Comparison and empirical validation of optimizing and agent-based models of the Italian electricity market.

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Abstract

This paper compares the explanatory performances of an agent-based model with a supply function equilibrium model on the same dataset, as a first step within a research programme aimed at designing reliable tools for addressing key energy policy questions. The models are validated on a unique plant-level dataset on the Italian power exchange. As suggested by our findings, the agent-based model is better able to capture the intraday profile of power prices, but both models tend to overestimate the degree of competition among generating companies.

Electricity Markets, Agent-based, Supply Function Equilibrium

1   Introduction

An important player in the European energy liberalization movement, Italy has recently been reforming its electricity sector at a fast pace. New legislation has been passed on several key issues, spawning active debates that are most stimulating for economists.

A first instance is given by Law 27/01/09 n.2, article 3, that establishes April 1, 2012 as the starting day for the implementation of a pay-as-bid or discriminatory pricing rule for the day-ahead session (DAM) in place of the current uniform price rule. Specific actions to increase the integration of the Italian market with the emerging European one, too, have been envisaged within that law. For instance, market coupling with Slovenia has been already established for a power-flow of 300MW since January 1, 2011. This aim is partially in contradiction with previous action. All European markets have implemented uniform auction rules to set national prices as the final outcome of a long-term regulatory process that involved independently several national wholesale power markets and passed through successful and unsuccessful attempts. Another

relevant issue was raised in 2009, when the Italian government launched a plan (law 23/07/09 n. 99 and ff.) to build at least four new nuclear power plants in the near future. As a consequence of the new trend, Ente Nazionale per l'Energia Elettrica (ENEL), the major electricity producer in Italy, has signed a memorandum of understanding with Electricite de France (EDF) aimed at adopting third-generation European pressurised reactor (EPR) technology for the new plants. This law reverts a long-standing policy orientation emerged after the nuclear phase-out commenced in 1987.

While practitioners, opinion-leaders and the general public take sides in heated politically-laden debates, the economic profession needs reliable modelling tools to help formulating correct predictions on policy effects. In the economic analysis of energy policy, the use of "toy models" yields useful insights on what directions should be taken by policy-makers. However, the gross simplifications needed to obtain closed-form solutions come at the cost of potential inaccuracy in describing how companies react to incentives. Indeed, simple models neglect the importance of computational complexity in decision-making when a large number of decision variables and constraints are involved. Power generating companies often seek computer-aided decision-making and forecasting tools precisely to overcome the computational hurdles they face. Policy-making and policy assessment would similarly benefit from the use of models and algorithms that prove effective in describing individual strategies and market outcomes.

With a view toward potential applications to key policy issues as those summarized above, this paper proposes a twofold approach to modeling the Italian wholesale electricity market, by means of both an optimal-choice supply function equilibrium model and an agent-based computational model. Both models are empirically validated on historical scenarios, considering a realistic market structure, i.e., the forward and day-ahead market (DAM) mechanisms, the Italian high-voltage transmission network with its zonal subdivision, and the zonal loads. The aim of the paper is to compare the two modeling approaches with respect to their explanatory performances.

In the Supply Function Equilibrium (SFE) model introduced by Klemperer and Meyer (1989), the power generating companies (GenCos) simultaneously submit upward-sloping supply functions. Each GenCo chooses the supply function parameters in such a way as to maximize its profits, as the best reply to its opponents' choices. The model solution is a Nash equilibrium. In other words, the agents take advantage of full rationality in their decision-making. The Nash equilibrium concept has been used quite pervasively in the analysis of electricity markets (Ventosa et al. 2005), even beyond the SFE. In Borenstein et al. (1995) and Borenstein e Bushnell (1999) the Cournot model is the framework for the authors' analysis of market power in the main liberalized power exchanges. Auction-theoretic modeling has been introduced in the analysis of power exchanges by von der Fehr and Harbord (1993) and reviewed by Fabra, von der Fehr and Harbord (2006).

