Electric Power Systems Research 80 (2010) 778–787

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A decision support system for generation expansion planning in competitive electricity markets

Adelino J.C. Pereira [a], João Tomé Saraiva [b,*]

[a] Departamento de Engenharia Electrotécnica, Instituto Superior de Engenharia de Coimbra, Instituto Politécnico de Coimbra, Rua Pedro Nunes, 3030-199 Coimbra, Portugal
[b] INESC Porto and Departamento de Engenharia Electrotécnica e Computadores, Faculdade de Engenharia da Universidade do Porto, Campus da FEUP, Rua Dr. Roberto Frias, 4200–465 Porto, Portugal

ARTICLE INFO

Article history:
Received 4 April 2008
Received in revised form 4 December 2009
Accepted 9 December 2009
Available online 6 January 2010

Keywords:
Generation expansion planning
Investments
Uncertainties
Electricity markets
Long run strategies

ABSTRACT

This paper describes an approach to address the generation expansion-planning problem in order to help generation companies to decide whether to invest on new assets. This approach was developed in the scope of the implementation of electricity markets that eliminated the traditional centralized planning and lead to the creation of several generation companies competing for the delivery of power. As a result, this activity is more risky than in the past and so it is important to develop decision support tools to help generation companies to adequately analyse the available investment options in view of the possible behavior of other competitors. The developed model aims at maximizing the expected revenues of a generation company while ensuring the safe operation of the power system and incorporating uncertainties related with price volatility, with the reliability of generation units, with the demand evolution and with investment and operation costs. These uncertainties are modeled by pdf functions and the solution approach is based on Genetic Algorithms. Finally, the paper includes a Case Study to illustrate the application and interest of the developed approach.

1. Introduction

Generation expansion planning (GEP) has historically addressed the problem of identifying the most adequate technology, expansion size, sitting, and timing for the construction of new plant capacity considering economic criteria while ensuring that the installed capacity adequately met the expected demand growth. However, the development of market mechanisms in the electricity sector altered the traditional GEP assumptions, models, and solution approaches. In fact, the traditional utility practice typically involved the solution of centralized planning problems to identify cost-minimizing plans for the utility. Under competition, multiple agents individually prepare their investment plans in order to maximize their profits. The development of market mechanisms also contributed to anticipate other changes as shortening planning horizons due to the elimination of traditional guaranteed return on investment as well as the advent of strategic interaction and gaming among companies involved in the generation activity [1]. This means that competition is determining that agents face higher risks, that they try to obtain faster returns and that the individual decisions of particular agents will mutually affect the profits and decisions of other players.

Because power plants need a long time to be built and they will be amortized over several years, investment decisions are based on expectations on future profits. Unfortunately, forecasting these profits is a difficult task since they are highly uncertain, volatile and dependent on a large number of risky factors. This implies that this type of problems certainly has to address and inherently incorporate uncertainty modeling and that risk concepts also play a crucial role. These long-term uncertainties can influence the profitability of a project, either directly as an uncertain cost element or indirectly through the market price of electricity, or in both ways.

In the new formulation of the GEP to be used in restructured electricity markets, the objective of each company is to maximize its total expected profit over a planning horizon, while contributing to guaranty the safe operation of the power system through the competition between generation agents. The new formulation has to incorporate the volatility of market prices for electricity and fuels, load growth, the expected revenues based on the predicted market price, construction costs, and operation and maintenance costs. Due to their own nature, some sources of uncertainty determining future operation such as the forecasted market price of electricity, load growth rates, fuel costs and equipment availability have to be taken into consideration explicitly in the generation planning model.

* Corresponding author. Tel.: +351 22 2094230; fax: +351 22 2094150.
E-mail addresses: ajcp@isec.pt (A.J.C. Pereira), jsaraiva@fe.up.pt (J.T. Saraiva).

0378-7796/$ – see front matter
doi:10.1016/j.epsr.2009.12.003

According to these general ideas, this paper presents a decision support approach to help generation companies in preparing and gaining insight on their investment strategies in competitive power systems. This decision support model can be used by individual companies to help them to identify the most adequate investment strategy in new generation capacity simulating the possible behavior of other participants. This tool can also be used to perform sensitivity analysis in order to check if the developed strategy is robust enough in view of possible changes in several parameters. The developed approach is able to consider various types of units and capacities, operating constraints, forced outages and timing for the addition of new units. The uncertain data is modeled by Probability Distribution Functions and the solution approach uses Genetic Algorithms.

Apart from this introductory section, this paper is structured as follows. Section 2 addresses generation expansion planning approaches detailing the main assumptions associated to them and the models adopted to represent uncertain data. Section 3 details the developed model and Section 4 describes the algorithm adopted to solve it. Finally, the paper includes results from a Case Study developed for a 15-year horizon. This Case Study is used to illustrate the interest of the proposed planning approach and also to discuss its effectiveness.

2. Generation expansion planning approaches

The introduction of market mechanisms originated major changes in the way decisions are taken namely at the investment level [2]. The opening of the sector to competition implies that companies now have to internalise risk in investment decision-making since investors examine the available options according to the financial risks inherent to the different technologies.

Before the liberalisation of electricity markets, investment decisions on new capacity, technology and location of new generation were developed inside vertically integrated utilities meaning that the whole value chain was controlled from generation to the final relationship with consumers. In several cases, these investment plans were developed in close relation or with the explicit approval of public entities and all investment costs were easily passed to consumers and internalized in the tariffs. In this typically easily forecasted environment, the profits of vertical companies were guaranteed and there was little incentive to take into account several factors that could impact on profits. Market mechanisms changed this status in a deep way given that the market now determines the prices and the unbundling of traditional companies implies that there is now a larger number of agents, each one trying to maximize its own profit. Profitability driven decisions impose that generation agents consider factors such as revenues, costs and risks that can influence their profits.

Another important consequence from the advent of electricity markets is that agents in the sector are no longer protected by a regulatory shield but, on the contrary, they are exposed to different risks and to a large number of uncertain factors, several of them having exogenous nature. This is even more serious given the time between the moment new investments are studied, a decision is taken, and finally a new plant is commissioned. According to [3], these long-term uncertainties can influence the profitability of a project, either directly as an uncertain cost element or indirectly through the market price of electricity, or sometimes in both ways. In this framework, it is crucial to adequately address and internalize the uncertainties that affect investment decisions in new generation plants. In the next paragraphs we refer some of these uncertainties:

- macro-economic factors impacting on the demand of electricity, on labour or capital costs. Subsequently, all these aspects will affect the profitability of the project;
- future electricity demand is affected by uncertainty namely when building long-term models. This aspect becomes even more important in restructured power systems because the demand will influence the price and, to a certain extent, it can also display some elasticity regarding price evolution. This means that the total demand over the horizon changes along time and it influences the price and the profitability of new investments;
- changes in the price of fuels used in thermal stations have a direct impact on operation costs. This can influence the demand and so the profitability of the investments;
- risk related with the scheme adopted to finance the investment. This risk will be mitigated if the capital structure of the company under analysis is stronger;
- in a more decentralized and market driven power system, the electricity balance and price are dependent on the system load and on the decisions adopted by each investor. It is clear that investments from other players in new capacity will also have an impact on that balance and can determine price variations;
- some factors are under the control of policy-makers, such as regulatory and political agents. This represents a new level of risk since more volatile regulatory and political scenarios have direct impacts on costs, financing conditions and profits;
- factors under the control of the company, as the capacity and the diversity of technologies to consider in the investment portfolio, as well as cost control actions adopted during construction and operation.

