Energy 36 (2011) 5180–5199

Contents lists available at ScienceDirect

Energy

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

Generation expansion planning (GEP) – A long-term approach using system dynamics and genetic algorithms (GAs)

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 21 January 2011
Received in revised form
8 June 2011
Accepted 11 June 2011
Available online 13 July 2011

Keywords:
GEP
Investments
Electricity markets
System dynamics
GAs
Uncertainties

ABSTRACT

This paper presents a model to solve the Generation Expansion Planning (GEP), problem in competitive electricity markets. The developed approach recognizes the presence of several generation agents aiming at maximizing their profits and that the planning environment is influenced by uncertainties affecting the demand, fuel prices, investment and maintenance costs and the electricity price. Several of these variables have interrelations between them turning it important to develop an approach that adequately captures the long-run behavior of electricity markets. In the developed approach we used System Dynamics to capture this behavior and to characterize the evolution of electricity prices and of the demand. Using this information, generation agents can then prepare their individual expansion plans. The resulting individual optimization problems have a mixed integer nature, justifying the use of Genetic Algorithms (GAs). Once individual plans are obtained, they are input once again on the System Dynamics model to update the evolution of the price, of the demand and of the capacity factors. This defines a feedback mechanism between the individual expansion planning problems and the long-term System Dynamics model. This approach can be used by a generation agent to build a robust expansion plan in the sense it can simulate different reactions of the other competitors and also by regulatory or state agencies to investigate the impact of regulatory decisions on the evolution of the generation system. Finally, the paper includes a Case Study to illustrate the use and the results of this approach.

1. Introduction

Generation Expansion Planning (GEP) is a complex multiyear mixed integer problem that typically aims at identifying the most adequate schedule for generation investments together with the selection of the locations and technologies to use. This is not a new problem in the sense that utilities well before the advent of deregulation and liberalization already addressed it and the academic community developed different models and algorithms to solve it. However, the nature of this problem changed in recent years. Before the deregulation and liberalization movements, this problem was addressed in the scope of vertically integrated companies and several models reflected this integrated nature including in the optimization problems a model of the transmission network. Generation expansion investments displayed some characteristics that turned GEP a complex problem. They were capital intensive investments, they typically were one-step investments in which the capital was committed before stations were commissioned, they typically corresponded to irreversible decisions that, once taken, could hardly be changed or reverted and they displayed long pay back periods. These characteristics turned the GEP a complex multiyear problem based on expectations on future profits.

The development of deregulation and liberalization of the electricity sector introduced new dimensions to this problem. Deregulation lead to the unbundling of the traditional integrated companies with the identification of generation and retailing activities typically provided under competition together with wiring transmission and distribution activities provided by regulated monopolies. This new structure induced a number of important consequences that increased the difficulty in performing long-term expansion studies since several market mechanisms have a strong accent on short-term activities. Regarding the GEP in particular, the development of electricity markets brought new dimensions to the problem as follows:

- there are now several generation agents competing to supply the demand. This means that each agent is planning the

* 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).

0360-5442/$ – see front matter
doi:10.1016/j.energy.2011.06.021

expansion of its own generation assets but it will have to consider the possible behavior of the other competitors and the impact of their expansion plans both in terms of the timing and the technologies they will include;
- this means that this problem is much more contaminated by uncertainties. These uncertainties are related with the long-term evolution of the demand, of fuel prices, of investment and maintenance prices and also with the behavior of the other generation agents, which means there is some degree of interaction between the decisions of the different generation agents. This ultimately means that rather than optimal expansion long-term plans, generation agents will certainly privilege whenever possible shorter term robust decisions and strategies;
- finally, there is a strong dependency on market prices that, at least on short-term markets, display a large volatility. These prices are influenced and influence the demand level and depend on fuel prices. These relations show that there is a complex set of dependencies between different parameters and variables suggesting the adoption of a systematic procedure to capture all of them.

These aspects suggest that it is important to develop models having two basic characteristics – the ability to capture the long-term behavior of the demand and of the prices and the relations between several variables, on one side, and the integer nature of investment decisions taken along a multiyear period. Given these concerns, this paper details an approach to the GEP using System Dynamics to model the long-term behavior of the electricity market, namely in terms of the demand and of the market prices, together with Genetic Algorithms (GAs) to solve the mixed integer optimization problems aiming at maximizing the profit of each generation agent along the planning horizon. This approach can be viewed as a decision support tool to aid a particular generation agent to build its expansion plan, investigating different possible reactions of its competitors or different regulatory frameworks. It can also be useful to state or regulatory agencies to build reference expansion plans or to investigate the adequacy of individual expansion plans given a possible evolution of the demand. The approach described in this paper corresponds to an enhanced version regarding the model detailed in Ref. [1]. In Ref. [1] we formulated the GEP problem as a two level problem in which each agent aimed at maximizing its profit and the set of individual plans were globally evaluated in a coordination step. In that case, the evolutions of the electricity prices and of the demand were modeled using the Cournot Model. Now, we are substituting the Cournot Model by System Dynamics to represent the long-term evolution of electricity markets given it is more adequate to model interdependencies between different variables and their long-term behavior. As a result, we built a global model that contains a feedback mechanism between the long-term System Dynamics model and the GENCO's profit maximization problems. Once an initial set of expansion plans are obtained, they are input in the System Dynamics model to characterize the evolution of the electricity price, of the demand and of the capacity factors along the planning horizon. Then, this evolution is used again by generation companies to update their expansion plans. These updated plans are then used again by the System Dynamics model and this process is continued till convergence is reached.

According to these ideas this paper is organized as follows. Section 2 reviews approaches to the GEP problem starting with models and algorithms used under the vertically integrated paradigm and continuing with approaches under competition. Section 3 details the basic concepts associated with System Dynamics used in this paper and Sections 4 and 5 describe the mathematical formulation of the problem and the developed solution approach. Section 6 presents a Case Study based on a three agent generation system together with a sensitivity analysis over the computed solution an finally, Section 7 draws the most relevant conclusions.

2. Review of GEP Models

Under the vertically integrated paradigm, the GEP problem corresponded to the identification of an investment schedule of generation plants together with their sitting and technology to supply the demand, considering a specified demand evolution along the planning period. In several publications this integrated view is well displayed when considering that one also aims at identifying the capacity of transmission lines that is required to ensure an economic and reliable operation of the entire system. This is the case of the approaches detailed in Refs. [2,3]. The approach in Ref. [2] considers uncertainties affecting the investment costs, the operation costs and the demand and uses stochastic programming together with Benders decomposition. Ref. [3] details a mixed integer linear programming problem to minimize the present value of the investment and operation costs plus costs associated to Demand Side Management (DSM) programs and the costs felt by consumers due to power interruptions. This model integrates several constraints namely a representation of the transmission network using the DC model. Several approaches explicitly recognize the complexity of the GEP problem and adopt decomposition techniques to profit from the particular structure of the optimization problem. This is the case of Refs. [2,4,5] that use Benders decomposition. In the case of Ref. [5], given an investment schedule the sub problems evaluate the operation costs and the solutions of these problems and their dual variables are used to formulate new constraints, Benders cuts, to include in the master investment problem. This defines an iterative process in which the master problem and the set of sub problems are solved in sequence. Still in the scope of the vertically integrated paradigm, Refs. [6, 7] describe the use of multiobjective concepts on the GEP. The model in Ref. [6] considers the following objectives: investment, operation and transmission costs, environmental impact, the value of imported fuel and the risk of getting a plan too much exposed to the volatility of the energy price. The solution approach is organized in two phases. In the first one it is built a set of non-dominated solutions. In the second phase, the solutions in this set are ranked using Analytical Hierarchy Processes. The model described in Ref. [7] minimizes the investment and operation costs, the environmental impact due to land use, large accidents and effects on ecosystems and, finally, the environmental cost due to emissions. This problem is solved using a step method, STEM, that involves a sequential identification and characterization of the solutions so that the Decision Maker gets insight on the problem and finally selects a good compromise solution. Recognizing that the GEP problem has a mixed integer nature, several authors developed approaches using metaheuristics as in Refs. [8–11]. These metaheuristics include GAs as in Refs. [8–11], Simulated Annealing as in Refs. [9–11], ant colonies and particle swarm algorithms [9], expert systems and fuzzy logic [10] and combinations of GAs and Simulated Annealing as in Ref. [11]. In general, all these models minimize investment and operation costs plus penalties on curtailed energy and they typically conclude that metaheuristics are powerful techniques specially suited to address complex large-scale combinatorial problems as it is the case of GEP.

With the advent of deregulation and liberalization of the electricity sector, a new set of approaches were developed. Before addressing some of them, Refs. [12–14] describe the change of paradigm through which the electricity sector went and its impact on long-term planning activities. Ref. [12] mentions the increased uncertainties affecting the demand and prices, the dependency on the prices coming from short-term volatile markets and the division of the demand by several agents turning each demand component more difficult to predict. As a result, the authors indicate that from traditional heavy optimization models the GEP problem now aims at identifying robust strategies in which smaller stations with more reduced construction periods are preferred. Ref. [14] reviews the performance of several electricity markets analyzing the impact of liberalization on long-term decisions. The authors concluded that, except for California, till 2003 there were enough investments in new capacity. Nevertheless, they indicate that in several systems the number of years during which market mechanisms were in place was by that time still short to take definite conclusions and that in several cases national governments were concerned with the adequacy and with the mix of the generation systems.

In the scope of the liberalization of the industry, Refs. [15–17] describe different approaches to the GEP problem. In Ref. [15] it is considered a partially deregulated system in which traditional utilities buy electricity from Independent Power Producers (IPPs). This problem maximizes the profit of traditional utilities modeled as the difference between the revenues from selling electricity and the operation and investment costs together with the cost of buying electricity from IPPs. The authors describe the use of several metaheuristic techniques as GAs, differential evolution, evolutionary programming, Tabu Search, Simulated Annealing and hybrid approaches. In Ref. [16] it is described a two-phase expansion planning approach. In the first step, individual generation agents prepare their expansion plans maximizing their profit and enforcing constraints associated with the supply of the demand and limits on the capability of building different types of plants. When these individual plans are ready, they are submitted to an "Upper Organization" phase to check the quality of the global schedule, namely computing LOLP and the reserve margin along the planning horizon. The approach described in Ref. [17] compares the GEP problem under the centralized and under the liberalized paradigms and it formulates an optimization investment problem to maximize the profit of the investors. The resulting problem is then solved using Dynamic Stochastic Programming together with discrete Markov Chains to model the uncertainty in the demand.

In recent years, System Dynamics [18] also started to be applied to the GEP problem. Section 3 includes some basic concepts on this methodology. Regarding applications to the GEP, Refs. [19–24] describe different approaches. In Ref. [19] it is developed a long-term model of the electricity market using System Dynamics. This model is then used to input information on the investment optimization problem using real options theory and solved using Dynamic Stochastic Programming. In Refs. [20,21] the authors indicate that System Dynamics is able to replicate the structure of power markets, the relationships between different components, variables and inputs. As a result, they consider it is able to adequately capture the long-term behavior of electricity prices and of the demand. The paper details the economic foundations of the model, it enumerates the characteristics of investments in generation capacity and details the model adopted to represent the behavior of the investors. Ref. [22] describes the use of System Dynamics to obtain a long-term model of the electricity market identifying the different inputs and variables as well as their interrelations. This includes the available capacity, the capacity under construction, the energy and capacity electricity markets, the demand, the economic growth as well as imports and exports, fuel prices, operation, investment and emission costs and interest rates. Ref. [23] provides an extensive literature review on GEP models and presents theoretical developments specially devoted to the modeling of oligopolistic structures existing in several electricity markets and the resulting market power. Finally, Ref. [24] describes general aspects of the application of System Dynamics to the GEP in New Zealand till 2050. This paper does not provide details on the developed mathematic model but it is important given that it presents results regarding a real generation system.

3. System dynamics – an overview

System Dynamics was introduced in the 1960s by Jay Forrester [18] in order to model and simulate the long-term behavior of complex systems. This means analyzing how a system evolves along time, how past and present behaviors impact on the future and also investigating the interrelations between different parts of the system. The electricity sector and in particular the expansion planning of the generation system display some characteristics that turn System Dynamics very adequate to model its long-term behavior. In fact, there is feedback information that is used by investing agents in the sense that the impact of current and past decisions is evaluated, namely in terms of its impact on future electricity prices, and this evolution will then be used again to reshape expansion plans. There are also delays between the moment at which an investment decision is taken and the moment at which a generation station is commissioned. These delays can be crucial for the evolution of the system in the long-run and these aspects are not completely captured by traditional models.

