Electricity Market (Virtual) Agents

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***Abstract*—This paper describes a multi-agent based simulation (MABS) framework to construct an artificial electric power market populated with learning agents. The artificial market, named TEMMAS (The Electricity Market Multi-Agent Simulator), explores the integration of two design constructs: i) the specification of the environmental physical market properties, and ii) the specification of the decision-making (deliberative) and reactive agents. TEMMAS is materialized in an experimental setup involving distinct power generator companies which operate in the market and search for the trading strategies that best exploit their generating units' resources. The experimental results show a coherent market behavior that emerges from the overall simulated environment.**

I. Introduction

The start-up of nation-wide electric markets, along with its recent expansion to intercountry markets, aims at providing competitive electricity service to consumers. The new market-based power industry calls for human decision-making in order to settle the energy assets' trading strategies. The interactions and influences among the market participants are usually described by game theoretic approaches which are based on the determination of equilibrium points to which compare the actual market performance [1], [2]. However, those approaches find it difficult to incorporate the ability of market participants to repeatedly probe markets and adapt their strategies. Usually, the problem of finding the equilibria strategies is relaxed (simplified) both in terms of: i) the human agents' bidding policies, and ii) the technical and economical operation of the power system.

As an alternative to the equilibrium approaches, the multi--agent based simulation (MABS) comes forth as being particulary well fitted to analyze dynamic and adaptive systems with complex interactions among constituents [3], [4].

In this paper we describe a MABS modeling framework that provides constructs for the (human) designer to specify a dynamic environment, its resources, observable properties and its inhabitant decision-making agents. We used the framework to capture the behavior of the electricity market and to build a simulator, named TEMMAS (The Electricity Market Multi-Agent Simulator), which incorporates the operation of several generator company (*GenCo*) operators, each with distinct power generating units (*GenUnit*), and a market operator (*Pool*) which computes the hourly market price (driven by the electricity demand).

TEMMAS agents exhibit bounded rationality, i.e., they make decisions based on local information (partial knowledge) of the system and of other agents while learning and adapting their strategies during a simulation. The TEMMAS purpose is not to explicitly search for equilibrium points, but rather to reveal and assist to understand the complex and aggregate system behaviors that emerge from the interactions of the market agents.

II. The MABS Modeling Framework

We describe the structural MABS constituents by means of two concepts: i) the *environmental entity*, which owns a distinct existence in the real environment, e.g. a resource such as an electricity producer, or a decision-making agent such as a market bidder generator company, and ii) the *environmental property*, which is a measurable aspect of the real environment, e.g. the price of a bid or the demand for electricity. Hence, we define the *environmental entity* set, $\mathcal{E}_\mathcal{T} = \{ e_1, \ldots, e_n \}$, and the *environmental property* set, $\mathcal{E}_\mathcal{Y} = \{ p_1, \ldots, p_m \}$. The whole environment is the union of its entities and properties: $\mathcal{E} = \mathcal{E}_\mathcal{T} \cup \mathcal{E}_\mathcal{Y}$.

The environmental entities, $\mathcal{E}_\mathcal{T}$, are often clustered in different classes, or types, thus partitioning $\mathcal{E}_\mathcal{T}$ into a set, $\mathcal{P}_{\mathcal{E}_\mathcal{T}}$, of disjoints subsets, $\mathcal{P}^i_{\mathcal{E}_\mathcal{T}}$, each containing entities that belong to the same class. Formally, $\mathcal{P}_{\mathcal{E}_\mathcal{T}} = \left\{ \mathcal{P}^1_{\mathcal{E}_\mathcal{T}}, \ldots, \mathcal{P}^k_{\mathcal{E}_\mathcal{T}} \right\}$ defines a full partition of $\mathcal{E}_\mathcal{T}$, such that $\mathcal{P}^i_{\mathcal{E}_\mathcal{T}} \subseteq \mathcal{E}_\mathcal{T}$ and $\mathcal{P}_{\mathcal{E}_\mathcal{T}} = \cup_{i=1 \ldots k} \mathcal{P}^i_{\mathcal{E}_\mathcal{T}}$ and $\mathcal{P}^i_{\mathcal{E}_\mathcal{T}} \cap \mathcal{P}^j_{\mathcal{E}_\mathcal{T}} = \emptyset \ \forall i \neq j$. The partitioning may be used to distinguish between decision-making agents and available resources, e.g. a company that decides the biding strategy to pursue or a plant that provides the demanded power.

