Abstract—The ability to analyze the market performance is essential for regulators. In this context, simulation models represent powerful tools to assist the regulator.  

The objective of this paper is to illustrate and deal with the proper definition of metrics to evaluate whether, in the presence of demand elasticity, the market is reaching an efficient outcome. To do so, we first extend the classic formulation of the classic Probabilistic Production Costing models (PPC) by proposing an algorithm that allows easily and efficiently to introduce demand elasticity and then, on this basis, we illustrate how traditional reliability measures are no longer suitable metrics to be used by the regulator to assess security of electricity supply when a non-negligible part of the demand is elastic.

Index Terms—Electricity markets, security of electricity supply, Probabilistic Production Costing models, demand elasticity

I. INTRODUCTION

The ability to analyze the electricity market performance, in order to set proper objectives (if necessary) is essential for regulators. In this context, simulation models represent powerful tools to assist them in their duties.

In particular, the first necessary step in the complex task of achieving an optimal level of security of generation supply is to detect whether or not (and assess to what extent) there is a problem. In order to carry out such an assessment it is necessary to define metrics to evaluate the electric power system and market performance. These metrics have been usually expressed in terms of “pure” reliability. For instance, based on the values of Lost of Load Probability (LOLP), Lost of Load Expectancy (LOLE) and/or Expected Non-Served Energy (ENSE), assigning a secondary role to the actual cost of enjoying the level required.

One of the simulation tools which has been traditionally used to carry out electric power generation system reliability assessments is the so-called Probabilistic Production Costing (PPC) model.

In this paper, our purpose is to contribute to the development of this approach and also to the regulatory metrics to assess the market performance:

- We first face one of the challenges in this context: we propose to use an algorithm that allows extending the classic PPC models design to explicitly represent demand elasticity. The methodology proposed is a simple and robust solution to deal with a step-wise demand elasticity function, which clears up the task without complicating the original approach.

- Then, this redesign will serve us to illustrate how, in the presence of demand elasticity, the aforementioned traditional reliability measures are no longer a consistent proxy to estimate the system performance, since as we discuss, they leave aside relevant information. Indeed, in a fully elastic demand context, the LOLP or the ENSE value as traditionally defined, would take a zero value, no matter which the generation availability would be.

Next, in the remainder of this introduction, we describe the basic PPC model methodology. Then in section II the algorithm to model demand elasticity is developed. Finally, in section III, we discuss the reasons that lead us to state that reliability measures are not suitable metrics in a context in which demand elasticity is significant. This will lead to the discussion on the ways to better define a proper metric to estimate to what extent the market outcomes are adequate.

A. Probabilistic production cost models: a classic tool to measure the reliability of a power system

PPC models have been traditionally used as a support tool in the centralized long-term decision-making process in electric power systems. These models are characterized for centering all the computational efforts in representing the random nature of some of the most relevant variables involved in the long-term planning problem (typically the demand values and the forced outage rates of each generating unit). They allow for reliability assessments of real-size electric power systems with little computational effort. However, this is achieved at the cost of making strong simplifications regarding short- and medium-term operational and planning constraints of the generation plants.

This approach has attracted considerable efforts from academia since the late 60’s. The basic model corresponds to its application to a non-constrained thermal system; see the pioneering works of [1] and [2].
The major outputs that were first calculated using these models were:

- Reliability measures: the loss of load probability, the loss of load expectancy, the expected value of the non served energy, etc.
- Expected production schedules, that is, the expected energy generated by each generating unit.
- Expected production costs.

Although for the purposes of this paper, this basic approach serves as starting point to illustrate how to model demand elasticity, it is important to note that there are dozens of papers where several developments have been introduced to the classic approach. For instance, there are remarkable works focused on introducing simplified alternatives to include hydraulic units [3], [4] or [5], storage units [6] or [7], time dependent units [8] or frequency and duration considerations [9].

There are also different approaches to compute some additional results, for instance in [10] or in [11] a means to calculate the underlying variance of the results is provided. A description on how to estimate derivatives (e.g. marginal values), can be found in [12] and also in [13].

These PPC models have been applied to determine the marginal contribution of each generating unit to the regulator’s reliability objectives. One of the first works in this respect is the one developed in [14]. A more recent work trying to determine this contribution to reliability objectives (in this case, the contribution of wind energy) by means of a PPC model can be found in [15]. This sort of calculations have served for instance to set the remuneration for each generating unit in some real systems in which a capacity payment serves as starting point to illustrate how to model demand elasticity mechanism had been implemented (e.g. this was the case of the former Chilean mechanism or the Panamanian case1).

