Agent-Based Models in Electricity Markets: A Literature Review

Priyanka Shinde, Mikael Amelin
Division of Electric Power and Energy Systems
KTH Royal Institute of Technology, Stockholm, Sweden
Email: {pvshinde, amelin}@kth.se

***Abstract*—The complexity of modeling electricity markets is increasing, due to for example increased penetration of renewable energy sources, electric vehicles and more active participation from the demand side. An analysis of a system with multiple market participants displaying certain behavior, could be difficult through an optimization problem. Due to several advantages, agent based approach can be followed to model the behavior of different market participants in the electricity markets. Lately, considerable amount of research work has been carried out on developing Agent-Based Models (ABMs) for electricity markets. This paper is aimed at providing a review of the literature on different applications of ABM in electricity markets. It is shown that ABMs have been applied to a wide range of studies of different parts of electricity trading. Some specific electricity markets modeled with ABMs have also been mentioned. According to the literature survey, the research gap is highlighted and future scope of work in this area is discussed.**

Keywords— Agent-based modeling, Electricity market, Literature review

I. Introduction

The transition from vertically integrated electricity markets to deregulated electricity markets and the initiation of market-based energy management has given rise to several decision-making agents that need to optimize their own objectives. Many electricity market models assume that all players have access to the same information and have the same objectives. Under such conditions, the market can be modelled as one or more optimisation problems [1]. However, with the increased integration of renewable energy sources, the power system is subjected to higher uncertainty. Distributed generation, increased penetration of electric vehicles (EV), seasonal variation of load are few of the reasons for variability of the electrical load in the system. These factors together are responsible for making the outcome of electricity market difficult to predict. A normal or sequential game that does not have any random variable could be modeled with game-theoritical models. However, for a dynamic model with several parameters and randomness, Agent-Based Models (ABMs) would be a better approach. ABMs refer to a category of computational models that invoke dynamic action, reaction and intercommunication protocols amongst the agents in their shared environment. These models do this for evaluating the performance of agents and also, derive insights about their emerging properties and behavior. Therefore, ABMs can model the complex issues in the electricity markets as they can model the complex behavior of the system participants including asymmetric information, different strategies etc. Also, for large systems with various system participants interacting with each other and playing different roles, the agent-based modeling is more suitable as they are capable of reproducing the behavior of real world market participants [2]–[4].

Several literature review studies on ABMs in electricity markets have been performed in the past. Reference [5] discussed the ABMs based on the learning algorithms, integration of electricity demand and grid constraints in the model and single or multiple markets considered in the ABM. In [6], four agent-based simulation packages (EMCAS, SEPIA, NEMSIM and STEMS-RT) and some ABMs for electricity markets have been discussed and compared based on their features. References [7], [8] discuss several papers based Agent-based Computational Economics (ACE) as applied to electricity markets. These two papers mostly focus on the learning methods adopted in the models and point out the shortcomings of the approaches adopted in the literature. Reference [9] discusses three ABM frameworks for electricity markets namely EMCAS, AMES and OPTIMATE. But most of the ABMs discussed in [5]–[9] were developed more than ten years ago. Reference [10] reviews some literature on ABM for future energy market modeling. In [11], ABM for smart grid related issues are discussed and to some extent those for electricity markets. However, there is a need to discuss the state-of-art on ABM for electricity market applications in recent times.

II. Basic principle of ABM

ABM works on the principle that each agent chooses its strategy based on its previous experiences with other agents and through interaction with the environment. The agents usually have local and imperfect information, which combined with their past experiences help them improve their decisions by modifying their strategies. The three basic concepts of ABM would be: 1) Agents: It could be a computer code, which can perform some tasks autonomously in a particular environment. Main features of an agent could include autonomy, reactivity, social ability and pro-activity. In electricity markets, generators, system operators, customers, regulators, and retailers could be the agents. 2) Artifacts: They are the components of the systems that are passive and are developed, shared, modified and utilized by the agents to carry out their activities in a competitive or cooperative manner. One of the example of artifacts in electricity markets could be

