Experience With Electricity Market Test Suite: Students Versus Computational Agents

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***Abstract*—This paper applies two experimental economics methods (i.e., agent-based modeling and laboratory experiment) to a market test suite that is based on a fictional European wholesale electricity market. Quantitative results of generators' strategic behavior in this market context are separated between generators played by human subjects (i.e., master students) in a laboratory experiment and generators represented by computational agents in an agent-based model. The behavior is measured through offers that students or agents make when participating in the electricity trading auction and the market outcomes under both methods are discussed in order to illustrate the difference between the behavior of human and computational agents. The paper also identifies the improvements that would need to be made to the market test suite to allow for a more conclusive comparison in future experiments.**

***Index Terms*—Agent-based modeling, electricity market, experimental economics, simulation game, strategic behavior.**

I. Introduction

EXPERIENCE with electricity markets worldwide provides evidence that market design affects market performance [1]. Testing the efficiency of market design in the real world can be costly, so it is desirable to simulate market behavior to anticipate problems before the implementation of new designs [2].

Game theory (or equilibrium modeling) [3]–[8] has been the dominant approach for simulating market behavior. However, this approach is limited in capturing the dynamics of the liberalized electricity market [9]. Therefore, more flexible models coming from experimental and computational economics are increasingly used. The computational method (i.e., agent-based modeling [10]–[18]) is strong in studying systems that are complex, while laboratory experiments [19]–[22] could provide information on how people behave and learn in a given environment. Most studies consider the behavior of certain players in a particular market design [11], [12] or compare the impact of design options on specific players or the system as a whole [13], [14]. Laboratory experiments study the behavior of human subjects in a controlled market environment, and they have also been used in university laboratories for educational purposes [19], [20].

Together with the rise of new market study methods, several researchers started comparing these experimental economics approaches with the traditional game theoretic approaches. For example, [23] uses a simple three-node market to compare the result of an Equilibrium Program with Equilibrium Constraint (EPEC) model with that of a Reinforcement Learning agent-based model. In [24], a pool market with inelastic and constant loads is the environment for comparing Nash equilibrium analysis and agent-based modeling using Q-learning.

The contribution of this paper is to provide an initial comparison of computational agent-based and laboratory experiments with a market test suite that is based on a fictional European electricity market. The approach used does not allow us to be conclusive, but the results illustrate that this is a promising line of research that merits further investigation, and we give some recommendations for this.

The remainder of this paper is organized as follows. Section II briefly presents and characterizes the two approaches, as well as identifies their advantages and limitations. Section III describes the case study and settings by which the two approaches are applied. Quantitative results of the computational agent-based models and lab experiments are presented in Section IV. Based on the results, detailed analysis and comparison on the experiments' and models' settings are discussed in Section V. Finally, Section VI concludes the paper.

II. Characterizing the Two Approaches

Here, the laboratory experiment and agent-based modeling are presented together with their advantages and limitations.

A. Laboratory Experiments

Laboratory experiments—or in this paper, laboratory simulation games—are applications of experimental economics which have human subjects as agents to study economics theories and systems. The computerization of experiments in recent years has made this method sufficiently affordable to be performed in universities, serving educational purposes. Also, it facilitates tests with more complicated interactions between subjects and more sophisticated simulated economic structures than "paper-and-pencil" experiments used previously [25]. Examples of simulation games in universities about electricity markets include [19] and [20]. These laboratory games usually focus on competitive trading auctions in the electricity market. Students typically take

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the role of generators which have tools for calculating their electricity generation costs so that they can formulate their bids. By playing the game repeatedly, students obtain practical experience on how trading in a electricity market works and how bids and offers should be made.

In laboratory experiments, the behavior of human subjects can be observed in a controlled environment, including their learning process over time. For testing impacts of an environment (e.g., a certain kind of market design) on relevant participants, these observations are extremely meaningful. However, objections to this method also relate to the nature of human subjects. Humans are complicated in term of motivation, cognition, preference and experience, and so cautious control is required when setting the experiment. Laboratory simulation games are also constrained by time and number of subjects, which limit their repetition and diversity as it actually happens in the real world.

