

# A model based in numerical simulation techniques as a tool for decision-making and risk management in a wholesale electricity market.

## Part I: General structure and scenario generators

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**Abstract:** Changes in the electricity industry have lead to less regulated and more competitive energy market where risk management becomes a key issue. Decision-making and Risk analysis in a competitive environment require powerful simulation models to assess alternatives and evaluate risks. These simulation tools have to be adapted to the peculiarities of the wholesale electricity markets. With this aim, a model based on numerical simulation techniques is presented in two parts. This first part includes a general overview of the model structure and a description of the scenario generators that are developed to represent some of the risk factors. In the second part, the imbedded market model is presented in detail.

**Keywords:** Marginal price, decision-making, risk management, agent's behavior, operational constraints, risk factors, scenario analysis.

### I. INTRODUCTION

The electricity industry nowadays is immersed in a deep changing process. The electric sector, formerly configured by vertically integrated utilities, was subject to the Administration planning and the remuneration was based on standard production costs.

The technologic development, mainly represented by the evolution of combined cycle gas turbines, and the new economic determinants, as the development of the financial energy markets, have promoted fundamental changes in the electric business, based on the introduction of competition.

#### A. The risk growth in electricity markets

One of the elements that characterizes this new market environment is the risk that agents are exposed to. Risk is transferred from the Administration, which formerly assumed the mistakes that a wrong planning could bring, to the new market participants, in whom the operation and investment decisions rely on. This risk is not only transferred but multiplied due to the appearance of new uncertainty factors,

such as the competitors behavior, the entry of new agents, the price volatility (associated both to the electricity market as to the commodities market), macroeconomic, political changes, etc.

Nevertheless, these risks have to be considered as a new business opportunity rather than a setback. Risk management offers the right mechanisms to let the agents establish synergies in such a way that risks could be properly diversified. Every agent can assume those risk factors for which it is better adapted due to its own characteristics and its knowledge of the electricity business.

Risk management allows an enterprise to achieve the proper balance between risk and profitability, through transactions and contracts.

#### B. The need of new risk analysis models adapted to the electric sector

Decision-making and Risk analysis in this new competitive environment described require powerful simulation models to assess alternatives and evaluate risks. These models have to be able to represent adequately all the peculiarities that distinguish a real electric market from other commodity markets [1], [2].

Risk management theories applied to electricity markets are still under development due to the specific characteristics of electricity. The models that traditionally have been developed for financial markets are not able to accurately evaluate the electricity risks. These models make assumptions that can not be applied to electricity markets [3], such as:

- The market is quasi-perfect and liquid, i. e. configured by many agents with little capacity to control prices.
- There are no regulatory mechanisms that can interfere in the course of the market (such as stranded costs, capacity payments, ...).
- These models are usually based on historical price data observation, both for applying time series analysis as for statistical measures calculation. These time series are questionable in the immature electricity markets at least in the mid-term, due to the lack and low quality of the available data.

In the same way, the electricity markets uniqueness needs to be reflected, such as:

- The impossibility of storing the product, the electricity.
- The physical constraints related to generation units and system operation (variable, no-load and start up costs, minimum generation, limited energy plants, ...)
- The strong dependence with respect to the meteorology and hydro conditions.
- The particular behavior of the demand, basically inelastic in the short-term, with daily, weekly and seasonal cycles.
- The existence of different production technologies, with varied cost structures and operating management.

The model presented in this paper is based on numerical simulation techniques and is adapted to the specific necessities that an electric supplier has in the new environment formerly described.

The model is presented in two parts. This first part includes a general overview of its structure and also a description of the scenario generators that are developed to represent some of the risk factors, focusing the attention on the demand scenario generator.

In the second part, the imbedded market model is presented in detail.

## II. THE MODEL RAPEL (RISKS ASSOCIATED TO THE PRODUCTION OF ELECTRICITY)

### A. Objectives

The model tries to support the decision-making process by simulating the electric supply market operation. Market agents not only make their offers but also establish financial trades through futures and options contracts. In this scheme, the model needs to be strict both in the way uncertainty is considered as well as in the way decisions are modeled.

