An ACE wholesale electricity market framework with bilateral trading

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Abstract In this paper, an agent-based simulation model for a hybrid power market structure is presented. A bilateral transaction mechanism is combined with a uniform-pricing auction settlement in order to isolate the impact of medium-term bilateral contracts on market power and spot prices in a competitive wholesale market setting. First we describe the negotiation method for bilateral trading of energy and then introduce a new approach for bidding in the DA market based on the load duration curve. We find that, despite the conventional concerns, the foreclosure effect produced by the bilateral agreement between a generation and a retail business will not necessarily lead to higher prices, and will be manifested only according to the specific market characteristics.

1 Introduction

During the last 20 years, the traditional vertically integrated structure of the electricity market has undergone a worldwide transformation as many countries have begun to restructure and/or liberalize the sector. The new electricity markets have been characterised by an oligopoly of generators, very little demand-side elasticity in the short term, and complex market mechanisms designed to facilitate both financial trading and physical real-time system balancing. In many countries, therefore, the cost-based fully centralized dispatch has been abandoned towards a bid-based dispatch and/or a bilateral trading.

In order to figure out in advance the effects of these restructuring policies, more and more researchers have been developing electricity market models. In this research field, thanks to its capability of modelling large-scale complex systems better than the more traditional optimization and equilibrium models, the agent-based

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(AB) paradigm has become very popular. Moreover, increasingly powerful computational resources as well as the development of toolkits that facilitate the implementation of agent based models in object-oriented programming languages have further pushed the development of the Agent-based Computational Economics (ACE)[1].

An AB model of the England and Wales electricity market[2] is implemented by Bower and Bunn [2] to compare different market mechanisms, i.e. daily versus hourly bidding and uniform versus discriminatory pricing. A very detailed discussion of the results of this model can be found in [3] where the basic model is validated against classical models of monopoly, duopoly, and perfect competition. The same model is also applied to the case of German electricity sector in [4] to analyze the impact of four mergers of large German utilities that were probable at the time of the study (and have actually taken place shortly after). A more detailed model of the New Electricity Trading Arrangements of England and Wales (NETA) is discussed in [6] where, differently from the precedent study, the authors explicitly model an active demand side and the interactions between the bilateral market and the balancing mechanism as a call market with pay-as-bid settlement. An extension of the same model and further analysis is presented in [7] where it is analyzed whether two specific generation companies in the England and Wales electricity market can manipulate market prices to increase their profits. The same model has also been applied in [5] to the analysis of the market power on the electricity market in England and Wales.

In the present work a simplified power generating sector has been modeled. A medium-term bilateral transaction mechanism is combined with a uniform-pricing auction settlement. Generation Companies (GenCos, i.e. companies possibly owning several plants with different generation technologies) and Suppliers (Supps, i.e. the agents purchasing from wholesale market in order to supply end-use customers) are not mandated to submit energy bids in the auction mechanism as they are allowed to sign bilateral medium-term (6 months or more) contracts. In this framework, we envisage a wholesale market with the demand side being price-taking and GenCos offering above the marginal cost.

An Independent System Operator (ISO) daily controls and coordinates the power exchange market whereas it does not have any role in the financial negotiations and settlements of a bilateral contract. In the auction market, clearing is given by the point in the (Euro, MW) space where demand and supply curves meet, resulting in a single price for the whole market, the marginal system price (MSP), assuming no operating and transmission constraints are violated.

Bilateral (B) exchange contracts are included in the day-ahead (DA) market, receiving a scheduling priority, and are concluded after a negotiation process based on a similarity measurement paradigm.

Within this agent-based framework, the proposed computer simulation model allows us to isolate the impact of medium-term bilateral trading on market power and spot prices in a competitive wholesale market setting.

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[1] A complete survey of tools for agent-based simulation of electricity markets can be found in [9].

[2] A complete survey of agent-based electricity market models can be found in [8].

