A Cobweb Bidding Model for Competitive Electricity Markets

Javier Contreras, *Member, IEEE*, Oscar Candiles, José Ignacio de la Fuente, and Tomás Gómez, *Member, IEEE*

***Abstract*—The new competitive framework that has been established in several electricity markets all over the world has changed the way that electric companies attain benefits. Under this new scenario, generation companies need to develop bidding models not only for the sake of achieving a feasible dispatch of their units, but also for maximizing their benefits. This paper presents a new bidding strategies model which considers the global policy of a company, but also specifies the bid of each generating unit. The proposed model produces a maximum price bid and an optimal bidding quantity by means of an iterative procedure using the generating company's residual demand curve. It is based on an economic principle known as the cobweb theorem, frequently used to study stability in trading markets. A realistic case study from the Spanish daily electric market is presented to illustrate the methodology.**

***Index Terms*—Bidding strategies, cobweb theorem, electricity markets, Nash–Cournot equilibrium, residual demand.**

NOMENCLATURE

i	Iteration number.
h	Hour of day.
j	Generating unit.
g	Number of generating units that belong to the company.
$D(h)$	Hourly demand in MW.
$q_i^j(h)$	Total production in MW that unit j offers in the hth hour at the ith iteration.
$q_{i\_2}^j(h)$	Production in MW that unit j offers in the hth hour at the ith iteration, corresponding to the block between minimum power and total production.
$pm_i(h)$	Marginal market price in \$/MWh in the hth hour at the ith iteration.
$P_{\max}^j$	Maximum power of generator j in MW.
$P_{\min}^j$	Minimum power of generator j in MW.
cv^j	Variable cost of generator j in \$/MWh.
cac^j	Fixed operating cost for unit j in \$/h.
$carr^j$	Start-up cost for unit j in \$.
$cpar^j$	Shut-down cost for unit j in \$.
dac^j	Commitment state variable (0–1) corresponding to unit j, in the hth hour at the ith iteration.
$darr^j$	Start-up state variable (0–1) corresponding to unit j, in the hth hour at the ith iteration.
$dpar^j$	Shut-down state variable (0–1) corresponding to unit j, in the hth hour at the ith iteration.
$Q_i(h)$	Sum of all the quantities that are offered by every generating unit of the company in the hth hour at the ith iteration.
$m_i(h)$	Slope of the straight line that joins the point $[Q_i(h), pm_i(h)]$ with $[Q_{i-1}(h), pm_{i-1}(h)]$, in \$/[(MW)^{2}h]. It is used to approximate the residual demand curve around a price.
rs^j	Start-up ramp rate of unit j in MW/h.
rb^j	Shut-down ramp rate of unit j in MW/h.
$Energmin^j$	Minimum energy to be produced by the hydro group j in the next 24 hours.
$Energmax^j$	Maximum energy to be produced by the hydro group j in the next 24 hours.

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J. Contreras is with the E.T.S. de Ingenieros Industriales, Universidad de Castilla—La Mancha, Ciudad Real, Spain (e-mail: javier@ind-cr.uclm.es).

O. Candiles is with Telefónica de España, Madrid, Spain (e-mail: oscar.candiles@telefonica.es).

J. I. de la Fuente and T. Gómez are with Escuela Técnica Superior de Ingeniería (ICAI), Instituto de Investigación Tecnológica, Universidad Pontificia de Comillas, Madrid, Spain (e-mail: nacho.delafuente@iit.upco.es; tomas.gomez@iit.upco.es).

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I. INTRODUCTION

FINDING an optimized bidding policy in a competitive electricity market has become one of the main issues in electricity deregulation. There are many factors that can affect the behavior of market participants, such as the size of players, market prices, technical constraints, intertemporal linkages, etc. Several of the mentioned factors are purely technical and the others are strictly economical. Thus there is a need to develop a methodology combining both issues in a structured way.

Daily electricity markets can be classified according to the market power that one or more players can exercise: monopolistic, oligopolistic, or perfectly competitive.