The main objectives of the model are:

- i) Consider the different risk factors, *exogenous* and *decision* variables (see III.B), that affect the utility assets management.
- ii) Simulate all the particularities that characterize real size electric power markets, such as the effect of different bidding strategies, possible regulatory decisions or some other issues affecting the market, and physical constraints related to the generation units and system operation.
- iii) Provide risk measures (Value at Risk, Profit at Risk, ...)

The proposed methodology obtains market prices and profits from a market model that takes into account the real structure of the electricity market, where companies behave as oligopolistic competitors (see Part II and [5], [6]).

Uncertainty is reflected through the variables (risk factors) that define a market scenario, for which the market model computes marginal prices. This is a key issue, as due to the lack of historical data the uncertainty analysis is not focused on market prices but on the risk factors that influence them. In fact, on the price prediction from these factors is where the electric supplier has its major competitive advantage, and thus is where it should center its efforts.

### B. A modular structure

The general model structure has been defined in a modular way (see Fig. 1). The aim of the modular design is to provide the model the necessary independence of the different modules to allow the development of every one of them according to the market evolution. The independence of the scenario generators that simulate the uncertain variables allows updating them separately when new data is available. In the same way, the market model can be adapted to new regulatory schemes without affecting the rest of the modules.

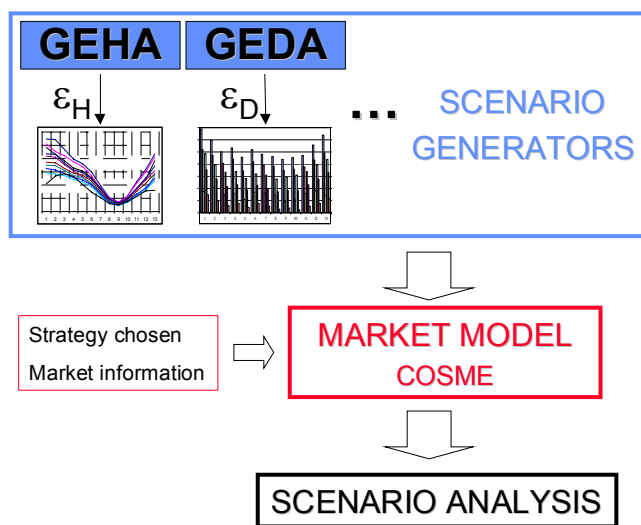


Fig. 1. The RAPEL modular structure.

The modules are fully related to the objectives just detailed in the previous sub-section.

- i) The uncertain variables, specially the ones defined as *exogenous* (those that can be considered as independent of the electricity market itself, such as hydro inflows, or demand) are modeled through scenario generators. These modules share the same structure. This structure is presented in detail in this paper together with a description of the demand generator (GEDA) that illustrates it.
- ii) Once all the input data that defines a market scenario is determined, the market model (see Part II), computes results (such as prices, market shares, profits, etc.), combining the firms strategic behavior and the units operational constraints.

iii) After running a significant number of scenarios, a statistical model analyses the results computing the different risk measures such as the Greeks or the Value at Risk [7].

### III. THE SCENARIO GENERATORS

#### A. The uncertainty modeling

Most risk management models applied to financial markets are based on stochastic processes to characterize the fundamental variable evolution, which is typically the market price. The most common are the Markov stochastic process, e. g. the Wiener process, as the one applied in the Black-Scholes model [3]. These processes assume that the variable's future increment, given the present state, is independent of the past realizations. This behavior can not be applied to some variables that have a major influence in the electric market, such as the hydro production or the demand.

In addition to these phenomena, the variables mentioned gather another major problem due to their complexity. For example, a hydro scenario is not only defined by the energy produced by the whole system, as the values of energy available have to be defined for every single unit and period considered.

In order to represent this kind of risk factors, the model generates complete paths based on its historical evolution. These scenario generators try to take advantage of the know-how of the firm (e. g. the knowledge of its own units operation to infer the competitors units behavior, whose casuistic is similar, specially in the case of the hydro production).

