Multilevel Negotiation in Smart Grids for VPP Management of Distributed Resources

Hugo Morais, Tiago Pinto, Zita Vale, and Isabel Praça

A multilevel negotiation mechanism for operating smart grids and negotiating in electricity markets considers the advantages of virtual power player management.

The increasing shortage of fossil fuels and their consequent increase in price, along with the environmental concerns associated with these types of fuel, have led to a direct increase in the use of renewable energy resources. From an environmental viewpoint, using such resources has clear advantages and presents a favorable scenario for growth in the distributed generation (DG) of electrical energy. However, before we can take advantage of this growth, we must consider economic and technical issues such as dispatch ability (namely, in wind and photovoltaic technologies), the participation of small producers in the market, and high maintenance costs.[1]

Aggregating strategies can help owners of renewable generation gain technical and commercial advantages, achieve higher profits by mixing several generation technologies, and overcome some technologies' serious disadvantages. The aggregation of DG plants gives rise to a new concept: multitechnology and multisite heterogeneous entities called *virtual power players*. VPP producers can ensure that their generators are optimally operated. At the same time, VPPs can commit to a more robust generation profile, raising the value of nondispatchable generation technologies.[2]

One way to realize DG's emerging potential is to take an approach that views generation and associated loads as a subsystem. This could let owners of renewable energy sources implement them on a large scale to limit green house gas emissions. Moreover, this approach could reduce transmission power losses and delay or even prevent the construction of new energy infrastructures. Coordinating all these generating and loading units is a challenging issue that requires distributed intelligence to cope with the smart grid concept.[3]

Simulation and artificial intelligence techniques could be very helpful under this context. With this aim, we use the Multiagent Simulator of Competitive Electricity Markets (MASCEM),[4] a modeling and simulation tool for studying the operation of complex restructured electricity markets. Other modeling tools directed to the study of restructured wholesale power markets have emerged in the past few years, including Agent-Based Modeling of Electricity Systems (AMES)[5] and the Electricity Market Complex Adaptive System (EMCAS).[6] MASCEM, however, can simulate both VPPs

and smart grid operation. To exploit this ability, we propose a multilevel negotiation mechanism for the optimal operation and negotiation of smart grids in the electricity market. We tested our negotiation methodology using real data from the Iberian market. However, we can also apply it to other markets, such as US wholesale markets, using MASCEM's model of the California Independent System Operator (CAISO).[7]

MASCEM Overview

MASCEM simulates market players such as buyers, sellers, and VPPs, each of which has its own decision-support resources, and lets players define their offers and strategies to gain competitive advantage.

Market players are complex, independent entities with different purposes, objectives, and behaviors who make decisions while interacting with each other. As a multiagent-based simulator, MASCEM modulates the complexity of dynamic market players, their interactions, and medium- and long-term information gathering (data and experience in the market).

Multiagent Model

MASCEM includes the following agents: market operator, system operator, market facilitator, buyers, sellers, VPPs, and VPP facilitators.

The market operator agent validates and analyzes the received bids from buyer and seller agents in pool market simulations. It then determines the market price and the accepted and refused bids.

The system operator agent ensures that all conditions are met within the system and is responsible for system security. After being informed of all ongoing negotiations, the system operator agent examines the technical feasibility from the power system's viewpoint and solves congestion problems that might arise. In fact, this agent connects with a power system simulator[8] through which the system operator can perform power-flow analysis.

The market facilitator agent coordinates and ensures proper market operation, regulating all communications. All the market players register with the facilitator in advance, specifying their roles and services.

Buyer and seller agents are the market's key elements. Buyer agents represent consumers and distribution companies, whereas seller agents represent electricity producers. Seller agents compete with each other to maximize their profits. However, they might also cooperate with buyers to establish agreements that meet both parties' objectives. For each scenario, users define the number of buyers and sellers, as well as their intrinsic and strategic characteristics.

A significant increase in small, independent producers negotiating in the market increases the need for coalitions that will let these small producers compete on equal footing with big producers. The VPP agents represent these alliances. They manage their aggregates' information and are viewed in the market as seller agents. Each VPP is modeled as an independent multiagent system that maintains high performance and lets agents be installed on separate machines. To achieve this independence, we created individual VPP facilitators[9] to manage the communications between VPPs and their members independently from the rest of the simulation.

Simulated Markets

MASCEM lets users simulate several market models: day-ahead pool, bilateral contracts, complex market, and balancing market. It also allows hybrid simulations that consist of combinations of these four market models.

