ABSTRACT— In this paper, a competitive coevolutionary approach based on the concept of Evolution stable strategies is used to analysis a day-ahead market. The day-ahead market is considered as a mixed bilateral/pool market, where participants can sign for forward bilateral contracts several months in advance from its delivery, and have to take part to the spot market 24h prior of the delivery. We consider market participants interaction as an evolutionary game played by bounded agents, adapting their strategies to maximize their profits in a competitive environment. Under the effect of the competition, the coevolved agents are led toward an equilibrium point where each agent population is invaded by an Evolutionary stable Strategy.


I. Introduction

Since the deregulation of electricity market has been initiated, different market structures have appeared. The anatomy of deregulated power markets worldwide shows that the reform process has taken a number of different forms in various countries. Economic and political reasons, due to local conditions, have led to the adoption of different paradigms by the newly established market [1].

Despite these differences, the competitive aspect of the generation sector is the most common basis in deregulated electricity markets models. Another common characteristic to deregulated electricity market is the oligopolistic aspect of the market. Few competing firms act strategically to maximize their profit. Unlike, perfect competition or monopoly markets where agents' interactions can be dealt with as a simple optimization problem, agents' strategic interactions in an oligopoly market need a game theoretic approach: traditional non-cooperative game theory, evolution game or agents based modeling.

The standard non-cooperative game theory models market agents by assuming that the game is played by fully rational players who have complete information about the game. However, emergent electricity markets present all sorts of imperfection, uncertainties and lack of information. As a result, the game theoretic approach is no longer suitable with the increasing complexity and imperfections that characterize an electricity market; it usually fails to represent the essence of human actions: the capability of learning through mistakes, and the impossibility of handling unavailable or unclear information.

Instead, Evolutionary Game Theory assumes that large populations of bounded rationality players are involved in an imperfect game. By this manner, evolutionary game theory is more suitable to analyze complex strategic interaction in an electricity market, in which agents cannot be considered as full rational due to the stochastic aspect of power system parameters.

The aim of this paper is to compute the market equilibrium point of a day-ahead electricity market, where market participants can trade in two markets. In forward bilateral market transactions are negotiated directly between suppliers and consumers several months prior the delivery, and in a centralized pool market where the Independent System Operator (ISO) acts as a single buyer in order to preserve the integrity of the power system.

In our approach the bidding strategies of the market participants is considered as a continuous asymmetric game played by bounded rationality evolutionary agents, where each agent is represented by a population of strategies. The coevolving populations are driven by a competitive Coevolutionary algorithm to reach the equilibrium point.

The paper is organized as follow: in the next section, the elements of Evolution Game Theory and Evolutionary Stable Strategies are presented. Market models are developed in section III. Section IV presents the Coevolutionary approach validated by some examples in section V. Finally, section VI concludes the paper.

II. Evolution game theory

Evolution game theory is originated from the use of non-cooperative game theory to formulate a mechanism for biological evolution. Each player in the population is assumed to repeatedly play a particular strategy against other players in the game [2, 3].

There are two strands to Evolutionary Game Theory; Evolution Stability and Replicator Dynamics. Evolution Stability concerns the ability of a strategy to resist to any mutant strategy invasion. It is hence concerned with the mechanism of mutation and fitness. From a game theoretic perspective, evolution stability provides criteria for assessing the relative robustness of Nash equilibrium against out of equilibrium behavior.

On the other hand, replicator dynamics provide a model of dynamic adjustments in the population of competing strategies. Replicator dynamics highlights the role of selection, focusing on the adjustments process in competing strategies or populations that emerge as a consequence of their relative fitness. In this paper, the emphasis is given to the evolution stability rather than replicator dynamics. In particular, we concentrate on the earliest stability criteria in evolution game theory: Evolutionary Stable Strategies.
2.1 Evolution Stable Strategies

The concept of Evolutionarily Stable Strategy (ESS), introduced by Maynard Smith [4], is usually applied to evolutionary processes where agents adopt a strategy and then learn of its comparative success. An ESS is based on the idea of relative robustness of Nash equilibrium against invasion by out of equilibrium alternatives. Hence, ESS is a particular strategy such that any player adopting a different strategy does no better than the average of all other players, all of whom are playing the same ESS strategy [5,6].