B. Agent-Based Modeling

In models using agent-based modeling, agents are defined to "think, "act," and "react" and to be "goal-oriented" all by themselves without interference from modelers during the evolution of the system. These features of agents are made possible through a "brain" that modelers assign to agents when developing the model. The "brain" is a learning algorithm. Learning algorithms have been derived from disciplines such as psychology (Roth–Erev reinforcement learning [26]), biology (genetic algorithms) or computer science (Q-learning). One example of agent-based models is presented in [14] where the problem of congestion is dealt with by using generator agents that apply Q-learning. Another example can be found in [15], where interrelated electricity markets (balancing, day-ahead, and CO2 emission markets) are subjected to the strategic behavior of generator agents.

Computational agents are less complicated to work with than human subjects, but the model setup is decided initially by modelers which can be biased in their choices. More importantly, computational agents are criticized for not being able to simulate human cognitive characteristics, such as subjective preferences, perception, and bounded rationality [27], [28], which have a great influence in the human decision-making process in reality.

III. Case of the Electricity Market to Apply the Two Approaches

Here, we first describe the market setting in which the two approaches are compared and then describe how the approaches have been applied in this context.

A. Market Setting Inspired by the European Electricity Market

The market context that has been chosen is defined as the interconnected market between eight European countries, namely France, Spain, Belgium, Germany, Switzerland, Italy, The Netherlands, and Austria. Each country is considered as a node with a fixed aggregated demand curve. Nodes are connected to each other by transmission lines with limited capacity and equal impedances for each line. Transmission-line capacities are set up in order to create congestion so that the learning experience includes the impact of congestion on the market. Fig. 1 describes the network and indicates which lines interconnect with which countries (nodes).

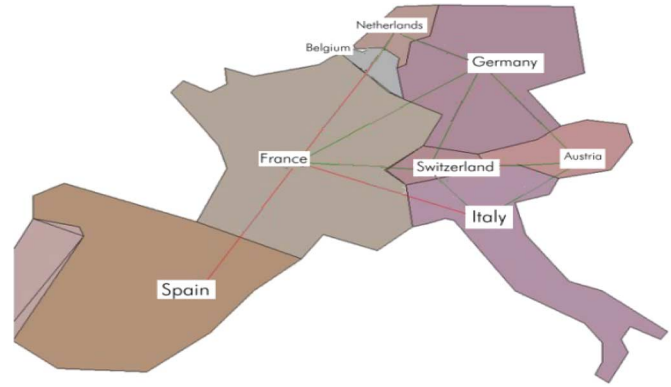

Fig. 1. European electricity market context for simulation and modeling.

TABLE I
List of Generators

No.	Name	Country
1	Gen1	Italy
2	Gen2	Switzerland
3	Gen3	Germany, Austria, Netherlands
4	Gen4	France, Germany, Austria
5	Gen5	Italy
6	Gen6	France, Belgium, Netherlands
7	Gen7	Germany
8	Gen8	France, Spain, Italy
9	Gen9	Spain, Italy
10	Gen10	Netherlands
11	Gen11	Spain
12	Gen12	Belgium, Netherlands
13	Gen13	Germany, Austria
14	Gen14	Germany

There are 14 fictive generators active in this interconnected market. As the demand side is considered fixed, the market participants that are modeled or play are these 14 market players (the market operator is not considered as a player). One generator can participate in more than one node, and, in each node, his generation is characterized by a given marginal cost curve and a maximum capacity of electricity production. Consequently, one generator can have different cost structures at different nodes. Names of 14 players and their active nodes are listed in Table I.

The set of generators and their cost functions have been chosen to represent a situation with strongly concentrated national electricity markets. The Herfindahl–Hirschmann Index (HHI)[1] of each market is provided in Table II. A market with an HHI value above 1800 is considered as a highly concentrated market. As can be seen in Table II, all nodes have HHI values in excess of 2000. This is also the situation in most actual electricity markets, as indicated in the Energy Sector Inquiry [29].

Trading is assumed to be concentrated in an hourly day-ahead auction. Offers from generators at each node are submitted to the auctioneer (i.e., market operator) which then calculates

[1]HHI is a standard measure of market concentration, equaling the sum of squares of the market shares of each generator.

TABLE II
GENERATORS' MARKET SHARES (%) AND MARKETS' HHI

Name	AT	BE	DE	FR	IT	NL	ES	CH
Gen1					4			
Gen2								50
Gen3	40		27			10		
Gen4	26		8	88				
Gen5					11			
Gen6		74		2		25		
Gen7			14					
Gen8				1	9		46	
Gen9					67		6	
Gen10						19		
Gen11							45	
Gen12		24				40		
Gen13	20		33					
Gen14			15					
Others	14	2	3	9	9	6	3	50
HHI	**2872**	**6056**	**2312**	**7830**	**4788**	**2722**	**4186**	**5000**

the market outcomes, including locational marginal price,[2] the resulting trade volumes, transmission flows and network congestion.