Quite interestingly, in most papers assessing the explanatory power of the models based on optimal choice the behavior of one or more GenCos significantly departs from optimal choice. Sioshansi and Oren (2007) and Hortacsu and Puller (2008) find that a SFE model does quite a good job in describing the actual behavior of large GenCos in the Texas balancing market, while smaller GenCos submit supply curves that are steeper than those implied by the SFE model. The authors conjecture that such a behavior by small GenCos can be rationalized by noting that balancing market offering entails rather high transaction costs related to high human asset specificity. Such costs are likely to be decreasing with the size of the generated power. In their analysis of the Italian electricity market, Boffa, Pingali and Vannoni (2010) find that the explanatory

power of their model dramatically improves if one assumes that Enel, the former monopolist, maximized a mixed objective function, corresponding to a weighted average of Enel's profits and of the consumer surplus. This is quite reasonable in light of the fact that the State owned a majority stake in Enel's capital. Hence, the authors argue that the assumption of pure profit maximization can be relaxed when a company institutionally pursues also other goals, without questioning the validity of the optimal choice paradigm. Using Italian plant-level data, Bosco, Parisio and Pelagatti (2010) derive the company-level cost functions under the assumption that GenCos behave according to an auction-theoretic model. Their estimated cost curves turn out to be downward sloped after a certain output level, which clearly indicates the inadequacy of the model. Apparently, the model underestimates the mark-ups required by the GenCos upon their less efficient units.

In the cases just reviewed, the general validity of the optimal choice paradigm is never under question: the authors would rather consider modifying assumptions on, say, the cost structures or the objective function than to give up explicit profit maximization altogether. Fine-tuning optimal-choice models, however, is not the only way to solve the above mentioned underperformance problems. Better performances may be obtained by means of models that more adequately simulate the way real-world GenCos cope with computational complexity. In particular, agent-based computational models are built upon the assumption that the decision entity/agent learns to strategically behave in the market by iteratively exploring strategies and exploiting them on the basis of their relative performances. One way to model the agents' adaptive decision-making processes, which we exploit here, relies on genetic algorithms, that is, the best experienced strategies - in profit terms - survive throughout competition. It is worth noting that in agent-based models agents do not explicitly formulate conjectures about the opponents' strategies, contrary to the optimal choice approach. Previous agent-based models of the electricity market include Bower and Bunn (2000), Sun and Tesfatsion (2007), and Rastegar, Guerci, and Cincotti (2009). Whether the agent-based modeling paradigm improves upon the optimal choice approach can be tested by directly comparing the predictive performances of an agent-based model and a SFE model. This is what the present paper does.

The comparison is performed with respect to the models' ability to reproduce the time dynamics of the Italian day-ahead buying price, the so-called PUN (Prezzo Unico Nazionale, or single national price). Both the agent-based and the SFE models use, as inputs, a unique dataset including detailed information on the cost parameters for a sample including the great majority of Italian thermal power plants. In both models, forward markets are also considered by estimating exact forward positions on historical data and by consequently adjusting the power-plants' offers in the day-ahead market (DAM) session. Furthermore, for the sake of a precise comparison between models, we adopt a common market-clearing procedure based on a DC-OPF procedure. This approach allows to compute highly realistic market outcomes. Our empirical validation exercise is performed on four distinct time periods, allowing us to test the predictive abilities of our models under different market regimes.

As suggested by our findings, the agent-based model is better able to capture the intraday profile of power prices, but both models tend to overestimate the degree of competition among generating companies, especially on days before the macroeconomic crisis. The model performances improve during the crisis: the sharp drop in the level of economic activity, coupled with new thermal capacity becoming operational, yielded a significant increase in market competition, therefore cutting the high spikes previously observed in the Italian power price series.

The paper is structured as follows. Section 2 describes the Italian power exchange, the dataset used in our analysis, and the concepts and variables that are common to both the models under testing. Section 3 gives the details of the agent-based model and of the SFE model, while Section 4 illustrates the results. Section 5 concludes.

2 The Italian power exchange: basic information and model inputs

In this section, we present a realistic outline of the Italian wholesale electricity market, which is then implemented in both models analyzed later in the paper.

Our Italian market model considers a two-settlement market configuration with a generic forward market and the day-ahead market (DAM). The DAM in the Italian electricity market is the most liquid market session, where around 60% of the total national production is sold hourly since 2004. The DAM price value is commonly adopted as underlying for forward contracts. Therefore in what follows we will refer to DAM as the spot market session for simplicity.[1] The forward market session is modeled by assuming a common and unique forward market price P^f for all market participants and by determining exact historical quantity commitments for each generating unit.

