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Modeling Dynamic Procurement Auctions of Standardized Supply Contracts in Electricity Markets including Bidders Adaptation

Henry C. Torres, and Luis E. Gallego,

***Abstract*—Descendant Clock Auctions have been increasingly used in power markets. Traditional approaches are focused on discovering the bidders' best response but neglecting the bidders' adaptation. This paper presents an algorithm based on decision theory to estimate the bidders' behavior along the auction. The proposed model uses portfolio concepts and historical data of spot market to estimate a long term contract supply curve. This model was applied to evaluate the Colombia's Organized Market (MOR). Demand curve parameters and round size were varied to evaluate their impact over auction outputs. Results show that demand curve has a quite small impact over bidders' decisions and round size management is useful to avoid non-competitive bidders' behavior. In addition, it is shown that auction's starting prices strongly influence auction's clearing prices. These results are extremely helpful to design market structures in power markets given that allows to model emerging behaviors along the proposed auctions.**

***Index Terms*—Dynamic Auction Model, Descending Clock Auction, Electric Energy Regulation, Colombian Electric Energy Market**

I. THE PROBLEM

AUCTIONS are an important allocation mechanism, and it has been employed to trade many goods since a long time ago. Nowadays, auctions are employed in many fields as one of the most important allocation mechanisms. This has increased the researchers' interest about enlarge auction's understanding. In fact, auction's modeling has been deeply explored in many areas of economics and engineering.

The first approach to auction modeling comes from economic theory, using mathematical models to determine equilibrium strategies for different types of auctions[1]. These models are useful to understand bidders' behavior and some auction's features, however mathematical models have limitations because strong assumptions are necessary to obtain a model's equilibrium.

Nowadays, computational models allows to overcome some of the mathematical model's limitations. There are many examples about computational agent-based models useful for auction design, comparison and performance evaluation.

About design auction, in [4] an auction mechanism is settled by using agent-based model. In [5] an agent-based model is proposed not only for an auction but for a fully automated negotiation system.

H. C. Torres and L. E. Gallego are with Research Group "Programa de Adquisición y Análisis de Señales (PAAS)", Gallego is also an Associated Professor at Universidad Nacional, Bogotá Colombia

e-mails: hctorresv@unal.edu.co, lgallegov@unal.edu.co

About evaluation of auctions' performance, many works have been carried out based on agent-based models. Several features has been studied, for example Shanshan Wang worked on the advantages of combinatorial auctions [6], Kim on the effect of auction repetition [7], Akkaya on the format of online auctions [8] and Sow on the risk-prone evaluation by using agent-based models [9].

Moreover, this computational models have been employed to compare different auction formats. In [10] Discriminatory and uniform price auctions are compared by using an experimental analysis based on multi-agents model and in [11] a similar comparison is done using learning agents.

In power markets, auctions are commonly used since deregulation became a trend. In the Colombian case, there is an electricity market composed of two mechanisms: bilateral financial contracts and spot market which is an uniform price auction. A sealed bid auction, like an uniform price auction, is the most common auction format in electricity markets and has been widely modeled even with agent-based learning in the colombian case [12][2][3].

Espinoza compared different formats of sealed bid auctions by determining an equilibrium strategy for each format using econometric models [13]. On the other hand, Gallego determined the bidders strategies by exploring the historical data about Colombian wholesale market and employed a learning algorithm. [14].

Recently, a new kind of auction has been included in electricity markets: multi-round (dynamic) auctions. This kind of auctions shows a distinctive feature when compared to traditional auctions: *Bidders adjust their bids along the auction so the analytic solution problem is harder to solve than sealed bid auctions*. Nevertheless, it is possible to find examples about modeling dynamic auctions using computational techniques, as it is shown in [15], where a multi-round english auction is modeled using genetic network programming.

On the other hand, some spot electricity markets have used dynamic auction, but the principal purpose of dynamic auctions is to trade Long Term Supply Contracts (LTSCs) [16][17]. In LTSCs auctions, it is specially important to avoid the so called *winner's curse*, this happens in common value auctions when the winner overpays because its estimate is higher than the other bidders' average estimate. Thus, dynamic auctions are often used to trade LTSCs given that allow bidders to fit their bids along the auction and thereby, to reduce a possible overpayment [18].

