SoftwareX 30 (2025) 102176

Contents lists available at ScienceDirect

SoftwareX

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

Original software publication

ASSUME: An agent-based simulation framework for exploring electricity market dynamics with reinforcement learning

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ARTICLE INFO

Keywords:
Agent-based modeling
Electricity markets
Reinforcement learning
Python

ABSTRACT

Electricity markets are undergoing transformative changes driven by integrating renewable energy and emerging technologies, and evolving market conditions such as shifting demand patterns, regulatory reforms, and increased price volatility. To address the complexity of electricity markets and their interactions, we present ASSUME, an open-source agent-based simulation framework that incorporates multi-agent deep reinforcement learning for modeling adaptive market participants. ASSUME offers a modular architecture for representing generator and demand-side agents, bidding strategies, and diverse market configurations. ASSUME has been proven effective in multiple research studies, demonstrating its ability to analyze complex bids, demand-side flexibility, and other market scenarios. By incorporating adaptive strategies through deep reinforcement learning, ASSUME supports dynamic strategy exploration, enabling a deeper understanding of electricity market behaviors. With its flexible architecture, documentation, tutorials, and broad accessibility, ASSUME ensures usability across different user groups, minimizing technical overhead and freeing up human resources for deeper insights into operational, economic, and policy-related challenges in this critical sector.

Code metadata

Current code version	v0.5.0
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX-D-25-00011
Permanent link to Reproducible Capsule	Not available
Legal Code License	GNU Affero General Public License v3.0
Code versioning system used	git
Software code languages, tools, and services used	Python (v3.10 or higher), mango (multi-agent system), pytorch (machine learning), pyomo (optimization), pypsa (power flow calculation)
Compilation requirements, operating environments & dependencies	Python 3.10 or higher; dependencies listed in `environment.yaml` (conda) and `pyproject.toml` (pip)
If available, link to developer documentation/manual	https://assume.readthedocs.io/
Support email for questions	contact@assume-project.de

1. Motivation and significance

Electricity markets are fundamental to the reliable and efficient operation of power systems, balancing supply and demand, coordinating investments, and fostering competition. However, the increasing integration of variable renewable energy (VRE) sources and emerging technologies such as electrolyzers and large-scale battery storage introduces substantial complexity to market dynamics due to their intermittent

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https://doi.org/10.1016/j.softx.2025.102176
Received 3 January 2025; Received in revised form 14 April 2025; Accepted 23 April 2025
Available online 9 May 2025

nature and novel operational characteristics. This diversification interacts with traditional electricity markets, such as day-ahead and control reserve markets [1], shifts the importance of these markets [2], and leads to emerging platforms like flexibility markets [3]. This transformation raises important research questions concerning market design, including how large-scale storage affects market outcomes and how market structures change as zero marginal cost technologies become predominant [4].

Market design changes and policy interventions in this dynamic environment are challenging. Modifications to market clearing rules, bid formats, and market sequences introduce interdependencies that may produce unintended consequences, such as the exploitation of strategic behavior [5], market power or inefficiencies [6]. For instance, implementing capacity markets may alter resource allocation and pricing mechanisms in day-ahead markets [7]. Addressing these challenges requires tools capable of modeling market interactions, evaluating policy impacts, and guiding efficient market design.

Energy system models are essential for electricity market research and are generally categorized into optimization and simulation models [8]. Optimization models, like ELMOD [9] and PyPSA [10], focus on system objectives such as minimizing costs or maximizing social welfare. While effective for system-level analysis, their reliance on centralized optimization limits their ability to represent decentralized decision-making and emergent behaviors [11].

Simulation models, and particularly the sub-class of agent-based models (ABMs), represent electricity markets as systems of interacting agents with distinct objectives. Existing ABMs, such as AMIRIS [12] and PowerACE [13], provide insights into specific aspects but often rely on fixed, rule-based behaviors, limiting adaptability to novel market designs. Only when coupled with adaptive strategies, ABMs enable the exploration of emergent outcomes of alternative market designs, which helps policy makers deciding on suitable rules and framework conditions for the real-world market. At the same time, many existing ABMs are designed with specific applications in mind, which can constrain their flexibility and usability for broader tasks or adaptation to diverse scenarios. Enhancing these aspects would reduce barriers to wider adoption and foster a more comprehensive exploration of electricity market dynamics.