Generating company (GenCo) g (with $g = 1, 2, ..., G$) owns ($i = 1, 2, ..., N_g$) generators. Each ith electrical generation unit has lower $\underline{Q}_{i,g}$ and upper $\overline{Q}_{i,g}$ production limits, that define the feasible production interval for its hourly real-power production level $\hat{Q}_{i,g} = \hat{Q}^f_{i,g} + \hat{Q}^s_{i,g}$ ([MW]) ($\underline{Q}_{i,g} \leq \hat{Q}_{i,g} \leq \overline{Q}_{i,g}$), where $\hat{Q}^f_{i,g}$ and $\hat{Q}^s_{i,g}$ are respectively the quantity sold in the forward market and the quantity accepted in the DAM. We assume that company g takes a long position in the forward market for each owned generator i_g, corresponding to a fraction $f_{i,g,h}$ of its hourly production capacity, that is, $\hat{Q}^f_{i,g,h} = f_{i,g,h}\overline{Q}_{i,g}$. The value of such fraction varies throughout the day. Indeed, forward contracts are commonly sold according to standard daily profiles. In our model, the value of $f_{i,g,h}$ has been estimated by looking at historical data and thus corresponds to a realistic daily profile for each generator. The revenue from forward contracts for company g is:

$$R^f_g = \sum_{i=1}^{N_g} \hat{Q}^f_{i,g} P^f \quad [\text{€/h}]. \tag{1}$$

The spot revenue per hour R^s_g for GenCo g is obtained as follows:

$$R^s_g = \sum_{i=1}^{N_g} \hat{P}^s_z \cdot \hat{Q}^s_{i,g} \quad [\text{€/h}]. \tag{2}$$

The total cost function of the ith generator of GenCo g is given by the following quadratic formula:

$$C_{i,g}(Q_{i,g}) = (P_l + P_{co^2} h_l) \cdot (a_{i,g}\hat{Q}^2_{i,g} + b_{i,g}\hat{Q}_{i,g} + c_{i,g}), \tag{3}$$

[€/h], where P_l and h_l ([€/GJ]) are the prices of the fuel l which is used by the ith generator and the conversion value to determine the amount of CO2 generated by the

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[1]Further, less liquid market sessions operate after the day-ahead market session up to real-time (MI - "Mercato Infragiornaliero" and MSD - "Mercato del Servizio di Dispacciamento"). These sessions are not considered in this paper.

combustion of a unit of fuel l ([GJ]), respectively. P_{co^2} is the price of carbon permits in the European Emission Trading System - EU ETS. In the model, we assume a mark-to-market hypothesis, that is, ETS prices are updated on a daily basis according to current values. The coefficients $a_{i,g}$ ([GJ/MWh^2]), $b_{i,g}$ ([GJ/MWh]) and $c_{i,g}$ ([GJ/h]) are assumed constant over time, but vary across power plants with different technologies and efficiency levels. The constant term $(P_l + P_{co^2}h_l) \cdot c_{i,g}$ corresponds to the no-load cost ([1]), i.e., quasi-fixed costs that generators bear if they keep running almost at zero output. However, these costs vanish once shut-down occurs.

Finally, the total profit per hour for GenCo g is equal to:

$$\pi_g = R_g^f + R_g^s - \sum_{i=1}^{N_g} C_i(\hat{Q}_i) \ \ [\text{€/h}]. \tag{4}$$

In both the agent-based and SFE models, only thermal power plants are considered, as they represent around three fourth of the national gross production capacity. Furthermore, the remaining national production (hydro, geothermal, solar, wind) and imported production can be reasonably modeled as quantity bids at zero price. Imports correspond in general to power generated abroad by cheap technologies such as hydro or nuclear power plants coming mainly from France and Switzerland. In any case, exact historical values have been assumed for both hydro and imports.

The considered set of thermal power plants consists of up to 225 generating units, the major units, comprising 5 different technologies, i.e., Coal-Fired (CF), Oil-Fired (OF), Combined Cycle (CC), Turbogas (TG) and Repower (RP). These power plants are independently owned by 19 GenCos. The number of generation companies and generating units offering in the DAM varies throughout the day. Based on historical data, we have determined for each period (day and hour) the active thermal power plants, i.e., the thermal power plants that offered in DAM. What plants were actually present is supposed to be common knowledge, since bid data are publicly available on the power exchange website with a one-week delay. For each power plant in the dataset, we have information on the minimum and maximum capacity limits, as well as on the parameters of the cost functions, as defined in Eq. 3. These data are used to calibrate the models in order to run realistic simulations for specific days.

The market clearing procedure for the DAM can be accurately defined by a modified version of the standard DC-Optimal Power Flow (DCOPF).

