STRATEGIC DECISION-MAKING OF FLEXIBLE INVESTMENTS UNDER UNCERTAINTIES IN LONG-TERM ELECTRICITY MARKETS

DANIEL ALBERTO RIOS FESTNER

Thesis submitted to the Polytechnic Faculty of the National University of Asunción, in partial fulfillments of the requirements for the degree of Master of Science in Electrical Engineering

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To Julia Carmen, Natalia, Fernando and Harald, an unusual but compelling group

A Julia Carmen, Natalia, Fernando y Harald, un grupo inusual pero convincente

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STRATEGIC DECISION-MAKING OF FLEXIBLE INVESTMENTS UNDER UNCERTAINTIES IN LONG-TERM ELECTRICITY MARKETS

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SUMMARY

In liberalized electricity markets, the investment postponement option is deemed to be decisive for understanding the addition of new generating capacity. Basically, it refers to the investors' chance to postpone projects for a period while waiting for the arrival of new and better information about the market evolution. When such development involves major uncertainties, the generation business becomes riskier, and the investors' "wait-and-see" behavior might limit the timely addition of new generation capacity. The literature provides solid empirical evidence about the occurrence of construction cycles in the deregulated electricity industry. However, the strategic flexibility inherent to defer investments in power plants has not been yet rigorously incorporated as an explicit input for investment signals in the revised long-term market models. Therefore, this paper proposes a new methodology to assess the long-term development of liberalized power markets based on a more realistic approach for valuing generation investments. The proposal is based on a stochastic dynamic market model, built upon a System Dynamics simulation approach. The model considers that the addition of new generation capacity is driven by the economic value of the strategic flexibility associated to defer investments under uncertainties. The value of the postponement option is quantified in monetary terms by means of Real Options analysis. Simulations explicitly confirm the cyclical behavior of the energy-only market in the long-run, as suggested by the empirical evidence found in the literature. Furthermore, the proposed method is used to test three regulatory schemes, implemented in order to dampen the arising construction cycles. Results show that, for ensuring the supply security in markets under huge uncertainties, investors would need complementary capacity incentives in order to deploy power generation investments in timely manner.

Key words: Generation, Real Options, Stochastic Simulation, Strategic Flexibility, System Dynamics.

MODELO DE TOMA DE DECISIONES BAJO INCERTIDUMBRE EN MERCADOS ELÉCTRICOS A LARGO PLAZO

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RESUMEN

En mercados de electricidad liberalizados, la opción de posponer inversiones se considera decisiva para entender la incorporación de nueva capacidad de generación. Básicamente, dicha opción se refiere a la posibilidad de que los inversores aplacen proyectos durante cierto tiempo mientras esperan la llegada de nueva y mejor información acerca de la evolución del mercado. Cuando tal desarrollo involucra grandes incertidumbres, el negocio de generación se vuelve más riesgoso, y el comporamiento de "esperar y ver" de los inversores puede limitar la adición oportuna de nueva capacidad de generación. La literatura proporciona evidencia empírica sólida sobre la ocurrencia de ciclos de construcción en la industria desregulada de electricidad. No obstante, la flexibilidad estratégica inherente a posponer inversiones en centrales eléctricas aún no ha sido rigurosamente incorporada como una entrada explícita de las señales de inversión en los modelos de mercado de largo plazo revisados. Por lo tanto, este trabajo propone una nueva metodología con el objetivo de evaluar el desarrollo a largo plazo de los mercados eléctricos liberalizados en base a un enfoque más realista para valorar inversiones en generación. La propuesta se basa en un modelo de mercado dinámico y estocástico, elaborado mediante el enfoque de simulación Dinámica de Sistemas. El modelo considera que la adición de nueva capacidad de generación está impulsada por el valor económico de la flexibilidad estratégica asociada a diferir inversiones bajo incertidumbre. El valor de la opción de posponer se cuantifica en términos monetarios mediante el análisis de las Opciones Reales. Las simulaciones confirman de forma explícita el comportamiento cíclico del mercado de energía a largo plazo, como lo sugiere la evidencia empírica encontrada en la literatura. Además, el método propuesto se utiliza para estudiar tres medidas regulatorias, aplicadas con el objetivo de amortiguar los ciclos resultantes. Los resultados muestran que, para asegurar la seguridad del suministro en mercados bajo grandes incertidumbres, los inversionistas necesitarían incentivos de capacidad complementarios para desplegar inversiones en centrales de generación de manera oportuna.

Palabras claves: Dinámica de Sistemas, Flexibilidad Estratégica, Generación, Opciones Reales, Simulación Estocástica.

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LIST OF ACRONYMS & ABBREVIATIONS

AUE	Annual-average Unitary Expenditure.
CCGT	Combined Cycle Gas Turbine.
CLD	Causal Loop Diagram.
CT	Construction Time
CVaR	Conditional Value at Risk.
DDE	Delay Differential Equation.
DPE	Dynamic Programming based on the Expected value.
DT	Decision Time
EUR	Euro.
FACTS	Flexible Alternative Current Transmission System.
FO	Financial Options
GAST	Gas Turbine.
GW	Gigawatt.
HACO	Hard Coal.
IEA	International Energy Agency.

IRR	Internal Revenuel Rate.
LDC	Load Duration Curve.
LGR	Load Growth Rate.
LOLP	Lost of Load Probability.
MW	Megawatt.
MWh	Megawatt-hour.
NPV	Net Present Value.
PDC	Price Duration Curve.
PDE	Partial Differential Equation.
PI	Profitability Index.
RO	Real Options.
RSME	Root Square Mean Error.
SD	System Dynamics.
TRM	Target Reserve Margin.
VaR	Value at Risk.
VOLL	Value of Lost Load.
WACC	Weighted Average Cost of Capital.

I INTRODUCTION

In the last three decades, the evolution towards liberalization of electricity markets has pursued the main objective of improving the economic efficiency of the supply side (IEA, 2003). The deregulation has been founded on strictly market mechanisms, which has led to the unbundling of the industry and the introduction of competition, mainly, in the generation segment. Despite many positive outcomes, the cumulated experience after the first stage of reforms has also raised concerns regarding the market attributes that needed to ensure the capacity adequacy (*e.g.* Rudnick *et al.*, 2005; Arango *et al.*, 2006; Joskow, 2006). At first, this seems counterintuitive, since *the theory of spot pricing*, upon which the deregulation is based, ideally provides sufficient investment incentives in the long run (Caramanis, 1982). However, it has been reported repeatedly since the beginning of the 1990s (*e.g.* Bunn and Larsen, 1992; Bunn and Larsen, 1994) that the liberalized power industry is instead prone to suffer *construction cycles*[1].

Many efforts have been put in order to understand the origins of this situation. One of the most accepted explanations poses that the theoretical models that have supported the deregulation rely on assumptions absent in real power markets, such as perfect competition, risk neutrality and full rational behavior of market participants. Indeed, actual markets are likely to deviate from ideal conditions, exhibiting imperfections such as information asymmetry, risk aversion, herding behavior and bounded rational expectations. Moreover, investors in power plants have the possibility of behaving strategically in order to collect extraordinary profits, being prone to exercise market

[1] This term refers to the fluctuating development that the capacity is perceived to have exhibited after being deregulated, due to the sequential episodes of over and under-investment.

power or to be unresponsive to straight market signals. In that sense, integrating the logic behind the strategic decision-making of new generating capacity has become vital when assessing the long-term market development.

A comprehensive literature compilation that suggests the appearance of cycles in the construction of investor-owned power plants has been proposed by Arango and Larsen (2011). Such work presents empirical evidence gathered from over 20 years of reforms in electriciy markets, with England and Wales, and Chile giving the most exemplary cases. The article explains that the unstable market behavior leads to periods with low reserve margins, mainly affecting the demand side in terms of high prices and recurrent shortages. However, in times of excess of capacity, generation companies are likely to endure substantial economic losses, and potential bankruptcy. Therefore, the cyclical investment pattern is deemed to pose major concerns for policymakers when assessing the long-run development of the market, since it ultimately affects the security of supply (Roques, 2008).

Despite the abundance of empirical evidence, the literature still lacks a rigorous mathematical framework for describing, in theoretical terms, the cyclical behavior of liberalized power markets. Nevertheless, it is worth to acknowledge that significant modeling efforts have been done for assessing the long-run behavior of the industry (Ventosa *et al.*, 2005). Several works have focused on including some behavioral aspects of investors in long-term power market models. Notwithstanding, the methods proposed up to this day are based on simplifying the risk-averse profile that defines the investors' response, by adjusting their expectations upon profitability according to predefined patterns. Thus, it is deemed that the literature can be enhanced by including the behavioral nature driving the adequacy of capacity in current power markets.

In that context, this research work pursues the following general objective:

Formulate mathematically the investment decision-making process within liberalized electricity markets with the consideration of the flexibility of postponing new power plants under uncertainty.

Likewise, the following specific objectives are aimed to be accomplish:

- Integrate a valuation framework of flexible investments with a long-term dynamic model of a liberalized electricity market.
- Provide a rigorous mathematical formulation for explaining the occurrence of construction cycles in liberalized electricity markets.
- Analyze aditional capacity remuneration mechanisms for dampening the arising business cycles in order to improve the long-term market stability.

As mentioned previously, the liberalization of electricity markets has changed the scope of decision-making in new generating capacity. Under this paradigm, multiple self-oriented companies aim at maximizing their own profits, defining a market behavior that is dynamic in nature. Therefore, investors need to develop sufficient certainty about the recovery of vast capital costs before undertaking new power plants. In fact, it has been perceived that investors are prone to postpone investments while waiting for the arrival of new and better information about the uncertain market evolution. In that context, firms might constrain the entrance of new generating capacity even during upward movements of the market, because they expect more profitable conditions in the future. The investment execution will become attractive eventually but then, an excess of optimism might lead to a situation of over-capacity, where more power plants than needed are undertaken.

By following this reasoning, this research work hypothesizes that the cyclical behavior of the deregulated electricity industry originate because of the inclination of companies for postponing new power plants under uncertainties, jointly with the delay due to the construction time. In order to prove this hypothesis, a novel framework for describing the decision-making of generation investments is integrated with a power industry model, aiming to assess its long-term development. The proposed approach is suitable for capturing the strategic behavior of investors when making investment decisions, mainly because it includes the possibility of postponing new power plants in the definition of an optimal investment policy.

Taking into consideration the unpredictable effects of construction cycles, the long-term development of liberalized electricity markets involves a key topic of study. Thus, it is supposed that the lack of a mathematical explanation for the origins of such fluctuating behavior prevents market stakeholders of conducting more refined assessments of their activities.

More specifically, this situation concerns power firms considering investments in generating capacity. According to the rules of the deregulated industry, these firms are set to take advantage of any market context in order to maximize their own profits. In that sense, opportunities for seizing market upward movements, or to cut losses during unfavorable situations, are of a great value. Hence, the formal description of factors driving the long-term market behavior implies the potential of significant benefits for generating firms.

Appropriate models are equally crucial for regulatory authorities. The availability of a rigorous market modeling framework is essential to simulate the suitability of different designs and policies intended to ensure the market stability and the security of supply in the long term. During the last years, this issue has been at the center of interest, since many countries have started to implement alternative mechanisms for remunerating the capacity, besides the energy-only market. This has aimed to promote a stable pace for the capacity expansion by reducing risks associated to the investment cycles in power generation.

The chapters at the thesis are organized as follows. Chapter 1 includes a state-of-the-art review about the subject under study. In accordance with such review, the scope of the research work is delimited specifically in Chapter 2. Then, in Chapter 3, the Real Options (RO) method for valuing flexible investments in the liberalized electricity industry is presented. Chapter 4 contains the mathematical formulation of the long-term dynamic market model adopted for this study; the description of uncertainties driving the market development; the investor's formation of expectations upon profitability, and the proposed decision-making framework based on RO analysis. Finally, results and key findings are analyzed in Chapter 5, including the base case simulations; sensitivity analyzes to test the robustness of the proposed framework; and the implementation of three regulatory schemes aiming to dampen the arising business cycles.

II STATE-OF-THE-ART REVIEW

Chapter 1
Power investment decision-making under uncertainty

1.1 Power investments in liberalized electricity markets

Two factors can be isolated in order to gain insights about the occurrence of construction cycles in the deregulated electricity industry. First, the decision to expand the system has decentralized to depend on multiple self-oriented, autonomous firms, who attempt to maximize solely their financial profits while managing risks. This defines a market behavior that is dynamic in nature, since it is determined by the actions of individual participants (de Vries and Heijnen, 2008). The second and most important factor indicates that the generation activity has become exposed to several risks, unforeseen in the former regulated industry. Such risks result from the internalization of numerous uncertainties that drive the development of the actual industry in the long run (IEA, 2003; Arango and Larsen, 2011).

The effects of these factors are multiplied by intrinsic features of generation investments. Some of these particularities are listed in the following (Olsina *et al.*, 2006):

- Capital-intensive: Investments in generating capacity involve large financial costs. In fact, power plants normally account for most of the capital expenditures inherent to the electricity industry.

- One-step: A significant proportion of the total financial costs must be committed before the power plant becomes operative.
- Long amortization periods: Several years are agreed so the incurred outlay can be paid off.
- Irreversibility: Power plants are unlikely to serve for other purposes if market conditions turn the generation activity unprofitable. Therefore, investments in generating capacity are considered *sunk costs*.

Given the characteristics of the competitive generation business, investors tend to be *risk-averse* when making investment decisions (Vázquez *et al.*, 2002). Generally, this rationale suggests that new generating units would be ordered only when large revenues are expected, and conversely decisions would be delayed if the estimated rents are insufficient. Hence, opportunities for investing in the generation sector are no longer of the *now-or-never* type since there is the possibility of waiting for future market conditions to be, at least partially, clarified. This opportunity incorporates one major attribute to the deregulated generation investments, termed *the postponement option* (Olsina *et al.*, 2006). It explains the investors' willingness to consider the flexibility of deferring new generation investment projects when facing uncertainties driving the evolution of key market variables (Blanco and Olsina, 2011).

1.2 Current development of long-term electricity market models

In the context of the present study, the model of a liberalized electricity market is used for gaining insights about the long-term evolution of its structural parameters, namely the installed capacity. Since the addition of new power plants now involves multiple, self-oriented companies, it is essential that the model incorporates the logic behind their autonomous decision-making.

Several modeling approaches are suitable for describing the long-run behavior of the deregulated industry, from a financial point of view (Sterman, 1991). In particular, it has been found that *simulation models* are appropriate for capturing actual behavioral features of investors in liberalized markets, such as bounded rationality, learning abilities, imperfect foresight, etc. (Ventosa *et al.*, 2005). In that context, *System Dynamics* (SD) is a modeling approach with a vast literature body regarding the development of simulation models of complex systems (Baum *et al.*, 2015). The SD-based approach focuses on identifying the feedback structure of a system, at a macroscopic level, and the logical interrelationships among its components. Then, it aims to deliver a dynamic response in the long term by solving the governing non-linear differential equations. A well-founded background on this subject is the work by Sterman (2000).