To overcome the limitations of fixed, rule-based behaviors in existing ABMs, advancements in artificial intelligence, particularly deep reinforcement learning (DRL), enable agents to adapt their behavior dynamically in response to market conditions. This approach is practical for modeling interactions among competing market participants and observing emergent patterns from these interactions.

To support market design analysis in transforming electricity systems, we developed the ASSUME framework — a flexible and modular agent-based modeling tool for electricity market research. ASSUME allows researchers to customize components like agent representations, market configurations, and bidding strategies, utilizing pre-built modules for standard operations. Integrating DRL enables modeling adaptive agent behaviors in competitive markets, which is suitable for analyzing novel market designs and emergent strategies. ASSUME is available via PyPI and GitHub and includes comprehensive documentation, tutorials, and examples, facilitating accessibility for researchers and professionals. ASSUME has been utilized in research studies addressing diverse questions in electricity market design and operation. It has explored the role of complex bids [14], demonstrated the effects of industrial demand-side flexibility for congestion management [15], and advanced the explainability of emergent strategies in learning agents [16].

Below, Section 2 presents a detailed description of ASSUME's architecture and functionality, Section 3 provides examples of its applications, Section 4 discusses the impact of the framework on the research and the goals within the energy modeling community, and Section 5 concludes with a summary and potential future research and development directions.

2. Software description

ASSUME is an open-source framework designed for agent-based simulations of electricity markets, emphasizing modularity, usability, and adaptability. It caters to a diverse audience, including researchers and industry professionals, offering tools that simplify research workflows and foster collaboration within the energy modeling community. ASSUME's modular architecture integrates seamlessly with its functionalities, enabling the implementation of interchangeable components such as bidding strategies and market configurations. This flexibility supports applications ranging from simulations of national or super-national wholesale markets at the transmission level to studies of decentralized energy systems in distribution grids. The following sections describe the primary functionalities of ASSUME and their connections to its architectural components, providing insight into how these features are structured and can be tailored to specific research needs.

The architecture of ASSUME is built around four core components: *units*, *bidding strategies*, *markets*, and an optional *learning module*, all coordinated by the central *World* class. These components interact flexibly to provide a customizable framework. Fig. 1 illustrates the interconnected structure of the given components. A compact overview of ASSUME's key functionalities is provided in Table 1.

Units

Units (on the right in Fig. 1) represent market participants, including power plants, storage systems, and demand-side entities. Each unit encapsulates technical and economic characteristics, enabling detailed modeling of operational constraints. Units are managed by *Units Operators*, which can group multiple units for portfolio optimization, reflecting real-world practices in asset management. The framework includes predefined classes for a wide range of units.

On the supply side, agents include power plants and storage units. Power plants are characterized by techno-economic parameters such as nominal capacities, ramp rates, efficiencies, and operational costs. Storage units, such as batteries and pumped hydro, are modeled with constraints like maximum charge/discharge power, efficiencies, ramp rates, and state-of-charge dynamics. These features align with models discussed in [17], which enable simulations of supply-side behavior under various market and operational conditions.

On the demand side, agents include residential households and industrial facilities. Residential units are modeled as households equipped with components such as electric vehicles, heat pumps, and photovoltaic systems. Industrial facilities include entities such as steel plants and electrolyzers, modeled with detailed process sequences and components like hydrogen storage and electric arc furnaces. These demand-side models enable comprehensive analyses of dynamic pricing effects, demand response programs [15], and the broader market impacts of diverse consumption behaviors. The modularity of these models allows users to simulate complex interactions between supply and demand in varied market scenarios.

Bidding

Bidding Strategies (next to units in Fig. 1) determine how units participate in markets. By decoupling bidding strategies from unit definitions, ASSUME allows flexible experimentation, enabling researchers to analyze strategic behaviors and assess profitability across various approaches. Portfolio optimization strategies further enhance this capability by enabling bid coordination across multiple assets.

