PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

SCHOOL OF ENGINEERING

TRENDS IN PORTFOLIO OPTIMIZATION IN A NEW RISK-DRIVEN MARKET ERA: A REVIEW AND APPLICATION OF MODELS FOR PLANNERS, INVESTORS AND MANAGERS

RODRIGO ANDRÉS PÉREZ ODEH

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree Doctor in Engineering Sciences

Advisor:

DAVID WATTS

Santiago de Chile, september 2019

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ABSTRACT

Today's quickly changing world forces society to deal with uncertainties that produce high levels of environmental, social, and economic risks, thereby jeopardizing sustainable development. Portfolio optimisation is an effective tool for formally dealing with such uncertainties, because the social and private optimum is not found by analysing cost/returns and risks of individual assets, projects, actions or plans, but rather requires analysing them all together in the form of a portfolio. This work first presents a review of portfolio optimisation applications from the perspective of energy planners. Multiple research opportunities were found, especially in spatial modelling, transmission, and renewable generation. The portfolio literature available to date excessively simplifies the power system. Supply, demand, and transmission modelling in portfolio analysis are not consistent with planning models, and therefore produce conflicting results. Despite abundant literature that analyses renewable complementarity, actual portfolio optimisation models ignore this effect, which leads to suboptimum portfolios.

Policymakers have the task of inducing private agents, through their regulatory designs, to make decisions that point toward social welfare maximization. Conversely, it is a task of private agents to protect themselves against the risks of the sector. This work presents a review of the main applications, voids and challenges of portfolio optimization for two key agents of the private sector: investors and managers. Two fundamental issues were found in the literature; the first and most important is excessive confidence in historical data and statistical analysis for predicting future price behavior for a changing future in detriment of more structural analysis. The second is the omission of renewable complementarities, which is a proven characteristic of dispersed renewable plants that may have important risk-mitigation effects, although it has largely been ignored in portfolio analysis due to insufficient data, modeling limitations, and computational complexity.

The literature on the way **spatial diversification** affects the entire power system, its prices and specifically renewable market value is scarce. Trying to cover part of this void, an

analysis is made using real data and a simplified dispatch model to show evidence of the effects of diversification on wind and solar market value in Chile. Results suggest that spatial diversification has a strong positive effect on the market value of renewable generators, especially in scenarios with active transmission and hydro-storage constraints. Indeed, wind market value vary up to US$10/MWh depending on the level of diversification and the spatial and temporal constraints of the system and, given current storage capacity of hydro reservoirs, the solar market value may increase by US$5/MWh if transmission capacity is enough. Even though these results must be observed with caution, because they depend on the assumptions made, they are an additional effect of renewable spatial diversification.

Uncertainty of the availability of transmission capacity affects the profitability of generation investments. Given the risk of suffering cuts in injections, an investor has the option of delaying the investment decision, developing the project in stages or simply canceling it. Renewable generation projects, especially solar photovoltaic (PV) and wind projects are modular and therefore suitable for being developed by stages. These flexibilities are generally ignored in the economic evaluations of such projects. This article presents a new methodology to evaluate different options of delaying and developing a project by stages, when facing the uncertainty of the availability of transmission infrastructure. A model to identify investments strategies based on a portfolio of real options is presented. It is shown that the value of the option depends essentially on the probabilities that are assigned to the commissioning date of the transmission infrastructure, on how important that infrastructure is for the evacuation of the generation project and the capital cost of the investor. This work is expected to assist investors by revealing the efficient frontier of their investment options and developing investment strategies to use the advantages of flexibilities of renewable projects.

CHAPTER 1: INTRODUCTION

1.1 Motivation: The growing uncertainty in the electricity sector

Modern energy systems and markets are overwhelmed by various sources of uncertainties, such as wind speed, hydrology, solar radiation, etc. which are becoming increasingly important due to the renewable energy revolution in recent years that introduces these new generation resources to electricity markets. But renewable generators also have the potential to cancel out or mitigate some of the risks associated with conventional energies, such as fuel prices. Furthermore, renewable energies also help mitigate uncertainties produced by conventional energies that go beyond energy markets, such as local pollution, that expose society and the environment to unprecedented levels of risks.

Uncertainties about the future increasingly burden society with higher levels of risks. Portfolio optimisation offers tools to formally deal with such uncertainties and states that the social optimum is not found by analysing costs/returns/impacts and risks of stand-alone projects, but rather by analysing them all together in the form of project portfolios (actions, plans, strategies, etc.) [1]. Social planners face the challenge of dealing with all of these uncertainties together, looking for a sustainable solution that balances economic costs with environmental and social impacts and their associated risks.

How will renewable energy technologies and their costs evolve over time? How long will this process take? How will fast and deeply distributed generation and micro-grids penetrate power systems in different places around the world? How active will future electricity consumers be? What will the role of electric vehicles and storage technologies be? How will fossil fuel prices behave in the future? Will fossil fuels be used for electricity generation in the future? What will the role of marine generation technologies be? When will seamless international interconnections become massive worldwide? These questions flood the electricity sector with uncertainty and increase the difficulty of decision making and long-term supply chain planning [2,3]. It is often necessary to make several assumptions about a series of variables (see Figure 1) or alternatively work with different pre-established scenarios [4–6]. Sadly, energy experts have done a poor job of predicting the future, and a good case in point is the renewable energy revolution, especially the solar PV boom we are seeing today.

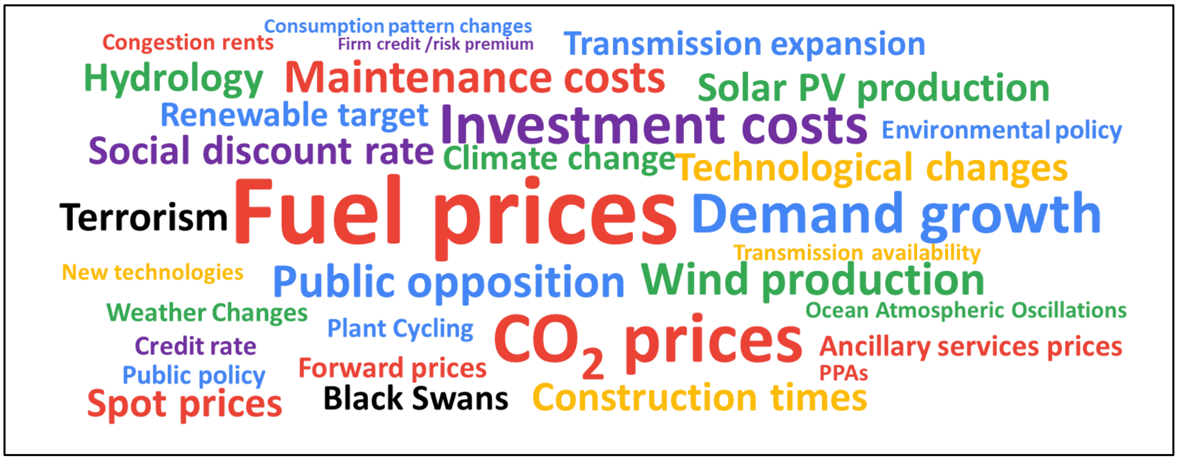

FIGURE 1: THE WIDE VARIETY OF UNCERTAINTIES FOUND IN THE LITERATURE REVIEW IN THE ELECTRICITY SECTOR: OUR OWN PREPARATION BASED MAINLY ON [5–20]

As shown in Figure 1, electricity market literature has largely focused on uncertainties stemming from fuel prices, demand growth, and CO_2 prices, among others. With arrival of new renewable energy technologies, more attention has been placed on the evolution of investment costs, weather variables (wind, hydrology, solar radiation, and others.), and construction times, etc., while social and environmental risks have received very little attention.

More generally, uncertainty is present in almost all processes, events, parameters, and measurements that affect a wide range of problems, from daily life to the most complex sciences. In these problems, where complete information is missing, the decision-making process becomes difficult, and the agent continuously faces the risk of making incorrect decisions. While the definition of risk depends on the discipline (finance, sociology, engineering, biology, etc.), there is agreement that risk makes the decision-making process more difficult [3,12], and therefore there is a growing need for tools to mitigate these risks, such as portfolio optimisation.

Portfolio optimisation is widely used in a number of problems and industries as a way to simultaneously deal with *expected returns/costs/impacts* and their *risks (i.e.: uncertainties)*. In lay terms, portfolio optimisation exploits the idea of "not putting all your eggs in one basket", which is known as *diversification*. In the context of energy generation projects, diversification can be achieved in many ways, such as through the "cancellation effect" that occurs with changes in returns from different projects, such as losses in hydro plants due to low production that partially cancels out the benefits from thermal plant energy sales during dry seasons or decreases in solar production in the afternoon that are partially cancelled out by simultaneous increases in wind production, etc. This diversification effect is sometimes studied by exploiting the complementarity between renewable energy and conventional energy or alternatively, by combining different renewable energies technologies for a carbon-free environment.

In the field of finance, Markowitz [21] was the first proposed a methodology to account for the following conflicting objective: solving investors' capital allocation problem by balancing both return and risks. Portfolio return is defined as the weighted sum of the expected rates of return on every investment (Eq. 1) (or project, in an energy context), and portfolio risk is the volatility of the portfolio return measured by its standard deviation (Eq. 2). The quantification concept of *diversification* through the joint movements of the return on each single investment, measured by the correlation matrix (Eq. 3), was the real novelty of Markowitz's research [22].

$$\text{Portfolio return: } r_p(\omega) = \omega_1 r_1 + \cdots + \omega_n r_2 = \omega^T r \qquad \text{EQ. 1}$$

$$\text{Portfolio risk: } V(\omega) = \omega^T \sum \omega \qquad \text{EQ. 2}$$

$$\text{Portfolio correlation: } \sum = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \qquad \textbf{EQ. 3}$$

Markowitz shifted the paradigm of classical financial analysis, which was focused on analysing the performance of **individual investments (or individual projects in an energy context)** ignoring the co-movements among them, rather than focusing on entire sets of investments and considering co-movements to diversify risk. Another relevant concept is the **efficient frontier** that represents the set of portfolios that are Pareto-optimal, namely, portfolios that cannot increase their return without increasing their risk or, as in other applications beyond finance, such as energy planning, portfolios that cannot decrease their costs without increasing their risk, as is shown in Figure 2.

In the energy sector, portfolios were initially used as financial tools to combine different conventional sources as explained below, but as society evolved towards a more sustainable future, these tools have shifted to combine existing conventional technologies with newer renewable technologies or combine different renewable technologies to work towards a carbon-free world.

In its simplest formulation, and looking solely at the economic dimension, portfolio optimisation enables diversification among different fuel and energy resources. Sometimes a portfolio composed of multi-fuel suppliers has a higher expected cost than a portfolio composed of just one inexpensive fuel, but it is less exposed to the variability of fuel prices and its supply chain, i.e. buying everything from the cheapest supplier could be more expensive in the end. This is one of the classical problems for energy planners. What technological mix should be planned for the next 30 years? Should the system be planned to point towards the minimum cost, the minimum risk, or somewhere in between? (See Figure 2 for an example of this cost-risk trade-off for a developing country that faces both high capital costs and expensive fossil fuels). Defining the future technological mix is one example of an application of portfolio optimisation for energy planners in the electricity sector.

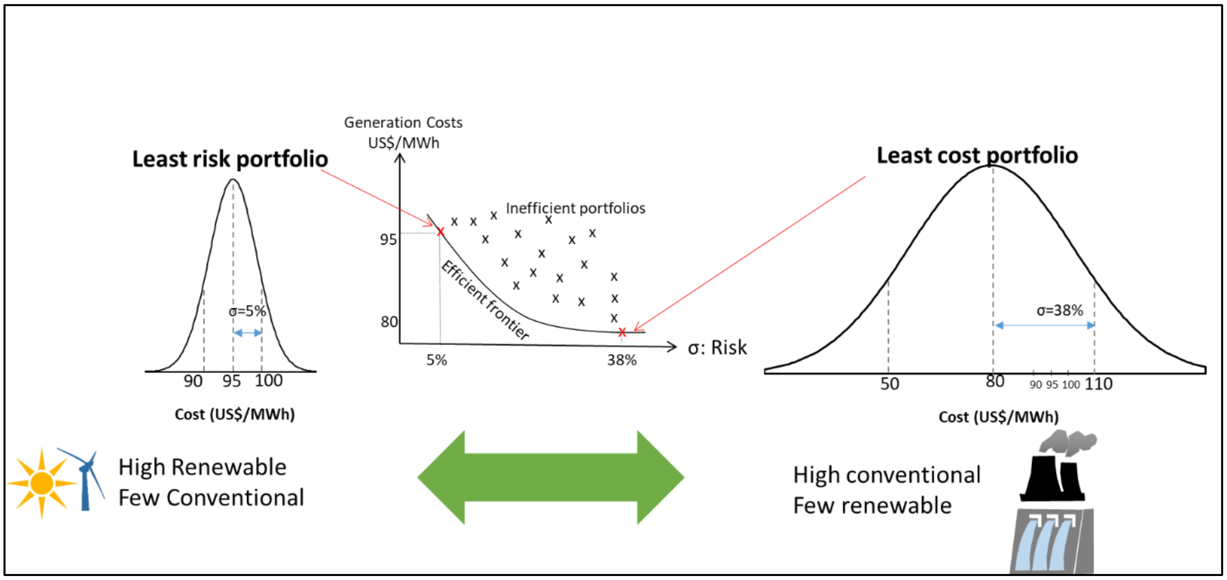

FIGURE 2: SAMPLE PORTFOLIO FOR A DEVELOPING COUNTRY: MINIMUM-RISK PORTFOLIO (LEFT) VS MINIMUM-COST PORTFOLIO (RIGHT)

1.2 Objectives and scope of the work

The general objective of this work is to understand the risks that agents like the regulator, investors and managers must deal with in the electricity markets, how to reduce their exposition (optimize) through an adequate selection of variables (location, technology, resources, etc.) and elaborate an analysis to understand how these variables impacts on the power system and the market value of renewable generation technologies.

1.3 Specific Objectives

- Gathering risks from the perspective of private agents in the electricity sector, their current treatment, the tools to manage them and the main research gaps in their treatment.
- Gathering risks associated with energy planning and the electricity generation mix, from the perspective of the regulator, the main tools to manage them and the main research gaps in their treatment.
- Modeling wind generation profiles in Chile at a regional level to analyze temporal and spatial variability and complementarity and identifying the most cost-effective wind generation zones for the development of generation projects in a portfolio fashion rather than a Myopic project view.
- Develop a portfolio-planning tool that integrates key features of an economic dispatch optimization model together with a simplified hydro-thermal unit-commitment planning tool (allowing switching on and off) with hourly resolution, for a horizon of at least one year that allows, in reasonable times, to analyze various supply and demand scenarios and wind profiles.
- Develop a methodology that allows to quantify the market value of renewable energies, especially in Chile, in situations of transmission and hydro storage constraints, with different levels of complementarity of wind resources.
- Develop and apply a model to identify optimal investment strategies in renewable projects facing uncertainties such as the operation date of future transmission expansion projects.

1.4 Hypothesis

a) While it is widely known and researched that risks can be mitigated or diversified by combining certain generation projects, the effects of these combinations on the power system, its prices and specifically on renewable market value is however, much scarcer. It is a hypothesis of this research that these effects and its impacts can be identified.

b) It is possible to use and adapt financial techniques such as portfolio theory and use it as a tool for choosing projects to develop (or to buy, depending on the perspective of the agent).

c) Some of the risks of the NCRE projects are common to the conventional ones and therefore one can learn from the knowledge developed in the risk management of conventional projects.

d) Some risks are inherent in NCRE and should be characterized and understood in detail, which requires knowing the particularities of each project: resource, technology, production, financial situation, etc.

1.5 Contributions of the research

In this work two types of contributions are presented: conceptual and empirical or practical contributions. The central topic is the treatment of relatively new sources of uncertainty of the electricity market, such as the unpredictability of renewable sources, the opposition to transmission development, among others. Part of the value of this work is the demonstration of financial techniques applied on electric power systems. The following main results of this work can be considered as conceptual contributions for the development of science in the electricity markets field.

1.5.1 Conceptual contributions

A critical contribution of this work is the identification of the sources of risks that threaten the electricity markets and, at the same time, the analysis of their treatment and modelling in the different risk management models that have been published. Risks such as the poor predictability of renewable sources, which is generally treated just in an operational level, but not in relation with the investment decision level and the uncertainty of the development of transmission are especially characterized in this work. This identification has allowed to find the main gaps in the state of the art and to focus on some of them where it is possible to contribute. Those are precisely the areas where this work developed more practical, empirical and modelling contributions.

Another contribution of this research is the specification of the risks and the treatment proposal under different categories: firstly, by source of risk (systemic, of the resource, of the regulation, etc.), secondly and more importantly, introduces a vision of two different points of view: from the perspective of the planner and from the perspective of private agents. From the perspective of the planner, for example, the main shortcomings of the portfolio models to determine the future energy mix are exposed. On the other hand, systematic research focusing on the perspective of private agents is very novel and this is the first work that groups, presents and studies the risks that these agents face and the tools that exist to manage them.

This research also deepens on the market value of renewable energy, especially wind generation and the impact on this value in the face of different variables and risks that can simultaneously affect it, as the renewable penetration level, transmission restrictions, water storage for hydraulic generation and the geographical diversification of generation. This work seek to quantify how renewable energy integration measures impacts on renewable market value.

1.5.2 Practical contributions

Introduction of wind supply functions: a study of the wind profiles all along Chile was carried out, achieving to model and characterize the profiles by zone and developing for the first time the wind supply function of Chile by area, as well as the studying of the statistical properties of the jointly profiles, including the correlation between them. The current literature is somewhat underdeveloped in this topic and the modeling has a lot of potential.

A methodology that combines geographically diversified portfolios of wind projects with and optimization model of multi-reservoir hydro-thermal dispatch and hourly resolution has been developed. This methodology allows analyzing the systemic impacts of different portfolios of wind projects when facing different scenarios and the impact on their own market value.

This methodology allows the planner to identify generation poles or focal areas of renewable energy, which separately do not represent a differentiating contribution (or additional value) to the electricity system, but together they complement each other, enhancing their value and thereby reducing the drop in the market value of renewable with the increase in their penetration.

Additionally, a risk management tool is proposed to assist investors in determining an optimal investment strategy in the face of real sources of uncertainties, such as the uncertainty of the date of commissioning of a transmission line and the time it takes the permitting process for a photovoltaic generation project. The application of this tool, which uses real option theory and portfolio optimization combined, allows to illustrate the effects of the aforementioned uncertainties in the decision making of investors, as well as to obtain the efficient frontier of investment alternatives and to value the flexibility of being able to wait to connect the project to the grid.

The conceptual and empirical contributions of this work have so far been resulted into four published articles in excellent international journals and a fifth article have been recently sent. The articles associated with this thesis are presented next:

1. Pérez Odeh, R., Watts, D., & Flores, Y. (2018). Planning in a changing environment: Applications of portfolio optimisation to deal with risk in the electricity sector. *Renewable and Sustainable Energy Reviews*, 82 (August 2017), 3808–3823. http://doi.org/10.1016/j.rser.2017.10.089 (Chapter 2)

2. Pérez Odeh, R., Watts, D., & Negrete-Pincetic, M. (2018). Portfolio applications in electricity markets review: Private investor and manager perspective trends. *Renewable and Sustainable Energy Reviews*, 81(July 2017), 192–204. http://doi.org/10.1016/j.rser.2017.07.031 (Chapter 3)
3. Pérez Odeh, R., & Watts D. (2019). Impacts of wind and solar spatial diversification on its market value: A case study of the Chilean electricity market. *Renewable and Sustainable Energy Reviews,* 111 (March 2018), 442–461. http://doi:10.1016/j.rser.2019.01.015 (Chapter 4)
4. Watts, D., Oses, N., & Pérez, R. (2016). Assessment of wind energy potential in Chile: A project-based regional wind supply function approach. *Renewable Energy*, 96, 738–755. http://doi.org/10.1016/j.renene.2016.05.038 (Chapter 4)
5. Perez Odeh, R., & Watts, D. (2019). Optimal investment strategy of PV plant under uncertainty on the expansion of transmission infrastructure: an application of real option theory and risk-return analysis. Manuscript in preparation. (Chapter 5)

1.6 Methodology and thesis structure

The work starts with a strong bibliographical review and analysis to understand the main past contributions on risk modeling with a special focus on portfolio optimization as one of the most important tools of risk management. This includes a multi-dimensional analysis not only applied to the energy sector, but also in other disciplines. Two perspectives are reviewed in the energy area: the perspective of the regulator/planner (Chapter 2) and the perspective of the private agents: investors and energy buyers/sellers or managers (Chapter 3).

Considering the needs for further research that came up from the revision, an application is presented in Chapter 4 to demonstrate the effects of one risk mitigation measure in the electricity market of Chile. Specifically, Chapter 4 present an application of wind spatial diversification, showing that it may reduce the risk of price depression and low market values in scenarios with active transmission capacity constraints or low storage capacity and therefore is a strong tool that the regulator should consider. Designing incentives for the optimal location of generators can alleviate the transmission system, as well as the operation of system itself. Additionally, Chapter 5 presents a novel methodology to evaluate different options of delaying and developing a project by stages, when facing the uncertainty of the availability of transmission infrastructure, this is an evaluation from the perspective of a private agent.

The stages of the research are presented in Figure 3: the review and analysis of risk and use of portfolio from the planner perspective and private perspective (investors and managers) and the analysis of a risk mitigation measure applied in the electricity market of Chile.

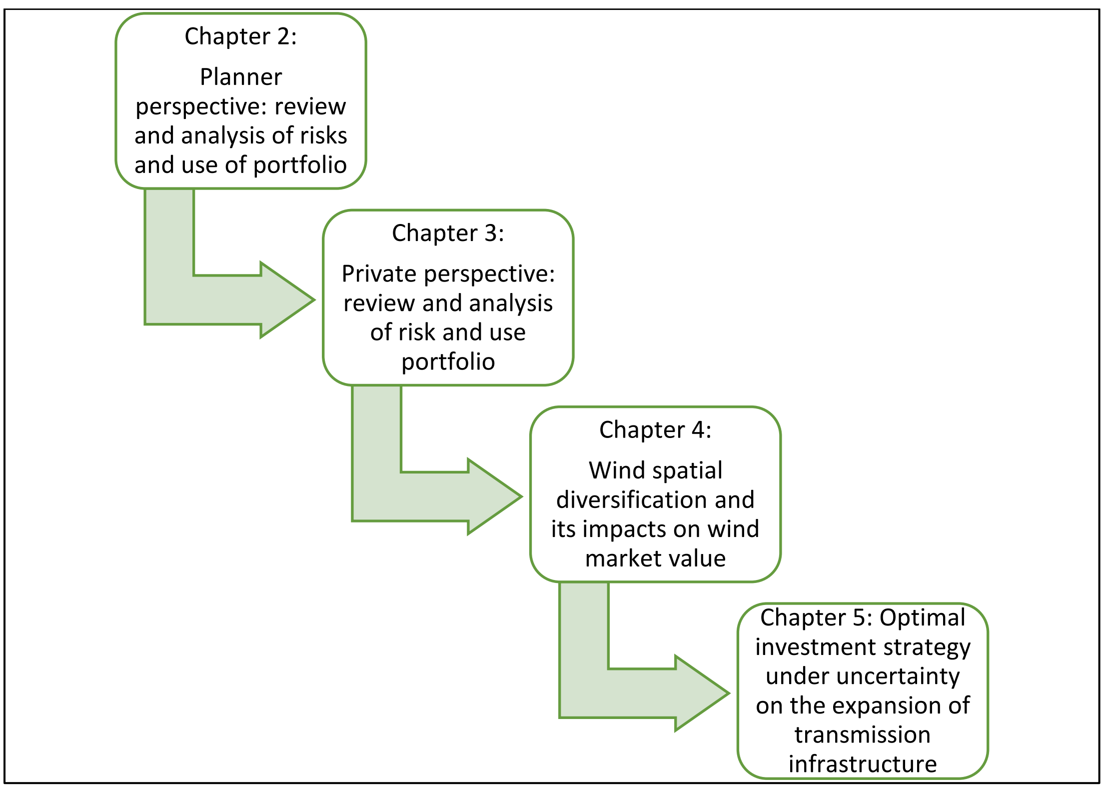

FIGURE 3: GENERAL STRUCUTRE OF THE THESIS

CHAPTER 2: PLANNING IN A CHANGING ENVIRONMENT: APPLICATIONS OF PORTFOLIO OPTIMISATION TO DEAL WITH RISK IN THE ELECTRICITY SECTOR

The countless publications that use portfolio theory and its associated concepts available today demonstrate its usefulness in different fields of research, and while most of the research on portfolio optimisation is found in the area of finance (see the review presented by Kolm et al. [23]), it also has applications in numerous other disciplines, such as economic analysis, project selection, environmental applications, water and land management, public health, psychology, and others (see Table 1). Bridges and Terris [24], for example, present concepts of the use of mean-variance portfolio theory to allocate resources among different health programs. Figure 4 presents some research areas that have made use of portfolio optimisation, and Table 1 presents some examples of these uses.

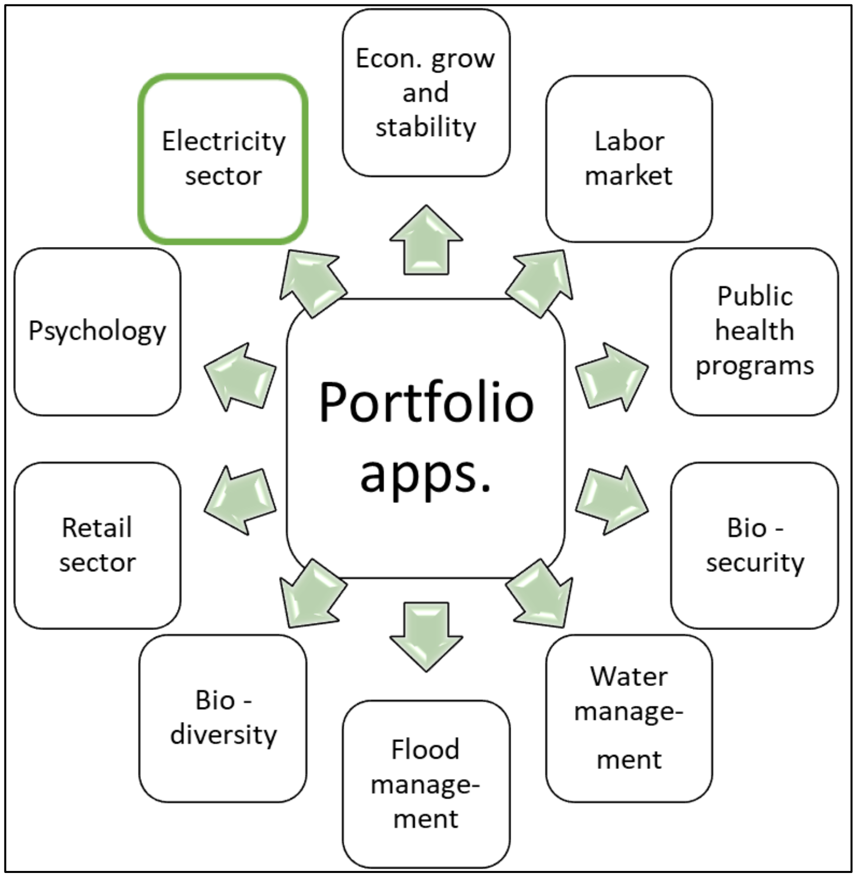

FIGURE 4: PORTFOLIO OPTIMISATION APPLICATIONS

TABLE 1: DIFFERENT APPLICATIONS OF PORTFOLIO OPTIMISATION IN DIVERSE RESEARCH FIELDS

Topic	Main application of portfolio optimization	Refs.
Economic growth and stability	Allocation of capital between sectors of economy to maximize rate of growth of economy subject to instability (variance of rate of growth).	[25–27]
Labor market	Optimization of the annual employment growth and risk (as the standard deviation of growth) to allocate efficiently among different economic development strategies.	[28–31]
Social sustainability	Explore how the variability of resources (temporal and spatial) in arid zones underpins most sectors of human endeavor. Return is the expected resource in a spatial unit while risk is related to resource variability.	[32]
Public health	Allocate public resources between different health care programs where the return is the health benefits and the risk is the variance associated with the outcomes considering costs and effects of the program.	[24,33]
Bio-security	Resource allocation across multiple pests that affect multiple environmental assets. In other words, allocate limited resources to bio-security measures to	[34]

	protect from invasion risks.	
Biodiversity	Resource allocation among mixes of species and ecosystems to optimize yield-risk-cost structure, where yield means any type of services provided by the ecosystem (e.g. biomass production in agriculture, forestry, carbon dioxide sequestration, flood mitigation) and risk is its variance in time and space.	[35,36]
Farm water management	Allocate resources among water exploitation options for irrigation to optimize farm return (farm return) and risk (variance of farm return).	[37]
Water planning and climate change	Allocate resources among intervention measures to maximize benefits (using criteria scores) for different climate scenarios. Examples of intervention measures are the construction of artificial wetlands or water treatment plants.	[38]
Flood management	Resource allocation between flood protection measures to optimize damage prevention return (in economic terms) and risk (variance of return).	[39]
Animal surveillance	Optimize the distribution of surveillance measures across time periods and geographic locations for animal protection. Return and risk are measured using criteria scores.	[40]
Psychology	Portfolio management is applied to the management of academic environments. Invest social or intellectual capital to diversify relationships and tasks in order to minimize the risk of adverse outcomes.	[41]
Retail format management	Allocation between investments in each retail formats[1] to maximize retail return and limit risk. The paper shows an application for the hotel industry to optimize the operation of brands.	[42]
Reforestation and restoration	Allocate between different seed sources. This is used to select a mixture of seed sources to minimize the risk of adaptation across all climate change scenarios.	[43]

It is important to observe problems in other disciplines, because they may share some risk structures with problems in the electricity and energy sectors, and risks that are new but increasingly important in the electricity sector may have already been studied and modelled in other fields. For example, hydrological risks have been studied in the field of agriculture for decades, if not centuries (see Hurst [44]), and several social and environmental risks that are new for the electricity sector have already been widely studied in other fields. As society shifts from a purely economic focus to a more sustainable perspective, greater emphasis should be placed on integrating social and environmental impacts, costs, and risks into the energy-planning problem. Sadly, we found no articles addressing sustainability from a planning portfolio perspective.

[1] "A retail format is the retailer type of retail mix (nature of merchandise services offered, pricing policy, advertising, and promotion program, approach to storage design and visual merchandising, and typical location" [42,286].

The rest of this Chapter is organized as follows: Section 2.1 provides an overview of the use of portfolio analysis in the electricity sector from two perspectives, public and private. Specifically, Section 2.1.1 presents the different sources of risks that the agents of the electricity sector must address, and Section 2.1.2 highlights portfolio challenges from the private agents' perspective. Section 2.2 presents a detailed discussion of one of the main planning problems for regulators—finding an appropriate generation mix. Section 2.2.1 presents the variables and return measures used in other articles using portfolio-planning tools, and Section 2.2.2 presents different measures of uncertainty used in the literature. Section 2.3 provides a description of the most critical needs for research to go forward using portfolios as a tool for planning. Section 2.3.1 focuses on renewable profiles and complementarities, Section 2.3.2 highlights the lack of sustainability factors beyond minimizing costs in the portfolio optimisation problem, and Section 2.3.3 discusses the importance of the dimensionality problem in a world full of uncertainty. Finally, Section 2.4 provides a summary.

2.1 Portfolio optimisation in the electricity sector: the public and private perspectives

The large number of applications using portfolio optimisation in the electricity sector can be classified in multiple ways. One is according to the private or public perspective. The former includes applications oriented towards investors (resources allocated to different projects) and managers (commercial strategy: allocate electricity sales/purchases to different trading mechanisms). The latter (public perspective) includes applications oriented towards regulators and planners (e.g. allocate resources to different generation technologies) for policy design, as is shown in Figure 5.