The deregulating experience in Europe, U.K. being the foremost example, Australia, New Zealand and California has shown that oligopoly is the most common type of electricity market. Frequently, two, three or four companies dominate the market, as can be seen in the British and Spanish markets, for instance.

The most relevant oligopolistic models [1] can be categorized as follows.

- Nash-Cournot models [2]–[4];
- Bertrand models;
- Supply function equilibria models [5]–[7];
- Quantity leadership models (Stackelberg) [8];
- Price leadership models.

Each one of these models uses different strategic variables, such as price and quantity, producing results that are sometimes close to a monopoly and other times close to perfect competition. For an updated literature survey on the topic of bidding in electricity markets see [9].

Nash–Cournot models have been widely studied to model daily electric markets due to its intuitive appeal and simple assumptions. Cournot models fix the quantity offered by the competitors finding the equilibrium if this assumption is held by all players. This assumption has been applied to the Californian market by Bushnell *et al.* [2], showing realistic results. A more theoretical model that includes both the use of the network and market equilibrium conditions can be found in [3] and [4].

From a strictly economic standpoint, Klemperer and Meyer [5] have developed a fairly general bidding function procedure specially suited to deal with uncertainty. Seminal applications of economic models to electricity markets have been brought to public attention since the opening of the England and Wales market in 1990, and in particular by the works of Green and Newbery [6]. A recent application of the bidding function model in the Spanish market can be seen in [7].

Finally, a Stackelberg leadership model, where there are a few large producers and a large number of small "fringe" producers, is presented in [8].

In contrast to the above, this paper presents a new Cournot-like model to find the optimal bidding policy of a company that comprises several thermal and hydro units. The model fixes the residual demand faced by the company at every hour, i.e., the rest of the bids offered by the competitors are already forecasted.[1] Later, it performs an iterative sequence of optimizations where the next hourly price is determined by the previous fictitious overall quantity that the company decides to produce. The process stops when the difference between two consecutive prices is smaller than a fixed tolerance ε, thus the iterative process has converged. The final market price results from the overall final quantity and any price bid below this final cap price would suffice.

The paper is organized as follows. Section II presents the basic theory that supports the "cobweb" model for general markets. Section III shows the overall optimization procedure to determine the optimal bidding strategy for electric daily markets. Section IV shows the quantity bid optimization module. Section V shows the price and residual demand slope updates modules. Section VI shows a realistic case study based on the Spanish daily market. And Section VII presents several conclusions derived from this work.

II. Cobweb Model

The bidding model proposed in this paper is based on the concept of Cournot iterative equilibria, as a result of a company maximizing its benefit, considering that the competitor's behavior is fixed. Note that a Cournot-like iterative method only consider quantities as variables, not prices.

[1]Residual demand function faced by an individual player is equal to the consumer demand function minus the sum of all the price–quantity bid functions offered by the rest of the competitors.

There can be two types of Cournot-type market equilibria: static and dynamic. The difference between them is the temporal sequence followed to obtain the solution. In the static case, the participants' benefits are maximized simultaneously. In the dynamic case, the equilibrium is achieved by the participants when they bid sequentially. An example of a realistic dynamic oligopolistic market based on a Cournot model can be seen in [10], where the dynamic behavior throughout the bidding process is investigated.

The dynamic Cournot equilibrium concept formulated by Borenstein *et al.*, the market agents can be classified as follows [2]:

- **Price Takers:** Their offer is not needed to match the demand. Slight variations in their bid result in slight changes in the market price. They are also called "competitive fringe [11]."
- **Cournot Competitors:** Total demand cannot be met without them. They have a big impact over the price due to their market power.

In a real market both types of agents would compete against each other, and their respective bidding strategies would be quite different. That difference comes from the concept of residual demand curve, as it can be seen in Figs. 1 and 2, respectively.

Considering an inelastic demand, in the Price Taker case, since market demand can be matched without this agent, a Price Taker optimal price/quantity bid would be in a certain spot of the residual demand curve that the agent is facing, as seen in Fig. 1.