Generally, dynamic models are well-known for suggesting a volatile long-term behavior of the deregulated power sector. The situation is explained due to the inherently unstable interaction between the power exchange and the profitability expectation of investors. In order to gain insights about this complex interaction, SD provides a tool known as the Causal Loop Diagram (CLD), which helps in giving an initial perspective about the feedback structure of the system under analysis. Such perspective eventually allows to formulate the differential equations that must describe rigorously the long-term system dynamics.

The literature contains an example of the feedback structure that formalizes the process of capacity expansion in this study context by means of a CLD (Olsina *et al.*, 2006). Such diagram is included in Figure 1. Unlike in the centralized paradigm, here a delay representing the investors' decision-making under uncertainties is one of the factors preventing the timely adequacy of the installed capacity. This delay represents the Decision Time (DT) necessary for investors to develop enough certainty about the recovery of capital costs. Since investments in power plants are no longer of the *now-or-never* type, investors are then likely to wait for the arrival of new and better information before undertaking new investment projects.

With the advent of deregulation of the power industry, the decision-making of new generation investments has come to depend upon profitability expectations. In that

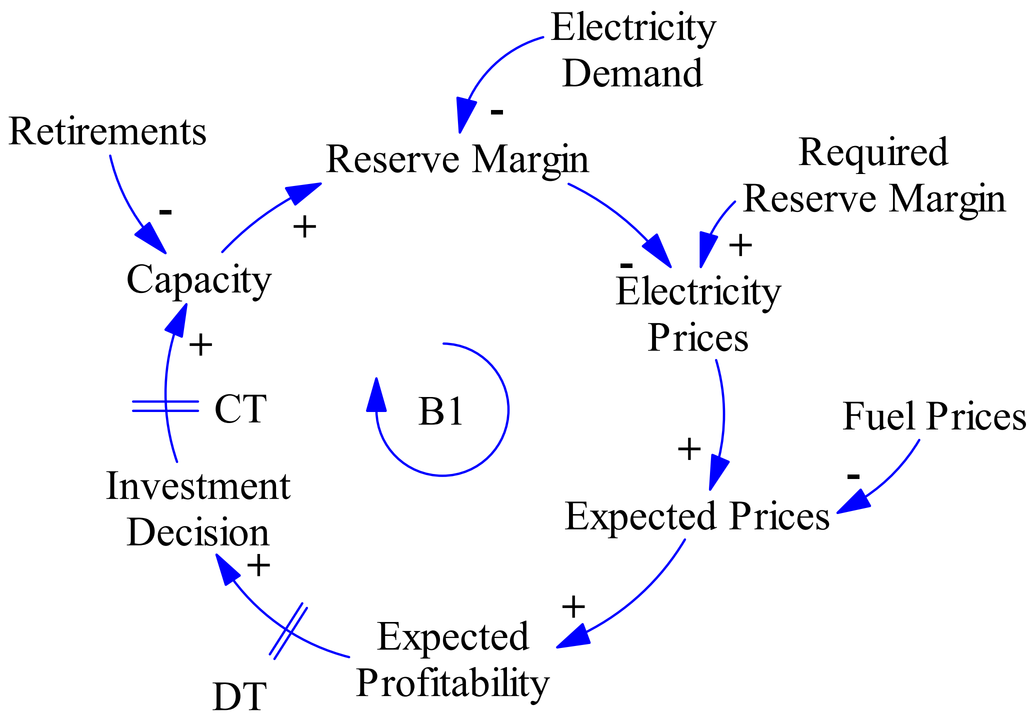

Figure 1: Causal Loop Diagram of the long-term dynamics of electricity markets according to the literature.

context, the prevailing market design has been the *energy-only market* (*e.g.* Bunn and Larsen, 1992; Bunn and Larsen, 1994; Kadoya *et al.*, 2005; Eager *et al.*, 2010; Pereira and Saraiva, 2011; Osorio and van Ackere, 2016; Movahednasab *et al.*, 2017). In addition, many works have discussed alternatives for the remuneration of generating capacity after acknowledging the existence of imperfections and flaws in real markets (*e.g.* Vázquez, *et al.*, 2002; Neuhoff and de Vries, 2004; Olsina, *et al.*, 2014). In that sense. most of the revised SD-based models have assessed the implementation of mechanisms such as the so-called *capacity payments* and *capacity markets* (*e.g.* Ford, 1999; Assili *et al.*, 2008; de Vries and Heijnen, 2008; Hasani and Hosseini, 2011; Pereira and Saraiva, 2013; Hary *et al.*, 2016; Ibanez-Lopez *et al.*, 2017)

According to the literature, an additional capacity remuneration mechanism can be either fixed or dynamic. Also, it can be classified as a price-based or quantity-based mechanism (Olsina *et al.*, 2014). An example of a price-based dynamic remuneration is the mechanism introduced in England and Wales between 1990 and 2001. Under this scheme, generators received a marginal clearing price in addition to a price uplift given by the probability of capacity shortfall, equal to the Loss of Load Probability (LOLP), times the electricity scarcity price, given by the Value of Lost Load (VOLL) (Olsina *et al.*, 2014).

A quantity-based method for remunerating the generators involves the *capacity market*. Here, an obligation of installed capacity is computed in advance, and it equals a peak demand forecast plus a target reserve margin. Suppliers make bids of existing and new capacity, juxtaposed to the conventional energy-only market, in order to reach that obligation. Then, the price set by the capacity market clearing is used to derive an additional remuneration for investors. This design is now operative in France and in Great-Britain (Hary *et al.*, 2016).

1.3 Valuing generation investments under uncertainties

Despite the general agreement on the investment dynamics, the prevailing modeling design still assumes a risk-neutral profile for investors. Therefore, so far only a few long-term models have characterized the risk-aversion of investors when deciding the addition of new capacity. Some examples incorporate an Internal Rate of Return (IRR) delayed by a fixed investment time, which denotes the time necessary for developing enough certainty about the project feasibility (*e.g.* Olsina *et al.*, 2006; Olsina and Garcés, 2008). In the work by Sánchez *et al.* (2008), the profitability of new power plants is based on a minimum rate of return, which represents the cost of debt incurred by the generating company, and is obtained by applying concepts of credit-risk theory. Other works focus on adjusting the investor's previous risk-neutral expectations. For instance, the model presented by Eager *et al.* (2012), includes the Value at Risk (VaR) in the definition of project profitability. Moreover, the paper by Abani *et al.* (2016), expands the previous concept by including the Conditional Value at Risk (CVaR) for correcting a risk-neutral Net Present Value (NPV) of new power plants. Finally, Petitet (2016), and Petitet *et al.* (2017), propose a concave utility function for representing the value of the project under a risk-aversion assumption.

The revised methods are mainly based on adjusting the profitability expectations in order to account for the risk-averse response of investors. Despite the efforts, it is deemed that the literature can be improved in order to describe further behavioral features governing the capacity adequacy in actual power markets. In fact, empirical evidence suggests that investors are likely to defer new projects under uncertainties about future rents and market conditions (Arango and Larsen, 2011). This implies that the value of strategic flexibility for seizing opportunities and cutting losses contingent upon market evolution is, at least intuitively, accounted for (Blanco and Olsina, 2011). In that sense, strategic flexibility involves a risk management technique, suitable for coping with major market uncertainties in order to achieve a timely investment execution.

The quantification of the strategic flexibility of an investment is strongly associated to the concept of Real Options (RO). RO analysis provides a well-founded background for valuing flexible investments under uncertainty, based on the theory of Financial Options (FO). In that context, the value of options embedded in investments in real assets can be computed by means of stochastic dynamic programming (Trigeorgis, 1996).

Unlike the traditional NPV approach, the RO method allows to seize the possibility of extraordinary profits, inherent to these high-risk projects. For this purpose, the available options are used for limiting the potential losses; while the possibility of high profits remains open. Therefore, the value given by the strategic flexibility is the key concept in the RO appraisal, since it is always positive and it adds significant value to the project. The availability of these options will generally impact on the actual decision-making process, and consequently, must be fairly quantified (Olafsson, 2003).

According to the literature review presented by Martinez-Ceseña *et al.* (2013), many articles have dealt with the RO-based financial valuation of generation projects. Notwithstanding, the revised works have assessed investment portfolios in such segment uniquely from the point of view of a single investor. It is deemed that the literature body should be expanded in order to propose a RO-based framework for valuing investments in power plants from a systemic point of view of the long-term market development.

It has been found that the use of RO analysis for assessing transmission investments has assumed a more general perspective of the electricity industry. For instance, the work by Blanco *et al.* (2011) proposes a technique based on stochastic simulation and Least-Square Monte Carlo for valuing the option of deferring transmission lines while gaining flexibility by investing in FACTS devices. Inspired by this concept, Konstantelos and Strbac (2015) assess the potential of additional flexible network and non-network technologies for creating valuable interim measures within a long-term planning strategy. Further articles focus on evaluating specific real options. The work by Pringles *et al.* (2015b) expands the work by Blanco *et al.* (2011) by proposing an approach for properly valuing the deferral option of a merchant transmission project. Moreover, the flexibility inherent to the option to defer, the option to expand and compound options, is appraised by Pringles *et al.* (2015a). Finally, the social benefit for a network planner given by the option to defer some transmission investments are studied by Henao *et al.* (2017).

III METHODOLOGY

Chapter 2
Scope of the thesis

It has been verified that System Dynamics (SD) simulation approach (Sterman, 2000) has been used widely during the last decade for addressing the problem of describing the long-term development of electricity markets, though recently is regaining interest among researchers (Leopold, 2015; Ahmad *et al.*, 2016; Rios *et al.*, 2016). The appealing of SD models relies on their usefulness for representing the logical interactions among market components that ultimately govern its long-term dynamical response.

In that sense, this research work is based on the dynamics of a competitive generation system formulated by Olsina *et al.* (2006). This is due such work is well-recognized for describing a rigorous feedback structure of the capacity expansion process as a result of generators' expectations upon profitability. However, this thesis is different as it focuses on modeling the microeconomics of investors' decision-making process. Here, it is considered that the construction of new power plants is a function of the strategic flexibility under uncertainties given by the postponement option. Thus, the RO valuation approach is used to derive an optimal investment policy. The integration of a mathematical decision-making framework that accounts for the strategic flexibility under uncertainties of power investments within a long-term power market model is the main contribution of this work.

This research takes into account only the option to postpone new investments in power plants. Basically, this option refers to an owner's right to defer the project execution while waiting for upcoming (though never complete) information about the market evolution. The proposed approach is designed to provide the profitability of both, immediately undertaking the investment, and postponing in order to wait for more favorable market conditions. In other words, the decision of new investments will be determined continuously by comparing the attractiveness of investing inmediately or in the future. This contribution aims to characterize the dynamics of capacity adequacy in a more realistic manner, and finally yield insights about the actual market evolution.

Likewise, this thesis is limited to study a generating system composed entirely of thermal units. Despite the mainstream academic discussion currently involves the transition towards renewables, here it is argued that fossil fuels will prevail as the world's primary energy source, even in the long run. In fact, as exposed by Covert *et al.* (2016), the International Energy Agency (IEA) estimates that fossil fuels will supply 79% of the global energy still in 2040, if strong policies regarding carbon emissions are not implemented (IEA, 2015). As far as electricity generation is concerned, the same organization also projects that in 2035, 55% of the total electricity generated will be produced from fossil fuels, thereby firmly establishing their dominance in the energy mix.

Despite the great potential, the aforementioned considerations imply that the transition towards renewable technologies will be rather slow, for instance, in emerging countries. Thus, accelerating their penetration will require an external impetus, absent until now in a grand scale (Toth, 2012). In this sense, and principally for less developed economies, the assessment of fossil-fuel-based investments remains especially important as conditions do not allow for costly sudden transitions. For instance, abrupt increases in the cost of energy may make it even more difficult for some developing countries to satisfy the energy needs of their populations (Toth, 2012).

In that context, the scope of this research work is delimited to yield insights about the factors driving the market with the prevailing energy mix. Consequently, work delving on the effects of large-scale energy transitions or the accomplishment of low-carbon policies is foreseen in further projects. In that sense, it is deemed that the availability of a RO-based investment decision-making model, in the context of a SD-based long-term electricity market model, will be very valuable for studying the transition of a system towards a low-carbon generation mix.

Chapter 3
Valuing flexible investments with Real Options

In this chapter, the reasoning behind the Real Options (RO) approach for valuing flexible investments in power markets is introduced. This chapter closely follows key outlines of the RO method presented by Blanco and Olsina (2011).

3.1 Traditional investment valuation approach

3.1.1 The Net Present Value (NPV)

Traditionally, the assessment of financial feasibility has been delimited to compute the NPV of investment projects. The idea behind the NPV is straightforward. It is based on comparing the present-equivalent of the future cash flows to be generated by the project once undertaken, with the investments costs incurred today. Mathematically, this is described by:

$$\boldsymbol{NPV} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \left[\frac{\boldsymbol{CF_i}}{\prod_{\boldsymbol{j=1}}^{\boldsymbol{i}} (\boldsymbol{1+k_j})} \right] \quad \boldsymbol{I} = \boldsymbol{PV} \quad \boldsymbol{I} \tag{1}$$

where $\boldsymbol{CF_i}$ denotes the cash flows to be generated in year $\boldsymbol{i}$ within the valuation horizon $\boldsymbol{N}$; and $\boldsymbol{I}$ represents the investments costs incurred in year 0. The discount rate $\boldsymbol{k}$ is the cost of capital for the company making the investment. This rate represents the project's hurdle rate, *i.e.*, the minimum acceptable rate of return in exchange of funding the project. It is worth to mention that the discount rate may vary during the valuation horizon, as reflected by the subscript $\boldsymbol{j}$. An investment is considered to be acceptable if the NPV is positive, that means, if the discounted cash flow exceeds the investment costs. Otherwise, *i.e.* the NPV equals zero or is negative, the project should be disregarded.

3.1.2 Flaws and drawbacks of the NPV

Key underlying assumptions of the NPV method might undermine its usefulness for the financial valuation of a project. For instance, the rule poses a *now-or-never* investment opportunity. This means that the only option available at the beginning is to execute the investment, or not. If the decision-maker does not execute the investment then, it will not be possible to execute it at any other year within the valuation horizon (Dixit and Pindyck, 1994). Hence, the decision-maker is confined to a fixed operating strategy.

Even though some projects satisfy this hypothesis, not all do. This is crucial for investments in the power industry, which are characterized for including a huge component of irreversibility. In practice, decision-makers appreciate the ability to adapt their investment strategies in response to undesired events that may occur within the power market. Consequently, a major drawback when applying the NPV approach is that strategic options, which are embedded into most of power investments, are simply overlooked.

3.2 Valuing investments under uncertainty and risk

3.2.1 Uncertainty and risk in the creation of worth

Generally, the evolution of some variables involved in the valuation process is essential for the project returns to accrue worth. If these variables unfold with uncertainty, the project value would develop a certain level of risk.