In the day-ahead pool, negotiations occur daily with regard to each hour of the following day. Players submit their bids in turn, and the market operator then organizes all the bids and applies a symmetric or asymmetric algorithm to find the market price. Successful proposals are sent to the system operator for technical validation; the market operator then uses these results to communicate to the respective agents whether their bids were accepted or rejected.

In bilateral contracts, buyer and seller agents can negotiate with each other directly to find proposals that are advantageous for both. After a contract negotiation concludes and both parties accept it, the contract is communicated to the system operator for technical approval before the deal can be closed. Bilateral contracts can be established for one negotiation period or for longer time periods. Buyer and seller agents can negotiate proposals at any time during the day.

The complex market allows for restrictions that let players leave the market if those conditions aren't respected (see www.omel.es)—that is, players aren't interested in participating unless the conditions are respected. Market agents also use complex conditions as strategies for achieving the highest profits.

In contrast with the day-ahead pool, the balancing market lets players negotiate for the present day.[10] Players can adjust the production and consumption needs that they didn't manage to fulfill in the day-ahead pool, and fluctuations can occur in the requirements, such as production forecasts that proved to be inadequate. By comparing the predicted prices for the balancing market and the day-ahead market, players

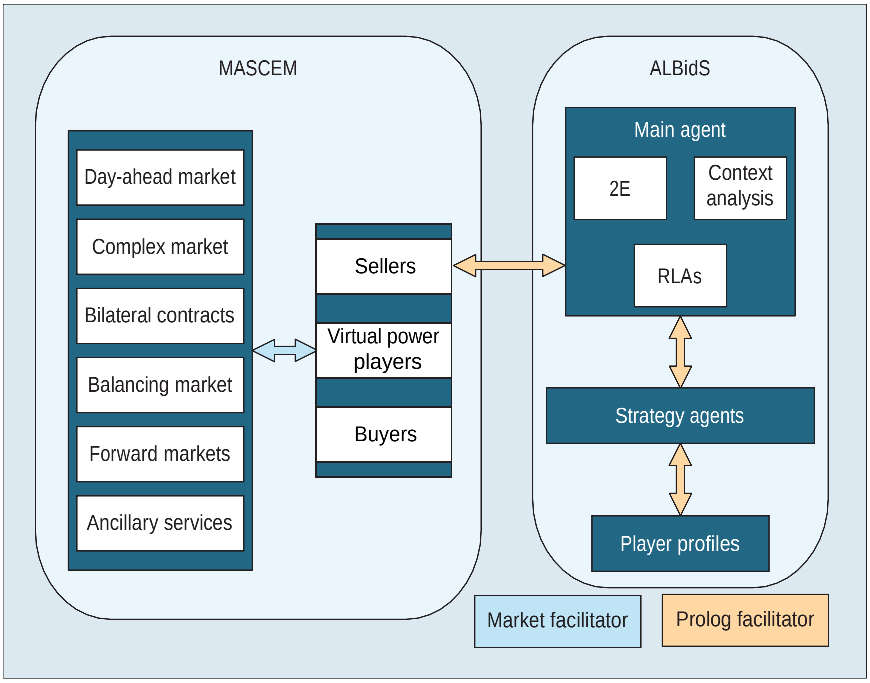

Figure 1. ALBidS integration with MASCEM. The ALBidS multiagent system gives agents the capability to analyze the context of their negotiations, using variables such as weather conditions and the day of the week.

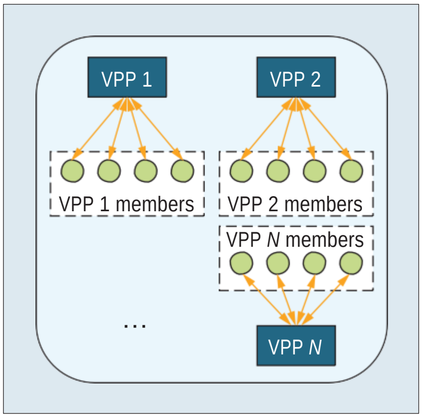

Figure 2. First level of negotiation. Here, an internal negotiation occurs between each virtual power player (VPP) and its aggregated members.

can choose to strategically invest more in one or the other. They can even send unrealistic proposals, such as offering to provide more power than they're capable of in the day-ahead market. They might then buy the extra value in the balancing market if they're expecting the practiced price to be more favorable—that is, if the expected balancing market price is more favorable than the spot market price.

The hybrid model combines features from several of the previous models. Simulating this type of model lets agents strategically decide their best negotiation options. To this end, they examine their history and strategies. Although they might be obligated to enter the pool, they can always choose to establish a bilateral contract for a certain amount of power or enter other markets if they find this to be a good business opportunity.