#### B. State variables classification

As the model faces a long-term analysis, it is necessary to divide the scope of the study in stages. Each of these stages is characterize by a set of variables that we classify in the following way:

- The *decision* variables are those over which the agents, have capacity of influence on (e. g. the management of the units, the financial contracts or even investments decisions). These decisions are determined by the ultimate firm's strategic objective, represented for example by its desired risk position.
- The *exogenous* variables are also distinguished in two types:
  - The *natural* exogenous variables are those that receive a stochastic treatment in the model through scenario generators. This tools use the historical data together with heuristic algorithms based either on the knowledge the firm has over its evolution or on instructions determined by superior range models. These variables are different from the rest because their uncertainty is

inherent to the nature of the problem. The values they take follow laws that have no, or at least a negligible, correlation with the state of the rest of the variables that characterize the electricity market (no economic parameter has an influence on the way it rains). In principle these category includes variables such as demand, hydraulicity, units outages, ...

- The *particular* exogenous variables are those variables for which it does not make sense to associate a probability distribution function, e. g. regulatory changes, market agents mergers, ...

As previously mentioned, the scenario generators described next cover those variables defined as *natural* exogenous variables. In particular the description that follows has been applied to the development of the hydraulicity (GEHA) and demand (GEDA) generators.

#### C. The hierarchical decomposition

The scenario generation process is divided in levels that follow a hierarchical order, from the lower to the greater detail of the variable.

For example, if we consider the hydro generator, where  $\Phi_i$  represents the *natural* variable  $i$ , then the sampling is completed into different steps:

$$\Phi_i \equiv \phi_{i1} \rightarrow \phi_{i2} \rightarrow \dots \rightarrow \phi_{ie}; \quad (1)$$

Step 1 represents the greater level of aggregation of the variable we can think of, e. g. if the risk factor is the demand of electricity, this step would represent the sampling of the demand for the whole scope of the study. Step  $e$  represents the greater level of detail in which the variable needs to be described, e. g. the hourly demand of electricity if we use the same example.

When the risk factor that is taken into account is the hydro production,  $H$ , the sampling process is decomposed in four steps:

$$\Phi_H \equiv \phi_{Ht} \rightarrow \phi_{Hp} \rightarrow \phi_{Hugh} \rightarrow \phi_{Hfm}; \quad (2)$$

where

- $\phi_{Ht} \equiv$  hydro production in the whole system along the time scope analyzed;
- $\phi_{Hp} \equiv$  hydro production distribution among the periods in which the time scope is divided in;
- $\phi_{Hugh} \equiv$  hydro production for period & hydro unit;
- $\phi_{Hfm} \equiv$  run-of-the-river energy allocation.

This hierarchical structure allows in first place to make the best possible usage of the few data available. As the sampling is done separately it is possible to take advantage of the different data sources in each step. For example, it is difficult to have hydro system production data for many years as the

electricity systems configuration has been continuously changing, as it has happened in the Spanish case. However, the decomposition allows to take advantage of the rainfall data, available for many years, and to relate it to the system hydro production obtaining a meaningful distribution function. The same effect can be achieved in the case of the demand generator: the demand growth for the whole time scope analyzed can be easily related to any econometric model that can provide information over the probability function.

This decomposition also allows to analyze the influence of each level of detail in order to reduce the number of samples (scenarios) needed. As the model is focused on long-term analysis and at the same time the market model represents the electric market operation with detail, it is fundamental to arrange methods that can accelerate the computation process.

The high number and complexity of the risk factors, inherent to the electricity markets, demand tools that allowed the user to control the trade-off between speed calculation and accuracy. The proposed decomposition allows controlling the sampling process what achieves the objective of enhancing the computation speed. Fig. 2 illustrates with an example the sensibility analysis that the hierarchical decomposition allows. In the example shown the hydro energy produced for year 2000 changes, while the rest of the variables that affect the market remain constant. The figure shows a clear trend that relates the hydro production in the whole system with the resultant average pool price. If this is the case, when the other variables change the sensitivity analysis to the hydro variable can be simplified and accelerated by just sampling around the distribution of this first level of aggregation.