ASSUME provides a range of pre-configured strategies, from simple rule-based methods, such as marginal cost bidding, to advanced approaches that integrate price forecasts and operational constraints [17]. Adaptive strategies that deploy DRL are specifically designed for power plants [18] and storage units [19]. DRL algorithms enable agents to

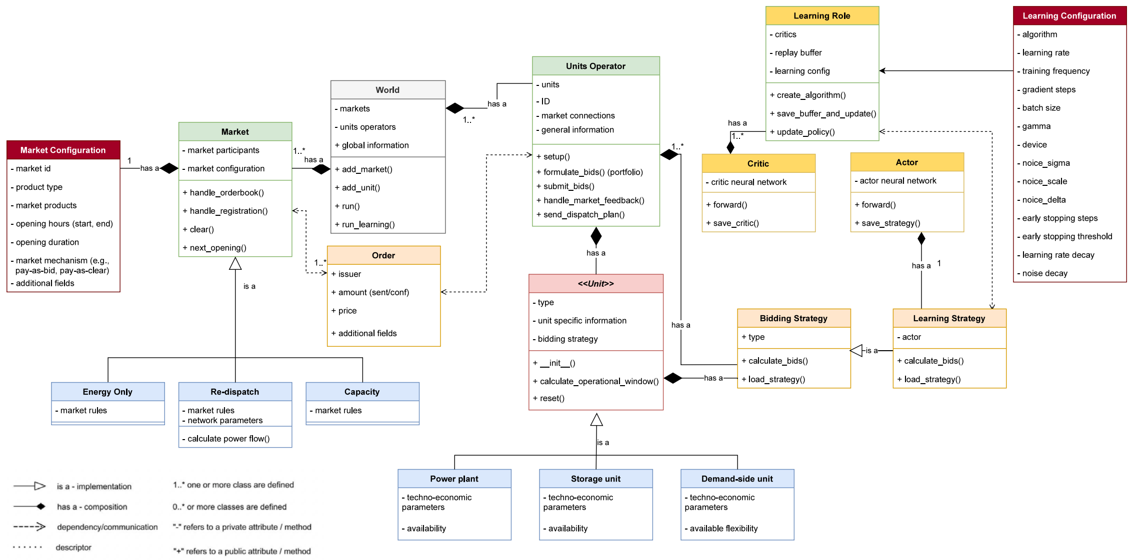

Fig. 1. An overview of the architecture of the ASSUME framework.

Table 1
Summary of ASSUME's functionalities.

	Description
Units	Predefined classes represent power plants, storage units (e.g., batteries, pumped hydro), and demand-side units, including residential households with electric vehicles, heat pumps, photovoltaic modules, and industrial units like steel plants and electrolyzers. Modular design allows custom unit configurations.
Bidding	Includes rule-based, optimization-based, and DRL-based strategies for adaptive bidding. Supports portfolio optimization for coordinating bids across multiple assets and allows custom strategies for tailored research.
Markets	Configurable parameters include opening/closing times, bidding formats, clearing mechanisms, and market design settings. Predefined algorithms: pay-as-clear, pay-as-bid, and optimization-based methods with support for zonal market coupling, complex bids (e.g., block and linked orders), nodal pricing, and re-dispatch methods for congestion management.
Learning	Integrated DRL capabilities using the MATD3 algorithm for centralized training and decentralized execution. Scales to simulations with 150+ agents. Provides pre-configured learning setups for power plants and storage units, with customization options for advanced users.
General	SQL-supported databases for simulation data, pre-configured Grafana dashboards for visualizing results (e.g., prices, trade volumes, dispatch), parallel execution, distributed simulations for scalability, and interoperability with input formats from AMIRIS, PyPSA, and custom loaders.

adjust their bids adaptively in response to market conditions. This facilitates the study of emergent behaviors and competitive dynamics. Additionally, the framework supports the development of custom strategies to suit specific research needs and objectives.

Markets

Markets (on the left in Fig. 1) represent various electricity market setups. They collect bids submitted by market participants through *Orders*, which are updated after market clearing and returned to the issuers with the relevant information such as accepted prices and volumes. Users can configure market parameters, including opening and closing times, products, bidding formats, and clearing mechanisms, aligning with the framework described in [20].

Predefined market clearing algorithms include pay-as-bid and pay-as-clear methods, as well as advanced optimization-based approaches that support zonal market coupling and complex bids, modeled after a simplified version of the EUPHEMIA algorithm [21]. The framework also supports network-coupled markets, incorporating mechanisms like nodal pricing to account for physical grid constraints and re-dispatch methods to manage transmission grid congestion. With the given features, the framework can model the entire European coupled electricity market, including zone-specific grid congestion resolution (e.g., cost-based re-dispatch) following market clearing.

