and objective

Several models for energy system modeling have been proposed in the literature for the planning and operation of centralized electrical power systems from the perspective of policymakers, regulators, and producers [57–62]. Such tools are used to determine investments in capacity expansion and optimal scheduling of generation units. As the power system moves from a centralized to a more decentralized system wherein the consumer has a possibility for more active participation, new modeling tools are required. End-user or local flexibility is an example of such a scenario where the consumer determines the level of flexibility without sacrificing individual comfort.

Avoiding the YAAWN syndrome [63], the scope of this study is to illustrate the ABM applications in four segments for sustainable energy transition — consumers, cities, grids, and electricity markets. The study also identifies the trends and patterns within each area of application. Below is a short introduction to the four segments.

Energy market — Electricity, heat, and fuel products are all dealt with in the energy market, a particular kind of commodities market. Electricity and natural gas constitute significant commodities. Oil, coal, carbon emissions (greenhouse gases), nuclear power, solar energy, and wind energy are additional commodities traded in the energy market. Current and upcoming energy prices are rarely correlated because of the challenges associated with energy storage and transportation.

Decentralized microgrid — A decentralized microgrid is a small-scale collection of various power sources, typically renewable sources, that can function independently or in conjunction with a larger energy grid. Grid-connected microgrids have the ability to disconnect from the larger grid when needed to run independently in "island mode". People can act as producer–consumers (also known as "prosumers") or simply as consumers thanks to microgrids, which operate on the idea of communal collaboration.

City dynamics — City dynamics refers to the city as a complex adaptive system (CAS) with heterogeneous and autonomous agents. With a focus on the transportation and electric grid, it includes several agents representing cars, buses, humans, and other transportation means. The simulation is conducted with the objective to understand the evolution of the city with dynamic changes in the transportation system. Moreover, the total power usage is observed in simulating the dynamics of the city under several operational policies.

Consumer behavior — The study of people, groups, or organizations and all the behaviors connected to the acquisition, consumption, and disposal of products and services is known as consumer behavior. Consumer behavior refers to how a person's feelings, attitudes, and preferences influence their purchasing decisions. Researchers in the energy sector frequently discuss "energy consumer behavior", which is frequently described as a collection of individual behaviors that affect energy production and consumption. In this context, behavioral economics plays a key role.

1.3. Methodology

The proposed framework is tested and validated with the 4 models presented in this work. The proposed framework provides a complete and holistic characteristic of an ABM that can be utilized to (a) identify potential knowledge gaps and (b) compare similar tools for an informed selection.

The metrics for the evaluation of ABMs that are proposed in this paper could meet the current needs and is an innovative artifact that could support the selection of an appropriate tool for modeling energy systems using ABM. The Design Science Research Method (DSRM) [64] from the field of Information Systems is an appropriate method for designing new artifacts, based on the needs of the environmental context (energy modeling in our case) and leveraging on the existing body of knowledge, methods, and theory. Thus, we have adopted DSRM as our methodology for the design of the metrics for evaluation. DSRM includes three closely related cycles of activities, which are called the relevance, rigor, and design cycles. The relevance cycle identifies the environment in which the designed artifact will be applied and the requirements for the designed artifact. The rigor cycle brings existing knowledge, methods, and theories into the design cycle and adds the new knowledge generated through the design process. The design cycle is an iterative process that includes the design, development, and evaluation of the design artifact until it has reached the desired quality and expectations [65]. Our adoption of Hevner's DSRM is illustrated in Fig. 2.

Previous research shows that several methods have been applied to studying the contextual environment, such as interviews and observations. Case studies [66] have been considered as one of the approaches that could be applied for studying the environment and collecting data before the design of the artifact [67]. The contextual environment in this research includes several ABMs in the energy sector, developed for a variety of purposes and ranging from single entities, such as a household, to larger systems, such as a microgrid or a city. These are presented as cases to illustrate a range of ABM approaches and methods in diverse application contexts. We have used the case study approach to describe some different ABM approaches for energy modeling. Each of these cases was a study by itself, conducted independently of each other and by different research groups. The authors represent researchers involved in each study. Hence, the main source of data for each case is the researchers themselves and the models, experimental data, and the relevant documents that relate to the specific studies. Each case description includes the specific literature relevant to the study, the specific research methods, and the modeling, design, simulation, and validation methodologies. The analyses of the case studies provided input for the design cycle in DSRM. The metrics for evaluation shown in Table 2, which is the new artifact that is developed, have been developed by synthesizing the different studies reported in this paper and by analyzing them to identify the main characteristics of these models. This result has been further used to both evaluate and compare the different ABM tools, which also serve as a validation of the metrics for the evaluation itself. As one of the objectives of DSRM, the new knowledge that is created through this research work is the analyses of the ABM cases in the energy sector, the metrics for evaluation, and an analysis of the ABM cases using the new artifact, described in Section 3.

1.4. Key contributions

This paper focuses on agent-based modeling for energy system planning. One of the primary motivations for utilizing agent-based modeling is its unique capability to model intricate energy systems at a micro-level. Such granularity and high-level detail are exclusive attributes of ABM, setting it apart from other modeling techniques. Agent-based modeling's emphasis on the micro-level permits a broad spectrum of perspectives for analysis. It begins at the individual agent level and extends to the system level when considering the interactions

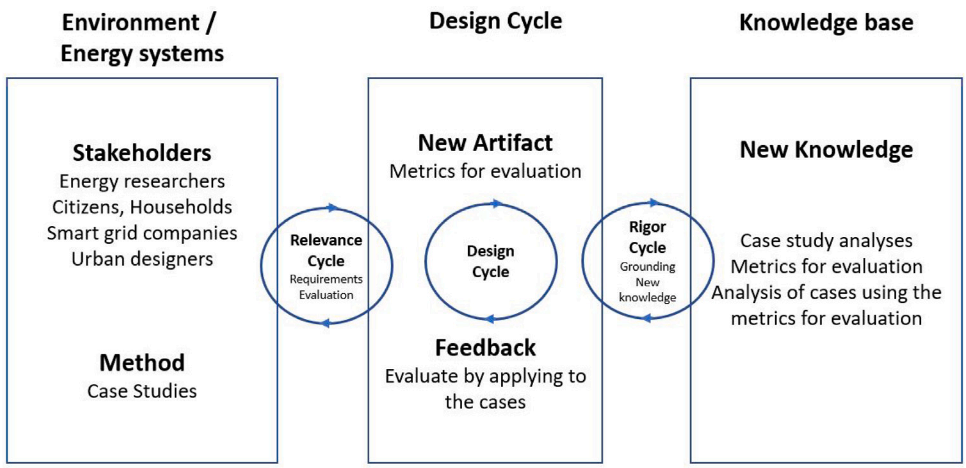


Fig. 2. Design science research method and case studies.

and interplay of multiple agents. Furthermore, ABM allows for the examination of different methodological and behavioral aspects. This provides an avenue to mirror the heterogeneity of actors in the energy system, capturing the vast diversity and individualistic behaviors.

The main contributions of this work can be summarized as follows:

- Systematic investigation of Agent-based models in four key energy transition areas — consumers, cities, electric grid, and electricity market
- Schematic description of a representative ABM use cases for each area, illustrating the decision making process and the related results.
- Outline the trends and patterns in terms of modeling, specifically agent-based modeling, for each area.
- Introduction and validation of a novel framework to characterize heterogeneous agent-based models to facilitate decision-making in subsequent areas
- Derivation of determinants for the future development of agent-based tools applied to energy system modeling

The rest of the paper is organized into three sections. Section 2 introduces the selection of agent-based models alongside a case study to demonstrate the working of the model. Section 3 introduces a framework to evaluate the agent-based model and applied it to the selection of models. Finally, a conclusion is drawn based on the findings and future outlook.

2. Portfolio of agent based models for energy transition

The inquiry first focuses on the energy transition from the perspective of the consumer and then moves on to the dynamics of the city, particularly the transportation sector. The inquiry then moves to the grid level, where the best growth planning choices are made using the ABM approach. Lastly, a presentation on the use of ABM to electricity market simulation is made. Presenting a fresh framework to characterize ABM technologies is the secondary goal. The suggested paradigm accomplishes two goals: (a) determining the benefits, drawbacks, and knowledge gaps of a specific ABM tool; (b) comparing tools of a similar nature.

The portfolio of the ABM tools and subsequent four energy segments are illustrated in Fig. 3.

The first case study investigates how the energy consumption-oriented behavioral aspects of a consumer can be modeled using ABM. The second case study expands to simulating the dynamics of a city such as traffic and transportation. The third case study presents how a multi-agent system can be applied to microgrid expansion planning under resource uncertainty. Finally, the fourth case study delves into how a multi-agent system can be unitized to simulate electricity markets.

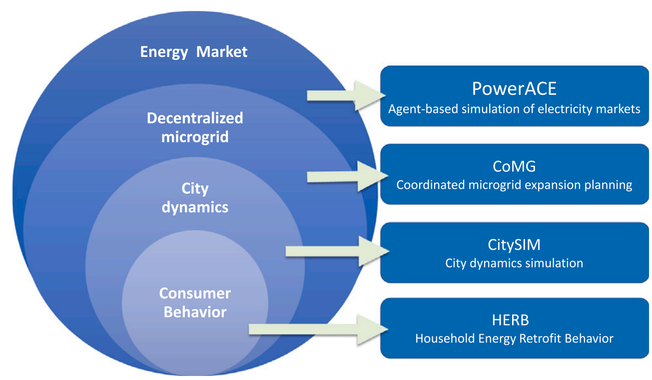


Fig. 3. Selection of applications using agent-based modeling tools.