In the case of a Cournot Competitor, if this agent decides not to produce, the market price would be infinite, since its presence is essential to cover the market demand, as seen in Fig. 2.

Focusing on price taker agents (or agents that cannot manipulate prices extensively), this paper proposes a new iterative bidding method such that every agent can adapt itself to its fixed residual demand in a sequential fashion.

The iterative process that is described below is an application of the "cobweb" theorem to electricity markets. This model was first introduced by Ezekiel [12] and since then has been widely used to study price and production dynamics in general markets [13]–[15]. The cobweb model describes a price equilibrium where production decisions are taken ex-post, once the current market price is available. A single bidding agent assumes that she will not significantly affect the market price with her bid, assuming that the competitor's bids are fixed.

The cobweb process begins with the agent's estimation of the final market price. After that, the agent calculates its optimal production based on the estimated price, and then observes the effect of its own production on the next resulting price by means of its residual demand curve. Once the price is observed, the agent re-calculates its optimal production with the new price. The process continues until convergence in prices is reached, a two-period price cycle is reached, or undamped oscillations begin.

The equilibrium price, where the overall bidding and demand curves intersect, is only obtained under the following assumption: the agent's bidding curve slope must be higher than the residual demand slope. If the slopes were equal, a two-period price cycle would be reached; if the bid slope was lower than

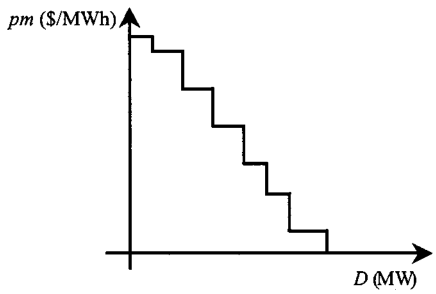

Fig. 1. Residual demand for a Price Taker.

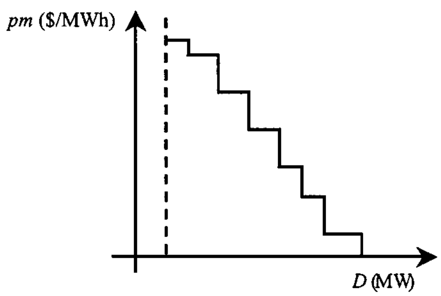

Fig. 2. Residual demand for a Cournot Competitor.

the residual demand slope, the price pattern would become unstable. Notice that the residual demand reflects the competitor's bids, such that a high residual demand slope means that the rest of the producers are expensive and vice versa. Finally, note that if a large player submits a bid whose slope is very low (i.e., it has many generators with low costs), a price taker–or small player–will encounter an almost flat residual demand and, therefore, no matter how much the small player bids in terms of quantity, the price will be almost the same. If the slope of the bids of the large player increases, for the same price taker bids, the number of iterations and the range of the iterative prices will increase. When the slopes of the price taker and the large player became equal, the convergence limit would be reached.

The convergence case is shown in Fig. 3 for linear supply and demand curves.[2]

III. Overall Bidding Algorithm Description

The proposed bidding algorithm is based on the methodology depicted in Section II. It has a modular structure to allow for maximum flexibility of the model. There are five main modules, as depicted in Fig. 4.

- Data and parameter initialization;
- Quantity optimization;
- Price and residual demand slope calculation;
- Convergence check;
- Presentation of results.

The most relevant modules, quantity optimization and residual demand slope calculation, are explained in detail in the next two sections.

[2]A more detailed explanation of the cobweb model can be also found in [14].

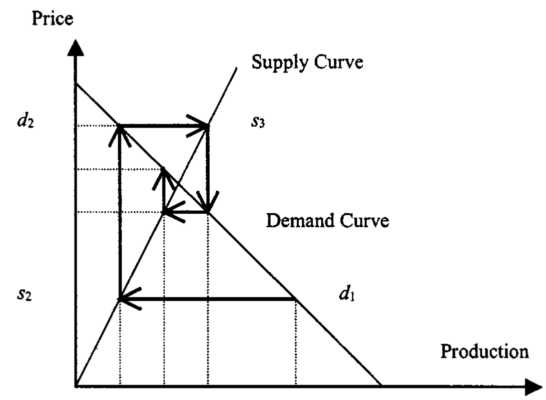

Fig. 3. Cobweb model.