Despite some LTSCs' auctions uses a static format, like

Chilean [19] and Peruvian [20] electricity markets, most of LTSCs' auctions are dynamic (New Jersey [21], Illinois [22] and New England [23]), Brazil [19], Spain [24] and Colombia [25]).

In addition, LTSCs' auctions differs from sealed bid auctions because bidders' decision making involves additional aspects such financial risk (due to spot prices' volatility) and generation uncertainty. Roubik [26] worked on generators' strategic behavior in LTSCs auctions by using portfolio concepts. Four variables were proposed to understand the generators behavior: 1) Mean spot price, 2) Spot price variance, 3) Contract price and 4) Risk aversion [26]. Other contract procurement auctions' models are the Moreno's that studied two static auctions format by using Bayesian equilibrium concepts [27], Azevedo's that also used Bayesian equilibrium but to analyze bilateral contract auction carried out in Brazil on 2003 [28] and Garcia-Gonzales' that modeled the bidding strategy of a wind power producer in a Descending Clock Auction [29].

A Descending Clock Auction is a dynamic procurement auction that has been recently introduced in several power markets. In short, this auction works as follows. The auctioneer calls bids in successive rounds. Each round has a maximum and a minimum price. The round's maximum price is equal to previous round's minimum price. Hence, the bid price is always descending. In every round the auctioneer adds all bids and announces the total aggregate supply. Auction ends when aggregate supply is equal or less than total demand [30].

From an economic approach, Ausbel & Cramton [31] and Milgrom [32] are the main references. They used a Lyapunov Function to find an equilibrium strategy and their main conclusion is that sincere bidding by the bidders is an equilibrium of the auction game and, starting from any price vector, the outcome converges to the competitive equilibrium. However, these models are based on strong assumptions about rationality, continuity, and others that allows to ease the analytic solution. Moreover, Ausbel, Cramton and Milgrom say that the most important feature of a dynamic auction is that the *winner's curse* is weakened given that bidders can fit their bids along the auction[33], however the model used to demonstrate the equilibrium strategy is static and the adjustment is not evident.

From an engineering approach, models about descending clock auction are pretty scarse. In [34], Barroso established an optimization model for a price-taker hydrothermal GENCO to devise bidding strategies in multi-item dynamic auctions of long-term contracts.

In order to fill the absence of auction's models from an engineering perspective, this paper presents a methodology that models the bidder's decision making at every round in order to maximize their revenues. For this purpose, a MATLAB program based on decision theory [35] and microeconomic theory [36] [37], was developed. This allows to simulate the bidders behavior along the auction. The bidders model use portfolio concepts [26] and historical information about their preferences in the Spot Market.

This paper is organized as follows. In Section II the proposed model is presented, first the bidder model and then the scenarios faced by the bidders in the auction and the possible rewards to a chosen strategy are presented. In Section III the model is applied to Colombian Energy Market. Section IV presents some results of model implementation. Finally, Section V summarizes the main conclusions.

II. Proposed Model

In this section, the proposed descending clock auction model is presented. This model fits an auction mechanism in the Colombian power market known as MOR, including two main parts:

- **Bidders Model:** This part focuses on representing the bidder's valuations about the product to be auctioned: A long term energy supply contract (LTSC). Since historic information about energy contracts is not available due to confidentiality reasons, it was necessary to design a methodology to set the valuations from the spot market's bids and financial portfolio concepts.
- **Decision Making:** In this part the decision making is modeled based on a set of scenarios, a set of bidding strategies and a set of rewards.

Below, both parts will be described.

A. Bidders Model

In a descending clock auction, the auctioneer asks bidders about their bids at every round price, i.e. bidders disclose supply curve point by point. In fact, bidders' behavior is based on this supply curve as a representation of their LTSC valuations.

In order to calculate their LTSC's valuations this paper proposes a methodology that consists of three stages: 1) Summarize the spot market information through an statistic supply curve 2) Estimate the GENCO's risk aversion and finally 3) Calculate the LTSC's valuation by using a utility function that includes expected generation (obtained from spot market information), risk aversion and variables about the commitment period of LTSCs (expected spot price, variance spot price).

On the other hand, the information about LTSC bids is not available but the information about bids in the spot market is plenty given that GENCOs daily offer a supply curve in this market. This curve is formed from individual generation plants' bids that must be ordered by price in such a way that the accumulated quantity is determined by adding every unit's offered quantity.