2.1. ABM for household Energy Retrofit Behavior (HERB)

The first case study focuses on households' energy retrofitting behavior and energy heating consumption. For the analyses, we use an agent-based model, the Household Energy Retrofit Behavior (HERB) model [68]. Different policies can be assessed using the model to observe their impact on energy consumption over time. This model was primarily based on a series of research investigating households' decisions to retrofit [69,70]. Their research found that households typically go through 4 stages of decision-making and that different factors influence the transition between different stages. In the first stages, when the households are still considering upgrading the thermal insulation of the house, the key variables are their self-efficacy, i.e. their belief in their capability to execute behaviors necessary to produce specific performance attainments (upgrading the thermal insulation of the house), and how wasteful they perceive their energy standard. In later stages, when the agent has already decided to perform the thermal insulation upgrade but is still considering the available options, financial factors are more important. How important each factor was to each stage was quantified through interviews and surveys in [69,70], and also based on other research studies [71].

In the HERB model, each agent, which represents a household, can therefore transition between four stages of decision-making, based on the four stages identified in this research. The main factors influencing the transitions were translated into mathematical form after technical discussions in a workshop with behavioral researchers. Still, a pseudo-random generator with a stochastic behavior was introduced in all stages of the decision-making algorithm in order to account for some factors which are hard to describe mathematically, such as free will

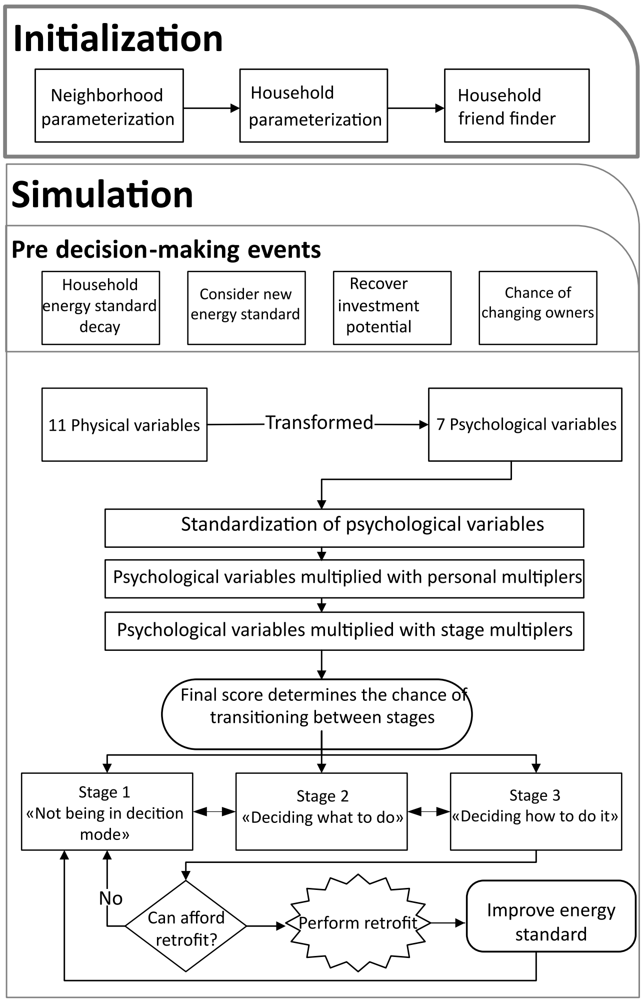


Fig. 4. HERB model schematic.

or intuition, e.g. "the right time has not yet come". To complete the model, a system for households to pick what energy standard they considered upgrading to had to be implemented. No research on this could be identified, so a general modeling approach was selected. The model-based itself on research regarding the availability heuristic, which refers to the phenomenon that humans make decisions based on readily available information [72]. The more readily available the information is, the more impact it has over the decision being made, regardless of its objective relevancy. Naturally, the most readily available energy standard of households was that of their neighbors and friends. Thus, households mostly considered upgrading to the energy standards they were exposed to through their neighbors and friends.

A schematic describing the model is depicted in Fig. 4. In the initialization phase, the neighborhood of study is instantiated with the corresponding physical and psychological variables of each household. In the sequence, a randomized algorithm selects the household friends including close neighbors and also other households residing a bit further within a certain radius from the household address. The household friends will influence their psychological variables in the decision-making process. In the simulation phase, prior to the decision-making, the model accounts for natural phenomena, such as a decay in the household energy standard, a continuous increase in the household investment potential, and also the possibility of agents moving to another neighborhood. The simulation transforms the physical variables of a household, e.g. their property size, income, and investment potential, into psychological variables, e.g. self-efficacy and financial worry. Then, it calculates a final score indicating the probability of the household transitioning between stages. Different scores are required to transition between different stages. The agent typically transitions from the first stage, where it is not considering a decision yet, to the second stage where it is deciding what to do, before reaching stage 3 where is deciding how to do the retrofit. After stage 3, the household performs retrofit if it is affordable or goes back to stage 1 and picks a new ambition.

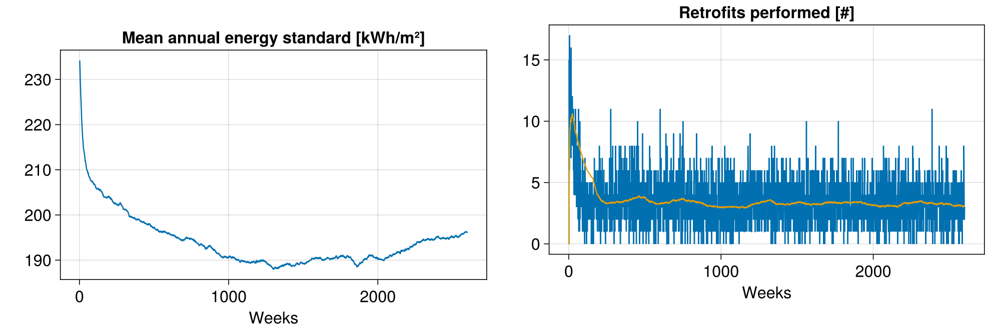
Case study 1 investigates the energy retrofitting decision-making process of private households using the HERB model. First, the HERB model aims to evaluate how well psychological decision-making, rather than economical, fits real-world data regarding the overall retrofitting rate, mean energy standard, consecutive retrofitting, and free-riding on subsidies. Secondly, it can enable investigation of the effect of current and proposed energy retrofit policies on overall energy consumption.

The neighborhood of study consists of 430 households spread over an area of 1 square km split into grid cells. Each Household lies on a grid cell of this simulated area and the model is simulated for 50 years with a 1-week tick. Each household has a set of state variables, such as property size, annual technical energy standard, current ambition the household aims to retrofit, an income docile to which the household belongs, some investment potential representing the amount of money available for retrofitting, and also some personal multipliers moderating the importance of the psychological variables.

An assumption was made that each household has also a social network consisting of 10 peers, being 5 neighbors and 5 closest friends who can live further away. Another assumption concerns the retrofitting actions that are performed by the households. In the current HERB model, retrofit actions are modeled as relative improvements in the energy standard, so there is no representation of specific retrofit measures as the focus of the ABM is on modeling the behavior of energy retrofitting. Still, differently from other ABMs available in the literature representing energy-oriented behavioral decisions [68], the HERB model represents the energy standard of buildings using energy efficiency metrics such as average energy consumption per household in total energy per square meter (kWh/m2). Extensions to the HERB model to consider a more accurate representation of different energy efficiency measures such as wall insulation, roof insulation, new windows and doors and better heat recovery ventilation that is feasible for each building is part of ongoing research activities in the Behavior project.

The HERB model uses input data from two surveys conducted by Enova SF in 2014 and 2019 with the aim to investigate the trends in private housing retrofitting in Norway. The surveys had 2605 and 3797 respondents, respectively. After removing answers with missing data and performing 5 imputations to the original data, a larger dataset with 28,000 entries was produced. The dataset and more details about the input data can be found at [68]. In the simulation results presented hereafter, we considered 430 households uniformly distributed across the 10 income deciles established by SSB (Statistics Norway) [73].

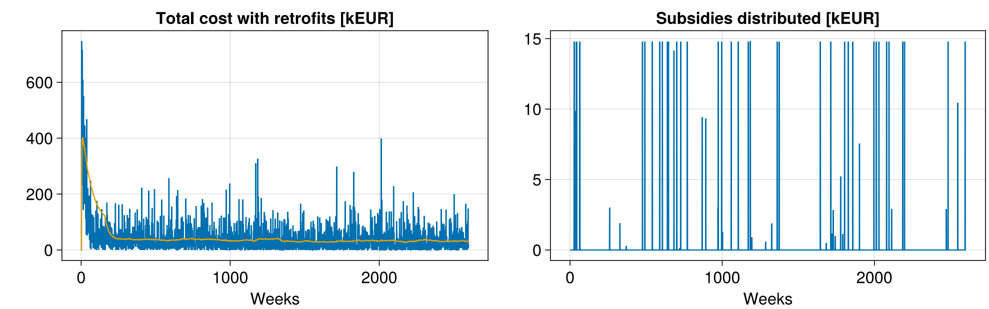
Fig. 5(a) depicts the average energy standard for all the buildings considered in the simulated neighborhood which is a measure of annual energy performance of the buildings based on their construction type, year, thermal insulation and installed equipment. On the right-hand side, Fig. 5(b) shows the number of retrofits (with the associated moving average for a 3-year period) performed over 50 years or 2600 weeks. As it is shown in Fig. 5(a), a continuous decrease in the mean annual energy standard is observed in the first 2000 weeks of simulation. After that, the mean energy standard starts to increase again until the end of the simulation. There are two opposing forces influencing the mean annual energy standard: a natural decay in the energy standard of the building due to aging, and the energy efficiency improvements achieved with the retrofits. The energy standard of the buildings in the simulations ranged within 190–235 kWh/m2 which is within the reference standard for Norway between the years 1995–2012 according to Statistics Norway (SSB) [74]. These results are show a potential realization of the future for the simulated neighborhood



(a) Mean energy standard for the buildings

(b) Retrofits performed (with an associated moving average with a 3-year window)

Fig. 5. Simulation results depicting the mean energy standard and retrofits performed in the 430 private houses.



(a) Total cost with retrofits performed per week

(b) Total amount of subsidies distributed per week

Fig. 6. Total cost of retrofits and subsidies distributed.

where subsidies remain the same as today and there are two opposing forces in action, the building depreciation impacting negatively and retrofitting actions impacting positively the energy standard.

