Distributed, Agent-Based Intelligent System for Demand Response Program Simulation in Smart Grids

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Intelligent systems have a great potential for addressing decision-making problems, because they can model the involved players and produce good results with low computational time. However, intelligent systems are still globally underutilized due to their isolation from the outside world.[1] To make better use of them, we need to connect intelligent systems to other systems so that the intelligent systems can make decisions based on the decisions of others and still achieve their goals. Distributed, intelligent systems can support adequate communications among agents, learning from agent behavior, considering player goals and, in this way, supporting individual player decision making. This approach provides good decisions to the overall system. Some successful agent-based simulators have already been developed for power systems, demonstrating the advantages of their use.[2,3]

This article describes a multiagent system (MAS), which models and simulates a smart grid with several different players each having independent goals. This distributed, intelligent system enables testing of demand response (DR) programs with both physical and virtual players that are simulated by computers using real data.[4]

The use of DR programs in a smart grid presents a promising opportunity for consumers, as it allows curtailment capacity, which is highly valuable for dealing with unexpected changes. It also allows small consumers to participate in large DR programs when aggregated, extending to them the benefits that have usually been accessible only to large consumers.[5]

Agents such as virtual power players (VPP) and curtailment service providers (CSP) aggregate several consumers, which makes these consumers strong enough to be represented in the electricity market and/or to participate

in DR programs. To participate in DR programs, agents representing distributed generation and parking lots can only be aggregated with VPPs. Industrial, commercial, and domestic consumers can either have a contract with a VPP or with a CSP.

The load-management methodology controls and manages the physical player on the distributed, intelligent system. The load management aims to control loads at the client side to increase the efficiency of both the client and the overall system operation. Electricity can be expensive in some time periods and less expensive in others, and this should be considered at the system and consumer level. Load management enables the system operator to control some costumer-side loads, turning off supply during consumption peaks and expensive energy generation periods and turning on supply during lower consumption times or whenever there is a surplus in energy generation.[6] This management flexibility is especially important for accommodating the increasing penetration of renewable-based generation plants with intermittent characteristics.

The system described in this article uses the advantages of MAS to address load management in the context of a smart grid with physical and simulated players and real consumption data. This is essential for testing demand response programs in a realistic way. Although the proposed system accommodates the modeling of a large set of DR programs, in this article we focus on two programs: *Real-Time Price (RTP)*, which requires efficient management of the consumer agents (domestic and commerce) to minimize the energy costs;[7] and *Real-Time Demand Response Program (RTDRP)*, which considers the contract phase and the actual event that involves the energy cut.[8]

Multiagent Smart Grid Simulation Tool

Our proposed MAS models a smart grid and the involved players. Each player is represented by one agent with the capability of representing the actual corresponding player and to simulate his actions. Figure 1 shows the multiagent architecture. Figure 1 presents a module called Multi-Agent Simulator of Competitive Electricity Markets (MASCEM), which corresponds to a different project that will interact with the distributed, intelligent system (Multi-Agent Smart Grid simulation Platform, or MASGriP) presented in this article. The MASCEM simulator[9] is a modeling and simulation tool that has been developed for studying complex restructured electricity markets.

All agents in MASGriP use communication by Internet sockets, allowing the use of almost any programming language as new agents in the system. In the present stage of implementation, the majority of the agents are implemented in C#. MASGriP is prepared to be integrated with MASCEM, which uses Java as the main programming languages, so together they can demonstrate the benefits associated with a MAS for the intended application. The use of Internet sockets lets the system communicate outside of a single machine using only the IP address and port. In its present state, the developed system makes extensive use of a diversity of Ethernet connections. The system uses a physical laboratory with several loads to simulate one domestic consumer. These loads are connected to a programmable logic controller (PLC) that manages and controls the loads using a specific IP address.

Each agent in MASGriP, with the exception of the facilitator agents, represents a physical player. These agents administer the information concerning the corresponding physical installation, including its geographic coordinate, electric, gas, water, and metadata information for each topic. The information administered by each agent depends on the type of player it represents. The way this information is shared with the other agents in the system depends on the business models and contracts in use. The sharing rules are based on permissions contained in the configuration file of each agent.

Communications in MASGriP are made using XML, which includes source and destination tags that allow routing in the facilitator agent. The destination tag can also have the values of “all” or “find.” The “all” value denotes broadcast messages; the “find” value is associated with the “IDHouse” tag, which indicates the ID of one installation (electric vehicles, micro storage units, micro distributed generation, small commerce, and domestic consumers) to which the facilitator must route messages.