Table I. Comparison table for different ABM in electricity markets

Ref.	Objective	Agents	Main characteristics	Market time frame
[12]	Oligopolistic model for WPP with market power to participate in DA, intraday and balancing markets and compete with Gencos	Wind power, other GenCos.	Bilevel optimization model, incomplete information game theory	DA, Intraday, Balancing
[13]	Market power by hydropower agents	Hydro, GenCos, SO, consumers, regulator	Q learning for MIBEL (Spain, Portugal market)	DA
[14]	Study how tacit collusion (TC) can be developed through capacity withholding (CW)	GenCos	Simulated Annealing Q-learning (SAQL), energy market as repeated game	DA
[15]	Analyze market power and price formation in market with high wind power	GenCos, wind power generator	NEAT algorithm	DA
[16]	Investigate the behavior of market participants under oligopoly circumstances	Conventional generators and WPPs	Game theory, oligopolistic market	DA
[17]	Study market power exerted by GenCos in ERCOT with high level of wind power	GenCos	RL algorithm, ABM of industry actors added to PLEXOS	DA
[18]	Payment scheme to compensate EV customers for participating in the VPP	Virtual power plants, wind power generators and EV	Linear programming poblem	DA
[19]	Show how home agents converge to behavior that benefits them and grid	Smart homes	Data- and Function-based model for wind, load and price resp.	RT
[20]	Study effect of level of participation of the commercial building in DR programs	GenCo, LSE, commercial building, and ISO	Roth-Erev reinforcement learning algorithm	RT
[21]	To capture decision-making process of DR program operator in electricity market	Retailer	RL algorithm	Balancing market
[22]	To design learning approach for strategic consumers in smart electricity markets	Consumers	Weather data is used to train renewable sources and consuming devices	DA
[23]	Design an electricity market considering hydropower stations	Hydro, thermal, renewable gen, market, system operators, consumers, regulator	Bidding strategy is function of water in reservoir, learning parameter of agent,decision support tool	DA
[24]	Model the DA electricity market which emphasizes on hydropower plants	same as in [13]	Q-learning algorithm	DA
[25]	Evaluate alternatives for dealing with transmission capacity in Colombian system	GenCos, retailers, SO, TranCo	Nodal pricing for Colombian system and a market for FTR	FTR, DA, imbalance
[26]	Analyze incentives to participate in forward market and its impact on DA prices	GenCos, consumers, ISO, TransCo	Roth Erev RL algorithm, Nash-Cournot game	forward and DA
[27]	Study impact of wind forecast error and high level of wind power generation on DA market outcomes	GenCos, wind generators, retailers	Wind forecast errors	DA
[28]	ABM to help different types of GenCos to optimally bid in wholesale electricity market	GenCos	Model predictive bidding algorithm, Dynamic programming	DA
[29]	Analyze behavior of market participants in oligopoly market	Renewable power producers, EVs and other DR consumers	stochastic multi-layer ABM, incomplete information game theory, SCUC and SCED	DA and RT
[30]	Simulate frequency activated reserve market using ABM	GenCos	Genetic algorithm	RT
[31]	Two step approach to mitigate imbalances due to wind power	Aggregator agent, wind generators	ANN for forecasting, case study on Gotland, Sweden	Imbalance settlement
[32]	Develop PowerACE model for electricity and CO_2 market	Supply, renewables, auctioneer, consumer	Bottom up modeling approach	DA
[33]	To capture the interactions between electricity and emission markets	GenCos, ISO	Q-learning	DA
[34]	Compare explanatory performances of ABMs with SFE model	GenCos	Genetic algorithm	DA
[35]	Effect of price probing strategies on GenCo profit and prices	GenCos	modeled in EMCAS	DA and RT
[36]	Study effect of wind and EVs on German wholesale electricity market	UCs, wind generators, EVs	RL combined with GA	DA
[37]	ABM for German wholesale electricity market	Demand,supply	Reinforcement learning	DA
[38]	Model trading and market mechanism in UK electricity market	power exchange, SO, Bal mechanism, settlement company	Roth-Erev learning	Balancing market
[39]	Market design based on virtual reservoir for Brazil	hydropower	Reinforcement Q-learning	short-term market
[40]	Simulate behavior of GenCos in NEMS	GenCos	Reinforcement learning,PSO	DA

transmission lines. 3) Workspaces: It accommodates the agents and artifacts. It helps to define the topology of the environment and the idea of locality.