B. KU Leuven Lab Game

The game has been developed for the first master year of the subject of energy in the engineering department of the KU Leuven. Providing that students are unfamiliar with electricity markets, the game helps them to understand better the market complexities.

The market is set up as described in the previous section. Students play the role of generators who make hourly offers in the auction by submitting their supply curves for the next day's delivery to the market operator. Based on a fixed marginal cost curve of their own generation (cost of supply in function of the volume) in each country they are active, students set up a offer curve which they believe would maximize their profit. Setting up a "good" offer curve implies that students understand the impact of network congestion on prices and take advantage of their market power. Naturally, it is hard for students to understand these issues from the start, but the game consists of several sessions (around ten) to help students learn from their previous results and improve their strategic behavior gradually. For the first session, students are asked to offer at their marginal costs, which then functions as the benchmark for their strategic behavior in the following sessions. After the first five sessions, when students are familiar with the game, realize their optimal strategy and observe some phenomena such as there being a very high price on the market even when their quantity offers are not fully accepted, they are introduced to the concepts of market power and congestion. This instruction remotivates students with new interesting concepts and also speeds up the students' learning in the next five rounds. Students' motivation therefore is maintained and their results converge in about ten rounds.

In the game, students' offers are submitted via a web browser in the form of ten price limit-volume combinations per country

[2]For a detailed explanation about the calculation of the locational marginal price, see [30].

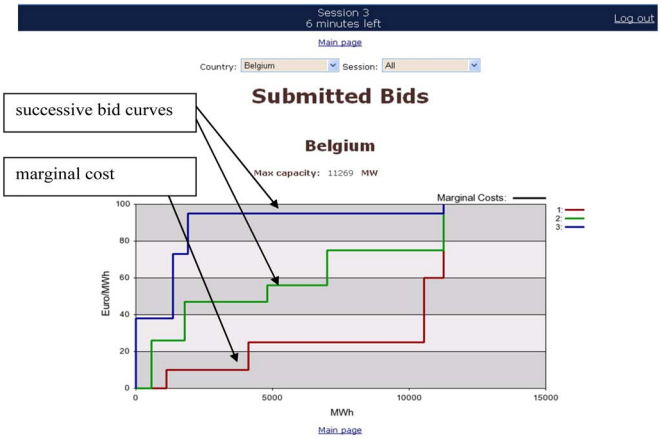

Fig. 2. Supply offering curves versus marginal cost curve.

per session. These offers are turned into a step function as illustrated in Fig. 2. Offers after submission are then put into the auction clearing function,[3] together with demand curves, in order to determine which offers should be accepted to maximize the total social surplus under the constraint of available transmission capacities. After solving the optimization, the market auctioneer returns the market outcomes to the students, including the market clearing prices at each node, aggregated demand curves, and their accepted production volumes (private information). Based on these results, students get insights about their profits[4] and consequently set up new offers for the next session.

C. Modeling the Market With Agents

Given the above defined market setting, students can be replaced by computational agents.

Similarly to students, agents in the model are generators which—based on their cost structures (i.e., marginal cost curves)—create offers for the auction. They also seek for profit maximization. Unlike students, agents behave according to a fixed set of actions and improve their strategic behavior systematically through a defined learning algorithm. This set of actions, however, is developed based on equivalent students' choices. In other words, the range of actions of each agent is made from actions of students who also play the role of this generator. Initially, in the first round, similar to the students, agents offer at their marginal cost curves then update the results and choose actions for the next round. After several rounds, by learning how the previous offering results (the profits they got) are, agents become more "expert" in making offers. At a certain stage, they finally can optimize their strategic behavior.

In this paper, the modified Roth–Erev Reinforcement Learning algorithm[5] has been chosen to be the "brain" of agents. The process of thinking, acting and learning of agents in an agent-based model is illustrated in Fig. 3.

[3]Details about the mathematical algorithm to solve the problem, refer to [31].

[4]The profit of each generator is calculated simply by deducting their generation cost (equaling their accepted volume multiplied by the equivalent marginal cost) from their total revenue (equaling their accepted volume multiplied by the market clearing price).