As it can be seen in Fig. 5(b), the weekly number of retrofits performed initially is quite high mainly due to model initialization. It settles at relatively low retrofit rates, between 0.5% and 1.1% (for a reference, the Norwegian energy retrofit rate is at a standstill compared to 4 years ago, with a yearly energy retrofitting rate of about 3.4%) [75], which explains the increase in the mean annual energy standard over time.

Figs. 6(a) and 6(b) depict the total weekly cost with retrofits and the corresponding distributed subsidies. The retrofit costs depend on the desired improvement, e.g., the difference between the actual energy standard and the household's ambition, the energy price, and the house size. The retrofit costs are based on the relative improvement in the energy efficiency of the building following the cost estimates proposed in [71]. As can be seen by looking at both the total costs with retrofits and total amount of subsidies distributed, there is a strong correlation between the number of retrofits being performed and the available subsidies. This means that more households are willing to perform retrofits if they are eligible for subsidies. The total amount of subsidies distributed in the simulations is a good measure of the impact of policies to foster retrofitting and its impact on the mean energy standard.

Fig. 7 shows the weekly distribution of households in the four decision stages. In this graph, it is possible to observe the number of agents in the different decision stages, namely from 1 to 4, and how they transition between the stages for a period of 50 years. After an initialization phase, the share per decision stage becomes relatively stable. Many factors influence the transitions between the decision stages, such as financial concerns related to the investment potentials and retrofit costs, but also social influence exerted by neighbors and friends in the households' social network. Although considering some financial concerns and randomness in such transitions, they are mostly driven by psychological variables rather than economic ones.

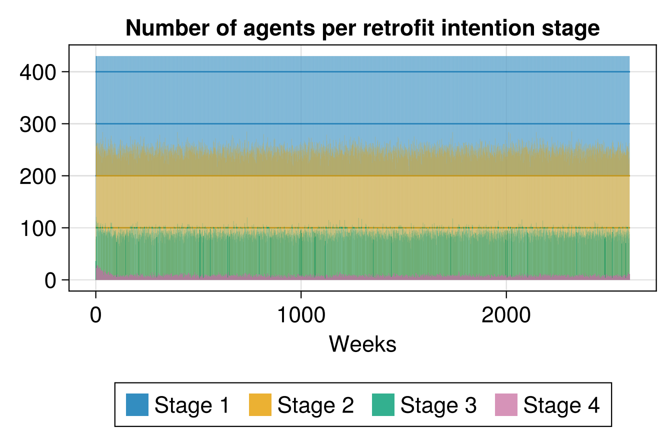


Fig. 7. Retrofit intention — decision stages.

Fig. 8 depicts the final mean energy standard for different policies regarding the distribution of subsidies. The value on the x-axis indicates the minimum energy standard required for households to be eligible for the most accessible subsidy when retrofitting. As can be seen in the plot, this relation is fairly non-linear but its initial trend shows a relative improvement in the final mean energy standard when the requirement on the minimum energy standard is increased. This result is logical as more households would be eligible for subsidies with a higher threshold on the minimum energy standard. The second trend showing an increase in the final mean energy standard could indicate that less ambitious retrofits occur initially (and not subsequently) and this affected negatively the final mean energy standard temporarily. As it was seen in Fig. 5(a), an improvement in the energy standard in a shorter horizon is not enough to ensure the best performance in the

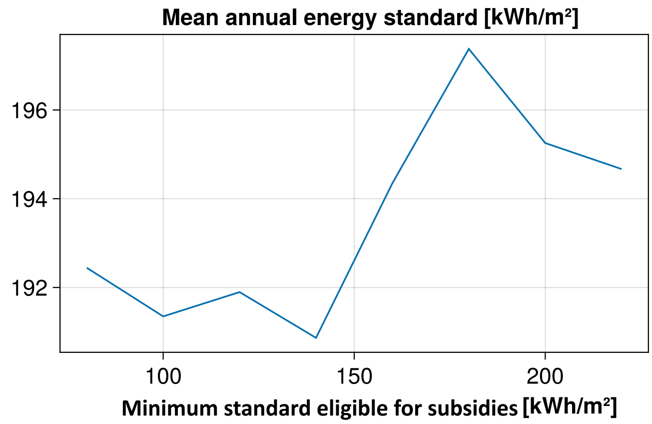


Fig. 8. Effect of subsidy policies on mean energy standard.

long term. Sensitivity analysis on key criteria for policy enforcement can be used as input by decision-makers to evaluate the performance and select the best policies for a given horizon of interest.

The main aim of this case study is to investigate households' energy retrofitting behavior and their influence on energy heating consumption in city districts or neighborhoods. Rather than traditional mathematical and financial-driven models, an ABM model focused on household energy retrofit behavior was adopted for the analyses. This model was selected based on previous behavioral research on energy retrofit which found that psychological variables, such as i.e. self-efficacy and how wasteful they perceive their energy standard are more important than economic variables, especially in the initial decision stages. The model allows to simulate of energy retrofitting behavior for different policies and neighborhoods, which has the potential to support policymakers to assess the impact of subsidies and other types of incentives impacting energy heating consumption.

The HERB simulation model has the potential to simulate the frequency and distribution of energy retrofits across city districts for many decades. Given the current energy situation in Europe and the significant share of energy consumption used for heating, this is an important aspect for decision-makers searching for the main energy consumption trends and favorable policies to foster energy savings. Further, the model can also provide insights on the unrealized potential and regional energy demand, which can provide insights to energy providers for prioritization of investments and deployment of the necessary energy infrastructure in a cost-effective manner.

2.2. ABM for city dynamics simulation (CitySIM)

In this case study, CitySIM, we have focused on the city as a whole and how the city and the entities within it evolve due to their interactions. The motivation for this study was to understand how individual citizens' decisions can affect the city. In particular, we have examined how an individual person's decision on their transport mode could affect the traffic picture and the evolution of the traffic condition in the city during the day. The main aim of this study was to explore the uses of an agent-based, modular micro simulator of a city as a Complex System. This study was conducted as a part of a Masters's thesis and the details of the implementation and simulation results are available from [76].

Cities have been described as Complex Systems, where the overall behavior emerges due to the behavior of its components [77]. Hence, we apply ideas from Complex Adaptive Systems (CAS) in combination with ABM. CAS is composed of interacting, autonomous agents [78]. To understand the behavior of such a system, the interconnections or the "interwovenness" of the entities as well as the behaviors of the individual entities are essential [79]. The overall behavior of such an entity, in this case, a city, thus emerges as a consequence of the interactions between the entities within the city, and this is called emergent behavior. Another way of explaining emergent behavior is that the whole is greater than the sum of the individual parts. One of the advantages of CAS modeling is the ease of modeling simple, individual entities bottom up, and the possibility to conduct population-level simulations [80]. The energy consumption and indeed the distribution of energy consumption across a city or the energy flow is linked to where people are and what they do.

The entities within a CAS can be modeled as agents using the ABM approach [81]. In the CitySIM case, the aspects of a city that were included in the model are traffic (cars and buses) and the electric grid. These agents interact through the traffic system and make decisions based on past experiences, which are measured in the costs of choices they make. The ABM model and the simulations were implemented using the Repast Simphony 2.6, released on 20 November 2018, which is a tightly integrated, richly interactive, cross-platform Java-based modeling system that runs under Microsoft Windows, Apple Mac OS X, and Linux. It supports the development of extremely flexible models of interacting agents for use on workstations and computing clusters.

An ABM is developed for the *environment* (the roads in a few blocks of the city of Trondheim, Norway) and for the entities that use the environment, and the *agents* we have identified, which are cars, buses, and persons. These are shown in Fig. 9(CitySIM case: Agents and Environment).

The agent "Persons" choose travel methods, which are by the agent types "Bus" or "Car". The population of people is a parameter, i.e. the no. of agents of type Persons, (e.g. 75 % of people go to work, 2 % do not go anywhere, 23 % go shopping). A Person chooses to use her own car or take the bus, e.g. depending on the bus fare or weather. The agent "Vehicles" use the road network, i.e. the "Environment" to move on. "Spawn" points are where vehicles enter the model, i.e. the road or the environment respectively, and "Despawn" points are where vehicles exit the model. Simple "Rules" are applied to vehicles to avoid collisions and to calculate their paths. For example, each vehicle has a destination to calculate their paths, and they avoid collision with the vehicles next to them (in front, behind, and to their sides).

The scenario that is modeled is that every person decides in the morning if they will stay at home or leave their homes to go to work or shopping. If they go to work or shopping, they will choose a transport vehicle. If the bus fare is low enough for them, they will take the bus. Otherwise, they will drive their own cars. The city area that is modeled has several entry points and depending on the locations of the population, each person will choose an entry point into the city. People who go shopping enter and leave the city at random times during the day, whereas people who go to work have set times for work and, during working hours, they will reside in the buildings in the city. Depending on where people are in the city, they will choose a parking space. If they have electric vehicles, they will charge their vehicles in the buildings with parking spaces.

In addition, for the implementation of the model in Repast Symphony, there is a *structures* package, which contains data structures that are used in different parts of the project. A *Utils* package contains the utilities and tools needed by other classes, such as algorithms and look-up functions. In addition, the CitySIM-Builder class is where all the initialization and setup for the simulation are done. Finally, the Reporter class keeps track of the measures, calculates the averages when new data comes in, and reports it to the GUI for display.