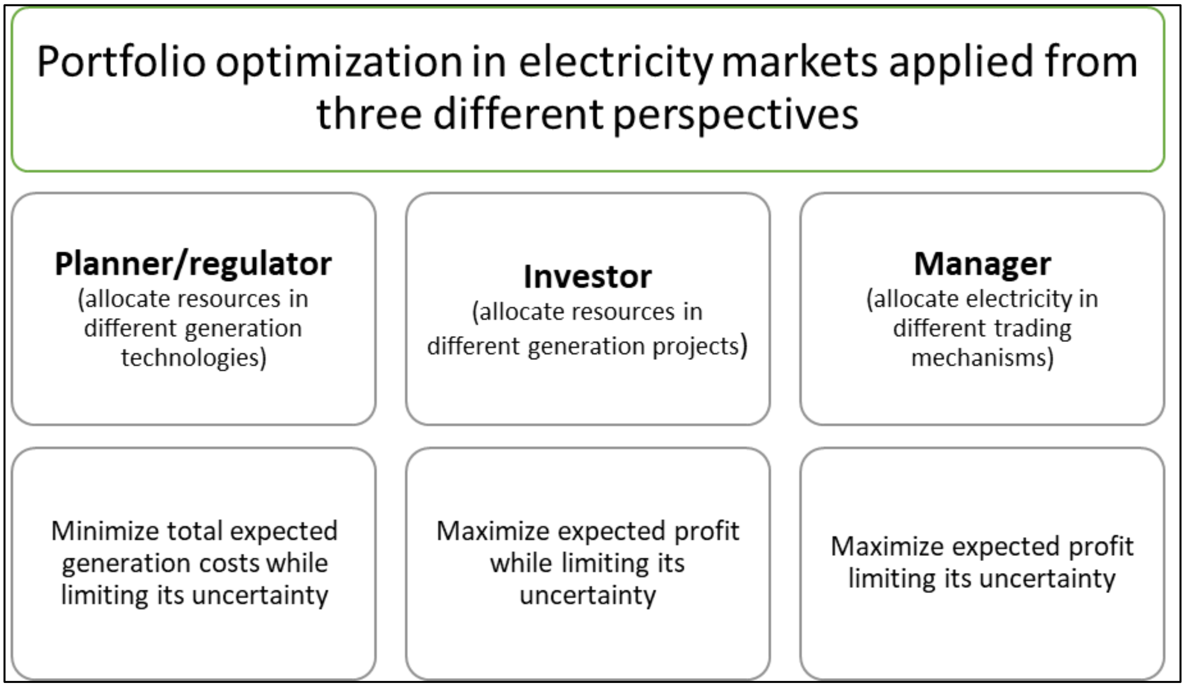

FIGURE 5: PORTFOLIO OPTIMISATION IN THE ELECTRICITY SECTOR FROM THREE DIFFERENT PERSPECTIVES: PLANNERS, INVESTORS, AND MANAGERS

The literature focused on the perspectives of investors and managers is limited to the market conditions of each country and its technological specifics. Therefore, that literature is segmented into a number of different topics rather than building one upon the other and evolving and improving over time. The literature focused on investors and managers is newer than that focused on planners because electricity markets in most countries are just two or three decades old, much younger than power electrical systems (the first electricity market was developed in Chile in 1982). Numerous papers on applications using portfolio optimisation from the planners' perspective have been published, especially over the past decade, in which the uncertainty of fossil fuel prices and renewable penetration have become greater (see Section 2.2). The literature for the three agents is evolving with a focus on renewable energy while addressing an increasingly more complex representation of renewable resources, technologies, productions, market arrangements and the way they all interact.

2.1.1 Uncertainty and risks in the electricity sector

The initial portfolio applications in the energy sector did not include renewable energies. After the oil crisis in 1973, fossil fuels became the primary expense for industries that were dependent upon them. These industries encouraged research that would help them reduce their exposure and vulnerability to fluctuations in oil prices. In that context, Bar-Lev and Katz [45] were the **first to use a portfolio approach in the electricity sector** for fossil fuel procurement for the purpose of determining the efficiency of fuel portfolios of utilities at that time. They discovered that utilities managed fuel portfolios efficiently, but at high risk, driven by the vertically integrated regulatory regime at the time. In recent decades, however, several countries have left the vertically integrated electricity sector behind and adopted a liberalized market scheme so that risk is currently an important part of management. Indeed, every agent in the sector is now concerned about profits, costs, risks, and efficiency in order to minimize costs and risk while maximizing profits and minimize risks.

Today there is uncertainty in most of the supply chain and for every agent because the electricity sector is subject to multiple sources of variability on both the supply and the demand sides and in the short and long runs, beginning with the primary resource (both renewable and conventional) and passing through conversion technology, production, sale, and financing. In addition, there are systemic uncertainties that involve public policies and consumption behaviour among other variables, that affect the entire supply chain, as presented in the review of Figure 6.

While a large body of literature has been developed to address uncertainty in prices and production technology in portfolio optimisation, little or no research is found on the portfolio optimisation associated with resources and systemic effects, such as the impact of system-wide renewable targets, transmission expansion, and net-load profile changes, etc.

This is shown in detail in Figure 6, where sources of uncertainties have been divided along the supply chain and classified according to the level of research available. “Unmodelled” indicates that sources of uncertainties have not received research attention in the portfolio literature at the corresponding section of the supply chain. “Modelled” indicates that there is literature available for such uncertainty.

The most common uncertainties modelled for the planner problem are fuel prices, investment costs, CO_2 prices, and maintenance costs, while for private agents, uncertainties produced by electricity spot prices are commonly factored in. Few applications model the uncertainties associated with technological changes, and none were found for portfolio optimisation modelling uncertainties produced by the generation of renewables, hydrologies, congestion rents, or demand growth, etc. Since these aspects are currently the target of a number of research initiatives, we expect to find much more research devoted to renewable and sustainable energy systems in the portfolio framework in the future.

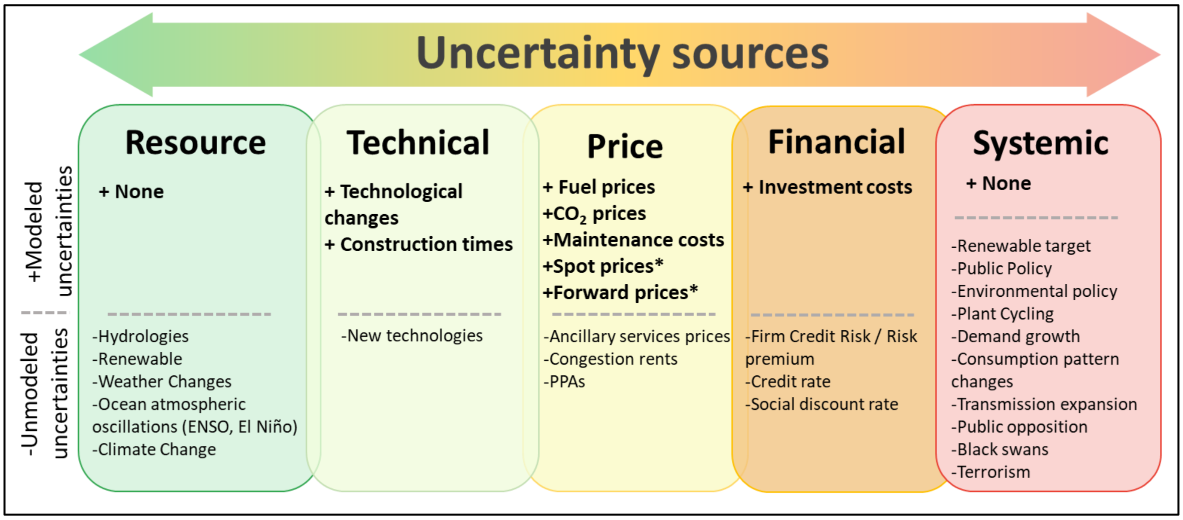

FIGURE 6: THE STRUCTURE OF UNCERTAINTIES FACED BY PLANNERS THROUGHOUT THE ELECTRICITY SUPPLY CHAIN: RESOURCE, TECHNOLOGY, PRODUCTION, SALE, AND FINANCING: RESEARCH HAS MAINLY TARGETED UNCERTAINTY IN TECHNOLOGY AND PRICES[2]*

Primary uncertainties faced by planners in the electricity sector

Planners face multiple sources of uncertainty on the **supply side,** such as investments and **fossil fuel prices** [8,13,14], which can be very unpredictable, especially in the long run because of their strong bonds with political issues. Furthermore, **renewable resources** composed of traditional hydrological uncertainty and non-conventional resources, such as solar irradiance and wind speed [16,46,47], are also important sources of uncertainty and variability. These are key factors, not only for the operation of the electricity system, but also for short- and medium-term planning. **Technological changes** are also part of the energy sector's long-run uncertainties [48,49], especially in the renewable sector, which has received most of the research attention in the past decade. Expectations for technological changes are very important in making investment decisions because they

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[2] * Some of these uncertainties, such as spot prices and forward prices, have been modelled in the portfolio literature for private agents, but not for a planning perspective.

directly affect expected **costs** [7]. For example, see the levelized cost ranking prepared by Mullen et al. [50], where large solar PV plants showed the biggest decline in relative cost among all other technologies, passing from the third most expensive technology in 2012 to the seventh low cost technology in 2014, out of 22 technologies presented in that ranking. Rapid cost decline is also observed in storage technologies, and along with PV, this is expected to fundamentally affect energy supply balance for 2020.

On the **demand side,** the primary uncertainty that planners face is electricity consumption in the temporal and the spatial dimension. Despite electricity demand's *identifiable* patterns in different time frames (hourly, daily, monthly, and seasonally), it still has an important stochastic component. In a society that constantly increases its electricity consumption and faces the massive entrance of electric vehicles, the challenge of correctly sizing the infrastructure becomes very difficult to solve. Furthermore, the spatial component of the demand is also a major source of uncertainty because demand is distributed along different sectors or nodes in the transmission system, and every node has its own demand pattern according to the type of consumers supplied (industrial, residential, or commercial, etc.), which, of course, can change over time [51].

Another source of uncertainty that affects the entire electricity sector in general as well as planners is **transmission expansion**, because it affects decisions on expansion and the placement of new generators. Even though planners can usually speed up the development of transmission corridors of national impact, these projects usually need longer to develop than the construction of individual generators. Similarly, regulatory changes also bring uncertainties that affect the entire market. **Environmental policy**, for example, in addition to its positive environmental effects, could introduce new uncertainty by creating new emission markets or by requiring new mitigation technologies [19,52].

Public opposition also brings new risks to the sector, especially for the development of big projects (new generation and new transmission corridors), which may be delayed for years. Growing sustainability concerns are increasing public participation and opposition to traditional sources of energy with large environmental and public health impacts. Regulators can encourage early participation processes to partially hedge this risk.

All of the above factors and short- and long-run uncertainties, along with the non-storability of electricity, inelastic demand and the steep supply function, cause very different equilibria between prices and quantities in the electricity sector as is shown in Figure 7, which is finally the variability and risk observed by the market agents (market prices and demanded quantities). Storage technologies still do not play a big enough role to decouple supply and demand in electricity markets, but in the long run, technology development and reductions in storage costs could change this paradigm [53–55].

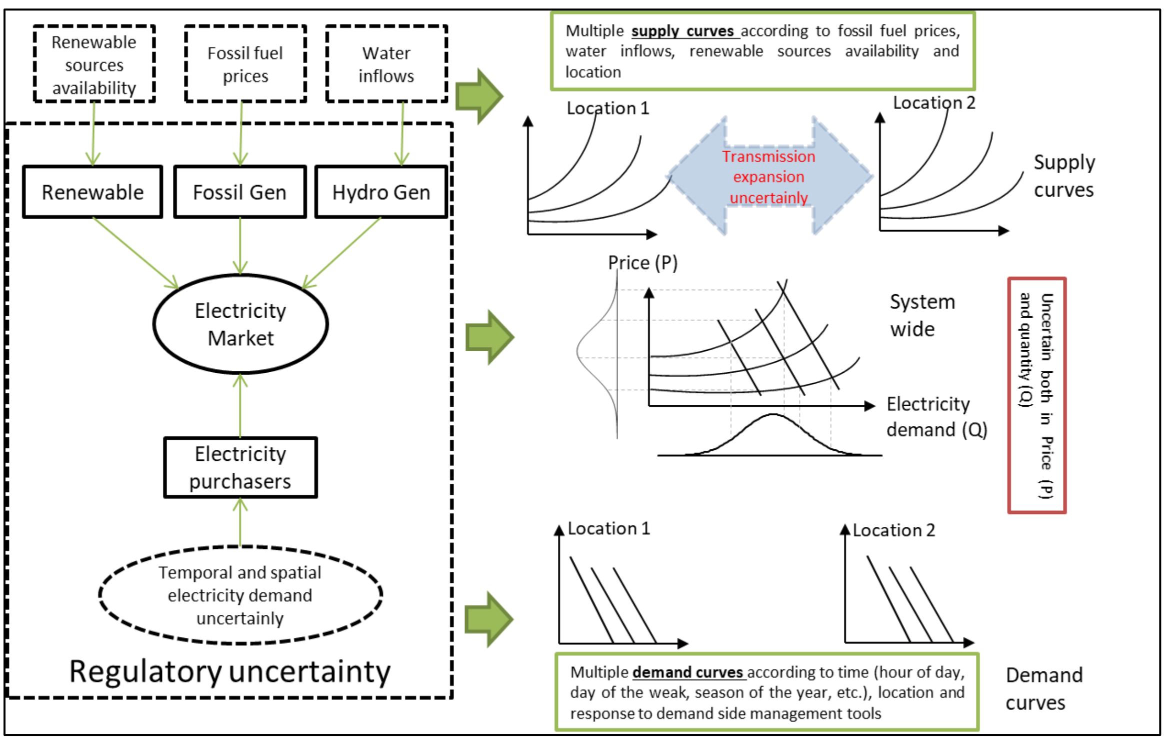

FIGURE 7: UNCERTAINTIES IN THE ELECTRICITY SECTOR THAT FEED THE ELECTRICITY MARKET THROUGH THEIR IMPACT ON SUPPLY AND DEMAND CURVES

2.1.2 Portfolio applications and problems from the private perspective: investors and managers

Unlike planners, investors do not seek to minimize social and environmental costs, but rather to maximize their profits and limit their risks. Here, risk is understood from an investor's perspective, because the uncertainty that can cause those future profits to be less than expected. Consequently, portfolio optimisation for investors is structurally different to portfolio optimisation for planners; it essentially focuses on financial profit rather than on an integral or sustainable perspective, which includes the impact on the environment, the society, and the economy.

In liberalized markets, however, generation investments are made by investors, not by governments [7], and therefore investments are driven by expected profit rather than by a sustainability evaluation. Investors need to analyse each possible project, their sources of risks (prices, technical, financial, and systemic risks), and their interactions with other projects. This is usually done by performing multiple cash flow analyses [8,9,56] and studying the distributions arising from them, such as the net present value and the internal rate of return, among others. The challenge for regulators and planners is to design regulatory frameworks to align private incentives with sustainable development.

Investors are not constrained by minimum investment or minimum capacity levels, so they need to consider **the value of waiting** [57] in their investment analysis (option value). The value of waiting reveals that the investor's optimisation problem has a dynamic component that is very important in the decision-making process. Indeed, investment in the electricity sector is marked by irreversibility due to the large sunk costs involved in electricity generation equipment and land acquisition, handling permits, and the availability of grid connections, among other factors that make the flexibility of waiting much more valuable. **Real Option Theory** [58] is the main tool used to assess the value of waiting in the investment decision problem, because it explicitly incorporates this effect [59]. These models are usually multi-staged (or dynamic). Traditional one-stage (static) models cannot capture the option value of waiting and postponing a project. Considering the decision of waiting adds value for investors because it allows them to acquire more information about the market and policies [60].

Portfolio optimisation for managers, on the other hand, is used to efficiently **choose among different financial instruments for selling and buying electricity**, for both electricity producers and electricity purchasers (wholesale purchasers or retailers). Since electricity is a good with very special properties, such as a steep supply curve, inelastic demand, and non-storability, real-time prices are very volatile and create high risks for agents and hedging against these risks through financial instruments is a fundamental task for managers. A complete review of financial and physical instruments used in electricity markets can be found in the paper by Deng and Oren [61].

The literature has dedicated much less attention to the optimisation problems of electricity purchasers than to those of other agents (planner, investors, sellers or power producers) [62]. In markets in which electricity is liberalized, small end-consumers are normally protected against price fluctuations by a fixed regulated price. Wholesale electricity purchasers (industrial consumer and retailers), on the other hand, must absorb the variability of electricity prices and use financial instruments to control this risk.

Publications on portfolio optimisation for electricity purchasers and sellers have used different modelling approaches. While **static approaches** use traditional mean-variance models [62–65] or mean-variance-skewness models [66,67], **dynamic approaches** use stochastic optimisation [68,69]. Static approaches solve the problem of how to allocate energy (buy or sell) to different markets (day-ahead market, forward, options, etc.) "here and now". In other words, the optimal solution of a static approach will answer how much energy should be allocated to each market without considering that the allocation decision on some markets can be delayed (e.g.: day-ahead market). Conversely, dynamic approaches are able to separate "here-and-now" decisions (e.g.: long-term contracts) and "wait-and-see" decisions (e.g.: day-ahead market, real-time market, own-generation, etc.).

Wait-and-see decisions are then a set of optimal solutions according to the realization of the uncertainty.

2.2 Portfolio optimisation as a tool for planners: pointing towards a sustainable development and the minimization of social cost and risks

Since portfolio optimisation in the electricity market was first applied, a number of efforts have been made to find the combination of generation technologies in efficient electricity systems that would save money for end-consumers. Beginning with the writings of Shimon Awerbuch [1,13,70], different methodologies that apply mean-variance portfolio approaches have been implemented to find the optimal technological mix in many countries or zones, as presented in Figure 8. Some publications also include sustainable factors as they are incorporated into the market as a carbon price system [13–18,71–79]

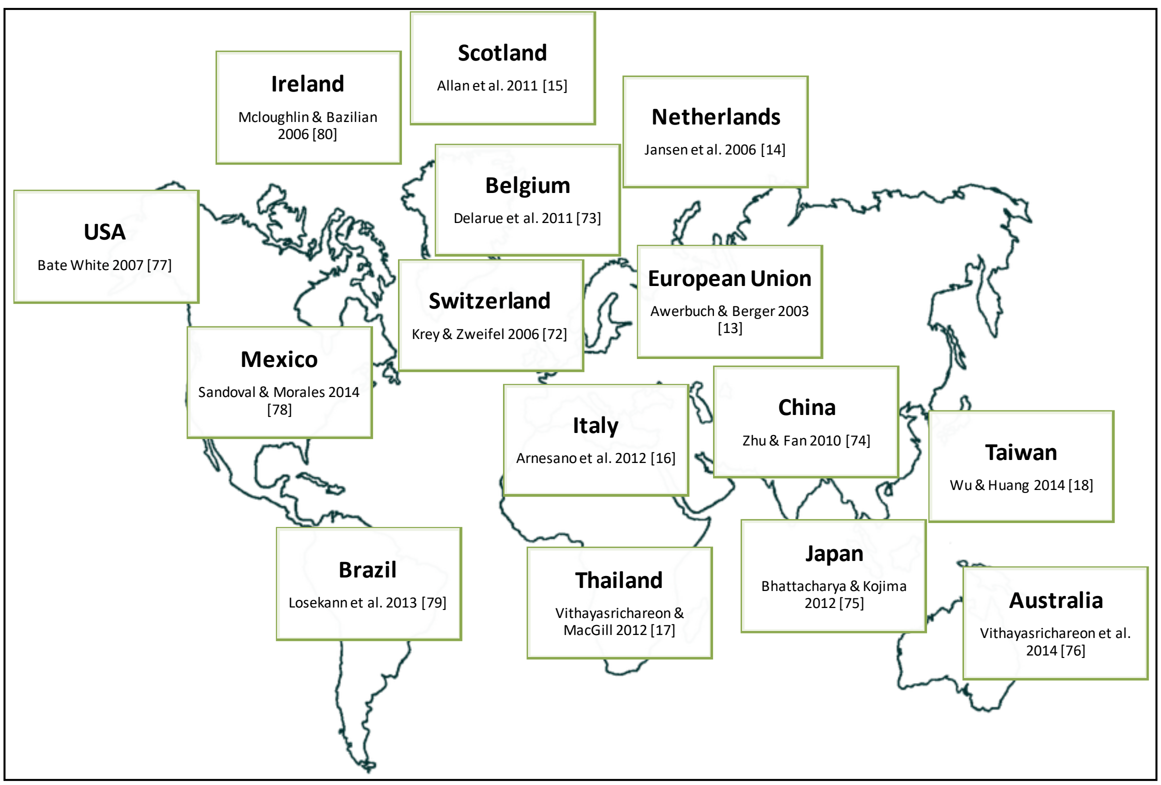

FIGURE 8: PORTFOLIO OPTIMISATION FROM THE PLANNER'S PERSPECTIVE HAS BEEN APPLIED IN DIFFERENT LOCATIONS AROUND THE WORLD

These applications not only minimize the expected investment and operational costs, but also restrict the level of risk faced by society. Risk is understood in these cases as the possibility that total cost may be greater than expected, and it is measured by different tools as explained in Section 2.2.2.

Finding an efficient generation portfolio allows planners to design policies that promote technologies that are part of the portfolio as well as to enable the grid to be prepared to receive those technologies (see Figure 9). In most countries, the sum of individual investors' decisions defines the final technological composition, although planners can always design policies and incentives to guide them towards the technological combination that is considered the most beneficial for society.

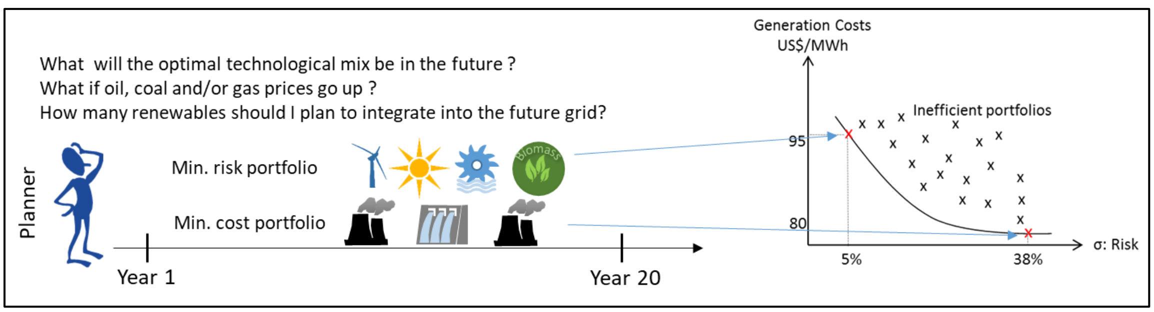

FIGURE 9: PLANNER'S PORTFOLIO PROBLEM: MOVING TOWARDS AN EFFICIENT ELECTRICITY-GENERATION MIX

The evaluation of each generation technology should consider the contribution to the portfolio's total expected cost and its total risk, rather than its individual cost alone [13]. That is, if the inclusion of a technology contributes by increasing the expected costs and at the same time contributes by decreasing the risk, it should be evaluated by considering both characteristics and not just from the cost perspective. Most papers on portfolio optimisation use a mean-variance approach to define an efficient technological mix, maximizing the inverse of levelized costs [13,16,74,80] or, alternatively, minimizing levelized costs [14,73,76,79,81]. In addition to the portfolio's return, publications differ on their approach to other important factors. While several publications seek to optimize the **generation share** of each technology and simplify the formulation by ignoring the effect of infrastructure usage and cost, others look at the **installed capacity** and the **generation share** of each technology separately. The latter (optimizing the capacity and generation share together), is much more difficult in terms of the mathematical optimisation, as will be shown in the next section. Other differences in the literature include the approach to the solution, the sources of uncertainties evaluated in the problem, and the generation technologies that participate as alternative technological combinations as is shown in Table 2.

TABLE 2: DIFFERENTIATING FACTORS IN APPLICATIONS OF PORTFOLIO OPTIMISATION TO DEFINE EFFICIENT ENERGY COMBINATIONS

Factor / Dimension	Modeling and solving alternatives
Return measure of the portfolio	Inverse of levelized cost (maximize) Levelized cost (minimize) Total cost (sum of fixed and variable costs)
Optimization variable	Generation share of each technology Installed capacity and generation share of each technology
Solution approach	Mean-variance analysis solved by: Optimization quadratic problem, quadratic constrained problem, simulation optimization, mixed integer problem
Source of uncertainty	Investment costs, fuel prices, fixed and variable O&M and CO2 prices, demand
Generation technologies that participate in the mix	Every paper uses different alternatives of generation technologies according to the availability of resources in each country

2.2.1 Optimisation variables and return measures

While most papers seek to find the optimal generation share (MWh) of each technology without proper differentiation between capacity and energy, other studies consider both installed capacity (MW) and generation (MWh). In the first case, it is sufficient to characterise each technology according to its levelized cost by incorporating assumptions on the capacity factor, interest rate and other parameters (see, for example, the paper by

Jansen et al. [14]). On the other hand, optimisation problems that seek to specify installed capacity and generation as independent optimisation variables must include the dispatch and its constraints as an endogenous problem, as presented by Delarue et al. [72]. A conceptual mathematical formulation of those optimisation problems based on the Markowitz mean-variance portfolio theory is presented in

Table 3.

TABLE 3: CONCEPTUAL MATHEMATICAL FORMULATION: OPTIMIZING TOTAL LEVELIZED COSTS VS TOTAL COST (FIXED + VARIABLE)

LCOE method (basic simplification)	**Install capacity + generation method (more realistic)**
Goal: Optimizing generation share of each technology using levelized costs	Goal: Optimizing installed capacity and generation share of each technology using explicitly fixed and variable costs
$Min \sum_i (LCOE_i) E_i$ **Subject to:** A maximum level of total levelized cost variability (standard deviation) Satisfying energy consumption V**ariables:** E_i: generation of technology i **Parameters:** $LCOE_i$: Expected levelized cost of electricity of technology i	$Min \sum_i (INV_i + FOM_i) P_i + (Fc_i + VOM_i) E_i$ **Subject to** A maximum level of total cost variability (standard deviation) Hourly or block demand Dispatch constraints **Variables:** P_i: installed capacity of technology i E_i: generation of technology i **Parameters:** INV_i : investment cost of technology i FOM_i : fixed O&M cost of technology i Fc_i: fuel cost of technology i VOM_i: variable O&M cost of technology i

Levelized cost of energy (LCOE) represents the minimum price of the energy at which a project can recover its costs [82] and it is widely used as a benchmarking tool to compare different generation technologies. LCOE essentially depends upon the discount rate, average system price, financing method, and energy generated over the lifetime [83], among other factors. Accordingly, LCOE depends on country-specific circumstances [84]. There is literature reporting a different range of LCOE values for different technologies. For example, the LCOE of wind power at the utility level in India is reported to be in the US$50–$100/MWh range [85], while in the United States, wind power is reported to be US$41.3–$71.3/MWh for new generation resources entering service in 2018 [86]. Likewise, solar PV is reported to be between US$62.6/MWh and US$120.2/MWh in the United States [86], while in Chile utility-scale solar PV plants reach US$67/MWh [87].

Calculating the LCOE requires multiple assumptions, such as capital investment, debt rate, future fuel costs, and maintenance costs throughout its economic life (e.g.: 25 years), but it also requires a strong assumption about the **expected generation** of such technology, which is translated into a **level of utilization** or **capacity factor** as is presented in Eq. 4.

$$LCOE_i = \frac{r_f \cdot INV_i(\frac{USD}{kW}) + FOM\ (\frac{USD}{kW})}{CP_i \cdot hours_{year}} + FC\ \left(\frac{USD}{MWh}\right) + VOM\ (\frac{US\$}{MWh}) \qquad \textbf{EQ. 4}$$

Where CP_i is the assumed capacity factor of the technology, and r_f is the capital recovery factor dependent on the discount rate to be used.

Defining a pre-established capacity factor for each technology to define a technological mix is a strong assumption because its implies that the capacity factor and the portfolio composition are independent of each other [88]. For example, take a portfolio with a high quota of non-dispatchable technologies, in such portfolio dispatchable technologies would have fewer hours of operation and less dispatched capacity compared with a portfolio without non-dispatchable technologies, as is presented in Figure 10. Therefore, **the capacity factor or level of utilization changes with the composition of the portfolio**. Consequently, levelized costs also may change depending on the portfolio. This simplification has strong implications for costs. For example, if the level of utilization is erroneously assumed to be too low for a technology with high investment cost and low variable cost (e.g.: run of the river), it will have a high levelized cost (capital cost divided into fewer energy units), and therefore the outcome of the analysis will be biased, resulting in a greater participation of other technologies to the detriment of that one.

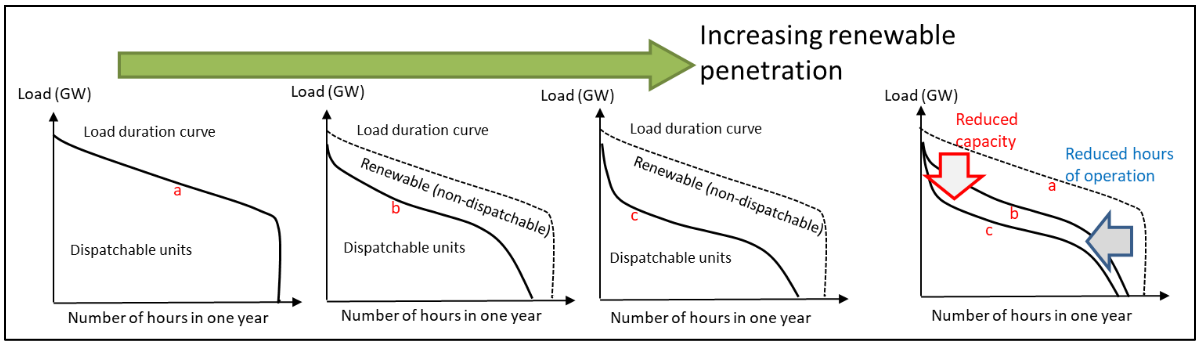

FIGURE 10: LOAD DURATION CURVES: AS NON-DISPATCHABLE TECHNOLOGIES ENTER THE PORTFOLIO, THE CAPACITY FACTOR OF DISPATCHABLE UNITS IS REDUCED. PORTFOLIO AND CAPACITY FACTORS ARE NOT INDEPENDENT

The assumption of the capacity factor is not the only drawback in the use of traditional LCOE in a portfolio analysis. A large body of literature has already shown many shortcomings of the LCOE analysis [89–92]. Traditional LCOE analysis does not include externalities such as air pollution and other environmental impacts, energy security, or transmission costs. Roth and Ambs [89] show that clean generation technologies are most attractive when all options are examined using a full-cost levelized approach. On the other hand, many authors have shown that intermittent sources have additional costs associated with grid integration that traditional LCOE fails to capture [90,91], resulting in the overvaluing of intermittent generating technologies such as wind and solar. Moreover, Ueckerdt et al. [91] proposed a "System-LCOE" metric that includes integration costs to allow a more realistic comparison between generation technologies. This metric takes into account when the energy is produced (profile cost), where it is produced (grid-related costs) and forecast errors (balancing costs), and it needs system-level data that require simulating the operation of the entire power system.

In addition to integration costs, large shares of intermittent generators have economic effects on traditional generators that cannot be captured using the LCOE methodology in a portfolio analysis. The integration of large quantities of intermittent sources in power systems represents a major challenge and generates a public policy debate [93]. Renewable power plants displace thermal generators and change their operational points, moving them away from their optimum, reducing their efficiency, and making them more expensive. Furthermore, non-intermittent generators must absorb the variability produced by intermittent generators and therefore assume new costs (such as cycling costs), which many countries do not take into account in their regulation. Cycling, defined as starting-up, shutting down, ramping up, and ramping down a power plant [94,95], has been and will be a major issue for thermal power plants. Over-cycling reduces the lifespan of power plants, reduces operational efficiency and therefore makes their generation more expensive (they have to recover capital costs in less time), since it has a degenerating effect on some components. In addition, the cycling requirement will lead to increased outages and plant depreciation, especially of base power plants that were not designed to operate flexibly [95].