The level of risk admitted by an investor is reflected in the level of return expected on that investment. The greater the business and financial risks, the higher the return that will be demanded. The combination of a long development and construction time, uncertain demand growth and price evolution determine the enlargement of the risk inherent to larger capacity projects and may favour smaller and less demanding ones.

Given these characteristics, investment decisions are typically based on expectations on future profits. However, it is very difficult to get an adequate degree of accuracy when forecasting these profits because they are very uncertain, volatile and dependent on a large number of exogenous aspects. Considering all these aspects, several authors recognize that the most important issue affecting the profitability of investments in liberalized markets corresponds to the uncertainty related with electricity prices. This uncertainty is no longer related to a short-term horizon but in fact to longer periods and it represents a risk for investors. In this sense, faster decision making, technologies leading to more reduced building periods and more robust expansion plans are the key aspects that will transform any investment plan into a successful one.

Regarding uncertainty, probabilistic measures such as probability distribution functions (pdf) can certainly be most useful. The parameters associated with probability distributions can be derived from historical data and prediction of future development [4]. In particular, when dealing with generation expansion problems several parameters as the energy price and fuel cost uncertainties can be modeled by normally distributed random variables around a base case value. The standard deviation can be obtained based on historical data, or alternatively it can reflect an expert judgment. In any case, these models map the knowledge that the planner has regarding that particular parameter in the initial stage. As an example, Fig. 1 displays the normal pdf function of the electricity day-ahead price in the Common Iberian Electricity Market, MIBEL, in operation between Portugal and Spain based on historical data. In this case, the average of this hourly day-ahead pool market price is 52.1 €/MW h and the standard deviation is 8.2 €/MW h.

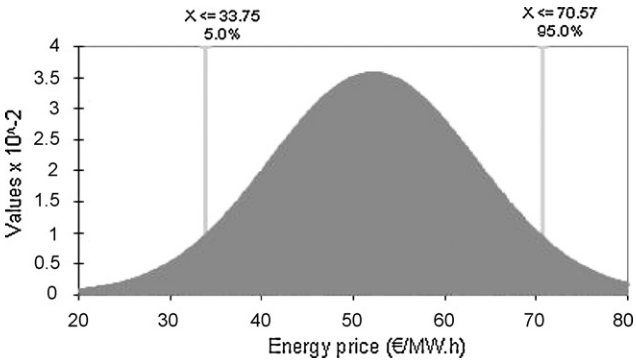

Fig. 1. Normal pdf function for the electricity price in the MIBEL.

The adoption of this kind of modeling implies recognizing the data affected by uncertainties and then modeling it in terms of pdf functions. Based on these results, one can perform several studies using a sampling Monte Carlo-based procedure on each pdf function so that we can then run an optimization problem for each sampled set of values. The combination of the results obtained from each run leads to the probability distribution of the results and this process can be interpreted as a way to transfer data uncertainty into the results of the problem under analysis.

Considering in particular the generation expansion problem, sampling is used to generate sets of possible values from probability distribution functions, each set representing a possible combination of the input values. Each of these sets is then used as input data for the optimization expansion problem. This sampling process is repeated so that the sampled values reflect the specified input probability distributions. The formulation to be described in the next section adopts this strategy as well as Genetic Algorithms to tackle the combinatorial nature of the optimization problem to be solved.

3. Generation expansion planning model

3.1. General approach

The generation expansion-planning problem was addressed considering the two-level structure in Fig. 2. Using this decomposition approach, generation agents, GENCO's, prepare expansion plans maximizing their own profit. These plans are then evaluated at a coordination level that aggregates them and assesses the global system adequacy, the technology mixes, and finally sends signals under the form of electricity prices along the horizon. Using these prices, the players update their plans and resubmit them. This iterative process is repeated until the plans prepared by all agents and the prices are not changed along two successive iterations. This approach enables that the decisions taken by an agent internalize the information involving each of them while also considering the impact of the behaviour of the other players. This means that this approach can be used by a generation company to simulate the behavior of generation agents, gaining insight on the robustness of its plan and analyzing possible interactions and impacts with possible decisions of other agents.

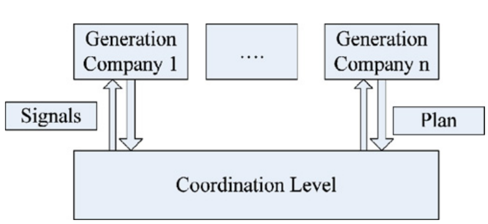

Fig. 2. Global structure of the generation expansion-planning problem.

In Section 3.2 we will now describe the optimization problem to be solved by each generation agent, Section 3.3 addresses the coordination analysis and Section 3.4 gives further details on the developed approach.

3.2. Formulation of the GENCO's problem

Under the market competitive scheme, each GENCO aims at maximizing its total expected profit over a planning horizon while guaranteeing the safe operation of the power system through the competition between generation companies [5,6]. As referred before, uncertainties affecting electricity and fuel prices, load growth, investment and operation costs are modeled by pdf functions. For each sampled set of values of the parameters affected by uncertainty, the optimization problem to be solved by each GENCO i can be formulated by (1) to (6):

$$\max z = \sum_{t=1}^{T} \left[(\pi^t . CC_t^i).\alpha_t^{ij} - \sum_{j=1}^{M} (Cinv_t^j . X_t^{ij}) - \sum_{j=1}^{M} (Cop_t^j . X_t^{ij}).\alpha_t^{ij} \right] \quad (1)$$

$$s.t. \quad X_t^{ij} \le \overline{CIT}_t^i \quad (2)$$

$$\sum_{j=1}^{M} X_t^{ij} \le MIC_t^i \quad (3)$$

$$CC_t^i = CC_{t-1}^i + \sum_{j=1}^{M} X_t^{ij} \quad (4)$$

$$\sum_{j=1}^{M} X_t^{ij}.Cinv_t^j \le LCI_t^i \quad (5)$$

$$t = 1, \ldots T; \qquad j = 1, \ldots, M \quad (6)$$

In this formulation:

T	number of stages in the planning horizon;
t	stage in the planning horizon (year);
M	number of candidate technologies;
j	type of candidate expansion technology;
π^t	electricity price in stage t;
α_t^{ij}	capacity factor in stage t for GENCO i and technology j;
$Cinv_t^j$	investment cost for technology j at stage t;
Cop_t^j	variable operation and maintenance cost for technology j at stage t;
CC_t^i	cumulative capacity installed in stage t for GENCO i;
X_t^{ij}	capacity addition of technology j in stage t by GENCO i;
LCI_t^i	maximum value specified for the capital investment of GENCO i at stage t;
MIC_t^i	maximum capacity installed in stage t by GENCO i;
$\overline{CIT}_t^i$	upper bound established for the capacity installed technology j in stage t by GENCO i.