The simulation is designed to show how the traffic evolves during the day, depending on an individual person's decision to leave their homes and their mode of transport. By varying several parameters, such as the total population of the people, the percentage of the population that chooses the bus or the car as their transport mode, closing, and opening entry and exit points in and out of the city, moving the location of parking spaces, which also include electric vehicle charging stations, we are able to obtain an overview of how it can affect the traffic

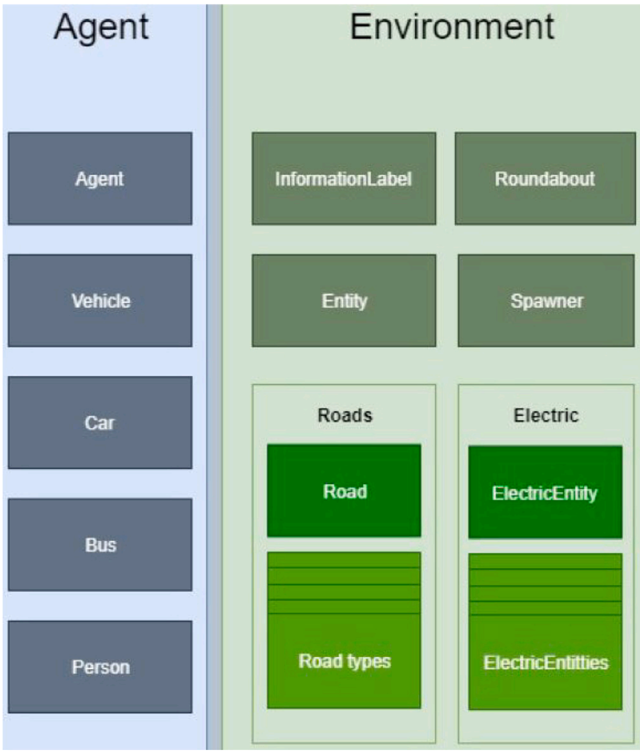


Fig. 9. CitySIM case – CitySIM case – Agents and environment overview.

situation in the city. In particular, how the traffic situation evolves in specific areas of the city.

An overview of the simulation environment is shown in Fig. 9 (CitySIM case — Agents and Environment simulation overview). Several elements, such as parking spaces, roundabouts, bus stops, and entry and exit points into this specific area of the city are modeled (see Fig. 10).

CAS simulations show the emergent behavior in a city and in this case, it is how the traffic evolves during the day. As the model illustrates, there are several entities that are in movement and interacting with one another, e.g. each vehicle is moving on the roads and avoiding collisions, some are looking for parking spaces, etc. It is impossible to show the emergence in 2-dimensional views or graphs. In addition, we have created a video of the simulation, available at [82]. Unlike several types of simulations, ABM simulations based on the CAS approach provide an opportunity to have a qualitative analysis of the situation as can be seen from the figures and the video.

The main aim of this case study is to illustrate how a city could be modeled as a CAS. In fact, a city could be considered a system consisting of several CAS or sub-systems, the traffic is one of them. Hence, this case study illustrates how several parameters that use the roads and other entities in a city affect the traffic in the city. The decisions and choices that lead to the total no. of people and vehicles in cities are dependent on several factors, such as working hours, no. of people working in the area, shops in the area (which affect the percentage of the population that come to the city to shop and at random times), social and economic factors, such as the ability to pay for higher bus fares. The CAS model provides an opportunity to vary such parameters and run simulations.

The model has the potential to simulate the flow and distribution of energy consumption across the city and throughout the day and night. Given the high market penetration of electric vehicles in Norway, this is an important aspect in the design and implementation of smart grids and the development of the charging infrastructure. The CitySIM simulation model is aimed at providing a broader insight into the parameters that could benefit the planning of energy-related issues, e.g. where people are located, where they park and charge their cars, how much time they spend driving, which also has an energy cost.

The complexity of energy transitions in a city and the diverse interactions that lead to de-centralized, emergent behaviors in cities that affect the energy picture can be challenging to capture through linear modeling approaches. CAS and ABM provide an appropriate means of representing such scenarios and highlighting the implications of small local-level changes that affect the overall behavior of the system; in the case of CitySIM, the decisions of individual citizens' decisions about their daily transportation mode, or closing off a road in a city, and how such individual decisions could affect the overall traffic picture of certain areas in the city. CAS enables modeling of diverse entities and how they relate to one another and these can be important in making decisions at the city level.

2.3. ABM for distributed microgrid expansion planning

Multi-agent system perspectives have been discussed in [83] where authors proposed a coordinated planning approach for electrical microgrid (MG) expansion under uncertainty, called CoMG. The main objective of the work was to propose new approaches to address the expansion planning problem of MGs, by integrating traditional optimization models within multi-agent frameworks, and developing a coordination and communications strategy between MGs. The main motivation behind the CoMG multi-agent framework is the need to address the transition between the traditional centralized power grid towards the current decentralized and distribute grid where peer-to-peer communication between consumers and prosumers becomes crucial. Because of the integration of renewable energy sources, such as wind and solar, into modern power grids, electricity generation is increasingly occurring in a distributed manner, with MGs representing the primary distributed power generation sources. MGs cover a tiny geographic region and provide novel optimization problems to the functioning of the electric power grid. MGs, in contrast to centralized power generation sources, frequently have a variety of sources of electricity generation. Power is sent in both directions. As a result, it becomes more difficult to maintain a balance between demand and supply, maintain an appropriate power reserve, and maximize resource use. New approaches for coordinated MG expansion planning are required in order to meet these issues. The CoMG framework is one of them.

While mathematical optimization has been widely used for decision-making within both electrical and thermal energy systems, its application to more modern problems coupled with multi-agent approaches is relatively new. The CoMG framework utilizes multi-agent approaches for MG expansion through optimization and math heuristics. It is a novel application of computer science to an energy and power systems-related problem, and it, therefore, falls within the so-called Energy Informatics domain where smart energy and power systems modeling is a core sub-field [6].

A summary of the overall concept that underpins the CoMG model with a focus on the agent configuration is shown in Fig. 11.

Three levels of the agent, each with its own set of strategies and functions, are depicted. It is allocated for internal operations, such as scheduling dispatchable generation, maximizing the use of renewable resources, and controlling storage units to their optimum performance in the primary layer. The secondary layer provides accurate optimization in terms of the most cost-effective investments in generation and transmission expansion. The third layer is dedicated to information organization, and it is responsible for coordinating information sharing and exchange. It will collect information on the marginal cost of generation for each MG, the energy needs of each MG, and the excess energy produced in each MG from conventional plants and energy produced from renewable resources. As part of this process, the tertiary layer will collect and distribute information, making it available to the MG so that they can make informed decisions. The third layer keeps track of the

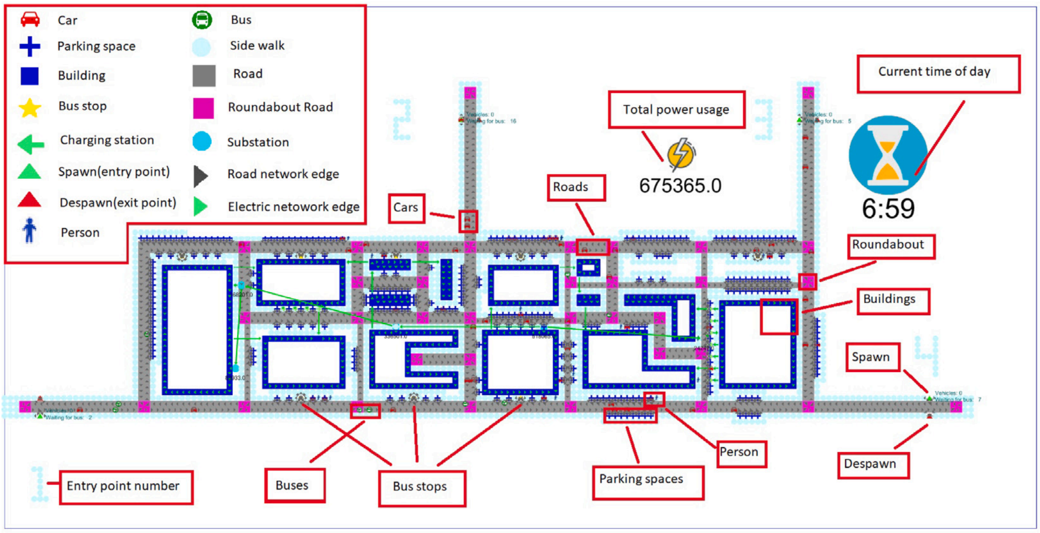


Fig. 10. CitySIM case — Agents and Environment simulation overview.

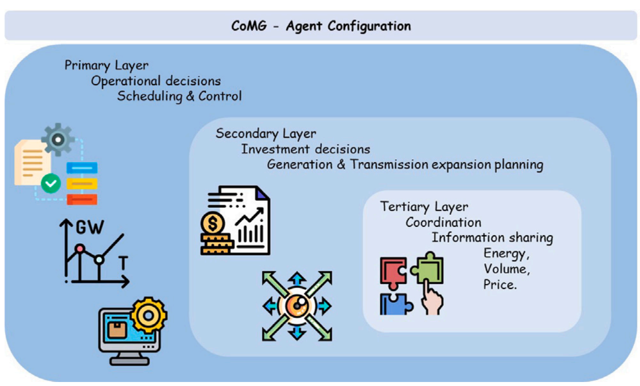


Fig. 11. Graphical representation of the main actions performed by an agent within the CoMG optimization framework.

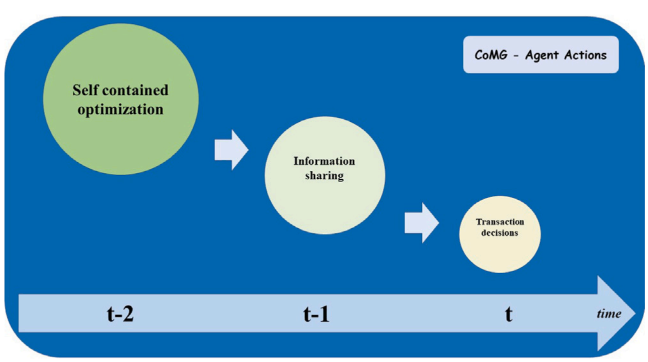


Fig. 12. Graphical representation of an agent within the CoMG optimization framework.

grid's status and receives updates from other agents. An agent's level of coordination in decision-making is depicted in Fig. 12.