Strategic behavior

Based on previously obtained results, buyer and seller agents review their strategies for future transactions. Each agent's strategic behavior defines its desired price and the amount of power to be negotiated in each market.

Recently, we integrated a new multiagent system with MASCEM called the Adaptive Learning Strategic Bidding System (ALBidS),[11] which lets agents analyze the context of their negotiations, such as the weekday, the period of the day, the particular market in which the player is negotiating, the economic situation, and weather conditions. Players can thus automatically adapt their strategic behavior according to their current situation. For this, ALBidS uses reinforcement learning algorithms[12] and the Bayes theorem[13] to choose the most adequate from several techniques according to each context. Techniques include neural networks,[14] data mining techniques,[12] statistical approaches, machine learning algorithms,[15] game theory[16] for scenario analysis, the prediction of competitor players' actions, and approaches based on strategies other simulators use for market analysis and cost forecasts.[5] Figure 1 presents MASCEM's structure integrated with ALBidS.

The distributed intelligence of ALBidS lets players perform different strategies in parallel, allowing them to take advantage of them all.

Multilevel Negotiation Mechanism

The proposed negotiation mechanism provides the tools for coordinating all the generating and loading units in a smart grid. Moreover, while managing such coordination, our negotiation mechanism must provide the best possible results for the involved players, taking advantage of the concepts and particularities of both smart grids and VPPs.

This mechanism considers three distinct negotiation levels.

First Negotiation Level

The first level is characterized by an internal negotiation between each VPP and its aggregated members. It considers the forecasted generation of all the producers and their expected transaction prices (see Figure 2).

VPPs manage the aggregated players' resources (distributed generation, demand response, and storage systems). The VPPs have two major goals: minimize the operation costs while supplying all possible loads and enforce the established contracts with the aggregated players (producers and consumers). In the developed methodology, we consider all relevant aspects—namely, power losses that result from the AC power flow as well as network congestion resulting from the limits of thermal lines and the bus voltage. We obtain the first-level result using a mixed-integer nonlinear programming problem.[17] The objective function represents each VPP's operation cost; we can represent this in a simplified way as

$$\text{Minimize } f = \text{Min}\sum_{t=1}^{T}\left[\begin{array}{l}\sum_{G=1}^{Ng} P_{\mathrm{Gen}(G,t)} \times c_{\mathrm{Gen}(G,t)} \\ +\sum_{S=1}^{Ns} P_{\mathrm{St}(S,t)} \times c_{\mathrm{St}(S,t)} \\ +\sum_{L=1}^{Nl} P_{\mathrm{DR}(L,t)} \times c_{\mathrm{DR}(L,t)}\end{array}\right] \quad (1)$$

$$\forall t \in \{1,\ldots,T\},$$

where G refers to the generation units, S to the storage systems, and L to the loads. P_{Gen}, P_{St}, and P_{DR} are the power of each generator, storage, and load demand response program, respectively; c_{Gen}, c_{St}, and c_{DR} are the costs of each resource in period t. Finally, Ng, Ns, and Nl represent the number of generators, storage systems, and loads, respectively. We implemented this problem in GAMS software.[18]

Second Negotiation Level

The second level aims to adjust any generation and consumption needs that weren't fulfilled inside the VPP. Players can search for deals by negotiating with neighbor control areas that different VPPs manage. Figure 3 presents the second-level negotiation structure.

Each player analyzes the market using the ALBidS system to obtain an expected value for the next market session. This value acts as a reference for analyzing possible deals that they might negotiate during this level.

If neighbors' proposals are more favorable than the expected market prices, players can choose to buy or sell some energy from them, obtaining better deals than they would have if they negotiated the entire amount in the market. If the offered proposals are worse than the expected market prices, players can always refuse them and negotiate exclusively in the market.

Besides this strategic analysis, players can use negotiation techniques to try to obtain the best deals with their neighbors. For this, we use several personality-based strategies for agent behavior in the negotiations:

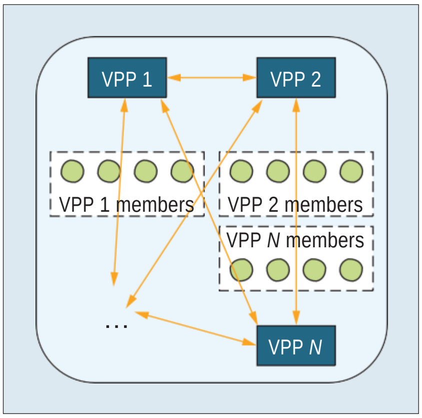

Figure 3. Second level of negotiation. Here, players can adjust any generation and consumption needs that weren't fulfilled inside the virtual power player (VPP).