However, the literature lacks of an efficient algorithm to integrate demand elasticity in PPC models. In [16], an approach aimed to represent the impact of demand-side programs is described, but the chief objective of this approach is to introduce and assess the effect of load shifting programs, which are demand side-management programs that seek to move the load consumption from peak to off-peak hours. This is carried out by breaking down the load shifting operation into two operations that can be separately modeled within the PPC context by means of limited energy generators. This way the model separates peak clipping (reduction of the consumption on the peak) and valley filling (increasing it on off-peak hours), and models the first operation as an equivalent hydro unit and the second as the process of loading a pump storage unit (for more details, see any of the references provided before on how to perform such operations). However, in this model, the energy to be shifted from peak load to valley load is introduced as an exogenous parameter; so in rigor no explicit response to prices is modeled.

As stated, our objective is not to model load shifting programs, but introducing explicitly demand response to prices. Here we propose a methodology that solves the problem in a simple and compact way. In order to ease and clarify the description, we will present the proposed new formulation on the basis of the simplest PPC model design (representing just non-energy-limited thermal generating plants, modeled through their maximum output and their forced outage rate). As it is latter shown, thanks to the consistency and straightforwardness of the algorithm proposed, the methodology allows further complication of the system representation on exactly the same basis as the traditional approach itself.

B. Description of the Basic PPC Model

The basic PPC model is built upon the assumption that all generation plants can produce at full capacity at any time unless when they are out-of-order due to a forced outage. Hourly demand is considered to be inelastic and stochastic.

These models were conceived to check a basic reliability condition: whenever the system’s (inelastic) demand exceeds the available generating capacity a loss of load takes place. The probability of such an event happening, the LOLP, and the corresponding ENSE, have been the main reliability results obtained from these PPC models.

In such a context, the loss of load probability distribution can be evaluated by means of the distribution of the difference between two random variables: the demand and the total generation available (if only loss of load is being evaluated, just positive values of such difference would be of interest). This difference is usually evaluated in a generic random hour. Longer-term results (e.g. the ENSE in a whole year) are calculated by directly extending the results obtained when computing this generic hour.

If all variables (demand and failure rates in the most simple case) are statistically independent, then the computation of the former difference considerably simplifies, since probabilistic distribution function of the sum (or difference) of two independent random variables is equal to the convolution of their probability distribution functions.

We next present how the demand and the thermal generating units are modeled and the order followed in the convolution operation to simulate the generating units’ scheduling. Then we explain how to interpret the results obtained when performing this operation.

1) Hourly load probability distribution

The probability curve for the electricity demand in a generic random hour should ideally be calculated by means of probabilistic forecasting techniques. However, it is commonly accepted as a well-suited proxy to take a large set of historical data and then assign the same probability to each one of the historical realizations of the demand, that is, each realization is supposed to have a probability of 1/n, being n the number of hourly data considered. This way, the percent of time that a

1 The Centro Nacional de Despacho (CND) of the Empresa de Transmisión Eléctrica S.A. (ETESA) in Panama uses the FLOP model (see www.iet.upcomillas.es/aramos/flop.htm), a PPC model to calculate the so-called Firm Capacity according to which generating plants are paid in the context of the capacity mechanism in force.
given load level (or a greater than a given load level) occurs in the set of data considered will be interpreted as a probability. Thus, at any given time (hour) there will be a probability of 1 that the load will be higher than the minimum load being considered.

Under the latter assumption, and as illustrated in Fig. 1, we can calculate the Load Complementary Distribution Function (LCDF) just by rotating the axes of the load duration curve corresponding to the historical horizon considered, and then normalizing the time period so that the vertical axis gives the percent of time (the probability) that a certain value of demand level is exceeded. This is the reason why the hourly Load Complementary Distribution Function (LCDF) is sometimes referred to as the Inverted Load Duration Curve (ILDC) or just Load Duration Curve (LDC).

However, it is important to bear in mind that the LDCF curve does not represent anymore a demand monotone, but a complementary distribution function of the demand in a generic hour.

2) Thermal plants modeling

The available capacity of each generating unit, $G_n$, is modeled as an independent discrete random variable. The simplest representation is the two-state model, where the plant either is able to produce at maximum capacity (probability $p$) or it cannot produce because of a forced outage (probability $q = 1 - p$).