The environmental properties, $\mathcal{E}_\mathcal{Y}$, can also be clustered, in a similar way as for the environmental entities, thus grouping properties that are related. The partitioning may be used to express distinct categories, e.g. economical, electrical, ecological or social aspects. Another, more technical usage, is to separate constant parameters from dynamic state variables.

The factored state space representation. The state of the simulated environment is implicitly defined by the state of all its environmental entities and properties. We follow a factored representation, that describes the state space as a set, $\mathcal{V}$, of discrete state variables [5]. Each state variable, $v_i \in \mathcal{V}$, takes on values in its domain $\mathcal{D}(v_i)$ and the global (i.e., over $\mathcal{E}$) state space, $\mathcal{S} \subseteq \times_{v_i \in \mathcal{V}} \mathcal{D}(v_i)$, is a subset of the Cartesian product of the state variable domains. A state $s \in \mathcal{S}$ is an assignment of values to the set of state variables $\mathcal{V}$. We define $f_{\mathcal{C}}$, $\mathcal{C} \subseteq \mathcal{V}$, as a projection such that if s is an assignment to $\mathcal{V}$, $f_{\mathcal{C}}(\,s\,)$ is the assignment of s to $\mathcal{C}$; we define a *context* c as an assignment to the subset $\mathcal{C} \subseteq \mathcal{V}$; the initial state variables of each entity and property are defined, respectively, by the functions $init_{\mathcal{E}_{\mathcal{T}}} : \mathcal{E}_{\mathcal{T}} \rightarrow \mathcal{C}$ and $init_{\mathcal{E}_{\mathcal{Y}}} : \mathcal{E}_{\mathcal{Y}} \rightarrow \mathcal{C}$.

From environmental entities to resources and agents. The *embodiment* is central in describing the relation between the entities and the environment [6]. Each *environmental entity* can be seen as a body, possibly with the capability to influence the environmental properties. Based on this idea of embodiment, two higher-level concepts (decoupled from the environment, $\mathcal{E}$, characterization) are introduced: i) *agent*, owing reasoning and decision-making capabilities, and ii) *resource*, without any reasoning capability. Thus, given a set of agents, Υ, we define an association function $embody : \Upsilon \rightarrow \mathcal{E}_{\mathcal{T}}$, which connects an agent to its physical entity. In a similar way, given a set of resources, Φ, we define the mapping function $identity : \Phi \rightarrow \mathcal{E}_{\mathcal{Y}}$. We consider that $|\mathcal{E}| = |\Upsilon| + |\Phi|$, thus each entity is either mapped to an agent or to a resource; there is no third category.

The decision-making approach. Each agent perceives (the market) and acts (sells or buys) and there are two main approaches to develop the reasoning and decision-making capabilities: i) the qualitative mental-state based reasoning, such as the belief-desire-intention (BDI) architecture [7], which is founded on logic theories, and ii) the quantitative, decision-theoretic, evaluation of causal effects, such as the Markov decision process (MDP) support for sequential decision-making in stochastic environments. There are also hybrid approaches that combine the qualitative and quantitative formulations [8], [9].

The qualitative mental-state approaches capture the relation between high level components (e.g. beliefs, desires, intentions) and tend to follow heuristic (or rule-based) decision--making strategies, thus being better fitted to tackle large-scale problems and worst fitted to deal with stochastic environments.

The quantitative decision-theoretic approaches deal with low level components (e.g., primitive actions and immediate rewards) and searches for long-term policies that maximize some utility function, thus being worst fitted to tackle large-scale problems and better fitted to deal with stochastic environments.

The electric power market is a stochastic environment and we currently formulate medium-scale problems that can fit a decision-theoretic agent model. Therefore, TEMMAS adaptive agents (e.g., market bidders) follow a MDP based approach and resort to experience (sampled sequences of states, actions and rewards from simulated interaction) to search for optimal, or near-optimal, policies using reinforcement learning methods such as Q-learning [10] or SARSA [11].