Based on every GENCO's daily bid, an statistical supply curve can be obtained by ordering every daily supply curves as follows:

1) Steps in supply curves are represented by points in a *scatter plot* (Figure 1).
2) Next, these points are clustered by price ranges. For each cluster a set of statistical measures are calculated (i.e. mean, max, min, quartiles) with the aim of build different statistical supply curves.
3) Finally, clusters are combined in such a way that every cluster's mean is greater than the previous one in order to ensure the supply curve‘s monotonicity (Figure 2).

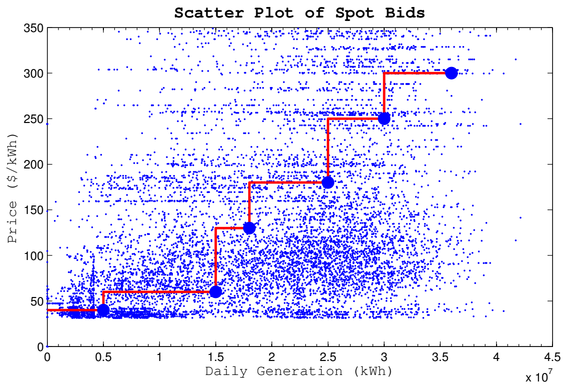

Fig. 1. Scatter Plot of Spot Market Bids

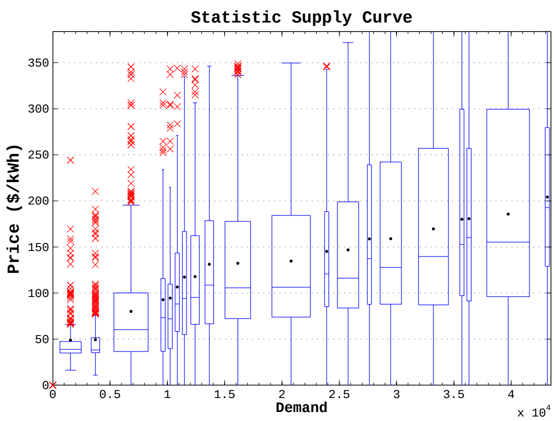

Fig. 2. Statistic Supply Curve of Spot Market Bids

Now, the resulting expected values for each price can be understood as the expected supply curve or *expected generation function* ($G(P)$). It is important to note that $G(P)$ represents the total generation (MW) allocated in both markets, spot and contracts rather than only the generation power allocated in the spot market. The amount to be sold in the spot market is calculated from substracting GENCO's contract obligations.

On the other hand, an optimal hedge level for a given contract price can be determined by using portfolio concepts [26] as follows:

1) First, it is necessary to represent hedge preferences by utility functions as it is commonly used in portfolio evaluations. This utility function allows to balance two objectives: the expected earnings maximization and financial risk mitigation.
In general terms, GENCO's revenue is calculated using equation 1 where b is the contract price, $G(b)$ is the expected generation at contract price b, h is the hedge level (contract sales), $(1-h)$ is the spot market sales and $\bar{p}$ is the mean spot price.

$$\tilde{\pi}(h,b) = G(b)((1-h)\tilde{p} + b * h) \tag{1}$$

2) Now, the expected value for the GENCO's revenue and its involved risk (understood as the revenue variance) can be balanced by using a *Linear Mean-Variance Utility Function* (LMVUF) having a risk aversion constant (γ) (equation 2)

$$U = E\left[\tilde{\pi}\right[+ \gamma VAR\left[\tilde{\pi}\right]$$
$$U = G(b)((1-h)\bar{p} + b*h) - \gamma(\sigma_p\left(G(b)(1-h)\right)^2) \tag{2}$$

3) From the LMVUF's derivative with respect to h, the optimal hedge level can be found. This optimal hedge level depends on the estimated average spot price, its variance and the GENCO's risk preferences (γ), as it is stated in equation 3.

$$h(P) = 1 - \frac{\bar{p} - P}{2\gamma\sigma_p} \tag{3}$$

4) Next, it is possible to estimate a hedge curve by calculating the optimal hedge level for several prices using equation 3.

