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Seller, Buyer and VPP Agents Behavior on a Simulated Electricity Market

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***Abstract*— Competitive electricity markets are complex environments, involving a large number of different entities, playing in a dynamic scene to obtain the best advantages and profits. MASCEM is an electricity market simulator able to model market players and simulate their operation in the market. As market players are complex entities, having their characteristics and objectives, making their decisions and interacting with other players, a multi-agent architecture is used and proved to be adequate. MASCEM players have learning capabilities and different risk preferences. They are able to refine their strategies according to their past experience (both real and simulated) and considering other agents' behavior. Agents' behavior is also subject to its risk preferences.**

Index Terms **— Decision Making, Dynamic Strategies, Electricity Markets, Multi-Agent Systems, Simulation.**

I. INTRODUCTION

MASCEM - Multi-Agent Simulator for Electricity Markets, is a simulator to test different agent strategies under a competitive electricity market, both considering Pool and Bilateral Contracts. There are different time and behavior dependent strategies. These strategies are used considering agents risk preference.

The notion of Virtual Power Producers (VPP) is being introduced into MASCEM. These are multi-technology and multi-site heterogeneous entities, being relationships among aggregated producers and among VPPs and the remaining Electricity Market (EM) agents a key factor for their success. Any type of generation unit or load may be included: wind turbines, photovoltaic, mini turbines, micro-turbine, fuel cells, energy storage units, non-controllable loads, controllable loads etc.

An aggregating strategy may enable aggregated producers to gain technical and commercial advantages, making profit of the specific advantages of a mix of several generation technologies and overcoming serious disadvantages of some of them. These VPP in MASCEM model are coalitions of agents that represent the aggregation of producers.

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There are experiences of using agents for studying Electricity Markets [1], [2] and [3]. In fact several tools and references are available at the "Agent-Based Computational Economics Research Area: Restructured Electricity Markets" maintained by L. Tesfatsion at www.econ.iastate.edu/tesfatsi, hosted by the Department of Economics, Iowa State University. However although there are very interesting tools none of them addresses the VPPs problem.

In this paper we explore the different MASCEM agents, concerning decisions related to agents market behavior and VPP agents coalition formation process.

II. MASCEM OVERVIEW

One of the main objectives of electricity markets is to decrease electricity costs through competition. Several market structure models exist that could help achieve this goal. The market environment typically consists of a Pool, as well as a floor for Bilateral Contracts [4].

There are several entities involved in the negotiations; we propose a multi-agent model to represent all the involved entities and their relationships. MASCEM multi-agent model includes: a Market Facilitator Agent, Seller Agents, Buyer Agents, a Market Operator Agent and a System Operator Agent. Three types of markets are simulated: Pool Markets, Bilateral Contracts and Hybrid Markets [5]. Figure 1 illustrates MASCEM core model.

The Market Facilitator is the coordinator of the market. It knows the identities of all the agents present in the market, regulates the negotiation process and assures the market is functioning according to the established rules. The first step agents' have to do to participate in the market is to register at the Market Facilitator, specifying their market role and services.

Seller and Buyer Agents are the two key players in the market, involved in Bilateral Contracts negotiations and presenting selling/buying bids to the Pool.

The System Operator Agent represents the responsible for the transmission grid and all the involved technical constraints. Every established contract, either through Bilateral Contracts or through the Pool, must first be communicated to the System Operator, who analyses its technical feasibility from the Power System point of view (e.g. analyzing line power flows).

The Market Operator Agent represents the responsible for the Pool mechanism. This agent is only present in simulations of Pool or Hybrid markets. The Market Operator will receive bids from Sellers and Buyers, analyze them and determine the market clearing price (MCP) and accepted bids.