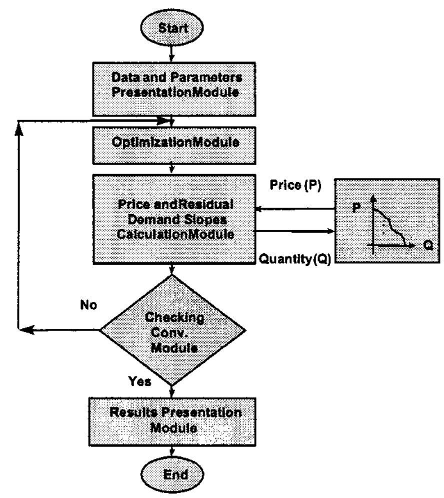

Fig. 4. Overall bidding algorithm description.

IV. Quantity Bid Optimization

Quantity bid optimization main objective is to obtain the production (MW) that maximizes the company's benefit at every hour: $q_i^j(h)$. If the goal is to maximize hourly revenue, then it requires the prices and slopes of the residual demand around this price, obtained after every iteration.

Residual demand curves are extremely difficult to describe by analytic functions in a real environment. In order to represent them as accurately as possible using mathematical programming, residual demand curves are approximated by a first order (linear) Taylor series around the price.

Fig. 5 shows the shape of the residual demand curve for one hour in a daily market. A Taylor's linear approximation is used to overcome the difficulty of describing this curve with an analytical function.

In Fig. 5, $Q_i(h) = \sum_{j=1}^{g} q_i^j(h)$ represents the overall production of all the generating units that belong to the company. The mathematical expression to model the variation in price at the $(i+1)$th iteration with respect to price at the ith iteration, assuming that the company's bid quantity at the ith iteration was fully accepted, is given by

$$pm_{i+1}(h) = pm_i(h) + m_i(h) \cdot [Q_{i+1}(h) - Q_i(h)]. \quad (1)$$

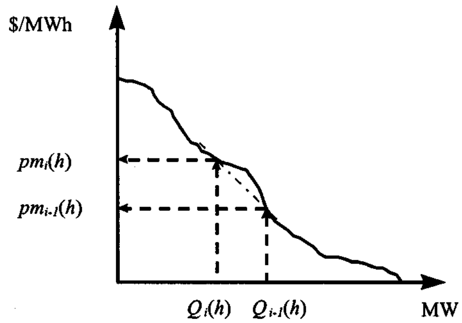

Fig. 5. Residual demand using Taylor's approximation.

Note that the sign of $m_i(h)$ is always negative, since residual demand curves are monotonically decreasing.

The generation mix of thermal and hydro units for a given spot price produces a benefit that the company optimizes at each iteration. Thus, the optimized daily production function that the company calculates previous to bid in the daily market is as follows [see (2) at the bottom of the page] where pm_{i+1} is given by (1). The value of cv^j is either the variable cost for thermal units or the opportunity cost of water provided by a higher order hydrothermal model. Note that since the new price is a linear function of the offered quantity, as shown in (1), the optimal daily production function that the company sends to the cobweb iterative process at the $(i+1)$th iteration is a quadratic function of the offered quantity. In (2), since the variables are both continuous and discrete, the resulting objective function is a mixed integer quadratic one subject to mixed linear constraints. This mixed integer quadratic function must be linearized such that the problem is solvable with standard mixed integer programming solvers.

In order to find a feasible solution, there are several restrictions that are described as follows.
Thermal units' constraints include the following.