Finally, a Contract Supply Curve (CSC) is calculated by multiplying $G(P)$ and the obtained hedge curve as it was described in step 4. However, some assumptions were necessary to calculate this curve. First, the generators are able to make good estimations about average and variance of spot price, otherwise, it is a mistake to use the historical data to calculate γ. Second, risk aversion does not present meaningful changes between commitment periods. Last but not least, generators plan their risk hedge using a LMVFU to represent their risk preferences.

Formally, the Contract Supply Curve is calculated as follows:

1) Choose a period of time and get its spot market historical information.
2) Determine contract sales, spot sales and weight them using equation 4.

$$(1-h) = \frac{SpotSales}{SpotSales + ContractSales} \tag{4}$$
$$h = \frac{ContractSales}{SpotSales + ContractSales}$$

3) Calculate the spot price mean($\bar{p}_h$), the spot price variance (σ_{ph}) and assume a contract price (b)(i.e. the average price of the contracts for the entire power market).
4) Calculate risk aversion by clearing (γ) from equation 3 as it is stated in equation 5.

$$\gamma = \frac{\bar{p}_h - b}{2(1-h)\sigma_{ph}} \tag{5}$$

5) Predict the mean ($\bar{p}$) and variance spot price (σ_p) for the commitment period of contract.
6) Calculate the hedge curve ($h(P)$) as shown in equation 6:

$$h(P) = 1 - max\left[\frac{\bar{p} - P}{2\gamma\sigma_p}, 0\right] \tag{6}$$

7) Determine the expected generation as a function of price ($G(P)$) for the commitment period of contract.
8) Calculate the Contract Supply Curve ($CSC(P)$) by multiplying point by point curves $h(P)$ and $G(P)$

$$CSC(P) = h(P)G(P) \tag{7}$$

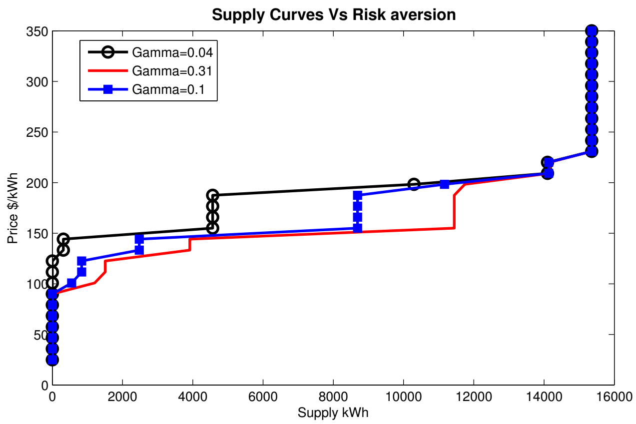

Fig. 3. Risk Aversion Effect on Contract Supply Curve

One of the most important contributions of the proposed methodology is that once a Contract Supply Curve is estimated, it is also possible to estimate the effect of the risk aversion in the Contract Supply Curve. Figure 3 shows the risk aversion effect on a contract supply curve. The three shown Contract Supply Curves were estimated with the following parameters: $\bar{p}$=200 $/kWh, σ_p = 1000 and $\gamma = \{0.04, 0.1, 0.31\}$. This figure shows that the higher the risk aversion the larger the amount of energy to be allocated in contracts for the same price.

B. Decision Making: Scenarios, Strategies and Rewards

Unlike sealed bid auctions, in a descending clock auction the allocations and payments not only depend on a single bid, but on bids sent in previous rounds; consequently, find an equilibrium strategy using game theory is more difficult in this kind of auctions. Thus, decision making was based on an alternative theoretical framework: Decision theory.

Decision theory is a set of criteria that allows to choose among different strategies under several feasible scenarios. When the scenarios' probability are known, it is called *Decision under risk* and consequently, decision making is based on the expected strategy revenue. The most common criterion in this kind of decision making is the *expected value criterion*. This criterion weights rewards by the scenario's probability to find the strategy's expected value [35].

In every round at a descending clock auction, bidders face two scenarios:

1) Next round in the auction will be the last one.
2) Next round in the auction won't be the last one.

These two scenarios are enough to understand the decision making. On one hand, if bidders have certainty that next round is not the last one, they will strategically bid to improve their position in the auction. On the other hand, if bidders has certainty that next round is the last one, they will bid in order to maximize their revenue.