3) Dispatch criteria: the merit order

When operating constraints are not considered, the dispatch that results in the minimum operating cost is the one in which generators are dispatched in order of increasing marginal cost (in practice, based on heuristic algorithms, this merit order can be modified in order to consider approximately some operating constraints, such as high start-up, on-line or shutdown costs, network transmission constraints, etc.). This ranking of the generators is usually known as the merit order or the loading order. This way, the convolution operation is performed following this merit order.

4) The equivalent load and the results provided by the basic model

As described in [2], let us introduce the concept of the “equivalent load after dispatching the first $n$ units”, denoted by $EqL_n$. This $EqL_n$ represents the distribution function of the non-served load after having dispatched the first $n$ generating groups in the merit order. This equivalent load can be computed by carrying out the convolution of the variables involved, as expressed next:

$$EqL_n = L - \sum_{n} C_n, \quad n = 0, 1, 2, 3,...$$  \hspace{1cm} (1)

The first equivalent curve ($n=0$) represents the complementary distribution function of the load consumption ($L$) of the system, when no generator has been dispatched yet. The successive equivalent loads represent the load yet to be covered after dispatching each generator in the system. The last curve, $EqL_N$, represents the complementary distribution function of the demand left uncovered once all the system generators have been dispatched. Fig. 2 illustrates this procedure, where the successive equivalent loads are calculated as a result of the successive probabilistic dispatch of the units.

II. INTRODUCING DEMAND ELASTICITY IN PPC MODELS

To introduce explicitly demand response to prices in PPC models we opt for modeling elastic demand bids by means of a set of equivalent thermal units, which as we show next, allows us to solve one of the pending issues in the literature regarding PPC modeling, introducing demand price elasticity in an extremely simple and robust way. This solution has been previously used in other modeling approaches, as for instance in the context of a long-term deterministic simulation tool representing market agents’ strategic behavior, see [17]. Our proposal allows clearing up the task without complicating the original approach.
A. Redefining the merit order: modeling demand offer bids as equivalent generators

For the sake of clarity we have opted for illustrating the basic idea of the algorithm proposed making use of both a deterministic demand and a deterministic set of the thermal units being available to produce. Once presented the main idea, it will be straightforward to introduce an analogous reasoning in the PPC methodology.

Let us consider that demand marginal utility (the demand offer curve) is given by the red step-wise curve shown in Fig. 3. The available generators’ capacities (MW) and their corresponding marginal costs (€/MWh) have been represented as an aggregated step-wise curve in the same chart.

![Fig. 3. Demand and generation offer curves in the original problem](image)

Note that in the demand representation there are two differentiated parts:

- The inelastic load consumption, denoted here by $L_{In}$. The associated offer price representing this portion of the consumption is assumed to be much higher than the variable cost of any of the generators. This price should ideally represent the Value of Loss of Load (VOLL), also known as the Non-Served Energy Cost (NSEC).
- The offers corresponding to elastic demand consumption; denoting each step of the elastic fragment by $L_i$, where $i$ represents the elastic offer index, offered at a price, $p_{iL}$.

The proposed algorithm consists in solving an equivalent problem, where the elastic demand is substituted by an inelastic demand and a set of fictitious generating units.

In the following, for the sake of simplicity we consider a unitary value for all the availability rates of the fictitious generating units. However, note that by means of the availability failure rate of the fictitious generating units we can represent stochastic demand elasticity (exactly in the same way that the thermal generating units are modeled).

As it has just been pointed out, the production of the fictitious generating units corresponds to demand consumption not committed at the corresponding price. This production can be calculated by means of the resulting equivalent load before (and after) dispatching each one of the fictitious unit.

![Fig. 4. The equivalent model formulation](image)

In the figure it can also be checked how the market outcome remains unchanged, since the resulting price, and the committed generators are exactly the same in both cases.

Note that in the equivalent problem, the production of the fictitious generating units corresponds to those blocks of the demand which were not supplied, that is, it corresponds to the energy that was not purchased because the offer price was below the resulting market price. In other words, the algorithm represents that when the market price rises up to the level of an elastic segment of demand, this energy is retired.

B. The PPC model with an elastic demand

The aforementioned methodology allows including demand elasticity in the PPC framework by performing well-known operations (the dispatch of thermal units). As described, the algorithm consists in solving an equivalent problem, where the elastic demand is substituted by an inelastic demand and a set of fictitious generating units.