III. TEMMAS Design

Within the current design model of TEMMAS the electricity asset is traded through a spot market (no bilateral agreements), which is operated via a *Pool* institutional power entity. Each generator company, *GenCo*, submits (to *Pool*) how much energy, each of its generating unit, $GenUnit_{GenCo}$, is willing to produce and at what price. Thus, we have: i) the power supply system comprises a set, $\mathcal{E}_{GenCo}$, of generator companies, ii) each generator company, *GenCo*, contains its own set, $\mathcal{E}_{GenUnit_{GenCo}}$, of generating units, iii) each generating unit, $GenUnit_{GenCo}$, of a *GenCo*, has constant marginal costs, and iv) the market operator, *Pool*, trades all the *GenCo*s' submitted energy.

The bidding procedure conforms to the so-called "block bids" approach [12], where a block represents a quantity of energy being bided for a certain price; also, *GenCo*s are not allowed to bid higher than a predefined price ceiling. Thus, the market supply essential measurable aspects are the energy price, quantity and production cost. The consumer side of the market is mainly described by the quantity of demanded energy; we assume that there is no price elasticity of demand (i.e., no demand-side market bidding).

Therefore, we have: $\mathcal{E}_{\mathcal{T}} = \{\, Pool \,\} \;\cup\; \mathcal{E}_{GenCo} \;\cup_{g \in \mathcal{E}_{GenCo}} \mathcal{E}_{GenUnit_g}$ where $\mathcal{E}_{\mathcal{Y}} = \{\, quantity, price, productionCost \,\}$. The $quantity$ refers both to the supply and demand sides of the market. The $price$ referes both to the supply bided values and to the market settled (by *Pool*) value.

The $\mathcal{E}_{GenCo}$ contains the decision-making agents. The *Pool* is a reactive agent that always applies the same predefined auction rules in order to determine the market price and hence the block bids that clear the market. Each $\mathcal{E}_{GenUnit_{GenCo}}$ represents the *GenCo*'s set of available resources.

The resources' specification. Each generating unit, $GenUnit_{GenCo}$, defines its marginal costs and constructs the block bids according to the strategy indicated by its generator company, *GenCo*. Each $GenUnit_{GenCo}$ calculates its marginal costs according to, either the "WithHeatRate" [13]) or the "WithCO_2" [14] formulation.

The "WithHeatRate" formulation estimates the marginal cost, *MC*, by combining the variable operations and maintenance costs, *vO&M*, the number of heat rate intervals, $nPat$, each interval's capacity, cap_i and the corresponding heat rate value, hr_i, and the price of the fuel, $fPrice$, being used; the marginal cost for a given $i \in [1, nPat]$ interval is given by,

$$MC_{i+1} = vO\&M + \frac{(cap_{i+1} \times hr_{i+1}) - (cap_i \times hr_i)}{blockCap_{i+1}} \times fPrice \tag{1}$$

where each block's capacity is given by: $blockCap_{i+1} = cap_{i+1} - cap_i$.

The "WithCO_2" marginal cost, *MC*, combines the variable operations and maintenance costs, *vO&M*, the price of the fuel, $fPrice$, the CO_2 cost, CO_2cost, and the unit's productivity, η, through the expression,

$$MC = \frac{fPrice}{\eta} \times K + CO_2cost + vO\&M \tag{2}$$

where K is a fuel-dependent constant factor, and CO_2cost is given by,

$$CO_2cost = CO_2price \times \frac{CO_2emit}{\eta} \times K \tag{3}$$

where CO_2emit is the CO_2 fuel's emissions. Here all blocks have the same capacity; given a unit's maximum capacity, $maxCap$, and a number of blocks, $nBlocks$, to sell, each block's capacity is given by: $blockCap = \frac{maxCap}{nBlocks}$.