The hybrid structure of the model presented in this paper is innovative in two key regards. First, to our knowledge, no prior research has focused on a wholesale energy market where the uniform-pricing auction settlement is combined with medium-term bilateral trading. Second, this model implements a price bidding for the auction market based on the load duration curve.
The remaining structure of the paper is organized as follows. Section 2 outlines the composition of the proposed power market. Section 3 discusses the bilateral algorithm and the trading behavior in the B market. Section 4 describes the demand side and the supply side in the DA market. Section 5 defines the simulation settings. Results are presented in Section 6. Section 7 concludes.

2 Market composition

The electricity production process can be divided into four different stages:

- Generation;
- Transmission along the high voltage network;
- Distribution along the medium and low voltage network;
- Supply to final customers.

While the network fixed sunk costs make the transmission and the distribution stages natural monopolies, at the national and regional level respectively, generation and retailing are instead potentially competitive, as the technology allows more than one firm on the market.

In the generation-retailing model under study N GenCos sell energy to M Supps in an electricity market where medium-term bilateral contracts are negotiated before a uniform-pricing auction takes place. Suppliers, in turn, re-sell the bought energy in the end-user market.
Firms are assumed to be capacity constrained. The generation capacity of the i-th GenCo at time t, $\overline{G}_i(t)$, is the maximum amount of power available to conclude B contracts, $G_i^B(t)$, and/or for bidding in the DA market, $G_i^{DA}(t)$[3].
$\Theta = \sum_{i=1}^{N} \overline{G}_i(t)$ is, therefore, the market capacity that includes a percentage β of reserve margin over the expected peak-demand, consistent with the normal operations of the most de-regulated energy markets.
Let q $(0 \leq q \leq 1)$ be the decision parameter to express the ratio of bilateral contracts with respect to the total trading activity of the generic agent; $\overline{S}_j(t)$ be the total quantity of energy supplier j is willing to buy at time t; $S_j^B(t)$ the total quantity of energy supplier j buys on the B market at time t; $S_j^{DA}(t)$ the total quantity of energy supplier j buys on the DA market at time t.
Then, the two markets together are described by the generation constraint

[3] Because of the short-term analysis the model assumes no investment over the whole simulation horizon and, therefore, $\overline{G}_i(t) = \overline{G}_i$.

$$\overline{G}_i(t) \geq qG_i^B(t) + (1-q)G_i^{DA}(t) \tag{1}$$

and the demand constraint

$$\overline{S}_j(t) \geq qS_j^B(t) + (1-q)S_j^{DA}(t) \tag{2}$$

$\forall i = 1,2,\ldots,N;\ j = 1,2,\ldots,M;\ t = 1,2,\ldots,T.$

Marginal costs are assumed to be constant throughout and no transmission constraints are assumed. Our model excludes blackouts due to extreme weather of technical failure.

The demand elasticity is set to zero (i.e. the demand bidding is considered independent from the market clearing price). This assumption is quite reasonable, since in the day-ahead markets worldwide loads have usually shown so far small changes with respect to energy prices. Demand is not subject to any type of curtailment and, therefore, loads are completely supplied both when they are involved in a bilateral transaction, and when they are traded in the DA.

3 The match-making of agents in the bilateral market of energy

B contracts are signed way ahead of time compared to the DA energy auctions and their agreed price could be, therefore, higher than the average DA market clearing prices (MCP). Yet, B contracts are financially safer for market participants because they can hedge against the high price volatilities of the real-time energy markets and their price, possibly higher than DA MCP, could be however convenient for the buyer during on-peak demand hours (during off-peak hours the convenience could work in the opposite direction).

Following [1] agents are assumed to represent their preferences in the electricity market by making use of a describing tree. Each node is labelled with a key factor a buyer considers in selecting its power supplier (i.e. price tariff, power quality, reliability, and customer service) and a set of weights, taken from the real interval [0,1], reflects the importance of branches on all levels of the tree. Therefore, node labels represent attributes of the energy system and branch weights represent their relative importance. The higher the weight, the higher the importance of that issue for the agent. Branches will always be labelled in lexicographic (alphabetical) left-to-right order while branch weights on the same level of any subtree are required to add up to 1.