System Dynamics are based on Casual Diagrams as the ones illustrated in Fig. 1a and b. Fig. 1a models a positive cause–effect relation in the sense that both variables x and y change in the same direction. On the contrary, Fig. 1b displays a negative cause–effect relation between x and y. Based on these diagrams, it is possible to build positive and negative feedback loops in which cause–effect relations create closed loops.

Apart from these simple diagrams, System Dynamics also intensively uses Diagrams of Stocks and Flows to model relations between different variables and to represent eventual delays. As an example, Fig. 2 shows a basic Stocks and Flows Diagram. Stocks characterize the state of the system and are used to generate the information on which decisions and actions are based. The flows represent the activity of the system, the decisions and actions, and also originate changes in the stocks. Associated to this Stocks and Flows Diagram, there is a mathematical model, in this case represented by (1) or (2).

$$\mathrm{Stock}(t) = \int_{t_o}^{t} (\mathrm{InpuFlow}(t) - \mathrm{OutputFlow}(t)).dt + \mathrm{Stock}(t_o) \tag{1}$$

$$\frac{\partial \mathrm{Stock}(t)}{\partial t} = \mathrm{InpuFlow}(t) - \mathrm{OutputFlow}(t) \tag{2}$$

As a result, a formulation using a System Dynamics Model usually includes a set of differential equations to represent the behavior of

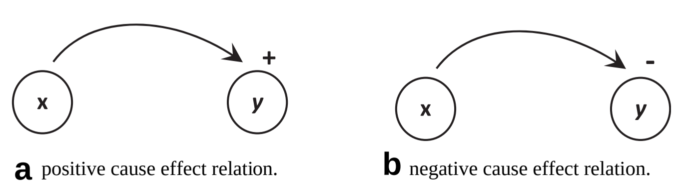

Fig. 1. Examples of casual diagrams – positive diagram (1a) and negative diagram (1b).

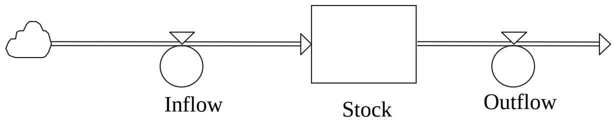

Fig. 2. Diagram of stocks and flows.

the system along time. Stocks correspond to an important concept in this framework because they have the following relevant characteristics:

- they have memory in the sense that an interruption of a flow determines that the level of the associated stock doesn't change. On the other hand, it is required an output flow larger than the input to reduce the current level of the stock;
- stocks characterize the state of the system given that the value of several variables depend on the evolution of the values of the stocks;
- stocks can be used to model delays, namely when the input flow level in larger than the output flow. Delays should be carefully identified in order to adequately model the behavior of the system. Not including the delay between a cause and its effect may simple originate that the decision maker will not get aware of the dependence between that cause and that effect;
- stocks can also be used to decouple the input and output flows. Stocks absorb the differences between input and output flows and the level of these flows can change according to different rates because they can be determined by different decision processes. This means that when separating a flow in an input and in an output flow using a stock we can create unbalances between them modeling different conditions controlling them, namely different information sources determining their behavior.

System Dynamics has a wide range of applications, including to several power system problems [25]. As indicated by this author, the success of System Dynamics is very much related with its ability to capture and model feedback loops that exist in many power system problems. In particular, the generation expansion problem displays a number of characteristics that turns System Dynamics specially interesting to address it. These aspects certainly include the interdependency between the long-term evolution of electricity prices, the demand and the new additions to the generation system. Increased electricity prices tend to induce a demand reduction (even though the elasticity of the demand to the price is typically reduced) but sends a signal to investors in order to build new power stations, given that the remuneration is attractive. This in turn, contributes to reduce the price and to enlarge the demand. As indicated in Ref. [19], System Dynamics is not concerned in analyzing small individual elements in a system, but rather to capture their relationships that contribute to create a dynamic system. In the next Sections, we detail the main modules of the developed long-term approach to the generation expansion problem using System Dynamics.

The concepts briefly explained in these paragraphs will be used to model the long-term evolution of electricity markets. This means that for an initial set of generators and for a specified schedule of new generators entering in the system it is possible to model the evolution of the demand and of the electricity prices along the planning horizon. This information will then be used to refine the expansion plans of the generation agents solving mixed integer optimization problems. This defines an iterative process that ends when pre-specified convergence conditions are met. In the developed approach, the Dynamic Model of the electricity system was developed using the Academic Version of the POWERSIM package of Powersim Software AS [26,27].

4. Mathematical formulation

4.1. General ideas

As mentioned in the last paragraph of Section 3, the developed approach is based in an iterative procedure that integrates three main steps. In the first one, we consider a given level of electricity and fuel prices and electricity demand along the planning horizon, so that each generation company, GENCO, builds its own multiyear expansion plan solving a mixed integer optimization problem. In this problem, each agent maximizes its profit along the planning horizon given by the difference between the revenue coming from selling electricity at the market price and the corresponding investment and operation cost. Using these individual plans, the global results are checked in order to evaluate some indicators as the reserve margin, a reliability index as LOLP or LOLE and eventually the generation mix resulting from these plans to check if limits specified for some technologies are not violated. If some of these coordination constraints are violated, the algorithm solves again the individual optimization problems to build a new set of plans. The formulation of these optimization problems requires knowing an updated estimate of the fuel and electricity prices as well as of the demand along the horizon. These estimates are obtained by the System Dynamics model as it will be detailed later on. Fig. 3 illustrates the dependencies between these three blocks together with the iterative process just outlined.

In the next sections, we will detail the individual optimization problem to be solved by each GENCO, the coordination analysis and the long-term modeling of the electricity market using System Dynamics to get the evolution of the electricity prices, of the demand and of the capacity factor of each generation technology.

4.2. Individual maximization of the profits

As outlined above, each GENCO solves the optimization problem (3–8) to maximize the profit that can be obtained along the planning horizon. This problem was already detailed in Ref. [1] and so it will now be only briefly described. It is important to mention that the decision variables of this problem correspond to the capacity to install of each technology in each year of the planning horizon. These capacities are typically available according to normalized values meaning that the variables X_t^{ij} can only assume particular values from a list of capacities available for each technology. As a result, the problem (3–8) has a combinatorial nature justifying the use of GAs to solve it, as detailed in Section 5.2.

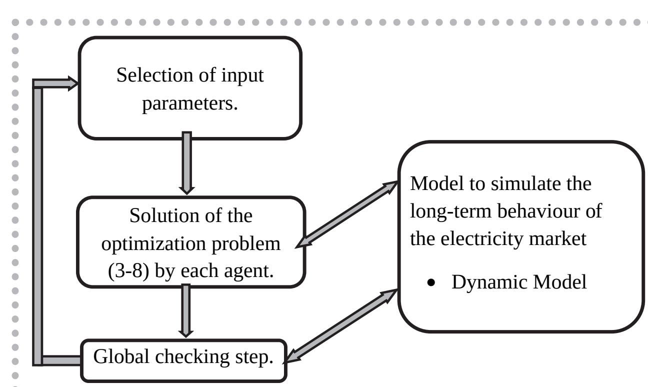

Fig. 3. Main blocks of the developed approach.

$$\max z = \sum_{t=1}^{T}\left[\left(\pi^t\cdot \mathrm{CC}_t^i\right)\cdot\alpha_t^{ij} - \sum_{j=1}^{M}\left(\mathrm{Cinv}_t^j\cdot X_t^{ij}\right) - \sum_{j=1}^{M}\left(\mathrm{Cop}_t^j\cdot X_t^{ij}\right)\cdot\alpha_t^{ij}\right] \quad (3)$$

$$\text{s.t. } X_t^{ij} \le \overline{\mathrm{CIT}}_t^i \quad \text{for every } j \text{ and } t \quad (4)$$

$$\sum_{j=1}^{M} X_t^{ij} \le \mathrm{MIC}_t^i \quad \text{for every } t \quad (5)$$

$$\mathrm{CC}_t^i = \mathrm{CC}_{t-1}^i + \sum_{j=1}^{M} X_t^{ij} \quad \text{for every } t \quad (6)$$

$$\sum_{j=1}^{M} X_t^{ij}\cdot \mathrm{Cinv}_t^j \le \mathrm{LCI}_t^i \quad \text{for every } t \quad (7)$$

$$t = 1,\ldots T; \quad j = 1,\ldots,M \quad (8)$$

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;
I	index associated to a particular GENCO;
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. This variable is integer and its possible values correspond to the normalized capacities that can be built for each technology j. These possible integer values are specified by the planner;
$\overline{\mathrm{CIT}}_t^i$	upper bound set for the installed capacity of technology j in stage t by GENCO i.
MIC_t^i	maximum capacity installed in stage t by GENCO i;
LCI_t^i	maximum value specified for the capital investment of GENCO i at stage t;

The objective function to be maximized (3) corresponds to the addition of the annualized profits computed as the difference of the revenues obtained from selling electricity at the market price and the investment and operation costs. These profits depend on the evolution of the electricity prices, on the capacity installed in each stage of the planning horizon, on the investment decisions modeled by the decision variables X_t^{ij} and on the generation mix leading to the operation costs. On a long-term basis, and apart from electricity prices, the profits also depend on the use of each technology modeled by the corresponding capacity factor, α_t^{ij}, determined for each technology j for each period t. Finally, it should be noticed that the terms in (3) are referred to the initial year using an adequate interest rate.

Regarding the constraints, (4) limits the capacity of each technology j that can be installed by each GENCO i in each stage t of the planning horizon. Constraints (5) limit the total amount of capacity for all M candidate technologies that can be installed by GENCO i in each stage t and (6) represents the cumulative amount of power installed by GENCO i till stage t. Finally, constraints (7) limit the amount of invested money in each stage t by GENCO i. This kind of constraints models the financial resources that agent i has available and can be established on a stage basis, as in (7), it can correspond to a set of constraints established for consecutive sets of stages, or it can be established in terms of a single constraint expressing a global financial limit for the entire T stages in the planning horizon.

Regarding this formulation, it is important to notice two aspects, as follows:

- in the first place, when solving this problem it is necessary to input the electricity prices along the planning horizon as well as the capacity factor of each technology and for each year. These values depend on the long-term evolution of the demand that, on its turn, is also determined by the electricity price, depending on its elasticity. As mentioned in the Introduction, this loop and these long-term effects suggested the use of System Dynamics to model these aspects;
- secondly, regulatory or state agencies can specify limits to frame the evolution and the mix of national generation systems according to pre-established objectives of national energy policies. In this problem, we can set the values of $\overline{\mathrm{CIT}}_t^i$ used on constraints (4) and of MIC_t^i used in (5). These constraints can be used to impose upper bounds to the installed capacity of specific technologies (4) or to limit the share of the installed capacity owned by a single agent as an attempt to limit market power.

4.3. Coordination analysis

Although the advent and the development of electricity markets lead to a more liberalized environment on the generation activity, national regulations can still impose public service obligations, for instance in terms of security of supply or quality of service requirements. This is recognized in EU Directives, for instance, and also in national electricity codes that progressively transposed these directive to national legal texts. For instance, the Portuguese Electricity Law passed in February 2006 [28] enumerates a set of public service obligations that includes the security and the quality of supply and also states that the government is responsible for defining the share of different energy vectors to generate electricity and for the promotion of the diversification of the primary resources used in the system. On the other hand, the Grid Codes of several countries establish maximum values for adequacy indices in an attempt to ensure that long-term planning is performed or individual expansion plans are evaluated so that security of supply is ensured. This means that a coordination analysis seems reasonable and adjusted to reality. It can incorporate a variety of constraints, which means that the conditions enumerated below just correspond to a possible set of conditions. As a result, these constraints can be modified or enlarged namely to reflect particular practices in force in some countries.