- *determined*—prices remain constant throughout the negotiation period;
- *anxious*—large changes to the price occur after a short trading time;
- *moderated*—small changes to the price occur in an intermediate stage of the negotiation period; and
- *gluttonous*—the price changes significantly, but only in late trading.

These strategies let players try different approaches when negotiating with their neighbors. They can then use the approach most suitable to obtaining the highest possible profit.

Third Negotiation Level

The third level is the actual market negotiation in which players submit their bids to the market. Players use the market to sell or buy the energy that they couldn't negotiate at better prices in the previous two levels. Figure 4 presents the negotiation structure for this level.

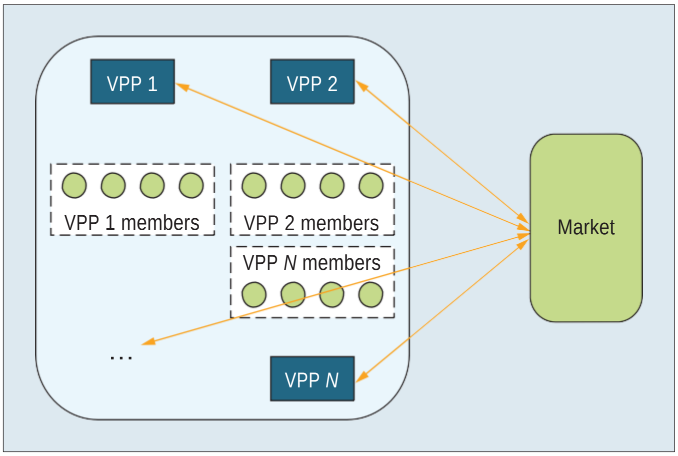

Figure 4. Third level of negotiation. Here, players submit their bids to the market, using it to buy or sell the energy they couldn't negotiate at better prices in the previous two levels.