Once the seller and buyer agents have constructed their trees, an algorithm measures the similarity bottom-up and recursively between every buyer-seller pair based on the weighted similarity of nodes belonging to the compared trees.

A similarity function $A(\sigma_{i,j}^{h,k})$ is defined to measure the similarity of nodes.

In the lowest level of the trees, $k = 1$, $\sigma_{i,j}^{h,k}$ is computed as follows:

$$\sigma_{i,j}^{h,k} = 1 - \frac{|x_i^{h,k} - x_j^{h,k}|}{max(x_i^{h,k}, x_j^{h,k})} \tag{3}$$

$\forall i = 1,2,\ldots,N;\ j = 1,2,\ldots,M;\ h = 1,2,\ldots,H;\ k = 1;$
where, $x_i^{h,k}$ and $x_j^{h,k}$ represent the value of nodes entitled to the h-th electricity factor at level k in the GenCo's and Supp's compared tree respectively.
The similarity of nodes, $\sigma_{i,j}^{h,k}$, is then adjusted to $A(\sigma_{i,j}^{h,k})$ by an arc function $A(\sigma_{i,j}^{h,k}) = \sqrt{\sigma_{i,j}^{h,k}}$.
The similarity of nodes at level $k+1$ is then computed by summing the similarities of nodes at level k, $A(\sigma_{i,j}^{h,k})$, weighted using the arithmetic mean of branches' weight, $(w_i^{h,k} + w_j^{h,k})/2$. The equation looks as follows:

$$A(\sigma_{i,j}^{r,k+1}) = \frac{\sum_{h=1}^{H} A(\sigma_{i,j}^{h,k})(w_i^{h,k} + w_j^{h,k})/2}{\sum_{h=1}^{H} (w_i^{h,k} + w_j^{h,k})/2} \tag{4}$$

$\forall k = 1,2,\ldots,K;$
where $r = 1,2,\ldots,R$ is the number of nodes at level $k+1$.

The similarity value of the compared trees ranges from zero to one. A value of zero (one) means that the seller-buyer pair under consideration is totally dishomogeneous (homogeneous).

3.1 The bilateral transaction mechanism

At the end of the similarity measurements each buyer lists its potential sellers in decreasing order of similarity value and starts the negotiation process with its top ranked seller in the priority list. If the bilateral agreement or the time constraint for negotiation is not met, the agent starts a negotiation with the next agent in the list. The ISO does not have any role in the financial negotiations and settlements of a bilateral contract and no broker fees are assumed for bilateral contracting.

Each agent has minimum and maximum reference values for each of the negotiation subjects, meaning for each of the key electricity factors.
Let a ($a \in \{i, j\}$) represents a generic agent and h the issue under negotiation, then $x_a^h \in [min_a^h, max_a^h]$. When negotiating, the value agent a offers to its client/server at time t for issue h, depends on time as shown by the following function:

$$x_a^{h,\cdot}(t) = \begin{cases} min_a^h + \lambda_a(t)(max_a^h - min_a^h) \\ min_a^h + (1 - \lambda_a(t))(max_a^h - min_a^h) \end{cases} \tag{5}$$

with the first or the second equation to be used if the agent's offer is increasing or decreasing respectively.
Many functions can be used to define $\lambda_a(t)$. In this paper we use an exponential function for $\lambda_a(t)$ formulated as:

$$\lambda_a(t) = \left(\frac{t}{\bar{t}_a}\right)^{\frac{1}{\beta_a}} \tag{6}$$

where β_a defines the convexity of the function and $\bar{t}_a$ defines the upper limit of the negotiation time acceptable for agent a.
If the offer of agents i and j, $x_i^{h,\cdot}(t)$ and $x_j^{h,\cdot}(t)$, intersect at a time equal or less than $min(\bar{t}_i, \bar{t}_j)$, then an agreement is met for the issue h. A bilateral contract for energy supply is concluded when an agreement is met for all the attributes of the energy system involved in the negotiation process.