On unit i generator, a bid is submitted to the DAM, consisting of a pair of values corresponding to the limit price P_i^s ([€/MWh]) and the maximum quantity of power $Q_i^s \leq \overline{Q}_i - \hat{Q}_i^f$ ([MW]) that it is willing to be paid and to produce, respectively. After receiving all bids, the market operator clears the DAM by performing a social welfare maximization subject to the following constraints: the zonal energy balance (Kirchhoff's laws), the maximum and minimum capacity of each power plant, and the inter-zonal transmission limits. It is worth noting that the Italian demand curve in the DAM is price-inelastic. Therefore, the social welfare maximization can be transformed into a minimization of the total reported production costs, i.e., of the bid prices (see Eq. 5). This clearing mechanism based on the DCOPF determines both the unit commitment for each generator and the Locational Marginal Price (LMP) for each bus. However, the Italian market introduces two slight modifications. Firstly, sellers are paid the zonal prices, i.e., LMP, whereas buyers pay a unique national price (PUN, Prezzo Unico Nazionale) common for the whole market and computed as a weighted average of the zonal prices with respect to the zonal loads. Secondly, transmission power-flow constraints differ according to the flow direction. In the following the exact formula-

tion is presented.

$$\min \sum_{i=1}^{N} P_i^s \cdot Q_i^s, \quad [\text{€/h}], \qquad (5)$$

subject to the following constraints:

- Active power generation limits:
  $\underline{Q_i} \leq \hat{Q}_i = \hat{Q}_i^s + \hat{Q}_i^f \leq Q_i^s + \hat{Q}_i^f, \quad [\text{MW}],$

- Active power balance equations for each zone z:
  $\sum_{i \in z} \hat{Q}_i - Q_{z,load} = Q_{z,inject}, \quad [\text{MW}],$
  being $\hat{Q}_i = \sum_{i=1}^{N_z} \hat{Q}_i$ the sum over all generators located in zone z, $Q_{z,load}$ the load demand at zone z and $Q_{z,inject}$ the net oriented power injection in the network at zone z.

- Real power flow limits of lines:
  $Q_{l,st} \leq \overline{Q}_{l,st}, \quad [\text{MW}],$
  $Q_{l,ts} \leq \overline{Q}_{l,ts}, \quad [\text{MW}],$
  being $Q_{l,st}$ the power flowing from zone s to zone t of line l and $\overline{Q}_{l,st}$ the maximum transmission capacity of line l in the same direction, i.e., from zone s to zone t. $Q_{l,st}$ are calculated with the standard DC Power flow model.

The solution consists of the set of the active powers $\hat{Q}_i^s$ generated by each power plant i and the set of zonal prices $\hat{P}_z^s$ (LMPs) for each zone $z \in \{1, 2, ..., K\}$.

The adopted market clearing procedure requires the definition of a transmission network. The grid model considered in this paper (Figure 1) reproduces exactly the zonal market structure and the relative maximum transmission capacities between neighboring zones of the Italian grid model. It corresponds to the grid model defined by the Italian transmission system operator, i.e., TERNA S.p.A., which is adopted by the market operator. The grid comprises 11 zones (BRNN (BR), Central North (CN), Central South (CS), FOGN (FG), MFTV, North (NO), PRGP (PR), ROSN (RS), Sardinia (SA), Sicily (SI), South (SO)) and 10 transmission lines depicting a chained shape which connects the North to the South of Italy. The different values of maximum transmission capacities for both directions of all transmission lines are also reported. The values are realistic, but just indicative. Exact values for the specific days that have been simulated have then been used. Figure 1 further shows also the distribution of generators in the network and the representative load serving entities (LSE) at a zonal level. The neighboring country's virtual zones[2] have been neglected in the definition of the grid model, but their contributions to national loads or production capacities have been adequately included in the simulations.

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[2]Neighboring Country's Virtual Zone are point of interconnection with neighboring countries. Please refer to www.mercatoelettrico.org.
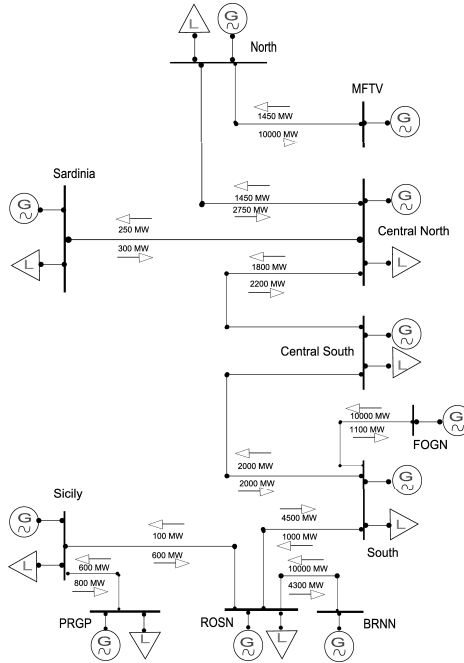
Figure 1: Italian grid model: circles define the presence of generators located in the zone, whereas triangles highlight the aggregate load serving entities (LSE) for each zone. The numbers above and below of the lines correspond to the lines' maximum transmission capacity constraints for both directions at hour 3 p.m.. Arrows indicate the power-flow direction relative to each transmission capacity constraints.

