Agents and Markets

MASCEM: A Multiagent System That Simulates Competitive Electricity Markets

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Around the world, the electricity industry, which has long been dominated by vertically integrated utilities, is experiencing major changes in the structure of its markets and regulations. Owing to new regulations, it’s evolving into a distributed industry in which market forces drive electricity’s price. The industry is becoming competitive; a market environment is replacing the traditional centralized-operation approach. This transformation is often called the deregulation of the electricity market.

Many electricity companies have split into several companies that specialize in energy generation, transmission, or distribution. These companies need to adopt new management approaches to survive in this market. The industry needs new software tools—such as price-based unit commitment and price-bidding tools—to support new market activities. Also, it needs new modeling approaches that simulate how electric power markets might evolve over time and how market participants might react to the changing economic, financial, and regulatory environment in which they operate.

To study electricity market behavior and evolution, we developed MASCEM, an agent-based simulator system where agents represent market entities such as generators, consumers, and market operators, and new participants such as traders. Agents can establish their own objectives and decision rules. Moreover, they can adapt their strategies as the simulation progresses on the basis of previous efforts’ success or failure. The simulator probes the effects of market rules and conditions by simulating the participants’ strategic behavior.

As a decision support tool, our simulator includes several types of negotiation mechanisms found in electricity markets to let the user test them and learn the best way to negotiate in each one. The simulator is flexible; the user completely defines the model he or she wants to simulate, including the number of agents, each agent’s type and strategies, and the market type. (See the “Related Work” sidebar for other approaches to simulation.) Electric companies as well as regulator entities can use MASCEM to analyze the impact of their potential decisions.

Market structure

An electricity market’s main objectives are to ensure the system’s secure and efficient operation and to decrease the cost of electricity through competition. Several market structure models exist that could help achieve this goal.2 The market environment typically consists of a pool, as well as a floor for bilateral contracts.

A pool, or power exchange, is a marketplace where electricity-generating companies submit production bids and their corresponding market prices, and consumer companies submit consumption bids (see the “Pool Mechanisms” sidebar). A market operator regulates the pool. The market operator uses a market-clearing tool to set the market price every hour; this results in a market-clearing price and a set of accepted production and consumption bids. In pools, an appropriate market-clearing tool is an auction mechanism—the most common being a standard uniform auction.

Bilateral contracts are negotiable agreements between sellers and buyers (or traders) about power supply and receipt. The bilateral-contract model is
Related Work

Some other approaches to agent-based simulation applications for competitive electricity markets are more targeted or limited than MASCN. PowerWeb (http://stealth.ee.cornell.edu/powerweb) considers single uniform auctions with fixed demand. The Auction Agents for the Electric Power Industry project (www.agent-builder.com/Documentation/EPRI) implements a Dutch auction, which is a specific type of auction mechanism. Sima (Simulator for Electric Power Industry Agents) studies just bilateral contracts (www.htc.honeywell.com/projects/sepia).

The works of Derek Bunn and Fernando Oliveira;1 François-Régis Monclar and Richard Quatrain;2 and James Nicolaelsen, Valentin Petrov, and Leigh Tesfatsion3 are relevant to our research in agent-based simulation; however, they discuss only the market in England and Wales. Jorge Villar and Hugh Rudnick present another important simulation application,4 focusing particularly on hydroelectric power station parameters. Javier Contreras and his colleagues present an interesting lab experience that shows the practical utility of electricity market simulators.5 The Electricity Market Complex Adaptive System (EMCAS)6 is a relevant and interesting e-laboratory for testing regulatory structures where agents have strategies based on learning and adaptation.

Overview of MASCN

Our market simulator is related to the electricity day-ahead market, with 24 negotiation periods each day. It includes these types of agents: a market facilitator, sellers, buyers, traders, a market operator, and a network operator (see Figure 1).