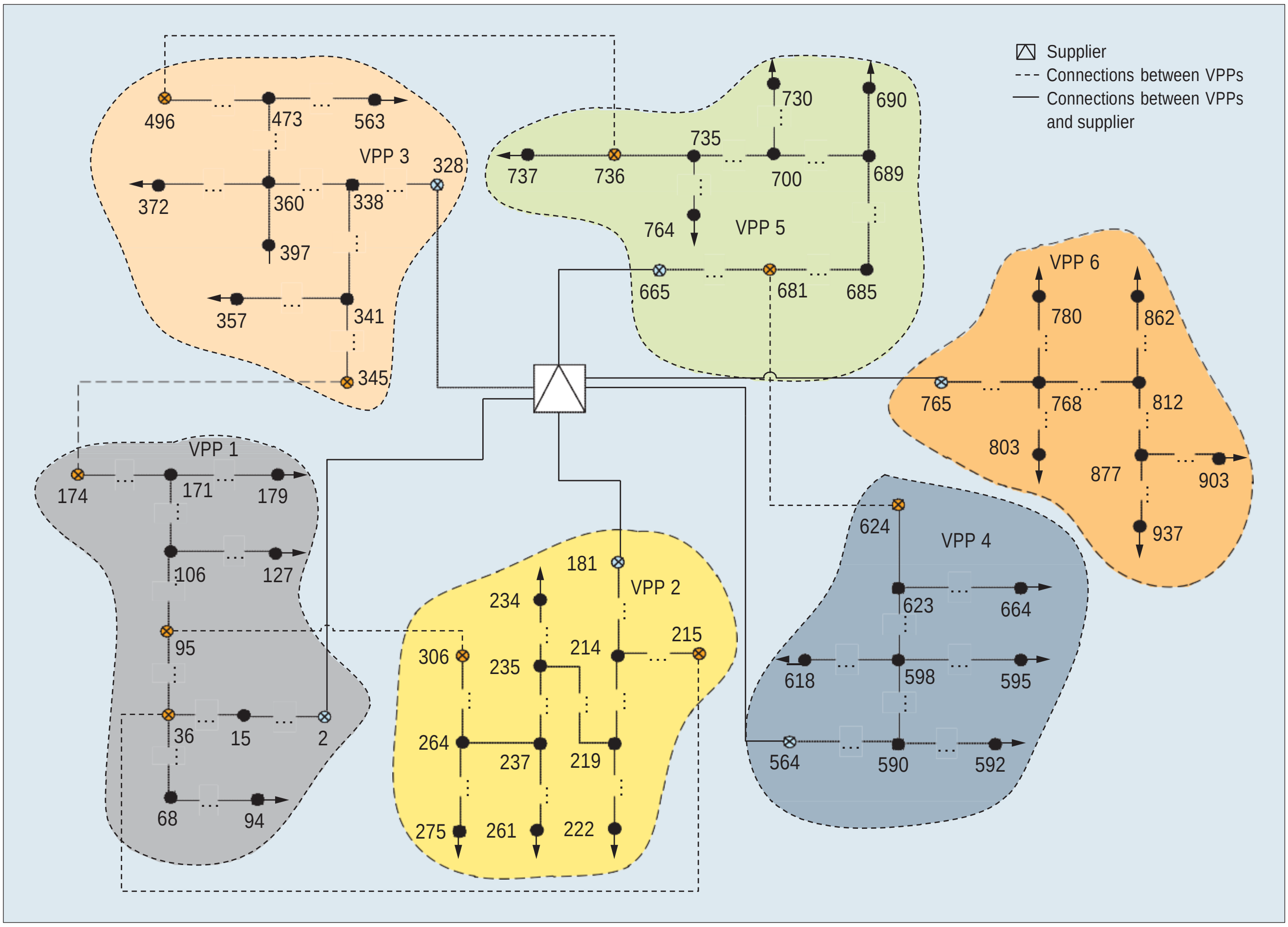

Figure 5. Smart grid with six control areas. Each area is managed by a different virtual power player (VPP).

After submitting their bids, players wait for the market operator to determine the market price for each period and respective traded energy amounts, according to the conjugation of all participating entities' proposals.

Case Study

To simulate the best negotiation procedure for the elements of a smart grid, we used our proposed multilevel mechanism in the following case study. The smart grid we considered includes six neighbor control areas managed by six different VPPs.

In the first level, VPPs manage their internal resources, balancing the production and consumption of the aggregated players. After this, some VPPs will have spare energy to sell, whereas others will have buying requirements. The main goal is for the VPPs to be able to sell or buy the required energy amounts at the best possible prices, using the proposed methodologies and technologies and taking advantage of the characteristics and possibilities that each negotiation level offers.

Figure 5 presents the considered 30 kV real distribution network, supplied by one high-voltage substation (60/30 kV) with 90 MVA of maximum power capacity distributed by six feeders, and a total of 937 buses and 464 medium voltage/low voltage (MV/LV) power transformers.

This distribution network has already been in use for many years and has undergone many reformulations. It consists of partly aluminum and partly copper conductors, and the distribution is made via power lines and underground cables.

To adapt the network to a future scenario, we needed to determine the DG evolution and storage system penetration (our case study considers evolution to the year 2040). We conducted our DG penetration evolution studies based on two prior studies,[19, 20] and determined the generation prices of the kilowatt-hour by generation type using another study.[21] We considered one aggregated MV load for each MV/LV transformer. The results of the referred studies led to 548 DG units, 31 storage systems, and 464 aggregated loads.

As Figure 5 shows, all VPPs present at least one connection point with all

Table 1. Amounts of power each virtual power player (VPP) negotiated (in MWh).

Period	VPP 1	VPP 2	VPP 3	VPP 4	VPP 5	VPP 6
1	12.5875*	1.9387	–3.8696	–4.8605	–1.4596	–4.3691
2	11.2365	1.6494	–3.0919	–4.3024	–1.2016	–3.9172
3	11.6310	1.3166	–2.8417	–3.9756	–1.0607	–3.5721
4	12.0695	1.2840	–2.7023	–3.8394	–0.9708	–3.7096
5	13.0434	1.2323	–2.6099	–3.8273	–0.9379	–3.4871
6	12.4151	1.4074	–3.1670	–4.0545	–1.1719	–3.6043
7	10.9888	1.6418	–3.2935	–4.2397	–1.1952	–3.8411
8	9.5504	–1.8410	–4.6569	–5.5706	–1.8182	–5.2356
9	3.0440	–0.6700	–6.4680	–7.3419	–2.7126	–6.6894
10	2.1869	0.6723	–7.2435	–8.1063	–2.9900	–7.4064
11	1.9028	1.4204	–7.5715	–8.5576	–3.1134	–7.8132
12	1.8501	1.5837	–7.7908	–8.6375	–2.9892	–7.7559
13	2.7979	1.0852	–7.2215	–7.8766	–2.8726	–7.1852
14	3.4551	–1.0000	–7.0957	–7.9733	–2.6846	–7.2279
15	3.1241	–5.9700	–7.0556	–7.8067	–2.7044	–7.1205
16	4.4112	–4.2300	–6.9027	–7.7041	–2.6898	–6.9616
17	4.7785	–2.6500	–6.7210	–7.6869	–2.5427	–6.8395
18	6.5212	–2.2800	–6.5514	–7.3733	–2.5673	–6.4853
19	5.0310	–1.4800	–6.6116	–7.5952	–2.6945	–6.8649
20	7.6735	0.4697	–6.7707	–7.8590	–2.7648	–7.0107
21	8.2638	4.0432	–6.6527	–7.8308	–2.5467	–6.8012
22	7.9851	3.7961	–6.1998	–7.3210	–2.3296	–6.3635
23	8.9664	3.1163	–5.3646	–6.5357	–1.9460	–5.6286
24	10.2039	2.3282	–4.4527	–5.6386	–1.5008	–4.7466

