A Novel Agent-Based Simulation Model for Analyzing Electricity Market Dynamics

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***Abstract*— This study introduces the development of a novel agent-based simulation (ABS) model to analyze electricity market dynamics. The model integrates AI agents representing generation companies, employing machine learning to forecast the price and bidding in the market. Evolutionary algorithms will be utilized for optimized decision-making. This approach simulates market behavior under various scenarios, including renewable energy integration and diverse market structures. The model aims to provide insights into policy change and technology impacts by examining competitiveness, financial stability, and transparency. When the study is completed, key contributions will include the unique ABS model, innovative machine learning and optimization algorithms. The new model will allow in-depth analyses of market and renewable energy transitions.**

***Index Terms*-- Agent-based simulation, Electricity markets, Machine Learning, Optimization.**

I. INTRODUCTION

Empirical analysis of complex systems like electricity markets can be prohibitively expensive, logistically challenging, or infeasible. Simulation offers a powerful alternative by utilizing mathematical and logical models to represent system behavior. This approach is particularly valuable when system complexity hinders accurate theoretical predictions, enabling researchers to explore emergent dynamics and potential outcomes in a controlled environment [1]. Agent-based simulations are a computational simulation technique that includes modeling agents that can make independent decisions, are described as agents, and the environment in which they will interact [2]. Agent-based modeling (ABM) has emerged as a versatile approach across diverse disciplines, with applications ranging from marketing and electricity markets to international migration [3-5]. Notably, iterative ABM frameworks, characterized by cyclical execution of agent behaviors and interactions, are prevalent in various domains. This iterative structure facilitates the exploration of complex system dynamics arising from the cumulative effects of individual agent actions over time [6, 7]. Electricity market models often exhibit an iterative agent-based structure characterized by the progression of market activities through distinct periods or time steps. Within each period, agents representing various market participants, such as generators, consumers, and traders, engage in decision-making processes and interactions that collectively shape market outcomes. This iterative nature allows for the simulation of dynamic market behavior, capturing the evolving interplay of supply, demand, and pricing over time. A literature review [5] of 29 studies on agent-based modeling in electricity markets revealed a primary focus on generating companies, energy consumers, and customers. Generating companies were the most common agent type, often incorporating diverse energy sources, including renewables. The day-ahead market was the most prevalent market type studied. Methodologies varied, including optimization, reinforcement learning, and machine learning. This project leverages these findings, acknowledging the dominance of generating companies as agents. It allows for customizing energy companies and market structures, enabling broader analysis. Flexible class architecture facilitates the integration of various problem formulations and solution methods, enhancing adaptability and allowing the exploration of diverse research questions and policy scenarios.

II. METHODOLOGY

A typical ABM contains three components:

- Agent Set: The agents in this project will be energy generation companies with various characteristics. Their behaviors include receiving market information, calculating bids, and submitting them.
- Agent Relationships and Interaction Methods: Agents will interact with the market environment by

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This study was funded by the Scientific and Technological Research Council of Türkiye (TUBITAK) ARDEB 3501 Grant No: 222M440.

submitting bids and indirectly with each other through those market bids. This competitive interaction through the market mechanism will shape the overall dynamics of the system.

- Environment: The agents will interact within a logical environment defined by market rules, pricing mechanisms, and information flows, emphasizing economic and strategic interactions rather than physical or geographical considerations.

This study employs a web-based application developed using the clean architecture principles [8] and a layered design approach [9]. The application developed in this study also provides a practical and simple interface for users, the structure of which is given in (Fig. 1). It provides functionalities for managing resources, creating simulation drafts, monitoring simulations, and visualizing results. In this interface, a dashboard welcomes the users with all other menus. The last five simulation runs and their final status can be accessed from this interface. Django, Bootstrap HTML, JavaScript-jQuery, and Soft UI, an open-source theme component, are used to develop the interface. Simulation templates can be run many times using copies of templates after creation. Templates can be modified at any time.

The application separates data and logic layers for improved organization and maintainability. An object-relational mapping (ORM) technique facilitates interaction with the PostgreSQL 16 database. The simulation model inherits from a base model and includes attributes such as name, mode, and status. It is linked to a market model containing agents, periods, and other relevant market characteristics. The agent model represents a generation company with a defined portfolio and bidding behavior. The application logic is managed through various services, including simulation, market, and agent services.