The market facilitator coordinates the simulated market and ensures that it functions correctly. It knows the identities of all agents in the market, regulates negotiation, and ensures the market operates according to established rules. Before entering the market, agents must first register with the market facilitator, specifying their role and services.

Sellers and buyers are the two key players in the market, so we devote special attention to them—particularly to their objectives and strategies to reach them. Sellers represent entities able to sell electricity in the market, such as generating companies holding electricity production units. Buyers represent electricity consumers and electricity distribution companies. The user completely defines the number of sellers and buyers in each scenario and must specify their intrinsic and strategic characteristics. “Intrinsic characteristics” refers to the agent’s individual knowledge related to limit price, preferred prices, and available capacity (or consumption needs if it’s a buyer). “Strategic characteristics” refers to the strategies the agent will use to reach the objective of selling the available capacity at the best price (if a seller) or buying the needed power (if a buyer). Seller agents will compete with each other because they’re all interested in selling their available capacity at the highest-possible market quote. On the other hand, seller agents will cooperate with buyer agents to establish an agreement that’s profitable for both. This is a rich domain for which it’s possible to develop and test several algorithms and negotiation mech-

References

Pool Mechanisms

In pools, the most common type of negotiation is a standard uniform auction.\textsuperscript{1,2} If only suppliers can compete in the pool, it’s called an asymmetric market. If both suppliers and buyers can compete, it’s a symmetric market (similar to a double auction in auction theory). Figure A shows both markets.

In an asymmetric market, the suppliers present their bids, and the market operator (the entity responsible for the pool’s nondiscriminatory functioning) organizes them starting with the lowest price and moving up. The consumers reveal their needs to set up the demand. Once the market operator knows the demand, it accepts the suppliers’ bids starting from the lowest and accepts as many as are necessary to fill the demand. The market price—to be paid to all accepted suppliers—is that of the last accepted bid (the one with the highest price).

In a symmetric market, suppliers and consumers both submit bids. The market operator orders the selling and demand offers: selling bids start with the lowest price and move up, and demand bids start with the highest price and move down. Then, the proposed bids form the supply and demand step curves, and the point at which both curves intersect determines the market price, paid to all accepted supplier and consumers. The bids of every supplier offering prices lower than the established market price will be accepted.

The increased competition creates opportunities for new players or agents to enter the market, such as traders. The introduction of traders promotes liberalization and competition and simplifies sellers’ and buyers’ dealings with each other and with the market operator. Traders are intermediaries between consumers and suppliers. They can act as retailers, brokers, aggregators, or marketers. Other simulators don’t include this agent type.

The network operator is specific to the application domain of electricity markets. It is responsible for the system’s security and all involved technical constraints. One network operator is present in every simulation and must be informed of every contract established—either through bilateral contracts or through the pool. It analyzes the contract’s technical viability from the power system viewpoint (for example, the feasibility of power flow to meet all needs) and manages to solve congestion situations.

The market operator manages the pool mechanism. This agent is present only in pool or hybrid market simulations. We’ll talk more about this in the next section.

The pool

The market operator starts the negotiation by sending a request for proposals at the beginning of each negotiation period. All interested agents—sellers, buyers, and traders—reply by sending bids to the pool. Then the market operator organizes the bids received, determines the market price, and determines the accepted and rejected bids. It performs bid matching according to the network operator’s technical viability analysis. After the market operator processes the bids and establishes the market price, it communicates the results to each pool participant.

Bilateral contracts

Bilateral contracts are established through requests for proposals distributed by buyers or traders—the demand agents. If a demand agent chooses to participate in the bilateral market, it will first send a request for electricity with its price expectations to all the sellers in the simulated market. In response, a seller analyzes its own capabilities, current availability, and past experience. The seller must be sure that it’s feasible to deliver energy to the buyer’s location. So, it must get the network operator’s feedback before reaching agreement with the demand agent. If the seller can make an offer to the requested parameters, it formulates a proposal and sends a message to the demand agent. The demand agent evaluates the proposals and accepts or rejects the offers. On the basis of the results from a negotiation period, sellers, buyers, and traders revise their strategies for the next period.

