RESIDUAL DEMAND MODELS FOR STRATEGIC BIDDING IN EUROPEAN POWER EXCHANGES: REVISITING THE METHODOLOGY IN THE PRESENCE OF A LARGE PENETRATION OF RENEWABLES

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Abstract

In the deregulated framework in place in most power systems, a significant part of the energy is traded through auctions on day-ahead markets where agents submit bids to either buy or sell energy. When defining a bidding strategy, generators usually resort to models that anticipate and simulate agent interactions. The residual demand curve (RDC), a well-known approach to representing competitor behaviour, enables generators to formulate effective oligopolistic strategies.

One way to estimate and build an RDC is to use information available about other agents' bids on previous and comparable days as a reference. This basic approach to market modelling has proven useful in the past in European power exchanges. In the current context, however, characterised by substantial market penetration on the part of non-dispatchable renewable resources, the suitability of this method of RDC building may need to be tested.

This paper first analyses how the results of day-ahead auctions on European power exchanges have been affected by the growing penetration of renewable energy. It then questions both the use of RDC as an approach in this changing context and the aforementioned simplified estimation method to compute these curves. The discussion is illustrated with empirical evidence from the Iberian market.

Keywords: electricity market, power exchange, strategic bidding, residual demand curve, MIBEL.

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1 INTRODUCTION

In the competitive framework that governs electricity production in many electric power systems, generating company (GenCo) revenues depend largely on generators' ability to devise a suitable bidding strategy for short-term markets. This is particularly true in European markets, which operate around power exchanges (PX), for two main reasons. On the one hand, auction design based on so-called semi-complex bidding protocols and the linear pricing rule requires GenCos to design a bidding strategy (which is not always obvious) that correctly internalises all operating costs. And on the other, large GenCos can optimise their entire generation portfolio to capitalise on (not necessarily acknowledged) oligopolistic strategies.

The bids that are ultimately sent to the market operator condition the overall market outcome, including dispatch efficiency and consequently consumers' power bills. Hence, it is not surprising that this issue has attracted a good deal of attention from both the industry (stakeholders and regulators) and academia.

Strategic bidding has been analysed from two main perspectives. The most common approach assesses the possible impact of imperfect competition and market power on the aforementioned market outcome: the ability of market agents to behave strategically and thus the potential need to design measures to mitigate market power; see for instance [1,2].

The second perspective is to broach the problem from the point of view of an individual GenCo seeking to optimise its energy sales on the spot market based on its portfolio, cost structure and operating constraints. The present discussion lies in this latter realm.

In particular, it focuses on single-agent profit maximisation models based on the residual demand curve (RDC) [3]. In this modelling framework, only the bids submitted by the target firm are optimised, while its competitors' strategies are fixed and introduced exogenously via the RDC. The RDC is a function that links a GenCo's sales to the market clearing price. In other words, it expresses how the amount of energy sold in a given hour by an individual GenCo affects the market clearing price in that hour. The RDC has been widely used in strategic bidding models; see for instance [4,5,6].

One basic but common method for plotting the RDC takes market data from previous and comparable[1] days to gather information about competitors' price-quantity bidding strategies. This information is used as a starting point to plot a series of RDCs in the belief that it constitutes the best proxy for competitors' short-term bidding strategies. The models developed in references [7,8] are examples of the use of this approach.

The objective of this paper is two-fold. It first focuses on how the results of day-ahead auctions on European power exchanges have been affected by the growing penetration of renewable energy. Secondly, it discusses how the applicability of the aforementioned simplified method for estimating RDC is affected by these changes.

The paper is structured as follows:

- Theoretical background is provided on the characteristics of the RDC approach and its capability to represent the different auction designs implemented worldwide. The reasons why RDCs are particularly well suited to markets with a simple auction mechanism are explained (Section 2).
- RDC suitability in the more complex auction designs implemented in Europe is qualitatively evaluated. The analysis focuses on the effect of significant market penetration by non-dispatchable and highly variable renewable energy sources (vRES). The behaviour of semi-complex auctions in this context is illustrated by the auction result patterns observed for the Iberian day-ahead market, MIBEL in recent years (Section 3). This market features the two characteristics dealt with in the present discussion: a day-ahead market based on semi-complex auctions and a power system with a vRES share that is among the world's highest.
- Section 4 introduces an ad hoc computation method for testing RDC applicability, which is then evaluated in the context of the MIBEL market.
- The main conclusions drawn from the foregoing are set out in Section 5.