4 The DA market

Once the time for bilateral contracting expires, the bidding activity starts in the energy market. The power capacity offered by any GenCo on the DA market will be up to the residual of its maximum capacity if a medium-term bilateral contract has been previously concluded.
On a hourly basis, each agent is allowed to submit a single offer for each hour of the next day. In the auction market the ISO collects bids from all generators and suppliers, sorts these offers in merit order (plants, starting from the cheapest to the most expensive one, are scheduled to generate until demand is met for each hourly period) and, matching the demand and supply curves into the (Euro, MW) space, clears the market at the price offered by the marginal unit on the merit order schedule: the marginal system price (MSP). Given the equilibrium quantity, Q^*, the ISO assigns full capacity, $q_i = G_i^{DA}$, to the n GenCos with bids below the MSP; the remaining capacity $q_i = Q^* - \sum_{i=1}^{n} G_i^{DA}$, to the GenCos with bids equal to the MSP[4]; whereas plants that have offered above the marginal plant's price are not scheduled to generate, and receive no payment. At the same time, Supps with bids above the MSP receive the exact quantity of energy demanded; Supps with bids equal to the MSP receive the remaining quantity of energy, and Supps submitting below the MSP reveice no energy at all. We assume that agents in the DA market estimate the quantity of energy to trade for each hour of the next day looking at the expected load shown by the energy load curve. In particular, the expected load $\overline{L}(t)$ is drawn, independently in each round, from a uniform distribution in $[L(t) - \varepsilon, L(t) + \varepsilon]$, where $L(t)$ is the value read on the energy load curve and ε accounts for the small uncertainty typical in day-ahead forecasting. Since load varies over time, the MSP

[4] In case of a tie, the GenCo is selected randomly.

fluctuates as long as more or less expensive generators become successful bidders and set the competitive price.

4.1 The supply side

We assume that any GenCo in the electricity market estimates its bidding price by making use of the load duration curve. Accumulating the time intervals for which load has a certain value during a period T (a year, a month, or a day) and plotting the ordered values of the load versus time will produce the load duration curve (LDC). Then, normalizing the values on time axis and reversing the axes, the resulting curve $F(X) = Pr(p \geq X)$ can be used for probability purposes. In fact, this curve estimates the probability that the average hourly demand takes on values greater than or equal to X in an hour of period T[5].

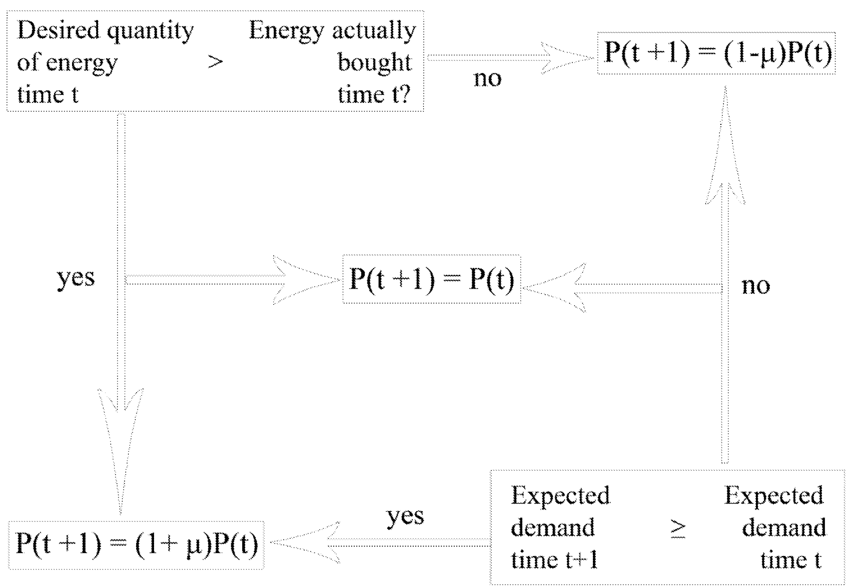

Fig. 1 The algorithm for agents compeating through price in the DA market.