Learning

The learning module (on the right in yellow in Fig. 1) enables agents to dynamically adapt their bidding strategies. It includes the *Learning Role*, which manages the learning processes, and the *Actor* and *Critic* classes. The *Actor* class connects to the bidding strategy, transforming it into an adaptable strategy, while the *Critic* class, dictated by the chosen algorithm, evaluates the quality of actions. The *Critic* may be absent in the future with the integration of additional algorithms that do not require this component. The current DRL implementation is based on the multi-agent variation of the Twin Delayed Deep Deterministic Policy Gradient (MATD3) algorithm [22], with plans to expand the range of supported algorithms. A detailed introduction to DRL and the rationale behind the choice of MATD3 in the context of ASSUME can be found in [19].

The DRL module supports centralized training with decentralized execution, allowing it to scale to simulations involving over 150 learning agents [16,18]. For users new to DRL-based modeling, ASSUME provides pre-configured *Learning Strategies* and *Learning Configurations* for power plants and storage units, offering an accessible starting point. Advanced users can customize learning setups by defining tailored reward functions, observation spaces, and action definitions. Example configurations with optimized hyper-parameters are included to further simplify the setup process. Recent developments focus on relaxing centralized assumptions, enhancing the framework's applicability and supporting increasingly complex scenarios [23].

General

The communication and scheduling foundation of ASSUME is built on the mango-agents framework [24], which supports both centralized and decentralized simulations. This design enables agents to be allocated across multiple hardware devices or cores, making the framework highly adaptable to large-scale studies and decentralized setups. It also facilitates hardware-in-the-loop experiments. For instance, a local electricity market can be simulated with households acting as units while market clearing operations are executed on separate hardware.

To enhance usability and streamline workflows, ASSUME integrates several practical tools. SQL-supported databases provide efficient storage, analysis, and post-processing capabilities for simulation outputs. Additionally, pre-configured Grafana dashboards allow users to intuitively visualize market outcomes, such as prices, trade volumes, dispatch, and agent behaviors, including submitted bids and individual profits. The framework ensures interoperability by supporting input formats from widely used models like AMIRIS [12] and PyPSA [10], while also allowing users to develop custom loaders for other formats. Comprehensive documentation, pre-configured examples, and tutorials implemented in Jupyter Notebooks further speed-up the learning curve, enabling researchers to quickly adapt the framework to their specific needs.

In summary, ASSUME offers a robust framework for simulating and analyzing electricity markets, characterized by its modular architecture and comprehensive functionalities. By incorporating pre-configured strategies and advanced DRL capabilities, the framework empowers both novice and experienced researchers to investigate market dynamics, assess policy interventions, and experiment with bidding strategies.

3. Illustrative examples

To demonstrate the practical applications of the ASSUME framework, we present two case studies that address challenges in electricity market modeling. The first case examines the application of multi-agent DRL to develop adaptive individual bidding strategies. It discusses the avalanche effect, a typical problem that can occur when several agents simultaneously try to succeed in the same environment. The second case explores the integration of demand-side units, specifically steel plants with electrified production routes, to leverage their flexibility for economic benefits and contribute to congestion management. These examples highlight the framework's ability to analyze diverse and complex scenarios in electricity markets.

Developing individual bidding strategies with MADRL

This first example demonstrates ASSUME's capability to model the development of individual agent strategies using multi-agent DRL and to analyze their subsequent impact on market dynamics. Specifically, it examines how DRL enables agents to mitigate the "avalanche effect" — a known challenge where agents employing homogeneous fixed strategies based on similar forecasts can collectively generate adverse market outcomes [25].

In the study [19] and its prior work [26], energy storage units using fixed heuristic strategies based on price forecasts were shown to alter market outcomes detrimentally, resulting in financial losses across all units. This is illustrated in Fig. 2, where the negative profits incurred by storage units under such strategies are evident for both rule-based and optimization-based agents. Multi-agent DRL was introduced as a solution to address this challenge. Using the MATD3 algorithm, agents in the market adapt their bidding behaviors dynamically in response to the evolving strategies of competitors. The results show that DRL-enabled adaptive agents, by interacting with the market environment, can mitigate the avalanche effect, develop diverse strategies, and enhance profitability compared to the centralized, least-cost unit commitment benchmark for fixed electricity demand. This advantage becomes even more pronounced when agents operate multiple storage units, as it enables them to leverage portfolio optimization strategies effectively.