To illustrate the concept of ESS, in the context of a monomorphic population, suppose individual fitness is the expected payoff in random pair wise contest. The ESS strategy $S^*$ must do at least as well as a mutant strategy $S$ in their contest against $S^*$ and, if these contests yield the same payoff, then $S^*$ must do better then $S$ in their rare contest against the mutant strategy $S$. $S^*$ is an ESS, if and only if, for all $S \neq S^*$:

\[ \pi(S, S^*) \leq \pi(S^*, S^*) \]  
\[ \text{if } \pi(S, S^*) = \pi(S^*, S^*), \pi(S, S) < \pi(S^*, S) \]  

Where $\pi(S, S^*)$ is the payoff of $S$ against $S^*$.

Equation (1), indicate that an ESS is a Nash Equilibrium (NE) with the extra refinement condition (2) which is related to dynamic stability [7]. From the classical game theory perspective of predicting individual rational behavior, ESS are Nash Equilibrium (NE) with added stability conditions and so can be regarded as equilibrium selection technique [6].

The previous definition of ESS is made for Symmetric two-player game. ESS theory has been extended to other game classes. In this work, we focus on the concept of Evolutionary Stability in continuous strategies space, which is more suitable for the problem on hand.

2.2 Continuous Stable Strategies

The Continuously Stable Strategies (CSS) was developed in the biological literature as a mean to predict the long run behavior of individuals in a single specie, when individual fitness is modeled by payoff in symmetric game with a continuous set $S$ of pure strategies. From this perspective, the CSS is a transcription of the concept of ESS in a continuous strategies space [6].

Commonly there are several definitions of CSS depending on the nature of the game; we focus on two major definitions: symmetric games and asymmetric games.

2.2.1 Symmetric Games

Let $G$ be a two-player symmetric game with pure strategy set $S$ and payoff function: $\pi: S \times S \rightarrow \mathbb{R}$ where $\pi(x, y)$ is a continuous payoff of $x, y \in S$. $x^* \in S$ is a CSS if:

1) $x^*$ is neighborhood superior which means that it can invade any nearby monomorphic population i.e.: 

\[ \pi(x^*, x) > \pi(x, x) \]  

For all $x \in S$ sufficiently close (but not equal) to $x^*$.

2) And $x^*$ is neighborhood strict Nash Equilibrium and cannot be invaded by any mutant strategy $x$, i.e. 

\[ \pi(x^*, x^*) > \pi(x, x^*) \forall x \in S, x \neq x^* \]  

Thus, $x^*$ is a symmetric continuously stable strategy if inequalities (3) and (4) are satisfied.

2.2.2 Asymmetric Games

In $N$-player asymmetric game with $N$ species, pairwise contests involve players in opposite roles, and each player is defined by a disjoint populations. All members of the same population $i$ have the same set of strategies $S_i, i = 1, \ldots, N$ with $N$ number of populations.

Suppose players 1 and 2 have continuous strategy space $S \subset \mathbb{R}^m$ and $T \subset \mathbb{R}^n$ respectively (supposed convex compact). Let $G$ an asymmetric two-player game with strategy set $S \times T$ and payoff functions: $\pi_i: S \times T \rightarrow \mathbb{R}$ for $i = 1,2$. We consider that $(x^*, y^*)$ is a CSS if it is a neighborhood strict NE, inequality (5) and asymptotically stable (locally invadable) inequality (6).

\[ \pi_i(x^*, y^*) > \pi_i(x, y^*) and \pi_2(x^*, y^*) > \pi_2(x^*, y) \]  
\[ \pi_1(x^*, y^*) > \pi_1(x, y) and \pi_2(x^*, y^*) > \pi_2(x, y) \]  

For all $x \neq x^*$ and $y \neq y^*$ sufficiently close to $x^*$ and $y^*$ respectively.

III. MODEL FORMULATION

In this paper we consider the day-ahead market as a mixed bilateral/pool market. Market participants have to take parts to the spot market (pool), suppliers submit their bids in term of a supply function and consumers submit their load.