The decision-making strategies. Each generator company defines the bidding strategy for each of its generating units. We designed two types of strategies: a) the *basic-adjustment*, that chooses among a set of basic rigid options, and b) the *heuristic-adjustment*, that selects and follows a predefined well-known heuristic. There are several *basic-adjustment* strategies already defined in TEMMAS. Here we outline seven of those strategies, $sttg_i$ where $i \in \{1, \ldots, 7\}$, available for a *GenCo* to apply: i) $sttg_1$, bid according to the marginal production cost of each $GenUnit_{GenCo}$ (follow heat rate curves, e.g., cf. tables II and III), ii) $sttg_2$, make a "small" increment in the prices of all the previous-day's block bids, iii) $sttg_3$, similar to $sttg_2$, but makes a "large" increment, iv) $sttg_4$, make a "small" decrement in the prices of all the previous-day's block bids, v) $sttg_5$, similar to $sttg_4$, but makes a "large" decrement, vi) $sttg_6$, hold the prices of all previous-day's block bids, vii) $sttg_7$ set the price to zero. There are two *heuristic-adjustment* defined strategies: a) the "Fixed Increment Price Probing" (FIPP) that uses a percentage to increment the price of last day's transacted energy blocks and to decrement the non-transacted blocks, and b) "Physical Withholding based on System Reserve" (PWSR) that reduces the block's capacity, as to decrement the next day's estimated system reserve (difference between total capacity and total demand), and then bids the remaining energy at the maximum market price.

The agents' decision process. The above strategies correspond to the *GenCo* agent's primary actions. The *GenCo* has a set, $\mathcal{E}_{GenUnit_{GenCo}}$, of generating units and, at each decision-epoch, it decides the strategy to apply to each generating unit, thus choosing a vector of strategies, $\overrightarrow{sttg}$, where the i^{th} vector's component refers to the $GenUnit^i_{GenCo}$ generating unit; thus, its action space is given by: $\mathcal{A} = \times_{i=1}^{\left|\mathcal{E}_{GenUnit_{GenCo}}\right|} \{ sttg_1, \ldots, sttg_7 \}_i \cup \{ \text{FIPP}, \text{PWSR} \}$. The *GenCo*'s perceived market share, *mShare*, is used to characterize the agent internal memory so its state space is given by *mShare* $\in [0..100]$. Each *GenCo* is a MDP decision-making agent such that the decision process *period* represents a daily market. At each decision-epoch each agent computes its daily profit (that is regarded as an internal reward function) and the *Pool* agent receives all the *GenCo*s's block bids for the 24 daily hours and settles the hourly market price by matching offers in a classic supply and demand equilibrium price (we assume a hourly constant demand).

TEMMAS *architecture and construction.* The TEMMAS agents along with the major inter-agent communication paths are represented in the bottom region of Figure 1; the top region represents the user interface that enables to specify the each of the resources' and agents' configurable parameters. The implementation of the TEMMAS architecture followed the INGENIAS [15] methodology and used its supporting development platform. Figure 2 presents the general "agent's perspective", where the tasks and the goals are clustered into individual and social perspectives. Figure 3 gives additional detail on the construction of tasks and goals using INGENIAS.

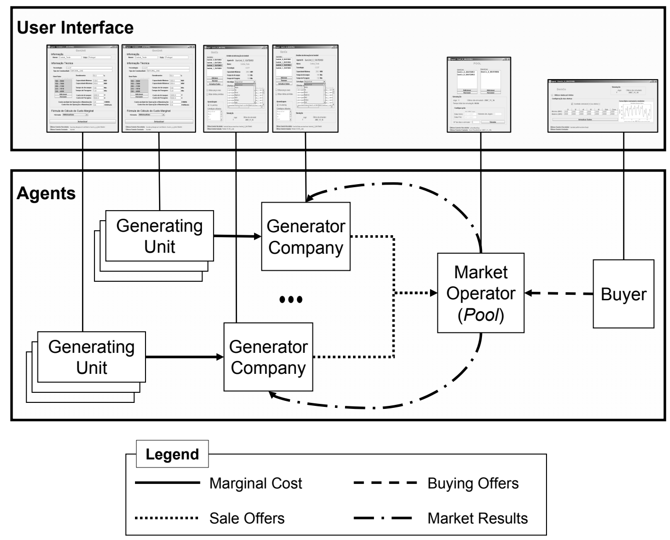

Fig. 1. The TEMMAS architecture and the configurable parameters.