At level t-2, each MG is responsible for solving its own optimization problem, which we shall refer to as "self-contained optimization". It is at this level that the necessity for energy transactions is determined since each MG will calculate energy requirements that exceed energy availability. At level t-1, each MG will exchange information with the rest of the neighborhood (during the information sharing stage, information is broadcasted and received). After then, at level t, each

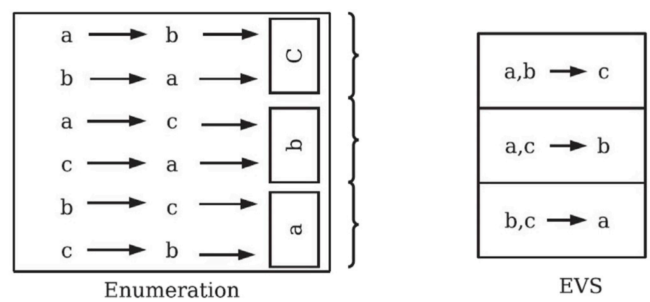


Fig. 13. Communication strategy, enumeration versus evolutionary sequencing algorithm EVS [83].

MG will solve its optimization problem by taking into consideration the information obtained from the other MG, along with the possibility to develop connections and conduct transactions.

The reader will note that each action depicted in Fig. 12 is contained in circles of different sizes. This refers to the time required for each action to be finalized. Self-contained optimization takes a long time to solve (for big instances it can take hours or even days), while information sharing takes less time, (in the form of seconds), and transaction decisions are even faster since the availability of information provided by the previous actions allows a fast response at the final stage. For the sake of communication, MGs are categorized by their size, the capacity of their generation units, and the capacity of their transmission lines.

There are three different capacities: high, medium, and low, as well as three different sizes: big, medium, and small. Following that, several communication tactics might be implemented. The authors present an evolutionary sequencing (EVS) methodology that lowers the number of permutations that must be performed. An example is shown in Fig. 13. Here *a, b, c* refer to different types of MGs obtained from different combinations of capacities and sizes. Two MG will solve their self-contained optimization problem simultaneously, lock their decisions, and then send their output to the third MG, who will make the final decision based on the information they have received.

The experiments that were performed in [83] showed that, when an MG receives information from neighboring MGs, they are able to make informed decisions and they are encouraged to establish new connections between them, resulting in fewer new generation infrastructure installations compared to the basic self-contained optimization. Indeed, MGs can receive electricity from the neighbors as a result of recently constructed connections. More often than not, the cost of establishing a new connection with a peer is less expensive than the cost of installing a new generation infrastructure. The experiments showed how capacity constraints, market, and competitive pricing can all affect peer-to-peer communication decision-making.

The models were tested with data from three islands off the coast of Norway, and they were commissioned to provide answers to problems that were of interest to the local system operator at the time. Especially with the emergence of intelligent technology, such as smart metering and thermostats, this strategy is now easily adaptable to other types of MGs. The coordinated MG is intended to make it easier for diverse MG agents (in this case, functional entities that share information) to collaborate in decision-making for both operational planning and investment decisions. MGs can collaborate in order to ensure that existing resources are utilized to their full potential. They can also determine whether or not the installation of new resources in a neighboring MG region is a wise investment. When evaluating these options in isolation, there are numerous downsides to be aware of. In the case of fresh investments in an MG, a neighboring MG may choose to join in those investments rather than pursue its own investments in the future. The findings of the models demonstrate that significant improvements in both planning efficiency and resource usage can be achieved. In six out of nine situations, the coordinated decision-making technique outperformed self-contained hierarchical decision-making, and the strategy resulted in cost savings that were possible for all MGs. In some cases, the expected profit growth can reach as high as 13 percent of the total revenue.

In a nutshell, the advantages can be summarized as follows:

- MG planning that is more efficient
- Profit increases of up to 13 percent have been observed.
- The development of a new approach for coordinated MG planning

The results of the experiments led to the conclusion that the value of coordination resides in the additional profit earned by a single MG as a result of coordination or synchronization with peers. In comparison to a self-contained hierarchical decision-making approach, the coordinated decision-making strategy outperforms it. On the methodological side, the sequence in which MGs are organized has an impact on the potential profit, and as a result, there is a need for additional research in this area to better understand the impact of different communication strategies. On the application side, the proposed methodology should be further tested and shaped for other problems, such as network restructuring and reconfiguration that have been first introduced in [84], while a more advanced multi-horizon version was proposed in [3]. Indeed peer-to-peer communication between MGs has the potential to minimize and/or delay costly investments in network restructuring and reconfiguration that arise within the power systems as a consequence of the increasing energy demand and the increasing maintenance costs of power lines. In addition, a multi-agent approach would be beneficial to analyze long-term investment decision-making of novel technologies, such as pumped thermal electricity storage [85]. By coupling it with machine learning algorithms, the multiagent approach can become a powerful methodology to apply within the cyberspace of cyber–physical energy systems as outlined in [86].

The proposed CoMG approach is a multi-agent system MAS and as such, it is a type of ABM. The results of the experiments demonstrate the value of an agent-based approach to enhance decision-making for optimal investment decisions within power systems. An approach based on peer-to-peer transactions is more realistic in the current decentralized scenario. In addition, solving subproblems within each MG and establishing communication protocols between them have positive effects on the computational time required to reach a solution.

2.4. ABM for electricity market simulation (PowerACE)

PowerACE is an agent-based simulation model for the analysis of liberalized electricity markets. The initial development of PowerACE only considered the German market. However, over the past years the scope of the model has been extended by adding major European market areas [87]. The focus of PowerACE lies on the simulation of European liberalized electricity markets considering model-endogenous yearly investment decisions. The model enables the investigation of a wide range of different scientific research questions, which allows, for example, the evaluation of different market designs and technologies on the European electricity markets [25,88].

As shown in Fig. 14 a central role in PowerACE is taken by different agents that represent market participants, such as various traders, regulators, and consumers [89]. Agents can interact with their environment dynamically by choosing appropriate actions. For the selection of suitable actions, decision-making algorithms are implemented for each agent. A decision-making algorithm can be based on a variety of different methodological approaches and consequently offer high flexibility.

Supply agents refer to big European utility companies that bring their dispatchable power plants to the market. Renewable agents create bids for priority feed-in of RES and offer these bids in the market. The hourly inelastic demand is marketed by demand agents. Further agents for electricity storage technologies, e.g., pumped hydro or battery, schedule the operation and submit the corresponding bids to the markets [90]. Additional agents dispatch flexibilities from sector coupling technologies, such as hydrogen electrolyzers [91] and controlled chargeable electric vehicles [92]. The operating strategies of respective sector coupling technologies can be varied with respect to different objectives, such as CO_2 minimization, dispatch cost minimization, or load smoothing. Lastly, operator agents manage the market framework, wherein bids can be submitted and the market outcome by market area is calculated.

Decisions within a PowerACE electricity market simulation can be characterized by short-term and long-term decision levels. For the short-term simulation, PowerACE assumes the day-ahead spot market as the best estimate for all electricity markets. However, further market segments i.e., the control reserve markets, are at least rudimentarily included. In each simulation, multiple demand and supply agents per market area participate. On each simulation day, the following four steps are performed:

(1) Forecasting: At the beginning of each spot market simulation step, the agents create an hourly price forecast for the following day. The forecast gives the agents information about the market environment. (2) Bidding: Agents prepare hourly demand or supply bids to buy or sell electricity on the spot market. Hereby, each trader agent can submit multiple bids for each hour of the subsequent day. The bidding strategy of each agent depends on the predefined settings. (3) Market clearing: After the submission of all bids, the operator agent is called and the market clearing algorithm is executed. Here, a linear optimization model is used to determine the market outcome (dispatch, cross-border flows, and wholesale market price) with the objective of maximizing the total welfare of all considered market areas subject to limited cross-border transmission capacities, balanced energy flows, and fulfilling the demand. (4) Dispatch: Subsequently, each supply agent aggregates its accepted bids and thus determines its individual load curve. Based on this demand to be met, each supply trading agent determines its daily power plant dispatch. For the spot market, the bids submitted by the agents for the individual market areas are collected by the market coupling operator.

In the long term, agents decide annually on the construction of new power plants based on the expected profitability of potential investment options, e.g., dispatchable power plants, battery storage facilities [88,90,93,94]. The underlying investment planning scheme is

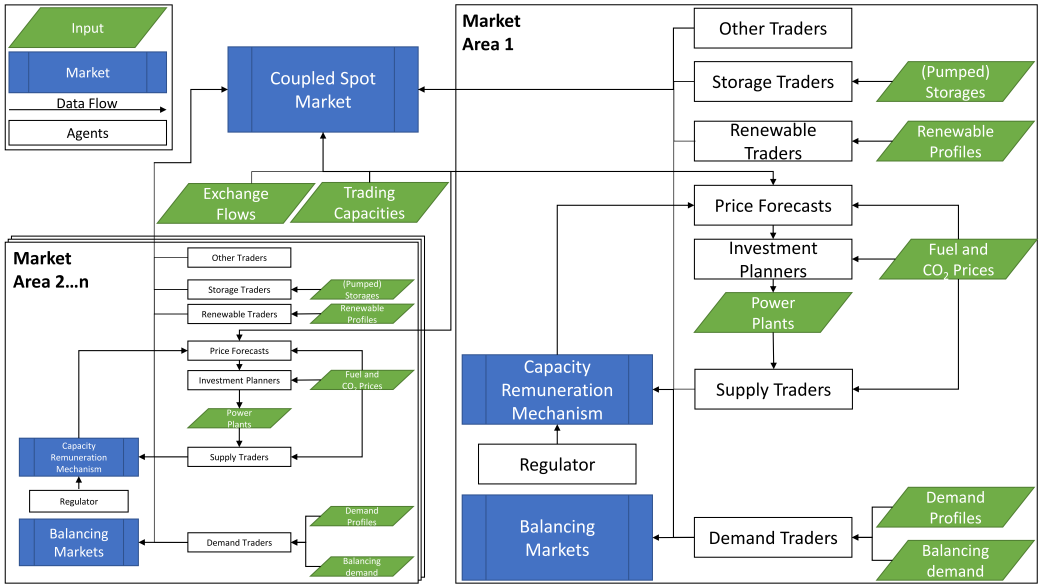


Fig. 14. Schematic overview of the main parts of the electricity market simulation model PowerACE [89].