On one hand, as exposed by Blanco and Olsina (2011), uncertainty is the randomness of the external environment. Investors cannot influence on its level, and must take it as an input to the investment decision-making process. Several factors determine the level of exposure of a project to uncertainty, but mainly it depends on the firm's business line, the cost structure and the nature of the market.

On the other hand, risk derives from the possibility of key market variables evolving with uncertainty. Risk can be strictly associated to the probability of receiving a different return of investment than expected. Therefore, risk involves not only negative results, *i.e.* returns that are lower than expected (downside risk), but also positive results, *i.e.* returns that are higher than expected (upside risk) (Blanco and Olsina, 2011).

From the traditional point of view, under large uncertainties, the project value is low. However, if they are actively and strategically managed, great uncertainties may even increase the asset value. This possibility involves the use of risk management tools, which allow including the proper description of sources of uncertainty, and consequently the quantification of the risk inherent to a project, within the decision-making process. Ultimately, this would permit investors to flexibly respond to uncertainty developments and define an optimal investment policy.

By means of using the aforementioned risk management tools, decision-makers would be able to create an opportunity of huge gain, necessary to compensate for the hazards incurred when entering the business. For this purpose, they should be able to identify and seize the strategic options embedded into their investment projects.

3.2.2 Uncertainty and risk in power generation investments

Some sources of uncertainty incumbent to investors that determine the evolution of electricity markets are listed in the following (Olsina *et al.*, 2006; Blanco and Olsina, 2011):

- Electricity demand: It is given by the variability in energy consumption along time. It can be attached to the demographical and macroeconomic development of each country.
- Generating costs: They can be tightly correlated with fuel prices. They are determined by a significant volatility present in actual fuel markets.
- Long-term prices expectations: They depend on the prevailing balance of supply and demand, and the imperfect foresight of investors.
- Technological innovation: The potential arrival of more efficient generating technologies represents a relevant threat for the firm's positioning within the market
- Regulatory: It represents the non-random uncertainty of periodical policy adjustment and regulatory intervention, given the particular context of each country or region.

3.3 Option analysis applied to power generation investments

The core concept behind RO analysis is to quantify the value generated by the intrinsic flexibility embedded into an investment project, and thereby provide a precise foundation for making strategic investment decisions (Brosch, 2001). In that sense, strategic flexibility involves the inherent asymmetry between gains and losses in the expected outcome of a project. The conventional (inflexible) NPV approach is then expanded by the RO notion, by means of adding the value associated to the flexibility inherent to an investment project (Olafsson, 2003):

$$\boldsymbol{Flexible\ NPV = Traditional\ NPV + Value\ of\ Flexibility} \qquad (2)$$

The value of flexibility is the key concept in the RO approach. Since it is always positive, its quantification allows increasing the value of the project. Therefore, the availability of strategic options will generally impact on the actual decision-making process, and consequently must be fairly quantified.

3.3.1 Financial Options (FO)

The RO appraisal is founded on the theory of Financial Options (FO). In general, an option is the right but not the obligation, to make a particular decision in the future. This, a financial option might also be understood as a bilateral contract by which a party pays a sum of money to another in order to acquire the right (option) to conduct a transaction (purchase or sale) or claim a specific sum of money in the future.

In this context, a financial option enables the owner to buy or sell an asset at a specified price on or before a certain date in the future. The amount agreed is called the *strike* or *exercise price*, and the date on or before which the option can be exercised is termed *maturity*. As referred by Blanco and Olsina (2011), FO are a particular type of financial assets named derivative securities. Thus, the value of the derivative is contingent upon the value of a primary asset, known as the *underlying asset*.

Basically, there exist two types of FO. On one hand, an option to buy (call option) entitles the holder to acquire an asset at a specified price on or before a certain date in the future. On the other hand, an option to sell (put option) implies the possibility to trade an asset at a specified price on or before a certain date. The holder of an option is deemed to assume a *long-position* in an option contract, while the issuer takes a *short-position*. The seller (the short-position) is obliged to buy or sell the asset (underlying) at the exercise price to or from the owner of the right (the long position), who aims to take advantage of her position.

Unlike the conventional strategy that involves buying assets directly (i.e. taking long-position in the underlying), the investor might be willing to defer the investment and purchase the right to buy the asset later (*i.e.* taking long-position in the call option), in response to the unfolding of market uncertainties. Thus, the holder of the option pays a premium to the call issuer, which represents the cost of the risk assumed by the seller for taking the short-position (Olafsson, 2003).

The profitability of a long-position in an asset is determined by the incurred costs of capital. If the asset value rises above the purchase price, there will be gain, and conversely if it falls below the purchase price, there will be loss. Hence, the expected returns vary linearly, both upward and downward, alongside with the asset value.

The rent profile of a long position in a call option is different. By ignoring the incurred premium, it can be described by the following expression (Blanco and Olsina, 2011):

$$\boldsymbol{Gain} = \mathbf{max}(\boldsymbol{S} \quad \boldsymbol{X}, \mathbf{0}) \tag{3}$$

In Eq. (3), $\boldsymbol{S}$ is the value of the underlying, while $\boldsymbol{X}$ denotes the exercise price. The difference between both values is termed the *intrinsic value* of the purchase option. In this case, the potential gains are also unbounded: an increase in the asset value leads to a linear increase in the option intrinsic value. Nevertheless, the profitability of a long position in a call option is limited underneath only by the loss equal to the premium paid for it.

3.3.2 Real Options

The RO approach applies the theory of FO in the decision-making of capital projects. Thus, the key issue is to use the available options in order to define a lower limit to potential losses while the opportunity of extraordinary profits remains open. The RO method allows strategically managing a portfolio which includes the underlying project together with all available options. As mentioned by Blanco and Olsina (2011), RO according to Copeland and Antikarov (2003), can be disaggregated into:

- Postponement option: It represents the right of an owner to postpone an investment for a period of time. In exchange, he rejects the cash flows that would be generated, if the project is executed immediately. From a financial point of view, it can be interpreted as a call option.

- Abandonment option: It allows suspending activities and selling off the assets that comprised the initial project. It is comparable to a put option with a strike price equal to the scrap value of the investment.
- Expansion or Growth option: It permits expanding production capacity and/or accelerating the use of available resources, if the market conditions that develop after the original investment is executed, are more favorable than expected. This option is equivalent to a call option.
- Reduction or Contraction option: It involves the opportunity of reducing the size of operations if conditions are unfavorable. Financially, it can be seen as a put option.
- Extension or Pre-cancellation option: It is the possibility to extend or reduce the lifespan of an asset or the term of a contract. The extension option is similar to a call option while the chance of reducing is equivalent to the put type.
- Switch option: It allows using the same assets and inputs to produce different products. Furthermore, it is also available if there is the possibility to change the primary inputs without altering the final product. These options can be interpreted as a financial portfolio with both call and put options.
- Closing and Re-opening option: It provides the opportunity to stop or restart the operation of the project according to market conditions. The possibility to restart operations is equal to a call option. Stopping operations is alike a put option.

3.4 Real Options valuation methods

According to Blanco and Olsina (2011), different methods were developed to value FO. However, their suitability for assessing RO is subject to the particularities of each problem. In that sense, three general solution methods can be classified. Such methods are presented in detail in the following.

3.4.1 Stochastic differential equations

The first method seeks for solving a Partial Differential Equation (PDE) in order to provide the option value as a direct function of model inputs. Formally, the PDE describes the dynamics of the option value under specific conditions. The Black-Scholes's equation represents a well-known analytic formulation of this solution (Black and Scholes, 1973).

This method involves many solution tools, while algorithms are quite fast. However, the computational complexity increases with the addition of sources of uncertainty. Furthermore, it usually works as a *black-box*, hampering the analysis of contingent decisions.

3.4.2 Stochastic dynamic programming

Dynamic programming is another useful approach to deal with dynamic optimization problems under uncertainty (Dixit and Pindyck, 1994). This method separates the whole decision sequence into two components: the immediate decision and the subsequent decisions deriving from it, which consequences are encapsulated by a valuation function. A renowned example is given by the binomial lattice method, introduced by Cox *et al.* (1979).

Such method allows analyzing a large number of applications of RO. Also, it is practical because it resembles the analysis of a discounted cash flow. Therefore, this model permits to develop a good picture of the problem so the decision can be easily traced. Nevertheless, the binomial lattice relies on strong assumptions. The most important include a perfect financial market, and a constant, short-term risk-free discount rate throughout the valuation period.

Another technique involves the stochastic Dynamic Programming based on the expected Present value (DPE) (Blanco *et al.*, 2012). It allows properly coping with problems associated to the implementation of binomial trees, *i.e.* expected returns with supernormal volatilities.

3.4.3 Stochastic simulation model

In this case, several potential paths of the underlying asset evolution from current date to the moment of decision-making are taken into account. A popular method for simulating these paths is given by the Monte Carlo technique. At the maturity, the optimal investment sequence for each realization can be obtained, and thus the probability distribution of expected returns can be computed.

Monte Carlo simulations are suitable for handling various aspects of real world applications, allows direct processing of all types of assets, whatever the number and stochastic behavior of uncertainties. In addition, the inclusion of new sources of uncertainty is much simpler in comparison with other models. As a drawback, it requires a huge computation effort (Blanco *et al.*, 2011).

Chapter 4
Decision-making of flexible investments under uncertainties within long-term electricity market models

4.1 Model overview

Figure 2 shows the Causal Loop Diagram (CLD) that explains the feedback structure governing the long-term market development under the proposed decision-making framework. Such diagram expands the CLD presented in Figure 1. First, investors assess the prevailing market prices, based on the current state of installed capacity, electricity demand and fuel prices, in order to estimate the profitability of undertaking new generation projects immediately, *i.e.* the *exercise value* (loop B1). At the same time, investors develop expectations upon future market prices, based on a stochastic sample denoting the potential upcoming values of the same market parameters. By means of Real Options (RO) analysis, these expectations are used to compute the *continuation value*, that is, the project value if the decision is to postpone its execution, waiting for more profitable conditions (loop B2). An investment *profitability index* is then obtained from the ratio between the exercise value and the continuation value. Such ratio determines the commissioning of new power plants, which come online, however, only after a given Construction Time (CT). Finally, a new state of installed capacity is defined by the existing capacity, the addition of new investments and the decommissioning of old power plants that have accomplished their lifetime.

The model by Olsina *et al.* (2006) is used to assess the implementation of the proposed investment valuation framework, since it is recognized for providing a comprehensive

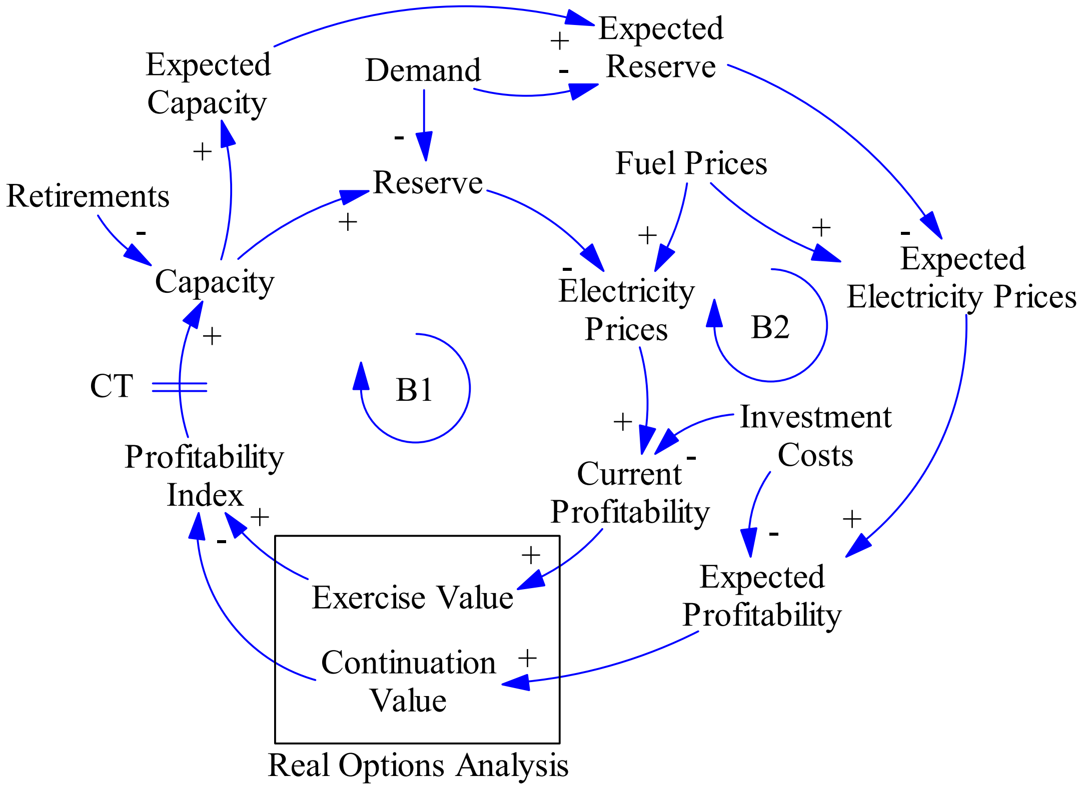

Figure 2: Causal Loop Diagram of the long-term dynamics of electricity markets with the proposed decision-making framework.

mathematical formulation of the long-term dynamics of liberalized electricity markets. The literature already contains examples of articles inspired by such work (Assili *et al.*, 2008; Olsina and Garcés, 2008; Hasani and Hosseini, 2011). Here, main outlines of the market model are included. For a deeper understanding, it is suggested to review the literature.