[5]For a detailed explanation of Roth–Erev Reinforcement Learning applied for agent-based modeling, refer to [32]

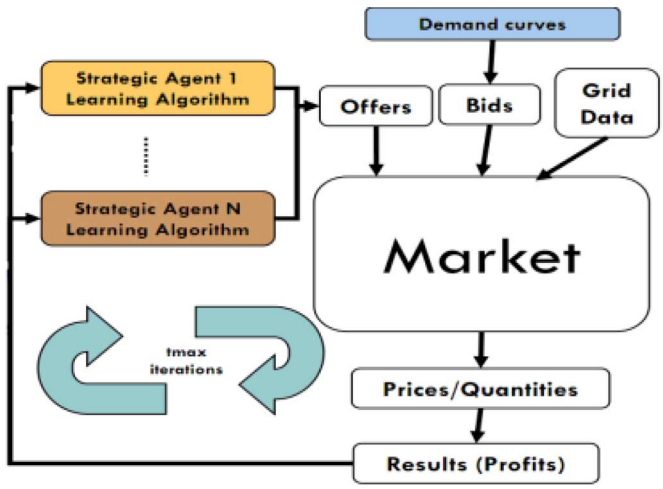

Fig. 3. Process in an agent-based model.

Actions of agents are defined as a number of mark-up values which agents add to their marginal costs to construct the supply offering curve. In other words, the supply curve of each agent has the same shape as their marginal cost curves but shifted upwards. Every agent chooses a mark-up value based on the goal of profit maximization. In the model of this paper, there are 100 possible actions agents can choose, equivalent to 100 possible mark-up values.

In the set of agent's actions, each action has its own specific probability to be chosen. This probability is changed (or updated) after each market outcomes that agents gain. In the Roth–Erev learning approach, the probability of choice is calculated through the propensity of the action. In general, the probability that an action is chosen over a set of 99 other actions equals to the proportion between this action propensity and the total propensity of all available actions:

$$p_{ik}(t) = \frac{q_{ik}(t)}{\sum_k q_{ik}(t)} \tag{1}$$

where $p_{ik}(t)$ is the probability that agent i will chose action k at round t and $q_{ik}(t)$ is the propensity of action k at round t with agent i.

At the initial round, q_{ik} is set based on the parameter "strength of initial propensity"—the scaling parameter—$s(1)$ of the algorithm. After that, q_{ik} is updated after every round. The formula to update q_{ik} requires knowing the reward that the agent gains from that round. In this paper, the reward R is defined by comparing the agent's profit of the current round with that of previous round:

$$R_k(t) = \begin{cases} 1, & \text{if profit in round t is larger than profit in round t-1} \\ 0, & \text{otherwise.} \end{cases}$$

where $R_k(t)$ is the reward for agent i of round t in which action k is chosen.

There are two other key parameters of the Roth–Erev method which are taken into account for updating q_{ik}: the recency θ (to slowly reduce the importance of the past experience) and the experimentation ε (to reinforce actions similar to the current choice).

Combining the three parameters, the modified Roth–Erev algorithm in this paper updates the propensity q_{ik} as follows:

$$q_{ik}(t+1) = (1-\theta).q_{ik}(t) + E_j\left(k, R_k(t)\right) \tag{2}$$

in which

$$E_j\left(k, R_k(t)\right) = \begin{cases} (1-\varepsilon).R_k(t), & \text{if j = k (current action)} \\ \frac{\varepsilon}{M-1}.R_k(t), & \text{if j} \neq \text{k (current action)} \end{cases}$$

and M is the total number of available actions for agent i.

The updated propensity q_{ik} of each action of each agent at each round then leads to the change in the equivalent probability p_{ik} as in (1). That result will affect the agent's choice in the next round. This loop repeats up to a certain point where agents reach their optimal choice of action and the learning process consequently converges.

In order to guarantee an unbiased trend of the model at its initial rounds, the agent-based model is set to run several times. In this paper, the number of runs is chosen to be 5, and the number of iterations within each run is set to 500 rounds. Results of the model are the average values of these five runs.

The founders of the Roth–Erev algorithm found in [26] that the most suitable set of the algorithm's three parameters for their human studies are: Scaling $s(1) = 1$, recency $\theta = 0.1$ and experimentation $\varepsilon = 0.2$. In [10], authors confirmed this set of parameters to be appropriate for their tests. Hence, the agent-based model of this paper also uses these parameter values.