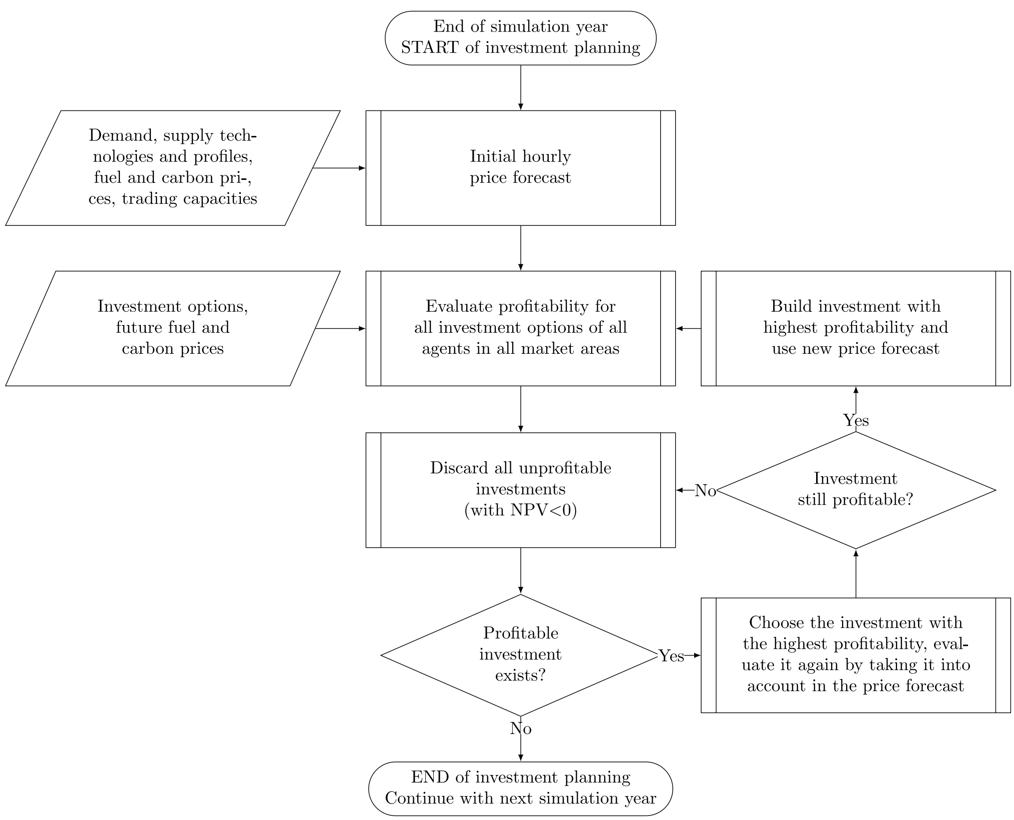


Fig. 15. Simplified schematic process overview of investment planning in PowerACE [89].

illustrated in Fig. 15. Capacity remuneration mechanisms that incentives large-scale investments in order to ensure long-term generation adequacy have been introduced in many European countries over the past decade. These mechanisms have a significant effect on investment planning and consequently the generation portfolio. Therefore, various capacity remuneration mechanisms have been implemented in PowerACE, i.e., capacity payments [95], a central buyer [96], decentralized obligations [97], and a strategic reserve [98].

Key outputs in PowerACE are hourly, i.e., spot market prices, facility-level dispatch decisions, flexibility operation decisions, CO_2 emissions, cross-border flows, long-term capacity developments, underlying investment decisions and decommissions, and ex-post profitability analyses. This has enabled numerous studies to be carried out with PowerACE in the past, only some of which are listed here. First, research was conducted by [25] on the possible market power behavior of large power generation utilities in Germany. This work was followed by further investigations. Generation security and welfare in the Central Western Europe-area was researched by the authors in [87]. The potential future impact of the introduction of capacity remuneration mechanisms in Germany was considered in [96]. The authors in [99] analyzed the different price drivers on the German spot electricity prices, such as commodity prices of gas, coal, or carbon certificates. Ensslen et al. [92] investigated the market impact of smart charging control of EVs on the German and French electricity markets, while [100] examined the impact of storage systems under capacity remuneration mechanisms. A study on cross-border effects on the Swiss electricity market due to market design changes in neighboring countries was provided by the autors in [94]. But also on a methodological level, regarding differences in modeling, a comparison of PowerACE with two optimizing models was addressed in [101]. This small selection of studies illustrates the flexible applicability of the PowerACE agent-based electricity market simulation model.

To give a better understanding of PowerACE's field of applications we present some exemplary results of previous studies subsequently. The boxplots in Fig. 16 show the electricity spot market prices that were determined in a study regarding state-based or market-based investments in new French nuclear power plants in the upcoming years. More specifically, the market impact of new nuclear power plants in the context of increasingly interconnected European electricity markets with high RES share was investigated. Typically, when working with PowerACE, several scenarios with different parameterizations are calculated. Thus, for the study about French nuclear power plants prices in two scenarios (state-based investments and market-based investments) are considered with a long-term horizon until the year 2050. In addition to France, the electricity markets of neighboring countries were highlighted in the study. This illustrates the large geographic scope of PowerACE.

When looking at the values that are displayed in the boxplots, the average prices in the different market areas appear to be synchronized in large parts. This can be attributed to the market coupling and the expansion of trans-border trading capacities. The endogenous-driven (state-based) investment results in the overall lowest average prices. In conclusion, the prices indicate a large impact of the French market on the prices in the neighboring market areas.

The major challenge in the power system is the temporal mismatch between financial and physical fulfillment. PowerACE was one of the first agent-based models to enable the tradeoff between modeling deregulated electricity markets, taking into account numerous technical details, multiple market areas, and a wide variety of actors active in the market. These four dimensions often cannot be represented jointly from other model classes. In particular, PowerACE's ability to model imperfect markets provides an excellent analytical tool, especially when investigating market designs to identify and eliminate misaligned incentives early on.

In summary, PowerACE is a comprehensive model that can serve as a sustainable and powerful tool for analyzing electricity markets and their effects due to the various methodological extension possibilities.

3. Discussions and characterization of ABM tools

The previous section illustrated how an agent-based model can facilitate simulation and decision-making in four key segments of the energy transition. In [102] authors have listed a comprehensive enumeration of ABM tools. The authors compared the tools using a list of specifications. However, there is a knowledge gap in comparing or characterizing the ABM tools for the energy sector. Moreover, a framework is required to characterize ABM tools. The following statements before the table of framework explain the reasoning behind it from the experience of the Authors who developed several tools. Typically, a framework is a real or conceptual structure that is meant to act as a support or guide for the construction of something that develops the structure into something useful. A framework's objective is to aid in development by providing standard, low-level functionality so that developers may concentrate their efforts on the components that distinguish the project. Using high-quality, pre-tested functionality improves software stability, reduces development time, and simplifies testing. The goal of frameworks is to provide a common structure so that developers do not have to reinvent the wheel and may reuse the code given. In this way, frameworks enable us to eliminate much of the labor and save a significant amount of time.

In this section, a novel framework to characterize such tools is developed and presented. The framework has 12 metrics ranging from methodology, agent variety, decision level, data variety, data horizon, model horizon, granularity, efficiency, uncertainty, randomness, model complexity, and availability. Together the metrics reflect how a certain ABM tool fairs in a specific decision-making objective — such as, how CoMG reflects the power system expansion planning problem. The framework is then validated by applying it to the models included in the study. Specifically, the framework explains how a specific ABM tool aids in decision-making for a set objective. In Table 1 the developed and proposed metrics are elaborated with descriptions.

Models are often data-dependent. Specifically, the variety and velocity of the data set impact the model and simulations. For instance, character-type data typically leads to a qualitative decision as opposed to a quantitative one from the numerical one. Simulations are dependent on both the volume and velocity of data. Digitalization of the energy sector has increased the volume of data that is available. The implementation of the Internet of Things results in more and more near-real and real-time data sets. ABM tools are typically dynamic that enable the introduction of high velocity and volume of the dataset in the simulation. However, the threshold to which the integration is possible varies among different models.

Efficiency is a typical metric that applies to most modeling tools. Efficiency could be expressed temporally through a time of convergence and iterations per minute. The programming language used to write the model is a determinant of further development operations, maintainability, and adaptation. There are several ABM packages in practice, such as Java agent-based modeling toolkit [103], MESA in python [104], and Agents in Julia language [105] and NetLogo [106].

Uncertainty and variability in the physical world have remained a challenge in physics-oriented modelings, such as non-dispatchable RES. Adding to that, human behavioral aspects bring forwards some predictable actions while increasing the complexity of modeling. Agent-based modeling fits well in such context as presented in the previous section. ABM tools are effective in simulating complex and dynamic environments that adapt well to physics-informed energy modeling. How uncertainty is addressed in ABM is an important distinction between various ABM tools. For instance, if variability is considered, and if spatial or temporal uncertainties are handled. Complexity can be understood as a result of uncertainty and variability. Complexity can be a part of the model, such as designing the reward function. It could also be a part of the decision-making process. Thereby complexity could be a metric to classify ABM tools. One method to reduce complexity could be flexibility. Flexibility in ABM tools could be assessed through the methodology behind the model. For instance, a rule-based method has little to no flexibility at all and the rules for application must be unambiguous. The availability of a model, for instance, if it is open-source and commercial solvers to solve a model are also factors to consider. Beyond that, model sizes also vary depending on various factors, such as the programming language and the method of modeling.

As highlighted in earlier sections, agent-based modeling offers significant advantages for analyzing energy systems. However, it is still an emerging approach in energy system modeling with limited comprehensive reviews available. Given ABM's bottom-up approach, it paves the way for numerous research opportunities. Considering the scarcity of publications, our newly developed metric becomes especially valuable for energy system planning. This metric empowers researchers to grasp a clearer understanding of ABM's impact on energy system modeling.

To validate the proposed framework, the metrics are applied to each ABM in this study. The Table 2 lists the metrics and corresponding values for each ABM. The selections and reasoning for them are further elaborated in the following subsections.