In order to ensure economical and physical reliability of the power system, the ISO performs an OPF to determine the quantity and the price to be dispatched to each supplier. Still, the market participants have to honor their forward bilateral contracts at the forward market price.

3.1 Model assumptions

We consider an electricity market with $N_g$ suppliers and $N_c$ Consumers.

- Each supplier is defined by a quadratic cost function in the form:

\[ C_i(q_i) = \frac{1}{2} a_i q_i^2 + b_i q_i + c_i, \]  

\[ i = 1, \ldots, N_g \]  
\[ q_{i_{\text{min}}} \leq q_i \leq q_{i_{\text{max}}} \]

Where:

- $q_i$ is the quantity generated by firm $i$:

- $a_i, b_i, c_i \geq 0$ are the coefficients of the cost function.

A. Bilateral market

In the bilateral forward market, suppliers and consumers directly negotiate the price and the quantity of traded energy several months prior to the delivery.
Forward transactions are purely financial, their concretization will occur in the real time, and they are not conditioned by production capacity or transmission limitations, agents can even trade energy they can not produce and in order to honor their contracts, the difference has to be purchased from the pool at spot price.

In this paper, the bilateral market is analyzed using Cournot model, suppliers compete in term of quantities to be sold, and consumers are defined by their demand function where the amount of energy to be acquired is inversely proportional to the price [8].

Consumers’ demand functions are of the form:

\[ D_j(p) = D_j^0 - ep_j \quad j = 1, \ldots, n_d \]  

(8)

Where:
- \( p_j \) is the electricity price
- \( D_j^0 \) is the intercept of the demand function.
- \( e \geq 0 \) is the elasticity against price.

The nodal marginal clearing price is defined by the inverse demand function as follow:

\[ p^b_j = D_i^{-1}(D_j^0 - \sum_{i=1}^{n} q_{ij}) \quad j = 1, \ldots, n_d \]  

(9)

Where:
- \( p^b_j \): electricity price
- \( D_j^0 \): is the demand
- \( e > 0 \): is the price elasticity

Then the suppliers’ payoff from the contracts is formulated as follow:

\[ \pi^b_i = \sum_{j=1}^{n_d} p_j q_{ij} \]  

(10)

Where
- \( p_j \): is the electricity price
- \( q_{ij} \): quantity sold by supplier \( i \) to consumer \( j \)

B. Spot Market:

The spot market is organized as a centralized market with maximalist ISO, where trading is done 24h prior to the delivery. In centralized market, there is no direct trading between suppliers and consumers, the ISO acts as single buyer, it collects bids for power to purchase from the consumers and decides on quantity to be purchased from suppliers, in such a way that leads to maximization of social welfare and preserving system constraints [8].

The spot market is analyzed using supply function model, where each agent submits an affine SFE of the form:

\[ p_i = b_i + x_i q_i \]

\[ q_i \leq q^\star_i \leq q_i \]

(11)

In [9], it is shown that \( b^\star_i \) should be equal to the true cost parameter \( b_i \).

Thus, suppliers’ utility function is defined as:

\[ U_i(q_i) = \int p_i dq_i = \frac{1}{2} x_i q_i^2 + b_i q_i \]  

(12)

In order to preserve network constraints and maximize social welfare, the ISO performs an Optimal Power Flow \[10]\)

\[ \min \sum_{j=1}^{n} U_j(q_j) \]

s.t.

\[ p_d - Y_{bus}\theta = P_d \]

\[ |\theta_i - \theta_j| \leq \delta_{ij} \]

Based on the outcome of the OPF, the ISO defines for each supplier the quantity to be dispatched \( P_{g_i} \) and the locational Marginal Price (LMP) \( P^s \). Thus the supplier’s profit in the spot market will be expressed as

\[ \pi^s_i = p^s_i \left( P_{g_i} - \sum q_{ij} \right) - C_i(P_{g_i}) \]

(14)

Where:
- \( p^s_i \) LMP of the bus \( i \)
- \( P_{g_i} \) quantity to be dispatched to supplier \( i \)
- \( \sum q_{ij} \) total quantity contracted in the bilateral market (sold at the bilateral market price)
- \( C_i(P_{g_i}) \) generation cost.