4.2 Simulation of the long-term power market dynamics

4.2.1 Modeling the development of generating capacity

The generating system is composed of three technologies: base (Hard Coal - HACO), middle (Gas-Fired Combined Cycles - CCGT) and peak (Gas Turbines - GAST). The capacity is distributed for each technology in five vintages, n_v, following a modeling approach proper of System Dynamics theory, known as the *aging chain*. This aims to describe the development of the age structure of generating units comprising the system, according to the progress of their thermal efficiency. Now, the capacity of technology i at each time t is described through an accumulation resulting from the rate at which new capacity enters its first vintage, and the rate at which old capacity abandons its last vintage, denoted by $K_{i1}^{in}(t)$ and $K_{i5}^{out}(t)$, respectively. Formally, this accumulation is represented by the following integral equation:

$$K_i(t) = \int_0^t \left(K_{i1}^{in}(\tau) - K_{i5}^{out}(\tau) \right) d\tau + K_i(0) \tag{4}$$

Here, $K_i(0)$ is the initial capacity of technology i; $K_{i1}^{in}(t)$ represents the rate at which power plants are being brought online; and $K_{i5}^{out}(t)$ is the decommissioning rate, which depends on the average technology lifetime. If Eq. (4) is differentiated by time, the net change in capacity for technology i at any time is expressed as:

$$K_i(t) = K_{i1}^{in}(t) - K_{i5}^{out}(t) \tag{5}$$

It is deemed that $K_{i1}^{in}(t)$ depends on the investment rate that prevailed at time $t - \bar{T}_i^C$, with $\bar{T}_i^C$ defining an average construction time for technology i. So, the investment rate at time $t - \bar{T}_i^C$, $I_i(t - \bar{T}_i^C)$, is computed as:

$$K_{i1}^{in}(t) = I_i(t - \bar{T}_i^C) = m_i\left(PI_i(t - \bar{T}_i^C)\right) \, I_i^{ref}(t - \bar{T}_i^C) \tag{6}$$

On one hand, $I_i^{ref}(t - \bar{T}_i^C)$ is the investment rate in technology i in the long-run equilibrium, which means, investments made under zero-profit expectations. It is expressed as the capacity decommissioning rate, $K_{i5}^{out}(t - \bar{T}_i^C)$, plus the addition rate necessary to cover the expected growth of maximum load served by such technology under an optimal generation mix, $L_i(t - \bar{T}_i^C)$:

$$I_i^{ref}(t \quad \bar{T}_i^C) = K_{i5}^{out}(t \quad \bar{T}_i^C) + L_i(t \quad \bar{T}_i^C) \tag{7}$$

On the other hand, the multiplier of the investment rate for technology i, $m_i\left(PI_i(t \quad \bar{T}_i^C)\right)$, depends upon profitability expectations formed at time $t \quad \bar{T}_i^C$. Taking into account the system's feedback structure, the expectation formation is based on the prevailing balance of supply and demand, jointly with fuel prices. Hence, the investment multiplier can be described as a function of the total capacity, demand and fuel prices at such time:

$$m_i\left(PI_i(t \quad \bar{T}_i^C)\right) = f_i\left(K_T(t \quad \bar{T}_i^C), L(t \quad \bar{T}_i^C), FP(t \quad \bar{T}_i^C)\right) \tag{8}$$

A logistic function is adopted for capturing the effect of the profitability index, PI_i, on the multiplier of the investment rate for each technology i, m_i. The three functions employed in the context of the present study, one for each technology, are displayed in Figure 3 (Olsina *et al.*, 2006). Such curves are obtained from the following expression:

$$m_i(t) = \frac{m_i^{max}}{1+e^{-(\alpha_i\, PI_i(t)+\beta_i)}} \tag{9}$$

where m_i^{max} is the saturation level; α_i controls the slope; and β_i determines the location of the function respect to the x-axis, for each technology i. The tipping point in every case is given when the corresponding profitability index equals one.

4.2.2 Modeling the development of thermal efficiency

It is supposed that the average thermal efficiency of the generating system evolves according to the efficiency progression and the development of capacity in each vintage. Then, the average thermal efficiency for vintage j of technology i at time t,

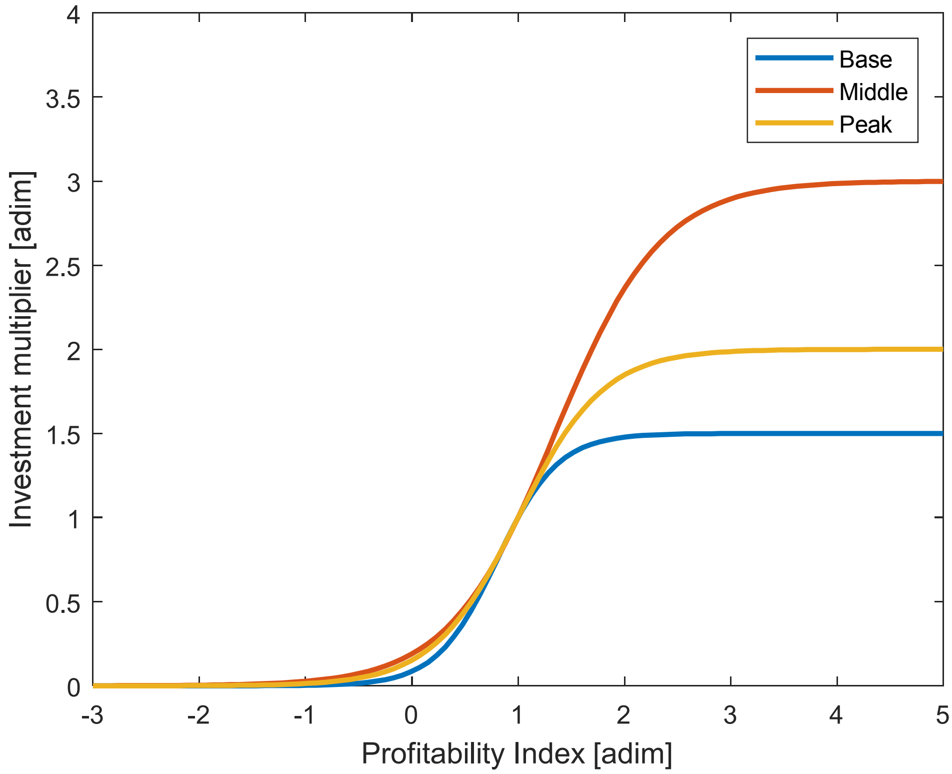

Figure 3: Investment multiplier as a function of the profitability index.

$\bar{\eta}_{ij}(t)$, results from the ratio between the accumulation of change in fuel consumption and the existing capacity. This is expressed as:

$$\frac{1}{\bar{\eta}_{ij}(t)} = \frac{1}{K_{ij}(t)} \int_0^t \left(\frac{K_{ij}^{in}(t)}{\eta_{ij}^{in}(t)} \quad \frac{K_{ij}^{out}(t)}{\eta_{ij}^{out}(t)} \right) dt + \frac{1}{\bar{\eta}_{ij}(0)} \tag{10}$$

where $K_{ij}^{in}(t)$ and $\eta_{ij}^{in}(t)$, and $K_{ij}^{out}(t)$ and $\eta_{ij}^{out}(t)$, represent, respectively, the rates and the efficiencies of the capacity entering and abandoning the vintage j of technology i at time t; while $K_{ij}(t)$ represents the existing capacity; and $\bar{\eta}_{ij}(0)$, accounts for the average initial efficiency. Finally, the average marginal cost of generation for the capacity of vintage j from technology i at time t, $\overline{MC}_{ij}(t)$, is formulated as:

$$\overline{MC}_{ij}(t) = \frac{FP_i(t)}{\bar{\eta}_{ij}(t)} \tag{11}$$

In Eq. (11), $FP_i(t)$ denotes the fuel price, and $\bar{\eta}_{ij}(t)$, the average thermal efficiency for vintage j of technology i at time t.

4.3 Simulation of investors' expectation formation upon profitability

4.3.1 Modeling expectations upon stochastic exogenous market variables

This thesis assumes that the market is driven exogenously by the demand and fuel prices. Alongside with the installed capacity and fuel consumption, the assessment of these variables is essential for investors when forming expectations upon profitability. In that sense, this model computes the current and the expected state of such variables at each step of the simulation horizon.

A deterministic growth pattern is assumed for describing the current state of demand and fuel prices. Therefore, the maximum and minimum demand, and the fuel price for technology i, at time t are formulated as:

$$L_{max}(t) = L_{max}(0) \quad e^{g_L\, t}; L_{min}(t) = L_{min}(0) \quad e^{g_L\, t} \tag{12}$$

$$FP_i(t) = FP_i(0) \quad e^{g_{FP_i}\, t} \tag{13}$$

Here, $L_{max}(0)$ and $L_{min}(0)$ refer to the initial maximum and minimum demand, while g_L represents the annual growth rate in the long run. Accordingly, $FP_i(0)$ denotes the initial fuel price for technology i, and g_{FP_i} is the annual rate driving its long-term evolution.

The expected state of system variables at any time is characterized by a stochastic evolution. In that sense, a mean-reverting stochastic process is prescribed for describing the uncertain path of growth rates under consideration. This implies a process where the uncertain variable evolves fluctuating around a known long-term mean. A common mean-reverting process, known as the arithmetic Ornstein-Uhlenbeck stochastic process, is given by:

$$dg = \eta(\bar{g} \quad g)dt + \sigma dz \tag{14}$$

Here, the expected change in a growth rate, dg, after a time increment, dt, depends upon the deviation from a long-run growth rate, $\bar{g}$, and a speed of the reversion towards the mean, η. It also depends upon a volatility parameter, σ, and a variable following a Wiener process, also known as Brownian Motion, dz. It can be shown that an infinitesimal increment of the Wiener process, dz, is represented in continuous time by:

$$dz = \varepsilon\sqrt{dt} \tag{15}$$

where ε is a normally distributed random variable with mean zero and standard deviation of 1, *i.e.* $\varepsilon = N(0,1)$.

In order to represent the market evolution in a more realistic way, the correlation between, in one hand, the growth rates of demand and total installed capacity, and on the other hand, prices of hard-coal and natural gas, is assumed. In that sense, the set of random variables $\varepsilon_n; n = 1,2, \ldots, N$ must be replaced by a set of correlated variables $\theta_n; n = 1,2, \ldots, N$. For computing the values of θ_n, the Cholesky decomposition is applied to the correlation matrix, B, of the corresponding growth rates (Huang, 2009; Pringles *et al.*, 2015b):

$$B = \begin{bmatrix} \beta_{11} & & \beta_{1N} \\ & & \\ \beta_{N1} & & \beta_{NN} \end{bmatrix} = AA^T \tag{16}$$

In Eq. (16), A is a lower triangular matrix with elements $\alpha_{ij}; i,j = 1,2,\dots,N$, and A^T is the transpose matrix of A. Then, the value of $\theta_n; n = 1,2,\dots,N$ is derived as the linear combination of A, and the vector of independent variables ε, which size is $N \times 1$:

$$\begin{bmatrix} \theta_1 \\ \\ \theta_N \end{bmatrix} = \begin{bmatrix} 1 & & 0 \\ & & \\ \alpha_{N1} & & 1 \end{bmatrix} \times \begin{bmatrix} \varepsilon_1 \\ \\ \varepsilon_N \end{bmatrix} \tag{17}$$

By writing Eq. (14) as a difference equation, Monte Carlo techniques can be applied for simulating multiple stochastic realizations of correlated growth rates. Finally, a realization r for the expected market parameters at time $T_e = t + dt$, is derived by:

$$L_{max}^r(T_e) = L_{max}(t) \quad e^{g_L^r\,dt}; L_{min}^r(T_e) = L_{min}(t) \quad e^{g_L^r\,dt} \tag{18}$$

$$K_I^r(T_e) = K_I(t) \quad e^{g_K^r\,dt} \tag{19}$$

$$FP_i^r(T_e) = FP_i(t) \quad e^{g_{FP_i}^r\,dt} \tag{20}$$

On one hand, $L_{max}^r(T_e)$ and $L_{min}^r(T_e)$ denote a realization of the expected maximum and minimum demand at time T_e, given a stochastic growth rate, g_L^r. Furthermore, a possible evolution of the total installed capacity is represented by $K_I^r(T_e)$, according to a correlated growth rate, g_K^r. In that context, $K_I(t)$ is the total capacity of the system at time t, which results from the dynamic model described in the previous subsection. On the other hand, $FP_i^r(T_e)$ illustrates a realization of the expected fuel price of technology i at time T_e, given a stochastic growth rate, $g_{FP_i}^r$. Similarly to the case of demand and installed capacity, the growth rates of prices for both technologies are correlated to each other.

The modeling approach presented here assumes that the aforementioned market variables are observable for each investor at any time t within the simulation horizon. Such parameters are therefore described by means of constant growth rates, aiming to characterize the development of the market in the long term. Notwithstanding, it is supposed that investors are equally concerned about the ongoing uncertainties that might divert the future growth rates from their average values. Thus, by using the observable values at each time, the proposed model allows computing a stochastic sample of future market variables. These parameters are employed in order to form each investor's expectations upon profitability at an expiration time $T_e = t + dt$. An example of the simulation of current (at time t) and expected (at time $T_e = t + dt$) values for the demand growth at any time is illustrated in Figure 4.

4.3.2 Modeling expectations upon operating profits

A price duration model, based on a probabilistic Price Duration Curve (PDC), is used for deriving the current and the expected short-term, infra-marginal revenue being perceived at each time by each technology, and thereby the market signals for decision-making of new power plants. In order to define the appropriate PDC for each case, the corresponding market variables, both at time t, and at time $T_e = t + dt$, are taken into account, by following the outlines exposed in the previous subsection.

Each PDC is computed schematically from a Load Duration Curve (LDC), jointly with an industry supply curve. An example of such definition is included in Figure 5. First, the LDC determines the annual probability for the system demand to equal or exceed a certain level between its maximum and minimum values. In that sense, it is assumed that the LDC accounts for a linear distribution, preserving such pattern over the entire simulation horizon. Second, the industry supply curve defines the costs of supplying to the different levels of system demand. This curve results from sorting the capacity available in each vintage of the system following an economic *dispatch merit order*, that is, according to their respective marginal cost of generation, from lower to higher. The availability of capacity for each vintage is computed by means of a probabilistic model, which accounts for the reliability of generating units, and the variability of electricity demand (Olsina *et al.*, 2006).

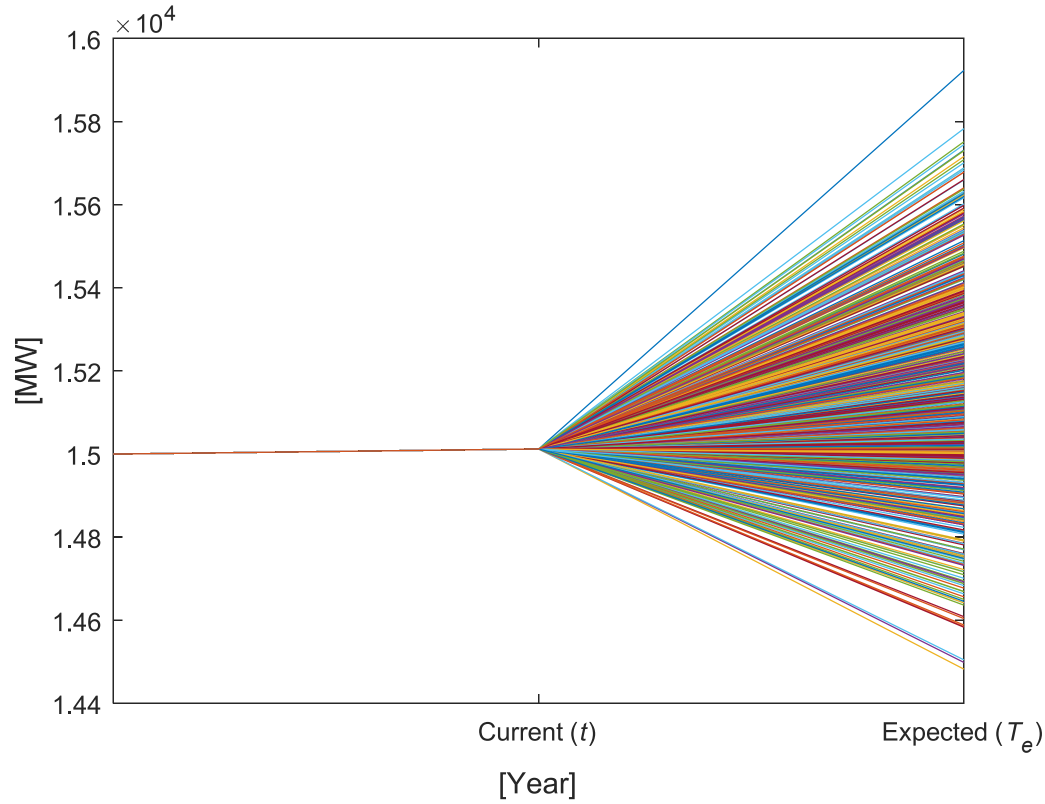

Figure 4: Simulation of current (at t) and expected (at T_e) demand growth at any time.