For the communications process the system will use the Foundation for Intelligent Physical Agents’ Agent Communication Language standards.[10] At this development stage, we only use the system for proof of concept, leaving the communications and system standards implementations for future work.

For this article, we’ve simulated 30 consumer agents (domestic and commerce), one CSP, four micro grids, one smart grid, and one independent system operator (ISO) agent. We ignore the management of the loads inside the consumer agents with the exception of the agent with the ID 26; all other agents simulate the values of consumption.

Intelligent Energy Systems Laboratory

Here, we present the laboratory that represents the physical players and describe the way we integrate it with the MAS.

Physical Laboratory

The Intelligent Energy Systems Laboratory of the Knowledge Engineering

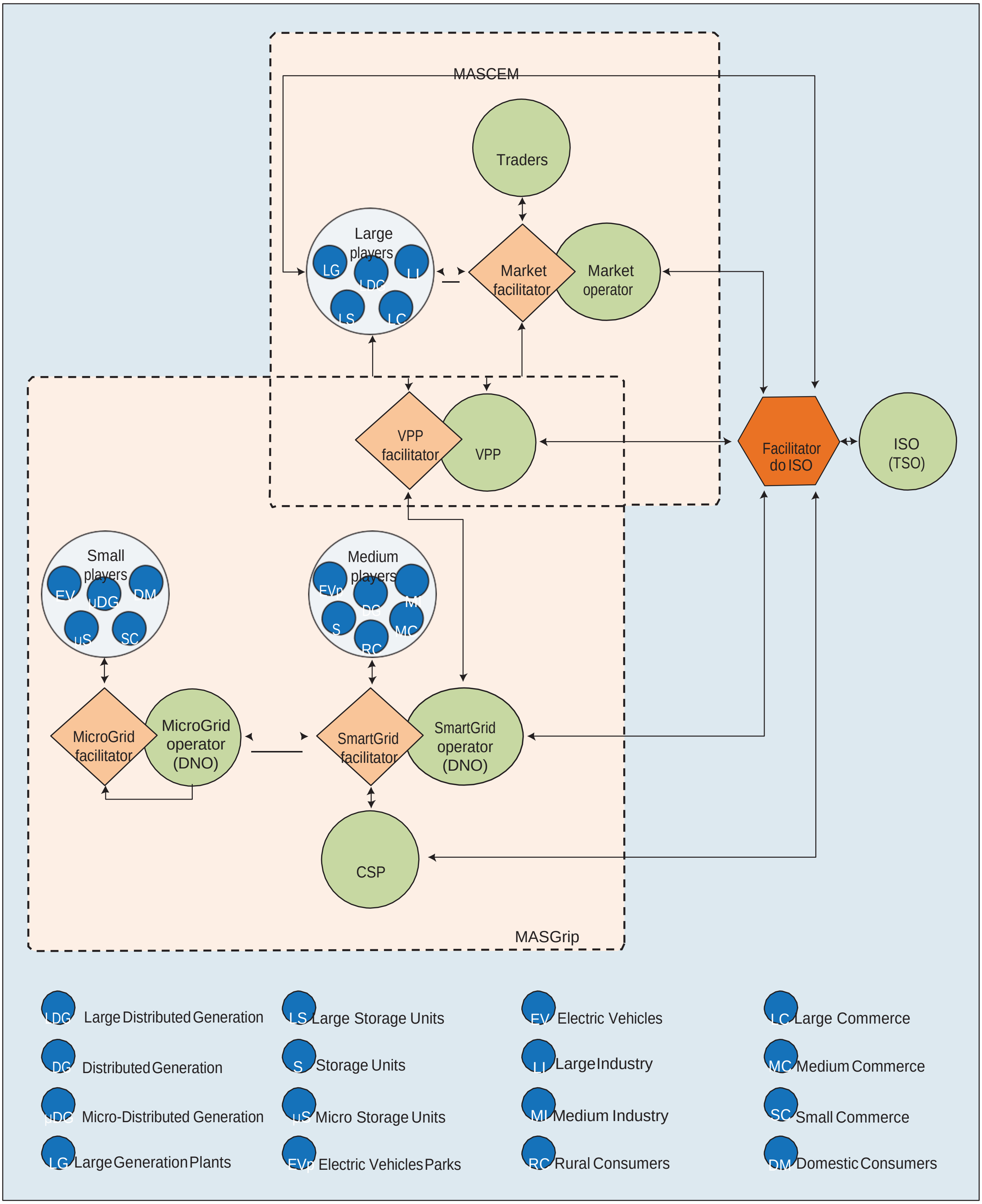

Figure 1. Architecture of communication between agents. The Multi-Agent Smart Grid simulation Platform (MASGriP) interacts with the Multi-Agent Simulator of Competitive Electricity Markets (MASCEM). In this way, it's possible to model the power system operation in the competitive electricity market context, including small and large generation and consumption players' behavior.