While these findings were initially developed in prior studies [19], ASSUME has since integrated the described methodology into its framework. Fig. 2 highlights the superior performance of DRL-based agents compared to heuristic and optimization-based strategies, showcasing their ability to avoid collective losses and achieve profitable market participation.

Leveraging demand-side flexibility for congestion management

Demand-side management (DSM) is a strategy used by electrical utilities to regulate electricity consumption, aiming to reduce overall electricity costs or to provide flexibility to other actors in the power system. DSM strategies are considered an important source of flexibility in future electricity markets, especially for addressing grid congestion and stable system operation. Industrial units, such as steel plants transitioning to electricity- and hydrogen-based production technologies, have a significant flexibility potential.

Khanra et al. [15] modeled the participation of 24 transformed steel plants as demand-side agents in several interacting electricity markets. These units submitted demand bids to the day-ahead market using a rule-based bidding strategy, where demand was submitted as inflexible at a price of 3000 €/MWh, and flexibility was offered to the re-dispatch market at its actual operational cost, calculated as the difference between optimal and flexible operation. The study demonstrates that the additional flexibilities offered by these plants, driven by market signals, allows them to compete effectively against conventional power plants in providing re-dispatch products for transmission grid congestion management. The study found that up to 88% of the total flexibility offered by the steel plants was accepted in the re-dispatch market, generating economic benefits for the plants. It is important to note that simulation outcomes are inherently dependent on the specific input data provided by the user, including network topology, generation fleet, and demand profiles. This case study primarily serves to demonstrate the framework's capability to model complex demand-side participation in coupled market mechanisms.

The study also showed that integrating such demand-side flexibility can substantially reduce renewable generation curtailment. By leveraging flexibility from steel plants, such as in a scenario with 30% production capacity and hydrogen storage available for flexibility provision, renewable curtailment was reduced by 9.2 TWh over the year. The case study effectively demonstrates how demand-side agents not only generated individual benefits through flexibility provision but also contributed to enhancing the overall efficiency of the system.

Fig. 3 compares the flexibility contributions of steel plants (blue dots) with those of conventional power plants (red dots). This comparison underscores the complementary role of industrial demand-side agents in providing flexibility, particularly in future market designs that integrate spot and flexibility markets. ASSUME facilitates the exploration of these scenarios, empowering researchers to evaluate policy interventions and market structures that promote demand-side participation.

4. Impact

The open-source and user-oriented design of the ASSUME framework, written in Python, complemented by transparent practices such as unit tests, pull request templates, and issue tracking, promotes collaborative contributions and ensures reproducibility. Unit tests are included to verify core functionality and support users in testing their

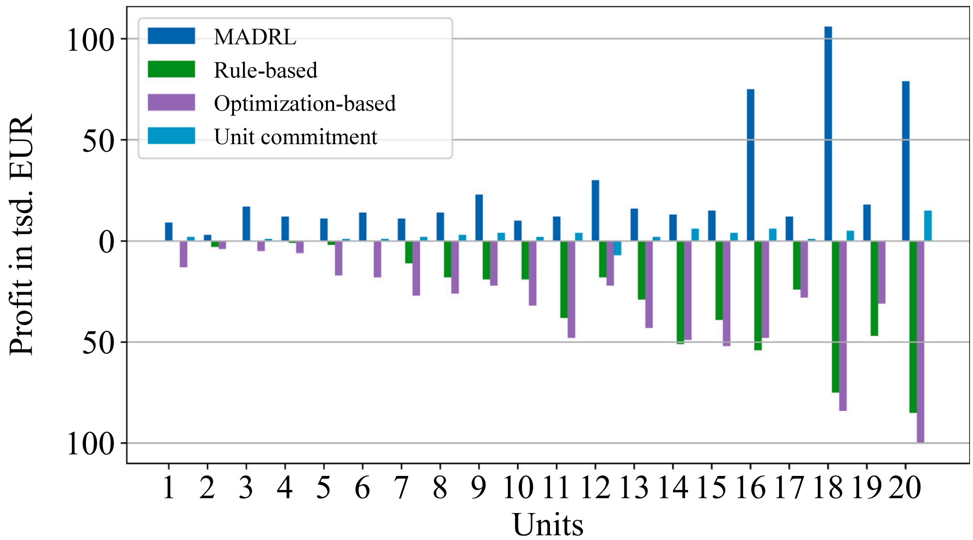

Fig. 2. Comparison of total profits for energy storage units under different bidding strategies published by [19]: multi-agent DRL, heuristic rule-based strategies, optimization-based strategies, and unit commitment models. The results highlight the superior performance of multi-agent DRL in avoiding collective losses and achieving profitable market participation.