III. Applications of ABM in electricity markets

ABM has been applied to a wide range of simulation problems for electricity markets. In this section, the literature for common applications of ABM will be summarized. An overview of the studied papers is given in Table I.

A. Market power

There is abundant literature available on market power using ABMs, which is due to the fact that market power is exerted by some strategic players in the market whose behavior can be modeled using ABM. In [12], the wind power producers (WPP) were found to be capable of exercising market power. Reference [13] concluded that agents have learning capabilities and MIBEL needs accurate hydropower model. An ABM is designed in [41] to study the strategic behavior of hydropower plants. The analysis on Swiss system showed that it would be beneficial for them to act strategically however, that would not happen in practice. Several congestion management schemes have been evaluated using ABMs in [42]. Optimization models for flow-based market coupling, market splitting and locational marginal pricing have been given for multiagent system. The results obtained from ABM and Nash equilibria analysis, for studying the GenCos' behaviors in network-constraint pool market, have been compared in [43]. Reference [44] proposes an RL algorithm to work in a non-Markovian and non-stationary environment having multidimensional and continuous action and state spaces. Under high market concentration, Generation Comapies (GenCos) were found to be doing capacity withholding, and in competitive conditions, GenCos were developing tacit collusion [14]. Reference [15] pointed out the importance of the options market with regards to market power and highlighted the need for a clear set of rules for the System Operator (SO) to take decisions. Reference [16] deduced that if strategic collusion of market participants is not considered then it has adverse consequences for wind power producers in long run. Market power exerted by GenCos in ERCOT with high level of wind power was studied by [17].

B. Smart grids

Several studies deal with ABM to model different entities in smart grids especially at the distribution level. With the increase in the number of EVs and DR customers, ABMs can be a potential solution to model challenging problems in smart grids. In [18], a payment scheme has been designed to compensate EV customers for participating in the Virtual Power Plant (VPP). It has been found to be beneficial for both EV customers and wind power generators. Reference [19] shows how home agents converge to behavior that benefits them and grid. Agents decide to buy, sell or store electricity depending on their demand, generation and storage. In [20], the effect of level of participation of the commercial building in DR programs has been studied. It was seen that DR by commercial buildings reduces electricity price, cost and enables peak shaving. Reference [21] tried to capture the decision-making process of DR program operator in the electricity market. They could assess the profitability of the DR program and also quantify the DR volume. In [22], a learning approach for strategic consumers in smart electricity markets has been designed. Machine learning algorithm has been used to smarten the customers.

C. Energy Storage

Energy storage can be seen as a promising solution for contemporary issues in electricity markets. However, there are many storage technologies, but few studies using ABM have been published for each technology.

For example, a Linear programming (LP) problem for DA optimization to design a payment scheme for compensating EV customers that participate in VPP was presented in [18]. It was shown in [19] how home agents converged to a behavior that benefits them and grid. Agents decided to buy, sell or store electricity depending on their demand, generation and storage.

Another topic of interest is storage in the form of reservoirs, which was discussed in [23] and [24] in the context of MIBEL. In [23], they found that accurate model for hydropower is important in Portuguese market as they often behave as price maker. Agents learn and maximize their profit but Q learning makes it complicated for large models [24].

D. Investment decisions

ABMs are well suited to study different investment decisions in electricity markets like generation, transmission and distribution level investments. However, more work might be required to properly account for the variability and uncertainty introduced by intermittent renewable power sources.

Reference [45] proposes an ABM to allocate cost of investment amongst different players in the market based on the benefit that each player gets by setting up the new transmission line in the system. A two-stage model for players that have both short and long-term strategies was developed in [46]. With forward contracts and new entry, market power was mitigated to some extent leading to lower electricity price and more investments. In [47], an ABM has been proposed to investigate the effects of investments in distributed generation and interrupted load from the distribution company's point-of-view. The long-term impact of DR on generation adequacy (which decides need for generation investment) in an energy-only market has been addressed in [48] with the help of an ABM. This work considers only German electricity market, however, with the expansion of interconnections and European electricity market coupling, the role of cross border exchange of electricity needs to be accounted for in the model. In [49], an ABM has been proposed for generation investment decisions when a GenCo agent doesn't have information about the operational and expansion decisions of the rivals. Reference [50] evaluate investment alternatives of GenCos by considering their expectations of risk and profit. Developed tool can assess performance of Investment Portfolio by linking its experience with electricity market conditions.