In the following, for the sake of simplicity we consider a unitary value for all the availability rates of the fictitious generating units. However, note that by means of the availability failure rate of the fictitious generating units we can represent stochastic demand elasticity (exactly in the same way that the thermal generating units are modeled).

As it has just been pointed out, the production of the fictitious generating units corresponds to demand consumption not committed at the corresponding price. This production can be calculated by means of the resulting equivalent load before (and after) dispatching each one of the fictitious unit.

In Fig. 5 it is shown how this production can be calculated using the equivalent load after dispatching the previous units in the merit order (i.e. $EqL_{n-1}$), and the capacity of the fictitious generating unit, $Q(G_{n}^{L})$. The striped area represents the expected production (i.e. the expected non-purchased energy at that price). In the figure it has also been represented the probability of the corresponding demand block not being committed, what will be termed here as non-purchased energy.
probability (NPEP). Note that this non-purchased energy probability is nothing but what is usually known as the LOLP, that is, the resulting LOLP after having dispatched all the preceding units in the merit order.

Fig. 5. Expected production of the fictitious generating unit

C. Numerical case example

To better illustrate the procedure, we resort to a case example. In Table I we list the thermal plants’ characteristics considered in the analysis. We have introduced the demand elastic offers in the model by means of the fictitious generating units, which are also inserted in the table according to the merit order of the so-called equivalent problem.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_1$ 5000</td>
<td>0.95</td>
<td>11.50</td>
<td>$G_{12}$ 700</td>
<td>0.92</td>
<td>38.45</td>
</tr>
<tr>
<td>$G_2$ 5000</td>
<td>0.95</td>
<td>11.50</td>
<td>$G_{13}$ 700</td>
<td>0.92</td>
<td>38.45</td>
</tr>
<tr>
<td>$G_{F_{1,12}}$ 2000</td>
<td>1.00</td>
<td>12.00</td>
<td>$G_{14}$ 700</td>
<td>0.92</td>
<td>39.05</td>
</tr>
<tr>
<td>$G_3$ 3000</td>
<td>0.93</td>
<td>14.00</td>
<td>$G_{15}$ 700</td>
<td>0.92</td>
<td>41.00</td>
</tr>
<tr>
<td>$G_4$ 2500</td>
<td>0.90</td>
<td>32.00</td>
<td>$G_{16}$ 700</td>
<td>0.92</td>
<td>41.00</td>
</tr>
<tr>
<td>$G_5$ 2500</td>
<td>0.90</td>
<td>32.00</td>
<td>$G_{17}$ 2000</td>
<td>0.92</td>
<td>41.42</td>
</tr>
<tr>
<td>$G_6$ 2500</td>
<td>0.50</td>
<td>32.00</td>
<td>$G_{F_{1,12}}$ 5000</td>
<td>1.00</td>
<td>60.00</td>
</tr>
<tr>
<td>$G_7$ 1500</td>
<td>0.90</td>
<td>32.29</td>
<td>$G_{18}$ 1000</td>
<td>0.78</td>
<td>60.85</td>
</tr>
<tr>
<td>$G_8$ 1500</td>
<td>0.93</td>
<td>32.29</td>
<td>$G_{19}$ 1000</td>
<td>0.78</td>
<td>60.85</td>
</tr>
<tr>
<td>$G_9$ 1250</td>
<td>0.93</td>
<td>32.29</td>
<td>$G_{20}$ 1000</td>
<td>0.78</td>
<td>61.00</td>
</tr>
<tr>
<td>$G_{F_{1,12}}$ 4000</td>
<td>1.00</td>
<td>33.00</td>
<td>$G_{21}$ 1000</td>
<td>0.78</td>
<td>61.00</td>
</tr>
<tr>
<td>$G_{10}$ 1000</td>
<td>0.92</td>
<td>37.41</td>
<td>$G_{22}$ 1000</td>
<td>0.78</td>
<td>80.00</td>
</tr>
<tr>
<td>$G_{11}$ 1000</td>
<td>0.92</td>
<td>37.41</td>
<td>$G_{23}$ 1500</td>
<td>0.78</td>
<td>120.00</td>
</tr>
</tbody>
</table>

In Fig. 6 we present the LCDF as well as the demand elasticity. Note that in order to simplify the algorithm understanding, we have implicitly assumed that demand elasticity remains unchanged during all the yearly blocks, i.e. roughly speaking it is the same in the off-peak hours than in the peak ones. The minimum demand value (including both the inelastic and elastic consumption) is equal to 1350 MWh, and the maximum 36580 MWh.