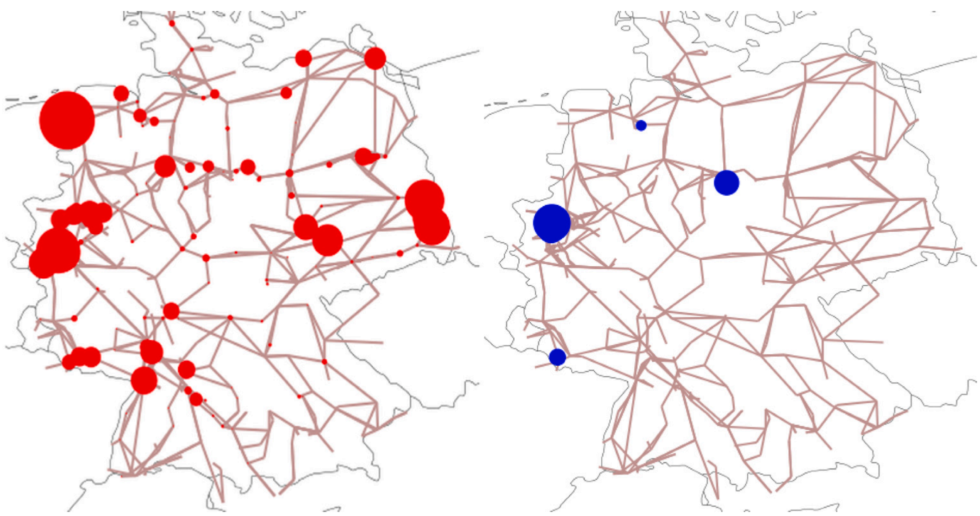

Fig. 3. Flexibility offered by supply-side units (red dots) and steel plants (blue dots) by [15]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

own modifications or new implementations; they can be executed using `pytest`, with instructions provided in the quick start guide within the documentation (https://assume.readthedocs.io/). Its independence from proprietary software and its simple input formats enhance usability and accessibility. This enables researchers to customize all provided artefacts to suit their specific research needs, without requiring them to build agent-based models from scratch. The resources offered in the ASSUME framework significantly reduce the time spent on software development, allowing users to focus on their research questions. This approach is particularly advantageous for stakeholders with limited programming expertise, as it lowers technical barriers and broadens accessibility.

In addition to the studies discussed in Section 3 and in [15,19,26], ASSUME has supported exploration of novel research questions in electricity markets. For example, [14] utilized ASSUME to investigate the impact of advanced order types, such as block and linked orders, in the day-ahead electricity market. The findings demonstrate that while these order types had limited macroeconomic impacts, they significantly influence dispatch outcomes and unit-specific profits. Linked bids, in particular, were shown to play a critical role when combined with block orders, providing valuable insights into their interplay and implications for market design.

In another study, [18] applied multi-agent DRL methods to simulate strategic bidding behaviors in energy markets. This research demonstrated the scalability of DRL-based strategies, successfully modeling up to 150 learning agents. This demonstrates the framework's ability to handle a significant number of learning agents within a research context. The study showcased the potential of DRL for diagnosing market manipulation and analyzing market liquidity, offering valuable insights into the adaptability and behavior of market participants under various conditions.

ASSUME's flexibility to represent diverse market setups was illustrated in [20], which introduced a methodology for defining market designs using unified parameters. This approach enabled the evaluation of various mechanisms, such as long-term contracts and over-the-counter trading, and was validated through case studies of pay-as-clear and pay-as-bid markets. Furthermore, the framework's reliability and accuracy were confirmed through a comparative validation study against the AMIRIS model [27], which found that both models closely matched benchmark outcomes, while ASSUME offered superior modularity.

The framework has also advanced the analysis of agent behaviors through explainable DRL methods, as shown in [16]. While DRL enables the revealing of bidding strategies found by the model rather than defined by the modeler, the need for a thorough interpretation of the learned behavior arises. This study introduced methods for making the decision-making processes of DRL-based agents interpretable, enhancing transparency in agent-based market modeling. Additionally, ASSUME has been employed to benchmark DRL strategies against bi-level optimization [28], confirming the effectiveness of DRL in complex market environments while identifying areas for future improvement. Investigating DRL convergence properties and long-term stability in multi-agent systems constitutes a significant research field in itself and is outside the scope of this software overview paper; however, specific studies applying ASSUME to explore these aspects can be found in the cited works [16,18,19,28].