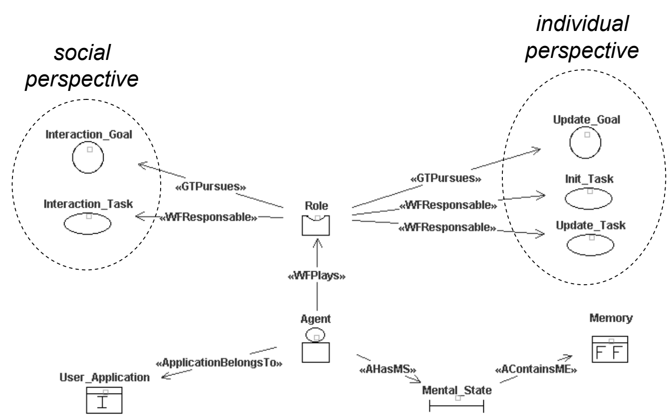

Fig. 2. TEMMAS agent's view using INGENIAS framework.

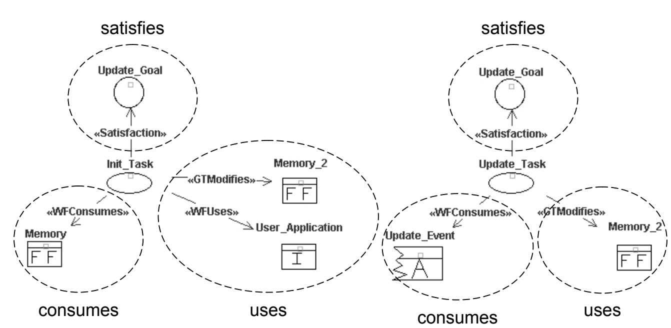

Fig. 3. TEMMAS tasks and goals specification using INGENIAS framework.

IV. TEMMAS ILLUSTRATIVE SETUP

We used TEMMAS to build a specific electric market simulation model. We picked the inspiration from the Iberian Electricity Market (MIBEL – "Mercado Ibérico de Electricidade") with Portuguese (e.g., EDP - "Electrividade de Portugal", "Turbogás", "Tejo Energia") and Spanish (e.g., "Endesa", "Iberdrola", "Union Fenosa", "Hidro Cantábrico", "Viesgo", "Bas Natural", "Elcogás") generator companies. Regarding the total electricity capacity installed the Iberian market is composed of a major player (Spain) and a minor player (Portugal). Our experiments exploit the combined market behavior of a major and a minor electricity market players.

We abstracted intra-nation market details and modeled each country as a single generator company (with several generating units). Figure 4 uses INGENIAS notation to depict the hierarchical structure of the electricity market; the *Pool* (OMEL – "Operador do Mercado Ibérico de Electricidade") settles the market price (and coupled bids) after the bids submitted by each *GenCo* (PT – "Portugal" and ES – "Spain") according to a strategy that depends on the marginal production costs of each *GenUnit*.

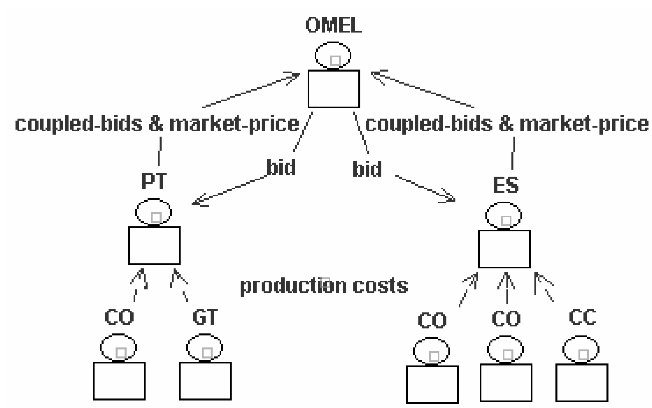

Fig. 4. An illustrative TEMMAS formulation (using INGENIAS notation).

We considered three types of generating units: i) one base load coal plant, CO, ii) one combined cycle plant, CC, to cover intermediate load, and iii) one gas turbine, GT, peaking unit. Table I shows the essential properties of each plant type and tables II and III shows the heat rate curves used to define the bidding blocks. The marginal cost was computed using expression (1); the bidding block's quantity is the capacity increment, e.g. for CO, the 11.9 marginal cost bidding block's quantity is $350 - 250 = 100$ MW (cf. Table II, CO, top lines 2 and 1).

V. EXPERIMENTS AND RESULTS

Our experiments have two main purposes: i) illustrate the TEMMAS functionality, and ii) analyze the agents' resulting behavior, e.g. the learnt bidding policies, in light of the market specific dynamics.