and Decision-Support Research Center is located at the Institute of Engineering, Polytechnic Institute of Porto. The laboratory includes an intelligent supervisory control and data acquisition (SCADA) house that simulates supervision and control of domestic electricity generation and consumption. The generation system includes two photovoltaic panels (one fixed and one tracking), two wind turbines, and one fuel cell. Several loads are available, including variable (induction motors and fluorescent lamps) and discrete (lamps, washing machines, refrigerators, and other electric appliances).[11,12]

The intelligent SCADA house is built in the installation agent that represents the physical laboratory in the system. This agent controls the PLC and, consequently, the physical loads. This control is made in C# using Modbus protocol for communications with the PLC. Despite the control that this agent has on the physical loads, it doesn't have an interface to control and manage the physical system. A separate program connected to the installation agent lets the user control and manage the loads. Programs that provide a capable interface can be developed in any technology as long as they have an Internet socket connection with the installation agent and identify themselves as interfaces.

As our future work will show, the agent representing this physical installation can also simulate some loads that aren't included in the physical system, or can even simulate all the installation loads. This possibility makes the system more flexible and adequate for the simulation of a wide set of distinct scenarios.

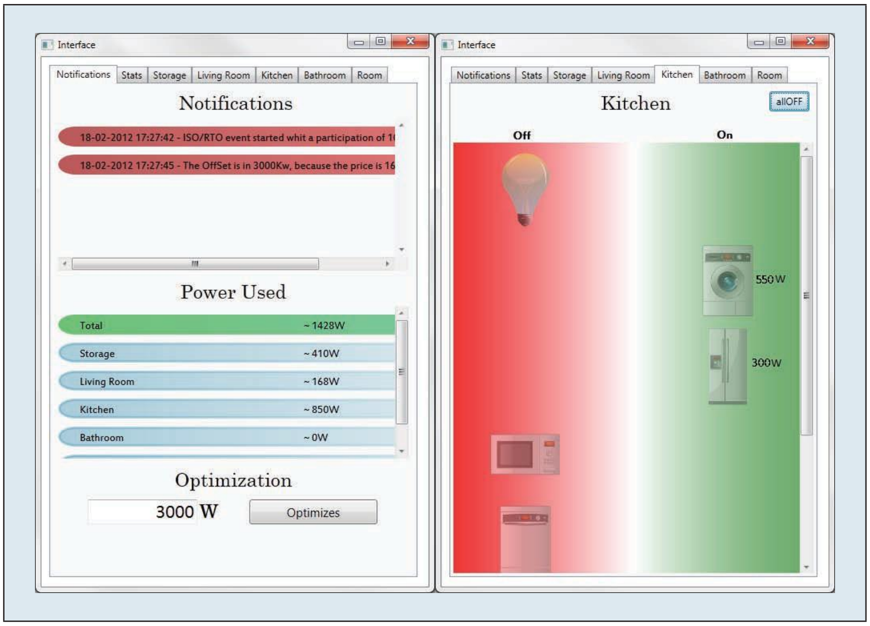

Figure 2. Interface of supervisory control and data acquisition house. The "notification" and "stats" tabs are static, while the other tabs are created based on installation agent provided information.

Multiagent System Integration

The SCADA house is connected to a PLC, which allows for an Ethernet network connection. Because this connection has an IP address and port, the MASGriP is able to connect to the PLC and manage the loads existing in the house.

The integration between the MASGriP and the PLC is built in the installation agent, using the Modbus protocol present on the PLC. This agent manages the information concerning all the installation loads, which can be real/physical loads or computationally simulated loads. Using this information, the agent is able to connect with an existing physical load or to computationally simulate one. In the XML configuration file, the only difference between a physical and a simulated load is the lack of a memory position inside the PLC. The agent representative of the physical laboratory is the agent with the ID 26.

It's possible to control the consumer physical structure by changing the XML configuration file. If a new load is added to the file, the system will connect to that load in the case of a physical load or computationally simulate it in the case of a simulated load. When an interface agent connects to the consumer agent, it will display to the user the state of the loads so she can manually control them.

Figure 2 shows a generic GUI. Besides the "notifications" and "stats" tabs, which are static, the other tabs are created dynamically according to the information provided by the installation agent. This makes it possible to use an interface code for several and distinct types of consumers. The information provided by the installation agent contains physical data concerning the loads and rooms of the house. We designed the interface layout so that it can be easily adapted to any mobile device.