On the other hand, when installed capacity is part of the variables of the portfolio optimisation problem, it is necessary to explicitly include variable (US$/MWh) and fixed costs (US$/MW) in the optimisation problem, as is shown on the right side of

Table 3. Defining the level of plant use in this case requires modelling a dispatch and its constraints. To do so, demand must be taken into account considering different demand levels over the year (and not only energy consumption as when optimizing with levelized costs) either by using **load duration curves or hourly load profiles**. Therefore, generation technologies are not only differentiated by their costs, but also by the relationship between their variable and fixed costs, thereby revealing that technologies are not perfect substitutes; some technologies are less expensive when under constant

production, while others are used only to meet peak demand [96], as is shown in Figure 11. This figure shows a particular example where an oil-fired power plant, which is dispatched a few hours a year, is the peaking power plant; gas plants peak and do some cycling; coal plants do some cycling and base load, and nuclear plants only base load. A better representation of technologies costs produces a much more difficult optimisation problem which in many cases cannot be solved.

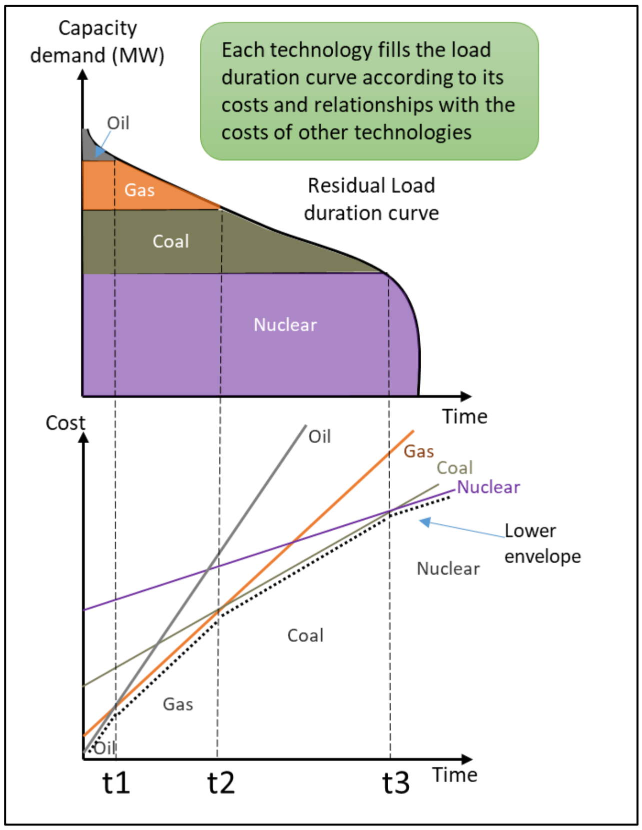

FIGURE 11: THE LOAD DURATION CURVE IS FILLED BY DIFFERENT TECHNOLOGIES IN ACCORDANCE WITH THEIR FIXED AND VARIABLE COSTS AND THE RELATIONSHIPS AMONG THEM. ADAPTED FROM [88]

2.2.2 Different sources of uncertainties and their measurements

The estimation of costs for each generation technology requires various sensible assumptions, such as fuel prices, discount rates and capacity factors, etc. A variation on these assumptions can dramatically change the costs and therefore constitute a risk for the planner because a low-cost portfolio may become very high-cost if, for example, the actual fuel price was higher than was expected when the portfolio was designed. As described before, there are multiple sources of uncertainty that affect electricity markets. However, most papers on portfolio optimisation from the planners' perspective consider risks to essentially be the result of the uncertainty of **fuel plus CO_2 prices** that cause different operational costs, the uncertainty of future **investment costs**, and the uncertainty of **maintenance costs** and their correlations [13–16,18,72–76,78,79,88].

All of these sources of uncertainty can dramatically change the expected cost of a portfolio (see Figure 12), although it is the uncertainty of fossil fuel prices that are crucial to finding the optimal technological mix. Indeed, most papers on portfolio optimisation from the planners' perspective have found that the integration of renewable technologies helps reduce the risk of supply costs, because renewable prices do not correlate to fossil fuel prices [13–16,18,71–74,76,77,79]. Most of their results suggest that policy variants with a high promotion of non-conventional renewables reduce portfolio risk significantly. Moreover, Escribano Frances et al. [97] focused on the contribution of renewables in terms of the security of supply using a portfolio theory approach and finding that renewable generation can be used to reduce vulnerabilities. They also found that renewable energy imports are strong candidates for improving energy security due to geographical diversification.

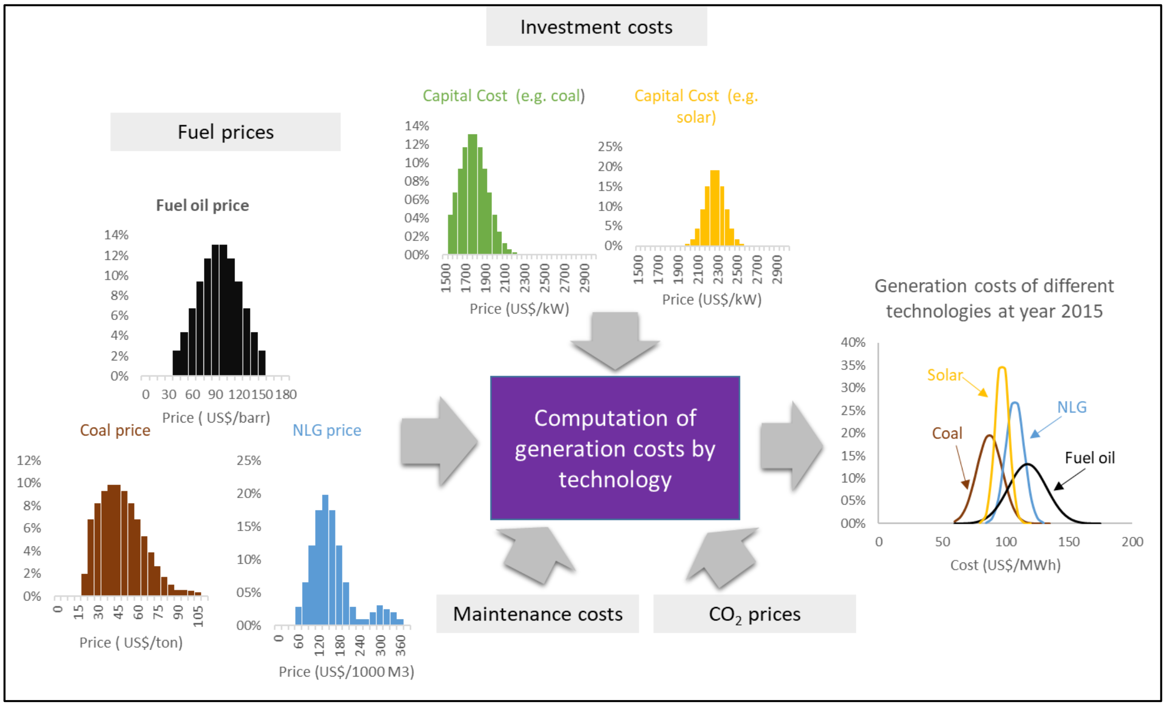

FIGURE 12: EXAMPLES OF FUEL PRICE VARIABILITY, CAPITAL COST VARIABILITY, AND OTHER SOURCES OF VARIABILITY AND THEIR IMPACT ON LEVELIZED COSTS

Beyond fuel costs, local and global emission (CO2e) costs are becoming increasingly more important and are considered part of generation costs and risks [65]. On the other hand, water inflows, demand uncertainty, transmission expansions, future technology improvements, and other sources of uncertainty are not explicitly incorporated into the portfolio optimisation analysis in most papers. Instead some of their effects are treated by introducing different scenarios [14].

Uncertainty on **technology development** and on the productive growth of new technologies (and the risk in the achievement of this growth) are also important factors for modelling, since technological changes and future capital cost reductions can change the optimal generation mix [96,98]. The inclusion of future uncertainty in capital cost can be implemented either by using technological learning curves [18,73,98] or by assuming a capital cost distribution of each technology and performing a Monte Carlo simulation approach [17,99,100]. Most articles assume either zero technology development and productivity growth to simplify the modelling or the lack of robust data to support alternatives assumptions.

Measures of uncertainty: standard deviation and higher moments, VaR and CVaR

Most papers characterize uncertainty by measuring it as the **standard deviation** of the historical data series. For example, Awerbuch and Berger [13], Jansen et al. [14] and Roques et al.[8] characterised fuel cost using standard deviation as the measure of risk. In mathematical terms, standard deviation is a measure of dispersion, so it accounts for both positive and negative values apart from the mean without distinction. In other words, standard deviation is a symmetrical measure of dispersion. If the variable is fuel costs, for example, standard deviation will measure how cost is dispersed to the left and to the right of the mean or expected cost, while the real risk for the agents is only the possibility that cost results higher than expected. Furthermore, measuring risk with standard deviation assumes an underlying normal distribution.

In addition to the standard deviation, higher *central moments*, such as **skewness** and **kurtosis** can be used to better describe risk. Skewness is the measure of the asymmetry about the mean, and kurtosis is the measure of the shape of the tails of the distribution. Additional central moments may better describe the real risks planners face, but it may be very difficult to integrate them in an optimisation problem. On the other side, in many portfolio optimisation applications, the importance of all the distribution moments beyond variance is much smaller than the expected value and variance [14,101].

Other frequently used measures of risk are **Value at Risk (VaR)** and **Expected Shortfall** or **Conditional Value at Risk (CVaR)** [14]. They are both exemplified in Figure 13 along with the probability distribution function of an example of a portfolio with a daily expected cost of 0.7 MM and a standard deviation of 0.2 MM. VaR is defined as the maximum potential loss of a portfolio with an α confidence level, where $\alpha$is a positive number between 0 and 100% [102]. For example, in a context of the cost of a daily generation electricity portfolio, a $VaR_{\alpha=5\%}$ of 1 million would mean that there is a probability that the portfolio will have a generation cost higher than 1 million (cost=c=1MM$)[3]. On the other hand, a CVaR is the expected cost of the portfolio in the 5% worst cases, so a $CVaR_{\alpha=5\%}$of 1.2 would mean that the expected cost of all of the portfolios over 1 MM is 1.2 MM. Accordingly, VaR and CVaR are usually used to control the probability of large losses for the portfolio.

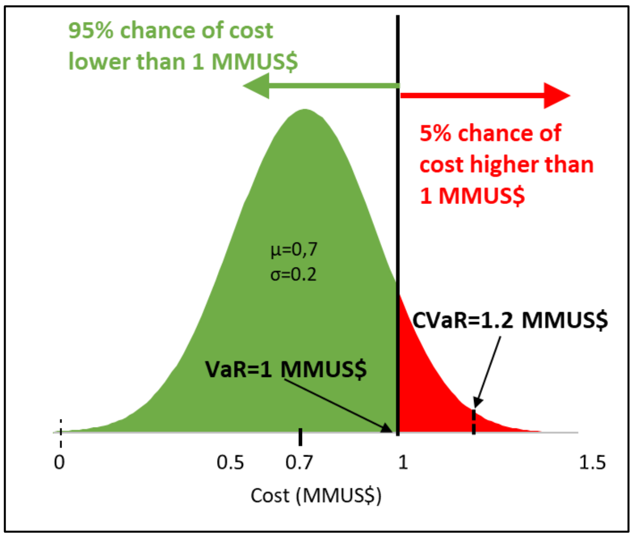

FIGURE 13: VAR AND CVAR AS MEASURES OF RISK FOR COST-BASED PORTFOLIOS

[3]More formally, if C is a random variable representing portfolio cost, then VaR is defined mathematically as the infimum value of such that the probability that C exceeds c is lower than α and is expressed as $inf\{c \; \varepsilon \; \Re: P(C \geq c) \leq \alpha\}$.

Most papers prefer to use CVaR instead of VaR as a measure of risk because it has superior mathematical properties. CVaR offers coherence[4] and computational ease. Moreover, VaR does not include losses exceeding the threshold value, while CVaR does, which may be very useful in very bad scenarios. More strengths and weaknesses of these risk measures in risk management and optimisation can be found in Sarykalin et al. [103].

Spatial risk: Transmission system and renewables

Limitations of the transmission system are becoming more frequent, and the literature has not addressed important issues in defining optimal technological mix using portfolio optimisation. Capacity transmission restrictions are important for short- and medium-term planning (less than 10 years) because space for right of way is increasingly scarcer and permits are increasingly stringent, which increases the time needed to develop lines. Transmission constraints may prevent the development of generation and can therefore change the technological mix. Take, for example, the case of northern Chile in 2015 and 2016 where the transmission constraints limited the generation of solar PV projects that had already been installed and prevented the entrance of additional capacity [104], thereby reaching spot prices equal to zero during some hours.

The relevance of modelling transmission network constraints is depicted in the work of Roque et al. [46] and Rombauts et al.[47], in which they developed a wind-planning model that considered cross-border transmission constraints. Their mean-variance portfolio model minimized the variance of wind production for a given level of production (wind power only), considering the geographical diversification of wind farms. By finding optimal portfolios with and without cross-border transmission constraints, they found that such transmission limitations could reduce the potential gains of the diversification of geographically disperse wind farms. To the extent of our knowledge, no portfolio model

[4] A coherent risk measure satisfies properties of monotonicity, subadditivity, homogeneity and translational invariance.

has included proper modelling of transmission networks, but the mentioned articles are getting closer by factoring in some key transmission constraints.

The lack of representation of the transmission system can affect the efficient technological mix in that if transmission is ignored, the proposed portfolio of technologies cannot be implemented in practice due to transmission congestion, high losses, and insufficient room in the infrastructure for new generation. In fact, transmission inadequacy is a barrier for the development of new power plants, especially for renewable power plants [105]. Furthermore, when transmission is ignored in the modelling the portfolio's efficient frontier is unrealistic (see Figure 14), not only because it may impede the entrance of new power plants, but also because dispatch constraints are ignored. Finally, when a transmission system is not modelled, generation **reserve** costs are also underestimated. A congested transmission line forces the need for reserve capacity on both sides of the congestion, whereas when there is room for more transmission, efficient reserves are used. In other words, local reserve levels depend, to some extent, on the availability of transmission capacity, particularly with the high penetration of renewable energy levels [100]. Operating reserves "do not travel much", and their capacity to do so depends upon transmission availability.

Therefore, there are important opportunities to contribute in the field of portfolio optimisation to define efficient technological mixes. Including capacity transmission constraints may allow the evaluation of a more realistic technological mix. It would also allow consideration of the spatial differentiation of renewable profiles and its complementarity. Quantifying not only the additional cost, but the additional risk caused by active transmission constraints as well would be a novel application in this field.

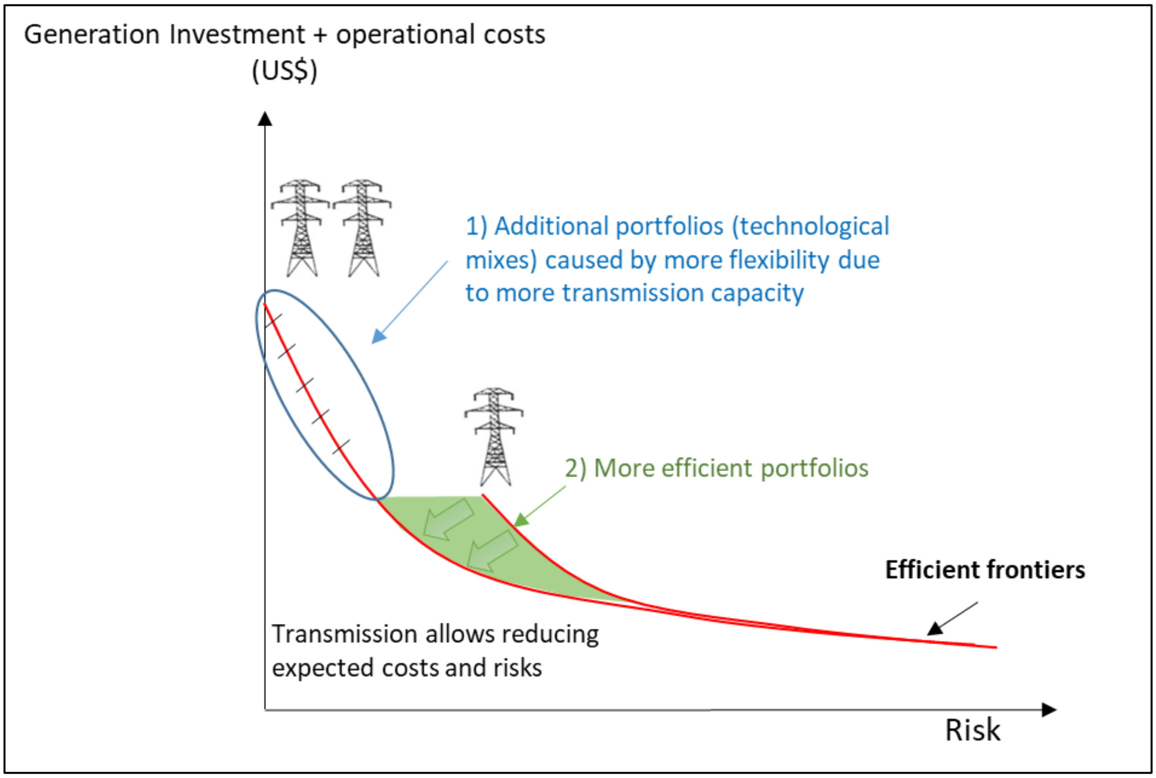

FIGURE14: DIFFERENT EFFICIENT FRONTIERS ACCORDING TO THE REPRESENTATION OF THE TRANSMISSION NETWORK

2.2.3 Technologies in the portfolio: conventional and unconventional mix

Most publications on portfolio optimisation add some form of renewable energy to the conventional generation in order to reduce the risk of exposure to fuel prices. In recent decades, however, publications have also included non-conventional renewable energies such as small hydro, wind, and solar PV in their portfolio optimisation models [18]. Some papers do not include all technologies because they focus on one specific form, as is the case with Roques et al. [46], who combined wind production from different wind farms to minimize the variability of the energy production by this resource. Less traditional generator technologies such as marine generation and their contribution to the portfolio of energy mix have been little studied, probably due to the scarcity of public information about the resource or because of an absolute lack of the resource in the location under study. One exception is the work of Allan et al. [15], who compared official Scottish planning scenarios of the generation mixes for 2020 with mean-variance efficient portfolios incorporating marine technologies, which they found to be inefficient, stating that wave and tidal technologies can significantly contribute to lowering the risk of electricity portfolios.

2.3 Urgent need for further research on renewable complementarity, sustainability, and optimisation dimensionality problem

Reviewing the literature on portfolios demonstrates an urgent need for research in three areas: including renewable profiles and their complementarity as a possible source of diversification, identifying the absence of social costs and risks in portfolio models as a key problem in energy project development, and finding a solution to the problem of dimensionality, which requires excessive computational burden.

2.3.1 Renewable profiles and complementarities

Non-conventional renewable resources such as wind and solar are sometimes shown as spatial and temporal complementarities in different time resolutions that may represent a significant reduction in risk for the agents, although surprisingly, this effect has not been taken into account in portfolio analysis. Indeed, complementary generation profiles between solar and wind have been studied in different countries (see Table 4), and as Widén et al. [106] points out, “There is clear empirical and theoretical evidence that dispersion of plants over a geographical area reduces the variability in the total power output from these systems.”

TABLE 4: STUDIES OF COMPLEMENTARITY BETWEEN SOLAR AND WIND POWER IN DIFFERENT LOCATIONS

Name	Complementarity	Renewable Resources	Location	Temporal resolution	Spatial Resolution	Data source
Hoicka and Rowlands [107]	Power output	Solar-Wind	Canada, Ontario	Hourly analysis (three years of data 20032005)	Four particular locations chosen by the authors	CWEEDS (solar irradiance and wind speed)
Widén [108]	Modeled power output	Solar-Wind	Sweden	Hourly to annual (eight years of data)	Eight particular locations chosen according to the availability of measured data	SMHI (solar irradiance and wind power output)
Y. Liu et al. [109]	Modeled power output	Solar-Wind	China	Hourly (one year data)	22 particular locations chosen by the authors	Without information
Santos-Alamillos et al. [110]	Daily integrated solar and wind energy	Solar-Wind	Southern half of the Iberian Peninsula	Daily integrated	9 km	Weather Research Forecasting (WRF) Meso-scale model
Monforti et al. [111]	Modeled power output	Solar-Wind	Italy	Hourly to monthly (one year data 2005	4 km	Satellite models Solar: SMSAF Wind: MINNI

Introducing geographical dispersion for renewable generation in portfolio analysis may be implemented with two levels of depth, first, by recognizing that the resource (e.g.: solar irradiation) at two different locations is not the same and leads to diverse capacity factors (e.g.: a solar plant in northern Chile produces 50% more energy per installed MW in a year than a solar plant in the central region), and second, by recognizing that there are complementarities among different locations and technologies, in other words, generation profiles using the same or different technologies are not perfectly correlated and therefore there are opportunities for diversification. While the former effect is sometimes included, the latter effect is always neglected (to the extent of our review) in the portfolio literature.

Using renewable complementarity in all its time scales helps mitigate planner risk from seconds to years. Complementarity at small time scales, i.e. from seconds to hours, helps reduce the expensive use of fast generators and reserve requirements, and therefore prevents the high costs peaks produced by the use of diesel fuel. Additionally, renewable complementarity at small time scales may also help reduce the cycling of fast thermal plants that are becoming a significant part of their operational costs. Complementarity in larger time scales, i.e. from days to months, helps efficiently optimize the use of water in the case of hydrothermal systems with large reservoirs (as in Brazil, Chile, and Colombia), but more importantly, it reduces the uncertainty of generation costs and allows the reduction of risk without a significant increase in costs. Complementarity therefore has positive effects on the operation of the power system as well as on its costs.

Arnesano et al. [16] developed an application of portfolio optimisation from the planner's perspective to define an efficient technological mix and recognizing different capacity factors by location for solar and wind plants. Surprisingly, this is the only effort to model the geographical heterogeneity of renewables that we have found in the literature on portfolios. They use pre-specified capacity factors for projects, although their methodology does not factor in solar and wind profiles (time series), and therefore they are implicitly assuming that different wind farms and solar PV generation profiles are perfectly correlated, which neglects the effect of complementarity. To the extent of our knowledge, no portfolio model has included proper modelling of renewable complementarity, i.e. using geographically differentiated profiles, to build optimal portfolios.

It should be noted that in the case of wind power, complementarity may exist in two plants in close proximity because the wind also depends on relief, and in some places the relief may change abruptly. For example, in Chile, the valleys and mountains near the coast are very close, and therefore different wind regimes can be found within just a few kilometres. Wind regimes in Chile are described in detail in the work of Watts and Jara [112] and more recently in the paper by Watts et al. [113].

2.3.2 Portfolio optimisation and sustainability

Of the three pillars of sustainable development—environmental, social, and economic—the environmental, and especially the social aspects, have traditionally been the weakest in the literature on energy [114]. Today, however, the social component is becoming increasingly important for project development. Contrary to what may be thought, all types of projects, including non-conventional renewable projects, are subject to social costs and risks. Wind power, for example, has provoked numerous controversies in some places where the most important concerns are the visual impact, noise, and bird strike [114–116]. Hydropower projects also have faced public opposition (for example, Chile’s large hydro project, Hydroaysen, where citizens were highly concerned about the impact of the dam [117,118]). Of course, thermal projects face opposition primarily due to the high emission of global and local pollutants. Ansolabehere and Konisky [119] analysed attitudes towards local construction of coal, natural gas, nuclear and wind power plants, and found an “overwhelming opposition” to coal, natural gas, and nuclear generators. Therefore, social issues are present in all generation projects, from renewable to conventional technologies, and are becoming increasingly important in project development.

Moreover, Talinli et al. [120] found in their work on the Turkish energy sector that among economic, technical, social, and environmental factors that affect decision making processes, social factors such as prosperity, community values, and health care have the highest importance, because public acceptance is essential in project development. For example, the “fracking” controversy in the gas industry in the United States [121], where the rapid development of hydraulic fracturing to exploit unconventional sources of oil and natural gas have sparked disputes where the main arguments of opponents have focused on the adverse impact on public health, the environment, and local communities. Therefore different methods have been used to address public opposition to project development, ranging from compensation schemes [119,122,123] and information campaigns [119,124] to more recent efforts to understand affective, emotional, and cognitive perceptions of citizens [125] and include public input, preferences, and early participation into the decision-making process and policies [126]. None of the above articles refer to portfolios, but they are examples that show that the social dimension is becoming an enormous factor in the decision-making process and therefore should be included in a portfolio environment to account for its costs and risks.

Even though environmental concerns have been included in the planning approaches, usually as imposing limits on power systems emissions, there are several other environmental impacts that have not been properly taken into account. The portfolio appears to be a good tool to explicitly include environmental impacts, costs, and risks and to extend the boundaries of the planner's evaluation beyond CO2 emissions. Moreover, portfolios may be a proper bridge to fill the gap between sustainability assessments, which rarely account for grid impacts [127], and planning models, which rarely account for environmental impacts other than emissions. Performing a comprehensive analysis, which includes environmental consequences as well as positive effects in the grid, is very important for evaluating technologies in their multiple dimensions.

For example, hydroelectric power plants play a very important role in adding flexibility to power system operations because they provide a very fast response (e.g. quick changes in production to compensate for wind fluctuations), allow peak shaving capability, and provide storage of water for use when more energy is needed (impoundment plants), thereby reducing the need of fossil fuel peaking plants. On the other hand, in most cases these plants require flooding large extensions of land, which reduces bio-diversity, forces the population away from the area, and has other negative environmental and social impacts. A proper sustainability portfolio analysis of hydro plants should include both the positive operational value and their negative environmental and social impacts.

Including social and environmental impacts in a portfolio model requires characterizing a set of technologies and their impacts for use as part of the analysis. One way to achieve this is to use indicators such as CO_2 emissions, land use, energy output, water consumption [128,129], biodiversity losses, impacts on flora and fauna, and the impact on local and global population, among others. More generally, Onat and Bayar [128] show a sustainability indicator for power production systems that includes the political, economical, resource, and market environments, as well as the influence of social and environmental dimensions.

Portfolio optimisation is a tool that allows the inclusion of the risks of a multiple criteria analysis, which is becoming increasingly relevant in the energy-planning problem.

2.3.3 The dimensionality problem

Dimensionality is the nightmare of optimisation problems, especially stochastic optimisation problems of electricity planning. They have thousands of variables, including multiple sources of uncertainties in different time spans and locations that make them extremely difficult, if not impossible, to resolve. Before renewable energies became widely available, planning models relied on load duration curves in which the demand data was arranged in descending order rather than chronologically, but now that renewable energies are more important, a chronological representation is necessary to correctly identify the interactions between renewable resources and demand patterns. Renewables not only change the way of modelling, but also introduce both temporal and spatial uncertainties. This is one of the primary reasons why most literature tends to ignore some dimensions of the problem (e.g.: some portfolio planning models assume a fixed demand and fixed renewable profiles) and address high dimensionality by using different strategies, such as reducing design space, decomposing design problems into sub-problems and parallel computing, among others [130].

This topic represents another research opportunity: developing new techniques that help reducing the computational burden, especially in high dimensional problems of large-scale power systems by designing new optimisation strategies [130] using scenario-reduction techniques [131], hybridizing existing techniques, and using new heuristic methods [3], etc.

2.4 Summary

In the current scenario of electricity markets, with growing concern about the environmental, social, and economic sustainability of the energy supply as well as increasing levels of uncertainties, it is essential to appropriately incorporate the risk associated with those uncertainties. It is no longer acceptable to simply address the scenarios and expected results for supply costs, profits, or other factors. This is inspiring a growing level of research that quantifies risks and incorporates both expected results and risks, thereby making the trade-off between risk-cost and risk-benefits more transparent. Portfolio optimisation is an important tool that incorporates expected results and risks associated with multiple decisions or multiple projects (portfolios), making it possible to factor **diversification** into planning models. This is the risk cancellation effect that comes from developing various energy sources, rather than a single energy source that is believed to be the least expensive. Examples include developing wind and solar projects that improve transmission infrastructure usage and reduce the need for complementary fossil fuel plants; developing wind farms with complementary wind resources to reduce congestion events, spill-over events, and produce a more steady output; and developing fossil fuel plants that complement the renewable plants with more flexibility, etc.

It is surprising that no article has yet explored the **complementarity** of wind and solar energies in different locations in a portfolio environment. While complementarity studies in renewable energy are becoming far more common, the overall effect of complementarity in power system performance in risk-cost, risk-benefit, or risk-impact environments are nearly absent in the literature. There are several research opportunities in the area of portfolio optimisation with renewables and proper power system modelling, although that presents a number of modelling challenges. The **dimensionality** of the problems grows exponentially when both power system details and the profiles of renewables are factored in properly.

The potential for portfolio optimisation has been identified in multiple areas outside finance, with applications from economics to psychology, and the electricity sector is no exception. Portfolio optimisation can be used in the electricity sector from a private perspective (investors and managers) as well as from a public perspective (regulators and planners). In this work we began by briefly addressing portfolio optimisation applications from the perspective of investors and managers, and then we explored the **planners’**

perspective in detail. We identified several voids in the literature as well as the corresponding research opportunities, some of which are summarized below.

Portfolio cost and risk in a sustainable system. Historically, after massive electrification has been achieved, one of the main goals of the planners has been to ensure a high-quality supply of electricity while keeping customers' bills low, aiming to boost economic development. Sustainable solutions have an increasingly important role in limiting environmental and social impacts and risks to the energy supply. Traditional cost minimization models do not take risk factors into account, so in a context in which fuel prices are increasingly volatile, the penetration of renewable sources is unstoppable and hard to quantify, and future emission control policies are under debate, the minimization of expected costs does not make sense without considering some measure of risk in an attempt to quantify the probability of reaching that cost or going beyond it. This is why many papers are introducing increasingly detailed portfolio analyses that aim to aid planners in their decision making with models that are progressively more realistic.

The role of renewables. Most papers using portfolio analysis rely on **mean-variance approaches** to suggest efficient technological mixes in different locations, and one of their main conclusions is the need to **increase the role of renewable energies** to limit exposure to the future uncertainty of fossil fuel prices. Most papers provide quantitative results, although they must be understood from qualitative perspective. The excessive simplification of their models limits their quantitative validity. This simplification is usually based on the large dimensionality associated with multiple renewable resources located in different areas of the system, with various profiles and variable correlation patterns.

Modelling dispatch and operational and infrastructure costs using portfolios. There are two primary approaches to planning using portfolio analysis in energy markets. While most papers minimize the portfolio cost using unrealistic exogenous levelized costs, others directly consider variable and fixed costs separately in an attempt to incorporate the effect of infrastructure usage into the cost. The use of levelized costs requires the level of utilization or load factors for each technology as one of many inputs, while the use of fixed and variable costs requires solving a dispatch, and therefore load factors are determined endogenously. Indeed, **there is an underlying assumption of simplification when using levelized costs to define an efficient portfolio, and this is that the level of utilization is independent of the technology mix and renewable energy penetration in the portfolio**. Furthermore, using only levelized costs does not allow the inclusion of dynamic constraints on the operation (e.g.: ramps) or transmission constraints that can eventually make it impossible to reach a specified technological mix in practice. On the other hand, the use of variable and fixed costs explicitly is more realistic and allows generation and installed capacity to be optimized together, although it requires significantly more computational effort. Both methodologies have found that renewables reduce exposure to risk.

Spatial representation of a sustainable grid. One important void in all these models is the spatial representation for both the **transmission system** and the geographic differentiation of renewable generators. Transmission constraints can occasionally prevent reaching an optimal electricity mix due to congestion, so ignoring transmission constraints in theoretical models merely results in an unfeasible optimal mix (renewables are often located far from consumption centres and therefore require a transmission infrastructure). Only two publications on portfolios [46,47] included constraints in transmission capacities, but they are only focused on the portfolios of wind power plants to reduce variability. Moreover, the massive emergence of renewable sources requires locational differentiation in portfolio analysis, because resources may change abruptly between two different places. This reinforces the need for spatial representation, because **renewable generation may present complementarities** that can, in fact, reduce output variability and form a well-behaved generation pattern, as is demonstrated in recent research on the complementarity of renewables (see [46,47,108]). A sustainable grid requires a robust transmission network to take full advantage of renewable resources spread out across the territory.