Hybrid market

In hybrid markets, agents must decide whether to establish a bilateral contract either before trying the pool or right after they learn pool results if their bids weren’t accepted. To make this decision, agents use past experiences and market strategies. We’ve given the details elsewhere about how the agents handle messages in the described market types.\textsuperscript{3}

Defining bids

Developing a strategic, highly profitable offer is a fundamental issue for market participants, so the policies that each agent implements must be analyzed carefully. Agents take into account their past experiences and expectations about market evolution. Sellers, buyers, and traders all have

Figure A. Two types of markets: (1) asymmetric (2) symmetric.
dynamic strategies to define the price at which they’re willing to sell or buy in each negotiation period.

These agents can also use a scenario analysis algorithm, which we describe in detail later. This algorithm offers more complex support for developing and implementing dynamic pricing strategies.

In terms of strategic behavior, sellers and demand agents (buyers or traders) have similar structures and somewhat symmetrical behavior owing to their opposite objectives. We’ll explain the strategies from a seller’s viewpoint. However, we’ll point out the differences when necessary.

Dynamic strategies

Agents use time-dependent strategies to change their price during a negotiation period. These strategies differ depending on both the point in time when the agent starts to modify the price and the amount it changes. Determined agents will maintain constant prices during the negotiation period. Anxious agents will start modifying prices early in the negotiation period by a small amount. Moderate agents will start changing prices in the middle of the period by a small amount. Gluttonous agents will start changing prices at the end of the period by a large amount.

Agents use behavior-dependent strategies to adjust their price between negotiation periods. The composed goal-directed strategy is based on two consecutive objectives—for example, selling (or buying) all the available capacity (consumption needs) and then increasing the profit (or reducing the payoff). Following this strategy, sellers will lower their price if, in the previous period, they succeeded in meeting their needs in the previous period and offer less if they already obtained some results. The following example illustrates some differences in how the two behavior-dependent strategies performed.

Consider a simple scenario with few buyers and sellers. One seller is more competitive than the others, and two sellers have similar prices. So, we can analyze the strategies’ behavior in a monopoly-like situation in periods of lower demand when only the competitive seller can sell. We can also consider how the strategies work when the market is competitive—in periods of higher demand.

The adapted derivative-following strategy obtained higher market prices than the composed goal-directed strategy (see Figure 2). After carefully analyzing the results, we conclude that when the demand is less than the most competitive seller’s available capacity, the seller will lose money when using the composed goal-directed strategy. The seller will decrease the price and try to sell more, which won’t be possible because of insufficient demand. However, the composed goal-directed strategy can be valuable, particularly to increase market share when two or more sellers are competing directly because of similar proposed prices.

It would be interesting to develop another strategy that combines the two described strategies. This way, an agent could select the most suitable strategy for each period on the basis of market conditions. For example, if a seller concludes that the demand is lower than its available capacity, it will use adapted derivative following. If it concludes that a competitor has similar prices, it will use the composed goal-directed strategy.

Scenario analysis algorithm

This algorithm is particularly suitable in pool or hybrid markets, to support not only agents’ decisions for proposing bids to the pool but also their decisions to accept or reject bilateral agreements (see Figure 3).

Agents can use the algorithm to analyze different scenarios and evaluate the expected returns. Seller and demand agents are like players in a game, and this algorithm analyzes the possible scenarios resulting from other agents’ past and likely future reactions. Then, the algorithm will apply a decision method to decide what to bid in the pool and whether to accept a bilateral contract. Every period includes the same steps, but the results of the analyses from each period update the agent’s market knowledge.

Scenarios and bid definition. Agents have historical information about the other agents in their market knowledge module. They can build a profile of other agents with the expected proposed prices, limit prices, and capacities. With this information, the agent constructs several scenarios and analyzes them to determine the best way to deal with competitors and how to bid to get a good—or the most reliable—payoff.