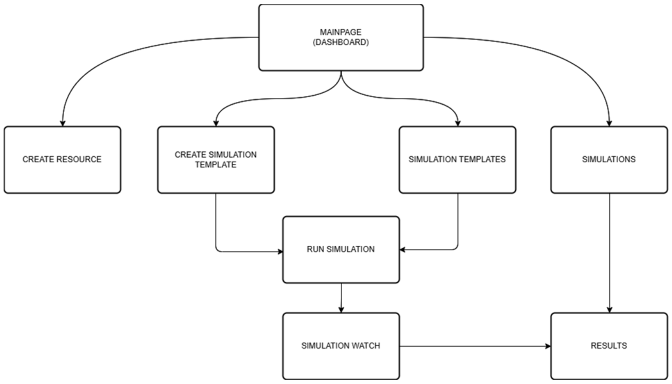

Fig. 1 Interface Structure

The simulation service handles the execution of simulation runs (Fig. 2), while the market service manages market operations and clearing mechanisms. The agent service controls agent actions, including learning, forecasting, and bidding. Simulations start with the user running a simulation draft through the interface and proceed in the flow. Simulations can be run in two different modes:

- Result-Only: The simulation flow is not interrupted, and when one period is finished, the next period is started, while the process is continuously displayed on the screen (updated every second).
- Period by Period: The simulation flow stops at the end of each period by displaying the current data of the current period and waits for the continuation request via the interface. When the continue button is clicked, the next period starts.

When a simulation is completed, apart from the database, all offers are saved in a JSON file depending on the agents and periods. Apart from the web project, a script that will analyze and visualize this JSON file has also been prepared within the scope of the study.

Market service works with the orders coming from the simulation service. Each cycle creates a new period, sends the period information, such as demand and past period information, to the agents, and accepts the bids from the agents to provide the minimum market-clearing price equally. Two different market types can be controlled through the simulation sketch:

- Pay-as-Bid (PaB): Accepted bids are paid at the bid price.
- Uniform Pricing: All accepted bids are paid at the MCP regardless of the bid price.

All agents work independently of each other in parallel processes, as shown in Fig. 3. Agents are coded by default to randomly bid between the lowest price that they will not lose in the market and the maximum price set by the user without a learning algorithm. However, it is coded modularly so that different algorithms can be easily implemented through the code.

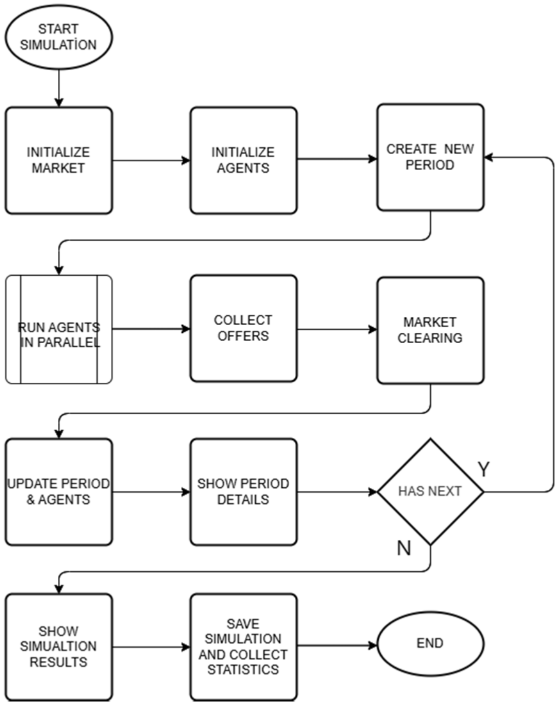

Fig. 2 Simulation Flow

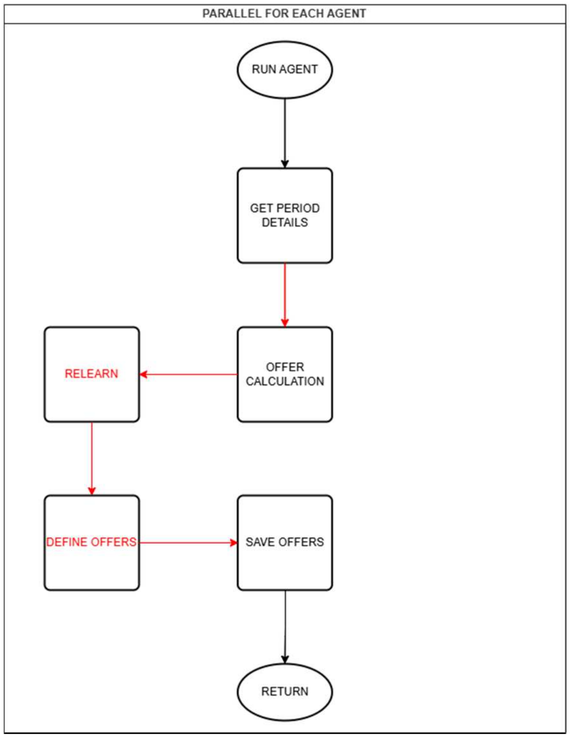

Fig. 3 Agent Flow Chart

Additionally, a simple Deep Deterministic Policy Gradient (DDPG) algorithm is implemented in the agents. DDPG is a reinforcement learning (RL) algorithm that uses actor-critical neural networks, as shown in Fig. 4, to solve continuous control problems when the action space is continuous.