In the current version of the developed application, we included the following constraints:

- reserve margin – the reserve margin corresponds to the surplus of installed capacity regarding the peak power. It should be considered carefully because installed capacity is not the same as available energy, as the use of hydro stations and wind parks clearly demonstrate. In any case, it is an indicator that planners often use to evaluate the robustness of a generation system purely from a capacity point of view. This margin should be evaluated for every stage of the planning horizon by

(9) and these yearly values are then compared with minimum and maximum values as in (10). In this constraint, RM_t, RM_t^{min} and RM_t^{max} represent the reserve margin and its minimum and maximum values in year t;

$$RM_t = \left(\frac{\text{Installed capacity}_t}{\text{Peak load}_t} - 1\right) \cdot 100\% \tag{9}$$

$$RM_t^{min} \le RM_t \le RM_t^{max} \quad \text{for } t = 1, \ldots, T \tag{10}$$

- secondly, admitting that there are N GENCO's that are preparing individual plans, regulatory or state agencies can monitor the total amount of capacity to install of a given technology j along the entire planning horizon (11). This constraint can be used to set guidelines regarding the participation of different technologies or primary resources to the supply of electricity along an extended period, according to the objectives of national energy policy. In (11) $\bar{J}^j$ is the maximum amount of capacity of technology j that can be installed in year t;

$$\sum_{i=1}^{N} X_t^{ij} \le \bar{J}^j \quad \text{for } t = 1, \ldots, T \text{ and } j = 1, \ldots, M \tag{11}$$

- in the third place, regulatory or state agencies in charge of ensuring competitive conditions in the economy can set a maximum share that GENCO i can own regarding the total amount of capacity in the system, (12). This constraint can be used to prevent market power in the sector and to ensure that entry conditions are facilitated in the generation activity. In (12), N represents the number of GENCO's, CC_t^i and CC_t^p are the cumulative installed capacity of GENCO's i and p and $Perc^{max}$ is the maximum percentage of installed capacity that can be owned by an individual GENCO, on each stage of the horizon;

$$CC_t^i \le \frac{Perc^{max}}{100} \cdot \sum_{p=1}^{N} CC_t^p \quad \text{for } t = 1, \ldots, T \text{ and } i = 1, \ldots, N \tag{12}$$

- finally, the developed approach also monitors an adequacy index corresponding to the Loss of Load Expectation, LOLE, expressed in terms of the number of hours it is expected that the generation system is unable to supply the demand. Ref. [1] gives several details on the computation of *LOLE* and the values calculated for every stage of the horizon should not exceed a maximum limit, $LOLE^{max}$ as indicated in (13).

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

If the developed individual plans originate a violation of some of these constraints, the optimization problems (3–8) should be solved again, using an updated set of electricity prices and capacity factors determined by the long-term System Dynamics Model, as detailed in the next section. It is also possible to include specific incentives to turn investments in new generation facilities more attractive, for instance, under the form of a capacity payment. If this is the case, the expression of the objective function (3) should be enlarged to include such a term in the revenue side. The capacity to remunerate can be evaluated as the difference between the installed capacity and the capacity scheduled to supply the expected demand and can be paid according to a regulated capacity tariff. If necessary, this regulated price can be increased to induce more investments. This suggests that regulatory or state agencies can use this approach to investigate the impact of different capacity prices on the long-term evolution of the generation system. In other words, this approach can be used to set in a more cautious and informed way the price to be paid for the provision of capacity, if this capacity payment is present in the regulations.

Finally, given the volatility of some renewable primary resources, namely wind, the model can be easily expanded to include constraints to impose minimum thermal or hydro installed capacity requirements, in view of the evolution of the wind installed capacity. This type of constraints would mean that at the coordination level, the plans developed by the GENCO's would also be checked against specified reserve requirements, contributing to turn the whole approach more realistic.

4.4. *Long-term behavior of electricity prices using system dynamics*

4.4.1. *Global casual loop diagram for the long-term electricity market evolution*

As mentioned before the operation of day-ahead electricity markets have a short-term nature that is strongly determined by long-term decisions, by interactions and by the evolution of several parameters and variables. Adopting a casual loop diagram similar to the one detailed in Ref. [21], Fig. 4 displays the casual diagram that illustrates these interactions.

According to this diagram, there is a positive cause–effect relation between the evolution of the installed capacity and the reserve in the generation system. On the other hand, when decommissioning a power station, there is a negative cause–effect regarding the installed capacity. Then, continuing to go along the diagram clockwise, a demand increase reduces the reserve and the reduction of this reserve will in general lead to an increase of the electricity price. It is clear that an increase on the fuel and coal costs have a positive impact on electricity prices and these variations will change the profits of the GENCO's. These profits are also affected by a cost increase (both in terms of operation, maintenance or investment costs). Large expected profits will have a positive impact in inducing new investment decisions in generation capacity. Using these profits, each GENCO solves its individual investment problem already detailed in Section 4.2 to update the investment plan along the horizon. Finally, it should be noticed that between the moment in which an investment decision is taken and the moment in which a power station is commissioned there is usually a long-term delay associated not only to the construction period but also to typically long periods to get licences or to organize the financial aspects of the investment. In this diagram, this delay is modeled by τ_1 and its consideration is important to get a more realistic model.

This diagram indicates there is a feedback model in which the individual investment decisions adopted by each GENCO determine the global installed capacity and the reserve. Using the existing generation system and the expected demand evolution, the System Dynamics model obtains a long-term estimate of the electricity price and of the capacity factor of each technology in each year of the horizon, certainly affected by the evolution of the fuel and coal prices. Electricity prices together with the evolution of fixed and variable costs determine the evolution of the profits that, at the end, will impact on the investment decisions. In the next sections we will detail some of the sub-models developed in the scope of the System Dynamics approach.

4.4.2. *Modeling the generation supply*

The developed approach admits that the demand can be supplied by thermal generators, by hydro stations grouped in run-

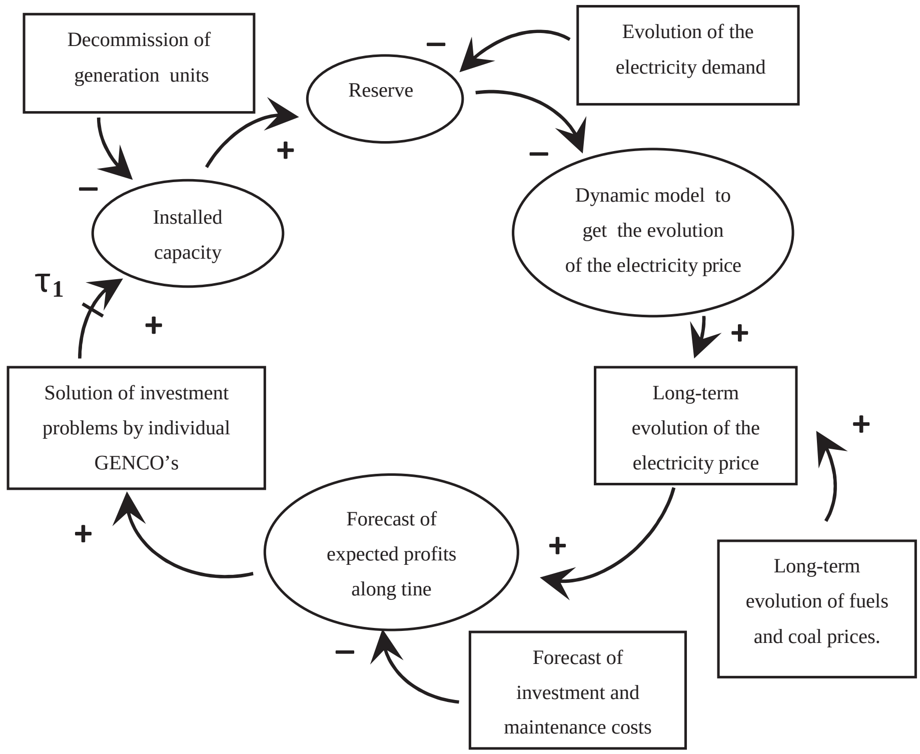

Fig. 4. Casual loop diagram detailing the long-term interactions on the electricity market.

of-river and in reservoirs and by Special Regime Generation (SRG) namely wind parks regarding which there are special provisions to pay their injections, in general determined by feed-in tariffs.

Regarding wind parks, we used historical values to determine the average amount of energy regarding the maximum value at full capacity, value in the range from 20 to 25%. Then, using the total installed capacity and the average number of hours that these parks are operating, we used a stochastic process to obtain the distribution of the capacity factor and of the energy along each year. Fig. 5 illustrates an outcome of this procedure in terms of the evolution of the capacity factor of the wind parks (in %) along a part of the planning horizon (in days).

In the developed application we started considering hydro stations as candidate technologies in the investment problems. Given the reduced operation costs of these stations, it was clear that these investments were very attractive. After running some trial simulations considering these stations as candidate technologies, we concluded that all agents would start investing in hydro stations leading, at the end, to investment plans in which the global amount of new hydro capacity would exceed the total hydro capacity that could be built. Therefore, we adopted a different approach admitting that the total hydro capacity that could be built was known in advance, depending on the number of feasible locations. In this approach we simply allocated this total capacity to all GENCO's according to a predefined proportion. This simplification is not due to any limitation of the long-term Dynamic Model but it is a result of the particular characteristics of these stations regarding their operation costs.

As mentioned above, hydro stations are grouped in run-of-river and reservoirs. For each of them we used historic data to estimate the average capacity factor and the corresponding standard deviation. As a result, we obtained the following values for these parameters – average value of the capacity factor for run-of-river stations of 30% and for reservoirs of 20%, standard deviation of

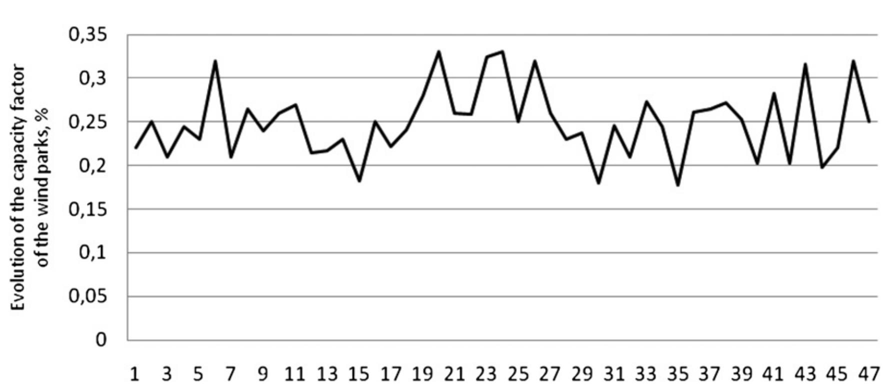

Fig. 5. Illustration of the evolution of the capacity factor of wind parks along a part of the planning horizon (in days).

5%. These values were then used to run stochastic processes to distribute the capacity factor along each year of the simulation period.

Finally, regarding thermal stations we used normalized curves representing the variable operation cost of each technology in function of the capacity factor. Fig. 6 illustrates a step-wise curve of this type. Using such a curve for each thermal candidate technology together with the installed capacity, the availability of each station along the year in terms of a period in h/year and the evolution of the electricity price, it is possible to obtain the output of each station and the total amount of energy generated by the set of thermal stations. Regarding this model it is important to notice two issues, as follows:

- in the first place, the step-wise curve as the one in Fig. 6 can be adjusted to accommodate changes in the fuel or coal costs along the horizon. This means that the generation cost associated to each step can increase or decrease to model these changes along the stages of the horizon;
- secondly, the availability of each thermal station depends on each technology, namely on the duration and location of its maintenance period. To model this issue, the planning horizon can be discretized in weeks so that each maintenance action is developed along a continuous set of weeks.

Finally, using the generated energy from the available sources, Fig. 7 displays the Dynamic Model that represents the global generation in the entire generation system. This model considers an estimate of the energy losses in the transmission and distribution networks, specified as a percentage of the demand to be supplied.

4.4.3. Modeling the evolution of the demand rate

The long-term evolution of the demand rate depends on an initial level, t_0, and on a long-term forecasted value, t_{LT}. In terms of Dynamic Systems, Fig. 8 displays the model of the annual evolution of the demand rate. This figure shows that this rate depends on the initial value and on a flow that results from a stochastic process.

From a mathematical point of view, this model corresponds to the Eqs. (14)–(18). In the first place, Eq. (14) indicates that the annual demand rate, t_{annual_demand} results from the addition of the initial value t_0, together with the result of an integral term that can be viewed as the output of a Stocks and Flows Diagram, as in (1). The term dx in the integral represents the long-term dynamic evolution of the demand rate regarding which we used an Ornstein-Uhlenbeck reversion process, detailed in Refs. [20,21], given its suitability to model the uncertainty of the long-term

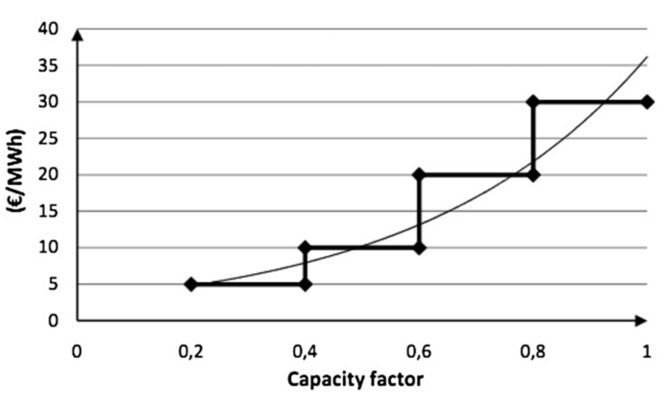

Fig. 6. Illustration of a normalized curve for the variable operation cost of a thermal generation technology.