- Power output margin above minimum power and below maximum power

$$q_{i\_2}^j(h) - \left(P_{\max}^j - P_{\min}^j\right) \cdot \mathrm{dac}_i^j(h) \le 0. \tag{3}$$

- Coherence of the commitment status variable

$$\left[q_i^j(h) - q_{i\_2}^j(h)\right] - P_{\min}^j \cdot \mathrm{dac}_i^j(h) = 0. \tag{4}$$

- Ramp-up rate limit

$$q_i^j(h) - q_i^j(h-1) \le rs^j. \tag{5}$$

- Ramp-down rate limit

$$q_i^j(h-1) - q_i^j(h) \le rb^j. \tag{6}$$

- Coherence among startup, commitment and shut-down statuses (see [16])

$$\mathrm{darr}_i^j(h) - \mathrm{dac}_i^j(h) + \mathrm{dac}_i^j(h-1) - \mathrm{dpar}_i^j(h) = 0. \tag{7}$$

- Generation lower bounds

$$\begin{aligned} q_i^j(h) &\ge 0 \\ q_{i\_2}^j(h) &\ge 0. \end{aligned} \tag{8}$$

Hydro units' constraints include the following.

- Minimum hydro power limit

$$q_i^j(h) \ge P_{\min}^j. \tag{9}$$

- Maximum hydro power limit

$$q_i^j(h) \le P_{\max}^j. \tag{10}$$

- Minimum hydro energy to be produced during the day (obtained from a higher order exploitation model)

$$\sum_{h=1}^{24} q_i^j(h) \ge \mathrm{Energmin}^j. \tag{11}$$

- Maximum hydro energy to be produced during the day (obtained from a higher order exploitation model)

$$\sum_{h=1}^{24} q_i^j(h) \le \mathrm{Energmax}^j. \tag{12}$$

V. Price and Residual Demand Slope Updates

Once the generation units know their optimal production at every hour, they need to know the resulting price and residual demand slope $m_i(h)$ that would result if all of their offered quantity bids were accepted.

A. *Initial Iteration* $(i = 1)$

The offered quantities that could produce the initial prices, and the starting residual demand slopes, are known at the first iteration. Thus, starting points to calculate prices and slopes are as follows.

- Initial quantities can be arbitrary.
- Initial residual demand slopes are equal to 0, i.e., the residual demand is completely inelastic. Thus, the bid is very ≪optimistic≫, offering a high quantity and ignoring its effect on price. Nevertheless, the starting point is not relevant in this process once convergence conditions are verified.

$$\max_{\substack{q_i^j, \mathrm{dac}_i^j, \mathrm{darr}_i^j, \\ \mathrm{dpar}_i^j, q_{i\_2}^j}} \left[\sum_{j=1}^{g} \sum_{h=1}^{24} \left\{ \begin{array}{l} pm_{i+1}(h) \cdot \left[q_{i+1}^j(h) - P\min^j + P\min^j \cdot \mathrm{dac}_{i+1}^j(h)\right] \\ -cv^j \cdot \left[q_{i+1}^j(h) - P\min^j + P\min^j \cdot \mathrm{dac}_{i+1}^j(h)\right] \\ -\mathrm{cac}^j \cdot \mathrm{dac}_{i+1}^j(h) - \mathrm{carr}^j \cdot \mathrm{darr}_{i+1}^j(h) \\ -\mathrm{cpar}^j \cdot \mathrm{dpar}_{i+1}^j(h) \end{array} \right\} \right]. \tag{2}$$

B. Following Iterations $(i > 1)$

1) Price Calculation: In every hour and at every iteration, the price is calculated as follows.

First, the overall production of all the generation units that belong to the company is accumulated in the variable $Q_i(h)$.

Secondly, the quantity $Q_i(h)$ is fictitiously ≪offered≫ at zero price in order to get the bid fully accepted in a fictitious market clearing procedure (this is in fact a Cournot offer, where the only variable is the quantity). The overall procedure can be seen in Fig. 5, where the whole amount $Q_i(h)$ that is accepted ≪trims≫ the most expensive part of the residual demand curve. Residual demand bids that are more expensive than $pm_i(h)$ will not be accepted.