Environmental and social costs in a portfolio environment. None of the portfolio papers reviewed included **social and environmental costs and risks, which are** key components of a sustainable grid, although social and environmental impacts are strong constraints for the development of energy projects today. The social component of project development is a fundamental factor for project success and needs to be studied further and included in portfolio modelling; to the contrary, ignoring it may translate into project delays and cancellations. Thus, planners should consider the risks not only in the financial cost dimension, but also those associated with environmental and social dimensions. Constraining local and global pollutants, water and land use, allowing extended time for public participation, concern for indigenous communities their lands and their natural resources, and incorporating the fact that all these factors added to massive public opposition could take a project out of the optimal portfolio. New generation projects can no longer overlook these variables; citizens are increasingly more empowered, and technology allows them to coordinate their efforts more efficiently. Environmental issues and social conflicts are gaining relevance for all decision-making processes in both public and private projects. As pointed out by Seddighi and Ahmadi-Javid [132], today the reality of power system management is evolving to a more complex and **multi-dimensional problem** because it not only has to address the alarming use of fossil fuels, but pollution, water and land use, climate change, social issues, and other externalities as well. Today including environmental and social costs and risks is more a need than an option.

2.5 Conclusions

This chapter presents a review of portfolio optimisation as applied to the energy sector, highlighting the role of renewable energies, transmission, storage, sustainability, and other challenges that characterize today's energy arena. Such fast-changing environments force society to consider several sources of uncertainties that produce high levels of economic risk. Portfolio optimisation is a tool to formally address such uncertainties, and we conclude with future research directions and broad recommendations.

- Traditional uncertainties (fuel prices, electricity demand, etc.), added to new uncertainties introduced by social and sustainability concerns (environmental policies, carbon price systems, social opposition to energy projects, etc.) and massive renewable penetration (resources, production, technological advances, project locations, etc.), call for the use of new methodologies to address such uncertainties.
- Portfolio optimisation is one tool to account for simultaneous sources of risks and interactions between them, limiting the level of risk that the economy, society, and environment must consider.
- Renewable energies add value not only because they reach competitive costs, but also because they reduce the exposure to uncertainty from several different sources, ranging from fuel costs to climate change. This conclusion is found in several articles, but their excessive simplification in power system modelling using portfolio approaches make it difficult to consider their quantitative results.
- The most significant absence in the portfolio literature is the **lack of spatial representation**, considering the constraints of the transmission system as well as the difference and complementarities among renewable profiles at different sites.
- The lack of representation of environmental and social costs, impacts, and risk in the portfolio literature is a great research opportunity because they are increasingly more important in the sector.
- Storage technologies are still not considered to be a solution for preventing or mitigating risks in portfolio analysis, although their costs are decreasing quickly and they are becoming commercially feasible. Research in this area is slowly being integrated into the planning framework.

CHAPTER 3: PORTFOLIO APPLICATIONS IN ELECTRICITY MARKETS REVIEW: PRIVATE INVESTOR AND MANAGER PERSPECTIVE TRENDS

New problems arising in the modern era such as global warming produced by anthropogenic greenhouse gas emissions on one side, and our dependence on electricity on the other, point toward the integration of new and clean technologies into the grid [133]. The concerns about the environment have not only pushed technological development, but also new regulations seeking to limit local and global emissions. New technologies dependent on natural resources such as solar and wind farms, new, more stringent local and global environmental regulations, and the new market arrangements that are necessary to accommodate such changes are added to a global context where **uncertainty** is the common denominator [3,134]. The feasibility of big investments, such as new large power plants and new, high-capacity transmission corridors, hinges on the risk perceptions of market agents on a series of uncertainties at the operational, commercial, planning, and regulatory levels. The electricity system is now flooded with these uncertainties in multiple time scales, increasing the difficulty of decision making and pushing for the development of new risk management tools, which are fundamental for developing energy projects with limited levels of risks [135,136].

There are three key agents in the electricity sector who are constantly in need of risk management tools: private investors, managers commercializing energy (for large energy holdings, industrial consumers, or load serving entities) and planners, which are often specialized units of the regulator seeking social welfare over both the long and short run. The three interact with each other under the same platform, the energy markets. However, they face entirely different problems with respect to risk management.

The risk management problem for planners, for instance, often consists of long-term planning for the generation mix and transmission updates that maximize social welfare along with the policy design to achieve that plan. There are multiple sources of uncertainty including fossil fuel prices, renewable resource availability, technology development, social opposition, and global and local emissions limits, among many other factors that matter in these long-time scales. The multiple sources of uncertainty notwithstanding, the vast majority of the literature over the last two decades has focused solely on fossil fuel price uncertainty [13–16,18,72–76,78,79,88]. Thus, the literature is paying limited or no attention to the other sources of uncertainties.

While market participants are key players in today's electricity sector, their risk management problems are less developed compared to the planner problem. However, after a decade of portfolio application for private agents, a systematic literature review is well justified by a number of important articles addressing diversification opportunities and efficient risk taking by trading in multiple markets in different time frames, investing in multiple technologies, and exploiting distant resources with non-coincident production connected to the transmission grid (temporal and geographical complementarity), etc. In addition, there are a number of new concepts, tools, and methodologies available in the literature that have not been fully integrated into private portfolio analysis such as complementarity assessment for multiple renewable sources, structural modeling of the power system physics, and the integration of real option analysis and portfolio optimization. This literature is reviewed in the following sections, highlighting research trends, opportunities, and challenges. Most of the key concepts found in the literature reviewed in this work are summarized in Figure 15. The key concepts appearing around the figure of the investor are option value, return and risk measures. Around the figure of the portfolio manager we found trading mechanisms, dynamic and multi-stage, static models, etc. We also found some key concepts around the literature dealing with both market agents, referred to here as cross-cutting issues, among these we are highlighting statistical price modeling, structural modeling, and renewable modeling. All of these concepts are briefly explained and referenced in this review.

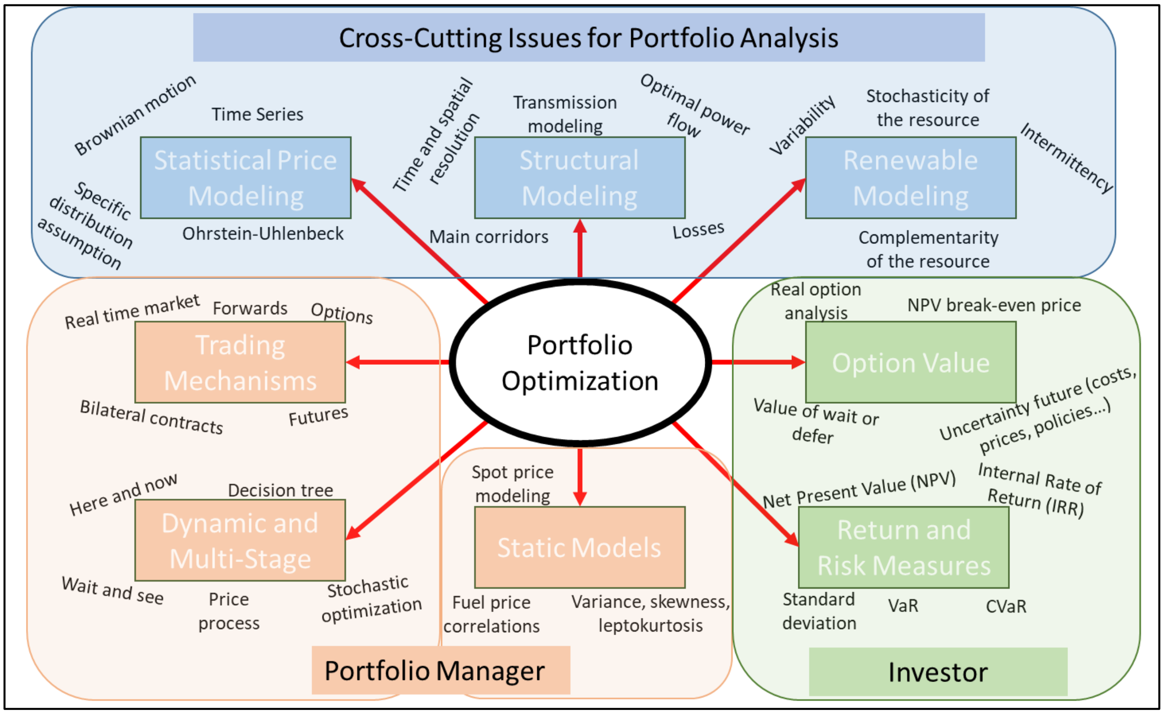

FIGURE 15: MOST IMPORTANT CONCEPTS REVIEWED IN THIS WORK

Existing articles are mostly focused on portfolio applications from the planner perspective. This is the traditional planning problem, where systems costs are minimized. Here, portfolio theory allows including the risks over such social solution, without specific attention to market details or market agents.

Given the current trends in power systems, every day is more relevant to consider the private agents´ perspective. The private sector has a growing role in power systems, especially in renewable energy development. This chapter is focused on the perspective of private agents and its contributions can be summarized as follows:

- To the best of our knowledge this is the first review on portfolio applications focused on private agents (both investors and managers). This perspective is of growing interest due to the current trend of implementation of electricity markets across the world and increasing the deployment of renewable energy technologies.

- The chapter presents an overview of different portfolio tools for the decision-making process of private agents in power systems with high penetration of renewable energies.
- In addition to the review of the existing literature, this chapter discusses cross-cutting issues emerging from the growing interaction of a new technological paradigm: markets and uncertainties sources driven by renewable energy development and technology evolution.

This Chapter is organized as follows: Section 3.1 provides an overview of the applications, problems, and challenges of portfolio optimization for **private investors**. Specifically, Section 3.1.1 presents the different measures of return/cost and risk typically covered in the literature, Section 3.1.2 highlights the lack of appropriate modeling of uncertainty factors that are usually ignored even when they play an important role for investors, and finally, Section 3.1.3 addresses the importance of considering the value of waiting in the investment decision problem and how to address it in a portfolio analysis. Section 3.2 discusses the main applications of portfolio optimization from the **manager's perspective** and presents two families of approaches: static and dynamic models. Section 3.2.1 presents static models that assume that all decisions must be made "here and now," and Section 3.2.2 presents dynamic models that are much more computationally demanding but they are able to separate "here and now" decisions and "wait and see" decisions, and finally, Section 3.2.3 presents alternative markets, such as capacity markets, demand response markets and others, to diversify services and mitigate risks. Section 3.3 presents cross-cutting issues, voids and challenges from both perspectives (investors and managers), Section 3.3.1 provides an overview of the most used modeling approaches to simulate price evolution, and Section 3.3.2 focuses on renewable profile complementarities and how they have been ignored by portfolio literature, even when there is literature available that provides estimations and measurements of high complementarity between geographically dispersed renewable resources.

3.1 Portfolio optimization as tool for investors to allocate capital in different generation projects

The problem that investors face is quite different from the problem planners face. Investors aim to define an efficient technological-locational mix by maximizing their return on the investment. Planners, on the other hand, aim to minimize costs. Investors may focus solely on some places and some technologies according to their preferences and possibilities, while planners may focus on the whole arrangement of places and technologies. Additionally, investors have the flexibility of waiting to invest in a project. However, when the investment is done, they have a high degree of inflexibility due to the high sunk costs involved. Planners, on the other hand, have to plan to meet the expected demand, but they also have the possibility of changing the long-term plans. Finally, investors are usually witnesses of policy changes, transmission expansions, new entrants, and environmental standards, while planners have a key decision-making role in these areas. Thus, the investor's portfolio problem involves a very large amount of capital and high levels of uncertainty in the returns on the investment, so diversification among technologies, resources, and places is a common strategy for hedging risk. Portfolio optimization is a tool used to deal with these risks through diversification.

The generation sector has historically faced high and volatile electricity spot prices caused by the variability of demand and the impact of physical constraints such as generation and transmission limitations. Such volatility has increased in recent years due to the integration of volatile renewable resources including wind and solar. The fast progress and aggressive entry to the market of these technologies (see the examples of penetrations of these technologies in Chile in Figure 16) has produced a decrease in the levels of spot prices as well as an increase in their variance [137–139]. In addition, the intermittency of renewables requires that high transmission capacities be available at all times to move its energy in the system. However, the time required to develop new transmission is much longer than the time to develop renewable projects, so it is not infrequent to see congestion on transmission lines near a set of renewable projects. This also dramatically impacts spot prices, either by marginal losses or simply by a decoupling of markets caused by congestion. For example, this is exactly the situation produced in the north of Chile where solar PV plants and coal-fired plants are subjected to long hours of zero marginal costs due to transmission congestion [140]. Unlike planners, who usually plan in the long term and therefore they assume that transmission systems will adapt and therefore congestion can be avoided in the portfolio analysis, investors do not have that possibility. If the analysis is done in the long term, investors have to include the transmission system and its future possible congestions in the financial modeling of their portfolio of projects, since electricity prices and energy production may change dramatically by a change in the transmission structure. Transmission equalizes spot prices over the space through the marginal loss and marginal congestion component of prices and is a key locational signal for generation siting.

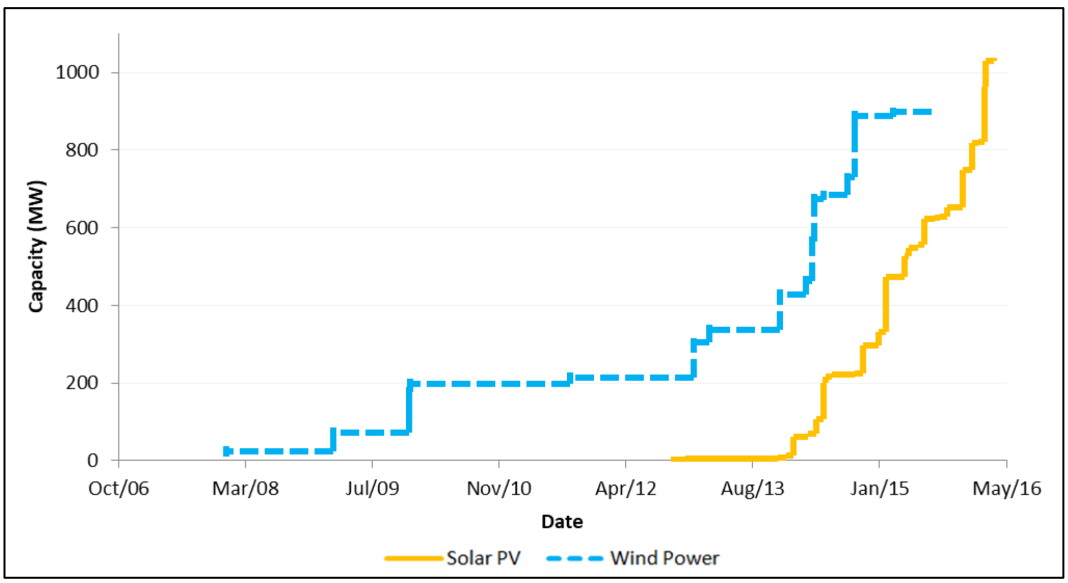

FIGURE 16: ACCUMULATED INSTALLED CAPACITY OF SOLAR PV AND WIND POWER PLANTS IN CHILE

Investors' capital allocation in the electricity sector is a particular case of the project portfolio selection problem (PPSP) that studies how to distribute capital among different projects such that the expected return is maximized for a given level of risk [141]. Despite that there are different investment situations[5], all investors seek the same goal: to maximize their return and limit their risks, so in all of these situations a measure of profitability has to be estimated using the projects' projected cash flows (see Figure 17). This means that for every year of a generation project's service life, the estimation of its income and its costs is required. At the same time, income and costs essentially depend on uncertain factors like electricity spot prices, project expected generation, fuel prices, and capital costs, among others. Cash flow calculations are then random variables that depend on the realization of different sources of uncertainty as illustrated in Figure 17. Return and risk measures arising from these cash flows feed into portfolio optimization models to guide investors in the design of efficient return-risk portfolios.

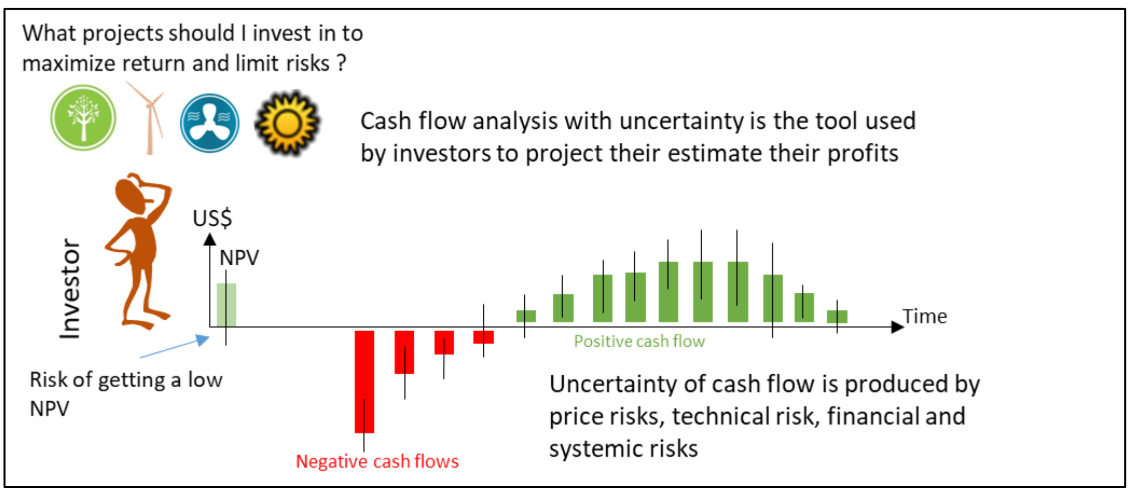

FIGURE 17: PORTFOLIO PROBLEM OF THE INVESTOR: DEFINING AN EFFICIENT INVESTMENT PLAN TO MAXIMIZE RETURN

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[5] For example: individual investors who have the opportunity to invest in any generation technology and their decision variables are continuous (i.e., they can invest part of their budget, from 0% to 100%, in one project or in a group of projects) or big energy companies that normally focus on investing in projects in areas of their technological expertise and their decision variables are more discrete—to invest or not to invest in a certain project, etc.

According to the investors' level of risk aversion and their current set of generation facilities, different portfolios of projects can be selected by buying or developing new projects, or alternatively, the investment could be delayed if the uncertainty is too great. Note that the option of deferral is an important difference compared with the problem of planners, who often have to plan to satisfy the expected demand without the ability to defer generation over time. This additional flexibility afforded to investors and the corresponding modeling approaches are explored in Section 3.1.3

3.1.1 Return and risk measures of investments in energy projects

A measure of profitability must be estimated in order to account for the risk of different projects. The main tool to estimate a project's return is cash flow analysis. Different estimations of profitability can be obtained from a discount cash flow analysis such as the Internal Rate of Return (IRR), the Net Present Value (NPV), or the Present Value Index, among others [142]. In fact, investors will choose the projects with highest NPV. This is the Marshallian approach [60,143] where utility is maximized subject to budget constraints. As an example, Roques et al. [8] used NPV in their portfolio model to design efficient investment combinations among baseload technologies (coal, nuclear, and CCGT plants). They studied how the impact of fuel, electricity, and CO_2 price uncertainties affect optimal portfolios. On the other hand, Muñoz et al. [9] used the internal rate of return (IRR) as a measure of profitability when analyzing renewable project portfolios for investment in the Spanish market. Both publications used the standard deviation of their return variables as a measure of risk. Table 5 presents the return measures and uncertainty factors modeled in some related publications by optimizing a portfolio from the investor perspective.

TABLE 5: RETURN MEASURE AND UNCERTAINTY FACTORS MODELED IN DIFFERENT PAPERS

References	Return measure	Uncertainty factor
Roques et al. [8]	NPV	Fuel, electricity, and CO_2 prices are represented by normally distributed random variables whose cross-correlation and standard deviation are derived from historical time series.
Madlener and Wenk [56]	NPV	Time series of electricity spot price of both base and peak load are used to best fit a distribution (log-normal distribution) Capacity factor: based on historical time series. Hydro capacity factor follows a log-normal. Annual variability for solar PV and wind power is approximated with the data from hydro technologies. Fuel costs: time series. Natural gas follows a Gumbel distribution, while a Gamma distribution is used for uranium.
Muñoz et al. [9]	IRR	Electricity price for the wind, mini-hydro, and solar thermo-electrical modeled with Pearson distribution adjusted from historical values. Electricity price for solar PV is regulated, and the value is pre-established. Other values (investment ratio, service operation life, capacity factor, etc.) of the cash flow are assumed normal with standard deviation depending on different scenarios proposed by the author.
Glensk and Madlener [144]	NPV	Historical series of electricity, fuel, and CO_2 prices used to fit different distributions. Electricity prices were fitted using a beta distribution.
Rohlfs and Madlener [59]	NPV	Future electricity price and future coal, gas, and CO_2 prices modeled assuming Geometric Brownian Motions. Monte Carlo method used to simulated paths of the price development.
Fleten et al. [60]	NPV	Future electricity price modeled assuming Geometric Brownian Motions.

Although IRR and NPV are both derived from discounted cash flows, they differ from one another. Indeed, when investments are ranked using these two methods, the result is not necessarily the same [145,146].Tang and Tang [145] go deeply into the difference between these two measures. They argue that IRR gives the private investor’s point of view, while NPV gives the society’s point of view. The authors explain this view because IRR varies with a change of financial arrangements (e.g., a change of taxation rate or equity-loan ratio), while NPV does not, so they proposed IRR as a financial indicator and NPV as an economic indicator.

Organizations may have additional requirements beyond profitability for investing in projects. In the case of power generation investment, for example, renewable generators have benefits that conventional technologies do not, including fewer environmental externalities, flexibility in production, modularity, and reversibility, among others, which rarely are included in the investment decision-making process [147,148]. However, there is research on investment decision-making that considers measures beyond profitability that depend on the strategy of the organization. Davoudpour et al. [149] used an approach based on Analytic Hierarchy Process (AHP) to select renewable projects for an R&D organization by using expert opinion to find a hierarchy model of a renewable technology portfolio considering market, competitiveness, technical, capability, and learning.

A project may add value in addition to its own return if it helps decrease risks. A new project could be used to enter the market or consolidate a company’s position, or it could be develop or acquire to learn about a specific technology or process [7]. Most literature on optimization portfolio does not take these factors into account, although they are already an important part of the literature on project valuation. Therefore, this is a line of research that needs to be exploited in order to better align the literature on portfolio optimization with reality and thus make it useful to investors.

3.1.2 Others risk sources in addition to electricity prices: technical, financial, systemic

Uncertainty is present in different dimensions and stages of a project development, from technical to systemic risks, including regulatory risks which are commonly accepted as one important risk in the sector [150], causing cost variations on one side and revenues variations on the other, as presented in Figure 18.

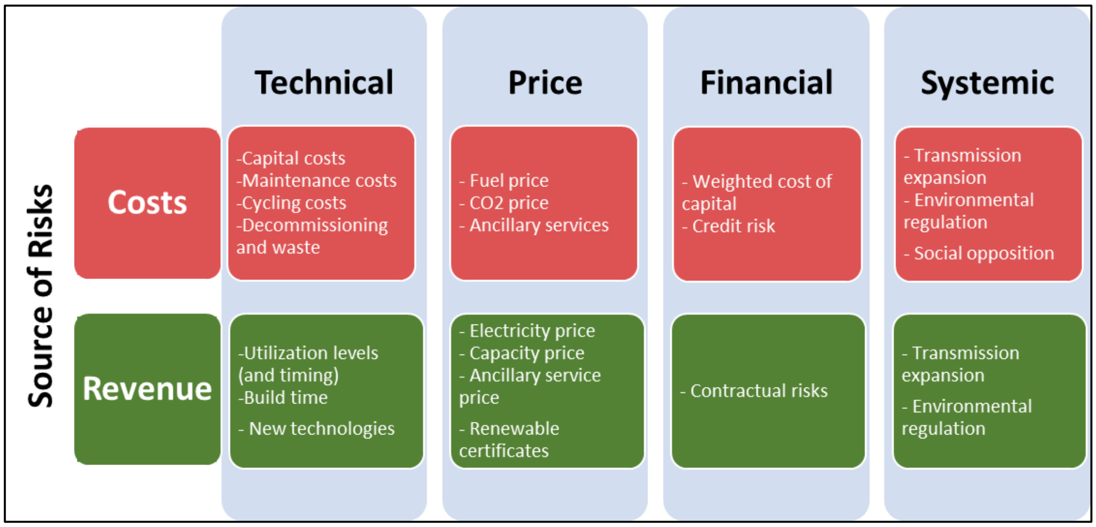

FIGURE 18: RISKS AFFECTING A FIRM'S CASH FLOW CALCULATION (ADAPTED FROM [20])

Most technical, financial, and systemic risks are difficult to explicitly include in optimization models, so most works either explicitly or implicitly assume that these factors remain constants and therefore do not affect income or costs or use scenario approaches to quantify them. On the other hand, uncertainty of prices is most treatable in optimization models, both on the income (electricity price) and the cost (fuel prices and CO_2 prices) sides. There are numerous methodologies for electricity spot price forecasting, as reviewed by Weron [151]. However, despite that, most portfolio papers only focus on statistical methods based on past information. This backward-looking strategy has limited value on a system that is evolving to a new carbon-free technological paradigm.

3.1.3 A dynamic problem and the value of waiting/project deferral

One important feature of project development in a competitive energy industry is that investors can "wait to invest," for example, to acquire more information about a regulatory reform. Considering the option of waiting before committing resources is very important because it recognizes that the firm has an opportunity cost and the possibility of improving its outcome. This is especially important in the renewable energy field, taking into account the possibility of waiting is very important because renewable projects show a high technological progress rate and require short construction times [133].

Static NPV cannot capture the value of waiting, so Real Option theory is the tool to include this flexibility in the evaluation [58]. Real Option Analysis (ROA) has been applied to the electricity sector for decades to account for the irreversibility of investments. A good **comprehensive review** of ROA is presented by Dixit and Pindyck [143]. In the electricity generation sector, there are several examples of applications of ROA. Indeed, Fernandes et al. [133] present a complete review of applications of ROA applied in the electricity sector. They found that **ROA applications applied to the renewable sector are still limited**. Moreover, the technique is mostly applied to wind and hydropower to the detriment of other newer renewable technologies like photovoltaic. However, recent publications are filling this gap. For example, Zhang et al.[152] present a good review of studies on renewable energy investment using real options method. The authors also propose a real option model for evaluating renewable energy investments by considering uncertain factor such as: CO_2 prices, non-renewable energy costs, investment costs and market prices of electricity. They use their model to evaluate the investment decision of a solar PV power plant in China and its optimal timing.

There are countless works using ROA to analyze investments in conventional technologies and also to evaluate the implementation of policies. For example, Ming Yang et al. [153] use a real option approach for analyzing the effects of government climate change policy in power investments. The authors investigated the flexibility that companies have to optimally time their investments given regulatory uncertainty. Climate change policy uncertainty is represented by means of an uncertain carbon price. Similarly, Sekar [154] uses a real options valuation methodology to evaluate investments in three coal-fired power generation technologies (pulverized coal (PC), integrated coal gasification combined cycle (IGCC), and IGCC with pre-investments that make future retrofit for CO2 capture less expensive in an environment of uncertain CO2 prices. Boomsma et al. [155] analyze investment timing and capacity choices for renewable energy projects under different support schemes, namely, feed-in tariffs and renewable energy certificates trading. The authors found, through an applied case of study in the Nordic electricity market that feed-in tariffs encourage earning investment in wind power, while certificates trading creates incentives for larger projects. Fleten et al. [60] use ROA to show that investment in a decentralized wind power generator facing uncertainty in electricity prices should be made at a price considerably above the NPV break-even price (electricity price that makes NPV negative) because of price uncertainty.

While optimization methodologies using ROA are usually performed from a power producer perspective to evaluate a single power plant, a large investor would typically prefer to invest in a portfolio of technologies [156]. There are only a few publications that combine ROA and portfolio optimization analysis to find efficient combinations of investments along with its timing. The first research to explicitly combine these methodologies from the perspective of an investor in the electricity sector is, to our knowledge, the research by Fortin et al. [156]. They use ROA to find the optimal timing of investing in carbon capture and storage modules for coal- and biomass-fired power plants and optimal installation time for wind power plants. Using different electricity price evolution paths, the authors derive return distribution for the investment of these technologies. These return distributions (which already include the value of flexibility given by project deferral) are then employed as the input of a CVaR portfolio optimization as presented in Figure 19.

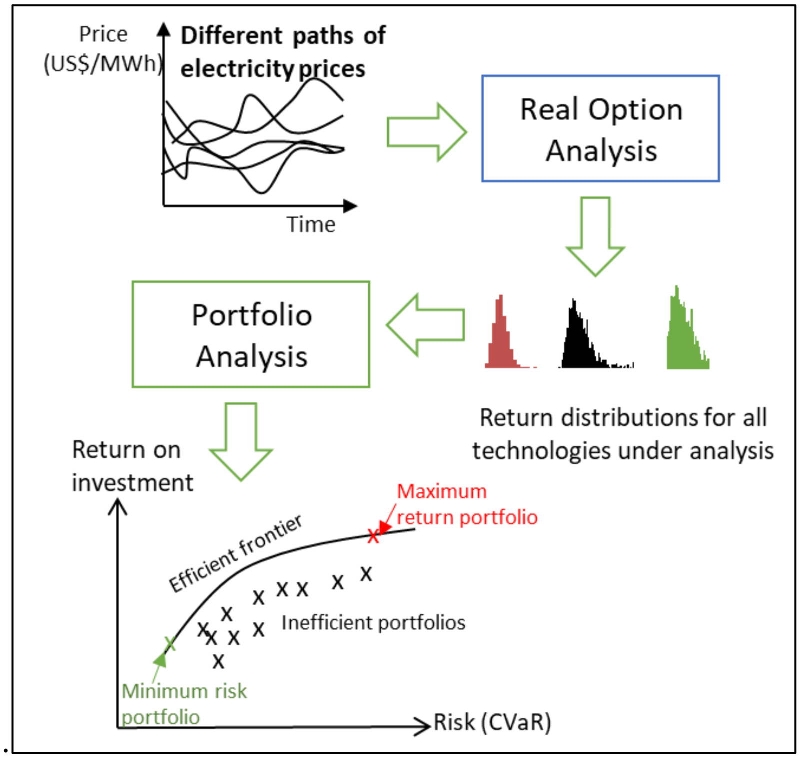

FIGURE 19: GENERAL METHODOLOGY USED IN [156]: **USE OF REAL OPTION ANALYSIS AND PORTFOLIO OPTIMIZATION**

Other papers expand the work of Fortin et al. [156] by taking into account diversification over time by considering the option of having a different portfolio at a future point. Indeed, Szolgayová et al. [157] find that the possibility of adapting the portfolio actually have a relevant effect on today's portfolio investment decisions. On the other hand, the paper by Fuss et al. [158] further contributes by applying the methodology to different socio-economic scenarios and different targets in greenhouse gasses emissions. Their extension takes into account that investors are completely uncertain about future carbon prices, and therefore it is impossible to assign probabilities to different targets. Thus, investors would seek robust portfolios that perform well even in the worst scenarios. They find that uncertainty associated with CO_2 prices has a profound effect on the optimal composition of technologies portfolios. Moreover, the authors find that uncertainty about stabilization is more important in the energy mix composition than the socio-economic scenario, especially for risk-averse investors.

Exploring the combination of these tools—real option analysis and portfolio optimization—in the investment decision-making process is a great research opportunity. All the publications mentioned above ignore sources of uncertainty such as fuel costs and their possible complementarities, e.g. biomass cost declining as carbon price increases [158] or renewable resource uncertainty (wind speed, solar radiation, hydrologies, etc.), among other sources of uncertainty that investors face in the real investment decision process.

3.2 Portfolio optimization as a management tool for electricity sellers and buyers

Energy managers, both managers of electricity production firms and of big energy consumers, seek to limit their price risks by using instruments to hedge against spot price fluctuations. As investors, managers seek to maximize the firm's expected return while limiting its risks. However, instead of allocating capital among different investment opportunities, managers allocate electricity among different instruments (day-ahead markets, real-time markets, bilateral contracts, forward, etc.) as is shown in Figure 20. Financial instruments have different delivery periods and maturity dates. While the spot market is nearly instantaneous, bilateral contracts can last for years. These facts introduce difficulties to the optimization because decisions for some trading instruments can be deferred in time according to new information on prices (e.g. how much energy to buy/sell on the spot market), while other decisions must be made in a specific period (e.g. how much energy buy/sell through a long-term forward contract).