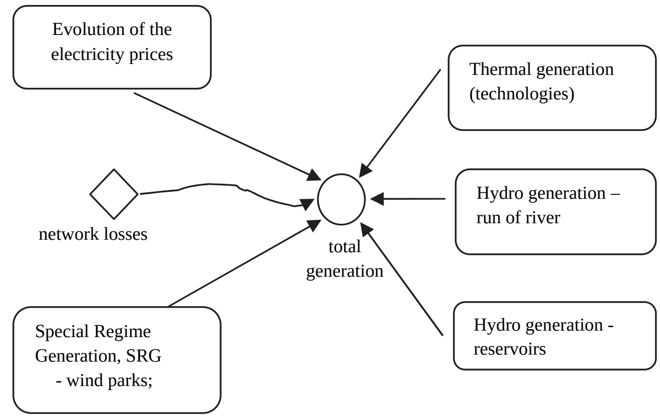

Fig. 7. Dynamic model of the generation electricity level obtained from different sources.

evolution of the electricity demand rate [29]. In particular, Ref. [20] indicates that electricity demand displays a long-term evolution pattern that, in the shorter term, is affected by several factors as weather conditions or particular economic activity peaks or valleys. In any case, these random variations tend to attenuate along time and so the demand rate gets back to its long-term evolution. This reasoning seems adequate and justifies the use of the mentioned mean reversion process.

This process depends on two terms indicated in Eq. (15). The first one is F_R and it represents the strength of the regression to the mean value. This term depends on the difference between the long-term forecasted demand rate, t_{LT}, and the annual demand rate, t_{annual_demand}, (16). This difference is then multiplied by the mean reversion rate, η, and by the step adopted in the simulation, Δt. On the other hand, the second term in Eq. (15) represents the volatility of the process. This is modeled by a Wienner process (17) in which the term dz depends on the volatility parameter, δ, and on a number sampled from a normal distribution with 0 mean and 1 standard deviation. As the value of the parameter δ becomes larger, the volatility of the demand rate along the horizon becomes larger, although displaying the same mean value, t_{LT}. On the other hand, for the same value of δ, if the mean reversion rate, η, becomes larger then the variations of the demand rate tend to dissipate faster in the sense that the process tends to the long-term mean value more rapidly.

$$t_{annual\_demand} = t_0 + \int_0^T dx \cdot dt \tag{14}$$

$$dx = F_R + dz \tag{15}$$

$$F_R = \eta \cdot (t_{LT} - t_{annualdemand}) \cdot \Delta t \tag{16}$$

$$dz = \varepsilon_t \cdot \delta \cdot \sqrt{\Delta t} \tag{17}$$

$$\varepsilon_t = \mathrm{RandomNormal}(0, 1) \tag{18}$$

4.4.4. Dynamic model of the demand evolution

The model adopted to obtain the long-term evolution of the demand is given by expressions (19) and (20). In the first place, the reference electricity demand, D_{elec_ref}, is given as the addition of the demand in the period prior to the simulation D_{elec_ref0}, with an

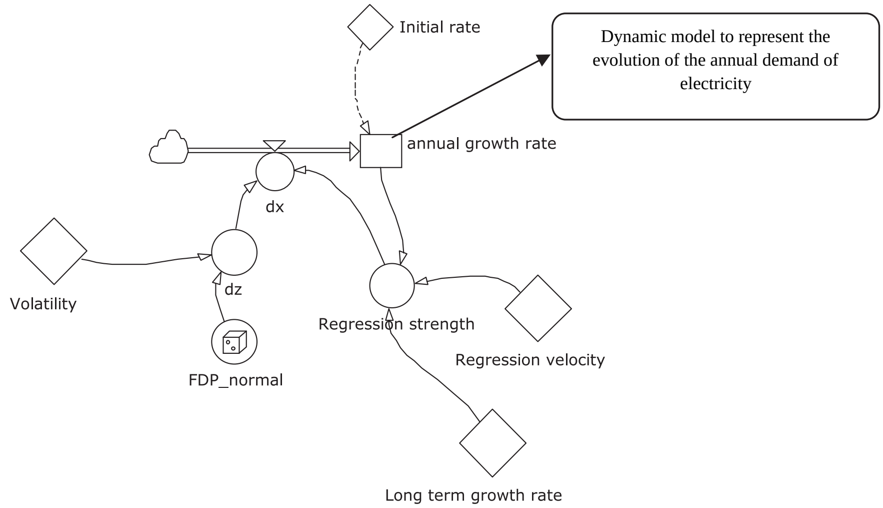

Fig. 8. Dynamic model of the long-term evolution of the demand rate.

adjustment term that depends on the evolution of the demand rate, obtained as detailed in Section 4.4.3. After obtaining the reference electricity demand, we still considered the elasticity of the demand to the price, E_{DP}, so that we used (20) to compute the final value of the demand in a given period of the simulation. This final demand value, D_{elec}, depends on the reference value obtained by (19), on the electricity price in period t, p_t, on the electricity price in the period prior to the simulation, p_0, and on the specified elasticity, E_{DP}. It is well known that electricity demand is typically very inelastic and several authors indicate values in the range 0.25–0.45 for long-term studies [30,31]. In any case, as the elasticity increases, the demand will display larger variations regarding the variation of the price. If the elasticity is assumed as zero, then the demand doesn't change regarding the reference even though large price variations may occur.

$$D_{elec\_ref} = D_{elec\_ref0} + \int_0^T t_{annual\_demand} \cdot D_{elec\_ref0} \cdot dt \tag{19}$$

$$D_{elec} = D_{elec\_ref} \cdot \left(\frac{p_t}{p_0}\right)^{E_{DP}} \tag{20}$$

Fig. 9 details the corresponding Dynamic Model. The electricity demand depends on the elasticity of the demand to the price, on the reference price and also on the price in period t. This value is a result of the Dynamic Model to detail in the next section that, on its turn, also depends on the electricity demand. This means there is a feedback loop given this interdependence between the price and the demand. On the other hand, the integral term in Eq. (19) indicates there is a Diagram of Stocks and Flows in this Dynamic Model that uses the annual demand rate as an input. Finally, once the reference demand is obtained, the final demand value is adjusted considering the specified elasticity of the demand to the price.

4.4.5. Dynamic model of the evolution of the electricity price

The evolution of the electricity price is computed using (21) that includes an initial reference value admitted for the period prior to the simulation, p_0, plus an integral term that determines its variations [32,33]. These variations are given by (22) and depend on the electricity price, on the deviation between the new computed demand, D_{elec}, and the total amount of generation, G_{total}, and also on an attenuation factor, AF, to smooth eventual large deviations between demand and generation in previous simulation periods.

$$p_t = p_0 + \int_0^T \Delta p_t \cdot dt \tag{21}$$

$$\Delta p_t = p_t \cdot \left(\frac{D_{elec} - G_{total}}{D_{elec}}\right) \cdot \frac{1}{AF} \tag{22}$$

Fig. 10 displays the corresponding Dynamic Model. Eq. (21) corresponds once again to a Diagram of Stocks and Flows, as shown in the left of Fig. 10 and the variations on the electricity price depend on the attenuation factor, on the deviation between the demand and the total generation and on the price itself. The output of this Stocks and Flows Diagram is then added to the reference electricity price, p_0, to determine the final electricity price in each simulation period. This price is then sent to the Dynamic Model that represents the demand evolution and also to the Dynamic Model to obtain the generation of the system. As sub results of this model, it is also possible to obtain average prices for periods to be specified, which in any case correspond to forecasted future values.

4.4.6. Complete dynamic model

Finally, putting together all these sub-models, Fig. 11 displays the complete Dynamic Model to get the long-term evolution of the demand and of the electricity price. In the lower part of this model

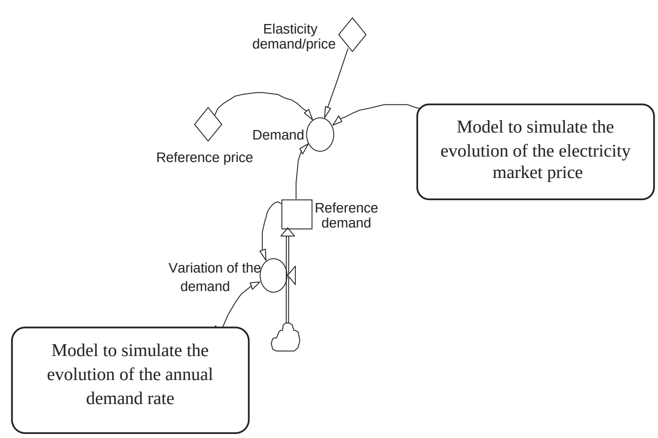

Fig. 9. Dynamic model of the long-term demand evolution.

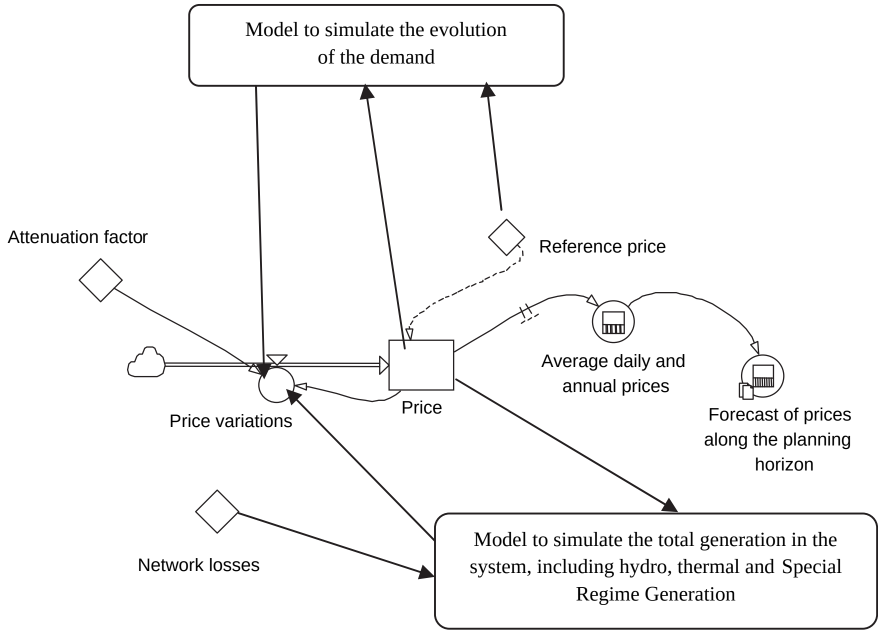

Fig. 10. Dynamic model of the evolution of the electricity price.

it is possible to identify the different components of the generation mix, namely run-of-river and reservoir hydro stations (Hy_RV and Hy_Res), SRG, and thermal stations (Ther_1 to Ther_n). The outputs of all these subsystems are added in the node Total Generation, incorporating an estimate of network losses. The amount of total generation is then used in the sub-model to compute the electricity price evolution that also has as input the evolution of the electricity demand obtained in the sub-model in the top right of Fig. 11. This price evolution is also used by the models of the thermal stations to obtain their output. Finally, the evolution of the demand uses the evolution of the demand rate, as indicated in the sub-model located in the top left side of Fig. 11.

5. Solution algorithm

5.1. General aspects

According to Fig. 3, the algorithm adopted to solve this problem involves an iterated solution of the individual profit maximization problems of each GENCO together with the long-term simulation of

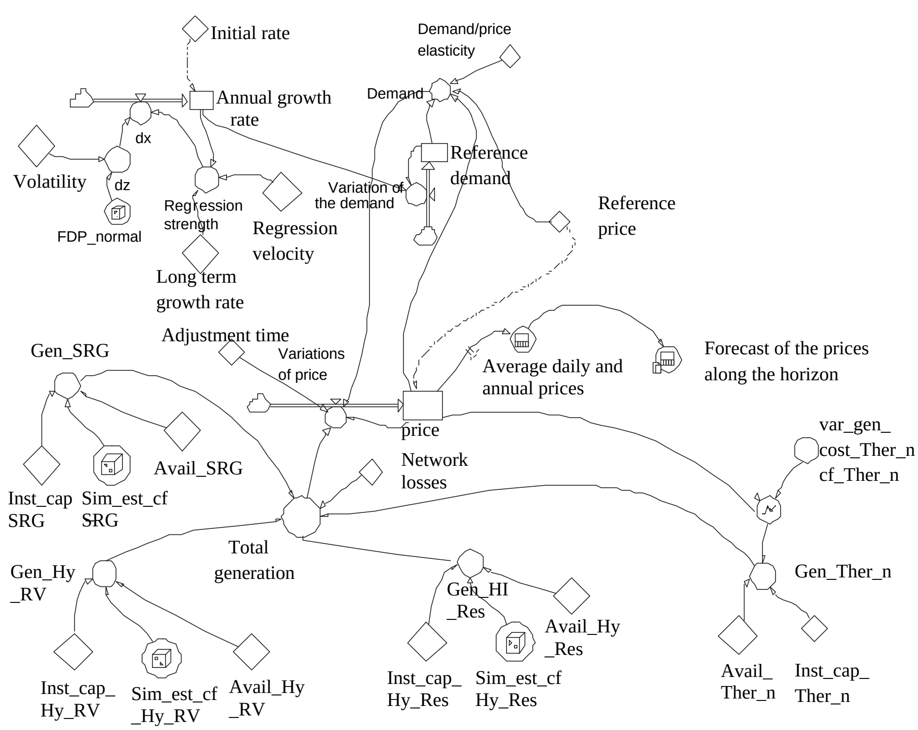

Fig. 11. Complete long-term dynamic model of the electricity market.