*Positive values indicate the amounts of energy available for sale, whereas negative values represent the amount each VPP needs to buy.

substations—that is, all VPPs can negotiate and transact with any of the other substations.

First-Level Negotiation

Table 1 shows the results of energy resource management in our case study. The positive values indicate the amounts of energy available for sale, whereas negative values represent the amount each VPP needs to buy.

In this level, only VPP 1 supplies all the load demand and has remaining energy capacity to sell in the neighbor control area negotiation level. VPP 3, VPP 4, VPP 5, and VPP 6 don't have enough resources to supply all the load demand and must buy energy during subsequent negotiation levels. VPP 2 must buy at some periods (8, 9, and 14–19), while in others it has excess energy capacity it can sell.

Second-Level Negotiation

In this level, the VPPs negotiate among themselves, trying to establish profitable contracts to avoid entering the market. Each VPP is attributed a strategic behavior randomly, according to the aforementioned specifications. VPP 1 and VPP 6 are determined, VPP 2 is anxious, VPP 3 is moderated, and VPP 4 and VPP 5 are gluttonous. Figure 6 presents the results from VPP 1 and VPP 2 after this negotiation.

As Figure 6 shows, VPP 2 sold all its available energy during this level at a price higher than the expected market price. VPP 1 also sold all of its energy, except for a small amount during period 5. The other VPPs, which had to buy energy, will still need to enter the electricity market despite having bought during this level to purchase the lacking amounts. Table 2 presents the amounts of power that each VPP must buy or sell in the market after the first two levels of negotiation.

From Table 2, we can see that the only positive value is for VPP 1 during period 5—the value this VPP couldn't sell in level 2. The other

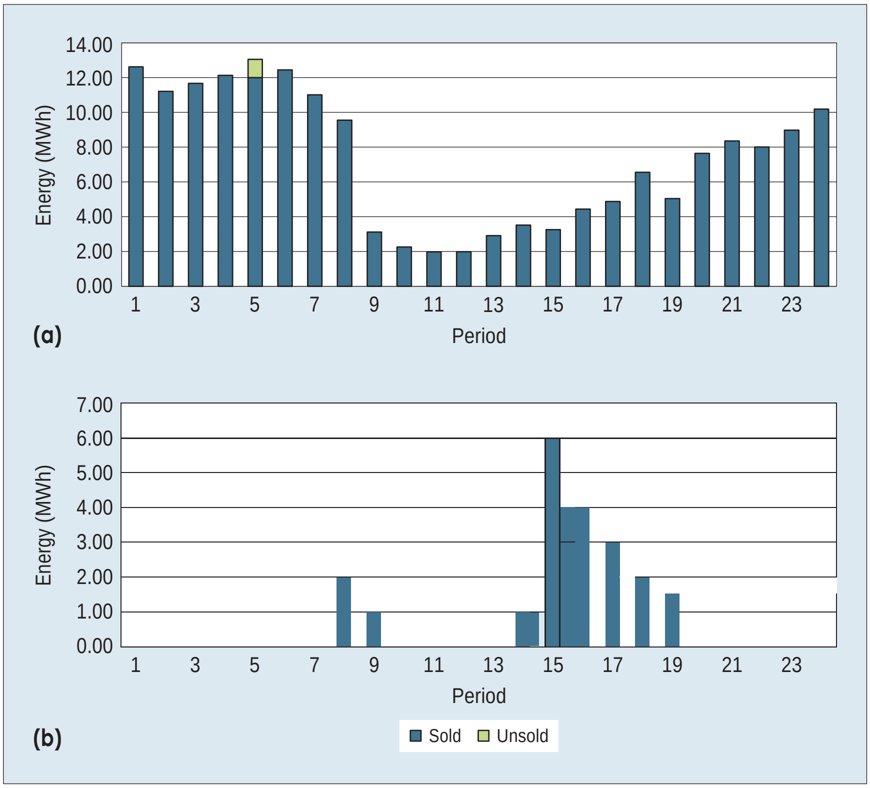

Figure 6. The second level of negotiations in our case study. We can see the results from (a) virtual power player (VPP) 1 and (b) VPP 2.