IV. Numerical Results

Here, the numerical results of the case study are presented, first for each approach separately and then a comparison of both approaches. In what follows, two approaches are evaluated based on two quantitative indicators of market outcomes: nodal market clearing prices and generators' individual profits.

A. Laboratory Sessions' Results

Different sets of students lead to different results. This section presents the average results of five lab sessions (the so-called "Lab Average") and the results of two individual lab sessions at the KUL in 2008 and 2010 (KUL-08 and KUL-10).

Fig. 4 shows that market clearing prices in lab session KUL-10 are the smallest among the three presented results while lab KUL-08 has the largest ones. The gap between both sessions is indeed very large. Price values of the Lab Average are closer to the price levels of lab KUL-10. The explanation for this observation lies in the fact that lab session KUL-08 is an extreme case where the group of students played substantially with their mark-up.

Although the absolute values of prices significantly differ between lab sessions, each individual lab session has its consistent trend of prices. If lab KUL-10 has price levels lower than 1000 EUR/MWh, this trend can be observed for every nodal price. For every node (i.e., country), the market clearing price of this node in lab KUL-10 is always smaller than that of lab KUL-08 (the lab with higher price level). In other words, the results illustrate the students are influenced by their classmates,

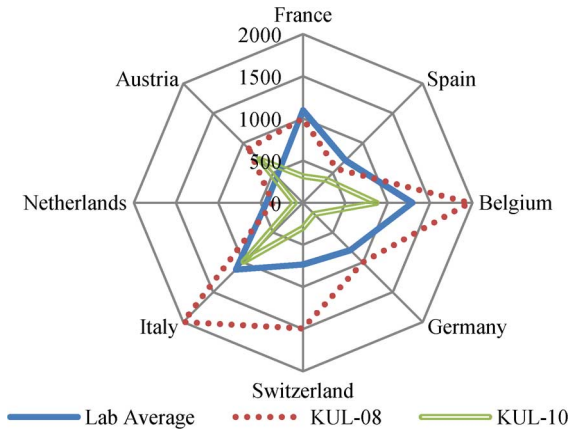

Fig. 4. Market clearing prices of laboratory simulation games.

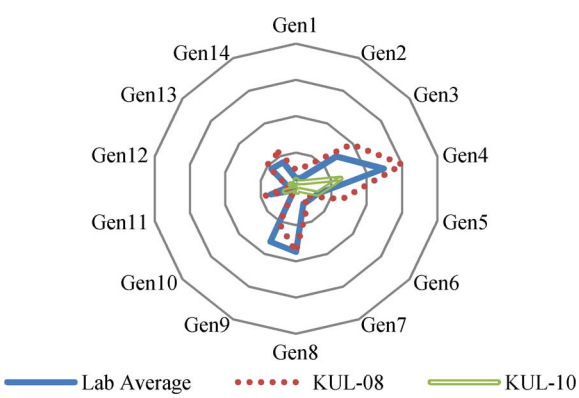

Fig. 5. Generators' profits in laboratory simulation games.

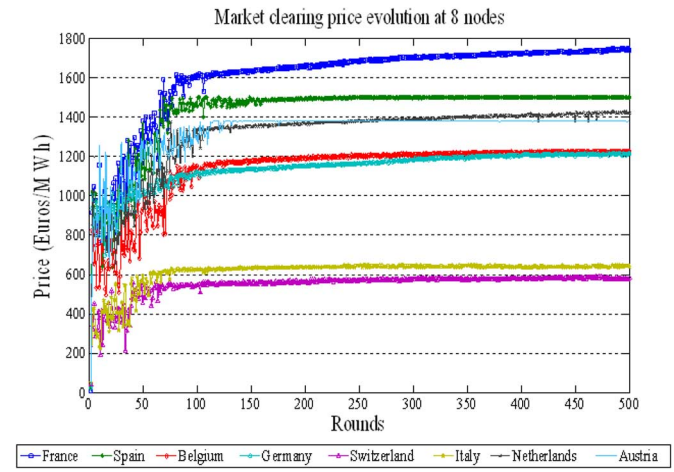

Fig. 6. Market clearing prices evolution of agent-based model.