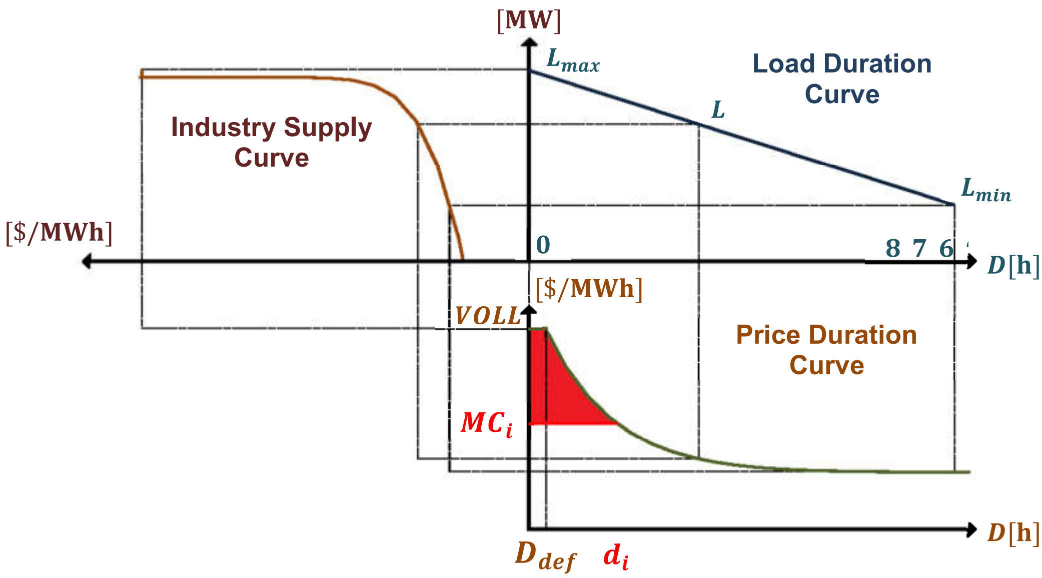

Figure 5: Example of the schematic definition of a Price Duration Curve (PDC).

Thus, the PDC yields (in the x-axis) the yearly probability, d_{ij}, for the capacity of vintage j from technology i to operate over its own marginal cost of generation (in the y-axis). These probabilities are computed as follows:

$$d_{ij} = \begin{cases} 1 & K_{ij}^{cum} < L_{min} \\ \frac{K_{ij}^{cum} - L_{max}}{L_{min} - L_{max}} & L_{min} \leq K_{ij}^{cum} \leq L_{max} \\ 0 & L_{max} < K_{ij}^{cum} \end{cases} \tag{21}$$

Here, K_{ij}^{cum} indicates the position of the cumulative available capacity of vintage j from technology i within the industry supply curve; while L_{max} and L_{min}, are the maximum and minimum load, respectively.

Generally, an annual equivalent of operating profits that a MW of capacity from technology i would make on the power market, denoted by π_i, is determined from the enclosed area between the PDC and the marginal generation cost for such technology, $\overline{MC_i}$ (the red area in Figure 5):

$$\pi_i = 8760 \quad \int_0^{d_i} [PDC \quad \overline{MC_i}] \, dD \tag{22}$$

where d_i, is the annual probability for the capacity of technology i to operate over its own marginal cost of generation.

The annual equivalent of operating profits includes the estimation of price-spikes revenues to be collected by online generators. This value is calculated as the yearly expected deficit duration, D_{def}, times the Value of Lost Load (VOLL):

$$\pi_{def} = 8760 \quad D_{def} \quad VOLL \tag{23}$$

Here, D_{def} is the approximate annual duration of load curtailment. This value is obtained from Eq. (21), accounting for the cumulative available capacity of the entire system. Moreover, 8760 represents the number of hours in a year, since $\overline{MC_i}$ in Eq. (22), and $VOLL$ in Eq. (23), are given by EUR[2]/MWh.

Assuming that the cash flows from the first year remain constant, the present value of the future stream of operating profits over the amortization period A_i for one MW from technology i, denoted by OP_i, can be approximated as:

$$OP_i = \pi_i \quad (1+\rho)^{-\bar{T}_i^C} \;\; \frac{1}{\rho} \;\; [1 \quad (1+\rho)^{-A_i}] \tag{24}$$

In Eq. (24), π_i is the annual equivalent of operating profits computed by technology i, in the first year of the amortization period, while ρ is assumed as the required revenue rate by which π_i must be discounted. Likewise, it is deemed that investors account for a time lag in the construction of new power plants. Consequently, π_i is also discounted by the average construction time for each technology, $\bar{T}_i^C$.

The approximation of future cash flows to be generated by the investment project can be interpreted as an efficient energy forward contract auction. In real markets, these auctions offer long-term contracts based on current price levels, aiming at reducing financial risks for newcomers in the generation activity (Moreno *et al.*, 2010).

4.4 Simulation of investors' decision-making under uncertainties

4.4.1 Computing a Profitability Index based on Real Options analysis

In this subsection, a new procedure for determining the addition of capacity based upon profitability expectations is detailed. For this purpose, a novel method elaborated

[2] EUR is the code for Euro, the official currency of the Eurozone, which is comprised by 19 of the 28 member states of the European Union.

upon the notion of RO analysis is proposed. This is the main contribution of this work, since it focuses on integrating a RO-based framework for valuing power plants under uncertainties within a long-term dynamic market model.

Rigorously, an optimal investment policy for each technology at each time can be derived by comparing the intrinsic value of immediately undertaking new generation projects with the value of keeping alive the postponement option. Backward Dynamic programming based on Expected Present value (DPE) is a suitable tool for performing this task (Blanco *et al.*, 2012). Moreover, it has been verified experimentally that the DPE allows avoiding problems related to applying other dynamic programming tools (*e.g.* the binomial lattice method), for instance, when dealing with highly-volatile future profits, as in this study case.

In that context, the exercise value for technology i, $V_i^{ex}(t)$, is defined by the Net Present Value (NPV) of new generation projects, according to the current state of the system at time t. This can be expressed as:

$$V_i^{ex}(t) = OP_i(t) \quad I_i(t) \tag{25}$$

where $OP_i(t)$ is the present value of cumulated operating profits perceived by technology i at time t; and $I_i(t)$ represents the capital outlay for bringing online a new generator of technology i at the same time.

On the other hand, an expiration time is used to represent the future threshold when the execution of the project must be reassessed, if the decision is to postpone it. At the expiration time, equal to $T_e = t + dt$, the decision problem for technology i can be therefore modeled as:

$$Exercise, if\ V_i(T_e) = \mathbb{E}[OP_i(T_e)] > I_i(T_e) \tag{26}$$

$$Do\ not\ exercise, if\ V_i(T_e) = \mathbb{E}[OP_i(T_e)] \leq I_i(T_e)$$

Thus, the optimal investment policy for technology i at time T_e, $V_i\ (T_e)$, can be defined as:

$$V_i\ (T_e) = max\left[\left(\mathbb{E}[OP_i(T_e)] \quad I_i(T_e)\right); 0\right] \tag{27}$$

On one hand, $\mathbb{E}[OP_i(T_e)]$ denotes the expected present value of cumulated operating profits for technology i at time T_e, which is obtained based on the stochastic sample of expected market conditions at such time. On the other hand, $I_i(T_e)$ represents the investment costs expected for the same technology at time T_e.

By considering only a single period, dt, between the current and the expiration time, the continuation value of the postponement option for technology i at time t, *i.e.* the project value if the decision is to postpone its execution, $V_i^{cont}(t)$, can be expressed as:

$$V_i^{cont}(t) = {V_i\ (T_e)} \Big/ {(1+q)^{dt}} \tag{28}$$

where q represents a risk-free discount rate. According to the implementation of the DPE method, this value is equal to a hurdle discount rate[3], which adjustment follows a non-neutral valuation of risk.

The optimal investment policy for technology i at each time t, $V_i\ (t)$, can be then derived from the following optimization problem (Blanco *et al.*, 2012):

$$V_i\ (t) = \max\left[\overbrace{OP_{T_{a,i}}(t) \quad I_i(t)}^{\text{Exercise Value}}; \quad \overbrace{{V_i\ (T_e)} \Big/ {(1+q)^{dt}}}^{\text{Continuation Value}}\right] \tag{29}$$

[3] The hurdle discount rate can be understood as the Weighted Average Cost of Capital (WACC) of investment projects.

As mentioned by Blanco *et al.* (2012), the relationship given by Eq. (29) allows extending the conventional NPV-based rule for characterizing the feasibility of new projects. In that sense, a new investment decision threshold can be defined as follows: "At time t, the decision-maker should not invest in a new project (and wait for reassessing it after a given period dt) unless the current NPV of the investment portfolio (the Exercise Value) is greater than the Continuation Value".

Accordingly, a new investment profitability index (PI) for technology i at time t can be defined as the ratio resulting from dividing the exercise value, $V_i^{ex}(t)$, by the continuation value, $V_i^{cont}(t)$:

$$PI_i(t) = {V_i^{ex}(t)}\Big/{V_i^{cont}(t)} \tag{30}$$

Finally, this profitability index is set to determine the addition of new investments within the dynamic model, which is adopted in order to analyze the long-term development of the liberalized electricity market.

4.4.2 Investor responsiveness under uncertainties

It is worth to notice that, under this new framework, the attractiveness of undertaking investments, as a function of the PI, can be described schematically, as in Figure 6 (Luehrman, 1998). Whenever the exercise value is positive and it exceeds the continuation value, the optimal strategy should be to invest now (Region 1). However, when the exercise value does not exceed the continuation value, the investor would be cautious about the market's uncertain conditions and would probably reconsider to invest later (Region 2).

It is intuitive to assume that the project appraisal will be much more pessimistic whenever its instant NPV is negative. In that context, it is natural for each generator to withhold investments until new information about the market evolution arrives (Region 3). Moreover, when the exercise value is negative, and its absolute exceeds the continuation value, there would be no incentives to invest whatsoever (Region 4). In this case, the investor could even consider switching of business.

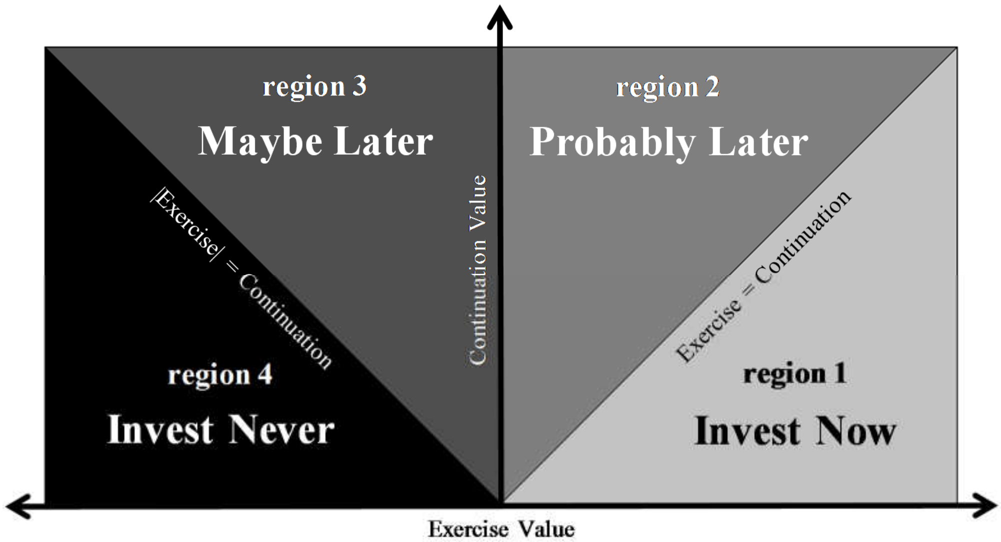

Figure 6: Investment decision regions in the Exercise-Continuation Value plane.

IV RESULTS & DISCUSSION

Chapter 5
Simulation analysis

5.1 System data and initial conditions

Simulations were carried out in order to apply the proposed framework. Information about the generation test system is included in Table 1. Likewise, Table 2 shows parameters of the logistic function that describe the effect of the profitability index on the multiplier of the investment rate for each technology. Now, the initial system installed capacity sums 16.47 GW, while the optimal technology mix indicates 69.6% for HACO; 18.7% for CCGT; and 11.7% for GAST, with a reserve margin of 9.78%[4]. The Delay Differential Equations (DDE) defining the system dynamics were solved by means of MATLAB's *dde23* function. The simulation period extends for over 20 years.

Electricity demand is characterized by an initial peak of 15 GW; an initial minimum of 10 GW; and a long-run growth rate of 1%/year. At the initial time, fuel prices are 6.50 EUR/MWh and 10.50 EUR/MWh, for hard coal and natural gas, respectively. It is assumed that both prices evolve following an average growth rate of 0.02%/year (Frydenberg *et al.*, 2014). In addition, parameters for describing the stochastic development of these variables are presented in Table 3.

[4] The study case is inspired by Olsina *et al.* (2006).

Table 1: Input data for the generation test system.

Technology	HACO	CCGT	GAST
Capacity [MW]	11460	3080	1930
Construction delay [month]	36	18	9
Lifetime [year]	40	30	20
Amortization period [year]	25	20	15
Investment costs [EUR/kW]	1000	600	300
Fuel costs [EUR/MWh]	6.50	10.50	10.50
Discount rate [%/year]	12.5	12.5	12.5

Table 2: Parameters of the logistic function for the multiplier of the investment rate for each technology.

Parameter	HACO	CCGT	GAST
Saturation, m_i^{max}	1.50	3.00	2.00
Alpha, α_i	3.50	2.00	2.50
Beta, β_i	-2.8069	-2.6932	-2.500

Table 3: Parameters to characterize the stochastic growth rates of maximum and minimum demand ($\boldsymbol{g_L}$), total installed capacity ($\boldsymbol{g_K}$), fuel price of hard-coal ($\boldsymbol{g_{FP,coal}}$) and fuel price of natural gas ($\boldsymbol{g_{FP,gas}}$).