3 Describing the models

3.1 The agent-based computational model

In the following, we describe how generation companies are modeled in the agent-based simulator. Each gth company ($g = 1, 2, ..., G$) owns $N_{g,z,f}$ thermal power plants in zone z with technology f. We collect the $N_{g,z,f}$ power plants of company g in zone z and of technology f in a representative generating unit $r = (z, f)$ and we assume that GenCo g adopts a common strategy for them. By doing so, we reduce the size of the strategy space. Let us denote N_g as the number of representative generating units of GenCo g. For every r and every hour h^3, each GenCo g bids to the DAM a pair of values corresponding to a limit price $P_{g,r,h}$ ([€/MWh]) and a quantity of power $Q_{g,r,h} = \sum_{i=1}^{N_{g,z,f}}(\overline{Q}_{i,g})$ [MW], that is, they are assumed to bid the maximum capacity of their power-plants. Indeed, the action space of GenCo g $\mathcal{M}_g$ is equal to the cartesian product of the action space of each of them $\mathcal{M}_g = \times_r \mathcal{M}_{g,r}$. The action space of the representative generating unit r $\mathcal{M}_{g,r}$ represents mark-up levels. $P_{g,r} = m_{g,r} \cdot MC_{g,r}$,

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[3]GenCos submit simultaneously 24 bids, one for each hourly DAM. GenCos learn independently to bid strategically on each hourly market, i.e., no interrelationship is considered among such markets. In Italy, the hourly bids are submitted simultaneously and furthermore, no block bidding is allowed.
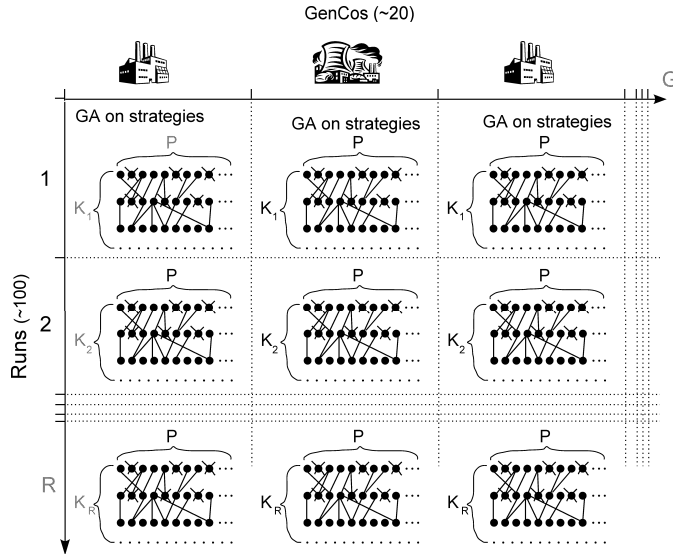
Figure 2: A schematic representation of the learning algorithms.

where $m_{g,r} \in \mathcal{M}_{g,r} = \{1.00, 1.06, 1.12, \ldots, 5.00\}$. Therefore, the cardinality of the action space of a generation company owning $N_{g,r} = 4$ representative generating units is that is $|\mathcal{M}_g| = | \times_r \mathcal{M}_{g,r}| = M_g = 10^4$. The strategy space is huge for each given GenCo. In the following, we describe how each GenCo independently learns to identify an optimal strategy, by repeatedly interacting with the market environment.

The multi-agent system is depicted in Figure 2. G GenCos are reported on the top of the Figure. These GenCos repeatedly interact among each other at the end of each run $r \in 1, \cdot, R$, that is they all submit bids to the DAM according to their current beliefs on opponents' strategies. At the beginning of run r, GenCos need to study the current market situation in order to identify a better reply to the opponents, to be played at run $r + 1$. In order to explore their strategy space in search of a better strategy, they need to repeatedly solve the market for different private strategies. A standard genetic algorithm is adopted, in order to keep a large population of candidate