The objective of this problem (1) corresponds to maximize the total expected profit over the whole planning horizon and it is formulated using three terms. The first term represents the revenue obtained by selling electricity. This term depends on the electricity price in each period t, π^t. For the first year of the planning horizon, electricity prices are represented by a normal pdf distribution considering that its mean value and standard deviation are obtained from historic market prices. For the years afterwards, and to start the iterative process, we admitted that the mean prices increase by a specified percentage that, in some way, reflects the forecasted demand evolution. In the subsequent iterations, the prices to be used to solve the problem (1) to (6) depend on the analysis to be conducted at the coordination level as detailed in Section 3.3.

Finally, the first term in (1) also depends on the load factor specified for each technology. This factor represents the percentage of hours that a station will in average be used along a year. Each technology will be characterized by a value of this parameter and the revenues along the horizon are transferred to the initial stage using a discount rate.

The second term in (1) represents the sum of the investment costs over the planning horizon. This term depends on the capacity to be installed in each period and on the selected technology. The values over the horizon are transferred to the initial stage using a specified discount rate. The developed application also admits introducing different values for the investment costs over the horizon. This is due to the fact that these costs are represented by pdf functions and problem (1) to (6) is run for a sample of costs that, in general, will be different from year to year.

Finally, the third term in (1) represents the operation and maintenance costs associated with each selected investment and technology. These costs depend on the fuel cost evolution and on the load factor of each technology in each stage. In a similar way to investment costs, operation and maintenance costs are also transferred to the initial year using a discount rate. The uncertainties affecting these costs are once again modeled by pdf functions. For the initial stage, their mean value and the standard deviation are specified taking into account the history of fuel prices and maintenance costs, as well as the performance of the different technologies. In subsequent periods, the application allows one to increase these prices and costs in order to model the problem in a more realistic way.

Regarding the constraints, inequalities (2) represent the limits set for the capacity to be added in each stage and for each technology. Constraints (3) enforce that the new additions accumulated in each stage by each GENCO should not exceed a maximum specified value namely to prevent market power. Finally, constraints (5) model the financial limitations felt by each agent.

3.3. The coordination analysis

Once all individual plans are obtained, it is conducted a coordination analysis to ensure that the global plan does not violate any constraints established for the whole system and for each stage in the horizon. If there is at least one violated constraint, the prices will be changed, or they will be set new limits for the capacity to be installed for each technology or for the total capacity that can be built by each GENCO. This defines an iterative process that will end when the plans prepared by the GENCO's and the prices do not change between two successive iterations.

The validation process of the global plan relies on the calculation of the reserve margin of the generation system regarding the demand, the capacity per technology, the installed capacity per GENCO and the value of the Loss of Load Expectation, LOLE. These values will then be compared with specified limits as detailed in the next paragraphs.

In the first place, the reserve margin in stage t, RM_t, in the planning horizon is computed by (7) considering the peak load estimate and the total power installed in the system. The T computed reserve margins are compared with minimum and maximum values as indicated in (8):

$$RM_t = \left(\frac{Installed\ capacity_t}{Peak\ load_t} - 1\right) 100\% \tag{7}$$

$$RM_t^{\min} \le RM_t \le RM_t^{\max} \quad for \;\; t = 1, \ldots, T \tag{8}$$

In the second place, it is checked if the sum of the installed capacity for each technology j does not exceed the maximum value admitted for stage t. These constraints are formulated by (9) and they can reflect strategic decisions regarding limitations on the contribution of each technology to the global mix. In this constraint, N represents the number of GENCO's, X_t^{ij} is the capacity of technology j installed by GENCO i in stage t and $\bar{J}^j$ is the maximum capacity value established for technology j:

$$\sum_{i=1}^{N} X_t^{ij} \le \bar{J}^j \quad for \;\; t = 1, \ldots, T \quad and \quad j = 1, \ldots, M \tag{9}$$

In the third place, we also introduced constraint (10) in order to evaluate if the cumulative capacity installed by GENCO i till stage t, CC_t^i, does not exceed a specified percentage, $Perc^{max}$, of the total installed capacity by all GENCO's. This percentage, $Perc^{max}$, can reflect a regulatory decision intending to prevent market power and it is evaluated at the end of each iteration of this process for all stages of the planning horizon and for all GENCO's:

$$CC_t^i \le \frac{Perc^{\max}}{100} \cdot \sum_{p=1}^{N} CC_t^p \quad for\; t = 1, \ldots, T \quad and \quad i = 1, \ldots, N \tag{10}$$

In the fourth place, it is computed a reliability index for each stage in the horizon in order to evaluate the risk of not being able to supply the demand inherent to the global plan. In this application, we used the Loss of Load Expectation, LOLE, to monitor the security of supply. This index can be interpreted as the number of days or hours over a certain period during which the generation system is likely not to meet the demand and it is closely related with the Loss of Load Probability index, LOLP [7]. LOLP is typically computed using the Capacity Outage Cumulative Probability Table, COCPT. This table has a number of entries each one representing the probability of having at least a certain capacity out of service and it is usually built using a recursive algorithm that considers the forced outage rate, FOR, of each unit and its capacity. Once the COCPT is built, the probability of not meeting the demand is the cumulative probability of having an outage larger than $(C_T - L)$, if C_T is the total capacity and L is the demand. For the load level L, this means that LOLP is given by (11):

$$LOLP = P(C_T - L) \tag{11}$$

If we now want to compute LOLE, it is necessary to know the demand along the period under analysis, typically 1 year, and the time during which the load is not inferior than L_k. If $P_k(C_T - L_k)$ is the value of LOLP for this load condition, then LOLE is given by (12). In this expression, s represents the number of load steps used to model the load duration curve and t_k is the number of hours in each step:

$$LOLE = \sum_{k=1}^{S} P_k(C_T - L_k) t_k \tag{12}$$

The values of LOLE along the horizon will then be compared with $LOLE^{max}$, as indicated by (13). In this expression, $LOLE^{max}$ represents the maximum number of hours along a year during which it is admitted that load is not served due to outages in the generation system. In several countries this limit is set in Quality of Service Codes, which means that the generation expansion plan is influenced in terms of continuity of service by this limit:

$$LOLE_t \le LOLE^{\max} \qquad t = 1, \ldots, T \tag{13}$$

As a whole, constraints (8), (9), (10) and (13) are checked and, if necessary, the prices along the horizon, the technology limits in (9) or the installed capacity limit in (10) are change. According to these ideas, $LOLE^{max}$ in constraint (13) is not changeable because this value directly reflects the maximum admitted unavailability of the generation system.