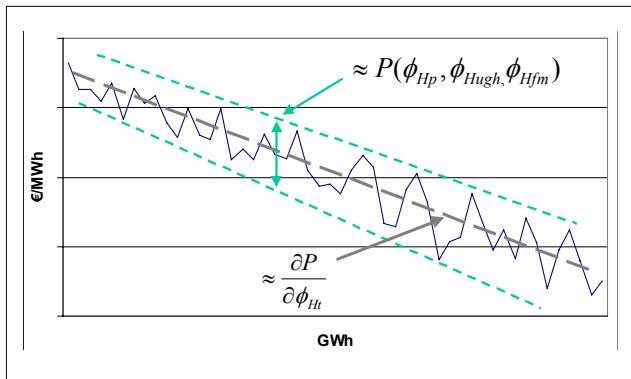


Fig. 2. Price sensitivity to hydro production (year 2000)

In Fig. 3, the same phenomena can be observed when varying both hydro and demand risk factors. The price sensitivity graph was obtained after combining just 25 samples of each variable (625 cases were thus computed). The 25 samples generated for each variable cover uniformly the possible values the distribution function determines for the first level of aggregation, as they were previously defined.

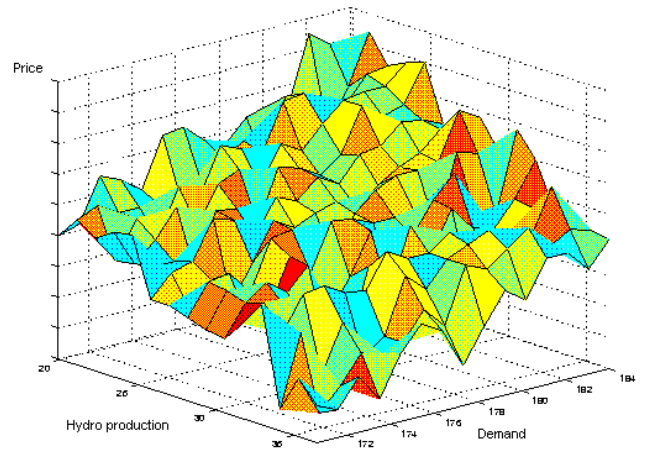


Fig. 3. Price vs. Hydro production and demand growth

#### IV. THE DEMAND GENERATOR (GEDA)

In order to show how the mix between Monte Carlo based sampling and heuristic algorithms works in the scenario generators, a description of the demand generator developed for the Spanish wholesale market is presented next.

The historical data considered in the model was the hourly electric system demand from year 1981 till the end of 1999 and the model samples possible future demand profiles for the year 2000.

##### A. Step 1: Total system demand of electricity sampling $\equiv \phi_{D1}$

As mentioned above, the first step consists of sampling values for the total system demand for the scope of the study (e. g. year 2000). This is achieved by generating *pseudo-random* numbers from an uniform distribution ( $v_s \in U[0,1]$ ) and obtaining the inverse transform from the annual increase demand distribution function ( $\phi_{D1}$ ), calculated either from the historical data available, either from some other superior range econometric model (see Fig. 4).

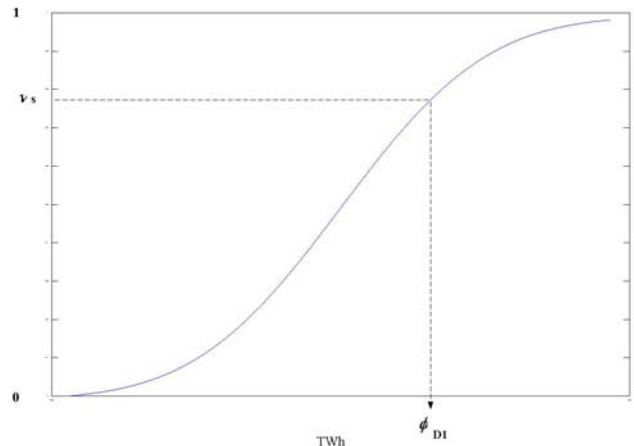


Fig. 4. Inverse transform for the step 1 sampling

## B. The model demand structure

As the model faces a long-term analysis, in order to make the study computationally feasible, it considers the demand structured in blocs. The model divides the scope of the study in:

- Periods (sets of weeks, e. g. 13 periods of 28 days to cover a year)
- Subperiods (e. g. S1 & S2, working and non-working weekdays)
- Blocs (e. g. peak and off-peak)

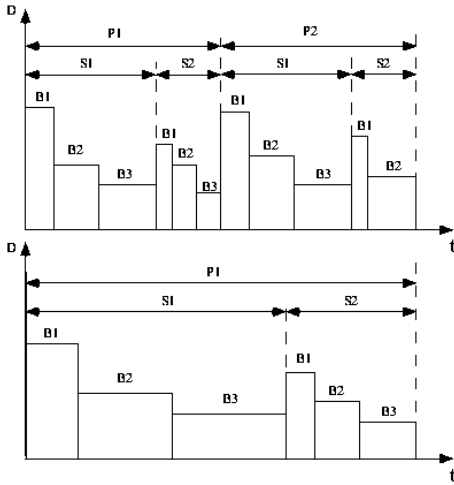


Fig. 5. Two possible structures for the same time scope

The proper definition of the better adapted structure to the market studied is one of the key issues where the electric supplier has to take advantage of its knowledge of the market *modus operandi*.

The criterion applied to the model period division into two subperiods is related to the Spanish electricity supply market. The model groups together the dispatched demand into two subperiods, S1 & S2. In long-term models where the demand is considered in blocs, typically S1 corresponds to the working weekdays while S2 represents weekends and non-working days. This division has an influence on the start-up decisions the market model considers. Nowadays, in the Spanish electricity market there are mainly two typical ways to operate a thermal unit. A unit can decide to start-up in the beginning of the week (on Monday) to be *on* for the whole week or to shut down at the end of the working days (on Friday).

The number of blocs and its length (e. g. the peak bloc number of hours) is the other parameter the user has to define. This definition should be coherent with the real market operation.

Once this division is defined for each period, the market model decides which units produce in each subperiod by taking the start-up decisions (see IV.C).

Also, to simplify the computation process, a *telescopic* approach can be applied. It is possible to study those periods closer to the beginning of the year with greater detail, while those periods far from the present time can be analyzed with less detail. This is reflected by considering periods that gather together a bigger number of weeks and less blocs in each period (see Table 1).

Table 1. A telescopic approach

1 year $\equiv$ 52 W	W $\equiv$ Weeks, P $\equiv$ Periods, S $\equiv$ Subperiods, B $\equiv$ Blocs				Hours out of 24			Hours out of 24		
Periods	W/P	S/P	B/S1	B/S2	B1 <sub>S1</sub>	B2 <sub>S1</sub>	B3 <sub>S1</sub>	B1 <sub>S2</sub>	B2 <sub>S2</sub>	B3 <sub>S2</sub>
4	4	2	3	3	5	8	11	5	8	11
4	4	2	3	2	5	8	11	5	19	0
2	6	2	3	2	5	8	11	8	16	0
1	8	2	3	2	5	8	11	11	13	0

## C. Step 2: Pattern demand profile determination $\equiv \phi_{D2}$

When it comes to allocate the total demand among the periods, an extra complication appears: the historical years calendar differ from one another. This implies that the data from two different years for two analogous periods can not be compared. The reason is that the weekdays that are non-working change from one year to the next. This is what we mean by different *laborality*. In Fig. 6 the demand of electricity profiles for the first week of two different years are shown, where January the 1<sup>st</sup> and the 6<sup>th</sup> are both non-working days.

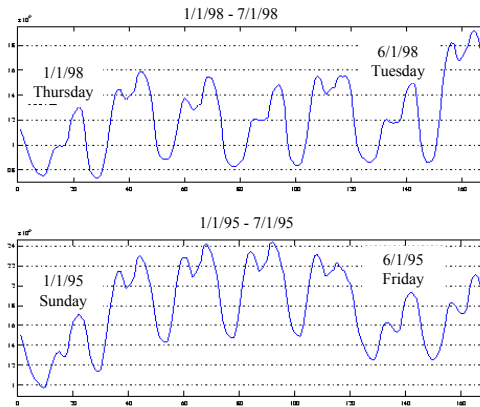


Fig. 6. The first week demand profile of two different years

For this reason, the model determines a pattern structure consistent with the calendar of the future period studied. This pattern structure that defines the demand hourly profile is taken from the closest historical year in which the *laborality* was equivalent to the future period in study, i. e. the closest year that began in the same weekday. In Fig. 7 an example is shown: if we wanted to simulate year 1995, it can be seen that 1989 demand profile would be a good pattern.