Table 1
Characteristics of the existing technologies.

no. Units	Technology	Generating size (MW)	Operation Cost (€/MW h)	FOR
3	Coal_1	300	25.25	0.02
2	Coal_2	400	28.00	0.02
5	Gas turbine	250	35.75	0.01
2	Oil turbine	200	40.00	0.03
6	CCGT	250	26.75	0.01

the electricity market. In brief, after setting initial values for the electricity price, for the demand and for the capacity factors, each GENCO solves its individual investment optimization problem (3–8). As a result, we get a set of expansion plans, that is, installed capacities and commissioning years of new generation assets along the planning horizon. These plans are then submitted to the coordination analysis to evaluate (9–13) and afterwards are used as inputs to the long-term System Dynamics model in order to update the demand evolution, the electricity price and the capacity factor of each technology along time. In general terms, the iterative process involves the following main steps:

i) set initial values for the electricity prices, demand and capacity factors along the planning horizon. These initial values can be set using historical series;
ii) using these values, the profit maximization problem associated to each GENCO is solved. To solve these problems, each GENCO maximizes its profit taken as the difference between the revenues from selling electricity and the investment, operation and maintenance costs incurred along the horizon. It is important to mention that the solution of these problems depends on the price evolution and on the estimated capacity factors. As the iterative process evolves, these estimates will change meaning that the profit will also change. In any case, it is important to clarify that the profit is maximum for the input conditions used on each particular iteration, that is for the evolution of the electricity price and of the capacity factors;
iii) using the new capacities coming from these plans, together with the existing ones and the information from the decommissioning plan, one evaluates the reserve margin, the LOLE, the maximum capacity that is possible to install for each candidate technology and the capacity owned by each GENCO;
iv) if the maximum capacity for a specific technology is exceeded, than the installed capacities obtained from the profit maximization problems are substituted by the limit. This can be seen as an administrative intervention at the coordination level to ensure that the global energy policy objectives are achieved. Similarly, if condition (12) is violated by the values obtained from the profit maximization analysis, then this limitation is sent back to that particular GENCO so that he solves again its profit maximization problem internalizing this constraint;
v) regarding the violation of LOLE and of the reserve margin limits, they are typically handled inside the long-term simulation as it will be detailed afterwards. In any case, if the long-term System Dynamics simulation is not able to provide price signals to turn new investments attractive, one can consider two possible ways to address the problem of insufficient capacity – force GENCO's to invest imposing minimum capacity limits to install in the problem (3–8) or inducing them to invest considering, for instance, a capacity term in the objective function (3). This alternative was already suggested at the end of Section 4.3;
vi) using the investment plans obtained by each GENCO, it is solved the long-term System Dynamics simulation. This means that we update the available installed capacity per technology for each year in the horizon, we determine along time the production of the SRG, and of the hydro stations using the capacity factors based on historical values. Then, for the rest of the demand, the System Dynamics model provides the contribution of each thermal technology, of the electricity price and of the corresponding capacity values. In this step, it should be mentioned that we consider all thermal stations, that is the ones already existing when the planning period started and the ones that were decided to install as a result of the problems solved in step ii). Finally, the calculation of the demand, of the prices and of the capacity factors just outlined includes a feedback loop as it will be detailed in Section 5.3 regarding particular issues on the Dynamic model;
vii) once the System Dynamics simulation ends, we get the evolution of the demand, of the electricity price and of the capacity factors for each technology along time. These values are sent back to each GENCO so that the algorithm returns to step ii) in order to update the investment plans.

Table 2
Generation mix of each GENCO.

Technology	GENCO_1	GENCO_2	GENCO_3
Coal_1 (MW)	300	300	–
Coal_2 (MW)	400	–	400
Gas turbine (MW)	250	250	500
Oil turbine (MW)	200	200	–
CCGT (MW)	250	500	250
Wind parks (MW)	100	100	200
Hydro (MW)	0	0	100

Table 3
Characteristics of the three candidate technologies.

Type of technology	Available capacities (MW)	Investment cost (€/MW)	Operation cost (€/MW h)	FOR
Tech_1	100 or 150 or 200	500,000	32.00	0.01
Tech_2	100 or 125 or 150	800,000	28.09	0.02
Tech_3	100 or 150 or 200	1,000,000	24.10	0.02

5.2. Solution of the individual maximization problems using GAs

As mentioned in Section 4.2, the individual optimization problem to be solved by each GENCO has an integer nature due to the normalized values typically available for power station capacities. These normalized values correspond to the possible capacities that can be selected by a GENCO to include in its expansion plan. This integer nature suggested using a GA, to solve the problem (3–8). Ref. [1] gives full details regarding the use of GA in this problem and now we will only briefly review its main steps, as follows:

Table 4
Data for the system dynamic simulation.

t_0 (%/year)	3	Dref_0 (GWh/year)	25.150
t_{LT}(%/year)	4	E_{DP}	0,25
η	0.50	T (years)	15
δ (%/year)	0.40	π^{t0} (€/MWh)	40

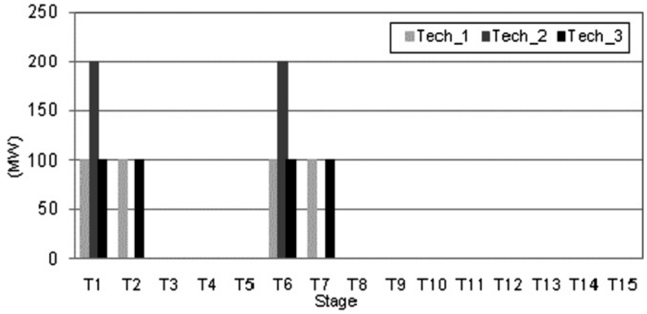

Fig. 12. Generation expansion plan for Genco_1.

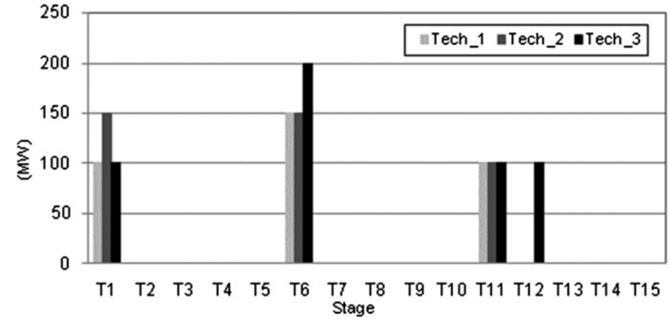

Fig. 14. Generation expansion plan for Genco_3.

i) the GA 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;

ii) once the initial population is built, it is evaluated using the set of electricity prices available at the current iteration as well as the investment and operation cost and an adequate rate to bring investments and costs to the initial period. Using these values, each element of the population is evaluated using a fitness function that includes two terms. The first one corresponds to the objective function (3) that we want to maximize. The second one corresponds to negative penalty terms that are activated if the constraints (4)–(7) are violated, given that the problem under analysis is a maximizing one;

iii) the convergence of the GA cycle is evaluated computing the average value and the standard deviation of the fitness function of all individuals in the current population. As the evolutionary 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 rise. 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 executed before the algorithms stops;

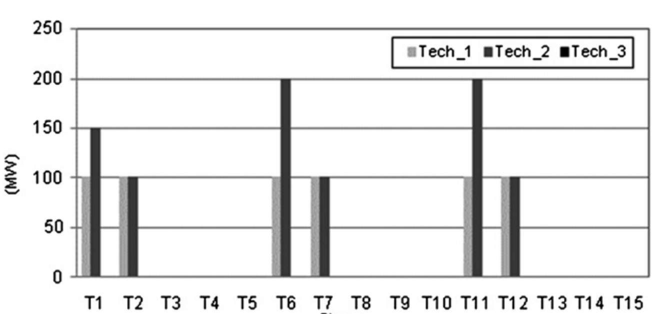

Fig. 13. Generation expansion plan for Genco_2.

iv) if convergence was not yet reached, the GA proceeds with the usual selection, cross-over and mutation operators in order to generate a new population. The individuals in this new population will then be subjected to the evaluation process detailed in ii) and the process iterates till it converges;

v) finally, from the final population, it is selected the individual associated with the best-identified investment expansion plan. This plan is interpreted as the one that maximizes the profit given by (3) along the planning period.

5.3. Use of the system dynamics model

Regarding the long-term simulation of the electricity market, the Dynamic Model detailed in Fig. 11 is associated to the mathematical formulation that includes the Eqs. (14)–(22). This model was implemented on an Academic Version of the POWERSIM package of Powersim Software AS [26,27]. The mathematical model is formed by a set of differential equations and this software allows the user to select the integration technique. In the simulations to be detailed in Section 6 we adopted the 4th order Runge Kuta method with an integration step of 1 h. This means that the long-term evolution of the demand, of the electricity price and other output variables as the capacity factors of each technology will be obtained with this discretization level.

Given this integration step, it becomes easy to integrate in the model some operational requirements that can have an impact on the long-term expansion planning. This is for instance the case of couplings between hydro stations to model the dependencies between upstream/downstream hydro stations and also couplings between the generation of thermal stations to accommodate information about up and down ramps. These requirements correspond to constraints that would condition the hourly evolution of the generations of the available technologies.

This model includes a feedback loop in a way that the prices influence the output of each generation technology and also the demand. These interrelations will now be addressed. Based on Fig. 11, let us consider that we start the whole iterative process using an initial set of values for the electricity price, for the demand, for the capacity factors of SRG and Hydro stations, as well as the information on the curves relating the operation cost of each thermal technology with the corresponding capacity factor, as illustrated in Fig. 6, Section 4.4.2. Once the individual profit maximization problems are solved as detailed above, we get an initial set of investment plans. Using this information we update the available thermal capacity along time and we estimate the contribution of SRG and Hydro stations to supply the demand along the horizon. The remaining demand will be supplied by thermal generation as follows. The initial price p_0 is used in Eq. (21)

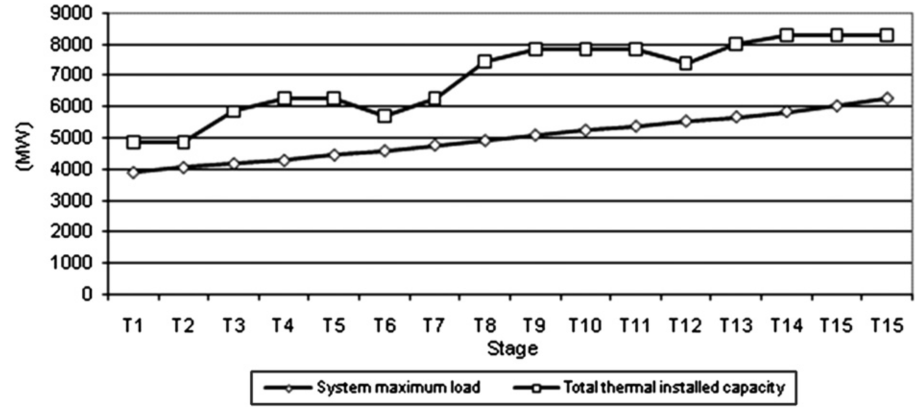

Fig. 15. Evolution of the yearly peak demand and of the total installed capacity in thermal stations.

as a reference value that can then be changed along the simulation as the time evolves. Using this price and the graphs illustrated in Fig. 6 for each technology, we estimate the corresponding capacity factor and using these factors and the installed capacity it is possible to compute the corresponding generations. These generation levels are added with the generation from hydro stations and Special Regime. This global generation is eventually corrected in order to internalize transmission losses as showed in the lower part of Fig. 11. This generation level is then combined with the demand in the Stocks and Flows diagram that models the electricity price evolution. Mathematically this is represented by expressions (21) and (22). Using Eq. (22) we compute a price mismatch for each period depending on the difference between the demand and the generation level. If the current demand level exceeds the total generation level computed above, the price mismatch is positive meaning that the price should be increased. Once this increased price is input again in the model of the thermal stations, the capacity factors will be increased as well as the corresponding generation. At the long-term, as the simulation evolves, we tend to an equilibrium between the demand and the generation and, at that point, the long-term simulation ends.