To get warrantable data, each agent uses techniques based on statistical analysis and knowledge discovery tools, which search historical data. Usually, after a confidential
Each market player has two prices. The *limit_price* is the minimum price if the player is a seller and maximum price if the player is a demand agent. The *expected_price* is the previewed bid price. The number of scenarios, which result from the different combinations possible considering the two prices for each agent, is $2^n$, where $n$ is the number of other agents in the model.

It’s necessary to define which bids or moves an agent or player should analyze. The agent should analyze the incomes that result from bidding its limit, desired prices, and competitive prices—those that are just slightly lower (or higher, in the demand agent’s case) than its competitors’ prices. Consider how a seller applies the algorithm. Let $j$ be the seller agent doing the analysis, $\text{cap}_j$ its available capacity, $\text{limit_price}_j$ its minimum acceptable price, and $\text{desired_price}_j$ its expected desired price. (A demand agent applies the algorithm similarly, except the limit price is a maximum price instead of a minimum and the objective is to buy all the energy it needs at the lowest price instead of to sell at the highest price.) Let $P$ denote the set of all players—sellers and demand agents—in the market. Let $\varepsilon$ be the smallest positive number allowed as a bidding increment. The bids that agent $j$ must analyze are

$$
\text{bid}(\text{limit_price}_i, \text{cap}_i) \\
\text{bid}(\text{desired_price}_i, \text{cap}_i) \\
\text{bid}(\text{limit_price}_i - \varepsilon, \text{cap}_i) \quad \forall i \in P, i \neq j, \\
\text{bid}(\text{expected_price}_i - \varepsilon, \text{cap}_i)
$$

subject to

$$\text{limit_price}_i - \varepsilon > \text{limit_price}_j$$

and

$$\text{expected_price}_i - \varepsilon > \text{limit_price}_j.$$

The number of bids to analyze is $2 \times n + 2$. This number hits the maximum when $\text{limit_price}_i$ is smaller than the other agents expected or the limit prices. We will call a bid–scenario pairing a *play*; then, the total number of plays to analyze is $\text{number_of_bids} \times \text{number_of_scenarios}$, and the maximum value it can achieve is $(2 \times n + 2)^2$.

So far we’ve considered only when agents bid their limit or expected prices. However, an agent might bid between its limit and the expected price, or even above it. So, if we say that each agent might bid $np$ prices, the number of scenarios becomes $np^n$, and the number of plays to analyze is $(np \times n + 2)^{np}$. Even in a model with few players, the number of plays can be high. For example,
if an agent is analyzing a scenario containing four other players and three different prices for each, the agent must analyze a maximum of 1,134 plays!

Furthermore, because the market is organized in several periods, an agent could increase, decrease, or maintain its bid—three possible actions—after each negotiation period, increasing the number of scenarios to analyze. So, after \( k \) periods, considering the possible bid updates, the number of plays to analyze becomes \((np \times n + 2)np^k \times 3^{k - 1}\).

Considering the same example, after three negotiation periods, an agent must analyze 7,440,174 plays, which is a huge number, even for a distributed execution of the model. However, must agents analyze every possible scenario?

Because our simulator is a decision support tool, the user should have the flexibility to decide which and how many scenarios to analyze. To do so, the user must define the scenarios to simulate by specifying the price that agents will propose:

\[
price_i = \lambda \times expected\_price_i + \phi \times limit\_price_i,
\]

where \( \lambda \) and \( \phi \) are scaling factors that can differ for each agent.

Suppose that the user selects \( \lambda = 0 \) and \( \phi = 1 \) for every seller and \( \lambda = 1 \) and \( \phi = 0 \) for every demand agent. This means he or she is interested in analyzing a pessimistic scenario (from the seller’s viewpoint). But, if the user selects \( \lambda = 1 \) and \( \phi = 0 \) for every agent, he or she is interested in analyzing the most probable scenario.