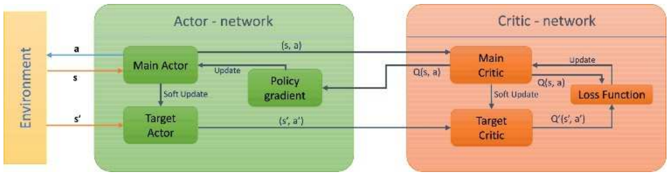

Fig. 4 DDPG Scheme [10]

In agent-based models, parallelization can offer substantial speed improvements [11]. Parallelization can be implemented through multithreading, which utilizes threads, or multiprocessing, which employs processes. While threads share common memory spaces, processes operate with their own independent memory spaces, enhancing isolation between them. This isolation can lead to performance gains, mainly when multiple threads are used within a single process. However, when these processes are completed, the changes in the child process memory are not directly transferred to the main memory and are deleted with the process. For this reason, the experiences added to the replay buffer during the learning phase and the weight changes in the neural network, that is, the learning process, remain in the child process memory. Thus, the learning process starts from scratch every period, i.e., when the processes are recreated, and no progress can be made. The structure in Fig. 5 has been implemented to ensure correct learning.

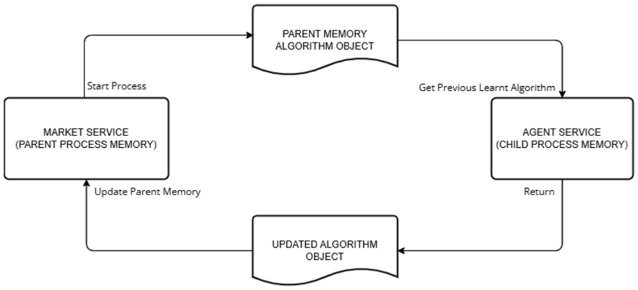

Fig. 5 Parallel DDPG Memory Structure

Thus, at the end of each period, the agents work together with the algorithm objects from the parent memory that are mapped with their ID and return the updated algorithm objects back to the parent memory to keep the parent memory up to date. In this way, progress is ensured in the learning process. Fig. 6 shows the results of an example run by the simulator using DDPG with technology-based agents with only the previous MCP as the state.

The fact that after the initial randomness, as the periods progress, the regions where the agents' bids are mainly concentrated follow the MCP line and compared to the random bids mentioned in the validation study section and shown in TABLE III indicates that the DDPG algorithm works correctly, although it needs to be improved.

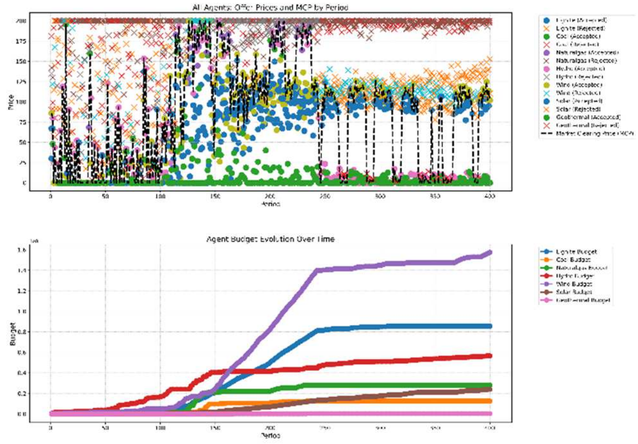

Fig. 6 DDPG Results

III. PRELIMINARY VALIDATION STUDY

This study validates the functionality and outputs of the developed preliminary agent-based modeling and simulation environment for electricity markets. A simplified test scenario was constructed and executed within the system, with the resulting data analyzed to assess the model's performance.