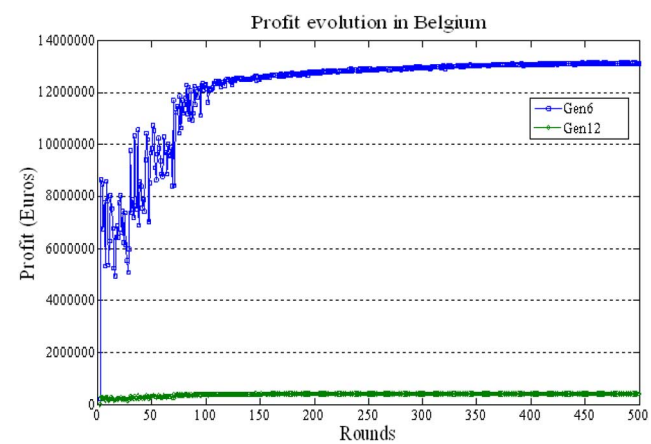

Fig. 7. Individual profit evolution in highly concentrated markets.

and learning has been different for different groups of students, with one group clearly outperforming the other groups.

The results in terms of generator profits confirm this observation (see Fig. 5). Individual profits of generators in lab KUL-10 are much smaller than those in lab KUL-08: the smallest profits value differs from 61 960 EUR in KUL-10 to 508 843 EUR in KUL-08 and has the value of 624 916 EUR in the Lab Average. The observation about the consistent trend in each lab also persists, i.e., the graph of KUL-08 also completely covers that of KUL-10. In addition, in terms of individual profits, different lab sessions share the same relative ranking of highest/lowest profits among the 14 generators. As illustrated in Fig. 5, a generator like Gen4 which trades in highly concentrated markets (France) with high market shares (88%) always gains the highest profits, while Gen1, Gen7, and Gen13 have much less profit as they are active in less concentrated markets (Germany) and have lower market shares.

B. Agent-Based Model's Results

Unlike students, agents fine-tune their strategies during many more rounds and then gain the optimal solution for their situation. Agents in our simulation converge after around 100 to 150 rounds.

Fig. 6 illustrates the evolution of nodal market clearing prices in the agent-based model (average values of five runs). After convergence, the electricity price in France is the highest among nodes and is around 1700 EUR/MWh. The electricity prices in Belgium and Italy—at around 700 EUR/MWh—are the lowest. It is observable that prices in countries with more concentration (i.e., France and Belgium) converge quicker. This can be explained by the fact that, in a more competitive market (lower concentration), it is harder for agents to define the optimal strategy as their market power is not strong and the market price is influenced by not only one agent but also by other agents' strategies.

In line with market prices, generators' profits reach the convergent point after 100 to 150 rounds. However, there are large differences between generators' profit values within a market as well as their oscillation ranges before convergence. During the first 150 rounds before convergence, the profit curves of agents which have higher profits fluctuate more strongly than their rivals which have less profit in the same market. The more their profits differ, the clearer this trend is observed.

For example, Fig. 7 illustrates the evolution of profits of Gen6 and Gen12 in the Belgian electricity market. This is a highly concentrated market where Gen6 predominates over Gen12. Gen6 gains much higher profits than Gen12 and its profit curve swings significantly before convergence at round 150. Gen12, in contrast, has a pretty stable curve.

In less concentrated markets, for example, The Netherlands (see Fig. 8), the same tendency can be observed, although the

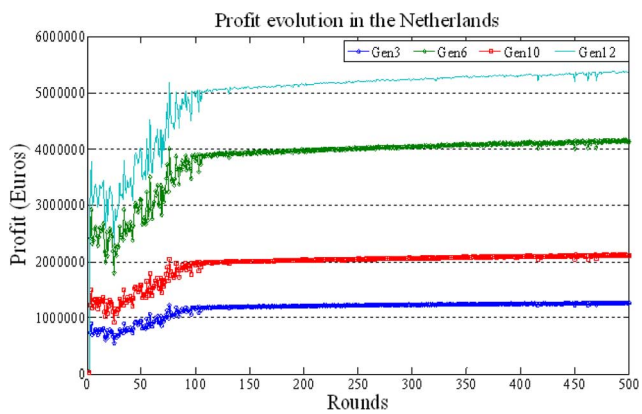

Fig. 8. Individual profit evolution in less concentrated markets.