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strategies and to improve at the same time their fitness/performance in the market.[4] Thus, we define a population of size P of strategies, which will evolve throughout the K_r generations. The number of generations varies with the run r. The idea is to favor exploration in initial rounds and then to exploit the gained experience, expressed in the final population of candidates by the relative frequency of occurrences of each candidate solution F_{m_g}. At the end of each run r, each GenCo bids to the market by selecting one strategy belonging to its current population of candidates. The selection is done according to a probabilistic choice model in order to favor the most represented strategy in the population, i.e., the one that has best responded to the evolutionary pressure by ensuring the highest fitness. The functional form of the probabilistic choice model which has been considered is the logit:

$$\pi_{m_g, r+1} = \frac{e^{F_{m_g}/\lambda}}{\sum_{m_g}^{\mathcal{M}_g} e^{F_{m_g}/\lambda}}, \tag{6}$$

where $\pi_{m_g, r+1}$ expresses the probability of selecting action m_g at run $r+1$.

3.2 The supply function equilibrium model

In the Supply Function Equilibrium (SFE) model, GenCo g (with $g = 1, 2, ..., G$) owns N_g thermal power plants in zone z. For every hour h, each GenCo g bids to the DAM for each of its plants i an affine supply function, specifying the quantity of power $Q_{i,g,h}$ it is available to sell at each price level; or, equivalently, a *reported* marginal cost curve. For each plant, the supply function spans the whole interval between the minimum and maximum capacity limits. The amount of power corresponding to the minimum capacity limit is assumed to be supplied inelastically at zero price.

The GenCos calculate the supply functions to be submitted to the DAM as follows. The total cost function of plant i run by generator g is given by Eq. 3. Thus the marginal cost function reads

$$MC_{i,g} = (P_l + P_{co^2} h_l) \cdot (b_{i,g} + 2a_{i,g} \hat{Q}_{i,g}) \tag{7}$$

As we have seen above, the market is solved by the market operator using the *reported* marginal costs submitted by the GenCos. Such curves may be different from the true marginal costs depending on the GenCo's abilities to exploit their market power. In this rendition of the SFE model, we assume that the reported marginal cost $MC_{i,g}^R$ is equal to true marginal cost curve shifted by a mark-up $m_{i,g}$. More formally:

$$MC_{i,g}^R = m_{i,g} + (P_l + P_{co^2} h_l) \cdot (b_{i,g} + 2a_{i,g} \hat{Q}_{i,g}) \tag{8}$$

Notice that the reported marginal cost curve can be seen as the inverse of a supply function $\hat{Q}_{i,g} = \frac{1}{a_{i,g}}(\hat{P}_z^s - b_{i,g} - m_{i,g})$. In the latter equation, $\hat{P}_z^s$ replaces $MC_{i,g}^R$, since the company receives a price equal to $MC_{i,g}^R$ on all its units if i is the marginal plant in zone z.

In this SFE model, GenCo g operating in zone z at a certain hour solves the following problem: choose the vector of mark-ups $m_{1,g}, ..., m_{i,g}..., m_{N_g,g}$ in order to maximize the profit function given by Eq. 4, that is, the sum of the profits obtained on all its plants in zone z, under the set of capacity constraints $\underline{Q}_{i,g} \leq \hat{Q}_{i,g} \leq \overline{Q}_{i,g}$, and given that (i) the conjectures about the opponents' mark-ups are correct in equilibrium,

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[4]Classical operators are implemented, that is, selection, mutation and crossover.

and (ii) the uniform price P^s equates the total supply (forwards plus spot) to the zonal load $Q_{z,load}$, assumed perfectly inelastic.

In other words, GenCos in this model make strategies on the intercept of the reported marginal cost curve. In Sun and Tesfatsion's (2007) agent-based model and in most affine SFE models (e.g. Newbery 1992, 1998, Baldick et al. 2004), the strategy space is defined by both the intercept and the slope, while here we hold the slope fixed. The reason is that, as observed in Hobbs, Metzler and Pang (2000) and in Sapio et al. (2009), if GenCos are assumed to submit one supply function for each of their plants, as in our case, and if the plant-level marginal cost slopes are small, as in our data, the SFE may not converge to a stable solution for realistic values of the cost function parameters.[5]

A couple of remarks are in order. First, notice that the real power flow limits between lines do not appear among the constraints of the above optimization problem. We assume that GenCos can perfectly predict the upcoming zonal subdivision of the Italian grid (or, which is equivalent, that the zonal subdivision is exogenous). Second, we assume that the GenCos are not allowed to switch off their plants, hence they will make their best to satisfy at least their minimum capacity constraint. This may lead them to set negative mark-ups on their less efficient units.