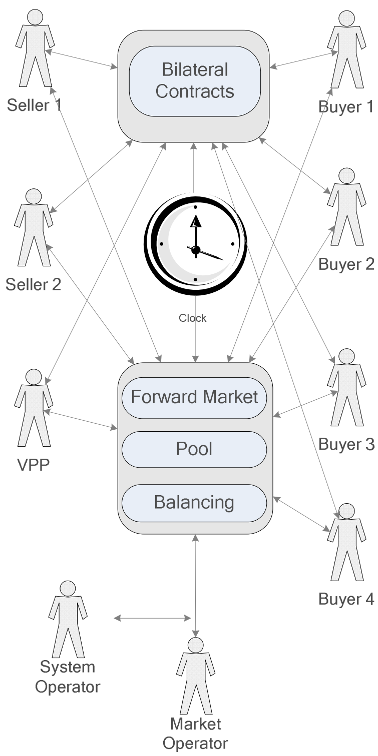

Fig. 1. MASCEM agents and negotiation framework

Agents establish their own objectives and decision rules. Moreover, they can adapt their strategies as the simulation progresses on the basis of previous effort's successes or failures. The simulator probes the conditions and the effects of market rules, by simulating the participant's strategic behavior [6].

III. MASCEM AGENTS BEHAVIOR

Seller and Buyer Agents are the two key players in the market. Sellers will compete with each other, since they are all interested in selling all their available capacity and in obtaining the highest possible market quote. On the other hand, Sellers will cooperate with Buyers while trying to establish some agreement that is profitable for both. This is a very rich domain where it is possible to develop and test several algorithms and negotiation mechanisms for both cooperation and competition.

A. *Agent Strategies*

On the basis of the results obtained in a period, Sellers and Buyers revise their strategies for the next S-period. Seller and Buyer Agents have strategic behavior to define their desired price. These agents have time-dependent strategies, and behavior-dependent strategies, to define the price in the following periods according to the results obtained in the previous ones.

MASCEM implements four basic types of strategies to change the price during a defined S-period: Determined, Anxious, Moderate and Gluttonous. The difference between these strategies is the time instant at which the agent starts to modify the price and the amount it changes. Although time-dependent strategies are simple to understand and implement [7], they are very important since they allow the simulation of important issues such as: emotional aspects and different risk behaviors.

For example, an agent using a Determined Strategy is a risk indifferent one. On the contrary, Gluttonous agents exhibit less risk aversion than agents using Anxious and Moderate Strategies, since they keep the price constant for a long time, taking the risk of not selling. Based on each agent goals and knowledge, alternative strategies are composed.

To adjust price between S-periods, also referred as behavior-dependent strategies, MASCEM provides two basic strategies: one called Composed Goal Directed and another called Adapted Derivative Following. These are important strategies that use the knowledge obtained with past experiences to define bid prices for next periods.

The Composed Goal Directed strategy is based on two consecutive objectives, the first one is selling (or buying) all the available capacity (power needed) and then increase the profit (reduce the payoff).

The Adapted Derivative Following strategy is based on a Derivative Following strategy proposed by Greenwald [8]. The Adapted Derivative-Following strategy adjusts its price by looking to the amount of revenue earned in the previous S-period as a result of the previous period's price change. If the last period's price change produced more revenue per good than the previous period, then the strategy makes a similar change in price. If the previous change produced less revenue per good, then the strategy makes a different price change.

The price adjustment is based on the same calculation for both strategies and takes into account the difference between the desired results and the obtained results in the previous period.

$$price_{i+1} = price_i \pm amount_{i+1} \quad (1)$$

$$amount_{i+1} = price_i * \left(\beta + \frac{\Delta_i}{capacity\_available_i * \alpha} \right) \quad (2)$$

$$\Delta_i = capacity\_available_i - energy\_sold_i \quad (3)$$

The price for the next period (1) will be the previous period price adjusted by some amount (2), that will increase or decrease the previous price according to the strategy used.

Instead of adjusting the price each day by a fixed percentage (like), the change is scaled by a ratio based on the objective of selling all the available capacity (3). The amount price changes increases with the difference between the power intended to sell and the power actually sold. and are just scaling factors.

In general, using a very simplified approach, one can say that the only goal of the player that participates in a market is to maximize its profits or minimize its costs. However, this does not correspond to the reality when there are more factors to consider than the economic ones or when these must be considered over relatively long periods of time.

In the case of electricity markets, buyers, when representing electricity consumers or consumer aggregations, although aiming at minimizing their costs, can have as primary goal to acquire all the required amount of electrical energy. In this case, the Composed Goal Directed strategy is more adapted to their objectives.