Beyond its scientific contributions, ASSUME has gained recognition in the research community. Workshops at prominent conferences, such as DACH+ Energy Informatics 2023 and 2024 and Agent-Based Modeling for Energy Economics and Energy Policy 2024, have consistently attracted an average of 25 participants. These events have increased the framework's visibility and supported its adoption across various applications and regions.

Future developments will extend ASSUME's capabilities to enable DRL-based bidding across interrelated energy markets [29], further expanding its applicability. The planned research will also address systems dominated by zero marginal cost technologies and large-scale storage capacities and the role of industrial demand-side flexibility in sector-coupled energy systems. These enhancements will support the investigation of critical questions concerning the design and operation of future electricity markets.

5. Conclusions

This paper introduced the ASSUME framework, a flexible and modular tool designed to advance research in electricity market modeling and analysis. By integrating adaptive strategies using DRL and enabling detailed market configurations with network constraints, ASSUME addresses the growing complexity of electricity systems. Its design emphasizes modularity and accessibility, allowing researchers to focus on their questions while leveraging pre-built components for other modeling needs. These features make ASSUME a versatile resource for exploring challenges in electricity markets, including market design iterations, strategic agent behaviors, and integrating emerging technologies.

By promoting open-source collaboration and engaging with the research community through workshops and publications, ASSUME aims to establish itself as a self-sustained and continuously evolving framework. Its emphasis on transparency and reproducibility fosters trust and collaboration, while its adaptability to diverse scenarios ensures broad applicability. The framework is versatile enough to be employed in smaller-scale projects, such as master's theses, while also robust enough for complex doctoral research or investigations conducted by industry professionals. This accessibility and scalability make ASSUME suitable for many users, from early-career researchers to experienced professionals.

Limitations: As a research tool developed in Python, ASSUME is intended purely for research purposes for modeling, analysis, and exploring market dynamics and agent strategies, rather than for deployment in production-level, safety- or mission-critical systems. The framework does not claim formal correctness guarantees, and the stability and numerical precision of results can depend on the specific runtime environment, Python distribution, and underlying numerical libraries used. Consequently, while ASSUME provides a flexible platform for experimentation, users are responsible for selecting and validating appropriate input data, and all simulation results must be interpreted strictly within the context of that specific data and scenario configuration.

As electricity markets adapt to accommodate renewable energy, storage technologies, and sector-coupled systems, ASSUME's ongoing development will position it to address emerging challenges. Planned advancements include modeling interrelated energy markets and exploring the role of industrial demand-side flexibility and large-scale battery storage in future energy systems. With its focus on flexibility, usability, and open collaboration, ASSUME is well-equipped to support advancements in electricity market research and contribute to the design of sustainable energy systems for the future.

CRediT authorship contribution statement

Nick Harder: Writing – original draft, Software, Project administration, Methodology, Conceptualization. **Kim K. Miskiw:** Writing – review & editing, Software, Methodology, Conceptualization. **Manish Khanra:** Writing – review & editing, Software, Methodology, Conceptualization. **Florian Maurer:** Software, Methodology, Conceptualization. **Parag Patil:** Software, Methodology, Conceptualization. **Ramiz Qussous:** Supervision, Methodology, Conceptualization. **Christof Weinhardt:** Supervision, Funding acquisition, Conceptualization. **Marian Klobasa:** Supervision, Funding acquisition, Conceptualization. **Mario Ragwitz:** Supervision, Funding acquisition, Conceptualization. **Anke Weidlich:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

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

During the preparation of this work the authors used ChatGPT in order to improve the readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

Acknowledgments

This work was conducted as part of the project "ASSUME: Agent-Based Electricity Markets Simulation Toolbox", funded by the German Federal Ministry for Economic Affairs and Energy under grant number BMWK 03EI1052A. Open Access funding enabled and organized by Projekt DEAL. We extend our sincere gratitude to our colleagues who contributed to the development of the ASSUME framework, including Johanna Adams, Michael Hafner, Marie Thederan, and Andreas Eppler.

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