Parameter	$\boldsymbol{g_L}$	$\boldsymbol{g_K}$	$\boldsymbol{g_{FP,coal}}$	$\boldsymbol{g_{FP,gas}}$
Initial growth rate [%/year]	1.00	1.00	0.02	0.02
Long-term growth rate [%/year]	1.00	1.00	0.02	0.02
Speed of reversion [%/year]	50.0	50.0	50.0	50.0
Volatility [%/year]	2.00	2.00	1.85	3.95
Correlation [dmnl]	0.80	0.80	0.71	0.71

The number of Monte Carlo realizations is 50,000, in order to satisfy convergence criteria in the statistical estimation of the expected value of future profits.

The RO investment valuation model considers European options with an expiration time, dt, equal to one year for each technology. Likewise, a hurdle discount rate equal to 12.5%/year is adopted for each technology. This value indicates a risk-free discount rate, adjusted following a non-neutral valuation. Finally, the Value of Lost Load (VOLL) is set to 1000 EUR/MWh.

5.2 Base case simulation

In Figure 7, the simulation of evolution of installed capacity and reserve margin in the test system is plotted, jointly with the expected value of peak demand. Results are relevant because it is observed that the proposed investment valuation approach allows reproducing explicitly the construction cycles that have occurred in several electricity markets after the liberalization (Arango and Larsen, 2011). This is explained due to the more refined characterization of investors' decision-making under uncertainties, in addition to the embedded construction delays for new power plants of each technology.

The system response is described as follows. Given the zero-profit conditions at the beginning of simulations, *i.e.* long-run market equilibrium, the continuation value outweighs the exercise value of power plants for each technology. Thus, generators find more attractive to withhold new projects because they have the possibility to invest later and collect extraordinary profits associated to situations of supply deficit (Region 2 and Region 3 in Figure 6). This leads to a dramatic reduction of reserve margins during the first years, just after the liberalization of the electricity market. Notwithstanding, it is worth to mention that such reduction displays a discontinuous behavior. An explanation is that the completion rate lag the investment rate by the construction time for each technology. Therefore, during the period $t \leq \bar{T}_i^C$, power plants are still being completed according to the ordering rate given under the long-run market equilibrium. Only after $t > \max(\bar{T}_i^C)$, the aggregate completion rate start to reflect investment rates resulting from the commercial decisions of investors in each technology. Then, the evolution of installed capacity and reserve margin begins to display a continuous behavior.

The installed capacity decreases until reaching an extremely low value around year 4, when the investment exercise is finally able to surpass the continuation value for each technology. Only then it becomes attractive to invest now due to the high revenues being perceived thanks to the critical supply condition (Region 1 of Figure 6). A stream of new units is thereby incorporated to the system, and remains until the continuation value begins to surpass the exercise value once again, due to the excess of capacity, around year 14. The construction cycle then starts over once more.

This remarkable fluctuating behavior impacts on the electricity prices that must be paid by consumers. In Figure 8, the annual-average market prices simulated under the proposed framework are depicted. According with the alerted cyclical behavior, the Real-Options-based case derives a market affected by significant price spikes, coincident with the critical reduction of installed capacity.

5.3 Sensitivity analysis on exogenous market variables

5.3.1 Mean of demand growth rate

A sensitivity analysis was carried out respect to the mean of demand growth rate. In that sense, the simulation of capacity adequacy with long-term load growth rates of 0%/year and 2%/year is depicted in Figure 9. Initially, it is verified that the system shows a more dramatic reduction of reserve margins with higher growth rates. An explanation is that increased growth rates yield greater expectations upon deficit conditions in the short term for each technology. Hence, the continuation value severely outweighs the exercise value, and investors constrain even more the addition of new capacity.

When investment exercise becomes attractive, it is observed that the stream of new power plants is incorporated to the system at a higher rate, for higher growth rates. This would cause later a pronounced situation of capacity excess, which would define

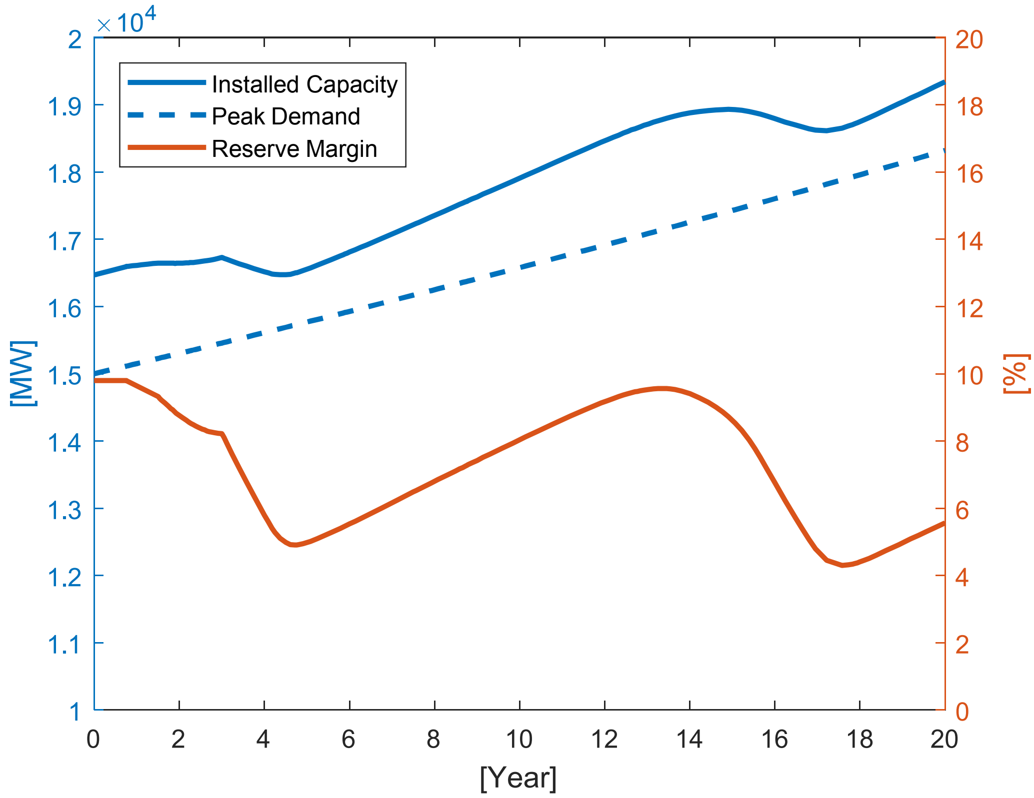

Figure 7: Simulation of evolution of installed capacity and reserve margin.

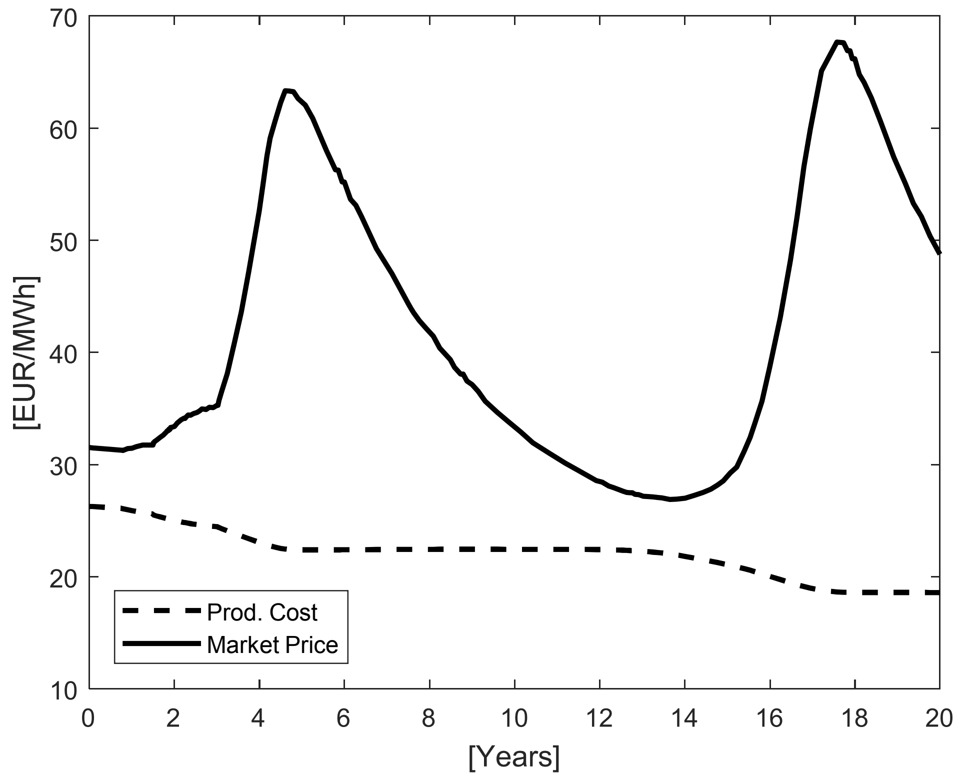

Figure 8: Simulation of evolution of market price.

again the start of a new construction cycle, but of increased amplitude. Therefore, it is reasonable to predict a more volatile market condition as the demand growth rate increases.

5.3.2 Volatility of demand growth rate

Figure 10 shows the simulation of capacity adequacy for different volatilities of the demand growth rate. With higher volatilities, it is found that the market experiences a more dramatic depletion of reserve margins along the first years. As in the previous example, this is explained because the higher the volatility, the more likely the deficit conditions that imply extraordinary profits in the short term for each technology.

After the first drop of reserve margins, the market with lower volatilities needs to reach an overstepped capacity situation for the continuation value to exceed once again the investment exercise value for each technology. This behavior is explained due to the fewer uncertainties about the market evolution, which leads to the reduction of the continuation value and gives the signal to invest in more power plants than required. Later on, this leads to a more dramatic reduction of reserve margins, which impacts directly on the stability of market prices.

On the opposite side, fewer investments are required to be added for the continuation value of each technology to surpass again the exercise value in a highly-volatile scenario. Despite the more stable market behavior, this means that the reserve margin is constantly below the economic optimum, which settles the market clearing prices on a rather high average value. An explanation is that investors are likely to execute new projects proportionally in order to maintain a low reserve margin and secure high deficit profits, in response to expectations upon a highly uncertain market evolution.

The described patterns are coherent with the experience in actual electricity markets. In fact, lessons learned suggest that the combination of strong demand growth rates, with high volatilities, was one of the main reasons that led to crises in supply security

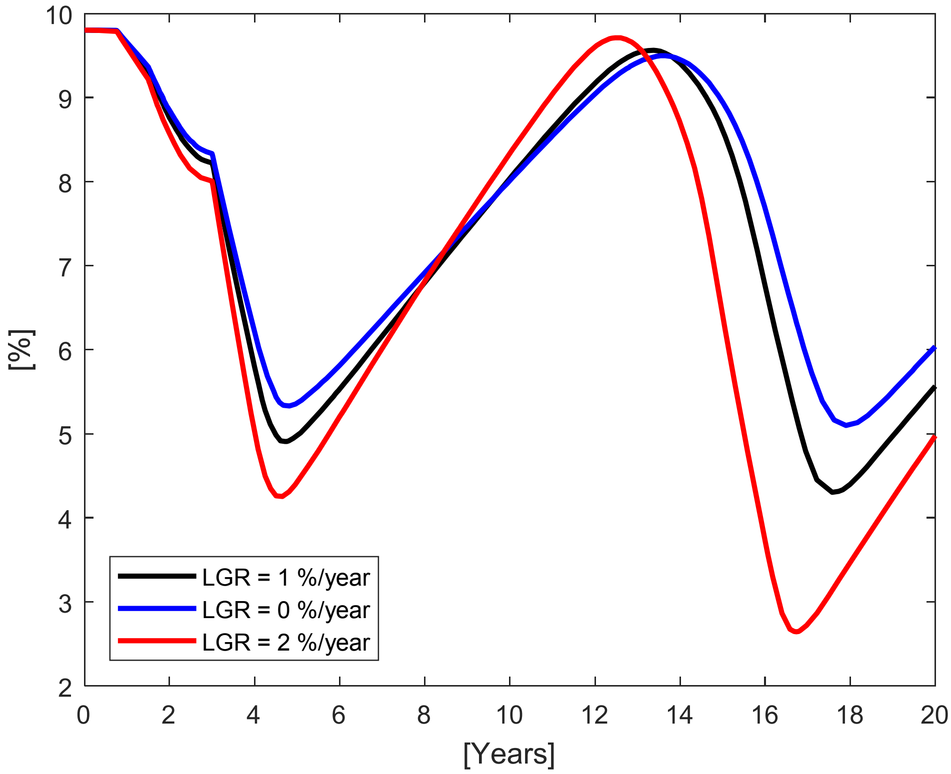

Figure 9: Simulation of evolution of reserve margin with different Load Growth Rates (LGR)

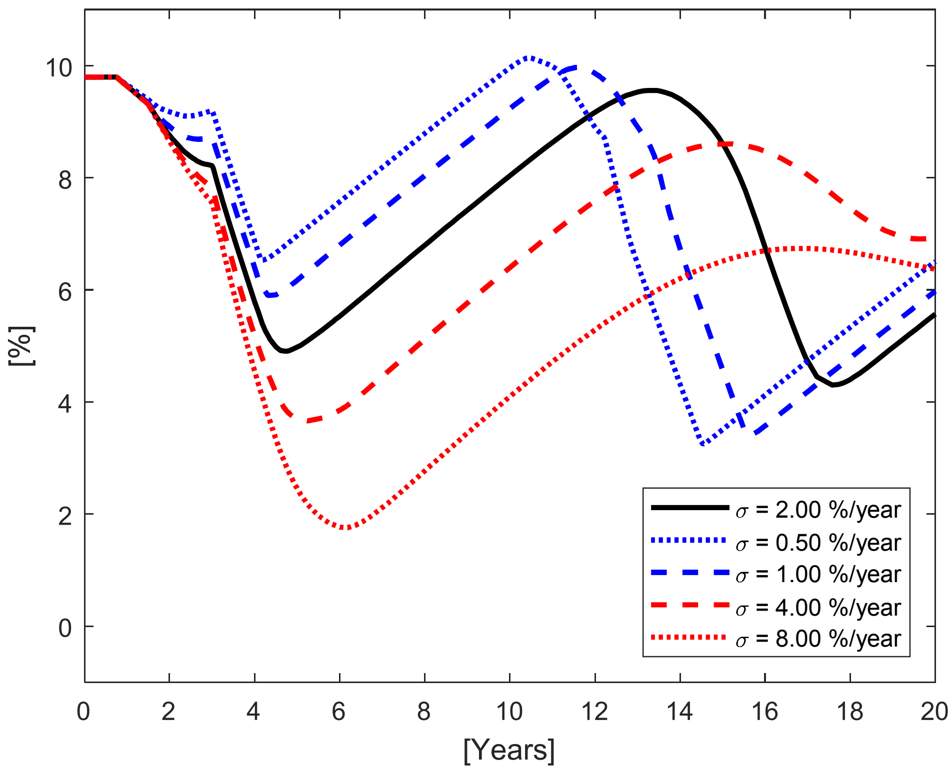

Figure 10: Simulation of evolution of reserve margin with different volatilities of the LGR.

in several liberalized markets. Specifically, this is consistent with the situation experienced in South America after the first step of the deregulation process during the 1990s (Rudnick *et al.*, 2005)

5.3.3 Volatility of fuel prices growth rates

The simulation of reserve margins with different volatilities for both fuel prices growth rates is depicted in Figure 11. It has been verified that for small increments of the volatility, a change in the system response respect to the base case is almost negligible. This might be explained because the uncertainty in the evolution of fuel prices mainly affects expectations upon profitability during normal operating conditions. However, the higher component of expected rents is derived from deficit situations, which are conditioned by the uncertainty of demand growth and future installed capacity. In that sense, only an unusually high amount of volatility for both fuel prices growth rates allows to determine by itself high expectations upon profits at the expiration time. Then, the system exhibits a similar behavior as with the high volatility of demand growth rate, described in the previous subsection.