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[1] By comparable it is meant a day whose market conditions (bids, demand, etc.) are similar to those applying to the following day.

2 BACKGROUND: THE PROBLEM OF MODELLING DAY-AHEAD ELECTRICITY AUCTIONS

The strategic bidding problem in short-term electricity markets is addressed in the literature with a variety of techniques; see for instance the reviews in [9,10]. As pointed out in the latter, many widely varying approaches are in place, fathered by the diversity of the spot market designs implemented worldwide.

A market model intended to accurately reproduce real market interactions and results must contain a detailed description of all the relevant features of the real market in question. These features include the clearing algorithm, network model and bidding protocol. A fully detailed description of all market rules and agents' interactions is seldom a realistic aspiration, however, for two major reasons: a) the lack of reliable data to feed the model, which mainly depends on the amount of market information disclosed by the market operator; and b) the size of the resulting problem. In practice, coping with these difficulties calls for a trade-off between the loss of accuracy stemming from representational simplification and the size of the resulting problem.

This section aims to describe how this trade-off is handled in practice. The complexities arising in electricity auction design are addressed in item 2.1 and exemplified by a particular type of auction design, the semi-complex model in place in the MIBEL (item 2.2). The standard RDC approach is discussed in item 2.3 and its suitability in the semi-complex market context in item 2.4.

2.1 Auction design in day-ahead electricity markets

The special features of electricity as a tradable product such as limited storability, the existence of inter-temporal technical constraints and non-linear cost function components have led to a variety of auction designs and pricing rules (see [11] for a review of electricity auction design criteria). One of the major differences that distinguishes one auction design from another is the extent to which agents and particularly GenCos are allowed to include their technical constraints and cost data in their offers. Based on this criterion, electric power auctions can be classified into three major categories: simple, complex and semi-complex.

At one end of the spectrum, GenCo bids may consist exclusively of a series of price-quantity pairs per time period as the terms of sale for the underlying product i.e., the MWh. Auctions implementing such one-item bid formats are simple auctions. In this model, the market can be cleared directly as the intersection between the aggregate supply and demand curves to obtain both the energy committed and the marginal clearing price. Note the absence of inter-temporal links among the hour-by-hour auctions. Simplicity and transparency are the two strong points of simple auctions. The drawback is that this design obliges GenCos to fully internalise all production costs in their price-quantity bids and exposes them to the risk of unfeasible or uneconomic scheduling[2]. These two considerations have prevented the rigorous implementation of simple auctions and restricted this design to a mainly theoretical alternative. Nonetheless, some market designs such as Italy's GME [12] or the former California Power Exchange [13] come very close to this textbook model.

On the other end of the spectrum, so-called complex auctions allow for multiple-part bidding. Multiple-part bidding implies that, in addition to the quantity-price pairs for energy, bids include non-convex cost data such as start-up/shut-downs as well as technical constraints such as load gradient limits or minimum stable loads. Such markets are cleared in much the same way as centralised paradigm, usually involving the use of the so-called security constrained economic dispatch (SCED) [14] (although in a market context SCED determines outputs as well as prices). Unlike simple auctions, optimisation-based formulations always reach technically feasible solutions. Complex auctions have sometimes been claimed to be scantly transparent, however [15]. US markets such as PJM, NYISO, ISO-NE, California ISO or MISO are examples of complex auctions; further details on the design of such auctions can be found in [15].

In an attempt to combine the transparency of simple auctions with the technical-economic constraints of complex auctions, many markets have evolved toward a trade-off approach referred to as hybrid or semi-complex auctions.