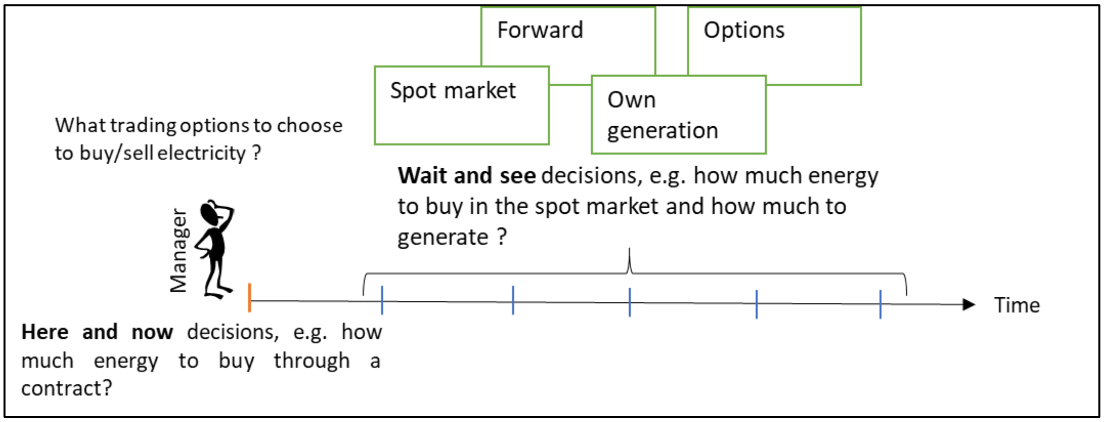

FIGURE 20: MANAGER'S PORTFOLIO PROBLEM: DEFINING EFFICIENT TRADING CHOICES TO MAXIMIZE PROFIT

A big energy consumer can take advantage of portfolio optimization not only by choosing among the instruments, but also by choosing among generation technologies. For a big energy consumer, there is a difference between signing a bilateral contract with a conventional generation plant or signing it with a solar PV plant, a wind power plant, or a combination of any of these alternatives. A consumer's preference for one supplier over another depends upon factors such as the demand profile, carbon footprint, and willingness to pay, etc. For example, the subway in Santiago de Chile recently signed two bilateral contracts, one with a solar PV plant and one with a wind power plant, and the two suppliers will cover approximately 60% of its energy needs. Because the subway system has greater energy needs during the day, the solar PV plant option is a good opportunity, although its daily load curve has two peaks, one in the morning and one in the late evening, just when the electricity produced by a solar PV plant is low, so the subway's energy managers chose a complementary wind power plant to avoid having to buy energy on the spot market. Portfolio optimization is a formal and well-tested tool for tackling this kind of problem, both for determining the type of instruments to use and for dealing with different technologies and locations.

Due to non-storability, inelastic demand, and a steep supply curve, electricity spot prices suffer from high variability. That is why most agents usually use contracts and other financial/physical instruments to hedge against these fluctuations. These instruments play a very important role in some electricity markets for future price discovery and price certainty. In fact, there are some electricity markets that rely entirely on bilateral contracts, such as the Chilean electricity markets. The most basic instruments that offer future price discovery and price certainty to electricity sellers and purchasers are forwards, futures, and swaps. All of these instruments may have different delivery periods and maturity dates. In fact, the maturity periods of forwards contracts range from hours to years [61].

The task of energy managers is to choose from among these instruments to maximize return and at the same time limit its risks. A correct strategy allows firms to avoid losses due to price fluctuations, reduce the volatility of earning, and meet regulatory requirements [159]. Portfolio optimization has been used in the literature as a tool to efficiently choose from among these instruments as well as from among real-time markets (real-time and day-ahead markets). It should be noted that managers have two types of decisions, “here and now” or “wait and see.” While “here and now” decisions are those that the manager has to make in the present, such as about how much energy to sell/buy using a long-term contract, “wait and see” decisions can be delayed to expect future developments, such as how much energy should be bought or sold using the real-time market, which is a decision that can be postponed until the need becomes urgent.

3.2.1 Static approaches: traditional portfolio optimization applied to the manager problem

A traditional static portfolio optimization approach is formulated by Liu and Wu [63], who consider the problem of energy allocation for a power producer allowing three types of trading approaches: risk-free (local) contracts, riskier contracts (non-local), and the spot market. In this formulation, the planning period may be one day, one week, one year, or several years, etc. Non-local bilateral contracts are subject to risk because generation companies may face congestion transmission charges that depend on the difference between nodal prices. The uncertainty is then only present in electricity locational spot prices because fuel prices are assumed to be fixed in their work. Liu and Wu [63] present a static approach in which spot prices are characterized only by mean, variance, and spatial correlations, and they assume that nodal prices follow a multivariate normal distribution.

Treating the spot market as an individual asset has the disadvantage of some loss of information, because hourly spot prices reflect seasonal behavior, which is usually given by the behavior of the demand. When spot prices are treated as an asset and represented by a price distribution, the known seasonality is wrongly translated as an additional variability. By contrast, treating each period as a different asset gives more degrees of freedom to include this seasonality as new information (see Figure 21). For example, Gokgoz and Atmaca [64] use mean-variance portfolio optimization by taking spot market hourly prices as separate assets in addition to bilateral contracts in the Turkish electricity market. Turkey has no local, zonal, or nodal pricing system, so spot pricing is used as a signal for the entire system, and therefore there are no congestion charges. The assumption of 24 selling alternatives is new in this kind of study and allows sellers to choose according to their risk-return preferences to sell different hours, either on the spot market or via bilateral contracts.

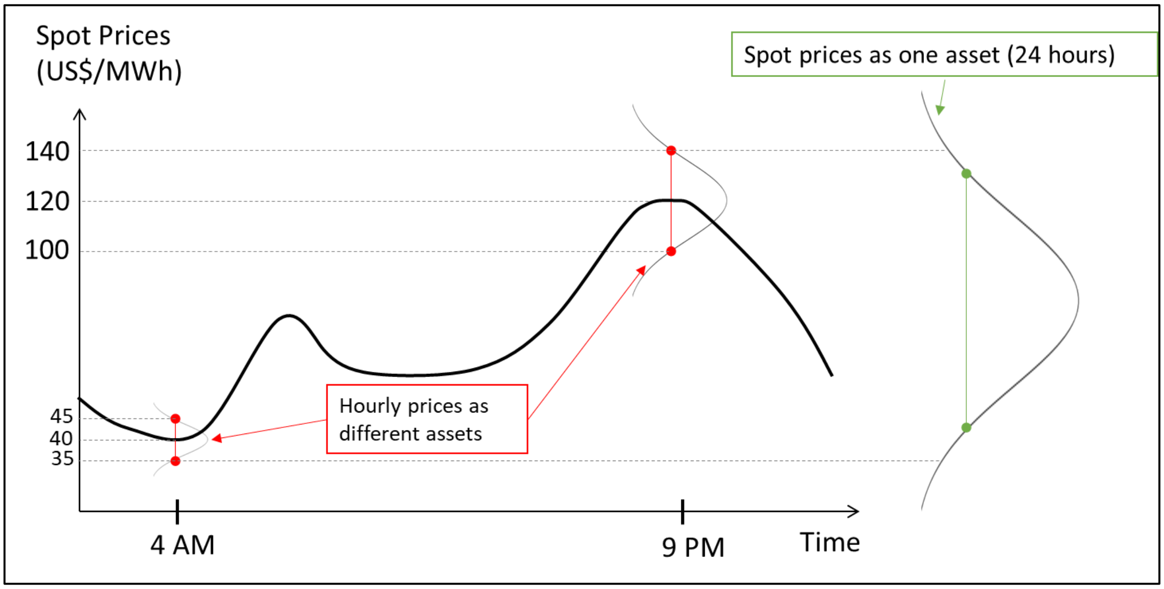

FIGURE 21: EXAMPLE OF NORMAL DISTRIBUTIONS CAPTURING DAILY AND HOURLY SPOT PRICES. SPOT PRICES OF LONG PERIODS LOSE SEASONAL INFORMATION THAT IS TRANSLATED INTO A GREATER VARIANCE

Unlike dynamic models, which require large computational capacities because uncertainties (prices, costs, resources, etc.,) are modeled in time, static models are simpler and therefore other sources, in addition to electricity prices, can be considered. For example, fossil fuel prices (oil, gas, and coal) present high variability, are highly correlated [160], and introduce uncertainty into generation costs. Mathuria et al. [65] consider spot market and bilateral contracts as trading options for a generation company in Sweden that faces risks from electricity prices, fuel prices, and from emission prices. The authors find a strong correlation between electricity spot prices and emission prices (see Figure 22). This enables risks to be hedged by changing the allocation on the spot market, since a price change in the emission market (cost side) is compensated by a corresponding price change on the spot market (income side).

Figure 22 shows estimated correlations by Mathuria et al. [65] between electricity prices, coal prices, gas prices, and the European Union Allowance (EUA), which are climate credits that represent the right to emit one ton of CO_2 into the atmosphere.

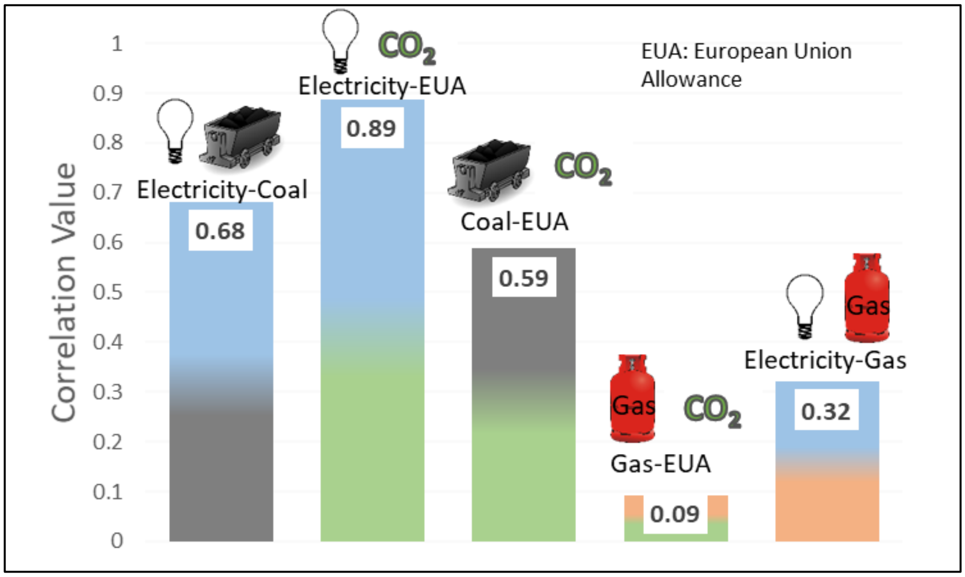

FIGURE 22: CORRELATIONS OF ELECTRICITY SPOT PRICES WITH COAL, EUA, AND GAS PRICES AND CORRELATIONS OF COAL AND GAS PRICES WITH EUA PRICES. SOURCE: MATHURIA ET AL. [65]

On the electricity purchaser side, Huisman et al. [62] propose the use of a static mean-variance framework to optimally allocate positions in the day-ahead energy market as well as peak and off-peak forward contracts. Peak-forward contracts involve the delivery of power capacity during certain hours of high demand; off-peak contracts involve the delivery of a base capacity at all hours. Uncertainty is introduced through prices of the day-ahead energy market and consumption volumes. Day-ahead prices and hourly demand are assumed to be entirely characterized by their historical mean and variance. The problem is then to minimize the total electricity cost subject to a maximum level of risk, where the total cost is given by the sum of the cost of off-peak forward contracts, peak forward contracts and day-ahead energy market purchases. The authors assume a price-taker purchaser, i.e., the trading of electricity does not affect prices, and they show that the optimal allocation to peak contracts relative to off-peak contracts is the same for all purchasers. The differences in the exact allocation, including positions in the day-ahead market, are determined by their risk attitude.

Several studies have argued that electricity prices and fossil fuel prices show a positive level of skewness and leptokurtosis [161–163], so it does not seem enough to characterize them solely by mean and variance. Skewness is the extent to which a statistical distribution is not symmetrical, and leptokurtosis occurs when the distribution is more peaked than normal. See, for example, the asymmetry and fat tails of the histogram of monthly average spot prices from January 2008 to January 2016 for the Alto Jahuel 220 kV, a key transmission node in central Chile, presented in Figure 23.

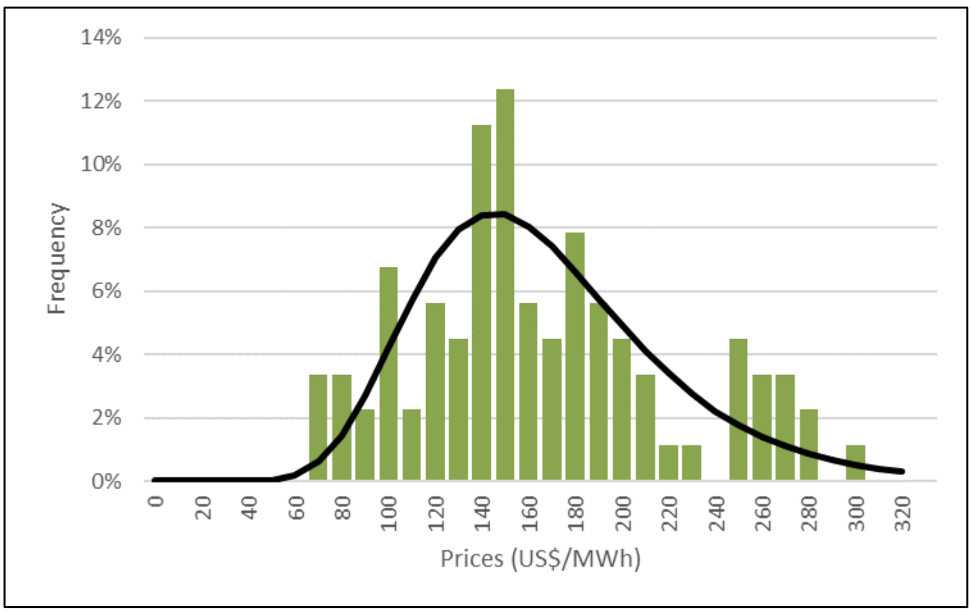

FIGURE 23: HISTOGRAM OF THE SPOT PRICES IN THE ALTO JAHUEL 220 KV NODE IN CHILE FROM 2008 TO 2015

Pindoriya et al. [164] include skewness in their portfolio optimization analysis. They propose a mean-variance-skewness (MVS) model to set the energy allocation of generation companies among the spot energy market and bilateral contracts with clients located in different zones. A positive skewness means that the density function has a right-handed tail and therefore maximizing skewness in a context in which the distribution reflects profitability, implies the minimization of possibilities of low profits. Accordingly, an MVS model maximizes the return and the skewness (first and third moments of the distribution) and minimizes the variance (second moment), transforming the problem into a multi-objective optimization problem.

Suksonghong et al. [67] proposed a similar problem, but also added maximizing **diversification** as another objective to the optimization. This was implemented by minimizing the difference between the highest and lowest allocations. According to the authors, including the fourth objective of diversification effectively caused a more uniform allocation among all the instruments. The inclusion of skewness and other conflicting objectives makes the optimization problem very difficult to solve, so different optimization tools are used for these types of problems. A multi-objective optimization problem can be tackled by different methods [165], such as scalarization techniques, e-constraints methods, goal programming, among others [166].

3.2.2 Dynamic and multi-stage approaches

New information might require the consideration of the allocation problem at multiple stages, requiring a transition from static to dynamic analysis. Only a few dynamic portfolio optimization approaches have been developed. Indeed, the application of multistage optimization models is relatively new in the literature on portfolio optimization in electricity markets for electricity sellers and purchasers. Multistage portfolios enable the modeling to optimize the rebalancing of the portfolio at multiple points in the future based on the information available at that time. The most common problem formulation in multi-stage stochastic optimization formulations is the equivalent deterministic form, which can be very large and require excessive computational capacities [167]. Thus, the most common multistage optimization application focuses on just two stages.

In stochastic problems with two stages, the first stage is when the decision maker takes action before random variables are revealed ("here-and now-decisions"), and the second stage decisions are made after the random effect occurs ("wait-and-see decisions"). García-González et al. [168] present an example of a two-stage stochastic optimization problem in an electricity market in which a generation company that owns a wind farm and pumped-storage facility optimizes its bidding policy in the first stage and the decision on the operation of the pumped-storage for each possible realization of the random variables in the second stage. In that case, random variables are wind production and market prices as presented in Figure 24.

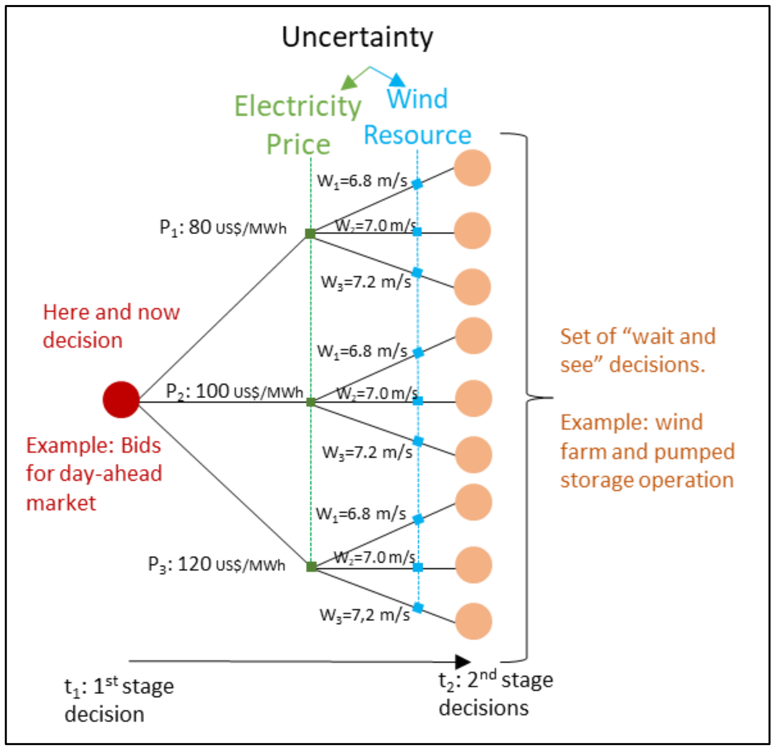

FIGURE 24: UNCERTAINTY REPRESENTATION IN A TWO-STAGE MODEL. ADAPTED FROM [168]

Lorca and Prina [68] tackle the problem for a **power producer** holding thermal generation units and considering locational electricity prices. They use a stochastic optimization model to optimize the trading of electricity from a power producer in two locations through forward contracts, a contract for differences, and the spot market. Their model obtains a set of contractual decisions at the beginning of the time horizon ("here-and-now decisions”) and a set of own-generation and spot market trading decisions in future time ("wait-and-see decisions”). They use a time series model to capture temporal and spatial correlations of locational electricity prices. The authors use CVaR as risk measurement, including it into the objective function multiplied by a risk aversion parameter. The main drawback to this formulation is the dimensionality problem. Modeling more than two buses makes the problem too large to solve in reasonable time. Accordingly, the methodology is very useful to theoretically assess how changes in price parameters cause changes in contractual and trading decisions, but it cannot be used in real-case scenarios in which the producer faces multiple locational electricity prices. Indeed, Lorca and Prina [68] found that changing the correlation parameter ρ_{ij} for locational electricity prices significantly affected the relationship between expected profit and risk. For fixed values of expected profit, as the correlation parameter between locational electricity prices decrease, the risk is also decreased.

On the electricity purchaser side, Rocha and Kuhn [69] present a multistage mean-variance model for the management of electricity derivatives from the point of view of an electricity purchaser who is a price-taker and the need to satisfy its clients' demand. Electricity purchasers have three alternatives for acquiring electricity in time—spot market, forwards contracts, and call options—and **stochasticity appears in the form of uncertain electricity demand, spot prices, and derivative prices,** which are revealed sequentially over time. They present a stochastic optimization problem with aggregation of decision stages and Linear Decision Rules (LDR) approximation, avoiding the use of a large decision trees and limiting the computational burden. Spot prices are modeled by an **Ornstein-Uhlenbeck process** with seasonality, which is a **mean-reversion** stochastic process traditionally used to simulate electricity prices [169,170]. Electricity demand is also modeled as a stochastic mean-reversion process with seasonality. Rocha and Kuhn [69] found that incorporating **adaptivity** in portfolio optimization models is beneficial, especially in the presence of high spot-price volatility. The authors show that adapting to different market conditions provides a flexibility that makes it possible to obtain to obtain a better mean-risk profile, particularly when the decision maker is risk averse.

3.2.3 Diversification beyond energy markets: ancillary services, capacity market, and demand response

In addition to energy markets, in some countries power producers have other markets that could allow them to diversify risks. For example, capacity markets, ancillary services markets, and regulation services markets are options in which some generators can participate to mitigate risks of electricity markets. Similarly, load-serving entities have other resources beyond bilateral contracts to manage risks, such as demand response programs. Few publications have included these markets as part of portfolio optimization models, although one exception is a paper by Yu [171], which presents a model that can be used for multiple commodity electricity products that may include electricity, spinning reserve, or regulation, etc. The objective function is the minimization of risk, defined as the portfolio cost variance subject to the exceedance of the desired net profit. The author presents a case study involving two power pools, NYPP and PJM, each with two available markets, day-ahead energy and spinning reserve. The model includes constraints such as transaction costs and wheeling contracting, leading to a mixed integer formulation.

On the other side, an electricity buyer such as a retailer may be able to hedge risk using demand response programs. High demand usually implies high electricity prices (because of electricity's steep supply function), and therefore there is a positive correlation between electricity spot price and customer demand [102]. Demand response (DR) programs help mitigate this correlation, lending an additional extent of flexibility to decrease exposure to risk. Deng and Xu [102] show that including DR programs, specifically in the form of interruptible contracts, significantly improve the profit-risk profile of portfolios for an electricity buyer considering the following instruments: spot market buyer, forwards contracts and DR programs. The authors used both variance and VaR as risk measures and found that the role played by DR program is dependent upon the choice of risk measure. Given a fixed expected profit, a 95%-VAR minimization problem holds all available interruptible programs, suggesting that DR programs may be especially useful in the worst-case scenarios.

3.3 Cross-cutting issues in portfolio optimization for investors and managers: price process modeling and renewable complementarity

There are cross-cutting issues to be found in the literature on portfolio optimization from the investor and the manager perspectives. First, most literature ignores the fundamentals of power system structures in price modeling, while in turn there is an excessive support on technical approaches that attempt to model stochastic behavior by using statistical analysis and historical data. Second, renewable complementarity is ignored, although there is strong evidence that the geographic diversification of solar and wind power plants in different locations may present complementarity generation profiles [107–111], and this complementarity has not yet been included in portfolio models.

3.3.1 Modeling price process in portfolio optimization models

Modeling electricity prices is critical for evaluating risks for both investors and managers. Electricity prices directly affect incomes, so it is crucial to model them properly to account for the corresponding risk. There are mainly two families of approaches to model electricity price processes [61,172], structural or fundamental approaches that rely on simulation of the operation of the electricity system, and technical approaches which rely on historical data and statistical analysis to model the future behavior of prices. Fundamental approaches are more realistic since they allow for simulating new scenarios that cannot be considered with technical approaches, although they do require extensive computational effort. Most publications on portfolio optimization rely on technical approaches. Moreover, most publications on portfolio analysis simply use price processes such as those presented in Table 6, without using more complex price forecasting models like those reviewed by Weron [151].

TABLE 6: FREQUENTLY USED PRICE PROCESSES IN PORTFOLIO OPTIMIZATION LITERATURE

Price Processes	Description	References
Distribution fitting	Fit a probability distribution to a series of historical data of prices. Examples of the distributions used are Normal distribution, Lognormal, Beta, and Pearson, among	[8,9,56,144]
Time series models	Time series are widely used for multiple applications, and price modeling is no exception. Markets with locational prices require a multivariate time series model. Examples of time series models are ARMA models, ARIMA model, GARCH models,	[68,169,173]
Continuous-time stochastic process	Geometric Brownian Motion (GBM) and Ornstein-Uhlenbeck processes are examples of continuous-time stochastic processes. These models are widely used in mathematical finance to model price evolution. While GBM has a constant drift over time, the Ornstein-Uhlenbeck process tends to drift toward a long-term mean (mean-reverting).	[59,69,174]

Among the most common techniques used by publications on portfolio optimization to model long-run electricity and fuel prices are the Geometric Brownian Motion (GBM) process [59,60] and distribution fitting. GBM processes are governed by a stochastic differential equation that describes a process in which the relative change of price is a **combination of deterministic proportional growth plus a normally distributed random change.**[6] The choice for GMB is often driven by the simplicity of its closed-form solution. However, real price statistics and patterns often don’t match such process, presenting cycles driven by demand patterns and price spikes driven by supply and demand

[6]Geometric Brownian Motion (GBM) process stochastic differential equation: $\frac{dP(t)}{P(t)} = \mu \cdot dt + \sigma \cdot dW_t$, where W_t is a Wiener process and its solution (for any value of t) is a log-normally distributed random variable.

shocks. Examples using GBM to generate different simulations of annual electricity prices are presented in Figure 25.[7]

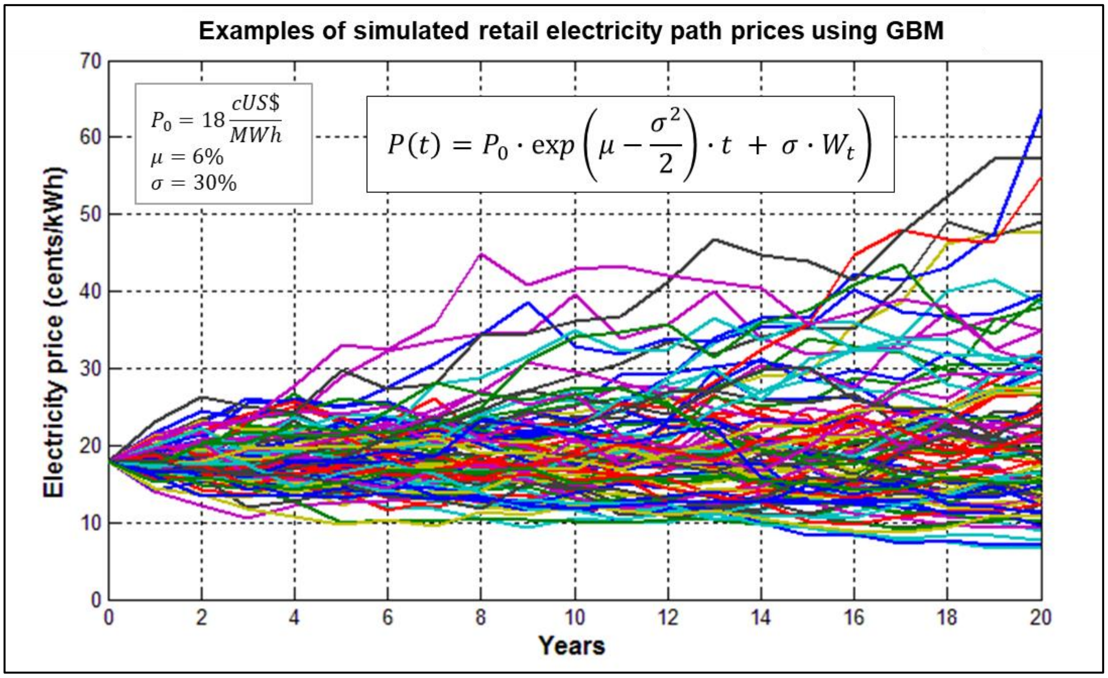

FIGURE 25: EXAMPLES OF SIMULATED PATHS OF RETAIL ELECTRICITY PRICES USING GBM OVER 20 YEARS

Eydeland and Wolyniec [161] describe the main pros and cons of using GBM to model the spot prices of energy commodities. On one side, GBM is an industry standard, its properties are well known and can be easily implemented in efficient computer implementations, and it is very useful for modeling cross-commodity correlations. But on the other side, the downside of using GBM as described in reference [161] includes the difficulty of calibrating because it offers few degrees of freedom (just two parameters) to match historical data. Furthermore, if it is used for pricing power products, the problem of non-storability of power makes it impossible to use the standard no-arbitrage argument to

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[7] The price function has an initial value of P_0=18 US$/MWh, an annual trend of μ= 6%, and a standard deviation of σ=30%.

validate the common pricing formulas. Finally, the GBM price process does not allow for modeling the fat tails of price distributions or price spikes with the magnitude of real energy markets. In summary, GBM processes may be appropriate for some applications based on the criteria of normality and independence, but not for other applications, depending on the characteristics of the process and time frame, etc. For example, a process in which the drift is dependent upon time is not appropriate for GBM because GBM has a constant drift and variance over time. More examples of using GBM in different applications can be found in reference [175]).

Other publications on portfolio optimization often assume some well-known probability distributions and estimate their parameters from time-series data and performing Monte Carlo simulation later to generate price trajectories. For example, some articles, such as Roques et al. [8], assume a normal distribution for fuel, electricity, and CO2 prices, and the parameters of these distributions (mean and variance) are estimated from historical time series. Similarly, Muñoz et al. [9] fitted a **Pearson distribution** to historical electricity pool prices in the Spanish market and assumed three scenarios with different degrees of growth per year. Madlener and Wenk [56] fitted a **log-normal distribution** to time-series price data derived from the European Electricity Exchange (EEX), and Glensk and Madlener [144] fitted a **beta distribution** to their electricity price data. After deciding how uncertainty factors are to be modeled and estimating parameters, these papers run simulations to compute cash flows and their main measures (NPV, IRR, etc.) and their distributions. These distributions and their correlations are then used in portfolio models.

The main issue with technical approaches is that past price values only do a good job representing the behavior of future prices while the system (transmission system, demand, and supply) remains static. But, if the system changes, prices can also change dramatically and therefore the risk analysis is no longer useful. In contrast, structural analyses allow for the production of price series that are consistent with the system and its possible changes in the future. This is a topic of active research as the greater penetration of renewable generation and operational and transmission constraints is becoming more important to defining prices.

Additionally, on the demand side, most consumers today are protected against price fluctuations by regulations and therefore do not directly see major risks, although they pay for them in the form of risk premiums embedded into their tariffs. This is rapidly changing, however, as the smart grid and distributed generation is becoming massive and makes consumers more proactive. These changes on the distribution network will have an impact on the wholesale market too affecting prices, expansion times, power flows, etc. The system is changing on all fronts, which reinforces the need for a structural analysis that considers different technological scenarios that cannot be captured by statistical analyses.

The failure to considering transmission capacity constraints could lead to an incorrect measure of income for some generation projects. Transmission constraints isolate different areas of electricity markets and sometimes create the possibility of exercising market power [176], such that local transmission constraints may lead to price risks (significant reduction of local marginal prices) as well as to volumetric risks (less electricity production caused by a capacity constraint). As an example, the mismatch in China between the installed wind capacity and wind generation is mainly explained by the inadequacy of the power transmission grid [177]. Transmission constraints affecting specific generation projects should be included in the modeling. The capacity of a transmission line determines the degree to which generators in different locations can compete with each other [178], and therefore ignoring transmission constraints may lead to significant errors in estimating the revenue for a generator firm.

Theoretically, spot prices vary spatially according to their contribution to marginal losses and the marginal congestion component. These prices show the instant value of the energy for the system, and it can differ greatly from one zone to another, and therefore ignoring the location of injections despite these components and assigning the same value to an MWh injected anywhere in the system is sometimes quite wrong. This inefficiency is ignored in a market of a global spot price (mainly in Europe), but it is an issue for investors in the market of nodal prices (mainly in America). However, papers on portfolio optimization from the investor's perspective tend to ignore this effect.

3.3.2 Renewable profiles and complementarities

Renewable profiles, especially wind power profiles, depend on local meteorological features and atmospheric and geographic phenomena that are very volatile and difficult to predict. Therefore, two wind power plants with the same model and number of units will produce very different power profiles when placed in locations with different meteorological and relief conditions. Using two complementary profiles helps to reduce the need for storage and produce a smoother combined output profile, which may be a much more appealing "product" for a buyer.