Fig. 6. LCDF and demand elasticity function

The resulting generating mix considered, including these fictitious units, is represented in the supply function in Fig. 7.

Fig. 7. Equivalent thermal unit problem in the case example

1) Results

In Fig. 8 we represent the successive results obtained from dispatching probabilistically each one of generators considered in the equivalent problem. The striped areas correspond to the probabilistic dispatch of the fictitious generating units, which we denote as the Non-Purchased Energy (NPE). Therefore, the total area itself is the Expected Non-Purchased Energy (ENPE).

Fig. 8. Case example results

Following the procedure illustrated in Fig. 5, we can calculate the probability that each one of the offers does not result accepted for falling below the market price. We have termed this probability associated to each offer as the Non-Purchased Energy Probability (NPEP). It is also possible to calculate the ENPE corresponding to each one of the demand offers.

In the following table we have gathered these results.
This way, the first block is never dispatched, since the NPEP value is 1, and the value of the ENPE is equal to the quantity being offered. On the other extreme, the block offered at a highest price is not dispatched 6% of the time, and the expected energy not being committed is 102 MWh.

The classic reliability measures take the following values:

<table>
<thead>
<tr>
<th>LOLP [p.u.]</th>
<th>ENSE [MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.8E-04</td>
<td>0.232</td>
</tr>
</tbody>
</table>

III. NON-SERVED ENERGY AND NON-PURCHASED ENERGY

In real markets, the regulator is particularly concerned about guaranteeing the electricity supply for the inelastic demand. This happens for several reasons, among which we can highlight the following:

- The inelastic consumption represents a large percentage of overall energy consumption,
- The underlying marginal demand utility (ideally, the demand’s offer price) is considered to be much higher than the one corresponding to the elastic demand,

In many systems the regulator has either administratively calculated or even imposed price limits avoiding the system to reflect the true marginal demand utility. There are many analysis aimed at calculating this VOLL which illustrate this fact, see for instance [18], [19]. On the price cap side, an illustrative example is the case in Spain, where a limit of 180 €/MWh is in force since the electricity market was introduced. Fig. 9 shows a real example of both the system demand and supply curves corresponding to the Spanish spot market. It can be clearly observed the two types of consumption already mentioned (i.e. the inelastic $L_{I\text{e}}$ and elastic consumption $L_{E\text{l}}$).

For the reasons just mentioned, traditionally the regulator has defined its security of supply objectives in terms of the system capability to supply the inelastic consumption. This capability to provide this “critical” fraction of the demand is what is usually analyzed by the different so-called reliability measures. This way, the LOLP represents the probability of not being able to supply this inelastic consumption and the Non-Served Energy (NSE) the non-supplied energy corresponding to this inelastic consumption.

Therefore, the non-served consumption corresponding to the elastic demand blocks not being committed, which we denoted as NPE, does not intervene in the reliability measures.

To illustrate this, we have taken the example of Fig. 3 and Fig. 4, with a tighter generation availability scenario (just three thermal groups are now available). In this new case we have represented the NSE and the NPE in both the real market situation and in the equivalent problem formulation.

A. Reliability measures in the presence of demand elasticity

We next show the fact that, when assessing the system performance by means of the reliability measures, since we are just taking into account the inelastic consumption, we are leaving aside relevant information. This has been illustrated in the following figures, which serve us as the basis to give rise to the discussion about the weakness of these reliability measures in the presence of an elastic demand.

Two different scenarios of demand have been considered: a fully inelastic scenario and a fully elastic scenario. Both scenarios have been confronted with three deterministic
scenarios of generation availability, one presenting a sufficient reserve margin, one in which several groups are unavailable and also one representing a severe scarcity (just a few groups are available). This is what we can observe:

In the case of the fully inelastic demand scenario, see Fig. 11, there are two generation availability scenarios which lead to non-served energy.

In the case of the fully elastic demand scenario, see Fig. 12, when resorting to the classic definition of the aforementioned reliability measures, the NSE is equal to zero.

Does this mean that in a context where demand is fully elastic, reliability is no longer a problem? Resorting to the definition provided previously the answer is that effectively, reliability as classically defined is no longer a problem. However, note that in this fully elastic demand case, a permanent scenario of severe scarcity will clearly be a problem from the regulator perspective. The objective of the regulator is to maximize the net social benefit, which implies assessing if (and to what extent) the market mechanism performance may not be yielding the expected/required outcomes. This does not just mean accomplishing with a reliability standard based just on the inelastic consumption (like the one day in ten years), but rather meeting a sufficiently cost effective supply for all consumption (through the most efficient investments, resource management, scheduling, etc.).