2.2 MIBEL, example of semi-complex auctions

The core idea in this design is to allow agents to reflect constraints in their bids to some extent through so-called complex conditions. The number and features of the complex conditions defined in a market's bidding protocol should suffice to mitigate the risks facing GenCos in simple auctions, while keeping auction clearing as transparent and easy to interpret as possible. In practice, this trade-off has entailed either the direct inclusion of some of the constraints that are hardest to internalise, such as the load-

[2] This can be mitigated through complementary arrangements such as intraday markets.

gradient, or by allowing some useful experience-based inter-temporal constraints. In most cases, the latter represent neither an actual single technical constraint nor cost component, but rather a combined effect of several. This is the case of the block orders used in a number of European markets [17], for instance, under which agents can submit bids covering an interval of consecutive hours and the minimum average price to which they are willing to commit for the interval. Where all-or-nothing terms are in place, if the average price offered for the interval is not reached, the simple hourly bids are removed from the eligible set of bids (or "killed") in the market clearing process.

Once the killed bids are identified, clearing of the accepted bids is highly reminiscent of a simple auction. In other words, prices are determined as the point where the aggregate supply (accepted bids only) and aggregate demand curves intersect. Note that since some bids are killed in the clearing process, the aggregate curve of accepted bids differs from the original aggregate curve. Furthermore, accepted bids curve is defined only for prices lower than the marginal price. Figure 1 depicts the outcome of an hourly MIBEL auction in which a number of block bids on the original curve were killed and are therefore absent from the accepted curve.

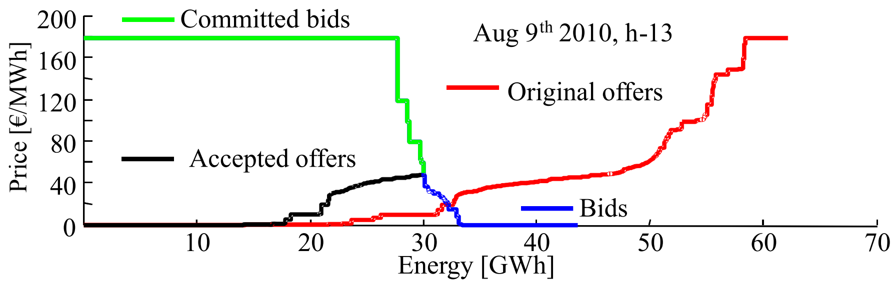

Figure 1. Aggregate original and accepted curves in a MIBEL hourly auction

In the MIBEL, a type of block order, called the Minimum Income Condition (MIC), enable a generating unit[3] to define a bottom threshold condition for its income in the full day-ahead session. The MIC implies that the unit will be committed if and only if Equation (1) holds:

$$F + V \sum_{h=1}^{24} Q_h \geq \sum_{h=1}^{24} Q_h * MCP_h \tag{1}$$

where:

Q_h unit energy committed in hour h [MWh].

[3] The MIBEL bidding protocol makes no allowance for portfolio bidding: i.e., the bids are defined on a unit-by-unit basis.

MCP_h market clearing price in hour h [€/MWh].

F MIC fixed term [€].

V MIC variable term [€/MWh].

Otherwise, the unit's bids for all the hours in the interval are killed. For further details on MIBEL day-ahead market rules, see [18-19] for an overview of MIBEL market operation.

The following item analyses whether residual demand is a suitable approach to simulating the actual operation of MIBEL day-ahead auctions as described above.

2.3 Standard RDC approach

Attaining a suitable trade-off between computation plausibility, input data requirements and the ability to accurately represent market interaction usually calls for model simplifications. Computational complexity and the amount of input data required can be reduced in essentially two ways.

- The characteristics of the auction design represented in the model can be simplified to reduce the number of variables to be optimised by each agent and simplify the auction clearing mechanism.
- The number of agents whose variables are optimised can be reduced.

In practice, both types of simplification are applied. Single agent profit maximisation models based on the RDC, for instance, entail simplifying the bidding protocol and auction clearing mechanism for equivalence to the simple auction paradigm, as well as reducing the number of agents whose variables are to be optimised to one: the target firm. Optimising the bidding strategy of the target firm, which involves formulating its own unit commitment problem, lies outside the scope of this paper. A thorough description of the single-agent profit maximisation problem can be found in [5].