In this step the model just determines the future demand profile (in p. u.) used to define the hours that correspond to each bloc.

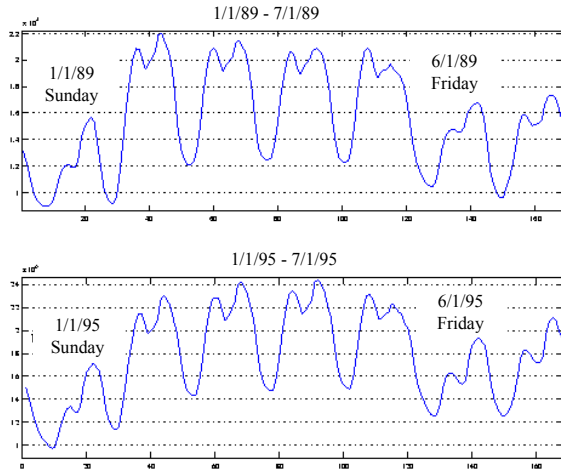


Fig. 7. 1989 as a valid pattern for 1995

Once the pattern profile of the hourly demand is fixed, the model transforms it into the previously defined bloc profile. First, following the criterion presented in IV.B, it assigns every hourly demand value to its correspondent subperiod (see Fig. 8 and notice that the Wednesday non-working day, W, is assigned to the S1). As the figure shows, the blocs are calculated by averaging on the subperiod load duration curves.

This bloc profile is a common reference for all samples.

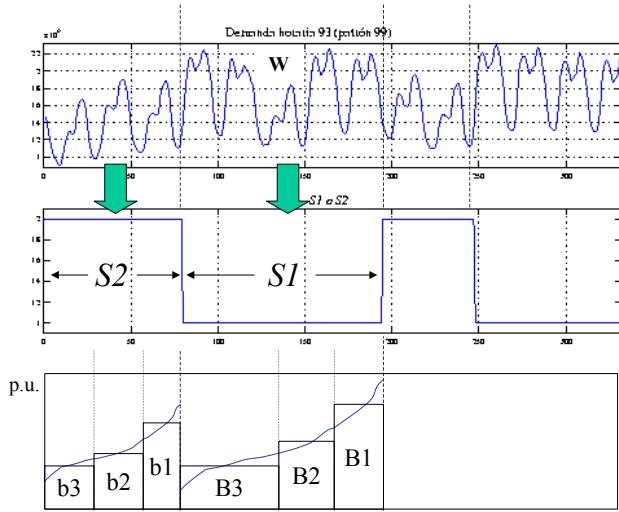


Fig. 8. Pattern demand in blocs

The bloc power values for each scenario generated are determined through the step 3 sampling.

#### D. Step 3: Bloc energy determination $\equiv \phi_{D3}$

After the pattern bloc profile is defined, the energy sampled in step 1 has to be allocated among the different periods. The chosen variable as the reference for the sampling process in this step is the Sunday's demanded energy for each period. It has been considered as a good

pattern as it is the only one that never changes. Sundays are always non-working, while working days demand profile may vary significantly as in some cases it could be non-working or just be close to a non-working day. These values are related to the ones calculated in the year chosen as pattern to set the energy values for each bloc.

The sampling process is completed as follows (see Fig. 9):

- The demanded energy of the 52 Sundays is computed for each one of the Y years for which the hourly demand data is available.
- For each one of the 52 time series, the quadratic polynomial that fits the data is calculated. In Fig. 9 two of the 52 series are shown for the mentioned 19 available years. Above, it represents the Sunday's demand evolution of the third week of the year (winter) and below the 24<sup>th</sup> Sunday series (summer) is shown. Notice the inverted trend due to the air conditioning growth.
- The historical deviations with respect to the quadratic polynomial  $\delta_{Su}^y$  are measured,  $y = 1, \dots, Y$ .
- For each scenario, one of the historical deviations previously calculated is sampled for every Sunday  $\varphi_{Su}^{SC}$ , where SC denotes the scenario.