4 Simulation results: the Italian market case

We calibrate and validate the two computational models on historical data. As previously mentioned, the models are calibrated on an hourly basis using the observed zonal demand values, active thermal power plants (by adopting real cost functions, forward commitments and maximum and minimum levels of production capacities), and power flow transmission limits on the grid. These values are thus assumed as exogenous parameters for both models. Given these inputs, both models have been computed and then validated at a macro level by studying the relative abilities to reproduce the daily PUN time series.

It is worth noting that the price time-series of the Italian electricity market is highly predictable in the short term. Given the inelastic demand, the price pattern exhibits the typical weekly and daily seasonalities of the power consumption. Therefore, we have preferred to simulate four different working days (20 Dec 2006, 10 Sep 2007, 11 Nov 2009, 13 Sep 2010) rather than simulating consecutive days. This enables to study four different market conditions and thus to better test the explanatory power of our models. The first day represents a typical working day before the irruption of the global financial crisis, the second working day corresponds to the early periods of the crisis, whereas the last two days are selected during the economic downturn. Due to the economic downswing, economic activities have been reduced: the national power consumption levels have indeed dropped by almost 7% as compared to pre-crisis demand levels. At the same time, several new mid-merit power-plants became operational during and after 2009, because of optimistic investment decisions. This twofold effect has contributed to progressively and significantly change the competitive structure of the market. This is clearly highlighted in Figures 4 and 6, reporting the 24 histori-

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[5]Rudkevich et al. (1998), Baldick et al. (2004), and Rudkevich (2005) have extended the SFE model to allow for more general assumptions. As those works made clear, the existence and uniqueness of the equilibrium are difficult to prove, except in some very simple versions of the model. In some cases, one needs numerical methods to find the equilibrium solution, thereby increasing the computational burden of the model.

cal PUN prices of the considered days (circle marker). These four Figures report also the simulation results of the agent-based model (diamond marker) and of the supply-function equilibrium model (cross marker). Figure 4 exhibits very high prices during peak hours. A debated rationale for such behavior is the exercise of market power or even collusive behavior by major market players (ENEL S.p.A. and Endesa).
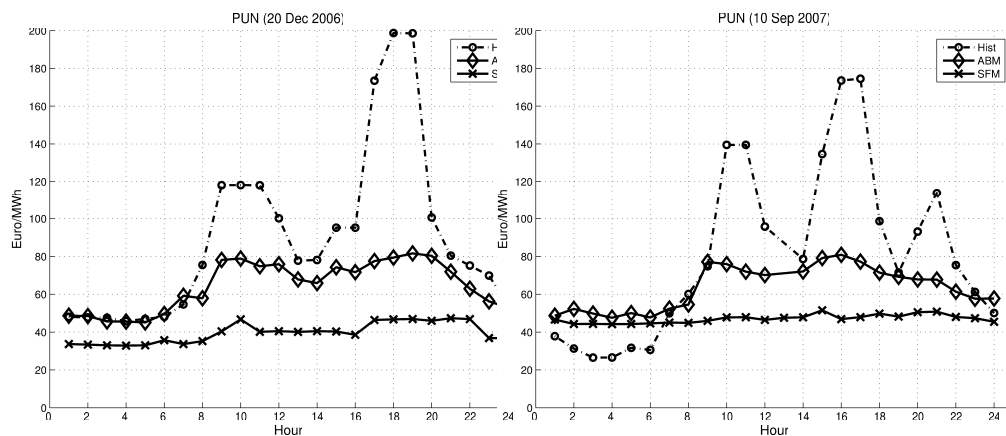

Figure 3: Real and simulated PUNs for 2006-12-20 (left) and 2007-09-10 (right). The dotted and dashed line with circles reports historical outcomes. The line with diamond as a marker shows the agent-based simulation results (ABM), whereas the cross markers are the supply function model (SFM).