A. *Test Scenario*

The validation scenario comprised five agents with identical capacities but differing energy source portfolios (TABLE I). These agents utilized power plants based on the resources and associated parameters detailed in TABLE II. The simulation environment was configured with a 0-250 price limit, a pay-as-bid market mechanism, and a results-only mode. A constant demand of 1500 MWh was maintained across 48 hours. Agents employed a randomized bidding algorithm designed to prevent financial losses. The market-clearing mechanism aims to minimize market-clearing prices. This setup allowed for the evaluation of system functionality and the interplay of agent and market algorithms under stable demand conditions.

TABLE I SOURCE PARAMETERS

Source	Type	Fuel Cost $/MWh	Emissions lbs/MWh
Uranium	Nuclear	18.0	0.0
Wind	Renewable	0.0	0.0
Solar	Renewable	0.0	0.0
Hydroelectric	Renewable	0.0	0.0
Natural gas	Fossil	30.0	1130.0

TABLE II TEST CASE AGENT PARAMETERS

Agent	Budget $	Type	Plant MW	Plant MW	Capacity MW
A01	0	Nuclear	Uranium (300)	-	500
A02	0	Renew.	Wind (250)	Solar (250)	500
A03	0	Renew.	Hydroelectric (500)	-	500
A04	0	Fossil	Natural gas (300)	Natural gas (200)	500
A05	0	Hybrid	Natural gas (300)	Wind (200)	500

B. *Simulation Results and Evaluation*

The simulation run generated a market-clearing price for each period, visually represented in Fig. 7**Error! Reference source not found.**. A detailed breakdown of agent bids and their acceptance status for a sample period is shown in TABLE III.

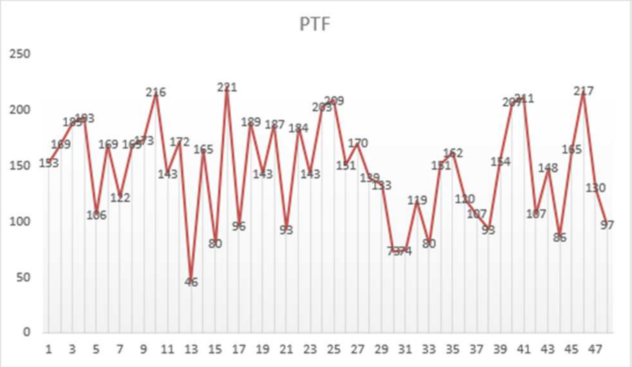

Fig. 7 MCP of Each Period

Analysis of **Error! Reference source not found.** and TABLE III confirms that the simulation model operated as expected, progressing through the defined periods. The market model and clearing algorithm effectively determined the minimum price required to meet demand in each period. Furthermore, the agent algorithm successfully generated randomized bids within the defined price limits, ensuring no agent incurred losses.

TABLE III AGENT BIDS

P	Ag.	Bid Quantity MWh	Bid Price $	Status[a]	Accepted price $	Accepted Amount MWh
1	A01	500	99.00	A	99.00	500
1	A05	200	195.00	R	-	0
1	A04	300	81.00	A	81.00	300
1	A03	500	153.00	A	153.00	250
1	A05	300	222.00	R	-	0
1	A02	250	34.00	A	34.00	250
1	A02	250	243.00	R	-	0
1	A04	200	137.00	A	137.00	200

a. A: Accepted, R: Rejected.

This validation study provides evidence that the developed agent-based modeling environment for electricity markets functions correctly and produces the anticipated outputs, supporting its use in further research and analysis.

IV. CONCLUSION

This paper presents developing and validating an agent-based simulation model for analyzing electricity market dynamics. The model incorporates AI agents representing generation companies, utilizing machine learning for price and bid forecasting. The validation study confirmed the model's accurate operation and the effectiveness of its market-clearing algorithm in determining the minimum price to meet demand. The randomized bidding algorithm successfully prevented agent losses, demonstrating the model's ability to simulate realistic market behavior. It will be available to simulate market behavior under various scenarios, providing insights into the impacts of policy changes and technological advancements. The model's flexible architecture will allow for customizing agent characteristics, market structures, and purchasing mechanisms. This adaptability will enable the exploration of diverse research questions and policy scenarios within a controlled simulation environment.

The DDPG algorithm is a simplified version. It is open for improvement and optimization. In addition, a price prediction algorithm is being developed. It will be implemented in the system for more accurate MCP forecasting, which will be used to create a better bidding strategy. Furthermore, machine learning-assisted optimization algorithms will be implemented to support agent decision-making. The ABS model will be published for open access.

ACKNOWLEDGMENT *(HEADING 5)*

This study was funded by the Scientific and Technological Research Council of Türkiye (TUBITAK) ARDEB 3501 Grant No: 222M440.

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