Regarding the prices update, it is important to recognize that there are two distinct situations. In the periods in which there are violated constraints, the scarcity of resources would determine a rise of the market price. Therefore, for this type of periods, the prices will rise regarding the historic average of energy prices. Regarding the periods in which there are no violated constraints, we admitted that competition exists and so we use the Cournot Model to determine the prices, as it will be detailed in Section 4.3.

3.4. Relevant characteristics of the developed approach

Before detailing the solution algorithm developed for this problem, it is important to mention some relevant characteristics of the developed approach:

- although market mechanisms are typically related with a short term horizon, investment problems both in generation and transmission activities display a longer term nature. It is clear that these two horizons, short term for operation and long term for investment planning, are not always easy to turn compatible namely given that licensing and building periods for new power stations or transmission lines are typically long, for instance due to environmental impact evaluations. In this context, it is not unusual to have periods of 7–10 years to commission new generation or transmission infrastructures. This means that performing investment generation expansion studies for 10–15 years horizons seems quite reasonable, even though these studies can be updated as time goes on using more recent information. In any case, the planning horizon is a parameter of the problem to be specified by the planner and does not affect the formulation itself;
- given this long term nature, it is crucial to internalize uncertainties affecting, as mentioned in Section 2 several parameters and data of the problem. This includes investment and operation costs and electricity prices. In this approach these uncertainties are represented by pdf functions;
- regarding the demand, for the first year in the horizon we considered a load duration curve organized in steps. For subsequent years, the demand in each of these steps is multiplied by an annual increasing rate. This means that when computing the reserve margin (7) in each year of the planning horizon we considered the peak annual demand, but when computing the reliability indices for each year in the planning horizon (12) we considered the complete load duration curve;
- the model was essentially developed to plan the addition of thermal power plants but it can also be used for hydro stations or for wind parks. In these cases, we should recall that new investments are typically most welcomed by governments, namely in the EU having in mind the commitments to incorporate increasing percentages of renewables. Hydro stations with storage capacity have an extra important role in this area given the flexibility they can bring to power system operation in case the penetration of wind power is very large. In any case, the developed model can accommodate hydro stations and wind parks as candidate technologies, in a similar way to other types of stations. In these cases, it would be important to have historical date of hydro inflows and wind speeds in the possible locations of new hydro stations and wind parks in order to obtain more accurate results. This means that hydro inflows and wind speeds would correspond to new uncertain data to be subjected to a similar sampling procedure as the one to be described in Section 4.2;
- the developed model can be extended to incorporate the cost of carbon dioxide emissions. This would imply including a new term in the objective function of the optimization problem ((1)–(6)) to be solved by each generation agent. This would require defining the emissions cost possibly leading to a new uncertain parameter to be represented by a pdf function and subjected to the sampling procedure to be detailed in Section 4.2;
- finally, as the two-level structure in Fig. 2 indicates, the constraints and risk indices (8), (9), (10) and (13) are evaluated outside the optimization process developed for each generation agent but, in some sense, inside the global optimization procedure because they can be interpreted as a control mechanism of the quality of the global investment plan. This means that each agent builds its own investment plan and then the information from all agents is gathered in the coordination step so that the risk indices are evaluated. This scheme is repeated until convergence is obtained.

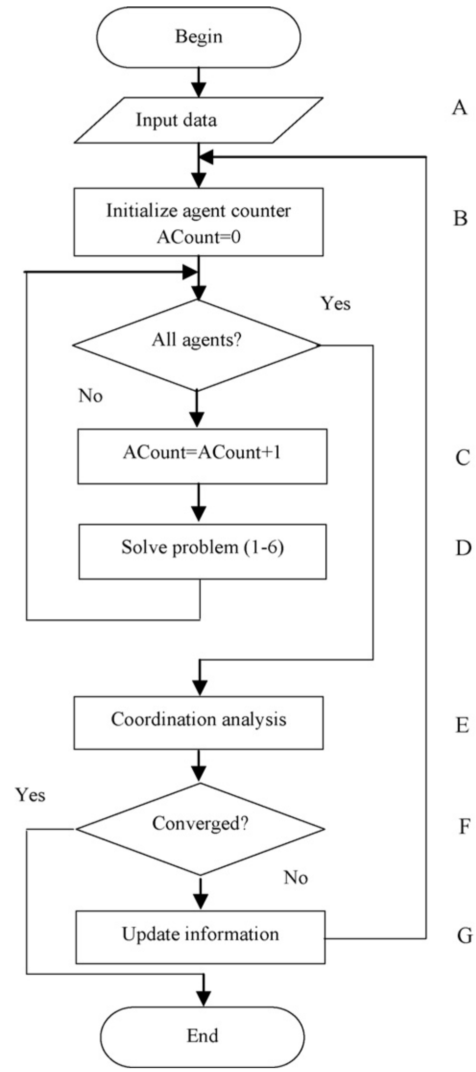

Fig. 3. Flowchart of the implemented algorithm.

4. Solution algorithm

4.1. General description

Having in mind the two level structure illustrated in Fig. 2, the developed solution algorithm is presented in Fig. 3.

This flowchart is organized in the following Blocks:

- Block A—in this block we define the relevant data and parameters of the problem. This means defining the candidate technologies, investment, operation and maintenance costs, forced outage rates and unit sizes. At this level, we also specify the pdf functions regarding uncertain data, that is, electricity and fuel prices, operation costs and annual peak demand. In general, this information will be derived from the past history of these variables;

- Blocks B, C and D—in these blocks one initializes the Agent Counter, ACounter, in order to go through all generation agents solving for each of them the problem ((1)–(6)) using the currently available information, namely regarding electricity prices. This problem has in general a combinatorial nature given the possibility of investing in a number of normalized capacity values specified for each technology. Given this integer nature, we used a Genetic Algorithm to solve this problem, as it will be described in Section 4.2;
- Block E—once there is an individual investment plan built for each generation agent, the new additions, capacities, technologies and commissioning years are conveyed to the coordination level to check constraints (8), (9), (10) and (13);
- Block F—convergence is obtained when there are no violated constraints along the horizon. This means that the individual plans and the prices did not change from one iteration to the next one. If there is at least one violated constraint the iterative process is repeated going back to Block B after updating relevant information in Block G;
- Block G—if there is at least one violated constraint the prices are changed eventually together with the limits used in constraints (8), (9) or (10). Regarding the price update, there are two possible situations to consider, as follows:

  ◦ in the periods in which there is at least one violated constraint the prices will be raised by a pre-specified multiplicative factor. This strategy replicates the typical behavior of markets indicating that when the level of available resources is limited regarding the demand the price tends to rise;
  ◦ for the periods in which no constraints are violated, competition plays its role and the Cournot Model is used to set the prices to be used in the next iteration. This procedure will be detailed in Section 4.3.