Since in the RDC model, auctions are assumed to be simple, market agents' bids just consist of hourly price-quantity pairs. With this simplification, the rest of the market agents can be modelled with the aggregate representation provided by the residual demand curve[4]. A supplier's RDC is a function that relates the market clearing price in a given hour to the quantity sold by the supplier in that hour. Mathematically, it can be formulated as:

$$RDC^{-1}(p) = D^{-1}(p) - G_{n-1}^{-1}(p), \tag{2}$$

where $D^{-1}(p)$ stands for is the inverse function of demand $D(q)$. $D^{-1}(p)$, then, is the function that yields the quantity that the demand would be willing to purchase at price p. Analogously, $G_{n-1}^{-1}(p)$ stands for the total quantity that all other suppliers would be willing to sell at price p. The residual demand $RDC(q)$ is the inverse function of $RDC^{-1}(p)$.

Figure 2 shows how to compute a given GenCo's RDC, $R(q)$, from the residual aggregate supply curve, $G_{n-1}(q)$, and aggregate demand, $D(q)$.

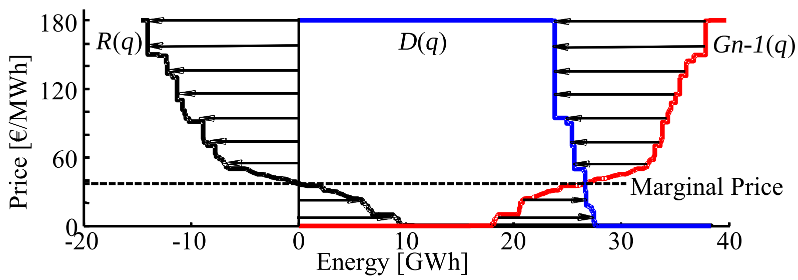

Figure 2. Computing RDC

By subtracting the sum of competitors' offers at price p from the cumulative demand at that price, the market clearing price becomes a function only of the energy sold by the target firm.

2.4 Preliminary assessment of RDC models in MIBEL

With the single agent RDC-based model simplifications described in item 2.3, the resulting optimisation problem is computationally plausible [8]. Regarding the market data available for MIBEL, GenCos have access after every day-ahead market session[5] to the following pieces of information [18]:

[4] The RDC should be used when target firm decisions can affect market prices. When GenCos can be regarded as price-takers, market interactions can be modelled directly, using price as an exogenous input.

[5] A day-ahead session comprises the 24 hourly auctions for the following day.

- original price-quantity supply and demand aggregate curves: the offers and bids submitted by suppliers and demand, excluding the associated complex conditions
- aggregate accepted price-quantity supply and demand curves, i.e., the block bids committed in the auction because their price was lower than the marginal price and they formed part of offers not killed in the clearing process[6].

The above information, which is published on the market operator's (OMIE) website (omie.es) can be used to compute a GenCo's RDC under certain assumptions.

RDC-based modelling approach disregards the inter-temporal links in bids introduced by complex conditions. In the following we focus on the role of these links.

3 THE INCREASING IMPORTANCE OF COMPLEX CONDITIONS: THE ROLE OF RENEWABLES

In MIBEL, GenCos are free to decide whether or not they include complex conditions in their thermal unit offers. Note that where they do not the market operates as if it were a simple auction.

That was approximately the situation in the first few years after MIBEL was launched in 1998. Figure 3 depicts a typical market outcome in 2003, when very few block bids were killed, yielding an outcome similar to what would be expected of a simple auction.

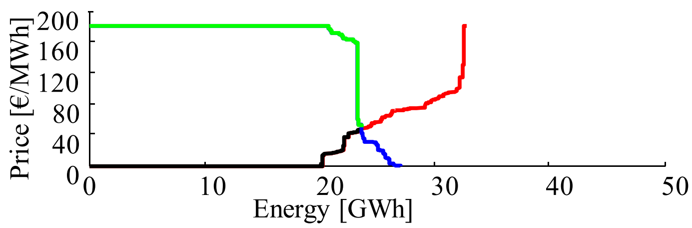

Figure 3. Typical early MIBEL hourly auction (29 June 2003, hour 23)

Such auction outcomes reflect a fairly predictable market in which the most prominent uncertain short-term variable is demand, which market agents can forecast very accurately. This environment of low uncertainty allowed GenCos to simplify their offers to price-quantity pairs.