Demand Response Programs

The two examples that we present in this article consider two distinct DR programs. The first example will present a single day of consumption using RTP and a maximum consumption limit for each price range. The second example involves the establishment of contracts before the actual DR events (for example, the moment of the actions) can occur. Depending on the minimum power amount required by the program, the agents can make a contract directly with the ISO agent or can make an aggregation with other agents using a CSP agent to reach the minimum required power. The example will detail the behavior of the CSP during a DR event. This DR program is inspired on the energy type service of RTDRP implemented by the ISO New England.[8]

Both DR programs presented in this case study bring several advantages for consumers and network operators, while reducing energy costs and improving the operation flexibility, respectively.

In the first program, RTP, real-time prices are applied to the consumers, which have determined an amount of load reduction when facing a determined value of variation in the electricity price. Then, the proposed methodology performs the decision on how to attain the desired demand reduction.

The second program, RTDRP, takes into account a sequence of information exchange between the consumer and the operator. This program is more advantageous because in addition to the diminution in the consumption and respective payment, consumers are remunerated regarding the power reduction capacity itself and the availability to participate in the DR event.

Real-Time Price

This example illustrates the use of RTP using agent 26. The agent that represents this domestic consumer uses a maximum consumption limit for each price range. This example uses the followed maximum consumption limits:

- lower than 0.12 euros/kilowatt hour (kWh), no consumption limit;
- higher or equal to 0.12 and lower that 0.14 euros/kWh, consumption limit of 4 kW;
- higher or equal to 0.14 and lower that 0.16 euros/kWh, consumption limit of 3 kW;
- higher or equal to 0.16 and lower that 0.18 euros/kWh, consumption limit of 2.5 kW;
- higher or equal to 0.18 and lower that 0.20 euros/kWh, consumption limit of 2kW; and
- higher than 0.20 euros/kWh, consumption limit of 1.75 kW.

For example, if the price exceeds 0.12 euros/kWh and if it's below 0.14 euros/kWh, the house will try not to consume more than 4 kWs. To achieve the offset imposed by the respective maximum consumption limit for the price in question, the agent uses the optimization module.[13]

We used the price of energy on 21 February 2012 in Portugal as a guideline for the simulation. The energy price we considered in this simulation (the electricity price for end-use consumers) was twice the real-price energy in generation (the electricity price in the electricity market).

Considering these maximum consumption limits and the energy price, we performed a simulation for a complete day of consumption for agent 26. Figure 3 shows the consumption and the energy price for the last six hours of that day. It's clear that the optimization process considering the maximum consumption limits according to the real-time price range produced the expected result. The agent is able to control the consumer's consumption so that it doesn't exceed the established limit.

In fact, there's only one way to exceed the imposed limit, and this might happen during the learning process of the optimization module. The learning process makes the optimization module learn the loads that the users want to turn on in each context (contexts are defined according to the period of the day and their conditions, like the season, luminosity, and temperature). The machine learning module is active in every optimization, waiting for the eventual subsequent users' reactions to learn from them and adapt itself to the will of the installation users.[14] The optimization can occur by user demand or during the existence of an offset; in this case, the optimization will occur every time the consumption value is higher than the offset.

The optimization process doesn't consider inputs given directly by the users.[13] It uses the artificial-neural-network-based machine learning module results that determine the current preferences factors for each load. These preferences factors indicate the priority of each load to maintain its state before the optimization process.

Figure 3a shows the evolution of the price of energy between 6:10 p.m. and 11:55 p.m. The prices in red represent a price that triggers an offset for consumer agent 26. Figure 3b shows the consumptions values of the agent. The blue represents consumption values without any kind of optimization module during the hours with a high energy price; green shows consumption values using the optimization module when offsets occur during the day; and red represent the offsets present on the agent described previously. The blue values can be the same as the green or higher, but never less.