IV. TIME-LINE OF ELECTRICITY TRADING USING ABMS

The electricity market is divided in several phases with different time horizons as shown in Fig. 1. ABMs are useful for modelling the interaction between trading in different market places. In this section, we will outline which markets are included in different ABMs. As can be seen in Table I most ABMs consider the Day-Ahead (DA) market. However, there are also some examples of ABMs that consider other markets.

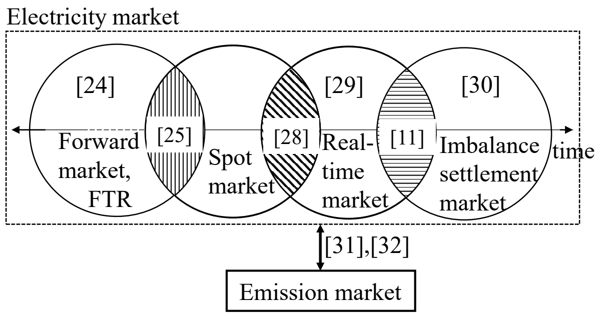

Figure 1: ABM based on electricity market time-line

A. Financial Transmission Rights

Financial trading has been studied in [25], which investigated whether a transition from unimodal market having stamp charges to a nodal market with financial Transmission Rights (FTR) would improve the system performance. The combination of nodal market with a market for FTR was found to improve signals for investment in transmission and generation assets while reducing prices in some areas.

B. Forward electricity market

An ABM has been developed in [26] to study the dynamics of two-settlement electricity market which comprises of forward and spot market. It was found that introducing a forward market provides incentives for GenCos to take part in forward contracts, which influences their bidding strategies in DA market. These incentives lower the electricity prices in DA market and also reduce the price volatility. However, this research was performed more than ten years ago and with increasing penetration of renewable energy sources this topic could be interesting to study further.

C. Day-ahead electricity market

In [27], a method is introduced to forecast wind generation and then an ABM has been proposed to study the impact of wind forecast error and high level of wind power generation on the day ahead market outcomes. The work concluded that wind power forecast errors can affect DA market outcomes and they propose moving the gate closure near to the time of delivery as a solution for this. But they do not explicitly mention if the focus should then be on intraday market or how can this solution be realized, which is an open topic of discussion. An ABM model is presented in [28] based on model predictive bidding algorithm to help generation as well as storage power plants to optimally bid in the wholesale electricity markets and hence maximize their profits. A more active participation of consumers improved the competition and market efficiency, reducing the market prices.

A stochastic multi-layer ABM has been presented in [29] to analyze the behavior of participants in the market. The first layer of the ABM comprises of renewable power producers, who aim to optimize their bidding/offering strategies. The second layer includes electric vehicle customers and other consumers who participate in DR programs.

Little literature has been found on RT and imbalance markets using ABMs which needs to be explored further.

D. Real-time electricity market

An ABM for simulating frequency activated reserve markets has been proposed in [30]. Most of the agents preferred marginal cost pricing while some showed monopolistic or oligopolistic behavior. The model can be further enhanced by adding seasonality and agent specifications.

E. Imbalance settlement market

A two-step approach has been developed in [31], for mitigating the imbalance due to integration of wind power in the grid. In the first step, an ANN based forecasting has been used for predicting wind power generation with the aim to quantify the power imbalances. An ABM is used in the second step for mitigation of power imbalances by committed flexible DERs. They conclude that by properly utilizing customer flexibility, imbalance due to wind power can be mitigated significantly.

F. Interaction between electricity and emission markets

There are examples that ABMs have been used to study the relation between the electricity market and other markets, such as emission markets. The PowerACE model has been proposed in [32], which is a bottom-up modeling approach for electricity and CO_2 markets. But there is a scope to study the effect of the European power system on the electricity and CO_2-certificate prices in Germany. In [33], an ABM is developed to capture the interactions between electricity and emission markets. It offers insights on how initial allowance influences operation of GenCos and some GenCos increase bid prices for recovering their expenses for getting additional allowances. The case study is carried out on a simple two node example using data from EEX and the results cannot be generalized. There is an opportunity to investigate this area further using ABM.