[6] The information published includes how the underlying complex conditions affected the final result (if offers where matched or not), but not the complex conditions themselves. Individual offers in full, including the associated complex conditions, are not disclosed until 90 days after closure of the market session. The RDC approach described here assumes that limitation.

However, cost internalisation becomes much more complicated as uncertainty grows [20,21] and with it the risk that not all production costs will be recovered. In this context the minimum income condition provides thermal units with a means to hedge against potential non-recovery of start-up costs[7]. Since high vRES penetration may constitute a major source of uncertainty, agents should be expected to resort more frequently to complex conditions in such a scenario.

In the MIBEL, renewable, particularly wind, energy output has increased dramatically over the last ten years. Wind market share grew from 4 % in 2002 to 16 % in 2011 (ree.es). The impact on the presence of complex conditions has been evident. As a way to illustrate the influence of wind on this, we next compare the total energy withdrawn in a given hour in the day-ahead market, defined as the amount of energy in the offers killed in that hour, to daily wind production. The period studied is 2002 to 2010. The results, extracted from Iberian market operator OMIE data for one off-peak and one peak hour, are depicted in Figure 4.

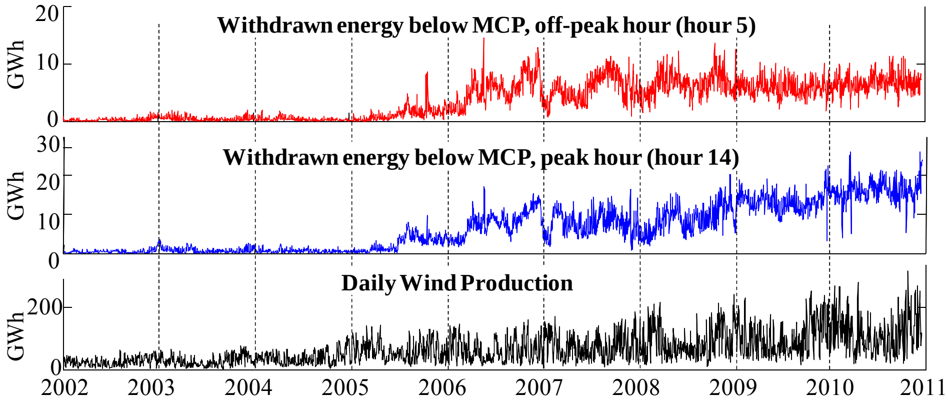

Figure 4. Withdrawn energy and wind production, 2002- 2010

In the early years of the series the amount of energy in killed in the clearing process offers was very small (almost non-existent). As wind output grew, however, that amount rose significantly, particularly in peak hours, providing empirical evidence of the increasing use of complex conditions with rising vRES penetration levels. One outcome of the more intense use of these conditions is the gradual disappearance of the resemblance to simple auctions observed in the early years. The supply curves depicted in Figure 1, in which a significant amount of block bids in the original supply curve are killed, are representative examples of recent market outcomes. This suggests, a priori,

7 In this vein, [22] analyses the greater social welfare attained with complex conditions than simple auctions in the presence of uncertainty.

that RDC-based models were a more accurate approach for MIBEL at the outset than they are today.

4 APPLICATION OF RESIDUAL DEMAND-BASED MODELS IN THE PRESENT CONTEXT OF MIBEL

Further to the intuitive notion set out at the end of section 3, an analysis was conducted of when the RDC approach reviewed here is suitable for modelling markets and estimating prices and when it is not, because the error may be too large.

4.1 Adapting the RDC computation to the MIBEL semi-complex auction context

Strictly speaking, RDC methodology can only be applied to simple auctions, for the curve is plotted on the grounds of price-quantity pairs only. As noted in item 2.1, however, MIBEL can be viewed as adhering to a simple-auction-like design in which some of the original simple bids are removed for failure to meet the complex conditions. Therefore, if it were possible to know in advance which simple bids would not be killed, RDC computation would be straightforward. Since that information is only available *ex-post*, however, an assumption must be made to identify the accepted bids for the *ex-ante* computation of RDC and hence of an optimal bidding strategy. The most basic way to estimate and build an RDC is to use information available about other agents' accepted bids on previous (and comparable) days.