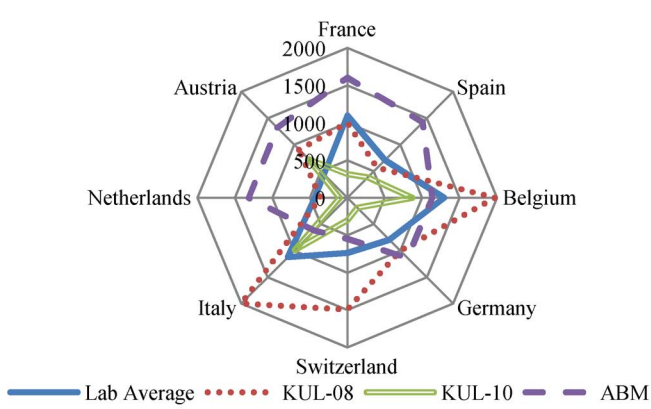

Fig. 9. Price comparison between the two approaches.

gap between agents' profit values as well as the difference between their profit curves' oscillation are much smaller than that in highly concentrated markets.

C. Comparison

Fig. 9 compares the average market clearing prices in 8 countries of the agent-based simulation with the results of the Lab Average as well as the individual labs KUL-08 and KUL-10. Apart from the extreme case of KUL-08, in general, market clearing prices at the eight nodes of the agent-based model are higher than those of students' experiments. The gaps between prices under the two approaches in these nodes are rather high: 1700 compared with 1097 EUR/MWh in France or 1323 compared with 437 EUR/MWh in Austria. In the meantime, at nodes where the prices of the Lab Average are higher than those of the agent-based model (Belgium, Italy), the difference is not that large.

Unlike prices, the individual profits of generators in the agent-based model completely surpass those of the students' experiments, with a large difference (Fig. 10). Individual profits of every generator as agent are superior to those of generators played by students. Gen4, for example, gets a total profit of 52 million EUR in the agent-based model but only 24 million EUR in the Lab Average or 30 and 12 million EUR in KUL-08 and KUL-10, respectively.

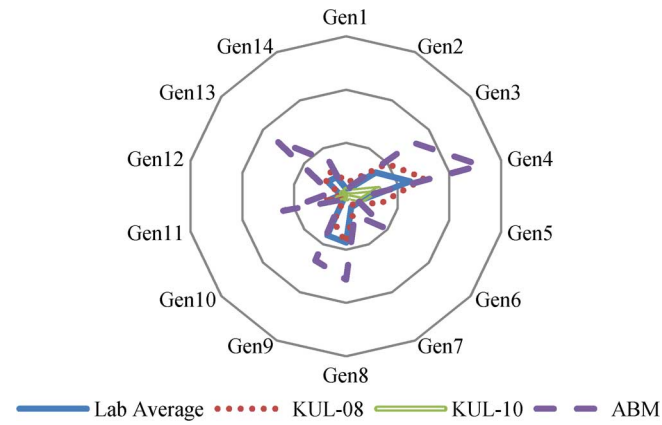

Fig. 10. Individual profits comparison between the two approaches.

V. Discussion

Quantitative results presented in the previous section shows that computational agents achieved higher generators' profits than students in the given market simulation. However, it is difficult to conclude which agent or method is superior. In what follows, we discuss the comparability of the two approaches in the way we have applied them, and we also identify improvements that would need to be made to the market test suite to permit more conclusive comparisons from future experiments.

A. Agents' Motivation

Controlling players' motivation is the most important but challenging task of laboratory experiments. The motivation that an experiment can provide to its human subjects can be intrinsic or extrinsic. Experimental economics literature often stresses the importance of extrinsic motivation using monetary incentives. However, Gneezy and Rustichini [34] showed that monetary compensation does not always induce higher performance. If participants perceive the experiment as a monetary environment, their efforts will be determined by the reward. A small payoff can therefore lead to worse performance than no payoff at all. The psychology literature puts even more emphasis on intrinsic motivation. Rydval and Ortmann [35], for instance, found that cognitive abilities could be twice as important as financial incentives. Others have warned that money may have detrimental effects on motivation [34]. Educational experiments where students are agents usually use grades as alternative extrinsic incentives while often emphasizing the importance of inducing intrinsic motivation in the simulation games they offer to students [36]–[40]. The intrinsic motivation of students comes from their interests in doing actions which are new and fun to them, and can also come from the element of competition against oneself or others [38].

In this paper, students have been mainly intrinsically motivated to maximize profits in the game. A survey organized by the didactics unit of the university that performed an audit of the game [20] did confirm students' motivation to play the game and learn how to maximize profits during the laboratory sessions. However, when compared with computational agents which are programmed to maximize profits, the motivation of students seems to be uncontrollable and incompatible. As money (i.e.,

profits) is the incentive of computational agents, a compatible extrinsic incentive should be given to students. Besides grades for the participation, grades proportional to the profit students earned could motivate students as strongly as the profit motivation to real traders. By that means, or by actual payments, the motivation gap between the two approaches could be mitigated.