4.2. The use of genetic algorithms and Monte Carlo sampling

In each iteration of the general algorithm described in Section 4.1, the problem ((1)–(6)) is solved as many times as the number of generation agents. This problem has two important features that determined the adopted solution approach, as follows:

- in the first place, it has a discrete combinatorial nature given that each generation agent has a limited number of candidate technologies and for each of them there will typically be a number of available normalized capacity values that can be selected;
- secondly, the solution of this problem requires using values for several parameters that are typically affected by uncertainty. This is the case, for instance, of operation and maintenance costs, electricity market prices and annual peak demand.

These two characteristics suggested the use of a Genetic Algorithm to address the combinatorial nature of problem ((1)–(6)) combined with a Monte Carlo simulation to sample values from the pdf functions of the uncertain parameters as a way to deal with these uncertainties. Considering this reasoning, Fig. 4 presents the flowchart of the solution of problem ((1)–(6)) for a given generation agent. This means this flowchart corresponds to the algorithm run in Block D of the generic algorithm in Fig. 3. This algorithm is run as many times as the number of generation agents considered in the planning exercise.

Having defined all relevant data, namely the candidate technologies and the list of normalized capacity values that can be

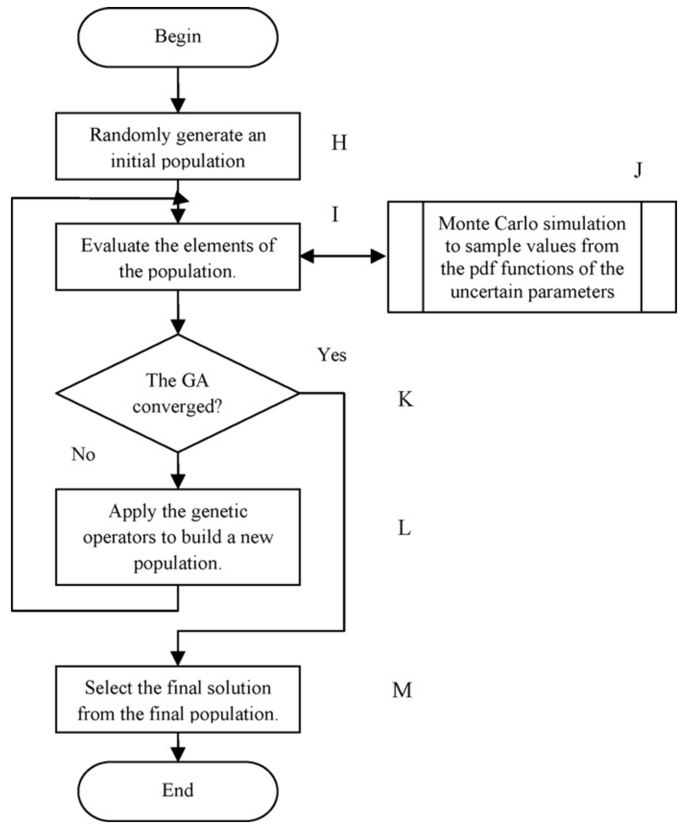

Fig. 4. Flowchart of Block D in Fig. 3.

eventually selected, we used a standard Genetic Algorithm [8] that is organized in the following blocks:

- Block H—the Genetic Algorithm starts with an initial population randomly generated having in mind the feasible values specified for the decision variables, that is, for the capacity of each technology to build in each year. This means that each element of the population corresponds to an investment plan that is randomly generated in the first iteration;
- Blocks I and J—once the population is known, we have to evaluate it, recognizing that several parameters are described by pdf functions. Therefore, for each element in the population we run a Monte Carlo simulation to sample particular values from the pdf functions of the uncertain parameters. Using these sampled values, each element of the population is evaluated using a fitness function that includes two terms. The first one corresponds to the objective function (1) that we want to maximize. The second one corresponds to negative penalty terms that are activated if the constraints (2) to (5) are violated, given that the problem under analysis is a maximizing one. This evaluation process is run for a large number of samples extracted from the pdf functions so that one can estimate the average value of the fitness function of each individual in the population. The number of samples to extract from the pdf functions is controlled computing the quality of the current estimate of the average profit. As in other sampling simulations, this can be done by computing the Uncertainty Coefficient β as it is described in [9]. This coefficient depends on the current estimates of the variance and of the expected value and it indicates if these values are already sufficiently stable so that it is not necessary to sample new sets of values from the pdf functions;
- Block K—the convergence of the Genetic Algorithm cycle is evaluated computing the average value and the standard deviation of all individuals in the current population. As the evolution-

ary process develops, it is expected that the average value tends to increase and that the standard deviation tends to get more reduced reflecting the fact that the individuals in the population will globally improve their performance, that is, the profit associated to each investment plan in the population will raise. According to these ideas, we considered that convergence is reached when the standard deviation is smaller than a specified threshold, the fitness function of the best individual is not improved at least by a specified percentage along a pre-specified number of iterations and the average value of the fitness function of the whole population is sufficiently stable from one iteration to the next one. It is also possible to impose a minimum number of iterations to be run to ensure that at least those iterations are run before the algorithms stops;

- Block L—if convergence was not yet reached, the Genetic Algorithm proceeds with the usual selection, cross-over and mutation [8] operators in order to generate a new population. The individuals in this new population will then be subjected to the evaluation process in Blocks I and J and the process iterates till it converges;
- Block M—from the final population, it is selected the individual associated to the best-identified investment expansion plan. This plan is interpreted as the one that maximizes the expected value of the profit given by (1) considering the uncertain parameters.

Once this process is completed, we have the solution of problem ((1)–(6)) for one generation agent. This scheme will then have to be run for the remaining agents completing Block D in Section 4.1. When we have an expansion plan for all generation agents, the algorithm in Section 4.1 proceeds with the coordination analysis in Block E of Section 4.1, that is, checking if constraints (8), (9), (10) and (13) are violated.