5.4 Policy implications

5.4.1 Implementation of regulatory schemes

The impact of different regulatory schemes in dampening the emerging construction cycles, considering rational delays in the investment decisions, is also studied. In that sense, three schemes are proposed in order to provide additional investment incentives:

- Setting the VOLL at double the value of the base case (VOLL = 2.00x).
- Implementing a capacity market mechanism (+ Cap. Market).
- Implementing a capacity payment mechanism (+ Cap. Paym.).

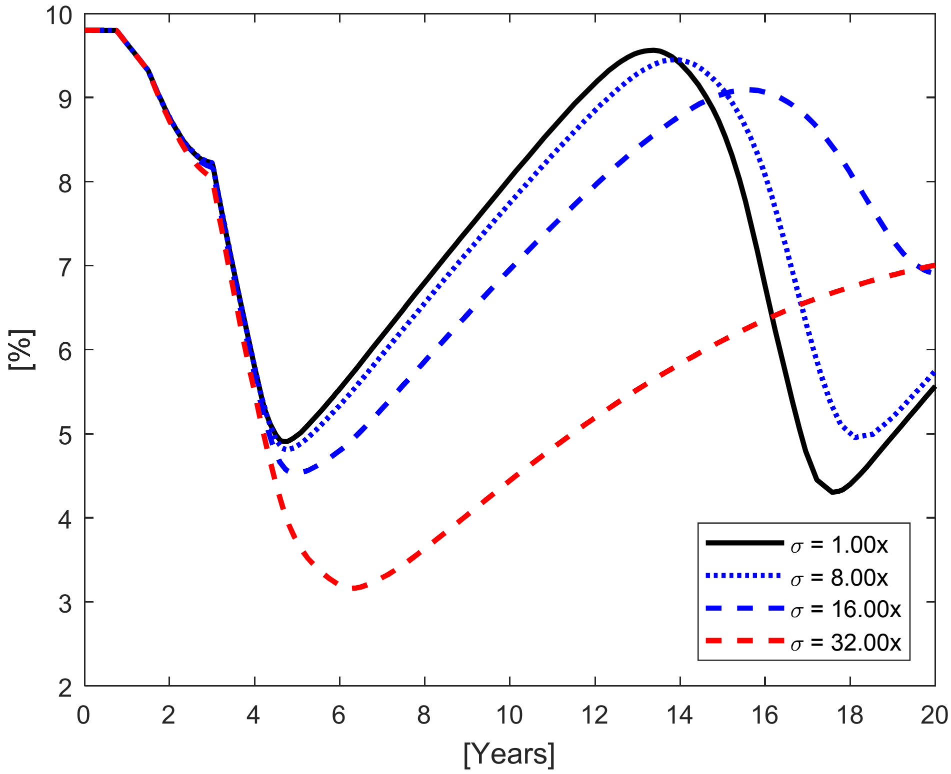

Figure 11: Simulation of evolution of reserve margin with different volatilities of fuel prices growth rates.

On one hand, the VOLL is a key variable which setting is within reach of regulators. It is deemed that a higher VOLL might help in timely undertaking new power plants because investors would perceive a higher profit in the energy-only market without arriving to a severe deficit situation. On the other hand, the capacity market and the capacity payment are regulatory mechanisms that intend to remunerate generators separately from the energy-only market. In that sense, the formulation of the additional revenues to be expected by each technology is given in detail in the Appendix. Such profits must be eventually summed to Eq. (22) in order to determine the full expected profitability for each technology with the implementation of each regulatory scheme.

At each time, it is assumed that the existing capacity participates entirely in the capacity market, while only the base technology makes bids of new capacity. It is supposed that these offers are always equal to the 15% of the instant system capacity

(Hary *et al.*, 2016). The target system capacity is given by the observable peak demand and the target optimal reserve margin, which is equal to 9.78%.

Accordingly, the LOLP necessary to compute the capacity payment is derived from the annual-average system availability. It remains constant over the simulation horizon, and is based on the optimal deficit duration, according to the system's initial conditions.

Results for the simulated reserve margin are included in Figure 12, while the simulated market prices are depicted in Figure 13.

5.4.2 Performance of the capacity adequacy

Two metrics are adopted to characterize the performance of capacity adequacy over the simulation horizon. First, the Root Square Mean Error (RSME) to the Target Reserve Margin (TRM) is used to indicate the degree of supply security. Next, the signal of economic performance is given by a so-called Annual-average Unitary Expenditure (AUE). It denotes the yearly equivalent amount that consumers would have paid for each MW of the system, over the average production costs, during the entire simulation horizon. This value can be computed from the enclosed area between the simulated market price and the corresponding production costs. For the sake of clarity, the mathematical expression for both metrics is included in the Appendix.

The performance of each market design according to the proposed metrics is illustrated in Figure 14. Numerical values are provided in Table 4. It is verified that the capacity payment mechanism offers the best performance regarding the security of supply. Nevertheless, this happens at expense of an extremely high profit for investors. From the point of view of consumers, the energy-only market derives a much more moderate amount of expenditure. However, in that case, there is a higher risk of deviating from the target reserve margin, even with the increase in the VOLL, affecting the security of supply.

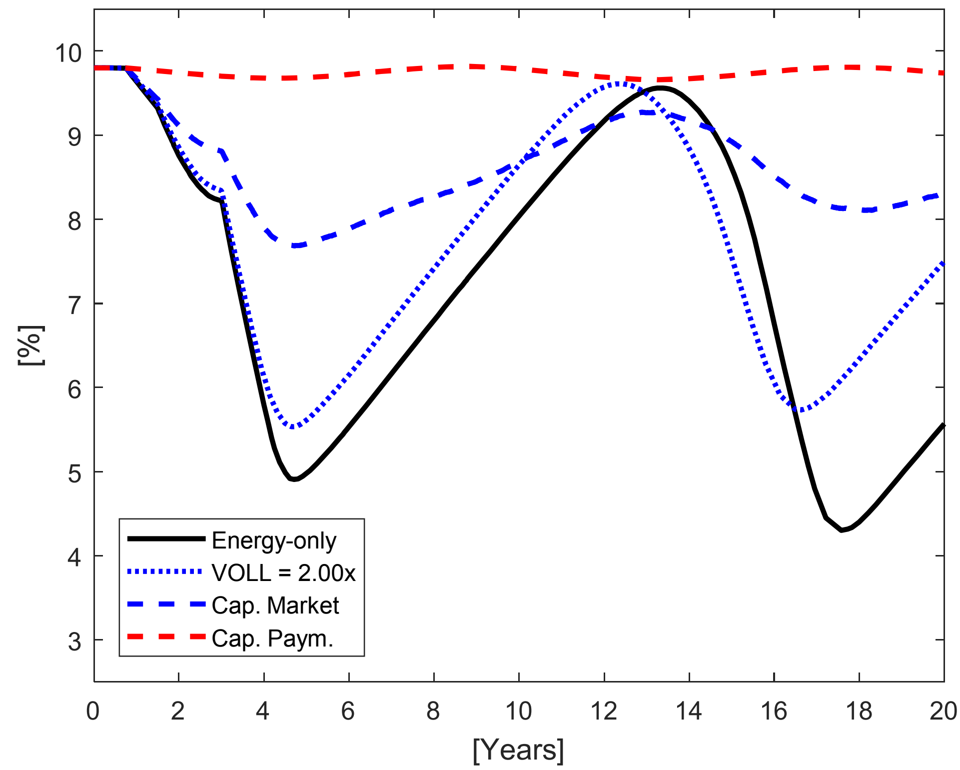

Figure 12: Simulation of evolution of reserve margin with the adoption of regulatory schemes.

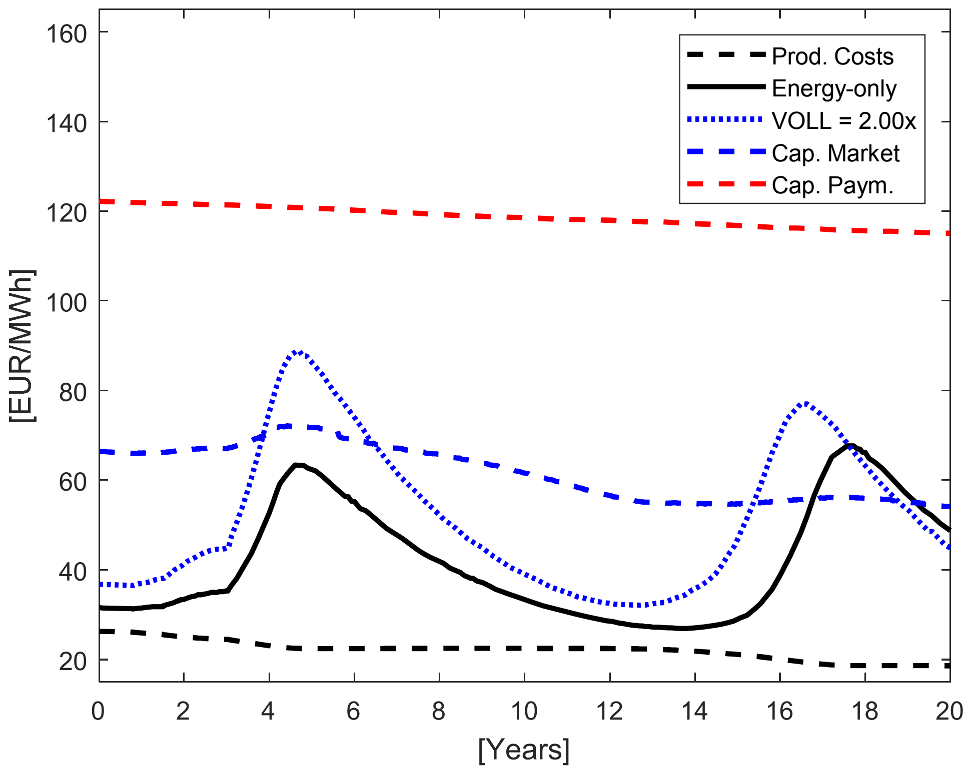

Figure 13: Simulation of evolution of market price with the adoption of regulatory schemes.

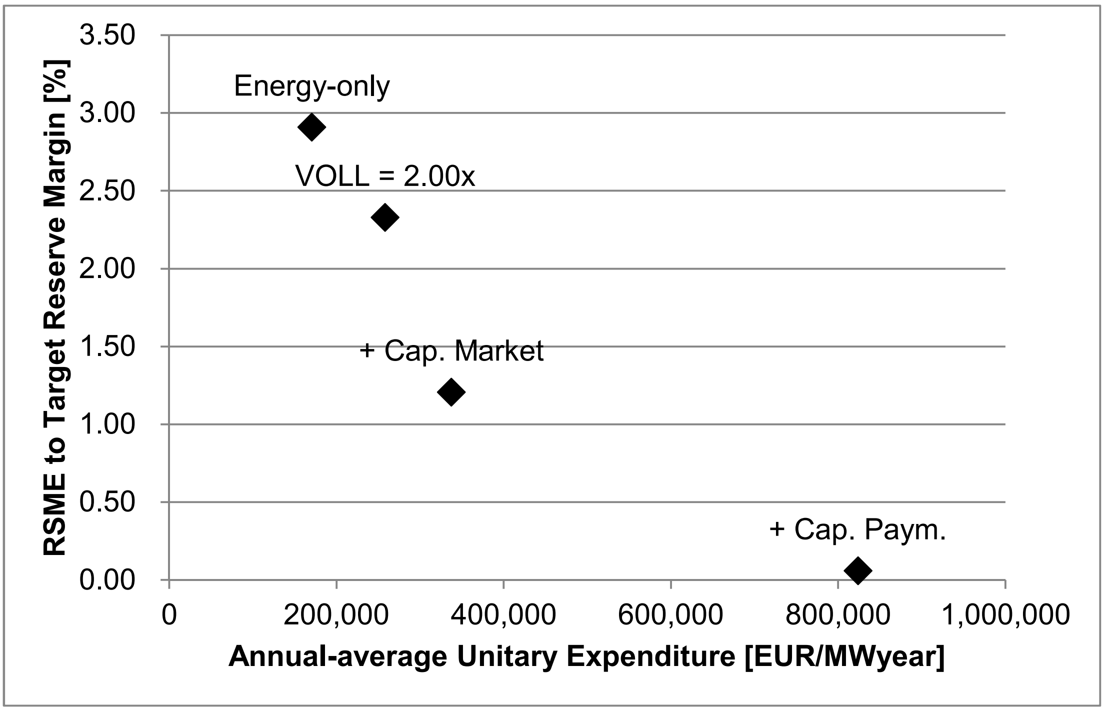

Figure 14: Performance metrics of capacity adequacy with the adoption of regulatory schemes.

Table 4: Performance metrics of capacity adequacy with the adoption of regulatory schemes.

Metric	Energy-only	VOLL = 2.00x	+ Cap. Market	+ Cap. Paym.
AUE [EUR/MW·year]	170,490	257,942	337,133	823,675
RSME to TRM [%]	2.91	2.33	1.21	0.06

Simulations are relevant considering that the expected profitability for each technology approximates to an efficient long-term contract auction. Supposedly, this mechanism is well-suited for reducing risks and deriving sufficient incentives to the addition of new capacity. However, according to the cyclical development of the market, investors still might be attracted to allocate new investments inefficiently, waiting for more profitable conditions defining their long-term contract auctions. In that context, only capacity remunerations mechanisms seem proper to give sufficient incentives for overcoming the investment threshold imposed by the postponement option, and thus ensuring a more stable capacity adequacy.

5.5 Sensitivity analysis on Real Options parameters

5.5.1 Expiration time

The impact of different expiration times is also subject of discussion. It is worth to recognize that the expiration time, also known as the option maturity, conventionally denotes a threshold after which investments can no longer be undertaken. Due to the irreversibility, this might derive in conveniently setting different expiration times for each generating technology. Therefore, here it is assumed that investors might consider investment expiration times equal to the multiple of 36, 18 and 9 months for HACO, CCGT and GAST, respectively. On one hand, this setting explains that investors in base technologies will be more cautious about the market uncertain development due to the higher sunk costs. On the other hand, investors in peak technologies will not be prone to delay investments excessively because of the lower irreversibility. The simulated scenarios are presented in Table 5.