The final bloc energy  $\phi_{PSB}^{SC}$  of the  $P^{\text{th}}$  period,  $S^{\text{th}}$  subperiod and  $B^{\text{th}}$  bloc is obtained by relating the sampled value with the calculated for the pattern demand  $\varphi_{Su}^{PT}$ :

$$\phi_{PSB}^{SC} = \frac{\varphi_{Su}^{SC}}{\varphi_{Su}^{PT}} \cdot \phi_{PSB}^{PT} \quad (3)$$

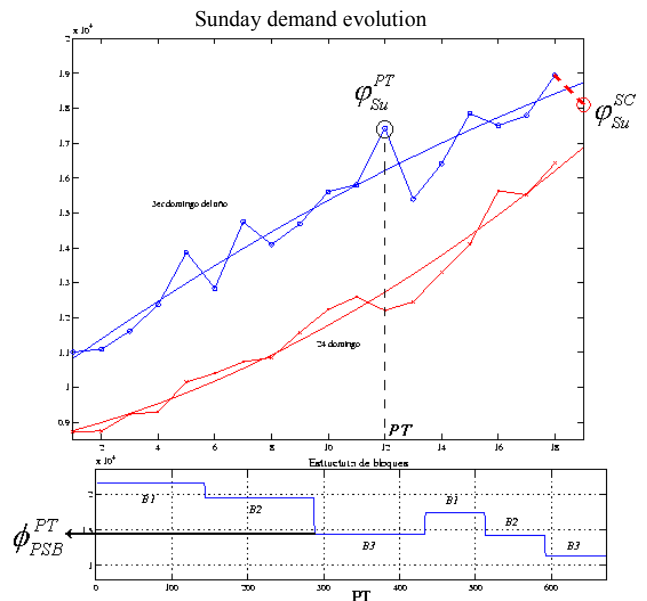


Fig. 9. Step 3 sampling process

Fig. 10 shows the complete bloc demand samples for two scenarios according to the structure defined in Table 1.

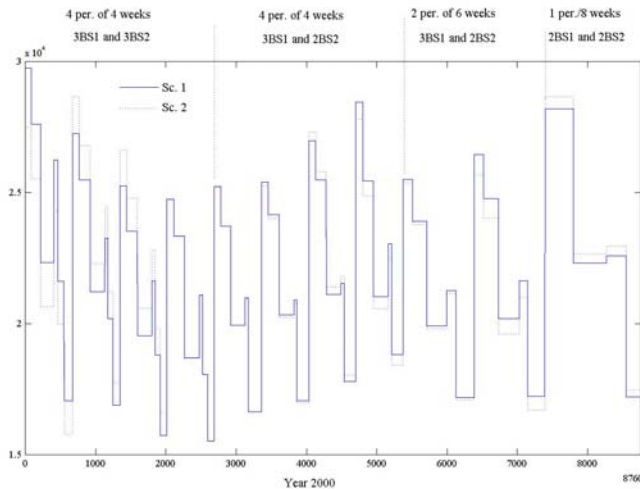


Fig. 10. Two complete scenario bloc demands

## V. CONCLUSION

The model presented faces the difficulties associated to the design of a tool that represents a real size electricity supply market.

When it comes to execute the real design, many problems need to be solved. These problems are related to the unique nature of the production process of the underlying asset, the electricity, together with the immaturity and complexity of the recently liberalized electricity markets.

In order to allow the correct consideration of the many variables that affect the market a classification has been done.

The two key market risk factors, the hydro production and the demand of electricity, have been modeled through Monte Carlo based scenario generators. Heuristic algorithms have been developed not only to allow the scenario generation from the little data available but also to have the possibility of enhancing the computation speed, necessary in this type of long-term analysis.

It constitutes a useful tool for analyzing the market agents behavior, and it is being intensively applied to planning, strategic and risk management studies.

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## VII. BIOGRAPHIES



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