B. Cognitive Issues and Expertise

While agents learn and update their data at a constant rate as they are programmed, humans, in contrast, often have a decreasing rate in their learning function. At a certain point, when knowledge reaches a certain level, learning is slower because it depends on a subjective assessment of efforts and gains, which is difficult to model. According to Hayek [27], this assessment is influenced by time, location, context, personal knowledge, perception, preferences, and other factors. Together they impose cognitive constraints[6] upon human decision-making process. In addition, when making decisions, individuals and organizations often rely on simple heuristics in an adaptive way and "ignoring part of the information can lead to more accurate judgments than weighting and adding all information" [41]. This is not the case of computational agents which are programmed to make careful decisions based on all information available to them.

The results of the KUL lab sessions above provide a clear illustration of the influence of cognitive issues on students' results. There is a large variation between individual sessions and between each of them with the average data. In particular, lab KUL-08 achieves much higher profit results due to the fact that one student started with a very high mark-up, leading all other students to behave similarly (heuristics decision). In addition, results of students in the laboratory are also more fickle than those of computational agents, perhaps explained by the absence of variations in cognitive characteristics in the agent-based model.

Students in the educational laboratory however could not represent the choices by traders in reality due to their lack of expertise. Different groups of students or even different students also have different knowledge and learning speeds which are hard to control for unless a careful selection of participants is made. Computational agents' expertise, in contrast, is more controllable. To compare computational and human agents, a group of selected trading experts might be more uniform and representative of actual trader behavior than students.

C. Number of Rounds and Sample Size

Due to limited time resources, our laboratory results include only 5 sessions with a maximum of 15 trading rounds for each. Comparing with 500 rounds of agent-based simulation, that creates a limitation on our comparative illustration and makes it hard to discuss the learning curve of the students.

The results that we compare are the outcomes that each approach converges to rather than the results they obtain after the same number of rounds, which was typically 100 rounds for computational agents and only ten rounds for students (Fig. 11).

[6]How cognitive characteristics influence an individual decision-maker are extensively discussed in psychology literature, especially concerning "bounded rationality" [28] and "heuristic decision making" [36].

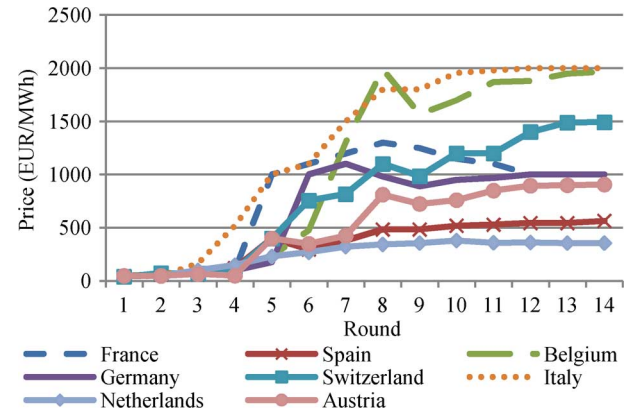

Fig. 11. Convergence of students' laboratory results (market clearing price of lab KUL-08).

Note, however, that the quick convergence of students might also be partly explained by inadequate motivation due to the lack of payment.

D. Freedom of Choice

Freedom of choice is one advantage of the human agents and is hard to model with computational agents who are constrained to a predefined limited "action space". Although our study tried to mitigate this factor by including the full range of students' offers into the agents' action domain, it could have an important impact on the results. Future comparisons need to reduce this inconsistency by either limiting possible choices for the human agents or increasing the action domain of computational agents.

VI. Conclusion

In the market test suite that we designed for students to learn about electricity market design and market behavior, computational agents outperform the groups of students we have had over the years.

The approach used does not allow us to generalize from this result, but the results do illustrate that this is a promising line of research that merits further investigation, and we have identified recommendations for further research.

A first improvement could be to motivate students extrinsically by grading them proportionally to their earned profits in the laboratory sessions or to make actual monetary payments. Note that the number of rounds in which students trade would then also need to be increased to allow this increased motivation to result in improved learning.

A second improvement could be to align better the action domain of students with that of agents, which could be done by reducing the action domain of students in the market test suite we developed.

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