2) Residual Demand Slope Calculation: The residual demand slope calculation utilizes the results from the ith and the $(i-1)$th iteration. In this manner, the expression to calculate the value of the slope at the ith iteration is given by

$$m_i(h) = \frac{pm_i(h) - pm_{i-1}(h)}{Q_i(h) - Q_{i-1}(h)}. \tag{13}$$

As it can be observed from Fig. 5, (13) provides the value of the residual demand slope that can be plugged into the optimization formula given in (2). Although this method of updating the residual demand slope is simple and effective, more sophisticated methods, such as the linear hinges model [17], [18], can be applied to obtain a residual demand linear function.

Note that the final company bid is produced after the cobweb iterative process ends. The quantity bid is given by the optimal quantity at the last iteration before converging in price, and the price bid has to be equal or slightly lower than the final equilibrium price to get accepted.

VI. Case Study

The algorithm has been programmed in the C programming language in a UNIX environment. The optimization module uses CPLEX to solve the Mixed-Integer Programming problem, following a simplex primal method. The algorithm has been applied to obtain the optimal bidding strategy of a fictitious generating company which comprises both thermal and hydro units in the Spanish day ahead market. This company is assumed to know the 24 hourly residual demand curves of her competitors.[3] Residual demand and price data are available to the company the day before the bidding. The chosen scenario is characterized by a small hydraulic production as a result of a dry season. The process required ten iterations, with a total computing time of 1,5 minutes in a Silicon Graphics Origin 2000 Workstation.

A. Evolution of the Iterative Algorithm

Fig. 6 indicates the evolution of the algorithm, showing the initial and final iterations over each one of three different residual demand curves. The curves selected represent a valley hour, a shoulder hour and a peak load hour.

The behavior of the algorithm is different in valley hours as compared to shoulder and peak hours. Valley hours present residual demand curves with great elasticity (horizontal profile), therefore no significant price alteration takes place if more or less quantity is offered. However, during valley and peak hours, the possibility of price modification is much higher, due to the lack of elasticity of the curves.

[3]The day ahead Spanish market pool provides the 24 hourly prices, aggregate offer and demand bids, and other relevant data at his web page: www.omel.es, just the day before bids can be submitted.

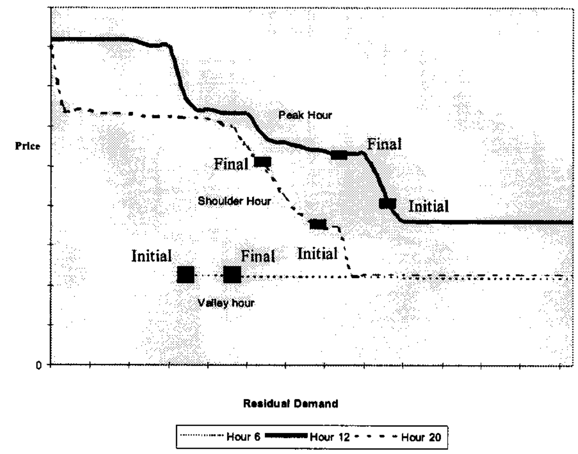

Fig. 6. Evolution of the Iterative Algorithm.

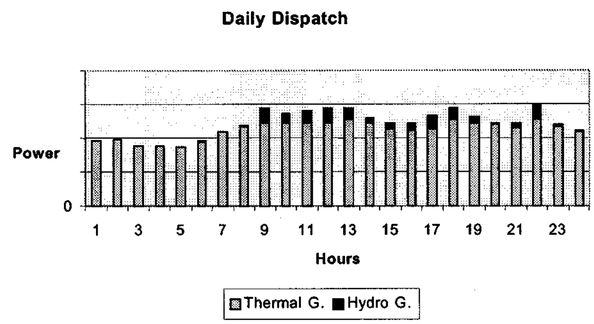

Fig. 7. Thermal and Hydro Dispatch.