On the contrary, sellers, representing directly a producer or an aggregation of producers, have profit maximization as the primary goal. Although this can seem very clear, there are some intrinsic factors that can make this problem more complex. For instance, profits must take into account not only the amount of produced energy but also the conditions of this production. According to the used production technology, it may be better to produce less in certain periods to attain better results in alternative periods. Moreover, penalties, which are applied in some market models, must also be considered.

According to each player model and knowledge, these strategies are composed with more specific strategies, giving place to specially tailored strategies for each agent. As an example, in the case of producers, strategies take into account the production technology. In the case of production technologies based on renewable sources, highly dependent from weather factors, these are considered. For each player, all relevant strategies are composed, according to the player defined goals and to the identified situation. In this way, player strategic behavior depends from several aspects, namely the following:

- player defined goals;
- player model (including technical characteristics);
- player knowledge (namely concerning other players' models);
- context (taking into account factors of different nature, including market regulation, external factors such as oil prices, weather forecasts, which is considered in the player model but also in a more general context, namely for load forecasting, …).

This approach makes players' strategies adaptive both to each player and to each situation.

B. *Agents Risk Preference*

Negotiations, namely on Bilateral Contracts, may involve a number of proposals and counter-proposals formulation.

We have incorporated utility to model the way in which the decision-maker algorithm evaluates different outcomes and objectives. The agent utility for the actions accept, reject, counter-propose and formulate an alternative proposal varies according to its risk behavior.

In MASCEM, an agent's risk preference is broadly classified into risk-avoidance, risk-indifference and risk-looking. The risk preference is modeled by using a von Neumann-Morgenstern expected multi-objective utility function.

Each agent can have a set of business objectives, like: minimizing production costs, maximizing profits, minimizing possible forecasts errors. Different types of agents have different types of objectives. Moreover, the different objectives of an individual agent may conflict with each other, since the achievement of one objective may negate the achievement of other objectives.

Each objective of an agent is represented by a minimum expected value (Xmin), a maximum expected value (Xmax), and a risk preference (RP). A scaling factor (k) for each objective is used to compute the overall expected utility as the sum of all single-objective expected utilities weighted by k.

During a negotiation period the agent calculates the utility values of the alternatives actions (accept, counter-propose or reject). The utility of actions varies with the specified risk preference.

A risk-looking agent will try to counter-propose an offer rather than accepting it. A risk-avoidance agent will accept no matter what is the offered price and will refrain from counter proposing in fear of losing. The action of formulate an alternative proposal also requires that the agent calculates the utility values of the different possible alternatives.

Risk-preference choice will lead to different behaviors.

IV. VPP

Power Systems Generation is a distributed problem by its own nature. In the past Electricity was based in a reduced number of installations (e.g. Thermo, Nuclear, and Hydro Power Plants). However, guaranteeing sustainable development is a huge challenge for Power Systems. This requires a significant increasing in Distributed Generation, mainly based on renewable sources. However, this leads to a system that is much more complex to control, since we have many more Power Generation plants, and the generation is more unpredictable than before, due to the difficulty in forecasting the energy production in some renewable sources (e.g. wind and photovoltaic). We are in the presence of a problem that is clearly a distributed problem and where intelligent behaviour needs to be assigned to the operation of Power Plants. Thus Multi-Agent Systems appear as the natural solution to model Power Systems Generation (even in a Cyber-Physical Systems perspective).

We have been working on models for the VPP [9] and also have some preliminary work regarding the evolution of the multi-agent model of MASCEM to face this new challenge [10]. We have concluded that agent coalitions are especially important to address VPPs issue as these can be seen as a coalition of agents.

Some algorithms have been developed for coalition formation [11], [12] [13]. Some researchers are studying dynamic environments, where agents may enter or leave the coalition formation process and many uncertainties are present (e.g. the coalition value is not fixed, but it is context-based [14].

Applications of coalitions include distributed vehicle routing [15], sensor networks [16], in e-commerce (where buyers may pool their requirements in order to obtain bigger group discounts [17], in grid computing (where multi-institution virtual organizations are viewed as being central to coordinated resource sharing and problem solving [18], and in e-business (where agile groupings of agents need to be formed in order to satisfy particular market niches [19]).