In fact, bidders can choose among many possible bids, but to limit the choices is important to balance the results accuracy and the spent time to get them. Therefore, it is proposed that the bidders' choices can be grouped in three strategies as follows:

1) Bidding a quantity of energy according their CSC curves.
2) Bidding a larger quantity of energy than the one set by their CSC curves.
3) Bidding an smaller quantity of energy than the one set by their CSC curves.

Now, for each pair scenario-strategy there is an associated reward, i.e. for an strategy i and an scenario j the associated reward is U_{ij}. When next round is the last one(Scenario 1), the reward (U_{i1}) is calculated from the equation 2 with b equal to the round price (P_a) given that payment is actually achieved in the final round.

In scenario 2 (next round is not the last one), rewards are not real revenues given that there is no payment. However, bidders choose an optimal strategy to drive the auction toward a convenient point where they can maximize their revenues at auction's ending. Therefore, the strategy's reward is the expected revenue derived from the current strategy.

In addition, if an auction have interdependent estimations, bidders may be motivated to send bids that differ from their real valuations. In other words, if each bidder's estimate is partially based on rivals' information, one bidder offering small quantities might induce his/her rivals to decrease their valuations and consequently, they may leave the auction. On the other hand, Bidders may also have incentives to hold their bids. A Bidder inflates its valuations in the hopes of exhausting the competitors' limited budgets. Then, a bidder shifts to bid its real valuation, now facing weakened competition for these goods[30]. The chosen strategy depends on the expected strategy's impact on aggregate supply. This impact basically depends on bidder's market power.

Assuming that all bidders have historical information about beside bidders, they can estimate the aggregate supply for each price based on the aggregate supply for the previous round price and the historical offers for the same price. Next, based on a supply curve estimate and a demand curve, the residual demand (DR) is calculated [36]. Once the bidder has the auction situation summarized in the residual demand, it is easy to estimate the expected revenues for a given strategy.

In order to estimate the expected revenue for a given strategy, an algorithm was implemented in MATLAB. This algorithm follows these steps:;

1) Calculate the probability that the current aggregate supply curve be greater than the historical aggregate supply curve for the current round price.
2) Estimate the beside bidders' aggregate supply (SO) for the next round price based on historical data and the probability found at step 1.
3) For the three possible strategies (s_i), calculate the aggregate supply for next round price $AS_{r+1}|s_i$ by adding SO and s_i.
4) Calculate the probability that $AS_{r+1}|s_i$ be greater than the historical aggregate supply for next round price.
5) Estimate the beside bidders' aggregate supply for the future price rounds ($SO_f(P_f)$). $SO_f(P_f)$ based on two limits: ($SO_f(P_f)_{max}$) and ($SO_f(P_f)_{min}$).

TABLE I
BIDDER'S DECISION MATRIX IN A DYNAMIC AUCTION

	$P_a = P_{clear}$	$P_a \neq P_{clear}$
$S_1 = CSC(Pa)$	U_{11}	U_{12}
$S_2 = CSC(Pa) + \Delta Q$	U_{21}	U_{22}
$S_3 = CSC(Pa) - \Delta Q$	U_{31}	U_{32}

- $SO_f(P_f)_{max}$ is the maximum beside bidders' aggregate offer at a future round price (P_f). For every P_f value, $SO_f(P_f)_{max}$ is such that the probability of $SO_f(P_f)_{max}$ being greater or equal than historical beside bidders' aggregate supply is equal to Pr_b.
- $SO_f(P_f)_{min}$ is the minimum beside bidders' aggregate offer at future round price (P_f) and is estimated by taking the minimum historical beside bidders' aggregate supply at price P_f.

6) Estimate maximum (DR_{max}) and minimum (DR_{min}) residual demand from $SO_f(P_f)_{min}$, $SO_f(P_f)_{max}$ and the demand curve ($DC(P_f)$) as follows:

$$DR(P_f)_{max} = DC(P_f) - SO_f(P_f)_{min} \quad (8)$$

$$DR(P_f)_{min} = DC(P_f) - SO_f(P_f)_{max} \quad (9)$$

7) Determine the set of possible clearing prices from $DR(P_f)_{min}$, $DR(P_f)_{max}$ and the range of possible own bids.
8) Calculate the expected reward (U_{i2}) based on the obtained set of possible clearing prices.