We designed three experimental scenarios and Table IV shows the *GenCo*'s name along with its production capacity,

TABLE I
PROPERTIES OF GENERATING UNITS; THE UNITS' TYPES ARE COAL (CO), COMBINED CYCLE (CC) AND GAS TURBINE (GT); THE O&M INDICATES "OPERATION AND MAINTENANCE" COST.

		Type of generating unit		
Property	*unit*	**CO**	**CC**	**GT**
Fuel	—	Coal (BIT)	Nat. Gas	Nat. Gas
Capacity	MW	500	250	125
Fuel price	€/MMBtu	1.5	5	5
Variable O&M	€/MWh	1.75	2.8	8

TABLE II
CO AND CC UNIT'S CAPACITY BLOCK (MW) AND HEAT RATE (BTU/KWH) AND THE CORRESPONDING MARGINAL COST (€/MWH).

CO generating unit		
Cap.	Heat rate	Marg. cost
250	12000	—
350	10500	11.9
400	10080	12.5
450	9770	12.7
500	9550	13.1

CC generating unit		
Cap.	Heat rate	Marg. cost
100	9000	—
150	7800	29.8
200	7200	29.8
225	7010	30.3
250	6880	31.4

TABLE III
GT UNIT'S CAPACITY BLOCK (MW) AND HEAT RATE (BTU/KWH) AND THE CORRESPONDING MARGINAL COST (€/MWH) .

GT generating unit		
Cap.	Heat rate	Marg. cost
50	14000	—
100	10600	44.0
110	10330	46.2
120	10150	48.9
125	10100	52.5

computed according to the respective *GenUnit*s (cf. Table I). The "*active*" suffix (cf. Table IV, *name* column) means that the *GenCo* searches for its *GenUnit*s best bidding strategies; i.e. "*active*" is a policy learning agent.

TABLE IV
THE EXPERIMENT'S *GenCo*S AND *GenUnit*S.

	GenCo		
Exp.	*name*	Prod. Capac.	***GenUnits***
#1	*GenCo_active*	875	CO & CC & GT
#2	*GenCo_major*	2000	2×CO & 4×CC
	GenCo_minor&active	875	3×CC & 1×GT
#3	*GenCo_major&active*	2000	2×CO & 4×CC
	GenCo_minor&active	875	3×CC & 1×GT

Experiment #1. The experiment sets a constant, 600 MW, hourly demand for electricity. Figure 5 shows the *GenCo_active* process of learning the bidding policy that gives the highest long-term profit. We used Q-learning, with an ϵ-greedy exploration strategy, which picks a random action with probability ϵ and behaves greedily otherwise (i.e., picks the action with the highest estimated action value); we defined $\epsilon = 0.2$. The learning factor rate of Q-learning was defined as $\alpha = 0.01$ and the discount factor (which measures the present value of future rewards) was set to $\gamma = 0.5$. Figure 6 shows the bid blocks that cleared the market (at the first hour of last simulated day). As there is no market competition the cheapest, CO, bids zero, the GT sets the market price (to its ceiling) and the most expensive 200 MW are distributed among the most expensive *GenUnit*s (CC, GT). Therefore, the *GenCo_active* agent found, for each perceived market share, *mShare*, the best strategy, $\overrightarrow{sttg}$, to bid its *GenUnit*s' energy blocks.

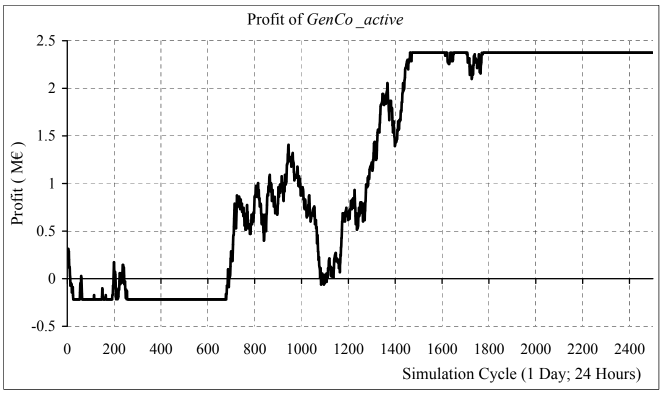

Fig. 5. The process of learning a bid policy to maximize profit. [*Exp. #1*]