Finally, and looking once again to Fig. 11, it is important to notice that the demand is not fixed a priori but in fact it displays some dependency on the price. This is represented by a new loop in the diagram of Fig. 11 now located in the upper part of this figure. Mathematically this loop is modeled by Eqs. (19) and (20). Based on Eq. (19), we use a reference demand value set in the beginning of the whole simulation. This value is updated based on the annual demand in order to obtain a reference demand value for each year, $D_{\text{elec\_ref}}$. Finally, the demand in each year, D_{elec}, is obtained using $D_{\text{elec\_ref}}$ and the demand price elasticity E_{DP}.

6. Case study

We will now illustrate the approach detailed in previous sections using a Case Study that includes 3 GENCO's, five existing generation technologies and three candidate technologies. The developed approach was implemented in MATLAB, POWERSIM and Microsoft Excel, as follows. MATLAB was used to implement the investment problem of individual GENCO's, detailed in Section 4.2. This module uses GAs and MATLAB was also used to compute the value of LOLE in each year of the planning horizon. As mentioned above, POWERSIM was used to develop the long-term dynamic simulation of the electricity market. In this module we used the Runge-Kutta 4th order numerical integration method considering a fix integration step of 1 h. Finally, Microsoft Excel was used as an interface with the previous two modules, both to specify data and to receive results, prepare graphs and output tables.

The Case Study to be presented below was prepared taking the Portuguese generation system as the basis, namely given that the global values on the installed capacity and on the demand in 2009 were divided by 2. As a result, we were able to use several historic series of data available publicly. For instance, Fig. 5 illustrates the behavior of the capacity factor of wind parks. This evolution was obtained using historic data available from the Portuguese TSO (www.ren.pt) for which we estimated the average value. Then,

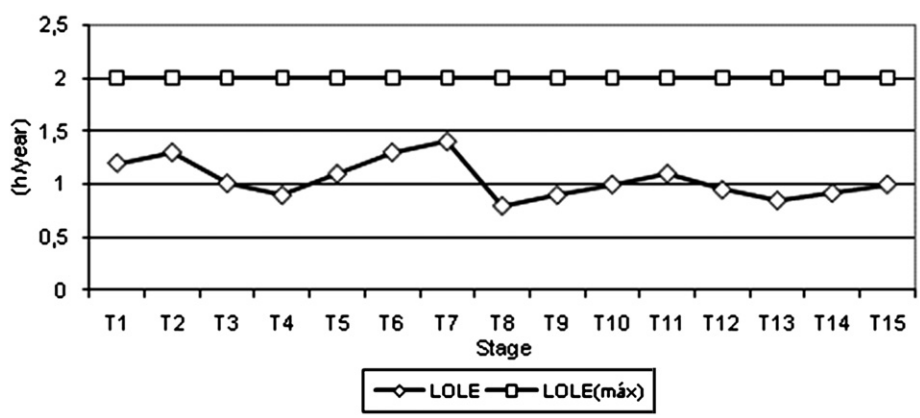

Fig. 16. Evolution of LOLE along the planning horizon.

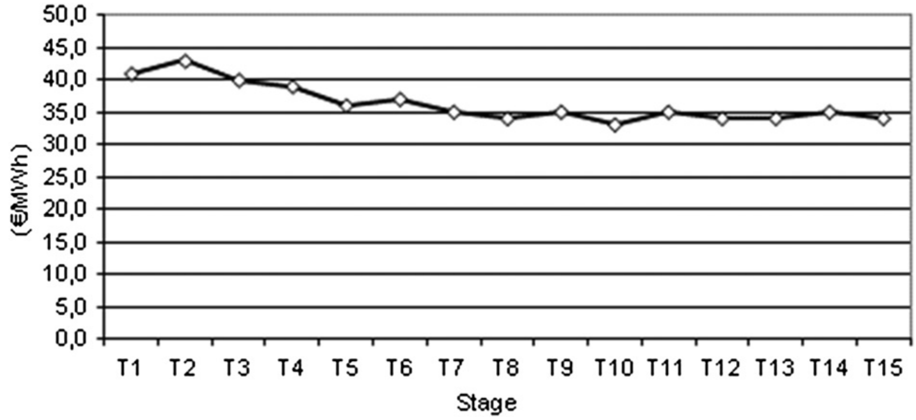

Fig. 17. Evolution of the electricity price along the planning horizon.

a stochastic process was used to obtain the evolution of the capacity factor as detailed in Section 4.4.2. Regarding the prices, we used historic series available in the Iberian Electricity Market (www.omel.es) namely for 2009. The demand in the initial year of the simulation was set at 25.150 GWh as indicated in Section 6.1, given that the yearly demand in Portugal corresponded to about 50.000 GWh in 2009.

6.1. Data and main assumptions

The existing generation system includes three GENCO's, five thermal generation technologies and a total of 6200 MW of installed capacity from which 4850 MW correspond to thermal stations. Table 1 details the characteristics of these five thermal technologies (Coal_1, Coal_2, Gas Turbines, Oil Turbines and CCGT) and it specifies the number of groups, the capacity of each group, the operation cost and the FOR. As indicated in Table 1, considering two types of coal stations allows us to specify different characteristics for each of them and, as a result of the simulation, to obtain different values for their capacity factors along the planning horizon.

The existing generation mix also includes stations using renewable resources, namely hydros and wind parks. Hydro stations were grouped in run-of-river (installed capacity of 300 MW) and reservoirs (450 MW). As for the coal stations, dividing hydro stations in two groups (run-of-river and reservoirs) allows representing the generation mix in a more realistic way and obtaining different values for the capacity factors of each group. Regarding the wind parks we admitted that the installed capacity prior to the expansion exercise is 600 MW.

Table 2 includes the composition of the generation mix of the three GENCO's. The share of these three GENCO's regarding the total installed capacity prior to the expansion simulation is as follows: GENCO_1 has 24.2%, GENCO_2 owns 21.8% and GENCO_3 owns 23.4%. The remaining 30.6% of the existing installed capacity is owned by other agents that we admitted were not interested in expanding their installed capacity. This means they were not considered as potential GENCO investors.

Regarding the demand, we considered that the peak annual power in the year prior to the simulation period was 3900 MW. Then, the annual demand duration curve was discretized in six steps. For each of these steps, we indicate below the power as a percentage of the annual peak power and the respective duration:

- 100% of the peak power (3900 MW) – 5% of the year;
- 90% of the peak power (3510 MW) – 20% of the year;
- 80% of the peak power (3120 MW) – 45% of the year;
- 70% of the peak power (2730 MW) – 65% of the year;
- 60% of the peak power (2340 MW) – 85% of the year;
- 50% of the peak power (1950 MW) – 100% of the year.

Considering this distribution of the annual peak power, we admitted that the total demand in the year prior to the planning period was 25.150 GWh. This yearly demand will evolve along the planning period according to the dynamic simulation (in particular using the model in Section 4.4.4) and we admitted that the duration of each of these six steps remains unchanged along the planning horizon. This means that using the value of the total annual demand outputted by the dynamic model for each year, it is then possible to obtain the annual peak power as well as the power associated to each of the remaining steps of the demand duration curve.

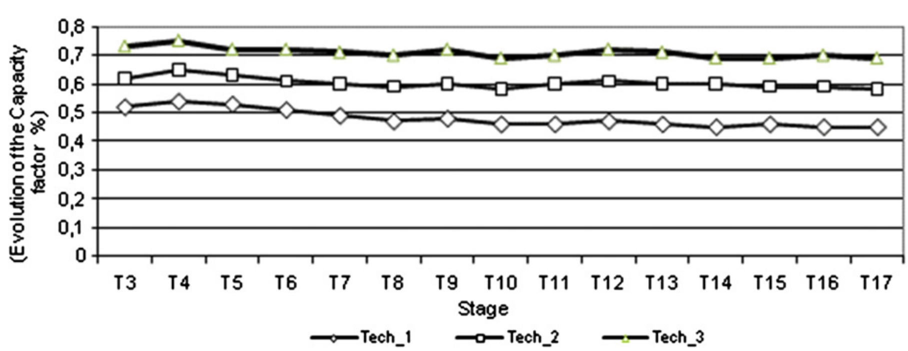

Fig. 18. Evolution of the capacity factors.

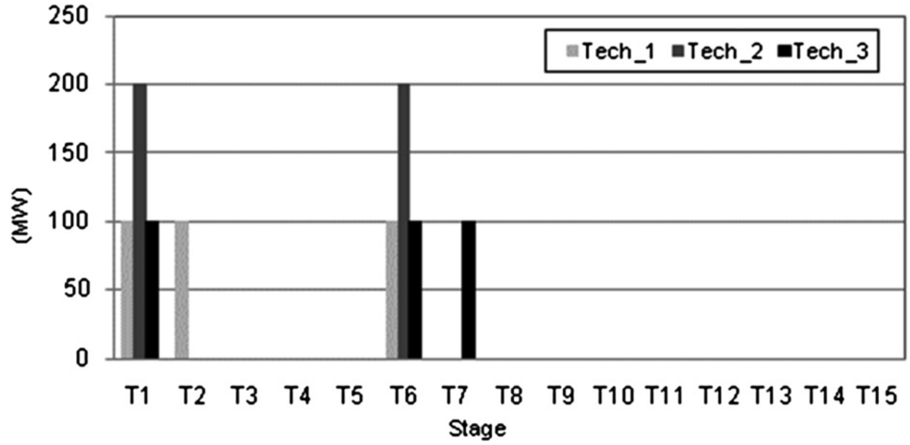

Fig. 19. Generation expansion plan for Genco_1 for the doubled hydro and wind park scenario.

Table 3 details the characteristics of the three candidate technologies, that is, the technologies among which the three GENCO's will select the groups to included in their expansion plans. These characteristics include the investment and operation costs, the available capacities that can be installed and the FOR. The construction period of the stations was set at 2 years and we admitted it is equal for the three candidates.

Table 4 details the values specified for a number of parameters used by the Dynamic Model detailed in Section 4. Apart from these parameters, the demand rate is modeled by a normal fdp distribution with mean 3% and sd of 1%. This allows running a stochastic process to obtain the evolution of this rate that will then be used by the model in Section 4.4.3. As indicated in Table 4, the elasticity of the demand to the electricity price was set at 0.25, a constant value along the 15 years in the planning horizon and the electricity price in the beginning of the simulation, p_0, was set at 40.0 €/MW h.

In the long-term simulation we also considered the following elements:

- GENCO_1 is interested in investing in the three candidate technologies. In the first set of 5 years of the horizon this agent has the amount of 500 M€ available to invest and during the remaining 10 years it has more 500 M€ available;
- GENCO_2 is not interested in investing in Tech_3 and the available capital is as follows: 350 M€ in the first 5 years, 350 M€ more from the 6th to the 10th year and finally 350 M€ more during the 5 last years of the horizon;
- GENCO_3 is interested in investing in the three candidate technologies and it has 400 M€ to invest during the first 5 years, 400 M€ from the 6th to the 10th year and finally 400 € in the last 5 years;
- on the other hand, the total installed capacity of each agent shall not exceed 40% of the total capacity in the generation system, the reserve margin in each year of the horizon should range from 20% to 40% and the maximum value of the LOLE was set at 2 h/year.

Given the characteristics of the exiting stations we specified a decommissioning plan. This information is relevant because it originates a reduction of the installed capacity that is considered by the Dynamic Model and it will impact on the electricity prices as indicated in the casual loop diagram of Fig. 4. This plan is as follows:

- in the 5th year of the horizon, 300 MW of coal type_1 and 250 MW of CCGT will be decommissioned;
- in the 10th year, all the capacity using oil (400 MW) will be decommissioned together with 200 MW of coal type_2 and 250 MW of gas turbines;
- finally, in the 15th year, 300 MW of coal type_1, 200 MW of hydro reservoirs and 200 MW of installed capacity in wind parks will be decommissioned.