Based on expected rewards a decision matrix can be written (table I). Once this matrix is established, it is necessary to estimate the probability of each scenario in order to use the *expected value criterion* to choose the most convenient strategy under the feasible scenarios.

The probability of the scenario 1 ($Prob_{sc1}$)(next round being the last), it is estimated based on the historical data about the clearing price. The probability of scenario 2 is calculated as 1-$Prob_{sc1}$.

III. MODEL APPLICATION

The proposed model was applied in the colombian power market and specifically to a new market auction scheme proposed in the last 5 years. The following sections describes this application.

A. Colombian electricity wholesale market

The colombian power market (known as MEM) was created in 1995, as a competitive environment for the generation and energy retail activities. This market structure assures the existence of enough sellers and buyers avoiding a direct influence of any agent over the final energy tariffs.[12]. In addition, MEM allows to trade energy by means of an Spot Market or Bilateral Contracts and both choices might be represented as an energy portfolio to manage the suppliers' revenue risk. In this market, hiring 100% of power generation lets suppliers know the expected annual revenues, implying lower levels of risk. Nevertheless, the average spot price is usually higher than the average contract price, so, hiring 0 % of Power Generation maximizes the expected revenue. Consequently, an optimal hedge level must be determined in order to maximize the revenue at an acceptable risk level.

In addition, there are two kinds of final cutomers: regulated and non-regulated customers. The regulated customers pay a tariff that is fixed by the regulator. This tariff transfers the purchase energy cost that was paid by its incumbent retailer. On th eother hand, non-regulated customers buy energy trough a competitive scheme.

B. Organized Market (MOR)

Since five years ago, a new scheme to trade energy for the regulated customers has been designed: the Organized Market (MOR). MOR is a *Descending Clock Auction* where standard long term energy supply obligations will be traded. In other words, the auction product is a standardized contract with a fixed commitment period (one year). According to this new market structure, Suppliers/Retailers who want/need to sell/buy Energy to regulated customers must bid exclusively trough this new market scheme (MOR).

Retailers have a passive role in MOR, the auctioneer ask them for the energy needed and sets an Aggregate Demand Curve by adding the retailers' requests. Moreover, the auctioneer fix two prices: PP1 and PP2. PP1 is the maximum price that the auctioneer is willing to buy for the total energy demand while PP2 is the maximum price that the auctioneer is willing to buy only for any fraction of the demand.

Before the auction takes place, the available information is limited. PP2 is known, PP1 is unknown, and a range of values for the possible total demand is given instead of an accurate total demand. Thereby, bidders don't know the real Demand Curve, instead they have an expectation that can be represented by lower and upper limits.

During an auction, the auctioneer sets a range of prices where the bidders are able to offer. This range sets a variable called *round size*. For each round, auctioneer sets the round size in order to balance auction's transaction costs and the available time to fit the bidders' bids. Additionally, a suitable handling of this round size allows to limit the chances of exercising market power.

Finally, the auction ends when the aggregate supply meets the total demand curve. Then, the auctioneer discloses the final allocations.

C. Simulation Parameters

The proposed model was applied to MOR in order to evaluate the impact of varying its parameters: PP2, PP1 and round size.

Six generators were modeled and their main features are presented in table II. These agents choose one of the following three strategies every round:

1) Bid according to their CSC at round price
2) Bid according 25th percentile of their historical bids at round price
3) Bid according 75th percentile of their historical bids at round price

TABLE II
CHOSEN GENERATORS TO MODEL MOR

	Plants	Risk Aversion
GENCO A	5	0.04
GENCO B	5	0.31
GENCO C	6	0.002
GENCO D	1	0.19
GENCO E	10	0.104
GENCO F	4	0.025

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TABLE III
DIFFERENT AUCTIONS TO BE SIMULATED

Parameter	Lower limit	Upper limit	Step
$PP2$	100	210	10
$PP1_{min}$	50	$PP2$	10
$PP1_{max}$	$PP1_{min}$	$PP2$	10
nr	30	130	20
ΔTD	0%	±20%	±5%

The simulation was set with the following values: average spot price (87 \$/kWh), spot price variance (1000 $(\$/kWh)^2$), PP2 was varied between 100 and 210 \$/kWh and PP1 between 50 and 210 \$/kWh. All these values were chosen from the historical data about Colombia's Spot Market.