As shown in Figure 3, this DR program can control the consumption in one installation every time the energy price is higher than expected. This procedure can save money to the user and relieve the distribution grid. This DR program can be applied in any installation as long as the required control and management resources exist

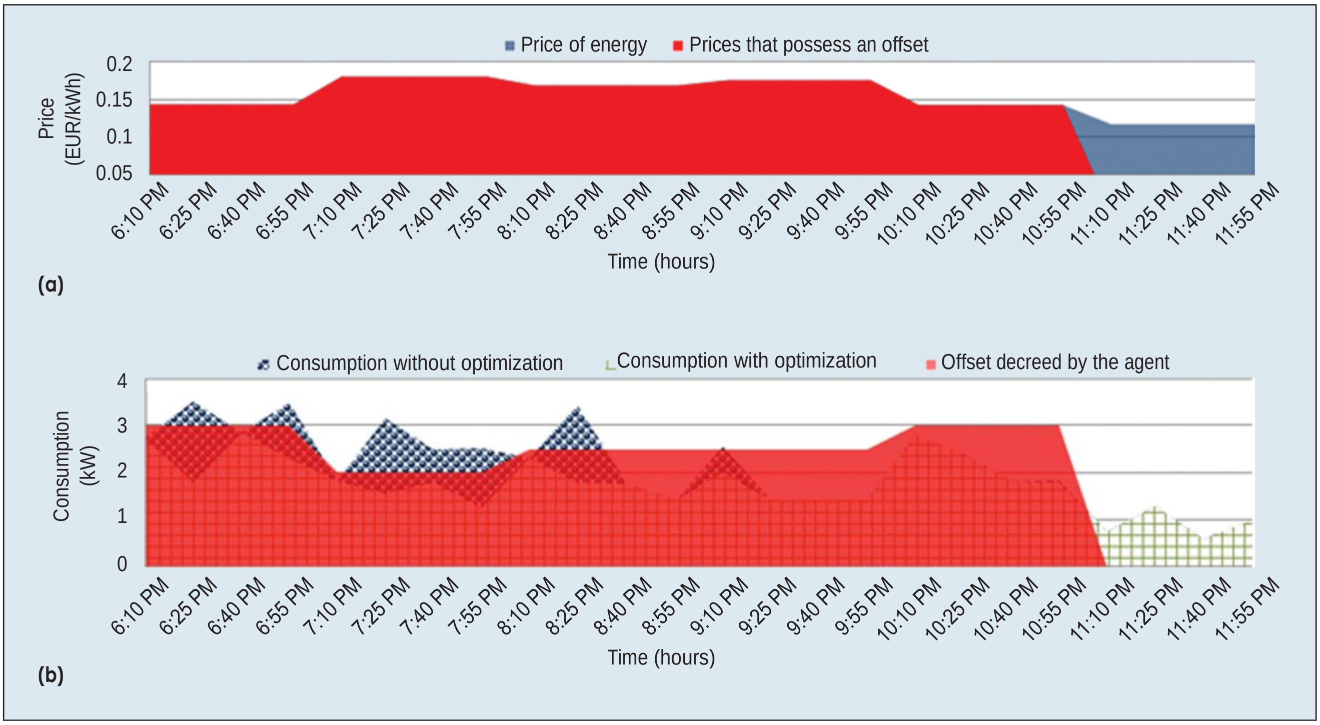

Figure 3. Six hours of energy consumption for agent 26: (a) energy price and (b) consumption. The optimization process lets the agent control the consumer's consumption so that it doesn't exceed the established limit.

on the user side. The grid only needs to provide the prices of energy to the consumers.

real-Time Demand response Program

A CSP can be defined as a special player aggregating consumers for DR participation, enabling small consumers to participate in DR programs and events. Small consumers without the reduction capacity required by the DR program managing entity (usually an ISO) establish a contract with a CSP, which aggregates several small and medium consumers and participates in the DR program as one. CSPs tasks are: to identify curtailable loads, enroll customers, manage curtailment events, and calculate payments or penalties for its customers.[14]

For this example, the ISO agent launches the DR program to all system players. Players with a sufficient amount of energy to cut use to achieve the minimum required by the program will build a direct contract with ISO. Players willing to participate but who don't have sufficient power to cut to achieve the minimum required by the program will try to build a contract with a CSP or VPP.

DR events are supported by contracts established between the consumers and the CSPs or the ISO and aim to reduce consumption. During the DR event, CSPs have a ramp period, which is the time needed to reach the contractual consumption reduction.

Letters A through G in Figure 4 represent key points in the ramp period, as follows:

- A: Beginning of the DR event, during which the CSP alerts the contracted players.
- B: The players return the values of both regular and additional response amounts to the CSP.
- C: The CSP evaluates the use of the regular response amount and performs the evaluation of additional amounts if the regular resources are insufficient for participation.
- D: The CSP sends the result of his decision regarding the use of both regular and additional response amounts to the houses, or performs the estimation of the available direct load control (DLC) power if the regular and additional resources are insufficient for participation in the DR event.
- E: The probable value of the available DLC amount is obtained, and the CSP performs the evaluation of the three referred amounts for participation.
- F: A CSP makes a decision regarding the participation of consumers in the DR event.