Ideally, strictly speaking, if the demand curve could be able to internalize the real opportunity costs in all the short, medium and long terms, there is no actual justification for this regulator concern. However, it is well known that short-term elasticity does not reflect long-term opportunity costs related to for instance system expansion or any kind of long-term externality. Some short-term demand elasticity can indeed be found in several electricity markets nowadays, particularly in the case of the so-called interruptible (often industrial) consumers. But clearly this short-term price elasticity does not reflect or solve the long-term problem, see for instance the discussion in [20].

B. The metric to evaluate market performance

In order to take into account the elastic consumption in the (now not just reliability but) overall performance measure, we propose to evaluate the distribution function of the total Value of Non-Purchased Energy, VNPE. This function would provide a more precise idea of how well the market is performing its “job” than the mere reliability criteria.

For the sake of simplicity, the VNPE distribution function could be reflected through any statistical metric, as for instance the mean value, $\mu$, the standard deviation, the VaR or the CVaR. In Fig. 13 it has been illustrated how these metrics could be performed in a generic case.

Note that the LOLP would no longer make sense in the fully elastic demand scenario. In this new context it can rather be calculated the probability of not supplying a certain demand block.

C. Numerical case example

The expected value of the previous case example\(^2\) can be computed taking into account, for each offer, the ENPE and the corresponding price (we have considered a VOLL equal to 10000 €/MWh).

The Expected Value of the total Non-Purchased Energy (EVNPE) in the case example solved:

$$EV_{NPE} = ENSE_{VOLL} + \sum_i ENPE_i \cdot p_i^L =$$

$$= 0.232 \cdot 10000 + 2000 \cdot 12 + 2718 \cdot 33 + 102 \cdot 60 = 122139 \text{ €}$$

As stated, compared to the traditional reliability

\(^2\) In our case example, the distribution function of the VNPE could also be easily computed taking into account that if any energy offer is not committed, then any energy offer presenting a lower price will also be left uncommitted. This is true since we are considering that demand elastic offers have a failure rate equal to zero.
measures, this reference benchmark value provides the regulator with information not only about the expected (both inelastic and elastic) demand not being supplied but also about the related opportunity costs.

IV. CONCLUSION

We have developed the Probabilistic Production Costing model approach by extending the classic formulation on the basis of a novel algorithm that allows modeling a step-wise demand elasticity function in a simple and robust way.

Then, we have taken advantage of this model formulation to show how the traditional reliability measures, such as the LOLP or the ENSE, as a measure to assess the level of security of supply should be reconsidered in the presence of significant demand elasticity. This has led us to propose a better way to define a proper metric to estimate if the market results comply with the regulator’s standards.

ACKNOWLEDGMENTS

The authors want to thank Luiz Barroso and Professors Ignacio J. Pérez-Arriaga and Andrés Ramos for their valuable comments and suggestions, as well as Mikel Ayala, who helped to improve the work developed in this paper.

REFERENCES


Pablo Rodilla obtained his Industrial Engineering degree and his Ph.D. in 2010 from the Comillas Pontifical University in Madrid, Spain. He is currently a researcher at the Institute for Research in Technology (IIT), where he has participated in several research projects for governments, international institutions, industrial associations, and utilities. His areas of interest are economics and regulation of energy markets, with emphasis on security of supply, risk analysis and oligopolistic market modeling.

Carlos Batlle is Research Professor in the Institute for Research in Technology (IIT) of the Comillas Pontifical University in Madrid, where he has headed more than 20 research projects and has taken part in many others. He has worked and lectured extensively on operation, planning and risk management of electric generation and networks, and particularly on regulatory issues concerning electric power systems, with special focus on market design and regulation for wholesale and retail electricity markets. In this latter topic he has been a consultant for governments, international institutions, industrial associations, and utilities in more than 15 countries, with special focus on Latin American power systems.

He has published more than 20 papers in national and international journals and conference proceedings. He is professor on Electric Power Systems Regulation and Electricity markets at the University Master’s degree in the Electric Power Industry (Erasmus Mundus) of the Comillas and member of the Training Program for European Energy Regulators at the Florence School of Regulation within the European University in Florence.