Results are shown in Figure 15. It is observed that the simulations with disaggregated option maturities exhibit a more significant reduction of reserve margins in the first years respect to the base case. This is explained due to the longer expiration times for base technologies, which results in market uncertainties determining even more profitable conditions if the decision is to postpone investments. This leads to a rapid reduction of reserve margins because of the insufficient addition of base capacity, which accounts for the greatest proportion of capacity within the system energy mix.

Furthermore, it is verified that the market with disaggregated maturities requires fewer investments for the continuation value to exceed the exercise value once again. This implies the setting of market prices on higher average values, representing the strategic behavior of base investors in response to increased uncertainties at the maturity. The situation also determines the reduction of the period in the construction cycles, which leads to an increased instability of the market development, when considering a higher irreversibility for base power investments.

Table 5: Input data for the scenario simulation with different maturities for the postponement option.

Expiration times by scenario	HACO	CCGT	GAST
Base case [month]	12	12	12
1.00x Maturity [month]	36	18	9
2.00x Maturity [month]	72	36	18

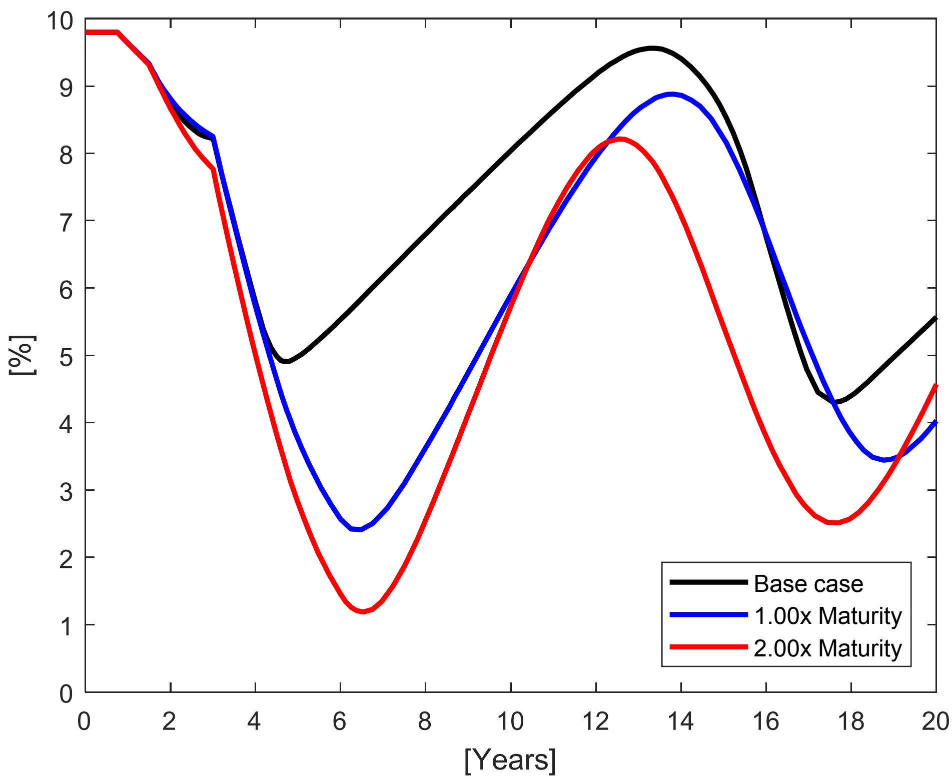

Figure 15: Simulation of evolution of reserve margin with different maturities for the postponement option.

5.5.2 Risk-free discount rate

The risk-free discount rate for the base case simulations was risk-adjusted following a non-neutral assumption. However, the valuation of real options according to a risk-neutral supposition might find sufficient to define risk-free discount rates at lower values than the conventional project hurdle rates. In that sense, a sensitivity analysis was carried out considering risk-free discount rates of 6.25%/year and 3.12 %/year.

The simulation of reserve margins in this case is depicted in Figure 16. It is verified that with lower risk-free discount rates the market suffers a more critical reduction of installed capacity during the first years. A reason is that the lower risk-free discount rates increase the continuation value for all technologies. Therefore, there are greater incentives for investors to withhold new power plants then because higher profits will be certainly collected later on.

Furthermore, it is observed that the cyclical behavior of the market dampens gradually with the reduction of the hurdle discount rate. This might be explained because, even when a reduction of reserve margins defines an increased exercise value, a low risk-free discount rate determines an interesting continuation value as well. Thus, after the critical decrease of reserve margins, the recovery of installed capacity results from slower addition rates with smaller discount rates. In that context, investors might be likely to execute investments proportionally in order to ensure low reserve margins and collect great deficit profits in response to a great value of project continuation.

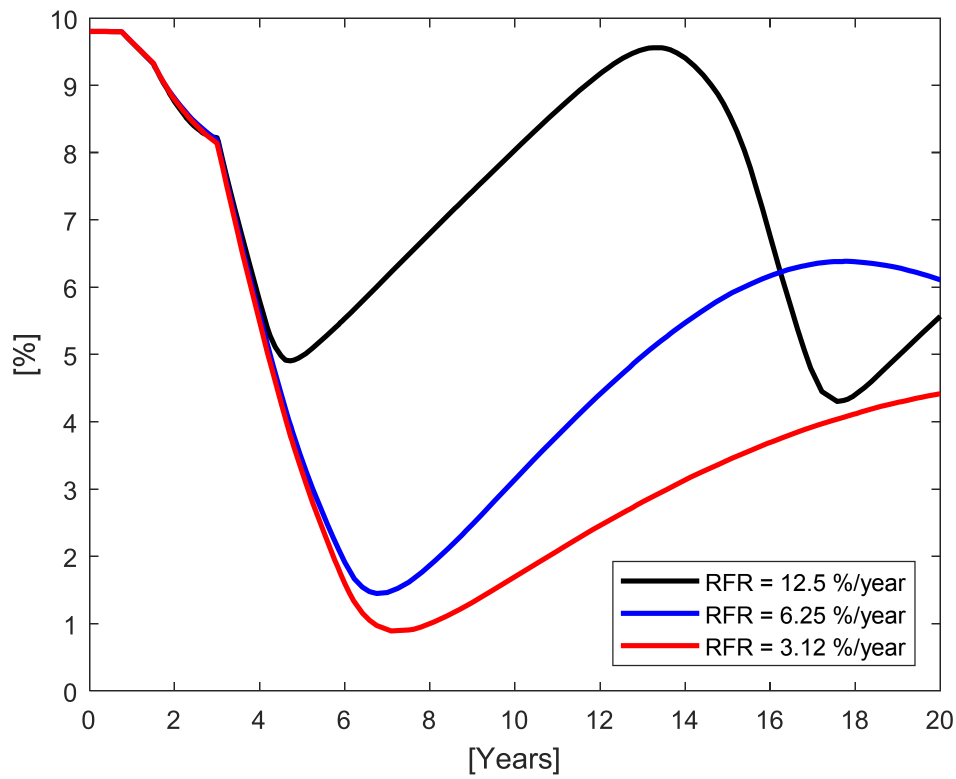

Figure 16: Simulation of evolution of reserve margin with different risk-free discount rates.

V CONCLUSIONS

After developing this research work, it is concluded that a novel decision-making framework to assess the long-run capacity adequacy in liberalized power markets has been proposed. The designing of the methodology has taken advantage of a well-founded background for simulating the long-term market dynamics, based on a System Dynamics simulation approach. However, the proposed research work is different as it has focused on modeling the investors' decision-making process, accounting for the strategic flexibility of generation investments under uncertainties. For this purpose, a new investment valuation framework, elaborated by means of Real Options analysis, has been presented.

In that context, the simulation of multiple scenarios for depicting the market uncertain evolution has allowed to quantify the value of postponing new power plants in order to be reconsidered later. At each time, a new profitability index has been obtained by relating such continuation value with the value of undertaking the investment immediately. This relation has ultimately defined the entrance of new capacity for each generating technology.

Results have shown that with the proposed model the long term market development has been defined by explicit construction cycles. Several sensitivity analyses respect to key market variables has been performed in order to test the robustness of the described framework. In that sense, it has been suggested that the combination of strong demand growth rates with large volatilities would derive an even more volatile evolution of installed capacity. Likewise, the new Real- Options-based methodology has been applied to assess the implementation of three different regulatory schemes intended to dampen the perceived construction cycles. Simulations have illustrated that, for ensuring the supply security, higher incentives must be offered in order to counteract the investor's behavior when deciding strategic projects under uncertainty.

Likewise, the impact of different maturity horizons and hurdle discount rates has been explored. In that sense, it has been verified that an increase in the expiration times for base technologies, due to the irreversibility, would determine an even more unstable market development. Furthermore, the reduction of the hurdle discount rate might suppress the perceived construction cycles, but at expense of significantly narrowing the market reserve margins, because of the increased value of investment continuation.

The cyclical investment pattern depicted in this research work has reproduced the empirical evidence that have been reported by several electricity markets after the deregulation. In that sense, the main contribution of this work has been a rigorous mathematical description of the origins of this phenomenon. This might help in the design of investment incentives, suitable for deriving a stable development of the liberalized power industry in the long term.

The following points will be included in further research:

- Critical review of the expectation formation model: The possibility of multiple paths for describing the uncertain evolution of the observable market variables will be considered from the beginning of the simulation horizon.
- Application of other Real Option methods: The impact of using binomial lattices or stochastic simulation models, like Least-Square Monte Carlo techniques, will be considered for valuing the American type of real options in the decision-making of each technology.
- Incorporation of non-thermal generating technologies: The generation test system will be expanded, in order to include further generating technologies, especially, renewables. This will help in studying the impact of large-scale integration of renewable energy, which is now center of interest.

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APPENDIX

A1 Modeling expectations upon profitability in the Capacity Market

At each time, the Capacity Market is defined analogously as an industry supply curve. It results from sorting the cumulated bids of new and existing capacity according to an economic dispatch merit order. On one hand, bids of existing capacity are given by the entire available capacity residing instantly at each vintage from each technology of the generating park, together with their respective marginal cost of generation. On the other hand, it is assumed that the bids of new capacity are an obligation only of the base technology. Thus, the bid quantity of new capacity at any time, $K_{bid,new}(t)$, can be expressed as a proportion of the total installed capacity:

$$K_{bid,new}(t) = p \quad K_I(t)$$

where $K_I(t)$ is the total installed capacity of the system at time t, and p is the bidding proportion of new generating capacity. Based on the revised literature, it is assumed that the value of p equals 15%, and remains constant over the whole simulation horizon. It is worth to acknowledge that a sensitivity analysis over the value of p would provide a more refined insight about its impact on the system response. Likewise, the bid price of new capacity at any time, $\pi_{bid,new}(t)$, can be derived from the marginal cost of generation from the base technology to be added into the system, $\overline{MC}_{base}(t)$:

$$\pi_{bid,new}(t) = \overline{MC}_{base}(t)$$

Now, the target installed capacity for the market at any time, $K_{target}(t)$, can be defined as a function of the expected peak demand, $L_{max}(t)$, jointly with the target reserve margin, RM_{target}:

$$K_{target}(t) = L_{max}(t) \quad \left(1 + RM_{target}\right)$$

The target reserve margin is assumed to equal the initial reserve margin, obtained according to the optimal energy mix at the beginning of simulations. Moreover, it is assumed to remain constant over the whole study horizon.

The capacity market clearing price at any time, $\pi_{CM}(t)$, can be formulated as the price at which the cumulated bid capacity equals, or immediately exceeds, the target installed capacity for the system:

$$\pi_{CM}(t) = \pi\left(K_{bid,cum}(t) \geq K_{target}(t)\right)$$

Finally, the expected annual profitability that a MW of technology i will make in the capacity market at any time, $\pi_{i,capacity}$, can be approximated by:

$$\pi_{i,capacity}(t) = 8760 \quad \left(\pi_{CM}(t) \quad \overline{MC}_i(t)\right)$$

At time t, $\pi_{CM}(t)$ denotes the capacity market clearing price; $\overline{MC}_i(t)$ represents the marginal cost of generation for technology i; and 8760 is the number of hours in a year, since prices and costs are given by EUR/MWh.

According to the literature, the capacity market mechanism presented here is inspired by the design that is now operative in France and in Great-Britain.

A2 Modeling expectations upon profitability with Capacity Payments

The expected annual profitability that a MW of technology i will make from capacity payments at any time, $\pi_{i,payment}(t)$, can be modeled as:

$$\pi_{i,payment}(t) = 8760 \quad LOLP \quad \left(VOLL \quad \overline{MC}_i(t)\right)$$

where $LOLP$, the Lost of Load Probability, represents the probability of capacity shortfall; $VOLL$ is the Value of Lost Load, fixed to 1000 EUR/MWh; and $\overline{MC}_i(t)$ denotes the marginal cost of generation for technology i. It is worth to note that this definition is inspired by price-based dynamic remuneration mechanism introduced in England and Wales between 1990 and 2001.

The $LOLP$ is assumed as an indicator of the optimal system availability. It is a function of the initial maximum and minimum demand, and the initial deficit duration and reserve margin, obtained according to the optimal energy mix at the beginning of the simulations. Mathematically, it can be expressed as:

$$LOLP = \frac{\left(L_{min}(0) \quad L_{max}(0)\right) \quad D_{def} + L_{max}(0)}{L_{max}(0) \quad \left(1 + RM_{target}\right)}$$

Here, $L_{min}(0)$ and $L_{max}(0)$ denote the initial maximum and minimum demand, respectively; D_{def} represent the initial optimal deficit duration; and RM_{target} is the initial optimal reserve margin. According to the microeconomics of investments in power plants, the optimal deficit duration can be understood as the duration of load curtailment necessary for the peak technology to recover completely its fixed costs thanks to the Value of Lost Load.

A3 Modeling the performance metrics of the capacity adequacy

First, the Root Square Mean Error (RSME) to the Target Reserve Margin (TRM) can be modeled as:

$$RSME = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(RM(n) \quad TRM)^2}$$

where $RM(n)$ is the simulated reserve margin for the time step n within the simulation horizon; TRM denotes the constant Target Reserve Margin (TRM); and N represents the number of integration steps, between the initial and the final simulation time, at which the solution of the delay differential equations is defined.

Then, the Annual-average Unitary Expenditure (AUE) can be expressed as:

$$AUE = \frac{1}{20}\int_{0}^{20}\big(MP(t) \quad PC(t)\big)\ dt$$

Here, $MP(t)$ is the simulated market price, and $PC(t)$ is the simulated production cost, at time t within the simulation horizon; while 0 and 20 denote the initial and the final simulation time.

PUBLICATIONS

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