Table 1 presents the consumer ID, type, average consumption, and DR contract main parameters for 30 participating agents in the RTDRP example. We assume that all the consumer agents only communicate with a single CSP. The RTDRP launched by the ISO agent has a minimum use of 100 kW for participation.

When an agent establishes a contract with the CSP it agrees to send

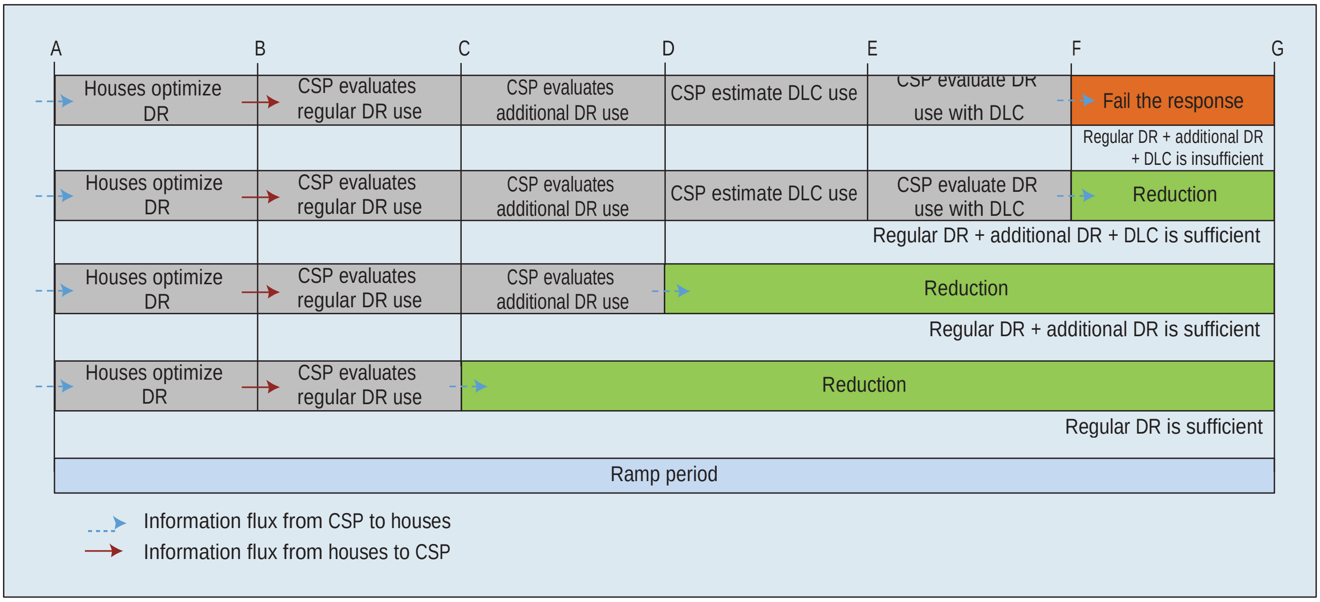

Figure 4. Curtailment service providers' ramp period of the acting process for the Real-Time Demand Response Program (RTDRP). The figure shows key points in the ramp period.

her two values at the beginning of a RTDRP event. These values are the regular cut and the additional cut that the agent is able to support in the present context. The regular cut is an approximate amount of energy that the agent can reduce in real time; this value can be calculated with the use of an optimization module, specific for each agent, and based on the value existing in the CSP contract. The additional cut is the amount of energy by which the agent can reduce above the regular cut; this value can be obtained by the level of comfort defined by the user—for example, if the comfort level is 70 percent, then a load with a preference factor of 20 percent can be turned off, but a load with preference factor of 35 percent can't be turned off. We used the optimization module for calculating the regular cut and the comfort level for calculating the additional cut by agent 26 that represents the laboratory described in this article.[13]

Equation 1 determines the amount of power that each consumer agent will contract to curtail. The result value can be calculated in different ways, and it's up to each agent to formulate the method that best fits his interests. The equation uses the past year consumption data to calculate the average power consumption during the same time duration of the DR program activation period. We consider three periods of consumption for this purpose: on-peak (P_{OnPeak}), mid-peak ($P_{MidPeak}$), and off-peak ($P_{OffPeak}$). To calculate the power of the contract ($P_{Contract}$), we use different weights for the three considered periods and combined them with the percentage of cut ($P_{CutPercentage}$) established by the user. Once the result is obtained, the agent will reduce this amount by 30 percent to prevent participation failure.

$$P_{contract} = \frac{P_{OnPeak} \times 4 + P_{MidPeak} \times 2 + P_{OffPeak}}{7} \times \frac{P_{CutPercentage}}{100} \times 0.7 \quad (1)$$

Agents 28, 29, and 30 don't establish any DR contract and, consequently, don't participate in any DR event, as Table 1 shows. To overcome consumer participation failures, the CSP adds 60 percent of power to the minimum stipulated on the RTDRP.