In order to vary the round size, an additional parameter was introduced: *maximum number of rounds* (nr). Thus, round size is calculated by dividing the difference between auction's starting price and minimum price over nr. Thereby, the higher the maximum number of rounds, the smaller the size of the rounds.

The simulation scenarios are composed of 5 variables: Price PP2, maximum number of rounds (nr), total demand uncertainty (ΔTD) and the two PP1's limits: $PP1_{max}$ and $PP1_{min}$.

Table III shows the parameters for the simulated auctions using the MATLAB algorithm described above. In all the auctions, more than 15.000 scenarios were simulated.

IV. RESULTS AND DISCUSSION

The main model's output is the auction's clearing price (P_c). However, P_c is impacted by the demand curve shape as it is shown in figure 4. To avoid this possible bias in the analysis, a *Modified Clearing Price* (P_{cm}) was introduced to filter this effect and accordingly, to identify the direct parameters' impact over bidders' decision along the auction.

Then the parameters' impact over P_c and P_{cm} is evaluated by applying the Pearson's coefficient to the simulation's outputs. Table IV summarizes the results.

From table IV, some conclusions can be inferred:

TABLE IV
PEARSON'S COEFFICIENT BETWEEN PARAMETERS AND P_c OR P_{cm}

Parmeter	**r** with P_c	**r** with P_{cm}
$PP2$	0.89	0.95
$PP1_{min}$	0.54	0.29
$PP1_{max}$	0.74	0.51
nr	0.088	0.034
ΔTD	0.028	0.0267

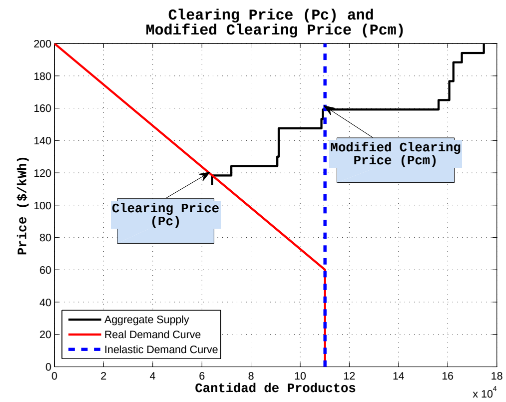

Fig. 4. Clearing Price (P_c) and Modified Clearing Price (P_{cm})

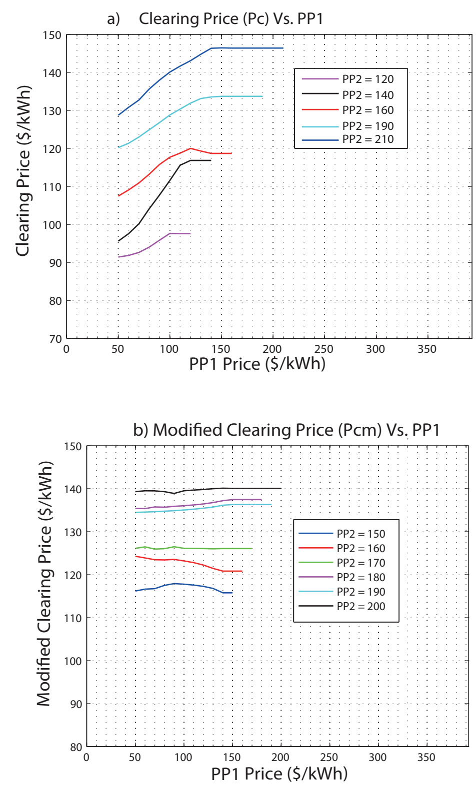

Fig. 5. Clearing Price (P_c) and Modified Clearing Price (P_{cm}) against PP1 price

1) PP2 has the greatest impact over P_c and P_{cm}. Thus, PP2 price influences the clearing price and also it directly influences bidders' decision making processes.
2) PP1 has an impact over P_c but not over P_{cm}. Thus, despite PP1 has an impact over the clearing price it doesn't have an impact over bidders' decisions.
3) The remaining parameters don't have a strong influence over the auction's outputs.