[5] An example of this curve is given in Fig.3 for the case under study.

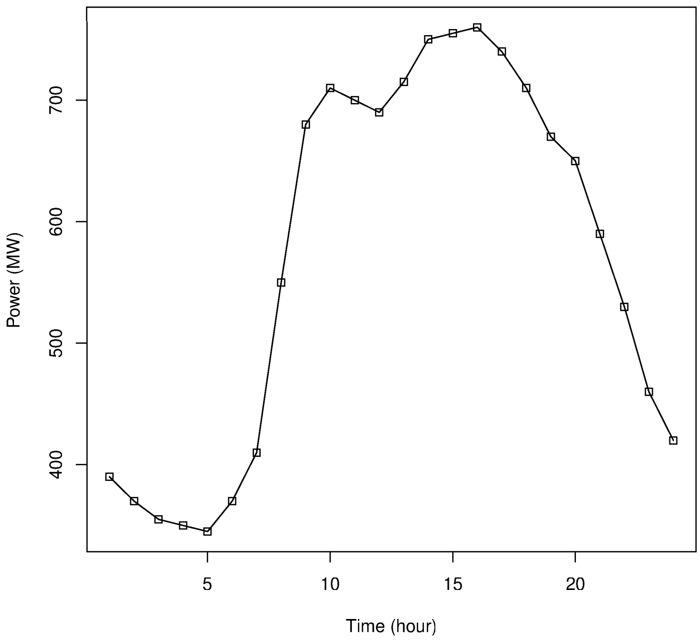

Fig. 2 A typical load curve for a Summer demand day.

4.2 The demand side

Supps decide the quantity of energy to bid by taking the pattern of variation of the electricity demand for each hour of the day into consideration.
The bidding price, instead, is fixed to the marginal price for the base load and then is it updated by following the algorithm shown in Fig. 1.

Given the marginal cost of the i-th GenCo at time t, $MC_i(t)$, its bidding price $p_i(t)$, is then defines as:

$$p_i(t) = MC_i(t)/g(F(X)) \tag{7}$$

where $g(F(X))$ is the mark-up function for the i-th generator, expressing how much the bidding price is increased above the marginal cost.
We assume a consistency rule such that the pricing strategies do not alter the sequence of plants in the marginal cost merit order: a more expensive plant will never undercut the bids of a less expensive one. The algorithm allows Supps competing through price to decide on their bids, at each iteration, looking at the quantity of energy actually bought for the bidding hour t (compared with the quantity of energy desired for the same hour), and considering the expected demand of energy for the next period of time (hour t+1).

If, for instance, the desired quantity of energy at time t is greater than the quantity actually bought, the difference might depend on a bidding price lower than or equal to the MSP. Therefore, if the demand at time $t+1$ is expected to be higher than the demand at time t, the agent increases the chances of being a successful bidder by increasing the bidding price. μ is the parameter used to update the price in accordance with the expected increase in the energy demand.