Spatial diversification of solar PV production can be achieved by distributing PV plants across different locations, taking advantage of differences on sunrise/sunset times (and therefore solar PV peak production times), cloud regimes, ground albedos, among other geographical features which allow smoothing out changes in PV production. The extent of the smoothing effect depends mainly on the number of PV plants, the composition of the ensemble, longitudinal differences between sites, area of dispersion and irradiation variability [179]. The impressive curve of declining costs of PV technology, its fast deployment in recent years across the globe and its expected growing participation in the energy markets have pushed for new research to address problems associated with short-term variability of PV production. This issue was initially seen as a potential limiting factor for PV integration into the grid [180]. Mills and Wiser [180] were one of the first to account for geographic diversity to reduce volatility of PV production. In fact, they concluded that the need for additional reserves to manage variability of PV plants is considerably reduced by geographic diversity in a wide area. More recently, David et al. [181] have shown that solar PV geographical diversification can also be achieved in small territories with different microclimates. Two different regimes of cloudiness appear to be enough to greatly improve the diversification effect in their study. Finally, several publications have pointed out that the smoothing effect could lead to lower forecasting errors, since plant spacing decreases the correlation value of their forecasting errors [182,183].

For investors, the most relevant profile complementarity is in the annual and monthly time scales, because they help to reduce financial risks to the portfolio. Investing in two different renewable power plants that have complementary generation profiles is less risky than investing all the capital in a single project that is twice the size. For managers, the complementarity of renewable profiles helps to increase profits (energy sellers), reduce costs (energy buyers) and mitigate risks overall. Complementarity allows energy sellers to offer output that is much less volatile, and that can result in a more valuable product for energy buyers who may be willing to pay more. On the other side, those who buy energy from different complementary renewable generators may reduce their exposure to the real spot market and their footprint at the same time. Moreover, technological and spatial diversification of renewable energies can reduce vulnerability of the entire power system [97].

Although there is active research underway on the quantification of the geographic complementarity of solar and wind power plants [107–111], there are currently no publications that integrate and analyze their effect on the technological portfolio. How does a smart choice of solar and/or wind power plants across a determined territory improve the return/cost - risk profile? This represents a significant opportunity for further research because everything suggest that renewable energy will continue its aggressive entrance into the market in the future.

3.4 Conclusions

Better use of infrastructure, avoiding unnecessary investment, and optimal resource management are essential skills for today’s energy companies. For investors, developing a generation project involves an enormous amount of capital along with very large risk, so investors usually adopt different diversification strategies to mitigate those risks, such as investing in power plants of different sizes and places, with different technologies and more importantly, with different types of fuel or resources. These strategies reveal that the return on a portfolio of projects is not simply the sum of the returns from all of the individual projects. The “correct” return is the result of the return on individual projects plus the “interaction” among them. This “interaction” is key in portfolio optimization; interaction among projects allows for diversification and the cancellation of risks. Most papers determine the proxy of projects’ profit and their interaction to be the **Net Present Value** or **Internal Rate of Return** of the projects and their respective correlations. This correlation between cash flows quantifies interaction gains or losses. In addition to diversification strategies, investors can wait and defer the investment if there is excessive uncertainty (due to a regulatory change for example). However, the literature places little emphasis on the **value of waiting** or deferring a project or a set of projects within the context of a portfolio. Decision makers who are unwilling to take risks in the face of insufficient information might be well advised to consider the option of waiting.

On the other side, portfolio managers of large electricity sellers/buyers must deal with electricity spot prices that are very volatile due to the special properties of electricity, such as non-storability and a non-linear, steeply rising supply curve. Unrestrained exposure to **price risks** may produce overwhelming consequences for agents. Take for example the price spikes presented in [61] in which high spot prices led different agents to bankruptcy, with devastating consequences for the economy. The California electricity crisis of 2000–2001 is one example in which prices persistently reached US$500/MWh, and retailers had not hedged against price risk through other financial instruments, leading to a major crisis in the sector. In the case of volumetric risk, retailers who are forced to serve their entire load must also be concerned with uncertainty on the load, since there are no simple financial instruments to deal with changes in the demanded volume, especially because mass electricity storage is still not an economically viable option. [61]. Exploiting the high correlation between demand and prices using **trading mechanisms** such as bilateral contracts, forwards, futures, call/put options, among others instruments are alternatives to mitigate part of the volumetric risks. In the portfolio literature, most applications rely on **static models**. Conversely, **dynamic and multi-stage** applications are more limited, mainly because of their need for great computational power, which restricts the design of real-world applications. Active research is required, therefore, in the development of new methodologies to deal with the current computational limits. Rocha et al. [69] have made notable advances in that direction by using linear decision rules to approximate the solution of a stochastic optimization.

One cross-cutting issue in the literature on portfolio optimization that affects both investors and portfolio managers is the frequent use of statistical rather than structural models. In fact, most of the available literature trusts statistical approaches to model future price behavior, although history will not repeat itself and the past is now a poor predictor of future behavior. Given the radical changes and uncertainties we are facing, structural-based methods are required to model future behavior of prices.

In addition to intermittency, renewable resources such as solar, wind and perhaps future tidal power plants bring other special features, and this is complementarity in different time scales. Unlike conventional generators, which are fully controllable, these renewable generators depend on the availability of natural resources that are beyond our control. Numerous publications have demonstrated that geographical diversification can significantly decrease variability in different time frames, especially of wind power production [46,47,107,108,111,184]. Spatial diversification of solar PV plants is very useful to smooth out the production in small time frames, ranging from seconds and minutes to hours. A smoother PV production decreases the cost of system integration allowing better forecasting and requiring less primary/secondary reserves. Depending on the market rules, this cost reduction could affect in more or less extent the income/cost of the project participant (project investors and portfolio managers). Nevertheless, renewable complementarity is currently entirely absent in planning portfolio literature. The potential gains in efficiency (return-risk) from geographical diversification are currently neglected, which minimizes the relevance of transmission capacity constraints and cross-border interconnections. Well distributed energy resources may offer investors and managers a good alternative for diversifying risks, but some of their diversification benefits are actually being overlooked.

Finally, the primary gap in the portfolio literature is the lack of the consideration for the small electricity users. Consumers are slowly taking a more active role in the electricity market through residential generation, smart metering infrastructure, demand response, smart grid deployments, and other areas associated with the raising figure of the "prosumer." Thus, an excellent opportunity for research lies in analyzing the impact of the new small and distributed energy systems with the active participation of the demand side of the portfolio, changing its composition, or becoming a component of the optimal portfolio as an energy resource.

CHAPTER 4: IMPACTS OF WIND AND SOLAR SPATIAL DIVERSIFICATION ON ITS MARKET VALUE: A CASE STUDY OF THE CHILEAN ELECTRICITY MARKET

4.1 The integration of variable renewable energies and its economic value

After several decades in which non-conventional renewable energies were expensive and impractical, solar and wind power have now reached a technological stage that allows them to be cost competitive with conventional generators without subsidies (hopefully tidal generators will also cross this line in the near future). Moreover, clean energy sources are now demanded by modern societies that are already suffering some of the consequences of climate change [185], so the rapid grown of solar and wind power generation the last five years it is expected to continue and eventually leave conventional sources behind (see 100% renewable literature [94,186–188]).

The integration of renewable energies is a major operational and political challenge. Regulators and operators must look for the best policies to integrate them into power systems dominated by conventional generators. Operationally, the integration of variable renewable energies (VRE) represents a challenge due to their intermittent and uncertain nature. Since supply and demand must be balanced every second, the variable nature of VRE must be absorbed by other resources of the power system (in Chile these resources are: hydro power plants, fast LNG power plants, diesel units and storage devices). The stochastic nature of renewable resources, along with the fact that the production is not fully controllable are the main causes of the value drop in renewable market as their penetration increases. Moreover, as more generators are installed in one location (seeking a good primary resource) the market value of that location decreases (due to the excess of supply). Usually, when renewable energies are concentrated in one location and there are active transmission constraints, spot prices or the marginal prices go down rapidly. This is what is happening in the north of Chile, the "sunniest place on earth," where solar PV plants are facing long hours of zero spot prices due to excess supply driven by transmission congestion [140].

The economic value of VRE is defined in this work as the revenue that generators can earn on markets [90,189]. Following Hirth [189], the market value of VRE is measured as its energy-weighted price. Maintaining a high market value is important for investors and for planners/regulators, since investors seek to recover their investments as soon as possible, and usually regulators seek to encourage more investments and increase the penetration of renewable energies (due to its low variables costs, zero emissions and social acceptance). Since electricity storage is expensive, production time greatly affects the value of electricity (given that demand and resources availability change over time). Similarly, electricity has different values depending on location, caused by marginal losses and more strongly by transmission constraints. Electricity loses part of its value if it cannot be efficiently transported to consumption centers when it is needed. Finally, the uncertainty of production also affects economic value since additional firm generation is required to compensate uncertainty [189,190]. This chapter is focused on the spatial and temporal property of renewable generators and how these properties affect its market value.

VRE market value depends strongly on the system and its conditions (such as the energy mix, grid topology, transmission capacities and distance of the consumption centers). Regulators can take measures to alleviate the market value drop with higher penetrations of VRE, such as implementing demand-side management, increasing bulk storage capacity, expanding transmission interconnection capacities, upgrading thermal power plants to improve flexibility, designing "system friendly" variable renewable generators [191], increasing geographic diversity of renewable generators.

Integration measures aim to make the system more flexible. Flexibility is understood as the ability of a system to withstand changes in power demand and generation, and more flexibility helps power systems to adopt more renewable energy, but also economically to mitigate the reduction of the economic value of VRE with increasing penetrations levels.

Flexibility options can be allocated on the demand-side and the supply side of the power system as well as in the transmission system and storage to provide spatial and temporal flexibility. On the demand-side, distributed generation [192,193], demand response [194,195] and dynamic tariffs [196,197] play an important role, while on the supply-side, upgrading conventional power plants [198–200], geographically diversifying renewable energies [46,201] and designing "system-friendly" wind turbines [191] are some of the measures mentioned in the literature, as is illustrated in Figure 26.

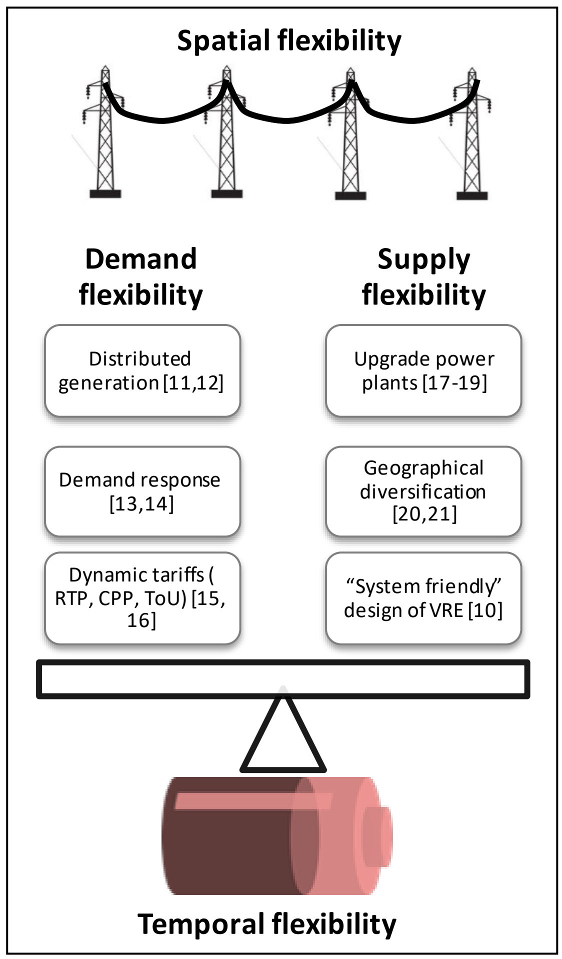

FIGURE 26: FLEXIBILITY MEASURES ON THE DEMAND AND SUPPLY SIDE

Spatial diversification, or spreading generators out in large interconnected areas, is an integration measure that reduces the variability of power production. The spatial diversification of VRE is a technique to ease the integration of renewable energies, not only because generation variability is reduced (which is very important for pure thermal power systems), but also because risks of a drop in the VRE market value caused by marginal losses and congestion (spatial) constraints and storage (temporal) constraints are reduced. Transmission capacity availability plays an important role in the effects of VRE diversification on its market value. Exploiting just one wind-power zone may stress a single transmission corridor because all wind power plants in the same zone have a strong possibility of reaching their maximum capacity at almost the same time.

This chapter shows the impact of transmission and storage constraints on wind and solar market value. In particular, the effects of spatial diversification of wind and solar power on its market value considering different levels of interconnections capacities and bulk storage is researched. Most articles of spatial diversification investigate the combination of wind power plants to reduce variability of total production rather than considering the effects on the entire power system and therefore on electricity prices and its market value. Similarly, literature studying the market value of renewable energies is focused on quantifying the market value drop at high penetration levels of renewable energies levels without analyzing factors that can alleviate this drop. This work makes the connection between diversification studies and the literature on renewable market value and quantifies spatial diversification as a measure for mitigating the value drop, with a closer inspection to the Chilean electricity market.

4.1.1 Chilean electricity market, resources and policies

The rapid development of the Chilean economy in recent decades (the GDP per capita grew 557% from 1990 to 2015[8]) has resulted in an enormous increase in electricity

[8] From US$ 2,401 per capita in 1990 to US$ 13,384 per capita in 2015 in current US$ [287]

consumption. At the same time, the Chilean government has committed to reducing emissions and has undertaken a number of mitigation actions such as establishing emissions taxes and reaching 20% of non-conventional energies in 2025. Chile has very favorable conditions for the development of renewable energy power plants with large amounts of primary resources (1,000,000 MW of solar, 40,000 MW of wind, 16,000 MW of geothermal and 12,000 MW of hydroelectricity [202,203]). In addition, Chile has low tax rates for imported technologies due to free trade agreements with different countries and a transparent economy, which is a very important factor for large investments [204].

By the end of 2016, Chile's electricity sector had an installed capacity of more than 20,000 MW, which is predominately based on thermal and hydropower generation as is shown on Figure 27. However, in the last 5 years, solar and wind power have led the expansion of the generation sector, as is shown on Figure 28.

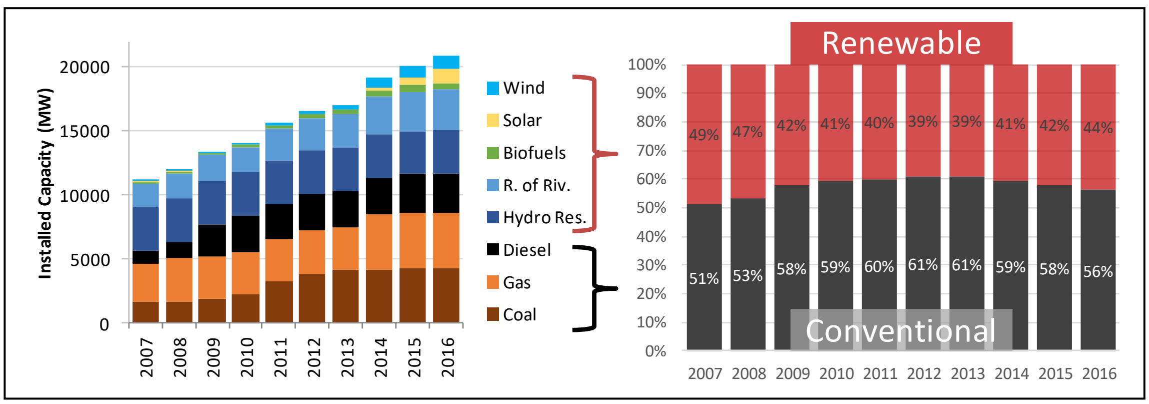

FIGURE 27: INSTALLED CAPACITY IN THE SIC AND SING SYSTEMS IN CHILE IN DECEMBER 2016. OWN ELABORATION BASED ON GENERATION CAPACITY REPORT PUBLISHED BY THE NATIONAL ENERGY COMMISSION OF CHILE [205]

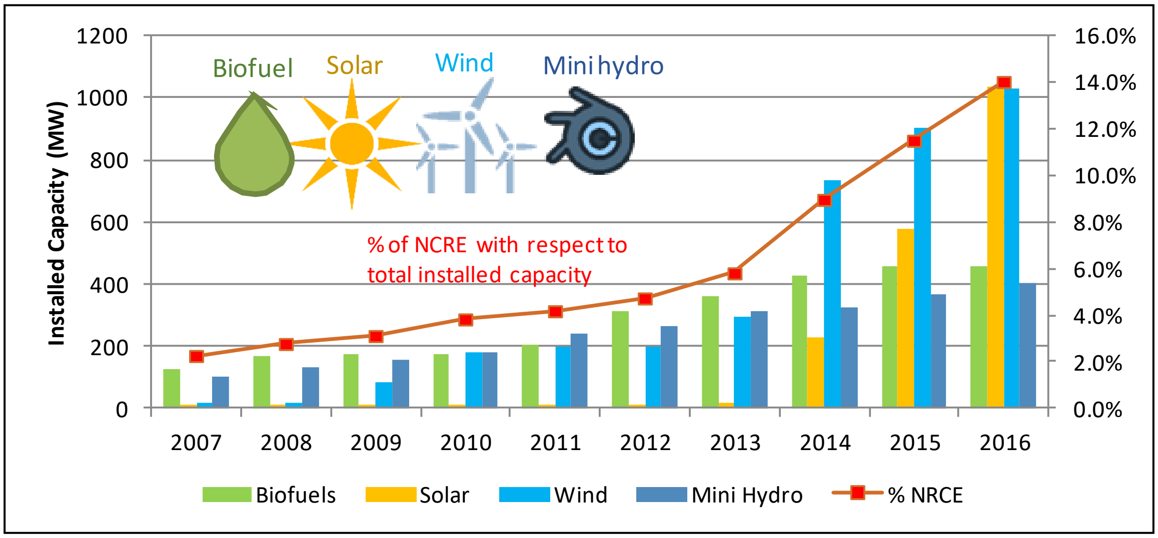

FIGURE 28: INSTALLED CAPACITY OF NON- CONVENTIONAL RENEWABLE ENERGIES (NCRE) IN CHILE. OWN ELABORATION BASED ON GENERATION CAPACITY REPORT PUBLISHED BY THE NATIONAL ENERGY COMMISSION OF CHILE [205]

The two most important electricity systems were the SING and the SIC, which together represent more than 99% of electricity sales and were interconnected in 2017. The north of Chile (old SING), has historically based its generation matrix primarily on coal and gas, but also has an impressive solar resource, so it is expected that solar PV production will continue to grow there. The south of Chile has a major presence of hydro resources and a variety of wind resources. Chile's extreme south has large bodies of water, they are not expected to be exploited soon due to community's opposition to the development of large hydropower projects. Figure 29 presents the old SIC and SING systems, the LNG and coal units and the gas pipelines along the country. It also presents the hydro resources in the south and the solar and wind resources maps. Note the high irradiance of the solar resource in the north reaching 7.5 kWh/m^2 day.

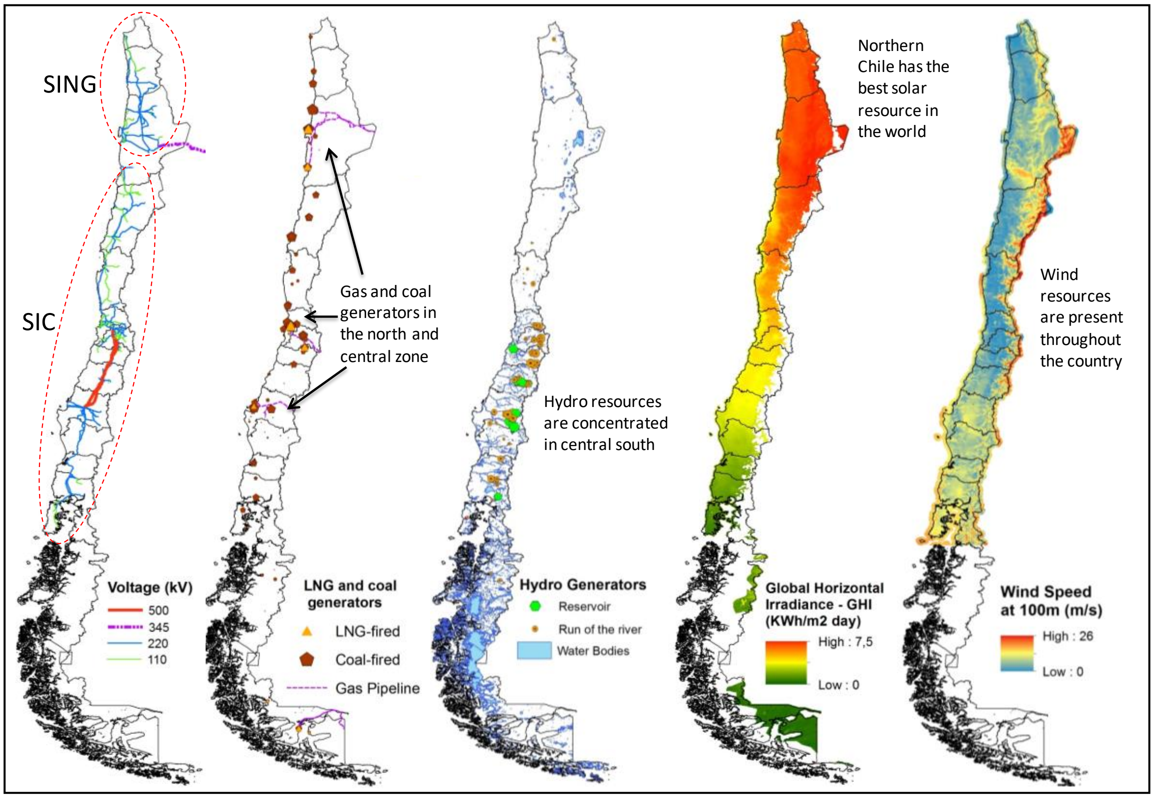

FIGURE 29: TRANSMISSION SYSTEM, COAL AND LNG UNITS, HYDRO GENERATORS, SOLAR AND WIND MAPS OF CHILE. DECEMBER 2016. OWN ELABORATION BASED ON DATA PUBLISHED BY THE GEOGRAPHICAL INFORMATION SYSTEM OF MINISTRY OF ENERGY [206] **, THE SOLAR RADIATION DATABASE FOR CHILE** [207,208]**, AND THE WIND ENERGY DATABASE FOR CHILE** [209]

Chile supports non-conventional renewable energies (NCRE) through a policy target that will increase annually until it reaches 20% of total electricity generation by 2025. The target was strongly surpassed in 2016, as shown in Figure 30. Indeed, the injection of NCRE in 2016 was 259% of the annual target.

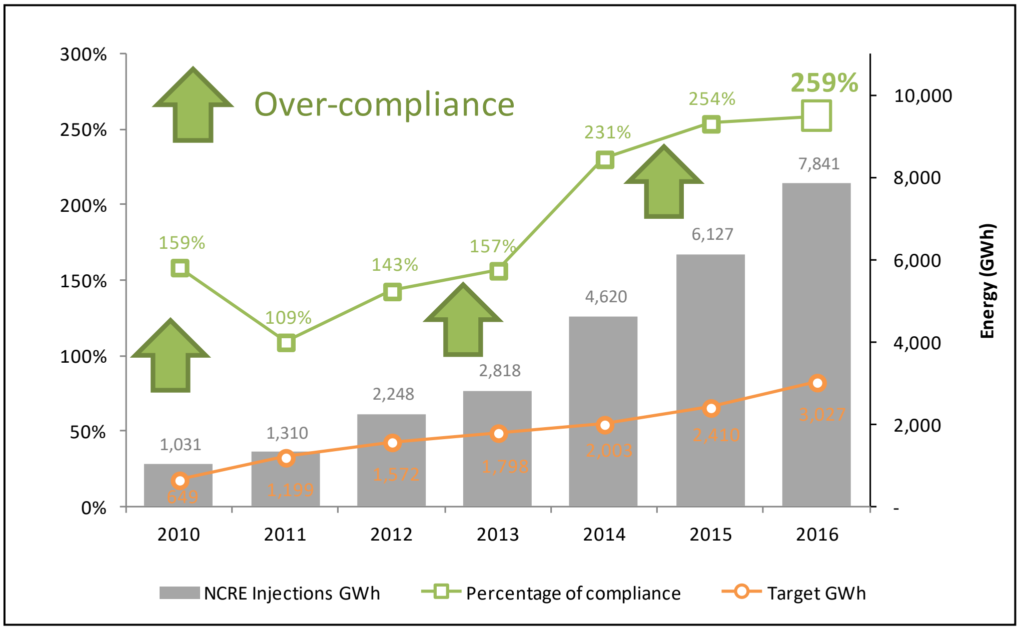

FIGURE 30:RENEWABLE INJECTIONS AND ANNUAL TARGETS IN CHILE. OWN ELABORATION BASED ON DATA PUBLISHED IN THE STATISTICAL YEARBOOK 2016 BY THE NATIONAL ENERGY COMMISSION OF CHILE [210]

Chile has great opportunities to diversify its generation resources, throughout its territory. This is especially important for wind resources, first, because of the presence of high variety over very short distances (coastal and desert climates occur within just four kilometers in some places), second, because the country is in the process of interconnecting and modernizing its main transmission corridors, and finally, because Chile has tremendous storage capacity through its multiple water reservoirs that help buffer VRE [211]). A good characterization of wind profiles in Chile can be found in the research of Watts et al. [113]. The spatial diversification of solar power is more limited due to the geography of the country.

The remainder of this chapter is structured as follows. Section 4.2 presents a general literature review on renewable market value, spatial diversification and policy strategies to integrate renewable energies. Section 4.3 presents the method and data used in this work to quantify the impact of diversification over the renewable market value in the Chilean electricity market. Section 4.4 presents the main results, showing how spatial diversification helps increasing renewable market value in a scenario of constrained transmission and showing how spatial diversification helps increasing renewable market value low storage scenario. Finally, Section 4.5 presents the main conclusions of this chapter.

4.2 Literature review on renewable market value and variable renewable integration

This section presents a literature review for renewable market value and some measures used to integrate renewable energies and mitigate decreases on its market value. It continues with a review of the literature on spatial diversification of VRE as an important and cost-effective integration measure. Finally, different policies and strategies to introduce integration measures are presented.

4.2.1 Renewable market value and integration of renewable energies

Market value is a measure of the revenue that generators can earn on markets, and therefore it is extremely important for investors and policy makers. Since renewable energy generation is an important measure for the reduction of greenhouse gas emissions [97], policy makers need to design markets and regulations to integrate them. The development of renewable energy technologies, as well as their market integration and support policies depend on their market value [212]. However, as renewable penetration increases, its market value goes down [189,213], and it becomes more difficult to integrate them. One of the main effects when renewable energy increases its share is a price drop, and this is known as the "merit-order effect" [214,215].

The merit-order effect

The merit-order effect produces a price reduction that seems appealing from a political perspective, although it is also well documented that the merit-order effect does not create welfare, but it produces a transfer of wealth from producers to consumers [216,217]. Lower prices reduce long-term appeal for investments, and, eventually, can cause a supply scarcity , increasing electricity prices. Several studies have shown the magnitude of the price reduction trying to quantify the merit-order effect in different markets. Table 7 presents some of these studies and their main findings.

TABLE 7: MAIN FINDINGS ABOUT THE "MERIT-ORDER EFFECT"

Country and technology	Price reduction	Main findings
Germany Solar and wind power [215]	6 €/MWh in 2010 10 €/MWh in 2012 14–16 €/MWh in 2016 Reduction of spot market price per additional GW of renewable energy	The authors highlight significant redistributive transfers under the current regulation in Germany. Some energy-intensive industries are benefiting from lower prices but are being exempted from the costs of the scheme.
Australia Wind power [218]	0.62 ₵/MWh in S. Australia 1.74 ₵/MWh in Victorian Currency: US$ Reduction of price per MWh of wind output	The presence of subsidized wind generation has a significant impact on spot market prices. Lower prices reduce incentives for additional generators to enter to the market. Over the long term, the increased requirement of peaking generation to support the unreliability of wind will means additional fixed costs, and therefore prices may move upward.
USA (Texas) Wind power [137]	1.4 US$/MWh in Houston 1.3 US$/MWh in the south 4.4 US$/MWh in the west Prediction of price reduction due to 100 MWh increase in wind generation	Increasing wind power generation tends to reduce wholesale price levels while enlarging their variance. New challenge for policy makers to deal with price risk is inseparable from increased reliance on intermittent sources of generation.
Italy Solar and wind power [219]	2.3–4.2 €/MWh (1 GWh from solar and wind)	Solar: savings have been lower than the cost of the supporting schemes. Wind: Cost-supporting schemes are entirely outweighed by monetary savings.
Spain [220]	7.42 €/MWh for 90% of real wind power production in 2012 10.94 €/MWh for 110% of real wind power production in 2012	Wind power has been beneficial from an economic point of view for the Spanish electrical system during the period 2005–2010 due to the savings over the spot market. The work does not assess other benefits or the implications of progressive integration of wind power on stability of the power system.

It should be noted that there is no standardized methodology to quantify the merit-order effect, so the magnitude of the price decrease not only depends on the characteristics of the power system, but also on the methodology of the study and its assumptions.

Close inspection at Chilean electricity market: Chile's electricity market is also a good example of how the merit-order effect and renewable energies, especially wind and solar power, have been pushing down marginal costs of the system. Figure 31 shows the monthly average price from 2012 to 2016 of a central node called "Alto Jahuel" (usually used as price reference for the system), and the wind and solar generation over the same period. The trend is clear—as solar and wind generation increases, the price goes down. It should be noted, however, that there are multiple other factors that affect prices and are not reflected in the figure below, such as hydrology, transmission upgrades, connecting new generation, among others.

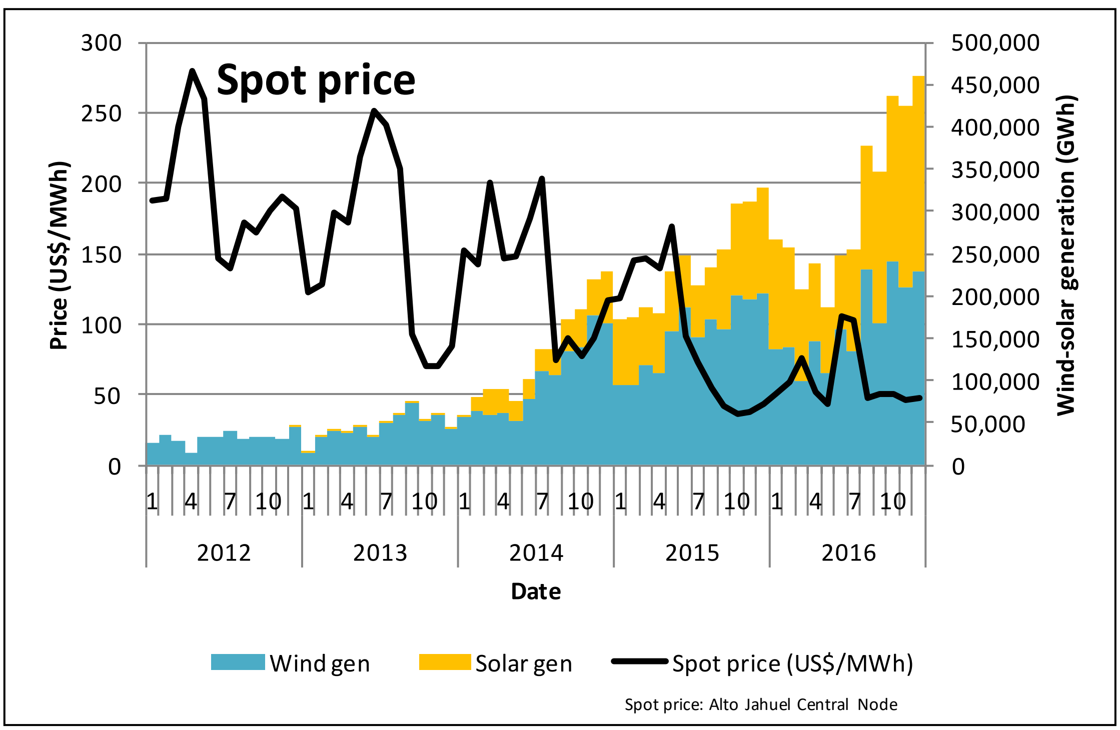

FIGURE 31: MARGINAL PRICE OF ALTO JAHUEL NODE AND WIND AND SOLAR GENERATION IN THE SIC SYSTEM IN CHILE 2012–2016. OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRIC COORDINATOR: REAL GENERATION DATA [221] **AND REAL MARGINAL PRICES** [222]

4.2.2 Spatial diversification of variable renewable energies

Under high VRE penetration, the reliance on peaking and intermediate generation supply is increased and the contribution of base-load generation is decreased [223]. Reducing intermittency and variability is important to decrease integration costs of VRE (increase reliance on peaking and intermediate generation supply). There are three key drivers that affect integration costs of renewable generation: diversity of the resource and capacity factor, location relative to the network, and the region’s generation mix [224]. This chapter focuses on the first and second drivers—diversification of the resource and location relative to the network.