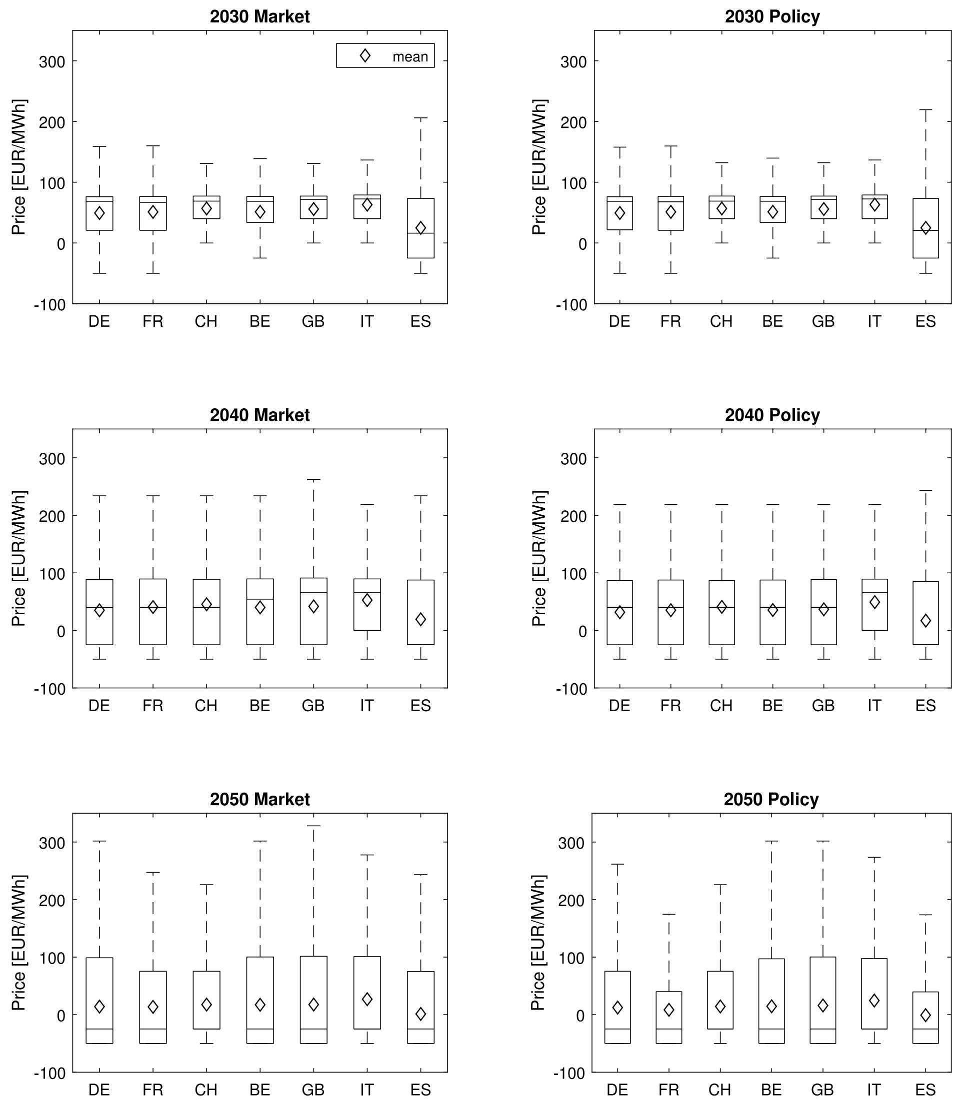


Fig. 16. Box plots of spot market prices between 2030 and 2050 for all market areas surrounding France with a comparably high CO_2 emission allowance price path; outliers are removed. The average is indicated as a diamond. None of the prices take into account levies for Gid, RES, or CRM [89].

Table 1
Framework with metrics for evaluation of agent-based models.

Metric	Description
Methodology	What is the method used for modeling? Rule-based/optimization/ etc.
Agent variety	How different are the agents from one another (if it is a multi-agent model) and how the agents are linked
Decision level	Are the decision(s) made at an individual agent or at the system level?
Data variety	Varieties of data processed, High = mixed (alphanumerical, spatial) inputs, Low = only numerical
Data horizon	When/How is the input data measured/generated? (Historical/ near-real-time/ future predictions)
Model horizon	Planning horizon of the specific tool, Short (near real-time)/medium (weeks-year)/long-term (more than 5 years)
Model granularity	What is the time step of the simulation?
Efficiency	Typical computational time to reach a solution. (Expressed in minutes)
Uncertainty	If and how the uncertainty is handled in the model? (Stochastic/sensitivity analysis/iterative/stochastic dynamic/etc. If not handled, then N.A.)
Randomness	If there is randomness involved in the model or in data generation?
Model complexity	Lines of code/number of processes/steps to reach the final solution/number of agents/amount of equation/size of formulation/computational time per agent
Availability	Tool freely available but code as a black box/tool freely available and code available/only data available/Partially available data/private only

Table 2
Evaluation of ABM characteristics based on the proposed framework.

	Behavior	City dynamics	Microgrids	Energy market
Methodology	Rule based	Complex adaptive system	Stochastic optimization	Combination
Agent variety	Heterogeneous, non-linear dependence	Heterogeneous	Homogeneous agents, linear dependence	Heterogeneous and non-linear dependency
Decision level	Agent	System	System	Agent (short-term) and System (long-term)
Data variety	High	High	Low	Very high
Data horizon	Historical surveys	Historical	Future predictions	Combination
Model horizon	Long term	Medium	Medium	Combination
Model granularity	Weeks	Minutes	Hours	Hourly
Efficiency	1–2 min	12 h	5760 min	4000 to 8000 min
Uncertainty	Sensitivity analysis	Iterative	Exact	Sensitivity analysis
Randomness	Yes	No	No	No
Model complexity	430 agents, 2600 steps (1 step per week for 50 years)	10 types of agents, agent population >100	3 types pf agents, exact solution	25–50 agents per Market Area, 16 Market areas
Availability	Open source	Private	Dataset available	Private

3.1. Characterization of ABM for consumer behavior

As mentioned in the introduction, behavioral ABMs can be roughly divided into financial-rational and psychological-behavioral systems. While the latter has historically received less attention [35], its role in energy system models is growing. In order for energy system models to encompass end users, the behavioral perspective must be included. The HERB model is an example of an ABM based on a psychological-behavioral perspective focused on household energy retrofitting and subsequent energy use for heating. Here, agents are based on previous behavioral research regarding private household energy retrofitting [69,70].

As the agent's behavior is based on previous behavioral research, it could be said to be rule-based. All agents are parameterized on an individual real-life survey respondent, making each agent unique. The agent is linked through a small world [107] system that does not change. All decisions regarding behaviors are made on an agent level. As both 'hard' factors, such as building energy standard, retrofitting costs, and neighborhood retrofitting rate, as well as 'soft' factors, such as worry, social desirability, self-efficacy, comfort, and personality, are simulated, the data variety is high. As the agents are based on survey responses, the data horizon is historical. Although the model can simulate shorter time periods (1–2 years), it is best suited for long-term simulations and thus has a long-term model horizon (20+ years). As retrofitting decisions do not happen frequently, the model granularity is one week. Although the model can under most circumstances reach a single solution rather quickly (2.5 m), one solution is rarely enough to answer a research question the model is fit for investigating, and hundreds or thousands of simulations are usually needed. The uncertainty caused by the lack of research on the behavior is handled by sensitivity analysis. Randomness exists in the model to account for unknown factors, true randomness in behavior, or free will. The model is fully available to download at [108].

As the model reflects behavioral research regarding household energy retrofitting, its strengths lie in a valid representation of human behavior. The model agent's rules are as representative of human behavior as the research allows. Thus, the methodology of the model can be said to be its strength. Simultaneously, relying on behavioral research leaves a lot of uncertainty in the model. Firstly, "translating" psychological parameters into code is a highly subjective undertaking, as there is no way to objectively represent variables, such as expected comfort in code. Secondly, no behavioral science can explain 100% of a behavior. Therefore, random variability due to unknown factors must be included in the model, further raising the uncertainty of the model. Thus, the model's uncertainty and randomness can be seen as its weaknesses. As soon as more behavioral research emerges regarding household energy retrofitting behavior, this will improve the model and should be implemented. To alleviate these weaknesses, the simulation is run numerous times. This way, a mean effect, and distribution can be presented in the results. From there, the researcher can present the "most likely" change in energy consumption as a result of the implemented policy. Note that this distribution of results is somewhat different from "scenarios" presented in other models [109]. The distribution of results in the HERB model represents true uncertainty as a consequence of unpredictable human behavior, not variation in circumstances. In the end, models based on behavioral research trade accuracy for validity, creating inaccurate but well-founded models. If the research question the researcher is addressing allows him or her to be roughly right rather than precisely wrong, behavioral modeling can be a solid option.

3.2. Characterization of ABM for city dynamics simulation

Cities have been described as Complex Systems, where the overall behavior emerges due to the behavior of its components [77]. However, the application of ABM and particularly CAS at the city level are limited. In [81], Batty explored the emerging properties on a city scale. The CAS approach has also been applied at the regional level to understand innovation systems, the competitive environment, and how the behaviors of the agents adapt to the environmental changes [110].

The CAS is a MAS, where there are multiple types of autonomous agents that represent the different types of entities within a city and the relationships among them. Each agent makes decentralized autonomous decisions, based on very simple rules and the current state of their environment. A single agent does not process such data. However, the system itself calculates a new set of values that reflect the behavior of the whole system frequently, which makes the system computationally resource-intensive and is, thus, the main factor affecting efficiency due to the long processing time. In fact, the simulation of the behavior of each agent and their collective behavior, which represents the emergent nature of the whole system, can provide a more complete and complex view of the system at the expense of efficiency.