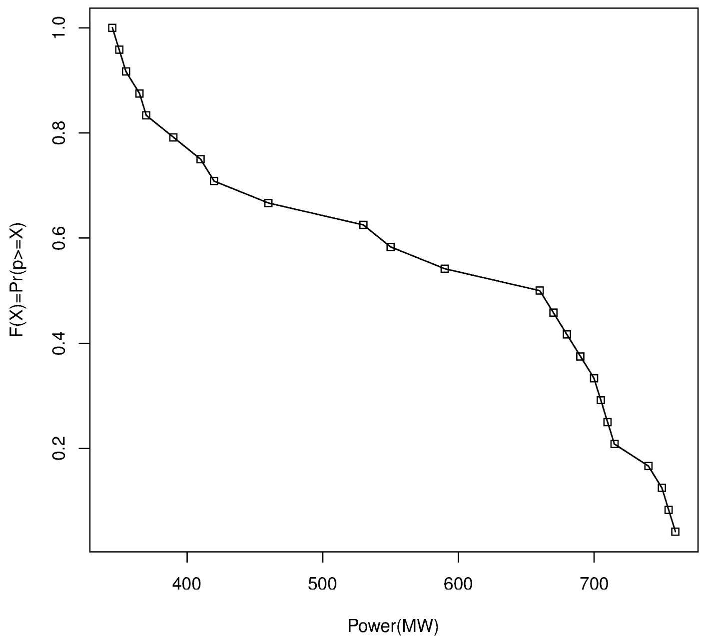

Fig. 3 The reversed load duration curve for probabilistic applications.

5 Simulation settings

Simulations are defined in terms of iterations of trading days, each one for a set of 24 hourly periods. To keep things simple, we only consider one-level trees where the energy attributes to be negotiated are energy price and energy quantity. We have assumed firms in each segment (generation or supply) to have the same market capacity. Hence, the individual GenCo capacity is $\theta^{GenCo} = \Theta/N$ and the individual Supp capacity is $\theta^{Supp} = \Theta/M$. Agents, however, hold different technologies

and, therefore, GenCos have different marginal costs, while Supps have different marginal benefits. Marginal costs and marginal benefits have been used to set the values of min_i^h and max_j^h respectively for the bilateral transaction mechanism.
β, meaning the percentage of reserve margin, has been set equal to 20%. Therefore, assuming the peak load around 760 MW, the total capacity installed in the power market is equal to about 900 MW. The variation of daily energy load ε has been fixed to 3%.
Simulations have been run with two different market structures. The first composed of 2 GenCos ($N = 2$) and 3 Supps ($M = 3$), and the second with 3 GenCos ($N = 3$) and 2 Supps ($M = 2$).
Loads agents consider to define their strategies are depicted in Fig. 2, whereas Fig. 3 shows the reversed load duration curve built as described in §4.1.
The ACE wholesale electricity market framework developed in this paper has been implemented in Java using AnyLogic.

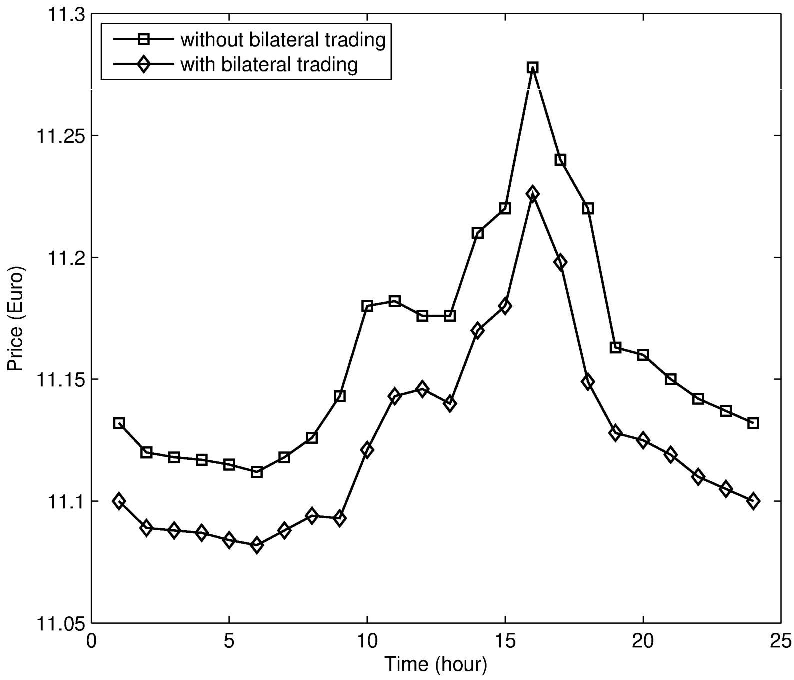

Fig. 4 The equilibrium price in the first DA market structure with and without bilateral negotiations.