Although there are several works related to agent coalitions, we have not found on the multi-agent systems community or on the Electricity Markets community, anyone addressing the VPPs problem based on agent coalitions.

From the point of view of the multi-agent system, Virtual Power Producers (VPP) may be seen as coalitions of agents, requiring specific procedures for coalition formation. Figure 2 illustrates the inclusion of VPP agents on the negotiation framework.

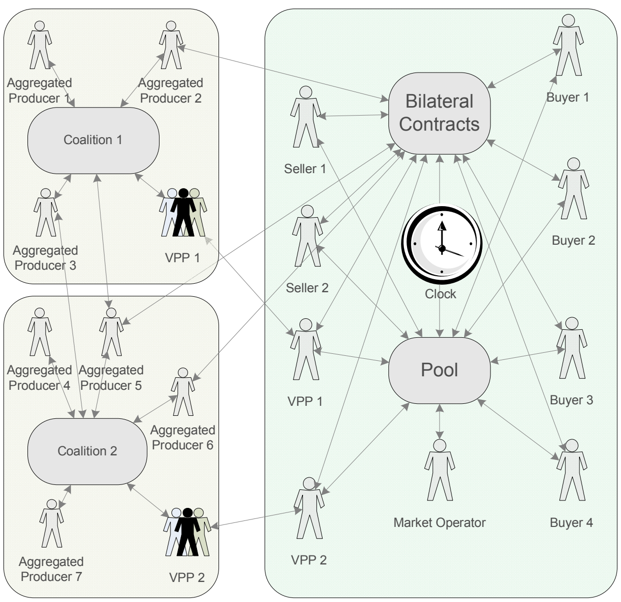

Fig. 2. Negotiation framework regarding VPPs

On one hand, each VPP classifies the producers according to several defined criteria. On the other hand, it establishes the goals of VPP formation or of VPP aggregation of more producers, according to its operating strategies and to its necessities at the moment. Aggregation proposals are then elaborated based on the resulting knowledge.

A negotiation mechanism regarding coalition formation under the scope of a VPP is in fact being included in MASCEM, and strategies developed considering the three phases of a coalition's formation process: the formation, the establishment of a set of rules to be used to coordinate the coalition, the operation and payoff distribution and evaluation; the possibility of entering or leaving the coalition.

VPP needs to have an adequate knowledge of each potential aggregated producer characteristics. We are working on a multi-criteria negotiation protocol.

Some of the most important characteristics are:

- Nominal Power: the sum of nominal power in-stalled in each producer;
- Available Power: the power a VPP can buy to the producer;
- Overload Power: some units may produce overload power for limited periods. The VPP may use this power in critical situations;
- Equipment characteristics: information concerning producers' equipment allows the VPP to know the power characteristic, reliability, maintenance periods, lifetime, relation with external factors, possible variations of the energy price in function of the cost of the primary resources, etc.
- Operating limits: for the units which are dependent from natural resources, it is possible that the primary resource must be below or above of equipment operating limits. This must be considered in risk analysis in the generation forecast. Usually when the resources forecast is near to the minimum machines operating limit the risk is small, but when they are near to the maximum limit the risk can be enormous;
- Grid connection characteristics: This is an important aspect if it is necessary to pay the losses in the lines; also the existence of two or more producers connected to the same electric substation should be considered; etc;
- Historical generation data: the availability of historic generation data can enable the VPP to get useful forecasting tools.

These issues must be carefully analyzed before a new producer enters the coalition. The multi-criteria decision function is a dynamic one, since the characteristics weights depends on the lack of already aggregated producers.

According to its member generation capabilities and consumption needs, for a given period, the VPP agent will need to sell or buy electricity. Regarding VPP market participation, the same market interface as Seller or Buyer agents will be used. However, there are some preliminary steps to define its proposals and to divide market results among VPP members. First all the capacity available from the different aggregated producers must be gathered, to establish the electricity amount to trade on the market, and the different production costs analyzed to define the interval for acceptable proposals. This means VPP agents will aggregate all the involved units' characteristics. The analysis of received proposals will be done according to each unit capabilities and costs.

Important is the use of previsions, such as climatic ones, to update the database of aggregated producers to forecast more and more efficiently the energy they will be able to provide to the VPP.