A refinement of this basic RDC approach, in which a simple assumption based on results observed on comparable days in the past is applied to identify the accepted bids is proposed below. More specifically, the methodology consists of the following four steps:

Step 1. A reference day is chosen, a comparable day regarded as the best proxy for plotting the series of 24 day-ahead RDCs. Representative RDC series are normally found with clustering techniques that generate weekly and hourly historical curve patterns [4].

Step 2. The residual supply and aggregate demand curves are plotted for the target day with the simple bids and the committed curves. Note that the committed curve is only defined below the marginal price for the supply curve (above the marginal price for the demand curve). To obtain a supply curve defined over the complete range of prices, the committed curve is extended above the marginal price, adding the original supply curve quantity/price block bids. The same procedure is applied to the aggregate demand curve. Figure 5 shows how the residual supply curve is built using the available market data.

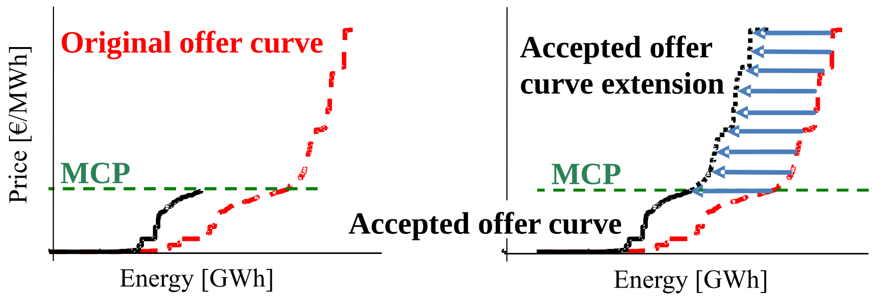

Figure 5. Construction of the residual supply curve in a semi-complex auction

The assumption of course is that the accepted bids will be the same as on the reference day. This is a strong assumption, since accepted bids actually depends on the resulting prices as per Equation (1).

Step 3. The RDC is plotted as explained in item 2.3.

Step 4. Lastly, a number of corrections are applied to the RDC to supplement the information on the expected conditions for the day-ahead session. Two main variables change in the short term in MIBEL: vRES output, which is typically offered at €0/MWh; and inelastic demand, typically tendered by retailers on behalf of households at the cap price, €180.3/MWh. The system operator publishes the forecasts for both on a daily basis. These corrections in the quantities bid at both the maximum and minimum prices, when incorporated directly into RDC models, shift the curve horizontally [1]. Rises in vRES output shift the curve to the left, while declines shift it to the right. Conversely, higher household demand shifts the curve to the right and lower demand to the left. The net shift is consequently equal to the difference in inelastic demand between the day ahead and the reference day, minus the difference in vRES on those two days.

All other things being equal, a change either in vRES or in inelastic demand modifies the price. While day-ahead inelastic demand can be quite accurately predicted, vRES, particularly as regards wind, cannot. Day-ahead forecast errors for this parameter are still significant. Since complex conditions depend on the market price, the accepted/killed block bids may differ in the presence of steep and unbalanced changes in those two variables and consequently in price. In light of this latter consideration, larger absolute deviations in "demand minus vRES" may reasonably be expected to detract more significantly from model accuracy.

4.2 Validity of the approach

By way of illustration of the aforementioned intuitive notion, data were gathered on all MIBEL day-ahead auction results from 2007 to 2011. For each pair of consecutive days across this period, the variable "demand minus wind[8]" was plotted against the rise or decline in the amount of energy in killed offers in the MIBEL. Wind production was measured as agents' offers on the day-ahead market[9]. The variable "demand minus wind" was computed as $\left[Demand_D^h - Demand_{D-1}^h\right] - \left[Wind_D^h - Wind_{D-1}^h\right]$ where subscripts *D-1* and *D* indicate two consecutive days[10] and superscript *h* the hour.

The point cloud for three different medium to large demand consumption hours and the respective linear regression are shown in Figure 6.