VPPs must all enter market negotiations to buy their respective power amounts.

Third-Level Negotiations

For this simulation, we considered a group of seller and buyer players that represent real-world Spain, reduced to a smaller, summarized group containing the essential aspects of different parts of the market to let us better analyze and study each actor's interactions and potentiality. The data we used in this simulation is based on real data from the Iberian market extracted from the Iberian Energy Market Operator (OMEL; www.omel.es). The data refers to Wednesday, 29 October 2008.

Figure 7 presents the results from VPP 3 and VPP 4 at the end of the day. Both VPPs use ALBidS for decision support of their actions in the market. The influence and impact of using ALBidS and the related strategies and tools is explained more clearly in our previous work.[11]

All VPPs were able to buy the required energy amounts in the market. The examples in Figure 7 show that VPP 3 and 4 bought energy both in the second- and third-level negotiations, depending on the deals they achieved.

Using multiagent technology to model players and their interactions lets us analyze the negotiation processes, which are based on different methodologies depending on each negotiation level's particularities. The optimization approach for resource management in the first level; modeling of direct negotiations between players and the attribution of different personalities for players in the second level; and the artificial intelligence and adaptive learning methodologies for market negotiation at the third level have proven themselves effective and advantageous, as our case study shows.

This type of management takes advantage of the distributed intelligence that an approach such as smart grids offers. Smart grid modeling and management by VPPs in a simulator such as MASCEM adds real value to understanding and enhancing real operation in electricity markets. ■

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References

1. Z. Vale, H. Morais, and H. Khodr, "Intelligent Multi-Player Smart Grid Management Considering Distributed Energy Resources and Demand Response," *Proc. 2010 IEEE Power and Energy Society General Meeting*, IEEE, 2010; doi:10.1109/PES.2010.5590170.
2. P. Oliveira et al., "MASCEM—An Electricity Market Simulator Providing Coalition Support for Virtual Power Players," *Proc. 15th Int'l Conf. Intelligent System Application to Power Systems*, IEEE, 2009; doi:10.1109/ISAP.2009.5352933.
3. *Smart Grid: Enabler of the New Energy Economy*, tech. report, Electricity Advisory Committee, Dec. 2008.
4. I. Praça et al., "MASCEM: A Multi-Agent System that Simulates Competitive Electricity Markets," *IEEE Intelligent Systems*, vol. 18, no. 6, 2003, pp. 54–60.
5. H. Li and L. Tesfatsion, "Development of Open Source Software for Power Market Research: The AMES Test Bed,"

Table 2. Amounts of power each virtual power player (VPP) must negotiate after the first two levels (in MWh).

Period	VPP 1	VPP 2	VPP 3	VPP 4	VPP 5	VPP 6
1	0.0000*	–1.9387	0.0000	–0.5116	–1.4596	0.0000
2	0.0000	–1.6494	0.0000	–0.0750	–1.2016	0.0000
3	0.0000	–0.0750	0.0000	0.0000	–1.0607	0.0000
4	0.0000	0.0000	0.0000	0.0000	–0.4364	0.0000
5	0.9489	0.0000	0.0000	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	–0.9900	0.0000
7	0.0000	–1.6418	0.0000	–0.3855	–1.1952	0.0000
8	0.0000	0.0000	0.0000	–5.5706	0.0000	–0.3193
9	0.0000	0.0000	–5.4666	–7.3419	0.0000	–6.6894
10	0.0000	–0.6723	–7.2435	–8.1063	–0.8031	–7.4064
11	0.0000	–1.4204	–7.5715	–8.5576	–1.2107	–7.8132
12	0.0000	–1.5837	–7.7908	–8.6375	–1.1391	–7.7559
13	0.0000	–1.0852	–7.2215	–7.8766	–0.0748	–7.1852
14	0.0000	0.0000	–2.6406	–7.9733	–2.6846	–7.2279
15	0.0000	0.0000	–0.6658	–7.8067	0.0000	–7.1205
16	0.0000	0.0000	–0.9513	–7.7041	0.0000	–6.9616
17	0.0000	0.0000	–1.8351	–7.6869	0.0000	–6.8395
18	0.0000	0.0000	–0.3175	–7.3733	0.0000	–6.4853
19	0.0000	0.0000	–2.7951	–7.5952	0.0000	–6.8649
20	0.0000	–0.4697	–1.8619	–7.8590	0.0000	–7.0107
21	0.0000	–4.0432	–0.9356	–7.8308	0.0000	–6.8012
22	0.0000	–3.7961	–0.5443	–7.3210	0.0000	–6.3635
23	0.0000	–3.1163	0.0000	–4.8799	0.0000	–5.6286
24	0.0000	–2.3282	0.0000	–1.3882	0.0000	–4.7466