4.3. The use of the Cournot Model

The Cournot Model [10] was introduced by Augustin Cournot in 1838 and it has a number of assumptions as for instance the non-storable and homogeneous nature of the product, there are no new entries during the game and the players take their bidding decisions simultaneously. According to this model, each agent selects an output quantity and the market price is obtained by an auction process that considers a demand function.

To formulate this problem, let us consider that $\overline{P}_i^t$ is the capacity of the agent i in stage t and that $D^t(\pi^t)$ is the demand function relating the demand level D in stage t with the price π^t. Expression (14) represents a linear version of this function where a and b are positive coefficients. In this case, coefficient a represents the maximum amount of electricity that consumers admit to buy:

$$D^t(\pi^t) = a^t - b^t\pi^t \tag{14}$$

Let us also admit that $C_i^t(P_i^t)$ is the cost function of GENCO$_i$ assumed linear as indicated in (15). As referred before, the generation of agent i corresponds to its decision variable and so its profit, $\Omega_i^t(P_i^t)$, is given by (16):

$$C_i^t(P^t) = c_i P_i^t \tag{15}$$

$$\Omega_i^t(P_i^t) = \pi^t P_i^t - C_i^t(P_i^t) \tag{16}$$

Table 1
Characteristics of the existing technologies.

No. units	Technology	Generating size (MW)	Operation cost (€/MW h)	FOR
3	Coal_1	300	30	0.02
2	Coal_2	400	25	0.02
5	Gas turbine	250	45	0.01
2	Oil	200	50	0.03
4	CCGT	250	35	0.01

Table 2
Generation mix of each GENCO.

Technology	GENCO_1	GENCO_2	GENCO_3
Coal_1 (MW)	300	600	–
Coal_2 (MW)	400	–	400
Gas turbine (MW)	500	500	250
Oil (MW)	200	200	–
CCGT (MW)	250	250	500

Since all N generation agents are competing, it is possible to formulate N optimality conditions (17), one per generation agent. These equations assume that the demand is a function of the price so we can formulate an extra equation given by (18). This leads to a set of $N+1$ equations used to compute the value of the N generations and of the price in the period under analysis. Using this price, one can finally get the corresponding demand using (14). This operation point is called a Cournot Equilibrium, and the price is then used as input data for the next iteration of the iterative process outlined in Section 4.1:

$$\frac{\partial \Omega_i^t}{\partial P_i^t} = \pi^t + P_i^t \frac{\partial \pi^t}{\partial D^t}\frac{\partial D^t}{\partial P_i^t} - \frac{\partial C_i^t}{\partial P_i^t} = 0 \quad \textit{for all } i = 1, \ldots, N \tag{17}$$

$$D^t(\pi^t) = a^t - b^t.\pi^t = \sum_{i=1}^{N} P_i^t \tag{18}$$

5. Case study

In this section we present the results obtained for a case study in which we considered that the initial total installed capacity is 4350 MW. The characteristics of the existing technologies are presented in Table 1. We assumed that there are 3 generation agents having the mixes indicated in Table 2.

Using these values and the FOR in Table 1 it is possible to obtain the reserve margin and the LOLE at the initial period. The expansion planning exercise was conducted for a 15-year horizon, three generation agents and three candidate technologies. Table 3 indicates the characteristics of these three candidate technologies in terms of the available capacities, the operation and maintenance costs, the investment cost and the FOR. According to Table 3 and as an example, if an agent selects Tech_1, then there are only three feasible capacities to install (100, 150 or 200 MW). This leads to a discrete problem addressed using Genetic Algorithms.

The peak demand at the initial year is 3500 MW. For this initial year we also specified the load duration curve as indicated in Fig. 5.

Table 3
Characteristics of the three candidate technologies.

Type of technology	Available capacities (MW)	Investment cost (€/MW)	Operation and maintenance cost (€/MW h)	FOR
Tech_1	100 or 150 or 200	500,000	45	0.01
Tech_2	100 or 125 or 150	800,000	30	0.02
Tech_3	100 or 150 or 200	1,000,000	25	0.02

Table 4
Parameters used for the normal pdf distributions.

Parameters	Technology	Mean	Standard desviation
Capacity factor (%)	All Tech's	70	10
Investment cost (€/MW)	Tech_1	500,000	10,000
	Tech_2	800,000	10,000
	Tech_3	1,000,000	10,000
Variable operation and maintenance cost (€/MW h)	Tech_1	45	5
	Tech_2	30	5
	Tech_3	25	5
Evolution of the variable operation and maintenance cost (%)	Tech_1	3	1
	Tech_2	2	1
	Tech_3	2	1

As mentioned in Sections 2–4, the expansion-planning problem is affected by uncertainties regarding several parameters. As detailed before, uncertainties are modeled by normal pdf distributions represented by its mean and standard deviation. These values reflect the level of knowledge available at the beginning of the study, namely considering historical data for these parameters whenever available or specified by an expert. Having this in mind, Table 4 indicates the mean and the standard deviation used for the following parameters: capacity factor, investment cost, variable operation and maintenance cost at the initial year and its percentage increase along the horizon. The mean and standard deviations are discriminated for each technology except for the capacity factor in which we considered the same value for all three technologies, although different values could have easily been used.

Apart from these parameters, we have also considered normal pdf distributions for the following two variables:

- electricity price at the initial period—mean of 52.0 €/MW h and standard deviation of 8.0 €/MW h;
- yearly increase of the electricity price along the horizon—mean of 2% and standard deviation of 1%.

Finally, the following data was also used:

- the demand displays an annual increase of 4%. This value was considered fixed along the horizon and it affects all steps of the load duration curve already mentioned. It could also have been modelled by a normal pdf distribution and so subjected to the sampling process as referred in Sections 2–4;
- the discount rate was set at 5%;
- the global value of each technology to be installed should lie in specified ranges. These minimum and maximum limits reflect strategic decisions and can induce the diversification of the primary fuels used and so reflect energy policy, strategic or environmental aspects. In this case, we considered the following ranges: [35%; 50%], [30%; 45%] and [20%; 30%] for Tech_1, Tech_2 and for Tech_3;
- in each period, it is also imposed that the capacity to install by each agent should not exceed 50% of the total new capacity. This can be used to prevent market power according to limits determined by regulatory boards and these constraints are modelled by (10);
- in each period, the reserve margin should lie in the interval [20%; 35%] and LOLE should be smaller than 8 h per year. These values can reflect indications in Quality of Service Codes as a way to ensure the reliability and the security of supply.

Using the above values, we ran the expansion planning algorithm admitting that GENCO_1 is building its own expansion plan using this tool to get insight on how the parameters and the possible behavior of the other two competitors influence the decision process. In the first place, Fig. 6 details the expansion plan that was obtained for GENCO_1. As a whole, this agent will install 750 MW for Tech_1, 450 MW for Tech_2 and 400 MW for Tech_3 along the planning horizon. Figs. 7 and 8 detail the expansion plans obtained for GENCO's 2 and 3.