The supplier overall profit from both transactions can be formulated as:

\[ \pi_i = \pi^b_i + \pi^s_i \]

\[ \pi_i = p_i^b q_i + \left( P_{g_i} - \sum q_{ij} \right) p_i^s - C_i(P_{g_i}) \]

(15)

3.3 Market equilibrium

Strategic bidding in a deregulated electricity market is inherently a repetitive non-cooperative game with incomplete information. Each player tries to find the best strategies in order to maximize his payoff. In this paper we consider that a supplier has two strategies: the quantities to be sold on bilateral forward market and supply function parameter.

\[ S_i = \{q_{i1}, \ldots, q_{iNd}, x_i\} \]

Where:
- \( q_{i1}, \ldots, q_{iNd} \) are the quantities to be sold in bilateral forward market
- \( x_i \) is the supply function parameter to be submitted to the ISO in the spot market.

In game theory, game equilibrium is defined by a particular set of strategies:

\[ S^* = \{S^*_1, \ldots, S^*_i, \ldots, S^*_n\} \]

Such that:
\[ \pi_i(S^*) \geq \pi(S_i^*, S_{1}^*, ..., S_{n_g}^*) \quad \forall S_i^* \neq S_{j}^* \quad (16) \]

By definition, the game is asymmetric with continuous strategies space. So to reach the equilibrium point, we search for a particular set of strategies: \( S^* = \{S_1^*, ..., S_{n_g}^*\} \) such that \( S^* \) is the set of asymmetric continuous stable strategies and satisfies the inequalities (5) and (6).

In order to find out the set of ESS and therefore the market equilibrium point, the electricity market is modeled as an evolutionary game, where suppliers are evolutionary agents with a finite population of strategies. Market agents are involved in a repeated non-cooperative game with imperfect information; agents have no information on their opponents’ strategies, and consider the market as a black box. Each agent submits his bid to the market operator and receives a payoff basis on his bid and opponents strategies.

IV. COMPETITIVE COEVOlUTIONARY ALGORITHMS

Coevolutionary Algorithm is an Evolutionary Algorithm (or collection of Evolutionary Algorithms) in which the fitness of an individual depends on the relationship between that individual and other individuals [11]. In biology, Coevolution is defined as reciprocity induced evolutionary change between two or more species or populations. In Competitive Coevolution, individual fitness is evaluated through competition against individuals of other populations. Considering this, fitness signifies only a relative strength of solutions [12,13].

Competitive Coevolution is traditionally used in non-cooperative Evolutionary game theory to gain insight into the dynamic of game theoretic problems [12]. Competing individuals use random variation and selection to seek out survival strategies that will give them an edge over their opponents. Therefore, populations are constantly evolved to exploit weaknesses in the opposing population. As a result, both populations are constantly being exposed to more fit individuals from the opposing population. Ideally, this leads to incremental improvement with each population continually evolving to meet the increasing pressure from the opposing one [14].

In host/parasite competitive Coevolution algorithm, fitness measure is relative. It depends on both host and parasite behavior. Fitness is no longer an absolute measure of how strategy is good; suboptimal strategies in earlier generations can become optimal in later generations. In a finite population, a strategy has to be successful in almost every generation to stay in population; if it fails, it is eliminated under the pressure of selection. Eliminated strategies can become optimal again. Loosing such strategies can make the progress toward optimality no longer guaranteed [15].

To ensure convergence toward optimal solution (Evolution Stable Strategies), individuals selected to be part of next generation have to be capable of defeating the prior individuals. If this is not ensured, the algorithm can get stuck in weak strategies. To counter that, we seek an algorithm that progresses by producing new strategies that defeat older ones, and avoids the loss of interesting strategies.

A. Approach

In this work, we develop a Competitive algorithm inspired from the host-parasite model where the term host refers to the individual whose fitness is under consideration, and parasites refers to the individuals that are testing the host.

In order to build a host-parasite Competitive Coevolutionary algorithm, for the problem on hand, and to ensure proper convergence toward the optimum, two techniques are proposed in the present paper: the nested evolution strategies and hall of fame techniques.