*Positive values indicate the amounts of energy available for sale, whereas negative values represent the amount each VPP needs to buy.

J. Energy Markets, vol. 2, no. 2, 2009, pp. 111–128.

6. V. Koritarov, “Real-World Market Representation with Agents: Modeling the Electricity Market as a Complex Adaptive System with an Agent-Based Approach,” *IEEE Power & Energy*, vol. 2, no. 4, 2004, pp. 39–46.
7. Z. Vale et al., “Ancillary Services Market Clearing Simulation: A Comparison between Deterministic and Heuristic Methods,” *Proc. IEEE 2010 Power and Energy Society General Meeting*, IEEE, 2010; doi:10.1109/PES.2010.5588202.
8. R. Zimmerman and D. Gan, *Matpower Manual*, PSERC Cornell Univ., 1997.
9. T. Pinto et al., “Multi-Agent Based Electricity Market Simulator With VPP: Conceptual and Implementation Issues,” *Proc. 2009 IEEE Power and Energy Society General Meeting*, IEEE, 2009; doi:10.1109/PES.2009.5275565.
10. M. Olsson and L. Söder, “Modeling Real-Time Balancing Power Market Prices Using Combined SARIMA and Markov Processes,” *IEEE Trans. Power Systems*, vol. 23, no. 2, 2008, pp. 443–450.
11. Z. Vale et al., “MASCEM—Electricity Markets Simulation with Strategic Agents,” *IEEE Intelligent Systems*, vol. 26, no. 2, 2011, pp. 9–17.
12. L. Cao, V. Gorodetsky, and P. Mitkas, “Agent Mining: The Synergy of Agents and Data Mining,” *IEEE Intelligent Systems*, vol. 24, no. 3, 2009, pp. 64–72.
13. A. Dore and C.S. Regazzoni, “Interaction Analysis with a Bayesian Trajectory Model,” *IEEE Intelligent Systems*, vol. 25, no. 3, 2010, pp. 32–40.
14. N. Amjady, A. Daraeepour, and F. Keynia1, “Day-Ahead Electricity Price Forecasting by Modified Relief Algorithm and Hybrid Neural Network,” *IET Generation, Transmission & Distribution*, vol. 4, no. 3, 2009, pp. 432–444.
15. Z. Jing et al., “Study on the Convergence Property of Re-Learning Model in Electricity Market Simulation,” *Proc. 8th Int’l Conf. Advances in Power*

Figure 7. Simulation results for the third-level negotiation. We can see the energy bought by (a) virtual power player (VPP) 3 and (b) VPP 4.

System Control, Operation, and Management, IEEE, 2009; doi: 10.1049/cp.2009.1813.

16. G. Owen, *Game Theory*, Academic Press, 1995.
17. H. Morais et al., "Optimal Scheduling of a Renewable Micro-Grid in an Isolated Load Area Using Mixed-Integer Linear Programming," *Renewable Energy J.*, vol. 35, no. 1, 2010, pp. 151–156.
18. *GAMS—The Solver Manuals*, GAMS Development Corp., 2009.
19. *Renewable Energy Scenario to 2040—Half of the Global Energy Supply from Renewables in 2040*, tech. report, European Renewable Energy Council (EREC), May 2004.
20. S. Teske, A. Zervos, and O. Schafer, "Energy Revolution—A Sustainable World Energy Outlook," Greenpeace Int'l, European Renewable Energy Council (EREC), Jan. 2007.
21. P. Faria, Z. Vale, and J. Ferreira, "Demsi—A Demand Response Simulator in the Context of Intensive Use of Distributed Generation," *Proc. IEEE Int'l Conf. Systems, Man, and Cybernetics*, IEEE, 2010, pp. 2025–2032.