Indeed, the Italian authority for energy had at that time investigated on market power abuse. In the two days after the crisis, such excessive swings in the price pattern disappear: the price levels and also the intradaily volatility diminish.
As far as simulation outcomes are concerned, a clear and stable behavior arises. ABM price and volatility values are always higher than SFE values. SFE outcomes tend to underestimate the price levels and are significantly flatter than in reality. On the contrary, ABM outcomes better account for the intradaily volatility and also for price levels. Another common behavior is that both models tend to overestimate the prices in off-peak hours for three days out of the four. A possible rationale is that our models do not consider that some thermal technologies and power-plants are not so flexible to
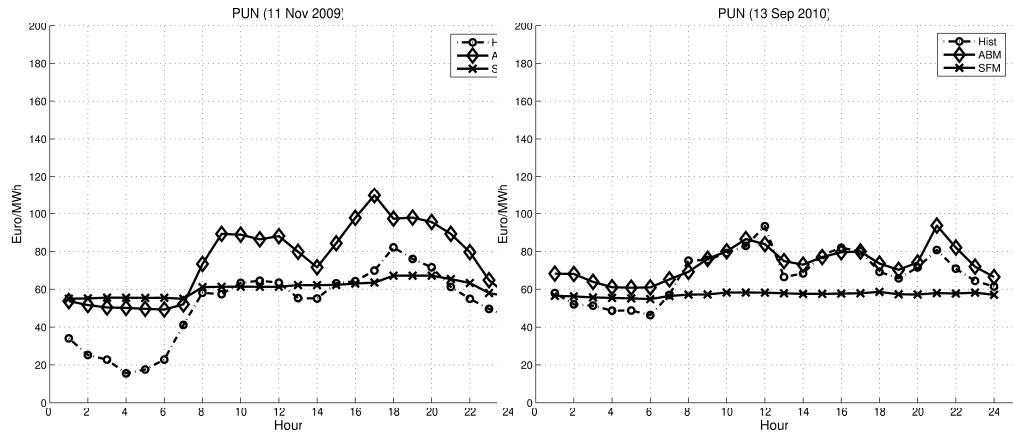
Figure 4: Real and simulated PUNs for 2009-11-11 (left) and 2010-09-13 (right). The dotted and dashed line with circles reports historical outcomes. The line with diamond as a marker shows the agent-based simulation results (ABM), whereas the cross markers are the supply function model (SFM).

switch off and on overnight. Shutdown and startup costs are not negligible thus pushing GenCos to bid below marginal costs their minimum power-plants operating capacity. This strategy is most likely to occur in days corresponding to a period after the economic downturn, when the demand levels and prices had significantly diminished. In particular, Figure 4 shows similar simulation outcomes, except for the overestimation of off-peak prices by both models. In general, both models tend to reproduce similar price levels than those of almost one year before, whereas historical values exhibit a significant decrease in prices during off-peak hours. The models do not seem able to depict the differences in the market competitive structure occurring mainly in off-peak hours. Historical outcomes are significantly different in the other two selected days. Figure 6 (left panel) represents a market condition with the lowest prices. Price levels in peak hours (except for 5, 6, 7, 8 p.m.) are close to the level of prices in off-peak hours reported in Figure 4 (left panel) corresponding to the market conditions of three years before. Only in this case, the ABM model exhibits a clear overestimation of price levels for all hours, whereas the SFE model correctly predicts the level of prices

mainly in peak hours. Most likely due to the market stress and competitive pressure, market operators were facing a particularly difficult period and profit were seriously compromised. Only for this day, the SFE model perform better in term of average price level, however it is still not able to reproduce the volatility pattern. Finally, in the last considered day (Figure 6, right panel) both models are close to average historical price levels. The ABM model better predicts both price levels and volatility except for the price levels of off-peak hours, whereas the SFE model predicts prices in off-peak hours. The market situation seems particularly suited for both models, the absence of high prices in peak hours (see Figure 4) might support the hypothesis of absence of market power abuse or collusion in this period. The demand levels are still far below the demand levels of 2006 (5% less) and an increased competition among mid-merit power-plants has certainly occurred. These two aspects might suggest that the two models improve their performances when competition is stronger. To put it another way, both models tend to overestimate the degree of market competition.

5   Conclusion

As regards the analysis of power exchanges, direct comparisons of optimizing and agent-based computational models have never been performed before. This work is nonetheless a first attempt in this direction. Our results are not completely satisfactory: both models are unable to predict the price peaks that occurred in the Italian power exchange before the macroeconomic crisis, and the SFE model, in particular, presumes an excessively high degree of competition among the GenCos.

Yet, our findings provide useful insights about what ingredients a successful power exchange model should embody. First, the models under analysis do not consider the strategies hypothesized by Ausubel and Cramton (2002): GenCos may find it convenient to ask very high prices on their less efficient plants while bidding low on their more efficient ones. This could indeed work as a capacity withholding strategy, in case the high bids are rejected, but may also grant extremely high prices in case the high bids are accepted. Second, in the proposed SFE model the GenCos do not strategically use their being pivotal, nor they enact collusive strategies which may be sustained over time due to the repetitive nature of the electricity market (see Ciarreta and Gutierrez-Hita 2006). Including these features in future versions of the models may allow us to better capture the peaked profile of the Italian electricity price series.

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