Fig. 9 details the evolution of the total installed capacity and of the demand along the horizon. This figure indicates that both the installed capacity and the demand have similar evolutions reflecting the fact that we included constraints related with the reserve margin and with LOLE along the horizon. The evolution of LOLE is presented in Fig. 10 showing that the steady behavior of this indicator is in line with the evolution of the reserve margin. Finally, Fig. 11 displays the evolution of the electricity price. It is possible

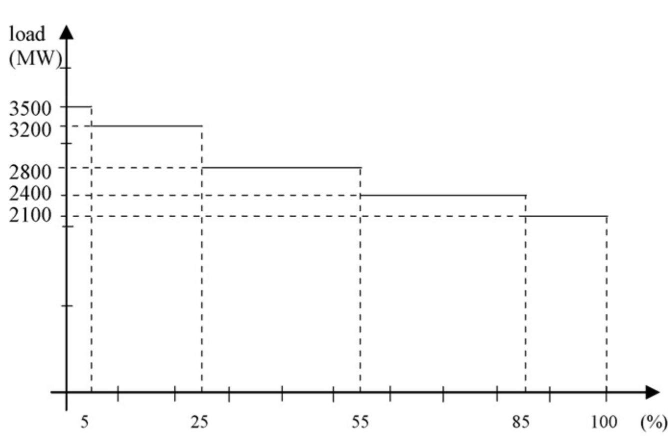

Fig. 5. Load duration curve for the initial year.

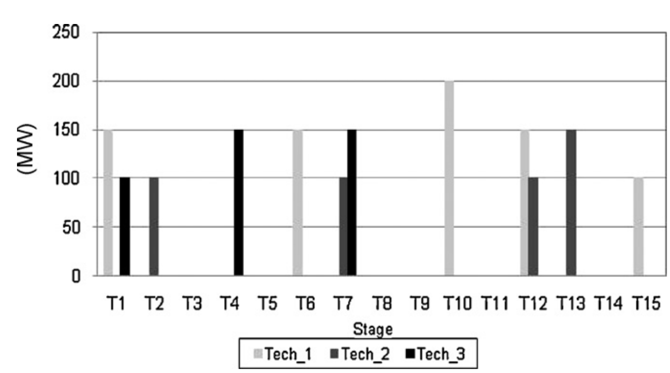

Fig. 6. Generation expansion plan for Genco_1.

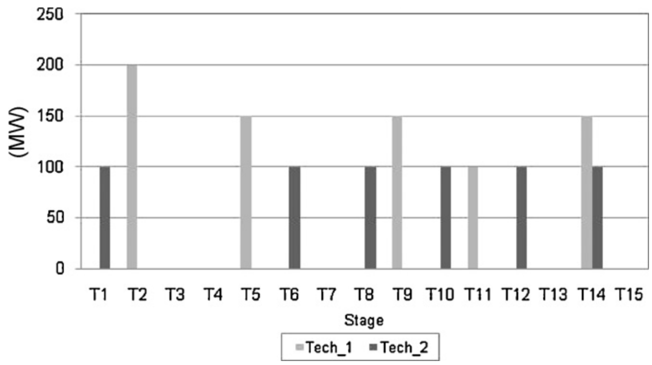

Fig. 7. Generation expansion plan for Genco_2.

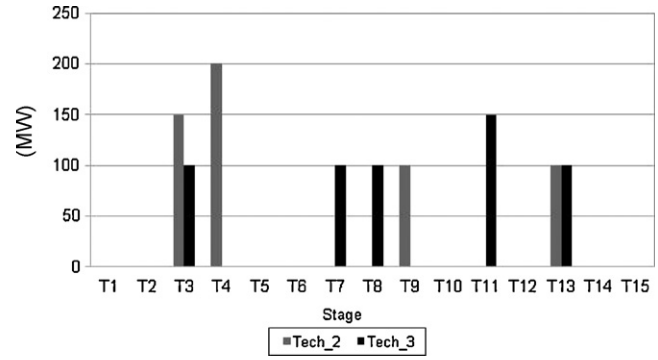

Fig. 8. Generation expansion plan for Genco_3.

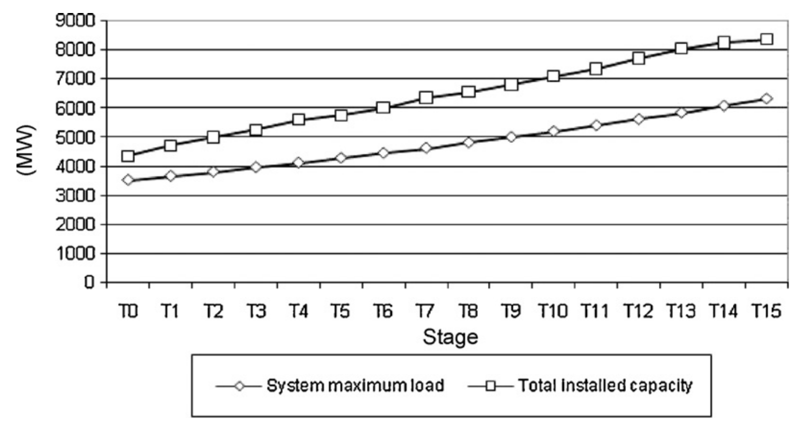

Fig. 9. Evolution of the total installed capacity and maximum demand.

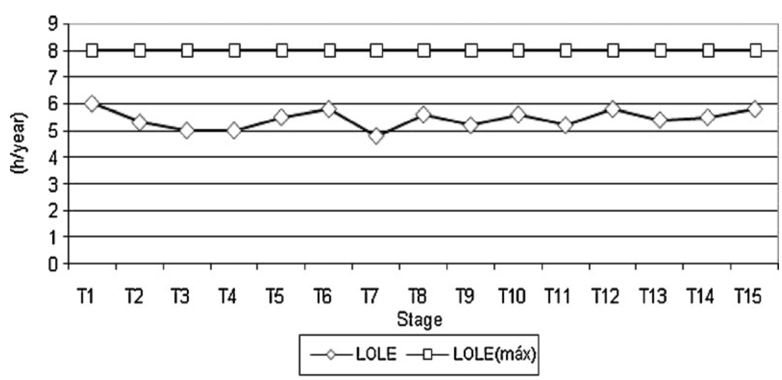

Fig. 10. Evolution of LOLE along the planning horizon.