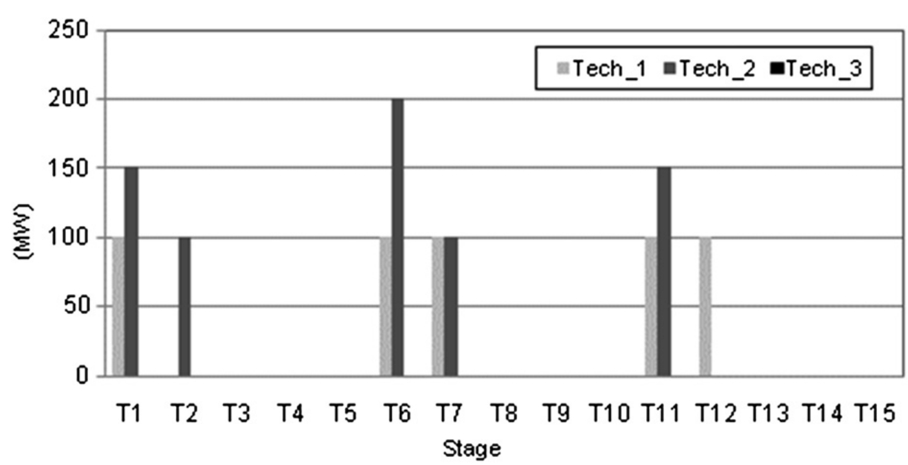

Fig. 20. Generation expansion plan for Genco_2 the doubled hydro and wind park scenario.

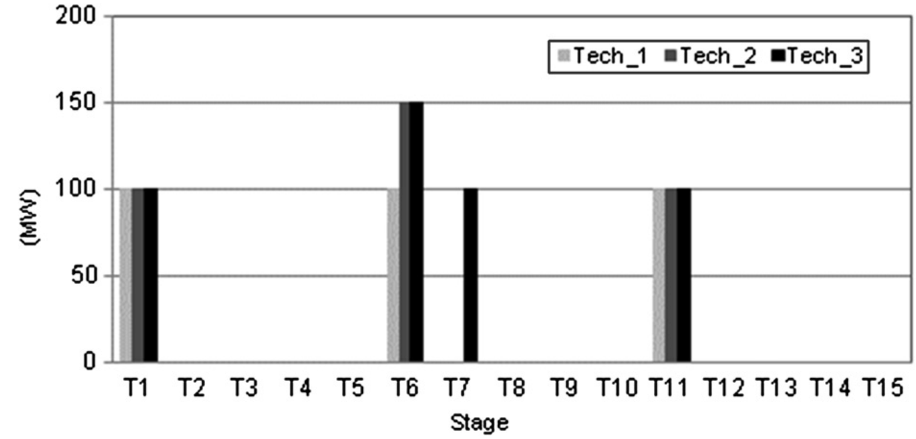

Fig. 21. Generation expansion plan for Genco_3 for the doubled hydro and wind park scenario.

Finally, we admitted that along the horizon there will be investments to expand the hydro and the wind capacity. These investments are not subjected to the expansion exercise given that we considered they were sufficiently attractive (due to the reduced marginal operation cost of hydro stations and the feed-in tariffs in force in several countries to remunerate renewable energies) that all GENCO's would be interested in these investments. Apart from that, governments usually open auctions to allocate hydro and wind capacities and so these investment decisions have a different rationale and the commissioning dates are not under the control of GENCO's, at least to a certain extent. As a result, we specified a commissioning plan both for the hydro stations and the wind parks. These entry dates are then considered by the long-term dynamic model in order to enlarge the installed capacity. This plan is as follows:

- 200 MW of new hydro reservoirs in the 4th year and 100 MW of run-of-river in the 8th year;
- regarding wind parks, 100 MW will be installed in the 2nd year, 100 MW in the 4th year, 150 MW in the 7th year, 100 MW in the 10th year and 150 MW in the 12th year.

6.2. Results

After running the developed algorithm, we obtained the investment plans detailed in Figs. 12–14 for GENCO's 1, 2 and 3. These results indicate that GENCO_1 wants to install 1200 MW of different technologies, GENCO_2 wants to install 1450 MW and the plan of GENCO_3 includes 1250 MW. After these investments, at the end of the 15 year horizon, the shares of the three candidate technologies will be as follows: Tech_1 with 34.61%, Tech_2 with 42.30% and Tech_3 with 23.09%. These results also indicate there is a concentration of investments in the beginning of each set of five years (that is, in years 1 and 2, 6 and 7 and 11 and 12) because when a new set of 5 years begin the three GENCO's have extra capital available to invest.

Fig. 15 shows the evolution of the yearly peak power along the 15 year horizon as well as the total installed capacity in thermal stations. The average rate obtained for the evolution of the demand was 3.12%/year. On the other hand, it should be noticed that in year 0, prior to the beginning of the planning horizon) the thermal installed capacity was 4850 MW and this value remains unchanged in years 1 and 2. Although in the plans in Figs. 12–14 there are new groups commissioned in year 1, these new stations will only start operation two years afterwards, that is, in year 3, given the 2 year construction period admitted for the three candidate technologies.

Fig. 16 presents the evolution of LOLE for each year of the planning horizon, together with the maximum specified value for this reliability index (2 h/year). This index displays several variations along the horizon reflecting the commissioning of new stations as well as the decommissioning of units according to the plan specified in Section 6.1. As shown in Figs. 12–14 there is a concentration of new stations starting operation in years 3, 8 and 13, given the years in which investment decisions are taken and the 2 years construction time that was specified. These increases in the installed capacity in

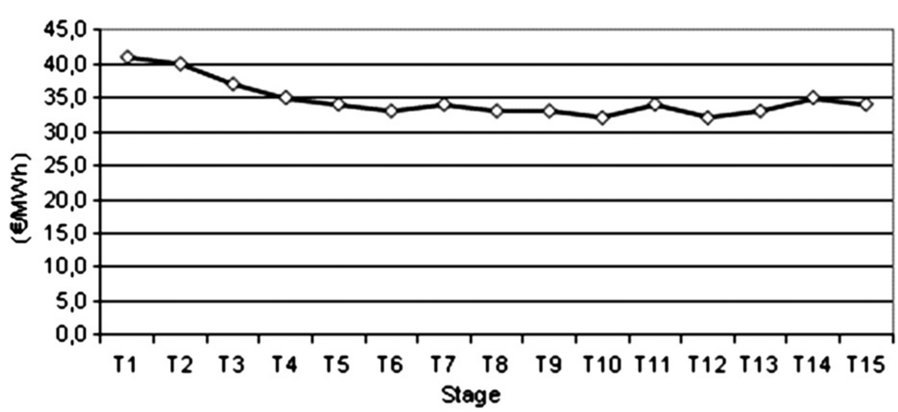

Fig. 22. Evolution of the electricity price along the planning horizon for the doubled hydro and wind park scenario.

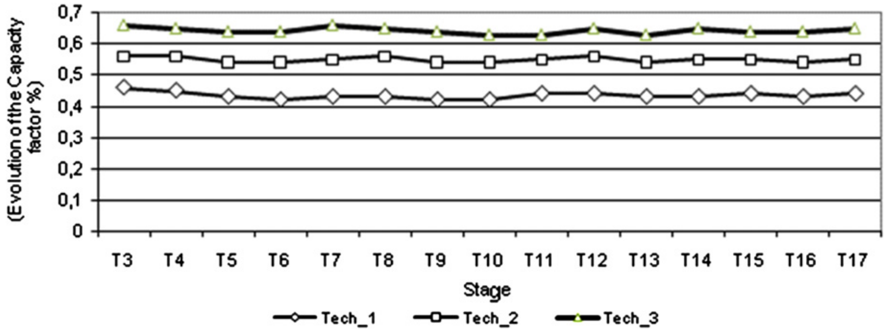

Fig. 23. Evolution of the capacity factors for the doubled hydro and wind park scenario.

years 3, 8 and 13 explain the decreases of the LOLE in these years and, in other words, the saw shape of the curve in Fig. 16.

The evolution of the average value of the electricity price along the planning horizon is shown in Fig. 17. This graph indicates that the electricity price rises in the two first years of the horizon since the new units commissioned in year 1 will only start operation in year 3. From year 3 onwards there is a gradual decrease of the average electricity price justified by the progressive entry of new stations.

Finally, Fig. 18 shows the evolution of the capacity factors of the three candidate technologies. The graphs in this figure show that the capacity factors tend to get reduced along the planning horizon. This is explained by the evolution of the demand, of the electricity price and mostly by the new injections coming both from hydro stations and from wind parks. In any case, Tech_3 displays the larger capacity factor namely because it has the most reduced operation cost, as indicated in Table 3. It is followed by Tech_2 and finally by Tech_1 that has the largest operation cost.

6.3. Sensitivity analysis

6.3.1. Doubling the installed capacities in hydro stations and in wind parks

The developed approach can be used in a fruitful way to conduct sensitivity studies, for instance to get the impact on the developed plans of changes on the investment or operation costs of the candidate technologies or to simulate a large penetration of hydro stations and wind parks. This type of studies will provide more insight about the expansion problem, will allow preparing more robust plans and will enable GENCO's to take more sounded decisions. As an illustration of this type of studies, we admitted that the installed capacity in hydro stations (both in reservoirs and in run-of-river stations) and in wind parks will double regarding the values specified in Section 6.1 and used in the Case Study detailed in Section 6.2. We admitted that the commissioning years are the same as indicated in Section 6.1. Figs. 19–21 present the expansion plans of the three GENCO's obtained in this situation.

Comparing these plans with the ones in Figs. 12–14 there is a reduction of the new installed capacity of Tech_1, 2 and 3. The new installed capacity of GENCO_1 is 1000 MW and was 1200 MW in the original exercise, regarding GENCO_2 the installed capacity gets reduced from 1450 MW to 1200 MW and for GENCO_3 the new capacity is reduced from 1250 MW to 1100 MW. These reductions are due to the larger share of energy injected by hydro stations and by wind parks that determine the reduction of the electricity market price. Fig. 22 shows the evolution of the average electricity price and comparing this graph with the one in Fig. 17 it is clear that this price got reduced. This doesn't mean that the final end user price gets reduced because we are admitting there are feed-in tariffs to pay the energy from wind parks. Finally, Fig. 23 shows the evolution of the capacity factors of Tech_1, Tech_2 and Tech_3. Comparing these graphs with the ones in Fig. 18 it is clear that the capacity factors got reduced due to the increased energy injected by hydro stations and by wind parks. In average, the capacity factors reduced by 10% in the three candidate technologies.

6.3.2. Initial demand increased by 10%

In this case, we admitted that the initial reference demand value D_{ref0} was increased by 10%, regarding the 25.150 GWh that was used in simulation reported in Section 6.2, that is, the initial value was increased to 27.665 GWh. Considering that all other input data are the same, Figs. 24 and 25 illustrate the results obtained in this case. Fig. 24 details the new investment plan for

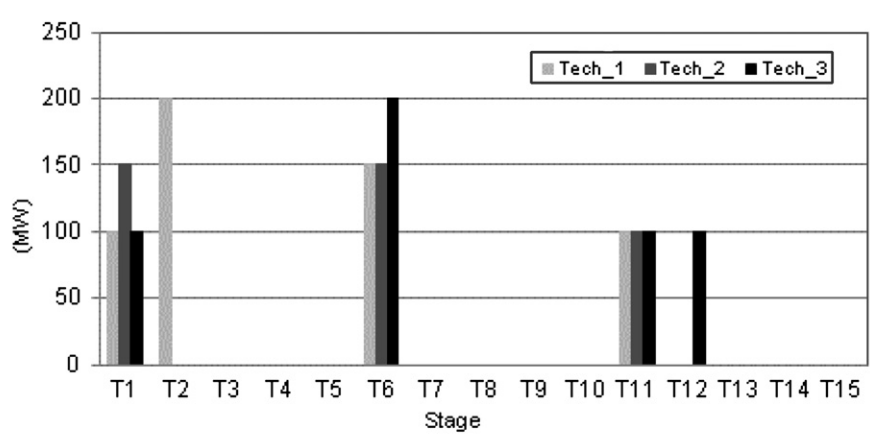

Fig. 24. Generation expansion plan for Genco_3, for the increase of the initial demand by 10%.

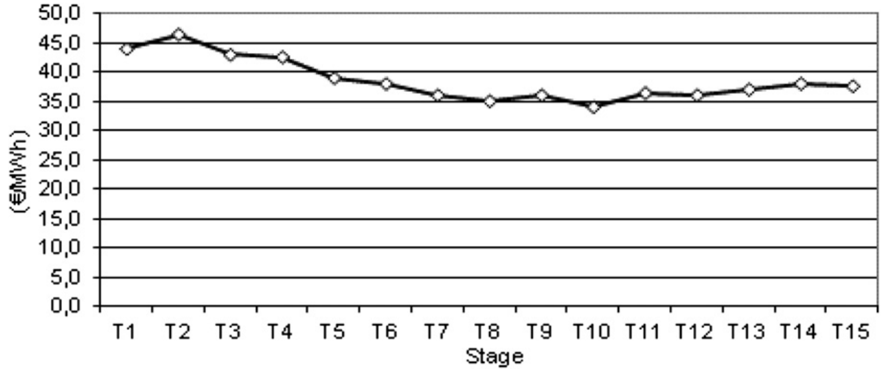

Fig. 25. Evolution of the electricity price along the planning horizon for the increase of the initial demand by 10%.