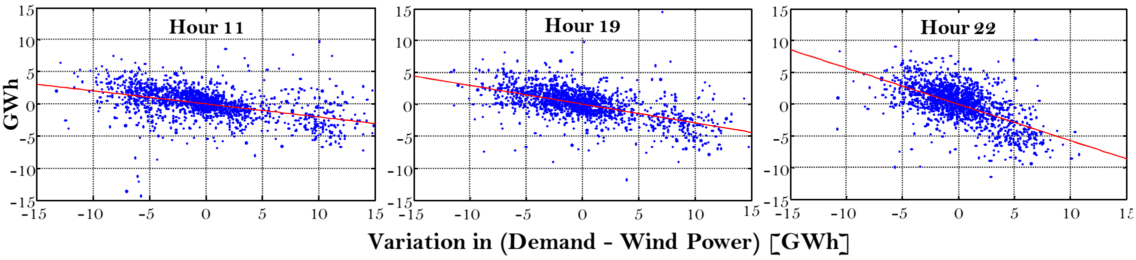

Figure 6. Variation on two consecutive days in the amount of energy in killed offers

While the strength of the correlation and the correlation itself depend on the hour analysed, the trend suggests that the larger the change in "demand minus wind" between the reference day and the day-ahead, the greater is the difference in the accepted/killed offers and therefore the less suitable is the approach described in item 4.1. The slope is negative because positive values of the variable mean higher prices and subsequently fewer killed offers. Conversely, a negative value means lower prices and therefore more killed offers.

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[8] Wind is the major source of vRES on the MIBEL day-ahead market.

[9] These offers are based on agents' best forecasts for the day-ahead and constitute the relevant measure for the day-ahead market, since deviations between these forecasts and real-time production are corrected in subsequent, e.g. intraday, markets.

[10] The Fri/Sat, Sun/Mon combinations were disregarded as they are not comparable days.

Two representative examples of the practical computation of a day-ahead RDC are set out below for fuller comprehension of this discussion[11]. The methodology described in item 4.1 was back-tested using real market data to analyse how accurately it could forecast MIBEL market behaviour and, more specifically, market prices. The methodology was applied to the two cases listed in Table 1: case A, with a minor variation in "demand minus wind" and case B, with a major variation.

Table 1. ΔDemand - ΔWind (MWh) in case A and case B. Source: OMIE.

	Hour 11	Hour 19	Hour 22
Case A	476	-1184	-1843
Case B	-3239	-6473	-7493

In Case A the prediction was for 23 September 2010 and in case B for 14 January 2010. In both cases hour *h* on day *D-1* was used as the reference for the same hour *h* on day *D*, for in both cases the previous day was a comparable day. The corrections considered in step 4 of the methodology for both household (inelastic) demand and wind production were the changes actually recorded: i.e., perfect foresight. Lastly, the adjusted RDC so computed was compared to the actual market RDC for hour *h* on day *D*.

The results for three representative hours (11, 19 and 22) are shown. The more closely the blue curve matches the red curve, the more accurate is the forecast. The results for case A are shown in Figure 7.

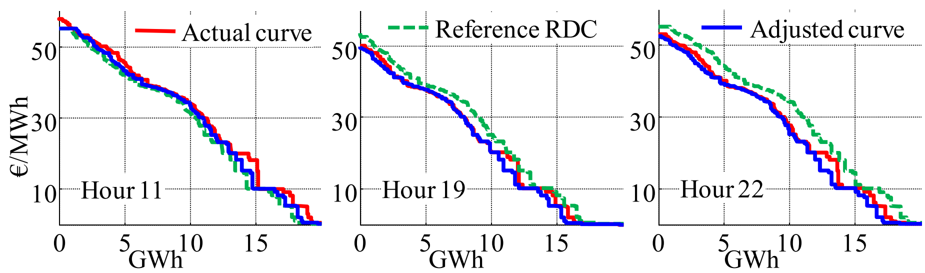

Figure 7. RDC for two consecutive days. Case A (adjusted curve (blue) computed from the reference RDC (dotted green) and the "actual" (red) curves)

A satisfactory fit was obtained for the adjusted curve at all hours. Therefore, prices were very accurately estimated in this case. For a hypothetical new entrant selling 5 GWh in all three hours studied, the forecasting errors would be 5.8, 0.3 and 1.8 % for hours 11, 19 and 22, respectively. The curves obtained for Case B are plotted in Figure 8.