Diversification and complementarity are usually used as interchangeable concepts. Complementarity is normally used to describe two or more profiles that together have fewer instances of zero power production and "full power production" or generally, profiles with low or even negative correlation patterns. However, diversification is a broader concept. In the context of energy projects, diversification is simply choosing different types of projects, locations, contracts and generation technologies to mitigate unnecessary risks. Spatial diversification means to diversify by choosing projects in different locations to capture part of the complementarity of renewable profiles, but also to avoid risk of congestion and lower market value levels.

Complementarity of geographical profiles

The complementarity of wind resources is one of many measures available to manage wind power variability on power systems. Indeed, the “smoothing effect” of aggregated wind power outputs has been widely studied in the literature, and their conclusions are similar; the dispersion of wind power significantly reduces the volatility of the aggregated power output.

Close inspection at Chilean electricity market: in Chile, as the distance between wind power plants increases, the correlation of their energy production decreases sharply, as is presented in Figure 32.

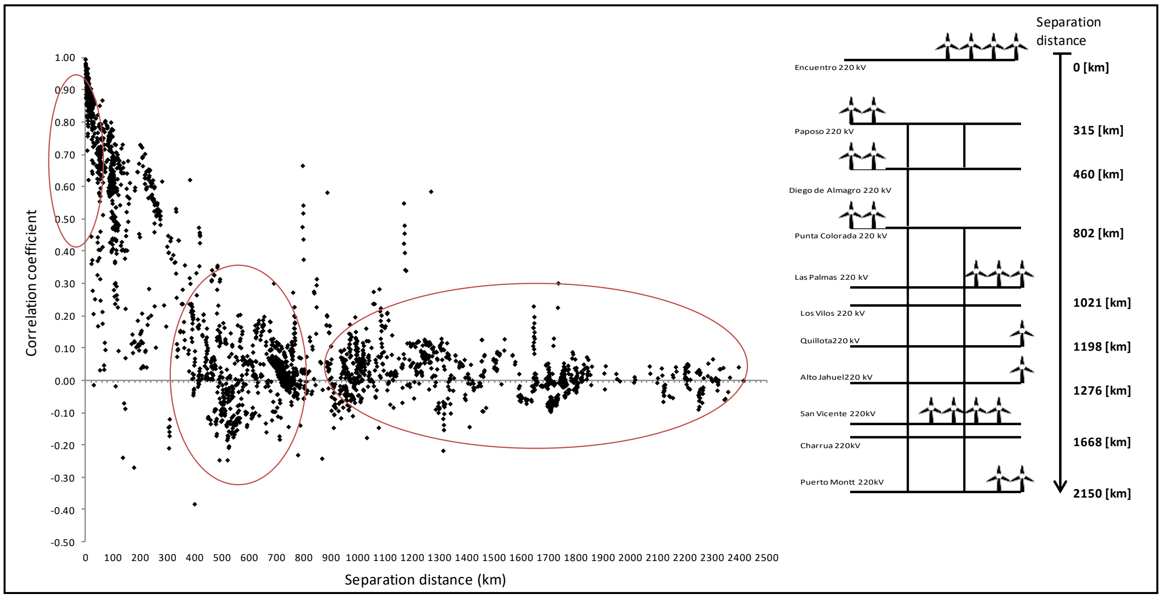

FIGURE 32: CORRELATION VS. DISTANCE OF WIND ENERGY PRODUCTION IN CHILE. OWN ELABORATION BASED ON THE WIND ENERGY DATABASE FOR CHILE [209]

The first study of the spatial aggregation of wind power plants was conducted by Kahn [225] in the state of California, and it was the first to quantify the improved reliability of distributed wind generators. A more recent study presents a frequency analysis of interconnected wind farms in the UK: using frequency-dependent approach the authors concluded that spatially diversifying wind power plants reduces the high-frequency variability of wind power, which in turn means lower costs for ancillary services [226]. Similarly, the results of a simulation analysis interconnecting wind power plants distributed along the eastern coast of the U.S. shows that the aggregate wind power production has much more stable behavior (fewer hours of zero production, fewer hours of full power, and a slowing change of rate) [227].

A methodology to minimize the variance of aggregated wind farm power output by distributing them in different zones to facilitate the penetration of this kind of energy was presented by Degeilh and Singh [201]. The authors presented different reliability indexes to characterize the improved reliability of distributing generators. Other studies show that complementarity of wind power resources can save some of the storage and cycling costs of traditional generation [111], but, taking full advantage of complementarity requires a strong transmission network [46,47,113].

Novacheck and Johnson recently presented a novel approach [228] that combined a portfolio methodology with a unit commitment and dispatch model to evaluate the effect of wind power diversity on decreasing system ramping. Unlike other studies on wind diversification, the authors use the portfolio framework to minimize ramps instead of minimizing the deviation from the average output. Using an empirical example, the authors show that diversification can reduce wind curtailment and transmission congestion. However, they found that even with diversified power plants, variability at the time of low ramping flexibility can cause higher costs for the system.

Diversification of VRE can be applied not only to new power plants, but also to repowering actions. Indeed, repowering of installed wind farms is one of the most effective actions to scale up capacity [229].

Renewable spatial diversification and its relationship with VRE market value

None of the above studies have evaluated how spatial diversification affects renewable market value. One notable exception is the work by Mills and Wiser [230] in which the authors present different strategies for mitigating the reduction in economic value of VRE with increasing penetrations levels of wind power. Those strategies included measures such as increasing the geographic diversity of wind power plants, more flexible new conventional generation, lower-cost bulk power storage, and price-elastic demand subject to real time pricing (RTP). They do not explore, however, scenarios of transmission and storage constraints or the interaction of these measures with renewable market value.

When geographic diversification of renewable power plants is studied solely in terms of the complementarity of profiles without considering the power system and its prices and transmission network, it may result in locating power plants where they do not add real value to the system. For example, if a diversification policy focuses on the wind resource alone, whether to maximize wind production or to reduce aggregate production volatility, without taking the power system into consideration, wind power plants may end up in places where transmission is already congested, adding little value to the system and injecting power into nodes where locational marginal prices are already very low, zero or even negative, and ultimately resulting in very low market value for new participants, as illustrated the left side of Figure 33.

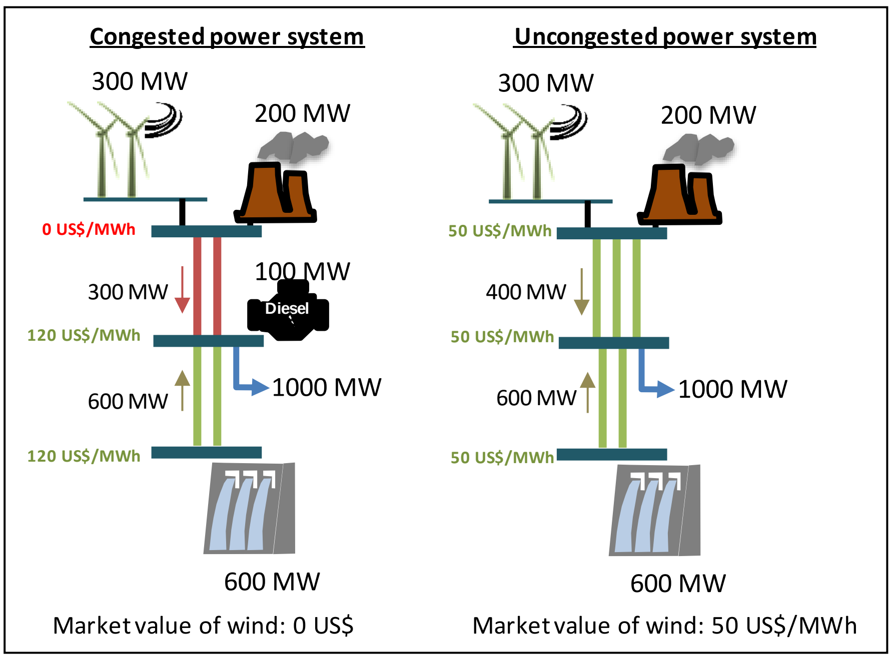

FIGURE 33: RELEVANCE OF TRANSMISSION NETWORK AND RENEWABLE MARKET VALUE

Locational marginal prices are useful signals of system insufficiency. High prices are a sign of transmission congestion, high losses, very high electricity demand or supply scarcity. High locational marginal prices are therefore temporal and spatial indicators that can be used along with the availability of resources to design siting policies for renewable power plants.

Close inspection at Chilean electricity market: a large share of Chile's generation capacity is in the central-south, but consumption is mainly concentrated in the central and north zone. Therefore, while adding wind power in the south could help the system to reduce CO_2 emissions or to reduce wind power volatility, those benefits cannot be captured if transmission is congested. Locational marginal prices of nodes in the north, central and south may be used in this case to quantify those congestions.

4.2.3 Policy strategies to integrate VRE

There are several policies strategies that regulators can adopt to make the system more flexible and mitigate the value drop of renewable energy as its share increases. There are many factors that affect renewable energy integration and its impact on system prices, such as the electricity market design (pricing, supporting schemes, market power), technical characteristics (system-friendly designs), emission market and its regulation (CO_2 prices, fuel prices), and system flexibility (mainly hot start-up time, ramp rates, minimum load and cold start-up time), which directly affects the renewable market [212]. These factors are also presented in Figure 34.

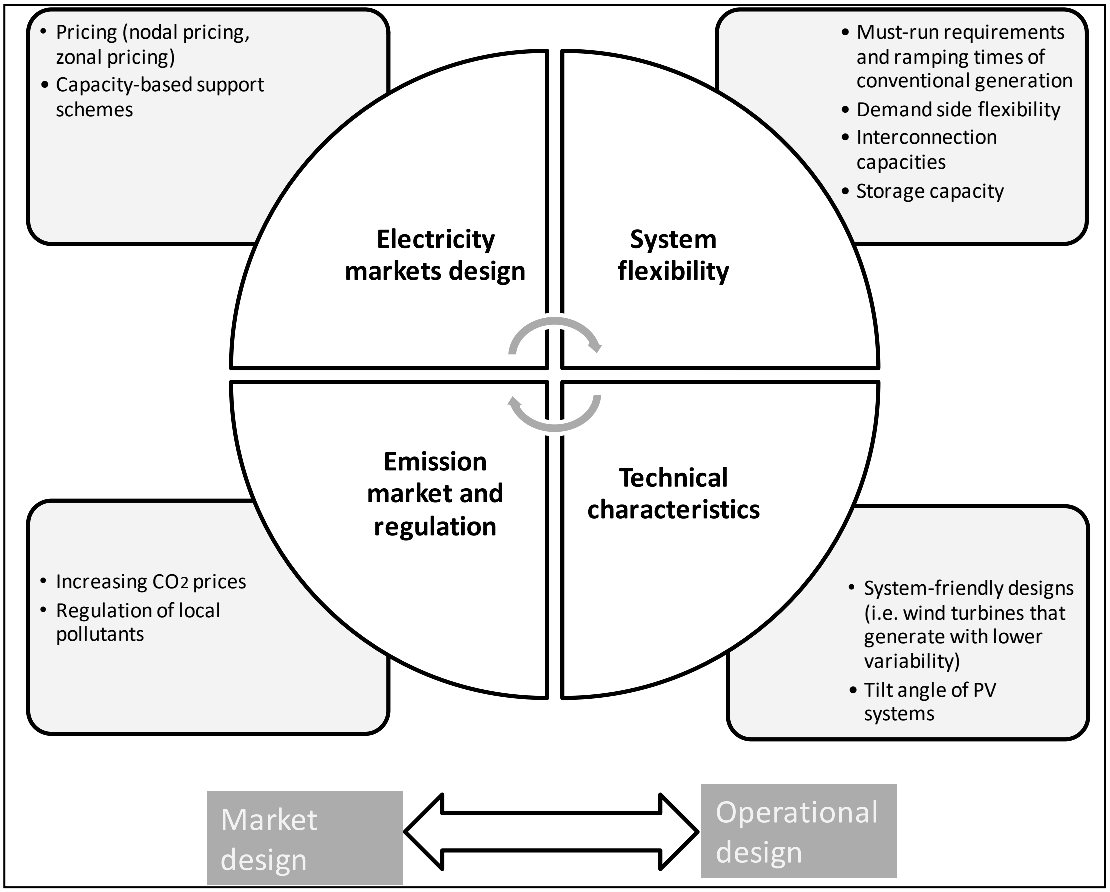

FIGURE 34: FACTORS AFFECTING RENEWABLE INTEGRATIONS. SOURCE: OWN ELABORATION BASED ON [212]

The energy mix essentially depends on the accessibility of resources. A significant portion of the cost of renewable energy integration depends on the current system's energy mix. For example, hydro generation is very flexible because it can ramp up and down very fast and it does not have the constraints on minimum run and stop times that traditional thermal units do. Accordingly, systems with a high quota of hydro generation have lower integration costs for variable renewable energies. However, the energy mix of a power system is determined by the accessibility of its resources, and therefore it is not a variable that can be controlled. However, there are additional measures that can be adopted to improve system flexibility, such as including energy storage, upgrading traditional power plants, expanding interconnection capacities, developing demand side management programs, encouraging system-friendly variable renewable generators and promoting renewable spatial diversification, as described previously.

Power systems must constantly balance supply and demand, and this task is more difficult with the presence of VRE. Storage can provide temporal flexibility to mitigate these difficulties. The main uses of a storage device are to store electricity during a surplus of generation, mitigate the intermittency of variable renewable generators, provide backup and power quality management and defer the need for transmission expansion. Each application may need a different type of storage device (e.g. pump storage, batteries, fuel cells) because they have different technical features that make them more appropriate for one task or another [231]. The three most important barriers described in the literature for the expansion of energy storage are regulation, costs, and the lack of awareness of the benefits of energy storage [232].

In pure thermal power systems, base-load ramps and minimum up and down time cause the short-term supply curve to remain static in the short-run, and therefore the only solution to following the demand is to use expensive units (usually diesel units) to absorb renewable variations. On the other side, hydrothermal systems usually have a lower integration cost due to the flexibility of hydro generation.

Close inspection at Chilean electricity market: Chile is an hydrothermal system with large reservoir capacities, so it can use hydro generation to provide inexpensive reserve requirements because they are fast enough to follow residual demand changes. Figure 35 illustrates the flexibility of the supply curve (the figure shows a supply curve with normal hydro generation capacity and other one without hydro generation capacity). The National Electric Coordinator adjusts supply by either turning on and off the marginal power plant (moving along a supply curve) or usingthe rapid hydro capacity to absorb short run net-demand variations (changing hydropower injections). Hydro generation with storage is a natural supplement of VRE, since water can provide backup capacity and flexibility to balance wind deviations and thereby avoid the need for peak-load generators [233,234].

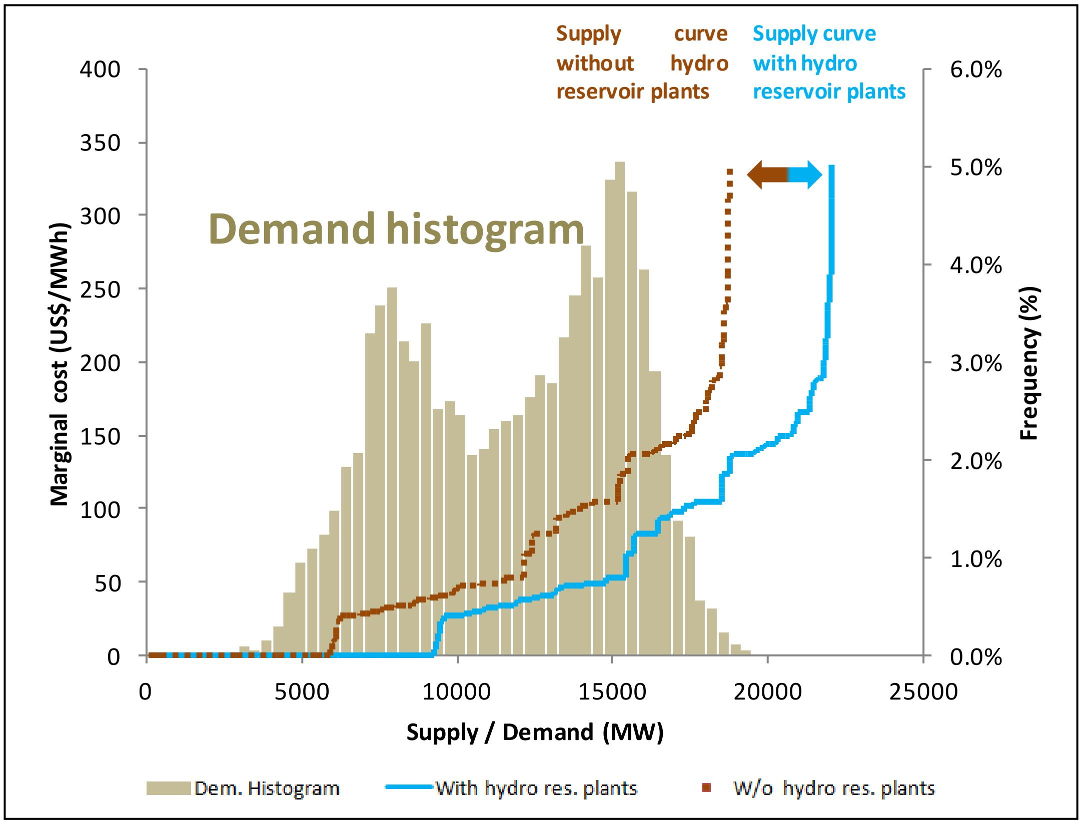

FIGURE 35: SHORT-TERM SUPPLY CURVE CAN CHANGE FAST WITH A HIGH AVAILABLE CAPACITY OF HYDRO RESERVOIR POWER PLANTS. OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRIC COORDINATOR AND THE NATIONAL ENERGY COMMISSION[9]

Although the potential of hydroelectric plants for integrating intermittent generation is widely known, few studies incorporate reservoir hydropower into the analysis (with only a few exceptions, such as the work by Kern et al. [211] and Benitez et al [235]). This is a noticeable gap in the literature regarding the significant source of flexibility that the reservoir hydro represents. This gap was also highlighted in reference [189]. This work is also an effort to quantify the ways that different levels of hydro storage affect renewable market value.

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[9] This figure is for illustration purposes only. The demand histogram was developed using the hourly real generation of year 2014 [221] assuming an annual growth factor of 3% to project it to the year 2020. The supply curve is constructed using data from a price a report from the National Energy Commission [252].

The flexibility of traditional power plants also plays an important role in accommodating renewable generation, and it has an impact on renewable market value of VRE. Increasing the flexibility of traditional power plants reduces operational costs when VRE increase its shares, specifically by decreasing the constraint of minimum generation levels of coal-fired power plants, more renewable generation can be used and curtailments are decreased [236]. Quick start and stop capabilities may also provide a good resource to use in real operations when forecast errors are larger, especially with high shares of renewable energies. Similarly, faster generators that can absorb power ramps may also be useful and provide value to the system by reducing the need of operational reserves. Minimum load levels, ramps rates and start-up time and costs are the main constraints of traditional generation, so traditional power plants must become much more flexible in the coming decade to survive to the accommodation of higher renewable generation [237].

Expanding interconnection capacities provides spatial flexibility to power systems, thereby allowing the complementation of different renewable and demand profiles. Interconnection among countries, especially in a future of very high penetration of variable renewable energies, has been reported to capture strong economic benefits. Indeed, international interconnections can reduce the balancing energy from 24% of the total annual electricity consumption to 15% in the EU [238]. Hourly mismatches between demand and renewable generation require high transmission capacities to provide balance. Several studies have recognized and designed methodologies to capture benefits of transmission expansion, especially regarding renewable integration [238–240].

Demand-side management has been mentioned as the lowest cost source of renewable energy support [241,242]. Adding demand flexibility using new technologies (such as electric cars) may add great value to power systems, although demand management takes time to develop, and the regulator should design and formulate plans to integrate it at an early stage [186]. Demand-side management policies recommendations include the implementation of demand response tariffs: direct load control tariffs (utilities can turn off consumer appliances during peak rates), implementing demand response tariffs, direct load control tariffs (utilities can turn off consumer appliances during peak rates) and information campaigns; providing incentives for distribution system operators to design campaigns and pilot projects; and designing institutional structures to develop these resources [186,243].

Variable renewable power plant design may be optimized for much smoother generation, which may be a much more valuable feature for the system than the energy itself. Indeed, Hirth and Muller [191] show that system-friendly wind power turbines are 15% more valuable than wind power from classic turbines. Advanced turbines have roughly the same annual generation as classic turbines, but they have very different power curves and produce much less variability.

There is scant literature on the study of policy strategies to directly encourage geographical diversification for renewable energy projects. One exception is the work by Schmidt et al. [244], who compare the effects of two types of feed-in tariffs (FIT): the fixed-price FIT (FFIT) and the premium based FIT (PFIT) over the wind spatial diversification. The authors develop an optimization model for an investor who maximizes the net present value under these two schemes, and from their results it follows that under a PFIT scheme, spatial diversification is incentivized, and variance of net demand is decreased.

The first stage before implementing any integration measure is improving the modeling of the power system. The energy models currently used for policy making usually have great technological detail but a highly stylized temporal resolution and a very poor spatial resolution [245–249]. The temporal and spatial resolutions are very important, however, for analyzing additional VRE costs. Poor temporal resolutions cannot truly capture intermittency, and therefore cycling, start-up and shutdown times and ramp requirements may be ignored [94,95,250,251]. Likewise, poor spatial and temporal resolution on planning energy models usually neglects the spatial diversification of renewable power generators. Accordingly, one of the most recurrent recommendations is to implement planning models with higher spatial resolution to facilitate long-term planning for the infrastructure needed to exploit renewable resources in a large region. To design policies, planners need to know where it is socially optimum, over the long run, to incentivize the development of renewable generators. Models with high spatial and temporal resolution are necessary to provide planners and regulators with sufficient insights to efficiently design policies and strategies in the development of power sector [245].

4.3 Method for evaluating and quantifying renewable market value: model and data

This study employs wind power siting methodologies and power system modeling to analyze the impact of different ways of expanding wind power in the Chilean electricity market. Different wind power portfolios are evaluated using a simplified unit commitment and dispatch model of Chile's national electricity system to analyze the market value of renewable energies. The power system is modeled assuming different levels of penetration for solar and wind energies, different levels of transmission constraints and different levels of storage (hydro storage). The methodology includes the evaluation of two portfolios—a reference portfolio and a spatially-diversified wind portfolio.

In the analysis, those portfolios are subject to multiple scenarios considering different wind and solar power penetration levels in different locations, scenarios with different transmission availability, and scenarios with different hydro-storage capacities. The renewable market value is analyzed for every portfolio and scenario. The general method is shown in Figure 36.

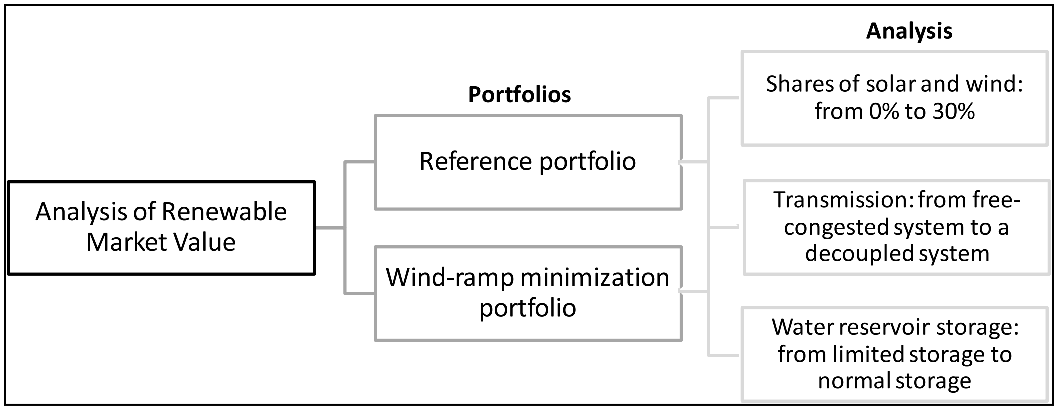

FIGURE 36: GENERAL METHODOLOGY TO QUANTIFY THE EFFECT OF TRANSMISSION AND STORAGE ON RENEWABLE MARKET VALUE

Reference Portfolio: The supply of the reference portfolio used on this research is obtained from the data published by National Energy Commission's for the year 2020 [252]. According to its connection point, each unit is assigned to one of the six interconnected zones that are represented in the modeling and that will be presented in the following sections.

Spatially diversified wind portfolio: The spatially diversified wind portfolio uses the same technological portfolio as the reference portfolio except for the wind power plants. Following reference [228], in this work is used a mean-variance portfolio (MVP) optimization model to minimize the wind-ramp-rate variability using spatial diversification. Wind power plants are located at nine wind sites to minimize the hourly ramps of the aggregated wind power production. The first objective is to minimize the variance of the wind ramps subject to a constraint so that the annual wind energy target is reached:

$$Min \sum_{i=1}^{n} \sigma_p^2 \qquad (1)$$

$$N° \; of \; hours \; \cdot \sum_{i=1}^{n} x_i \; \cdot CP_i = T \tag{2}$$

Where n is the number of sites (9 sites in this work), σ_p^2 is the variance of wind-ramps of the wind portfolio, CP_i is the annual capacity factor of the site i, and T is the annual wind energy target. The portfolio's wind ramps can be expressed mathematically as in the following equation:

$$\sigma_p^2 = \sum_{i=1}^{n} x_i^2 \sigma_i^2 + 2 \sum_{i<j}^{n} x_i x_j \sigma_{ij} \tag{3}$$

Where σ_i^2 is the variance of the ramp rate of site i and σ_{ij} is the covariance between ramp rates of sites i and site j.

4.3.1 Power system modeling details: storage, transmission and operational constraints in Chile

The model developed in reference [253] is extended to characterize the reality of the Chilean power system using six interconnected zones across the country as presented in Figure 37 with 153 generators and adding operational constraints for coal-fired power units. Given the high complexity of the problem, it is approached in two stages: a linear and simplified dispatch was modelled (without minimum operating capacity and ramp constraints) to determine the initial and final levels of each reservoir for each month and a more complete dispatch, considering minimum operating constraints, ramp constraints and using reservoir initial and final reservoirs levels as additional constraints for each month was modelled. Accordingly, in the second stage a mixed integer linear mathematical programming model is used. The objective function minimizes fuel costs (b_i) and operating and maintenance costs (OM_i) during the hours of a month (Hm).

$$Min\ TC = \sum_{t=1}^{Hm} \sum_{i} (OM_i + b_i) Q_{i,t} \qquad (4)$$

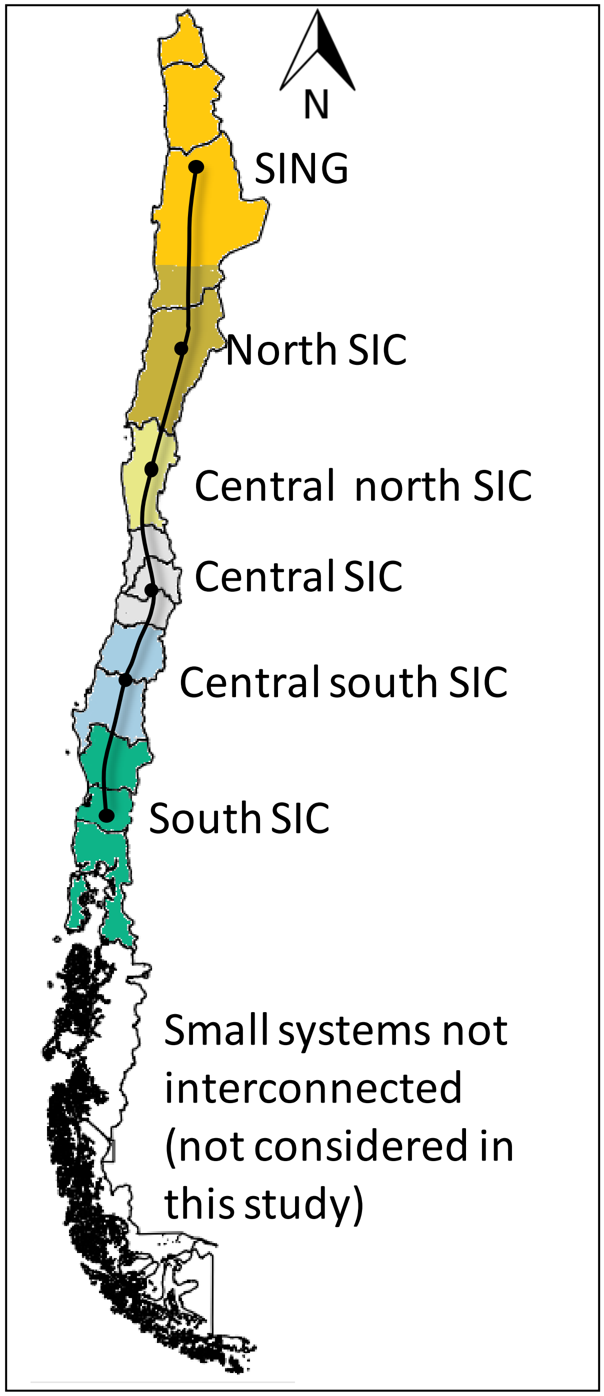

FIGURE 37: ZONES CONSIDERED IN THIS STUDY

For each zone (Z) and period (t), the sum of generator outputs $(Q_{i,t})$ plus the net imports $(Im_{t,Z})$ must be equal to the load $(L_{t,Z})$ as shown in (5), where Ng_Z is the number of generators in zone Z.

$$\sum_{i}^{Ng_Z} Q_{i,t,Z} - L_{t,Z} + Im_{t,Z} = 0, \forall Z; \forall t \tag{5}$$

Additionally, generators cannot exceed their maximum capacity ($\mathrm{CMax}_{\mathrm{i,t}}$), and their output must be above their minimum operating capacity ($\mathrm{CMin}_{\mathrm{i,t}}$) if they are on (only for the set $\boldsymbol{C}$ of coal units). For variable renewable generators (set $\boldsymbol{R}$) , such as wind, solar and run-of-river power plants, their maximum generation at each time t depend not only on their installed capacity, but also on the availability of the resource (R_a). Similarly, coal generators cannot exceed their ramp up (U_i) and ramp down (D_i) capabilities.

$$Q_{i,t} \le \mathrm{CMax}_{\mathrm{i,t}} \cdot U_{i,t}, \forall i \in \boldsymbol{C}, \forall t \tag{6}$$

$$Q_{i,t} \ge \mathrm{CMin}_{\mathrm{i,t}} \cdot U_{i,t}, \forall i \in \boldsymbol{C}, \forall t \tag{7}$$

$$Q_{i,t} \le \mathrm{CMax}_{\mathrm{i,t}} \cdot R_a, \forall i \in \boldsymbol{R}, \forall t \tag{8}$$

$$Q_{i,t} \le \mathrm{CMax}_{\mathrm{i,t}}, \forall i \notin \boldsymbol{C} \land \notin \boldsymbol{R} \tag{9}$$

$$Q_{i,t} - Q_{i,t-1} \le U_i, \forall i \in \boldsymbol{C} \tag{10}$$

$$Q_{i,t-1} - Q_{i,t-1} \le D_i, \forall i \in \boldsymbol{C} \tag{11}$$

$$U_{i,t} \in \{0,1\} \tag{12}$$

Finally, hydro reservoirs must also be modeled with a special set of equations to consider storage capacities. It is assumed that the generation of hydroelectric generator h at time t depends on generator efficiency (η_h), the gravitational constant (g), the density of water

(d), the flow of water $(F_{t,h})$ and a fixed head height (H_h). The volume of water stored behind the hydro dam $(V_{h,t})$ at time t depends on its level in the previous period $(V_{h,t-1})$, plus inflows $(I_{h,t})$, minus the sum of the flows through the turbine $(F_{h,t})$ and the water that is spilled $(S_{h,t})$. Additionally, minimum river flow or environmental flow is also considered so the water through the turbine plus the water spilled is greater than the environmental flow for the river.

$$Q_{t,h} = \eta_h \cdot g \cdot d \cdot F_{t,h} \cdot H_h \cdot 10^{-6}, \qquad \forall\, h, t \tag{13}$$

$$V_{h,t} = V_{h,t-1} + I_{h,t} - F_{h,t} - S_{h,t}, \forall\, h, t \neq 1 \tag{14}$$

$$F_{h,t} + S_{h,t} \geq EF_h, \forall\, h\,, t \tag{15}$$

$$V_{h,t} \leq \max V_h\,, \forall\, h, t \tag{16}$$

The transmission system is modeled as a transport system, so losses through these transmission corridors are not modeled. This simplification is based on the expansion of Chile's transmission system: a few years ago, the main transmission system was only on 220 kV, today the central and south-central zones are connected through a 500 kV line, and it is expected that the north end of the country will be connected to the center by a 500 kV line in 2018. Accordingly, transmission line connecting zone Y with zone Z was only modeled its maximum capacity as a constraint, as expressed in (17). Finally, the net imports of a zone Z is defined as the sum of the transmitted power to that zone as presented in (18).

$$|T_{Y-Z}| \leq Tmax_{Z-Y}, \forall\, Z, Y \tag{17}$$

$$Im_{t,Z} = \sum_{Y} T_{Y-Z} \tag{18}$$

In the mathematical description of the problem detailed above, some constraints are intentionally left out, such as border conditions associated with the initial and final reservoir levels, the initial state of coal generator, and non-negative variables.