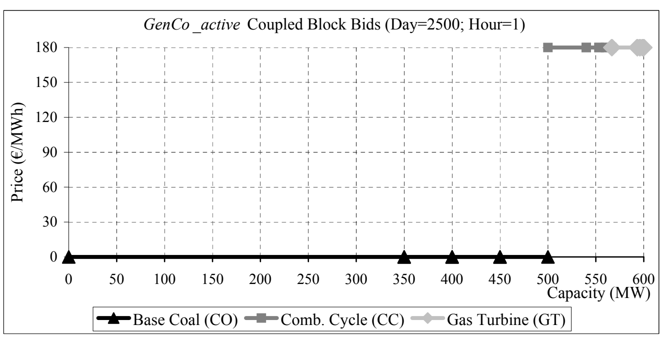

Fig. 6. The bid policy that maximizes profit (price ceiling is 180). [*Exp. #1*]

Experiment #2. The experiment sets a constant, 2000 MW, hourly demand for electricity. Figure 7 shows the market share evolution while *GenCo_minor&active* learns to play in the market with *GenCo_major*, which is a larger company with a fixed strategy: "bid each block 5€ higher than its marginal cost". We see that *GenCo_minor&active* gets around 18% $(75 - 57)$ of market from *GenCo_major*. To earn that market the *GenCo_minor&active* learnt to lower its prices in order to exploit the "5€ space" offered by *GenCo_major* fixed strategy.

Experiment #3. In this experiment both *GenCo*s are "*active*"; the remaining is the same as in experiment *#2*. Figure 8 shows the market share oscillation while each company reacts to the other's strategy to win the market. Despite the competition each company learns to secure its own fringe of the market.

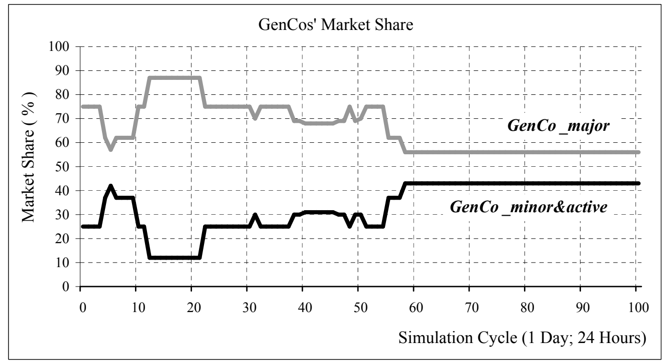

Fig. 7. Market share evolution induced by *GenCo_minor&active*. [*Exp. #2*]

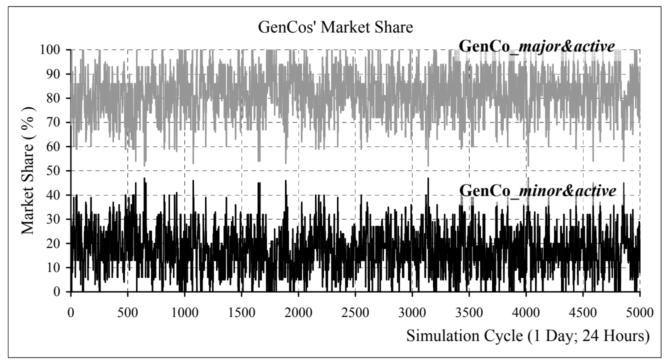

Fig. 8. Market share evolution induced by both *GenCo*s. [*Exp. #3*]

VI. Conclusions and Future Work

This paper describes our preliminary work in the construction of a MABS framework to analyze the macro-scale dynamics of the electric power market. Although both research fields (MABS and market simulation) achieved considerable progress there is a lack of cross-cutting approaches. We used the proposed MABS framework to support our preliminary work in the construction of the TEMMAS agent-based electricity market simulator.

Hence, our contribution is two folded: i) a comprehensive formulation of MABS, including the simulated environment and the inhabiting decision-making and learning agents, and ii) a simulation model (TEMMAS) of the electric power market framed in the proposed formulation.

Our initial results reveal an emerging and coherent market behavior, thus inciting us to further extend the experimental setup with additional bidding strategies and to incorporate specific market rules, such as congestion management and pricing regulation mechanisms.

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