The optimization used by agent 26 uses the machine learning module based on the artificial neural networks described in other work,[13] which updates the preference factors associated to each load present in the house. Based on the targeted reduction value, the optimization module performs a cut in the consumption according to the values of the preference factors. The preference factors are updated by the machine learning module that has as inputs the users' past actions (for example, if one user has never agreed to cutting a certain load, the optimization module will not reduce the consumption by cutting that specific load unless absolutely necessary).

Although the minimum energy use for participation is 100 kW, at the time of an event the CSP only participates if he has 120 percent of the minimum required to overcome possible failures in the anticipation of cuts or the eventuality of any player, deciding not to follow the cuts that he agreed to at the beginning of the event. In this example, the regular and additional cuts aren't enough to reach the 120 percent required by the CSP. This requires the use of DLC contracts. For

Table 1. Agent participation parameters using the RTDRP.

Agent information		Average consumption			DR* contract information			Information sent to CSP during DR event		
ID	Type	On-peak (W)	Mid-peak (W)	Off-peak (W)	Cut (%)	Cut capacity (W)	DR contract agent	Real cut (W)	Additional cut (W)	Direct load control (W)
1	Domestic	4,489	3,912	1,520	15	410	CSP	410	150	0
2	Commerce	100,456	80,165	50,468	40	24,505	CSP	899	342	200
3	Domestic	4,856	3,562	1,676	30	847	CSP	320	0	150
4	Domestic	5,132	3,465	246	18	499	CSP	0	0	0
5	Commerce	30,546	24,983	2,354	30	5,235	CSP	0	0	0
6	Domestic	6,542	5,132	3,645	50	2,004	CSP	0	0	0
7	Domestic	4,651	3,216	925	12	312	CSP	315	26	0
8	Commerce	70,468	50,468	25,987	30	12,264	CSP	0	0	0
9	Domestic	4,321	3,654	3,211	32	890	CSP	890	251	0
10	Domestic	8,329	6,548	3,546	20	999	CSP	999	856	0
11	Domestic	7,426	5,132	2,756	15	641	CSP	450	265	0
12	Commerce	230,455	200,897	165,444	50	74,453	CSP	64,321	5,423	2,300
13	Domestic	6,542	4,563	2,135	20	749	CSP	0	0	0
14	Domestic	4,521	2,468	2,465	20	510	CSP	500	785	0
15	Commerce	50,216	40,546	20,456	15	4,536	CSP	652	3,521	210
16	Domestic	5,132	3,546	1,584	10	292	CSP	290	210	0
17	Domestic	3,587	2,465	1,045	20	406	CSP	406	0	0
18	Domestic	7,324	5,132	3,498	25	1,076	CSP	890	260	0
19	Commerce	345,087	300,489	232,146	50	110,674	ISO	–	–	–
20	Domestic	3,549	2,468	1,548	20	414	CSP	414	32	0
21	Domestic	1,358	456	122	5	32	CSP	0	0	0
22	Domestic	6,245	4,878	3,425	35	1,336	CSP	1,309	350	320
23	Domestic	3,456	2,468	1,897	20	413	CSP	420	652	0
24	Commerce	565,218	498,252	420,465	35	128,724	ISO	–	–	–
25	Domestic	5,498	4,568	3,249	20	688	CSP	688	230	0
26	Domestic	4,238	3,254	3,218	15	400	CSP	400	978	0
27	Commerce	160,456	100,486	30,469	40	34,931	CSP	29,865	890	1,500
28	Domestic	6,543	4,688	2,468	30	1,140	None	–	–	–
29	Domestic	5,138	3,424	1,653	15	436	None	–	–	–
30	Domestic	4,235	3,218	1,532	15	374	None	–	–	–
							Total by event	104,438	15,221	4,680
							Total		124,339	

* DR = demand response; CSP = curtailment service provider; and ISO = independent system operator.

these contracts, the CSP is able to directly turn off loads that are in the contract between her and each player.

Therefore, this example shows the case of *Regular DR* + *Additional DR* + *DLC* presented in Figure 4. In this case, the CSP needs to use his last resource (DLC), the most expensive one, to achieve the minimum of participation required by him to participate in the DR event.