V. ABM DESIGNED FOR SPECIFIC ELECTRICITY MARKETS

ABMs have been tailored to suit different rules and regulations of the electricity markets all across the world as pointed out in Fig. 2. Few of the papers are highlighted as follows: An ABM is designed in [34], the explanatory performances of the ABM model are then compared with supply function equilibrium (SFE) model on a particular set of data of Italian power exchange. The paper [35] shows the possibility of applying ABMs to future Croatian electricity market by modeling it in EMCAS. An ABM for the German wholesale electricity market has been developed in [36]

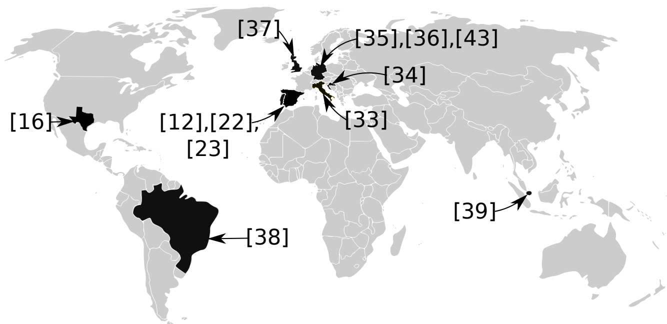

Figure 2: Real electricity markets studied in ABMs

considering its four major utility companies, wind power and 8 million PHEVs (Plug-In Hybrid Electric Vehicles). Short-term uncertainty factors such as intermittent renewable energy sources and power plant outages have been considered in the ABM designed in [37] for the German wholesale electricity market. In [38], the electricity market mechanism and trading in the UK has been modeled using ABM. A market design has been proposed in [39] which uses virtual reservoir to increase flexibility to help market participants to meet their contracts, at the same time ensure the security of supply and efficient utilization of the water. The case study has been performed on Brazilian electricity market which uses a centralized dispatch. ACE techniques are employed in [40] in order to simulate the GenCo participants' behavior in National Electricity Market of Singapore (NEMS).

VI. Future work

In this section, we highlight some possible future works using ABMs, based on our literature review. While dealing with a combined forward and spot markets model, it might be interesting to consider risk averse GenCos in the ABM. The impact of bid caps or regulatory price in DA market can also be studied in the future work of ABM. One of the possible works can be modeling SO's decision making process using an ABM. Windpower forecast errors were found to affect DA market outcomes, moving the gate closure near to the time of delivery was proposed as a solution thus indicating more future work about intraday markets. Limited work on frequency activated reserve markets was found majorly dealing with the Nordic countries and it can be interesting to see how other markets can be modeled with their frequency requirements. The interaction between electricity and emission markets using ABM has been studied on European system, while it could be promising to analyze it in other specific markets too.

VII. Conclusion

It might be difficult to analyse a system with different market participants behaving in a certain way, through an optimization problem. ABM is a useful tool for modeling such systems. This paper provides an overview of applications of ABM for simulating electricity markets. The studied papers have been classified both on the topic that they are used to study, how time is considered in the model as well as for which specific electricity market it is applied.

It is common to use ABM to study market power and investment decisions and there are many examples of such models. ABMs have also been applied to study smart grids, but mostly on distribution level. There are fewer studies that include energy storage in the ABM and considering that energy storage might be more important in future power systems, there will be a need to further study how agents should utilize energy storage. Most ABM for electricity markets are focused on the day-ahead market, but there are some examples of ABMs that also include other parts of the electricity trading, for example financial trading, real-time trading and imbalance settlement. There is probably a need to further develop the latter models. It can also be noted that very little work has been done to include intraday trading in ABMs.

Each electricity market in the world has its own specific regulations and ABMs must be tailored to model a certain electricity market. There will also be a need to develop alternative market designs in the future. It can be seen that ABMs are a useful tool in modeling the behavior of electricity market participants. Due to the several advantages of ABMs and increasing complexity in the electricity markets, ABMs will gain more popularity in this field of research.

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