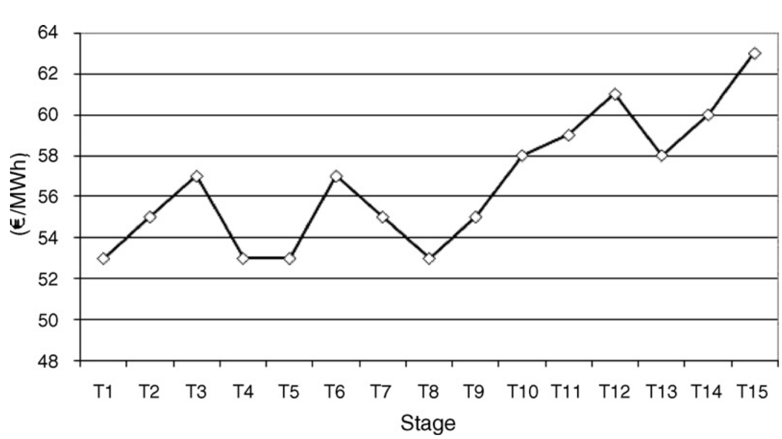

Fig. 11. Evolution of the electricity price along the planning horizon.

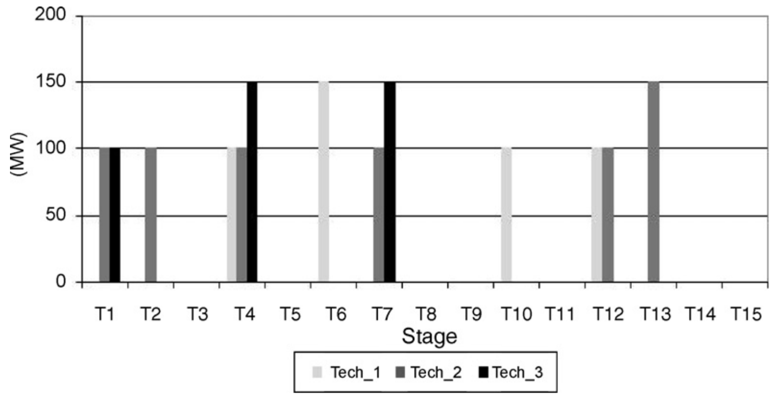

Fig. 12. New generation expansion plan for Genco_1.

to notice that the price tends to increase towards the final stages as a way to induce new investments so that the limits established for the LOLE and for the reserve margin are not violated. This means that the steady behaviors of the reserve margin and of LOLE are a result of the price increase that contributes to turn investments more attractive.

Let us now consider that GENCO_1 wants to perform a sensitivity analysis in order to evaluate the robustness of its plan regarding, for instance, a change on the Operation and Maintenance Cost of Tech_1. Admitting that the mean value of the Operation and Maintenance Cost of Tech_1 increases from 45 to 60 €/MW h, it is built a new expansion plan as shown in Fig. 12. One can notice that the total new capacity of Tech_1 is reduced by 300 MW, the capacity of Tech_2 is increased by 200 MW and Tech_3 remains at the same level. As a whole, these results indicate that the total capacity to install by GENCO_1 is reduced by 100 MW because constraint (5) limits the capital that GENCO_1 has to invest. It happens that Tech_2 has a larger investment cost when compared with Tech_1, which leads to a reduction of the total installed capacity by this agent. Accordingly, this new plan is a compromise resulting from the larger investment cost of Tech_2 and its more reduced operation cost.

6. Conclusions

In this paper we described a tool developed in order to help generation companies to build their own expansion plans while taking in consideration the possible behavior of its competitors. The developed tool incorporates uncertainties affecting several parameters modeled by pdf functions as well as a number of constraints related with financial limitations and to ensure the security of supply. This type of approaches can help generation companies to perform sensitivity analysis namely to build more robust plans in view of the increased risks affecting this activity in liberalized markets. As a whole, it can play an important role helping generation companies to build their expansion plans or gaining insight on how these plans behave regarding changes on input parameters so that these plans get more robust and the corresponding risk is minimized.

Acknowledgement

The first author would like to thank Fundação para a Ciência e Tecnologia, FCT, that partially funded this research work through the PhD grant no. SFRH/BD/29243/2006.

References

[1] S. Stoft, Power Systems Economics: Designing Markets for Electricity, IEEE Press/Wiley, New York, 2002.
[2] F. Olsina, F. Garces, H.-J. Haubrich, Modeling long-term dynamics of electricity markets, Energy Policy 34 (2006) 1411–1433.
[3] A. Botterud, M. Ilic, I. Wangensteen, Optimal investment in power generation under centralised and decentralised decision making, IEEE Transactions on Power Systems 20 (2005) 254–263.
[4] G.J. Anders, Probability Concepts in Electric Power Systems, John Wiley & Sons, New York, ISBN-0-471-50229-4, 1990.
[5] J. Zhu, M. Chow, A review of emerging techniques on generation expansion planning, IEEE Transactions on Power Systems 12 (1997) 1722–1728.
[6] J.-B. Park, J.-H. Kim, K.Y. Lee, Generation expansion planning in a competitive environment using a genetic algorithm, in: Proceedings of the 2002 IEEE PES Summer Meeting, Vol. 3, 2002, pp. 1169–1172.
[7] R. Billinton, R. Allan, Reliability Evaluation of Power Systems, 2nd ed., Plenum Press, New York, ISBN-0-306-45259-6, 1996.
[8] R.L. Haupt, S.E. Haupt, Practical Genetic Algorithms, 2nd ed., Wiley-InterScience, ISBN 978-0-471-45565-3, June 2004.
[9] J.T. Saraiva, V. Miranda, L. Pinto, Generation/transmission power system reliability evaluation by Monte-Carlo simulation assuming a fuzzy load description, IEEE Transactions on Power Systems 11 (1996) 690–695.
[10] D.S. Kirchen, G. Strbac, Fundamental of Power System Economics, John Wiley & Sons, ISBN 0-470-84572-4, 2004.

Adelino J.C. Pereira was born in Sanfins, Portugal in 1975. He received his diploma and M.Sc. degrees in Electrical Engineering and Computers from the Faculdade de Engenharia da Universidade do Porto, FEUP, Portugal, in 1998 and 2003. In 1998 he joined the Coimbra Polytechnic Institute (ISEC) where he is currently Equiparado to Adjunct Professor. He is a Ph.D. student at FEUP and his main research interest includes competitive markets, power systems operation and planning.

João Tomé Saraiva was born in Porto, Portugal in 1962. In 1987, 1993 and 2002 he got his M.Sc., Ph.D., and Agregado degrees in Electrical and Computer Engineering from the Faculdade de Engenharia da Universidade do Porto where he is currently Professor. In 1985 he joined INESC Porto where he was head researcher or collaborated in several projects related with the development of DMS systems, quality in power systems, and tariffs due for the use of transmission and distribution networks. Several of these projects were developed under consultancy contracts with the Portuguese Electricity Regulatory Agency.