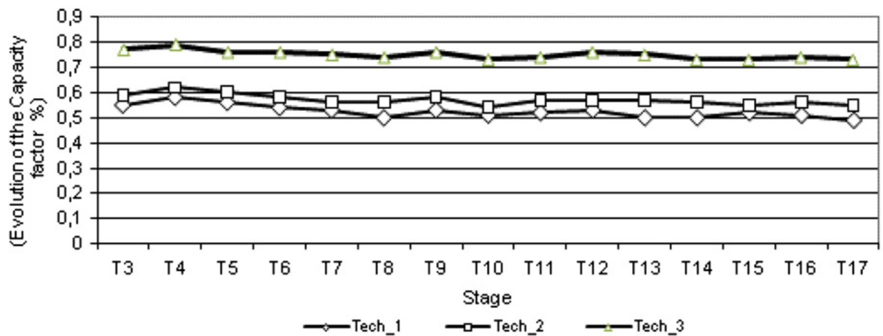

Fig. 26. Evolution of the capacity factors along the planning horizon for the increase of the operation cost of Tech_2 by 10%.

GENCO_3. Comparing this new plan with the one in Fig. 14, the installed capacity is increased by 200 MW. The investment plans of GENCO's 1 and 2 didn't change because the financial resources specified for these two GENCO's were already exhausted. Given that only GENCO_3 increased its installed capacity to face the increased demand, the capacity factors of all thermal technologies were increased. In average along the 15 year horizon, the capacity factor of Tech_1 increased from 0.48 to 0.51, of Tech_2 evolved from 0.60 to 0.65 and of Tech_3 from 0.70 to 0.73. As a result of the increased demand and of the more intensive use of thermal stations, the electricity price also increased. This evolution is now illustrated in Fig. 25. Regarding the original values reported in Section 6.2, the average electricity price increased by 6.33%.

6.3.3. Operation cost of Tech_2 increased by 10%

In this case, we increased the operation cost of Tech_2 by 10%. It should be noticed that Tech_2 was the candidate technology that was more intensively used in the investment plans designed in Section 6.2. As a result of this increase, the new investment plans include fewer stations using Tech_2 while Tech_1 is now the preferred one. Regarding the results in Section 6.2:

- Tech_1 passes from 34.61% to 49.33%;
- Tech_2 reduces from 42.30% to 26.66%;
- Tech_3 evolves from 23.09% to 24.01%.

On the other hand, Fig. 26 illustrates the evolution of the capacity factors for this case. Regarding the results in Section 6.2,

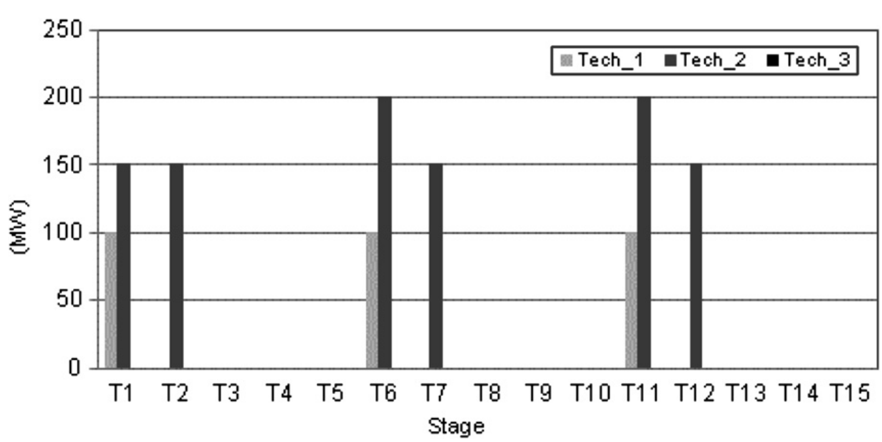

Fig. 27. Evolution of the generation expansion plan for GENCO_2 for the increase of the investment cost of Tech_1 by 20%.

the average capacity factor of Tech_3 remains the larger one (it increases from 0.70 to 0.74), the average capacity factor of Tech_1 increases from 0.48 to 0.52 and, finally, the average capacity factor of Tech_2 reduces from 0.60 to 0.57. This evolution translates the largest operation cost of Tech_2 determining its less intensive use and, on the contrary, the more intensive use of Tech_1 and Tech_3. As a result of this change, the average electricity price is increased by 1.22% regarding the results in Section 6.2.

6.3.4. Investment cost of Tech_1 increased by 20%

Finally, we simulated an increase of the investment cost of Tech_1 by 20%, that is from 500.000 to 600.000 €/MW. In this case, the global capacities to install by GENCO_1 and GENCO_3 remained almost unchanged while the investment plan designed by GENCO_2 changed regarding the results in Section 6.2. The new plan for GENCO_2 is shown in Fig. 27. Regarding the plan obtained in Section 6.2, this new one includes less 300 MW of Tech_1 and an increase of 150 MW of Tech_2. These results should be interpreted in view of that fact that we assumed that GENCO_2 was only interested in investing in technologies 1 and 2 as indicated in Section 6.1. This means that as the investment cost of Tech_1 got larger, GENCO_2 had less flexibility in adapting its investment plan, since Tech_3 was not an option and its financial resources were already used. Differently, GENCO's 1 and 3 didn't show any preference for any technology and so their options in terms of investment diversification were larger. As a result, their total installed capacities remained almost unchanged. Finally, as a result of the global reduction of the installed capacity by 200 MW, the capacity factors of the three thermal technologies suffered minor increases and the average electricity price got increased by 2.48%.

7. Conclusions

This paper presented an approach to help market agents to developed long-term generation investment plans. The developed approach integrates two main modules. The first one uses System Dynamics to characterize the long-term evolution of the capacity factors of the different generation technologies, of the electricity demand and of the market price. Then, using these results the second module solves the individual investment problems of the generation agents using GAs. The model also includes checking a number of global constraints designed to ensure the long-term ability of the generation system to supply the expected demand. This approach can be used in a fruitful way by generation companies in order to help them to develop their investment plans, considering possible investments of other competitors, and enabling getting more insight on this problem and taking more sounded and robust solutions. The possibility of conducting sensitivity studies as the ones described in the Case Study is just another value aided of this approach that can be very useful to investors. It can also be useful to regulatory or state agencies in order to characterize the possible evolution of the demand and of the electricity price and to study possible changes as for instance the impact of larger penetrations of renewable stations or the inclusion of a capacity term in the revenues of generation companies. As a whole, and given the larger uncertainties affecting our society, this kind of tools can play an increased role in the electricity sector.

Acknowledgment

The first author would like to thank Fundação para a Ciência e Tecnologia, FCT, that partially funded this research work through the PhD grant n° SFRH/BD/29243/2006.

References

[1] Pereira A, Saraiva JT. A decision support system for generation expansion planning in competitive electricity markets. Electric Power Systems Research 2010;80:778–87.
[2] Gorenstin BG, Campodonico NM, Costa JP, Pereira MV. Power system expansion planning under uncertainty. IEEE Transactions on Power Systems 1993;8:129–36.
[3] Hobbs BF. Optimization methods for electric utility resource planning. European Journal of Operational Research 2007;83:1–20.
[4] Vlahos K. Capacity planning in the electricity supply industry. PhD Thesis, London: London Business School, 1990.
[5] Sirikum J, Techanitisawad A, Kachitvichyanukul V. A new efficient GA-benders' decomposition method: for power generation expansion planning with emission controls. IEEE Transactions on Power Systems 2007;22:1092–100.
[6] Meza JC, Yildrim MB, Masud AS. A model for the multiperiod multiobjective power generation expansion planning. IEEE Transactions on Power Systems 2007;22:871–8.
[7] Antunes CH, Martins AG, Brito IS. A multiple objective mixed integer linear programming model for power generation expansion planning. Energy 2004;29:613–27.
[8] Park J-B, Park Y-M, Won J-R, Lee KY. An improved genetic algorithm for generation expansion planning. IEEE Transactions on Power Systems 2000;15:916–22.
[9] Wu F, Yen Z, Hou Y, Ni Y. Applications of AI Techniques to Generation Planning and Investment. In: Proceedings of the 2004 IEEE Power Engineering Society General Meeting, Denver, USA, June 2004.
[10] Zhu J, Chow M. A review of emerging techniques on generation expansion planning. IEEE Transactions on Power Systems 1997;12:1722–8.
[11] Yildirim M, Erkan K, Ozturk S. Power generation expansion planning with adaptive simulated annealing genetic algorithm. International Journal of Energy Research 2006;30:1188–99.
[12] Dyner I, Larsen ER. From planning to strategy in the electricity industry. Energy Policy 2001;29:1145–54.
[13] Zhang X. Investment in electricity generation and its determinants. Paris: University of Paris Sud; 2006. Working Paper, France.
[14] International Energy Agency. Power generation investment in electricity markets. International Energy Agency, OECD/IEA; 2003.
[15] Kannan S, Slochanal SR, Baskar S, Murugan P. Application and comparison of metaheuristic techniques to generation expansion planning in the partially deregulated environment. IET Generation Transmission Distribution 2007;1:111–8.
[16] Park J-B, Kim J-H, Lee KY. generation expansion planning in a competitive environment using a genetic algorithm. Proceedings of the 2002 IEEE PES Summer Meeting 2002;3:1169–72.
[17] Botterud A, Ilic M, Wangensteen I. Optimal investment in power generation under centralised and decentralised decision making. IEEE Transactions on Power Systems 2005;20:254–63.
[18] Forrester J. System Dynamics and the Lessons of 35 Years. In: De Greene KB, editor. The systemic basics of policy making in the 1990s. USA: Sloan School of Management, MIT; April 1991.
[19] Botterud A. Long-Term Planning in Restructured Power Systems. PhD Thesis. Trondheim, Norway: Norwegian University of Science and Technology; November 2003.
[20] Olsina F. Long-Term Dynamics of Liberalized Electricity Markets. PhD Thesis. San Juan, Argentina: Instituto de Energia Electrica, Universidad Nacional de San Juan, May 2005.
[21] Olsina F, Garces F, Haubrich H- J. Modelling long-term dynamics of electricity markets. Energy Policy 2006;34:1411–33.
[22] Kadoya T, Sasaki T, Ihara S, Larose E, Sanford M, Graham AK, et al. Utilizing system dynamics modelling to examine impact of deregulation on generation capacity growth. Proceeding of the IEEE 2005;93:2060–9.
[23] Sanchez JJ, Barquin J, Centeno E, Lopez-Pena A. System dynamics models for generation expansion planning in a competitive framework: oligopoly and market power representation. In: Proceedings of the 2007 System Dynamics Conference of the System Dynamics Society, Boston, USA, July/August 2007.
[24] Jalal TS, Bodger P. The development of a system dynamics model to evaluate generation expansion in New Zealand. In: Proceedings of AUPEC 2010, Australasian Universities Power Engineering Conference, Christchurch, New Zealand, December 2010.
[25] Ford A. System dynamics and the electric power industry. System Dynamics Review 1997;13:57–85.
[26] Powersim Software AS. Powersim 2.5 user's guide and reference manual. Powersim Press; 1996.
[27] Powersim Software AS. Powersim Studio 7 academic. Bergen, Norway: Powersim Software AS; 2006.
[28] Ministry of Economy and Innovation, "Decree-Law n° 29/2006 of February 15th", Law on the Electricity Sector, Portugal, 15th February 2006.
[29] Dixit A, Pindyck R. Investment under uncertainty. Princeton: Princeton University Press; 1994.

[30] Kirshen DS, Strbac G, Cumperayot P, Mendes DP. Factoring the elasticity of demand electricity prices. IEEE Transactions on Power Systems 2000;15:612–7.
[31] Patrick RH, Wolak FA. Estimating the customer-level demand under real-time market prices. Cambridge, USA: Bureau of Economic Research; 2001. Working Paper no 8213.
[32] Schotter A. Microeconomics: a modern approach. New York: Addison Wesley Series in Economics; 2001.
[33] Vogstad K. Stochasticity in electricity markets: combining system dynamics with financial economics. In: Proceedings of the 24th International Conference of the System Dynamics Society, Netherlands, July 2006.

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 Adjunct Professor. In July 2010 he concluded his Ph.D. at FEUP with a Thesis on long-term generation expansion planning using System Dynamics.

João Tomé Saraiva was born in Porto, Portugal in 1962. In 1987, 1993 and 2002 he got his MSc, PhD, 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.