B. Final Dispatch

The energy that the generating company must bid, divided in thermal and hydro energy blocks, is shown in Fig. 7.

Hydro units offer their energy during the hours where they can obtain larger profits, taking into account their "water opportunity costs." This conclusion can be inferred analyzing Fig. 7.

Having flexible hydro generation units is very important because they allow significant changes in the quantity bids, and these modifications may induce price alterations and bigger profits. In addition, the hydro generation dispatch smooths the thermal generation dispatch, as seen in Fig. 7.

VII. Conclusion

A new bidding method for day ahead electricity markets has been presented. It is based on the cobweb model, a simple dynamic model of cyclical demand and supply in which there is a time lag between the responses of producers to a change in price. The proposed methodology provides optimal price and quantity bids for a generating company, given the predicted (or actual) hourly residual demand curves, even if these curves cannot be expressed as functions. The cobweb model starts with an estimation of the hourly prices and produces a series of iterations of prices and residual demand slopes based on a first order approximation of the residual demand curve around a price. After a series of bounded iterations, the obtained solution is robust, since it does not depend on the starting point, but on the shape of the residual demand curve. The convergence of the method is based on a simple comparison between the bidding and residual demand slopes. Therefore, the knowledge or a good estimation of these demand curves is essential to obtain good results. The method has been successfully implemented to solve a realistic example of a generating company that bids in the Spanish day ahead market. Future research will implement an equilibrium price model where small agents may modify their residual demand slopes simultaneously, according to several heuristic rules.

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Javier Contreras (M'98) was born in Zaragoza, Spain, in 1965. He received the B.S. degree in electrical engineering from the University of Zaragoza, Zaragoza, Spain, the M.Sc. degree in electrical engineering from the University of Southern California, Los Angeles, and the Ph.D. degree in electrical engineering and computer sciences from the University of California, Berkeley, in 1989, 1992, and 1997, respectively.

From 1997 to 1998, he was a Researcher at the Instituto de Investigación Tecnológica, Universidad Pontificia Comillas (UPCo), Madrid, Spain. Currently, he is an Assistant Professor at the Universidad de Castilla—La Mancha, Ciudad Real, Spain. His research interests include power systems planning, operations and economics, and electricity markets.

Oscar Candiles was born in Madrid, Spain, in 1973. He received the electrical engineering degree from Universidad Pontificia de Comillas (ICAI), Madrid, Spain, in 1997.

He was with the Instituto de Investigación Tecnológica, Escuela Técnica Superior de Ingeniería (ICAI), Universidad Pontificia Comillas, Madrid, Spain, from 1997 to 1999. He is currently at Telefónica de España, Madrid, Spain.

José Ignacio de la Fuente was born in Soria, Spain, in 1967. He received the B.S. and Ph.D. degrees in electrical engineering from the Instituto de Investigación Tecnológica, Universidad Pontificia Comillas (UPCo), Madrid, Spain, in 1990 and 1997, respectively.

Currently, he is a Researcher at UPCo. He also teaches Power Systems at Escuela Técnica Superior de Ingeniería (ICAI), Universidad Pontificia Comillas. His research interests include power systems control and optimization, ancillary services procurement and remuneration, energy bidding strategies and power quality issues.

Tomás Gómez (M'84) received the Degree of Ingeniero Industrial in electrical engineering from the Universidad Pontificia Comillas (UPCo), Madrid, Spain, and the Degree of Doctor Ingeniero Industrial from the Universidad Politécnica, Madrid, Spain, in 1982 and 1989, respectively.

He joined Instituto de Investigación Tecnológica (IIT-UPCo) in 1984 as a Research Fellow. Currently, he is a Vice-Chancellor of the Universidad Pontificia Comillas (UPCo), Madrid, Spain. He has experience in industry joint research projects in collaboration with Spanish, Latinoamerican and European utilities. His areas of interest are operation and planning of transmission and distribution, power quality evaluation, and economic and regulatory issues in the electrical power sector.