1) Nested Evolution Strategies

The proposed Competitive Coevolutionary Algorithm is based on Evolution Strategies Algorithm (ES). ES is one of the main paradigms in Evolutionary Computation [16,17], unlike Genetic Algorithms, ES is primarily concerned by the mechanism of mutation, and the selection is based on the behavior (phenotype) of individuals, and are not concerned by the scheme theory as the GA are.

In nested ES or \( \{\mu, \lambda (\mu+\lambda)^\gamma\} \) ES, there are \( \mu \) populations of \( \mu \) parents, these are used to generate (eg. by merging) \( \lambda \) initial populations of \( \mu \) individuals each. For each of these \( \lambda \) populations a \( (\mu+\lambda) \) ES is run for \( \gamma \) generations. The criterion to rank the \( \lambda \) populations after termination might be the average fitness of the individuals in each population. This scheme is repeated \( \lambda \) times.

2) Hall of Fame

To ensure progress and avoid effect of finite population, the technique of Hall of Fame is introduced. The hall of fame preserves the best individuals from earlier generations for future testing. Hosts are tested against both current parasites and a sample of hall of fame, so the successful new strategies are robust against old parasites. To access the hall of fame, individuals are involved in a binary tournament [18].

The algorithm is run for a predefined number of generations, to allow agents’ population to be monomorph and test their robustness to mutated strategies invasions. By using the nested ES with isolated sub populations, the population cannot be mono-morph unless all subpopulations are constituted by the same strategy. Coupled with the hall of fame, the proposed algorithm is prevented from premature convergence to weak strategies.

V. CASE STUDY

To test the effectiveness of the proposed algorithm in the case of electricity market equilibrium, two cases studies are used based on IEEE 30 bus system where 6 suppliers and 20 consumers are carried out. The suppliers and consumers’ data are reported on tables 1 and 2.

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Bus</th>
<th>( a_i ) [$/MW*h]</th>
<th>( b_i ) [$/MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0.15</td>
<td>25</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>0.25</td>
<td>20</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>0.20</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>22</td>
<td>0.25</td>
<td>22</td>
</tr>
<tr>
<td>5</td>
<td>23</td>
<td>0.20</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>27</td>
<td>0.15</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 1: Suppliers Cost data
For comparison purpose, we use 03 cases studies:

1- In the first case market, agents compete in the bilateral forward market only.
2- In the second case, agents compete in the spot market only.
3- In the third case, agents compete in both markets.

Table 2: Consumers demand function parameters

<table>
<thead>
<tr>
<th>Consumer</th>
<th>$D_i^0$ (MWh)</th>
<th>$e_i$ ($$/MWh)</th>
<th>Consumer</th>
<th>$D_i^0$ (MWh)</th>
<th>$e_i$ ($$/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>62.5</td>
<td>1.00</td>
<td>11</td>
<td>50.0</td>
<td>0.90</td>
</tr>
<tr>
<td>2</td>
<td>40.0</td>
<td>0.80</td>
<td>12</td>
<td>50.0</td>
<td>1.00</td>
</tr>
<tr>
<td>3</td>
<td>50.0</td>
<td>0.80</td>
<td>13</td>
<td>37.5</td>
<td>0.70</td>
</tr>
<tr>
<td>4</td>
<td>75.0</td>
<td>1.00</td>
<td>14</td>
<td>25.0</td>
<td>0.60</td>
</tr>
<tr>
<td>5</td>
<td>60.0</td>
<td>0.90</td>
<td>15</td>
<td>25.0</td>
<td>0.90</td>
</tr>
<tr>
<td>6</td>
<td>50.0</td>
<td>1.00</td>
<td>16</td>
<td>25.0</td>
<td>0.60</td>
</tr>
<tr>
<td>7</td>
<td>40.0</td>
<td>0.70</td>
<td>17</td>
<td>37.5</td>
<td>0.80</td>
</tr>
<tr>
<td>8</td>
<td>25.0</td>
<td>0.60</td>
<td>18</td>
<td>25.0</td>
<td>1.00</td>
</tr>
<tr>
<td>9</td>
<td>40.0</td>
<td>0.80</td>
<td>19</td>
<td>37.5</td>
<td>0.80</td>
</tr>
<tr>
<td>10</td>
<td>25.0</td>
<td>1.00</td>
<td>20</td>
<td>37.5</td>
<td>0.80</td>
</tr>
</tbody>
</table>

2) Spot market Equilibrium

In the second case, we consider that agents make bids in the spot market only. We assume that suppliers submit linear affine supply function to the ISO who performs an OPF to compute the quantity and price to be dispatched to each supplier. By using the proposed algorithm, the spot market equilibrium is reported on table 6.