CitySIM model and simulations can be of benefit to several stakeholders. For example, urban designers may find it useful to experiment with such a model to determine the various elements and their locations and distributions within a physical area. A municipality or a city planner or a service provider, such as parking services or electrical charging stations, can benefit from such a model. Given the wide spectra of parameters, opportunities, and stakeholders for such a model, the focus is on the emergence arising from the interactions of the different entities and to support qualitative assessments and support decision-making. The visualizations of emergence and how the city evolves as the parameters are varied, provide a medium for discussions among stakeholder groups.

One of the main limitations of CAS and ABM models is, as with any form of modeling, the accuracy of the models and the assumptions the model is based upon. The case of CitySIM, which is our starting point for the development of a CAS model for a city has focused on the interactions among the entities to gain experience with the modeling and simulation. The models have been presented to CAS modeling experts, energy experts, and city planners who have all expressed their interest and provided positive feedback. CitySIM has paid less attention to making accurate models based on data and evidence, which will be a part of our future work. A technical challenge with CAS simulations is the computational resource demands and the time it can take to run simulations with several parameters.

3.3. Characterization of ABM for expansion planning of distributed microgrids

The model ComG is based on a math-heuristic formulation that combines a unique heuristic multi-agent approach together with an embedded mathematical optimization model based on exact methods. The embedded mathematical optimization model tackles investment decisions and operational decisions, with the latter handled through a stochastic formulation that accounts for uncertainty in demand, prices, and renewable production.

The data variety is low since only numerical data are involved. The dataset is based on predictions achieved through ARIMA-based formulations. Data are partially available upon request. The time horizon is one year, with a capital recovery factor that accounts for the forecast lifetime of each investment, and a granularity of one hour for the operational decisions. The computational time increases with the size of the problem, and with the size of the stochastic tree that directly depends on the number of scenarios included.

The combination of math-heuristic multi-agent formulations and exact mathematical optimization methods is the main strength and novelty of the CoMG model. The decision-making approach is based on microgrid communication in the form of agents. This represents a novel paradigm within energy and power systems modeling, based on peer-to-peer communication. The decentralized approach adopted by the model, the unique ABM approach, and the focus on renewable energy investment and operational decisions with stochastic approaches, make CoMG an appealing decision support tool for a variety of analyses within the ongoing energy transition towards low carbon energy systems.

Nevertheless, the CoMG approach has some weaknesses that will be improved with further research. The one-year horizon is a limitation in the context of the energy transition since multi-horizon approaches, such as those proposed in [111] could be developed and tested, in order to tackle future projections in demand development and investments of resources. In addition, the hourly granularity of the model may be improved and smaller granularity could be implemented for the operational decisions that are optimized behind the investment decisions. The partial data availability is another aspect that could be enhanced. Data could be normalized and anonymized to make them openly available and facilitate analyses for researchers involved in the energy transition. Finally, the computational time due to the use of exact methods for the optimal decisions within microgrids could represent a challenge when analyzing bigger instances, when many agents are involved, when a smaller granularity is needed, and when more complex forms of communication are implemented. Advanced decomposition techniques should be developed and tested to address such issues.

As highlighted in [11], human energy behavior is nowadays a very important trend of decision-making within the energy transition. However, it is often neglected and oversimplified when optimization-based decision support systems tools are developed. Even though some works like [11,112–114] kick-started the discussion, modeling the social and human aspects of energy transition and energy use in ways suitable for inclusion within mathematical optimization models is still a challenge and open field of research. Therefore future trends and directions for multi-agent approaches like CoMG should also consider the inclusion of human energy behavior variables to achieve more realistic modeling of the studied systems.

3.4. Characterization of ABM for electricity market simulation

Modeling complex electricity markets with a sufficient level of detail requires comprehensive and efficient simulation models. Over the course of the past decades, ABM has been deployed in an increasing number of applications and is to date among the most commonly used approaches in modeling electricity markets [115]. This development was facilitated as the behavioral level of market participants became increasingly important with the liberalization of European electricity markets [115]. Due to its explorative nature, ABM allows the reflection of non-optimal but real-world behavioral patterns of market participants when analyzing electricity markets. Notable agent-based simulation tools for analyzing one or multiple European electricity markets include AMIRIS [116], EMLab [117], and PowerACE.

Agents in PowerACE have very diverse roles, objectives, and action sets. The concrete method and (agent or system decision) level depend, among others, on the decision horizon. Price time series for fuels and carbon allowances, profiles of RE generation, demand time series, or behavioral studies in mostly hourly or daily resolution are just some of the comprehensive and varied input data of PowerACE. In addition, block-level power plant data with techno-economic parameters are further included. This input data is based on historical and scenario values that will typically be needed until 2050. PowerACE simulates annually in hourly resolution until 2050. The model efficiency, indicated by the run time, largely depends on the scenarios to be investigated and ranges between 4000 to 8000 min. The complexity of PowerACE is high and can only partially be derived by the number of agents. The complexity can only be partly derived from the number of agents since, for each large utility, there may also be different power plants whose individual hourly bids have to be determined. In addition, other technologies are aggregated but still needed for each market area. PowerACE is deterministic and only handles uncertainties by modeling different scenarios/sensitivities. The model code is currently not publicly available but is expected to be published in 2023.

The close-to-reality representation of European electricity markets and relevant stakeholders is a strength of PowerACE. In contrast to optimization models, imperfect markets and decisions can be depicted. The high level of detail combined with a large geographical scope allows the analysis of a wide range of multinational aspects with PowerACE, e.g. investment and dispatch decisions, electricity price developments, market designs, cross-border effects, or business models of the stakeholders.

PowerACE, like all other models, simplifies reality, which brings certain limitations. Particularly the representation of renewable energies in PowerACE can be improved. At present, renewable energies are aggregated in feed-in profiles and bid in the electricity market with priority at zero marginal cost. However, as the share of renewables increases, new bidding strategies are necessary to cover their investments. Introducing other bid types, e.g., linked block bids could ease the integration of flexibilities and storage facilities. Extensions that address these limitations are planned and implemented in the future.

Another major challenge is the complexity of the execution (long run times) and the interpretation of the broad results. They require a detailed understanding of the model, which can lead to incorrect conclusions without knowledge.

The future of ABM is strongly linked to the future of markets. As long as energy, and particularly electricity, is traded in markets, ABM has a justification for existence. Optimization models, however, may be easier to operate and interpret, but market rules, as well as the behavior of all participating agents, are never perfect, so adjustments must be made constantly, and impacts on the target (e.g., efficient dispatch, climate neutrality) must be investigated. One obstacle may be the complexity of models with many actors and markets, which the modeler must always take into account and make simplifications where necessary.

4. Concluding remarks

The sustainable energy transition will require changes in four investigated segments of the existing energy system — consumer engagement, city dynamics, distribution or micro-level grid structure, and the energy markets. The challenges in policymaking will expand as the characteristics of decision-making change. The 5-Ds act as a driver of this change — decentralization, distribution, decarbonization, digitalization, and democratization. To enable such a transition in the decision-making process the existing modeling tools are to be revised and new tools are to be developed.

Engaging different stakeholders at various levels is claimed to 'democratize' the energy sector. Challenges for future research can be summarized as follows.

- Different stakeholders even at the same level, can have very different preferences, and finding solutions that satisfy all, or even a majority is a difficult task, often involving compromises
- multi-stakeholder analyses should in general be conducted using multi-criteria methods in general and multi-objective optimization in particular.
- Omitting the multi-criteria element in ABM modeling will easily lead to 'segregation' effects

This work identified, described, and characterized agent-based modeling tools for a sustainable energy transition. A framework is required to characterize and compare several tools for a particular application. Note that, it is hard to develop and verify such characteristics as ABM are fine-tuned for a particular application. Therefore, such a framework to evaluate an agent based model is developed, proposed, and validated. This framework has 12 metrics to characterize an agent-based model. The proposed framework is tested by applying it to the selection of agent based models. In validation, the framework accurately and holistically elucidates — how does an agent based model perform in terms of data, method, variety, decision, efficiency, and availability? From there emerge the patterns and trends of agent-based models outlining challenges, functionalities, and a way forward.

4.1. Determinants of agent-based modeling approaches

- Traditionally analysis in the power sector is based on optimization models that focus on what solutions should be (normative).
- ABM has become a modeling approach to assess phenomena with a tight connection to behavioral and social sciences. Thereby, ABM reflects what solutions could be (explorative).
- Problems can increase in complexity, so more realistic reflections can be achieved.
- A versatile tool to assess a variety of problems from small to large-sized systems

Agent-based simulations are becoming more popular in electricity market modeling to model strategic behavior and provide additional insight, and future work should focus on reducing the complexity of such models [118] and developing suitable learning algorithms [119, 120]. The review further showed that the greatest potential contribution of ABM to energy transition studies lies in its practical application to decision-making in policy and planning. More interdisciplinary collaboration in model development is recommended to address the discrepancy between the relevance of social factors to modeling energy transitions and the ability of the social sciences to make effective use of ABM [121]. Over the years, these models have increased in size and complexity. Current ABMs can simulate thousands of individuals in realistic environments and with highly detailed internal physiology, perception, and ability to process the perceptions and make decisions based on those and their internal states. The implementation of decision-making in ABMs ranges from fairly simple to highly complex; the process of an individual deciding on action can occur through the use of logical and simple (if-then) rules to more sophisticated neural networks and genetic algorithms [122].

The investigation demonstrates that agent-based models can be an important part of the modeling suites for the energy transition. It has key advantages in terms of adaptability, representation of actors, and digitalization. It also has challenges specifically on a sub-optimal solution. The way to a holistic transition requires the engagement of actors at different levels, accelerated by digitalization, an agent-based model presents an optimal match to find a fitting solution to enable a sustainable energy transition. Moreover, a shift in decision-making strategies from a normative to an explorative approach fits well with agent-based modeling that is both explorative and reflective. While the agent-based models reviewed in this paper have a granularity of an hour or more, future research directions could aim at a finer granularity (like seconds or minutes) to better represent the system dynamics. In addition to that, multi-criteria decision-making considering stakeholders' preferences could also be studied to improve the reward functions of the agents in a multi-agent environment.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sambeet Mishra reports financial support was provided by Research Council of Norway.

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Data availability

The authors do not have permission to share data.

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