Figure 5 shows a sensitivity analysis of auction outputs against PP1 with different PP2 values. This figure supports the conclusion about the greater impact that PP2 has over clearing prices and hence, over bidder's decisions. As well, figure 5 is helpful to understand that PP1 impact is limited; PP1 only impacts the auction output given that PP1 defines the demand

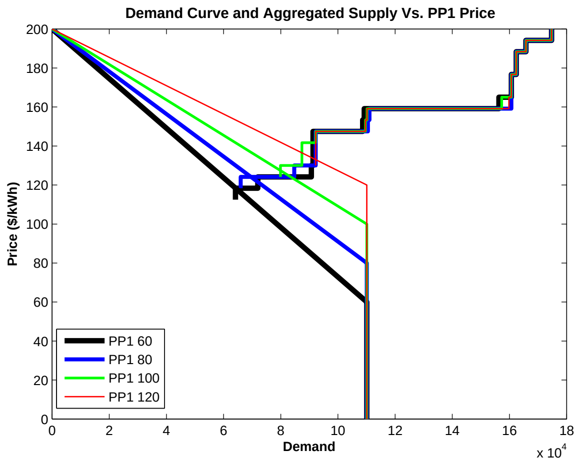

Fig. 6. Demand Curve and Aggregated Supply Curve with Different PP1 Price

curve shape and hence only P_c has a direct relation with PP1. Finally, an additional conclusion can be settled: PP1 doesn't influence bidder's decisions along the auction. Figure 6 shows this fact.

V. Contributions and Conclusions

Three paper's contributions must be highlighted as follows:

- First, this paper proposes a methodology to obtain a GENCO's contract supply curve from historical data about spot prices. Barroso [34] presented a similar methodology, however the proposed methodology in this paper summarize the GENCOs' risk preference in one constant (γ) instead of a piecewise function.
- Second, Roubik's work [26] proposed a methodology to establish the hiring level based on the GENCOs' risk preference, however this paper contributes to Roubik's work to the extend that proposes a methodology to calculate the expected generation from spot market historical data and so, GENCO's hiring profile is calculated from spot market information.
- Third, this paper proposes a methodology to summarize the spot market historical data in a statistic supply curve, this allows to get statistic information about GENCO's bidding profile.
- Finally, the modeling of GENCO's strategic behavior along a dynamic auction is an important contribution of this paper. Models like Barroso's obtain the GENCOs' *best response* to the auction but this response is independent of the auction's development. Instead, this paper presents a methodology to get the GENCOs' *best response* for the next round that allows understanding the bidders adaptation along the auction. This modeling feature is extremely helpful to understand bidding behaviors for the purpose of future power market designs.

Regarding the colombian power market (MOR) some conclusions arised from the application of the proposed model. This model allows to evaluate the auction sensitivity of several *demand curve parameters* and *round size*. This sensitivity analysis allows to state the following conclusions:

- The auction's starting price PP2 has the strongest impact on the auction's clearing price.
- Under MOR's rules, PP1 price does not influence bidders' decisions. However, PP1 has an important effect on clearing prices because PP1 modifies the demand curve and consequently, the equilibrium price.
- The *round size* strongly influences bidders' decisions along the auction. Hence, suitable round size management is helpful to prevent anticompetitive behaviors among bidders. However, the *round size* impact over auction's clearing price is low due to the strong relation between staring price and clearing price.

These conclusions are extremely helpful to design market structures in power markets given that allows to model emerging behaviors along the proposed auctions.

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Henry C. Torres Valderrama MSc. Eng. Henry C. Torres was born in Bogota, Colombia in 1987. He finished his studies in the Department of Electrical Engineering of the National University of Colombia in 2010. Eng. Torres has been research assistant in the Research Program of Acquisition and Analysis of Electromagnetic Signals of the National University of Colombia - PAAS-UN Group since 2010. His research interests are power markets, smart grids and energy efficiency.

Luis Eduardo Gallego PhD. MSc. Eng. Luis Eduardo Gallego was born I Bogota, Colombia, in 1976. He finished his undergraduate, Master and PhD studies in the Department of Electrical Engineering of the National University of Colombia. Eng. Gallego has been researcher in the Research Program of Acquisition and Analysis of Electromagnetic Signals of the National University of Colombia - PAAS-UN since 2000, working in research projects mainly related to power quality and lightning protection. Eng. Gallego has been enrolled in teaching activities related to power quality and computational intelligence. His research interests are power markets, power quality analysis and computational intelligence applied to power systems modelling.