Table 6 Suppliers’ equilibrium point in spot market

<table>
<thead>
<tr>
<th>x_i[$$/ MW•h]</th>
<th>P_i [MW]</th>
<th>Price [$$/ MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.11</td>
<td>177.15</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.16</td>
<td>129.67</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.13</td>
<td>154.07</td>
</tr>
<tr>
<td>supplier 4</td>
<td>0.16</td>
<td>126.75</td>
</tr>
<tr>
<td>supplier 5</td>
<td>0.13</td>
<td>159.85</td>
</tr>
<tr>
<td>supplier 6</td>
<td>0.08</td>
<td>200.00</td>
</tr>
</tbody>
</table>

3) Day-ahead electricity market equilibrium

In this case study, agents take part on both bilateral forward market and spot market. Using the developed competitive coevolutionary algorithm, we compute the Equilibrium point of the mixed bilateral/pool market. The obtained results are shown on Tables 7, 8 and 9.

Table 7 Suppliers’ optimal strategies in the bilateral market quantities contracted (MWh)

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tbody>
<tr>
<td>Supp 1</td>
<td>0.00</td>
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<td>0.00</td>
<td>4.67</td>
<td>0.00</td>
<td>1.16</td>
</tr>
<tr>
<td>Supp 2</td>
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<td>1.56</td>
<td>0.00</td>
<td>3.64</td>
<td>7.93</td>
<td>2.81</td>
</tr>
<tr>
<td>Supp 3</td>
<td>1.35</td>
<td>2.63</td>
<td>0.00</td>
<td>1.53</td>
<td>0.36</td>
<td>1.50</td>
</tr>
<tr>
<td>Supp 4</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>3.11</td>
<td>0.56</td>
</tr>
<tr>
<td>Supp 5</td>
<td>0.00</td>
<td>3.11</td>
<td>0.01</td>
<td>7.99</td>
<td>4.22</td>
<td>0.00</td>
</tr>
<tr>
<td>Supp 6</td>
<td>3.04</td>
<td>0.00</td>
<td>1.46</td>
<td>4.39</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 8: Consumers’ load and price at equilibrium point

<table>
<thead>
<tr>
<th>Consumer</th>
<th>D [MWh]</th>
<th>P [$$/MWh]</th>
<th>Consumer</th>
<th>D [MWh]</th>
<th>P [$$/MWh]</th>
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</tbody>
</table>
It is clearly observed from Tables 7 and 8 that in order to increase their profit, suppliers should withdraw some of their bids in the bilateral market and choose spot market where prices are higher.

VI. CONCLUSION

This paper presents a new approach to find out the market equilibrium in deregulated electricity markets using a competitive coevolutionary algorithm based on the concept of Evolution Stable Strategies. In the latter, each agent is represented by a population of strategies and uses nested evolution strategies as learning method to find the best behaviors to overcome opponents’ strategies.

In our approach, we consider the day-ahead market as a mixed bilateral/pool market, each agent acts strategically in order to maximize his profit: it submits bids in terms of quantity to be sold in the bilateral forward market, and a supply function in the spot market in order to maximize its profit.

To validate the proposed algorithm, an IEEE 30 bus test system is used as a case study. The proposed algorithm is applied to analyze strategic behavior of market’s agents in both bilateral forward market, spot market and day-ahead market. In the different cases considered, the proposed algorithm has succeeded in finding the ESS set and hence the market equilibrium point. Furthermore, the obtained results show that suppliers’ strategic behavior increases the market clearing price by withdrawing quantities to be sold in the bilateral market to increase the market price and there for their profits.

From the studied cases, one can notice that the main advantage of the proposed approach is the possibility to handle different market structures and pricing schemes, which makes it an appropriate simulation and analysis tool for deregulated electricity markets.

VII. BIBLIOGRAPHY


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