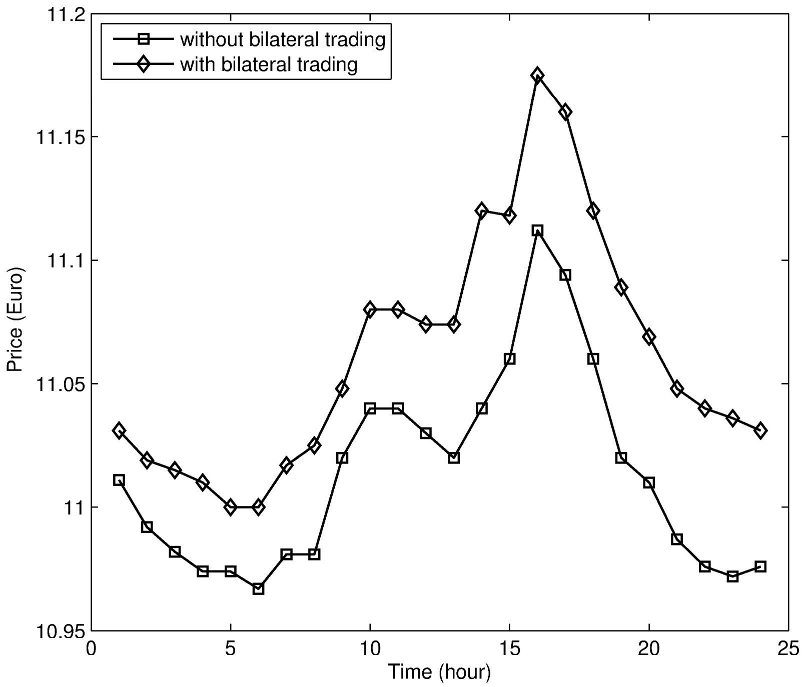

Fig. 5 The equilibrium price in the second DA market structure with and without bilateral negotiations.

6 Results

We have run our simulations assuming different percentages of bilateral contracts with respect to the total demand of electricity. In particular simulations have been run for $q = 0.0$ (no bilateral contracting), $0.6, 0.7, 0.9$, $\forall i = 1,2,\ldots,N$; $t = 1,2,\ldots,T$. Results are shown with reference to a typical trading day (24 hrs).

For the first market structure, where the number of Supps is higher than the number of GenCos, bilateral contracts have shown to have the effect of reducing prices in the DA market (Fig.4). This happens all the times the GenCo with bids equal to the MSP is involved in the bilateral agreement.

When the number of GenCos is higher than the number of Supps, simulations show that energy bought in the bilateral market may result in a potential increase of the energy prices in the DA market (Fig.5). As expected, this happens every time the bilateral agreement involves the most efficients agents.

In the very simple structure of the proposed model, the different percentages q of bilateral contracts do not produce any effect on the equilibrium price. Very probably, in an electricity market model with a greater number of agents the quantity of bilateral agreements would play a more active role.

7 Conclusions

The application of a computational agent-based model to the very simple energy market presented in this paper has provided some useful general insights.
It is plain that, a bilateral contract between a generation and a supplier effectively disengages two active players from each side of the wholesale market. Yet, this foreclosure effect will not necessarily lead to higher prices, despite the conventional concerns, and will be manifested only according to the specific market characteristics. In an energy market with a number of generation companies lower than the number of end-user suppliers, the bilateral contracs may produce lower equilibrium prices when the agreement involves the marginal unit in the merit order. The typical situation of increasing prices is instead reproduced in a market structure where the number of generation companies is greater than the number of suppliers and the bilateral agreement involves the most efficient agents.
We do believe that the proposed model contributes to the existing literature of power markets with new arguments about the effets of bilateral contracting and presents a new approach for bidding in the uniform-pricing auction settlement.

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