With this formula, the user can define each agent’s proposed prices for every scenario he or she wants to consider. If the user defines \( nc \) scenarios, the number of plays to analyze is \((nc \times n + 2)nc\).

After the agents analyze all the plays, the algorithm will construct a matrix, obtain the results, and apply a decision method to decide which bid to propose.

**Decision method.** The matrix analysis with the simulated plays’ results is inspired by the game theory\(^6,7\) concepts for a pure-strategy two-player game, assuming each player seeks to minimize the maximum possible loss or maximize the minimum possible gain.

A seller—like an offensive player—will try to maximize the minimum possible gain by using the MaxiMin decision method. A demand agent—like a defensive player—will select the strategy with the smallest maximum payoff by using the MiniMax decision method. In demand agents’ matrix analyses, they select only situations in which they can fulfill all their consumption needs. They avoid situations in which agents will accept reduced payoff but can’t satisfy their consumption needs completely.

After applying the decision method, the agent selects one bid that it will propose on the pool, unless it reaches an agreement for a bilateral contract that’s more profitable than the previe\(\overline{\text{d}}\) pool results.

This analysis not only provides the agent with decision support about the bid to propose in a pool but also helps improve the negotiation mechanism for establishing bilateral contracts. With this information, the agent can evaluate a bilateral contract’s potential benefits, compare them to the benefits expected in a pool, and make counterproposals.

**Scenario actualization.** As we stated earlier, the analysis of each period’s results will update the agent’s market knowledge and the scenarios to study.

After each negotiation period, instead of considering how other agents might increase, decrease, or maintain their bid, agents use knowledge rules that restrict modifications on the basis of other agents’ expected behavior. The following are some sample rules to update sellers’ behavior:

- If a demand agent bid is lower than the market price and lower than its limit price, the agent will increase its bid.
- If a demand agent bid is lower than the market price and equal to its limit price, the agent will maintain its bid.

Because a demand agent probably won’t decrease its bid if it couldn’t buy in the previous period, if it couldn’t buy but is already bidding its limit price, it will most likely keep its bid at the limit price.

The knowledge rules update agents’ bids in each scenario, but the number of scenarios remains the same.

If at the end of a negotiation period the agent concludes—by analyzing market results—that it incorrectly evaluated other agents’ behavior, it will fix other agents’ profiles on the basis of the calculated deviation from the real results.

**Implementation.**

We developed MASCEM in the Open Agent Architecture (www.ai.sri.com/~oaa) and Java. OAA, developed at SRI International, is a framework for integrating a community of heterogeneous software agents in a distributed environment. OAA is structured to minimize the effort of creating new agents written in various languages and operating platforms, to encourage the reuse of existing agents, and to allow the creation of dynamic, flexible agent communities.

The OAA’s Interagent Communication Language is the interface and communication language that all agents share, no matter which machine they run on or language they’re programmed in. Because the OAA framework isn’t specifically devoted to developing simulations, we made it suitable by extensions—for example, we included a clock to introduce the simulation’s time evolution mechanism.

We implemented each agent in Java as a Java thread. The model can be distributed over a computer network, which makes it easier to increase the number of simulation runs for scenarios with many agents.

Figure 4 shows the prototype interface for a simple scenario with three seller agents, two buyer agents, and a trader.
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ecause of the growing number of entities and the redefined rules in newly competitive electricity markets, MASCEM seems to be a valuable framework for studying market evolution. The multiagent technology allied to an object-oriented implementation enables easy future improvements and model enlargement. This is important, considering markets are still very much in the evolutionary process.

Market participants’ strategic behavior is very significant in the context of competition. Although we implemented some valuable, promising strategies, we must enlarge the portfolio of agents’ strategies and behaviors. For example, we’ll implement and test strategies based on learning algorithms, such as Q-learning.

Developing targeted studies to analyze specific markets, such as the emerging market between Portugal and Spain known as the Iberian Market, will also be an important step toward validating the profitability of using tools such as MASCEM.

References
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