[11] For reasons of confidentiality, the RDC computed is for a hypothetical new entrant, whose competitors are all the actual GenCos.

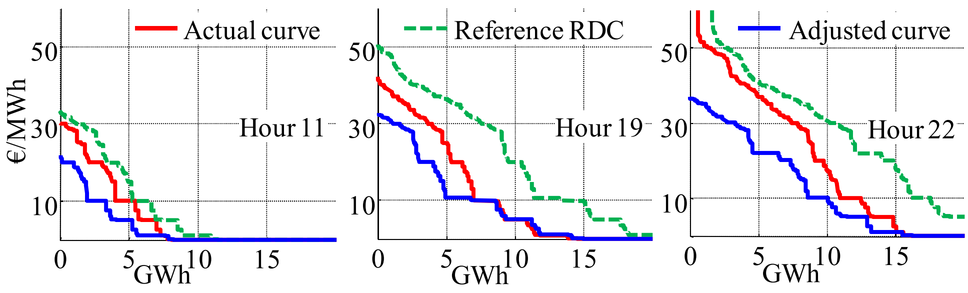

Figure 8. RDC for two consecutive days. Case B.

In this case the adjusted curve did not fit the actual curve. Moreover, the reference curve could not be made to fit the actual curve by mere horizontal shifting in light of their different shapes. Price forecast errors would be significant in this case: for the same new entrant selling 5 GWh, they would be 50, 57 and 51 %.

The explanation for the inaccuracy in Case B can be readily found by analysing the accepted/killed offers on the two consecutive day. Figure 9 shows the aggregate original and accepted curves (after filtering the offers priced at €0 €/MWh).

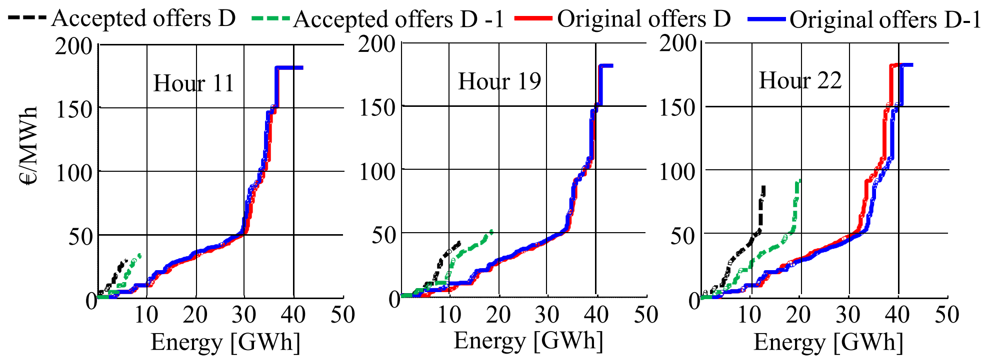

Figure 9. Case B: aggregate original and accepted curves

The figure represents the aggregate original supply curves and the block bids that were ultimately committed. While the original offers were very similar, complex conditions induced substantial variations in the simple bid acceptance/killing pattern, even though prices were fairly similar on both days at the hours analysed.

5 CONCLUSIONS

This paper analyses the suitability of single-firm optimisation models based on residual demand curves (RDC), focusing on methods that use historical data to build RDC scenarios for modelling day-ahead markets.

In the context of European power exchanges these methods have traditionally provided a suitable trade-off between accuracy, the amount of competitor data needed to feed the model and computational requirements.

The approach performs well when auctions are highly reminiscent of simple auctions in terms of behaviour and outcome. This study submits, however, that its applicability and accuracy decline under certain market conditions when complex conditions are widely used by GenCos. In particular, GenCos may obtain inaccurate estimates when substantial changes in vRES output are not offset by demand-side changes in the opposite direction. That premise is supported by the results observed in the Iberian electricity market, MIBEL, in recent years.

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