One of the problems of a small simulation like the one presented here is scalability. In the real world, the number of consumers largely exceeds the number simulated, and so smaller simulations must evolve to a larger scale to confirm their scalability. To ensure the successful outcome of this simulation in a larger scenario, each agent can only build a contract directly with the ISO or with one CSP or VPP in the smart grid. In this way, an excessive communication burden is prevented as each DR program manager (ISO, CSP, or VPP) knows a priori which consumers it can count on to manage each DR event

The adequate use of DR pro- grams is crucial to enabling ef- ficient and secure future smart grid operation, as they can ensure re- liable service at controlled costs. However, the lack of experience in this field makes DR program use far from successful. The proposed sys- tem supports decision making about DR design and use. Testing the use of these programs with real data and varying their parameterization al- lows putting in place DR programs that are adequate for the smart grids' characteristics.

The proposed MAS is able to model all the players that act in the scope of the smart grid, taking into account the characteristics, goals, and resources of each individual player. Moreover, this system can accommodate both physical (actual generation, storage, and consumption installations) and virtual (computationally simulated) agents that can be placed in any machine with Ethernet connection.

The use of the proposed system allows the performance of realistic simulations to assess the real impact that demand response programs have for the participating consumers and for the smart grid as a whole.

Further improvements in the presented system are being done in order to accommodate the realistic simulation validation allowed by real-time simulation hardware for electric power systems and components.

Acknowledgments

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References

1. V. Catterson, E. Davidson, and S. McArthur, "Embedded Intelligence for Electrical Network Operation and Control," *IEEE Intelligent Systems*, vol. 26, no. 2, 2011, pp. 38–45.
2. I. Praça et al., "Multi-Agent Electricity Market Simulation with Dynamic Strategies and Virtual Power Producers," *Proc. Power and Energy Society General Meeting – Conversion and Delivery of Electrical Energy in the 21st Century*, 2008, pp. 1–8.
3. T. Logenthiran et al., "Multiagent System for Real-Time Operation of a Microgrid in Real-Time Digital Simulator," *IEEE Trans. Smart Grid*, vol. 3, no. 2, 2012, pp. 925–933.
4. I. Beausoleil-Morrison, "The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (COGEN-SIM)," summary report, *EBC Annex 42,* 2007; www.iea-ebc.org/fileadmin/user_upload/docs/EBC_Annex_42_PSR.pdf.
5. P. Faria et al., "Demand Response Management in Power Systems Using Particle Swarm Optimization," *IEEE Intelligent Systems*, vol. 28, no. 4, 2013, pp. 43–51 doi:10.1109/MIS.2011.35.
6. F. Ygge and J.M. Akkermans, "On Resource-Oriented Multi-Commodity Market Computations," *Proc. 3rd IEEE Computer Society Int'l Conf. Multi-Agent Systems*, 1998, pp. 365–371; doi:10.1109/ICMAS.1998.699221.
7. P. Faria and Z. Vale, "Demand Response in Electrical Energy Supply: An Optimal Real Time Pricing Approach," *Energy*, vol. 36, no. 8, 2011, pp. 5374–5384.
8. North American Energy Standards Board, *Recommendation to NAESB Executive Committee: Review and Develop Business Practice Standards to Support DR and DSM-EE Programs*, 29 Sept. 2008; www.naesb.org/pdf4/weq_2008_api_5a_rec.doc.
9. Z. Vale et al., "MASCEM: Electricity Markets Simulation with Strategic Agents," *IEEE Intelligent Systems*, vol. 26, no. 2, 2011, pp. 9–17.
10. *FIPA ACL Message Structure Specifications, Version G*, Foundation for Intelligent Physical Agents, Dec. 2002.
11. F. Fernandes et al., "Genetic Algorithm Methodology Applied to Intelligent

House Control," *Proc. Symp. Computational Intelligence Applications in Smart Grid*, 2011; doi:10.1109/CIASG.2011.5953341.

12. F. Fernandes et al., "Intelligent SCADA for Load Control," *Proc. IEEE Int'l Conf. Systems, Man, and Cybernetics*, 2010, pp. 2987–2994.
13. L. Gomes et al., "Contextual Intelligent Load Management with ANN Adaptive Learning Module," *Proc. Int'l Conf. Intelligent System Applications to Power Systems*, 2011; doi:10.1109/ISAP.2011.6082226.
14. M. Braun and P. Strauss, "A Review on Aggregation Approaches of Controllable Distributed Energy Units in Electrical Power Systems," *Int'l J. Distributed Energy Resources*, vol. 4, no. 4, 2008, pp. 297–319.