Considering the VPP formation process finished, the VPP needs to co-ordinate its operation. The VPP must place bids in the market, considering the contracts with producers, the generation forecast, the reserves and its market strategy.

After the market session, the VPP agent undertakes an internal dispatch, analyzing and adjusting its generation and reserve to maximize profits. VPP informs the aggregated producers about their dispatch.

Finally, in function of the generation, the used and unused reserve of each producer and the established contracts of the VPP fulfillment, the VPP determines the producers' remuneration.

Once a coalition is established, it can aggregate more agents or even discard some agents. This allows modeling all the decision making concerning VPP formation and also subsequence aggregation of more producers. Each aggregated producer decision of participating or not in VPP coalition is dependent on agents' market strategies and risk preference.

V. Implementation

MASCEM is implemented on the top of OAA version 2.3.2, using OAA AgentLib library, and Java Virtual Machine 1.5.0. Figure 3 presents an aspect of MASCEM user interface.

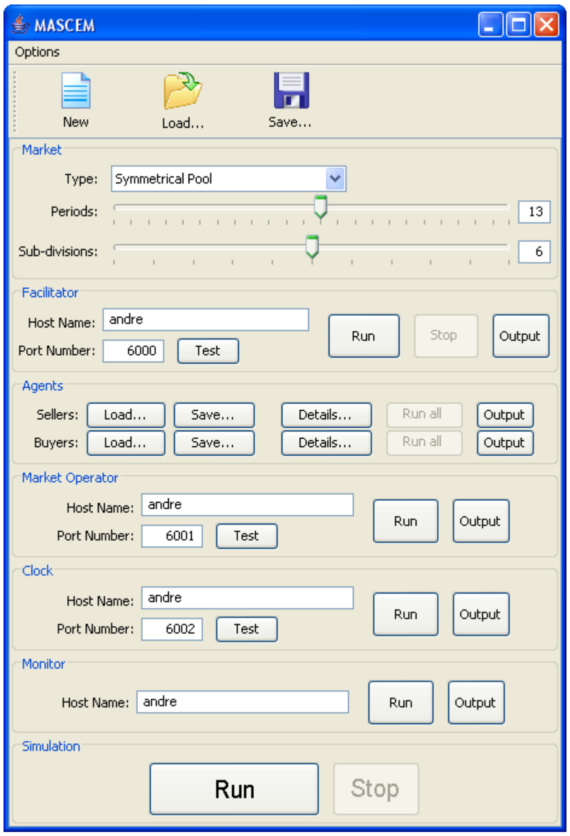

Fig. 3. MASCEM user interface

The introduction of VPP models in MASCEM required to re-think MASCEM architecture, namely in what concerns agent communication.

As the overall performance of the market simulator must be optimized, the VPP internal interactions should only overload the whole simulation in the exact required measure. Moreover, in order to make VPP coalitions act at their best performance the first step was to determine how to integrate them in the market negotiations with minimum degradation of the previous implementation performance. This led us to face each VPP as another multi-agent system, operating in the scope of the overall multi-agent system that simulates the electricity market.

Considering each VPP as a multi-agent system allows an interesting approach from both the performance and the conceptual point of view. In order to develop a computational implementation of this conceptual architecture, each VPP has to have its own facilitator. This means that each VPP has now its own facilitator that allows it to communicate with all the producers that are part of this coalition or intend to join it, independently from the rest of the simulation.

For the VPPs individual facilitators we decided to develop our own version of the OAA facilitator (which is used as the market facilitator). VPPs' facilitators are implemented in LPA Prolog. VPP facilitators have been implemented so they seem as an adaptation of the OAA facilitator's basic functionalities.

VI. Conclusions

The paper presented the market infrastructure provided by MASCEM, which supports the elaboration of complex composed strategies, specifically tailored to each market participant and to each situation. Market participants have strategic behavior based on a set of dynamic strategies subject to agents risk preference.

MASCEM supports Virtual Power Producers (VPP) models and simulation and decision-support decision tools specifically developed for this kind of agents.

The multi-agent technology allied to an objected-oriented implementation enables easy future improvements and model enlargement.

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VIII. Biographies

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