4.3.2 Data to feed the model: renewable profiles, demand profiles and variable costs of the Chilean electricity market

This section describes the sources of the data used as input for the model including renewable resources profiles and their generation patterns and installed capacities, locations and the variable costs of thermal power plants.

Detailed renewable resources modeling: wind, solar and hydro resources in Chile

Detailed Wind and solar profiles: The wind power profiles used in this study are based on an aggregated zonal analysis of the Chilean wind power sector by Watts et al. [113] and summarized in Figure 38. In that study, three models of wind turbines were selected for modeling wind farms: 3 MW Nordex N117, 2 MW Vestas V100 and 1.8 MW Vestas V100 depending on the wind regime of the zone. The authors showed that by aggregating dispersed wind generation, the total production tends to smooth out. However, the interaction with the system was not examined, and therefore the prices and the wind and solar power market value were not presented. On wind farms located on mountains and in high altitudes, the air density loss, reducing wind energy production was modeled using an equivalent reduction in wind speed as presented by Watts et al. [113].

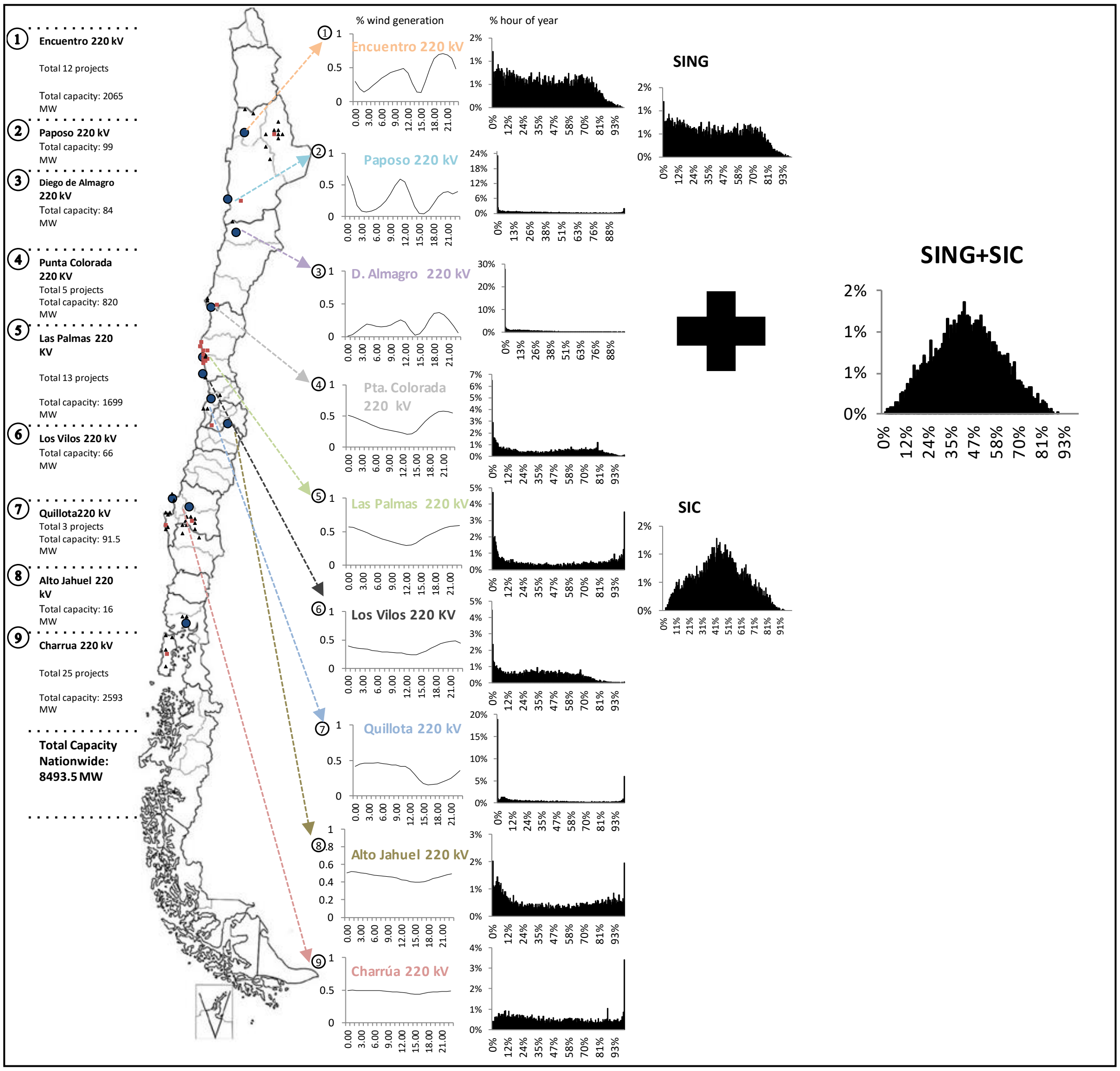

FIGURE 38: AGGREGATED ZONAL ANALYSIS OF THE CHILEAN WIND POWER SECTOR[10]. SOURCE: [113]

Solar resources are concentrated in northern Chile and to a lesser extent in the central zone, so only two solar profiles are used in the model, one for the northern zone and one for the central zone. Both profiles were obtained from publically available real generation profiles

[10] The first line of charts present the daily wind generation profile of each zone (% of wind generation vs. hour of a day) and the second line of charts present the histogram wind generation in the respective zone (% of hour of the year vs. % of wind generation).

of year 2015 in the north and central zones published by the National Electricity Coordinator [221].

Detailed Hydro resources modeling: dam hydro storage and run-of-river hydro of Chile

Chile's most important hydro reservoirs for electricity generation, sorted according to storage capacity are Lago Laja, Colbún, Ralco, Chapo, Rapel, Invernada, Melado and Pangue. All of them are in the central south and have associated different generation units. Table 8 presents their maximum and minimum operational capacity, electricity generation capacity (MW), net height and maximum turbinable flow. A reservoir's minimum operational capacity is the minimum level of water it needs to maintain its ability to generate electricity or for ecological restrictions. The difference between the maximum and the minimum capacity is the useful storage to generate electricity.

TABLE 8: CAPACITY OF CHILE'S MAIN HYDRO RESERVOIRS USED FOR ELECTRICITY GENERATION. SOURCE: NATIONAL ELECTRICITY COORDINATOR [254]

Reservoir	Max Capacity (hm3)	Min Capacity (hm3)	Useful Capacity (hm3)	Gen. Name	Installed Capacity (MW)	Net Height (m)	Turbinable Flow (m3/s)
Laja	5490	0	5490	El Toro	450	545	97.3
Colbún	1609	380	1229	Colbún	474	168	280
Ralco	1174	410	764	Ralco	690	200	450
Chapo	1040	0	1040	Canutillar	172	237	65
Rapel	508	270[11]	238	Rapel	377	76	535
Invernada	173	0	173	Cipreses	106	370	36
Melado	133	101	32	Pehuenche	570	206	300
Pangue	72	7	65	Pangue	467	99	500
Total	10199		9031		3306	222	335

[11] The minimum operational capacity of Rapel reservoir varies over time because the electric company that owns it has reached agreements with neighbors to keep the level of the reservoir above a certain threshold to allow recreational activities.

The reservoirs' regulation capacity can be deduced from the variation of their levels. If a reservoir shows a high variation on its level, it has a small regulation capacity; a small reservoir fills and empties very quickly, while one whose level varies only slightly is usually large and has a high storage capacity. Figure 39 presents the levels of the different reservoirs along the period 1985–2015.

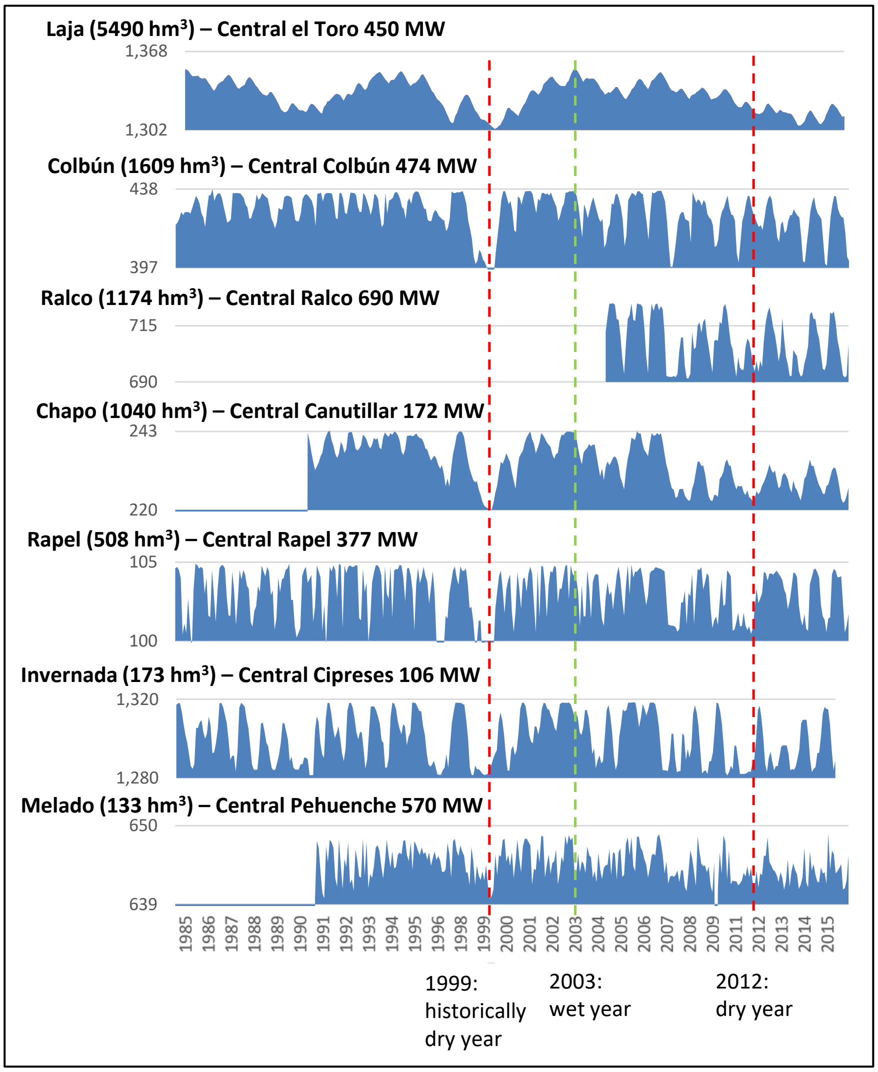

FIGURE 39: HISTORICAL LEVELS OF THE MAIN RESERVOIRS IN CHILE. OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRIC COORDINATOR [255]

Chile has very good hydro resources with a majority of dam hydro and run-of-river units, and as a result, the supply hinges on the hydrological year. Figure 40 presents the capacity factor of the most important hydro dam generators from 2010 to 2015, with an average of 37%.

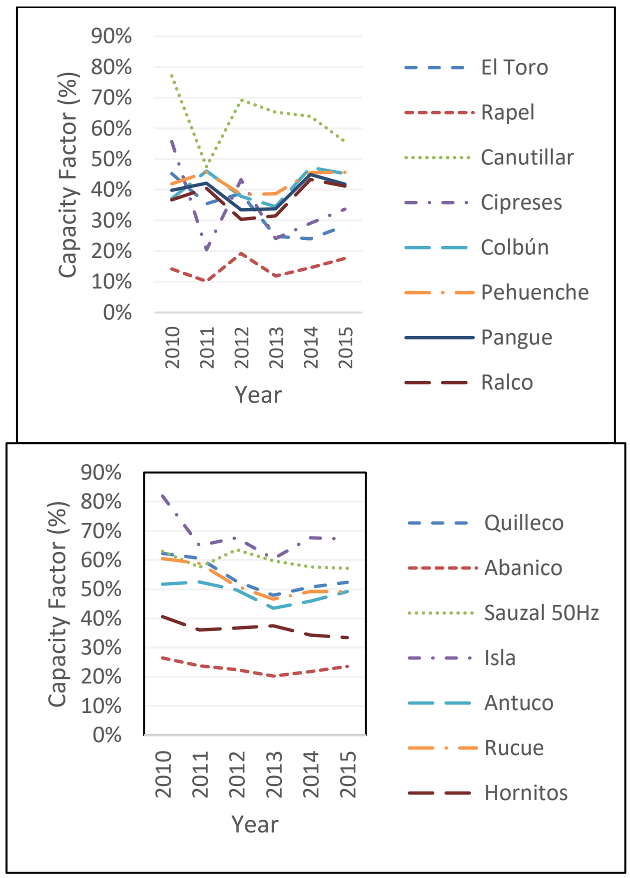

FIGURE 40: ANNUAL CAPACITY FACTOR OF RESERVOIR HYDRO PLANTS AND RUN-OF-RIVER PLANTS IN CHILE (2010–2015). OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRICITY COORDINATOR [221]

Run-of-river power plant production also depends on the hydrological year, so their production varies from year to year as is shown in Figure 40 for some of the most important power plants in Chile. Chile has more than 110 run-of-river power plants, which are concentrated in the central and southern regions. However, in 2015 just 20 of them represented the 75% of the total generation of all the run-of-river plants as presented in Table 9.

TABLE 9: GENERATION OF THE MAIN RUN-OF-RIVER PLANTS IN CHILE IN 2015. SOURCE: OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRICITY COORDINATOR [221]

Central	Reg.	Cap. (MW)	Yearly Gen. 2015 (GWh)	Acum. Gen (GWh)	Acum Gen RoR %
Antuco	8	320	1,378	1,378	11%
Angostura	8	316	1,221	2,599	21%
Rucúe	8	178	802	3,401	28%
Alfalfal	RM	178	694	4,096	34%
La Higuera	6	155	537	4,633	38%
Curillinque	7	89	483	5,116	42%
Chacayes	6	111	478	5,593	46%
La Confluencia	6	163	402	5,996	49%
Isla	7	68	400	6,396	52%
Sauzal 50Hz	6	76.8	384	6,780	56%
Quilleco	8	71	325	7,106	58%
Queltehues	RM	48.9	303	7,409	61%
Abanico	8	136	280	7,689	63%
Rucatayo	10	52.5	245	7,934	65%
Palmucho	8	32	237	8,171	67%
Pilmaiquén	9	40.6	221	8,392	69%
Pullinque	9	48.6	219	8,611	71%
Loma Alta	7	38.3	217	8,828	72%
Peuchén	8	85	196	9,024	74%
Los Quilos	5	39	175	9,200	75%

The generation profile of run-of-river power plants depends on the flow of the river. Accordingly, a generation profile will depend on whether the river's regime is pluvial, nival or mixed. Thus, the generation profiles of close run-of-river power plants are similar because their hydrological conditions are similar. Figure 41 shows that power plants in the central zone (the Metropolitan and Sixth regions) have a generation profile consistent with snowy regime, since their generation is higher in the hottest months (November, December, January and February) and very low in the colder months. This profile is different to the South (Seventh region) because the high rainfall increases river flow in the winter and generation is not as low in cold months as it is in the central zone. Even further south, rains are even more important, and the generation profile changes considerably, because the coldest months present a higher generation compared with the hottest months.

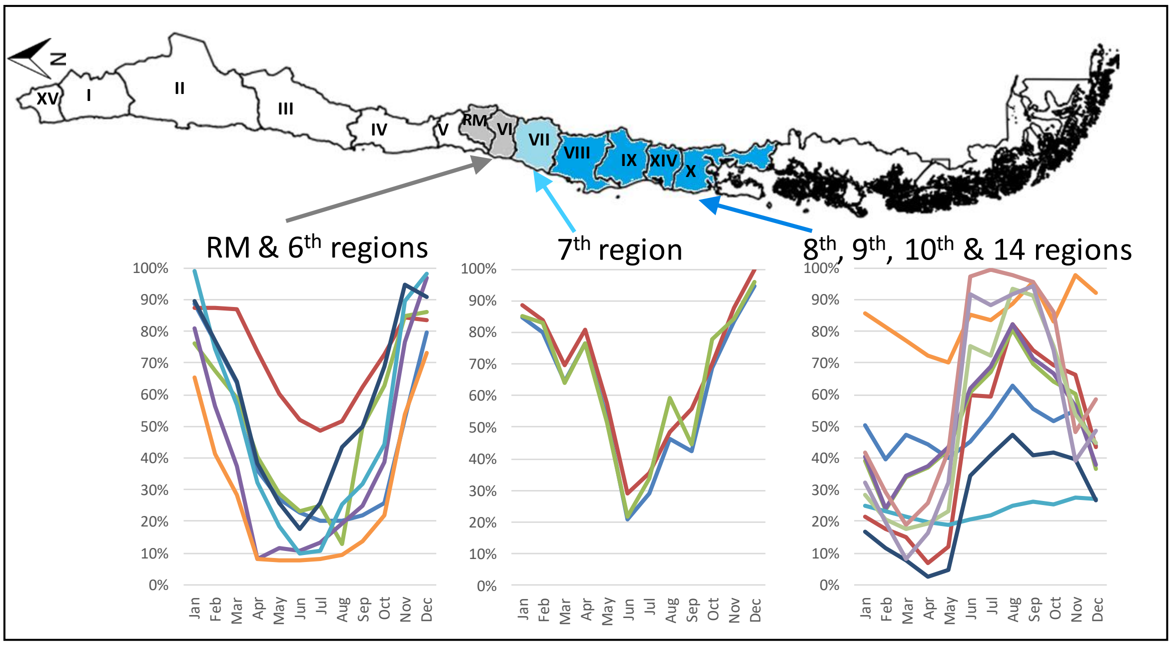

FIGURE 41: GENERATION PROFILE OF RUN-OF-RIVER POWER PLANTS ON THE DIFFERENT REGIONS OF CHILE. OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRICITY COORDINATOR [221]

The generation profile of run-of-river plants is similar when comparing different years. Figure 42 shows the annual generation profile for 2003 (dry year), 2013 (wet year) and

2015 of four plants located from the central to southern Chile. Their generation profiles have a similar shape in these years.

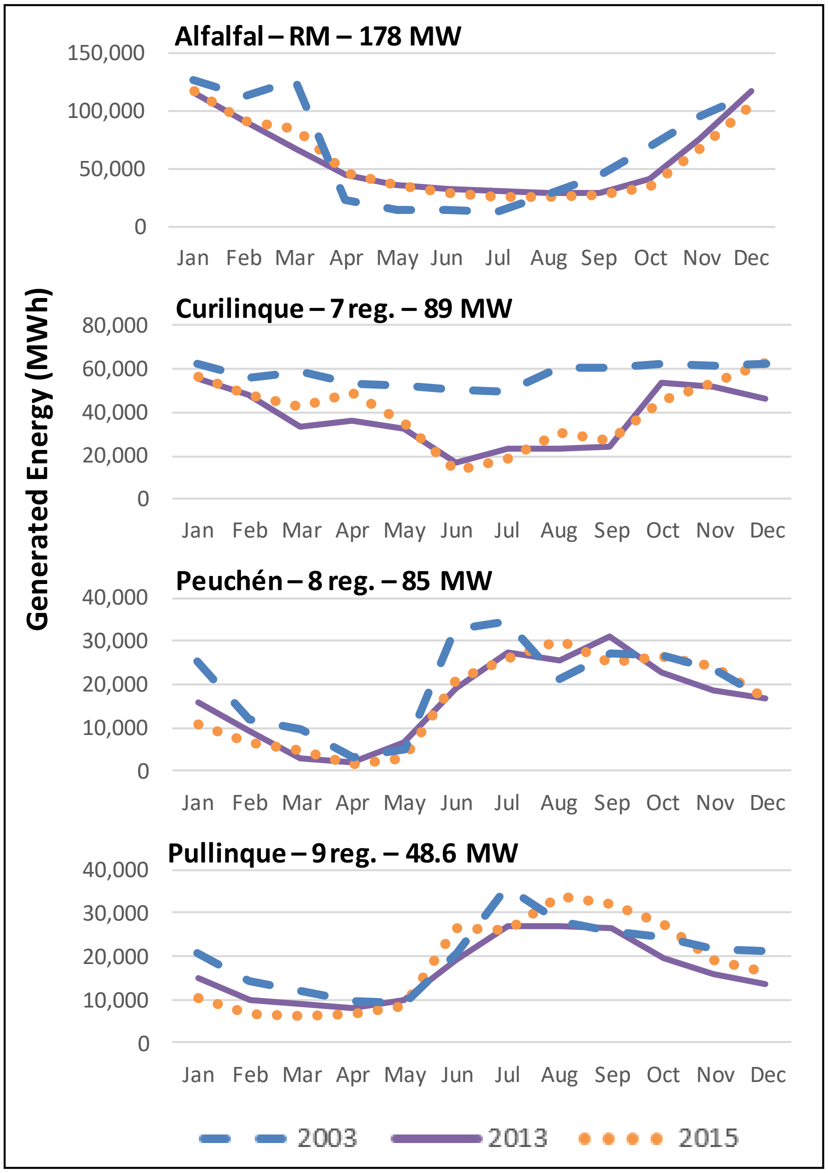

FIGURE 42: GENERATION PROFILE OF RUN-OF-RIVER PLANTS IN A DRY YEAR (2003), A WET YEAR (2013), AND THE LAST YEAR WITH COMPLETE DATA (2015). OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ELECTRICITY COORDINATOR [221]

Supply: installed capacities, its locations and variable costs

The current installed capacities, variable costs and locations of each power plant are obtained from data published and used by the National Energy Commission of Chile [252]. Table 10 presents the installed capacities per generation type and the zone of the Reference Portfolio. Note that solar and wind generation installed capacities are not presented in Table 10 because the supply of wind and solar energy are important variables in this study, so installed capacity of wind and solar power plants varies in the analysis to show different effects on their market value.

TABLE 10: INSTALLED CAPACITIES OF NON-SOLAR AND NON-WIND TECHNOLOGIES (MW). SOURCE: NATIONAL ENERGY COMMISSION [252]

Tec /Zone	SING	North SIC	C. North SIC	Central SIC	C. South SIC	South SIC	Total
Diesel	1,412	740	458	2,464	1,025	289	6,388
Coal	2,254	694	0	820	789	0	4,556
LNG	849	0	0	1,899	0	0	2,747
Biomass	0	0	0	47	39	0	86
Dam	0	0	0	0	2,736	570	3,306
Run of	0	5	26	1,523	1,704	500	3,758
Total	4,975	1,845	693	6,819	6,319	1,406	22,057

In the modeling, dam hydro, coal, and LNG units are represented separately and independently. However, some diesel units with similar variable prices and locations are grouped due to memory limitations. Similarly, some biomass units with similar variable prices are grouped. Additionally, run-of-river hydropower plants are also grouped into three different types depending on their location and generation profiles, as explained in the previous section. Variable costs of thermal power plants are obtained from data published by the Chilean National Energy Commission [252]. Different plants have different variable costs according to their efficiency and specific type of fuel. Figure 43 presents the variable cost of every unit of coal and LNG plant used in the model and a sample of the diesel plants.

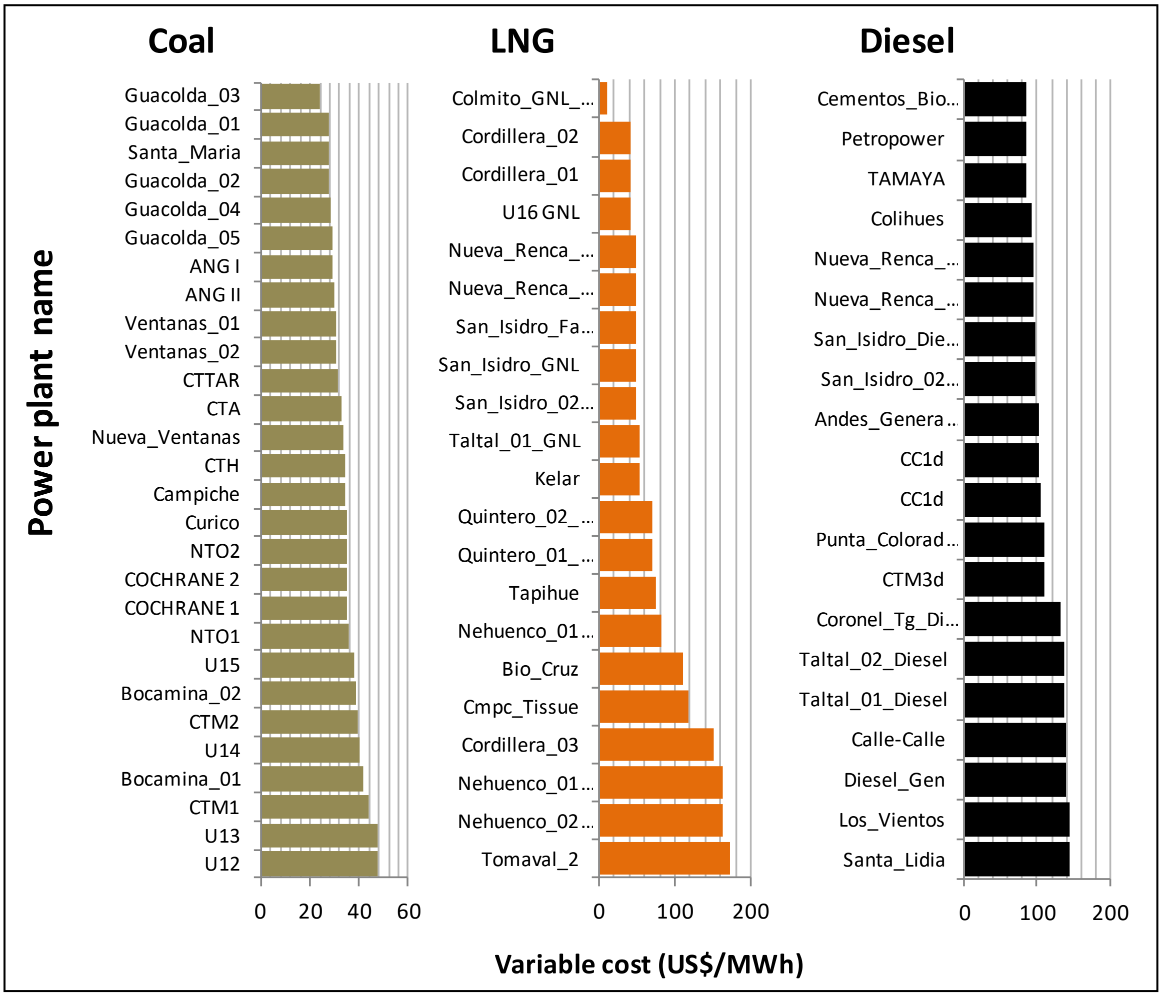

FIGURE 43: VARIABLE COSTS OF THERMAL POWER PLANTS (US$/MWH). SOURCE: OWN ELABORATION BASED ON DATA PUBLISHED BY THE NATIONAL ENERGY COMMISSION OF CHILE [252]

4.4 Model results: wind and solar market value in different scenarios of transmission and storage availability

Renewable energy market value is found to be quite dependent upon transmission and storage availability in the Chilean electricity market, and this deserves a review of two central results of this research. The first is how renewable profile diversification helps increase renewable market value in a scenario of constrained transmission, and the second is how renewable profile diversification and hydro storage disturbs renewable energy market value.

4.4.1 How spatial diversification helps increase renewable market value in a scenario of constrained transmission

Most recent literature has highlighted that the value of spatial diversification of renewable resources comes from the reduced variability of the output. Nevertheless, when transmission is constrained, the system cannot take full advantage of the natural complementarity of renewable energy profiles. The available infrastructure of the power system and its possible future upgrades should be considered when determining the location of renewable generators. The use of locational marginal prices (LMPs) or spot prices to signal locations where generation can address electricity system insufficiency is one possible instrument that regulators should observe [256,257]. Smart siting of renewable power plants, considering the diversification of the aggregated profile as well as the transmission availability, may provide an opportunity to improve system efficiency, and at the same time, improve the market value of renewable generators. Indeed, the effect of spatial diversification on the renewable market value has not yet been explored. Different portfolios of wind projects, even with the same annual generated energy, result in different average LMPs, depending on their location and transmission capacity availability, as is shown in Figure 44. A portfolio with diversified power plants will usually produce higher market value for renewable power plants than a portfolio with non-diversified power plants.

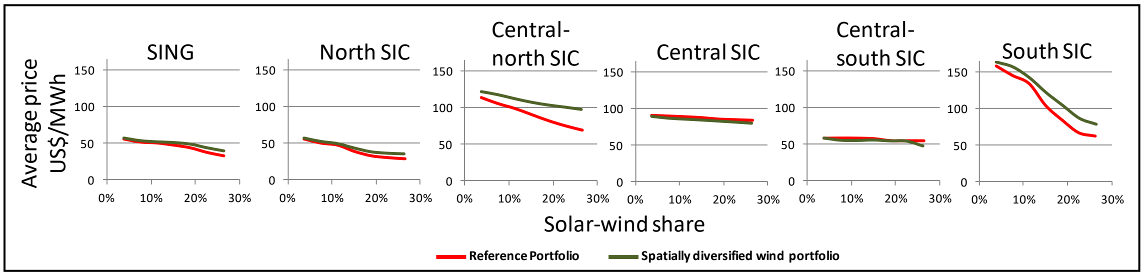

FIGURE 44: AVERAGE LOCATIONAL MARGINAL PRICES FOR DIFFERENT SOLAR-WIND SHARES AND DIFFERENT PORTFOLIOS

Market value, transmission constraints and geographic diversification. When transmission is constrained, some units increase their market value (those on the side of the generation supply shortage with respect to congested path), and some units decrease their market value (those on the excess supply side). The latter is what usually happens to renewable projects, because they are usually concentrated in zones seeking a good primary resource. This is the main reason why a good spatially diversified portfolio tends to surpass the market value of its renewable technologies when compared to a poorly diversified portfolio in the scenario of transmission constraint as is shown on Figure 45, in which the diversified portfolio achieves higher prices with increasing wind and solar generation. Promoting system-useful diversification of wind and solar power plants or addressing the siting issue of renewable generators adds value to the system in scenarios of constrained transmission capacity.

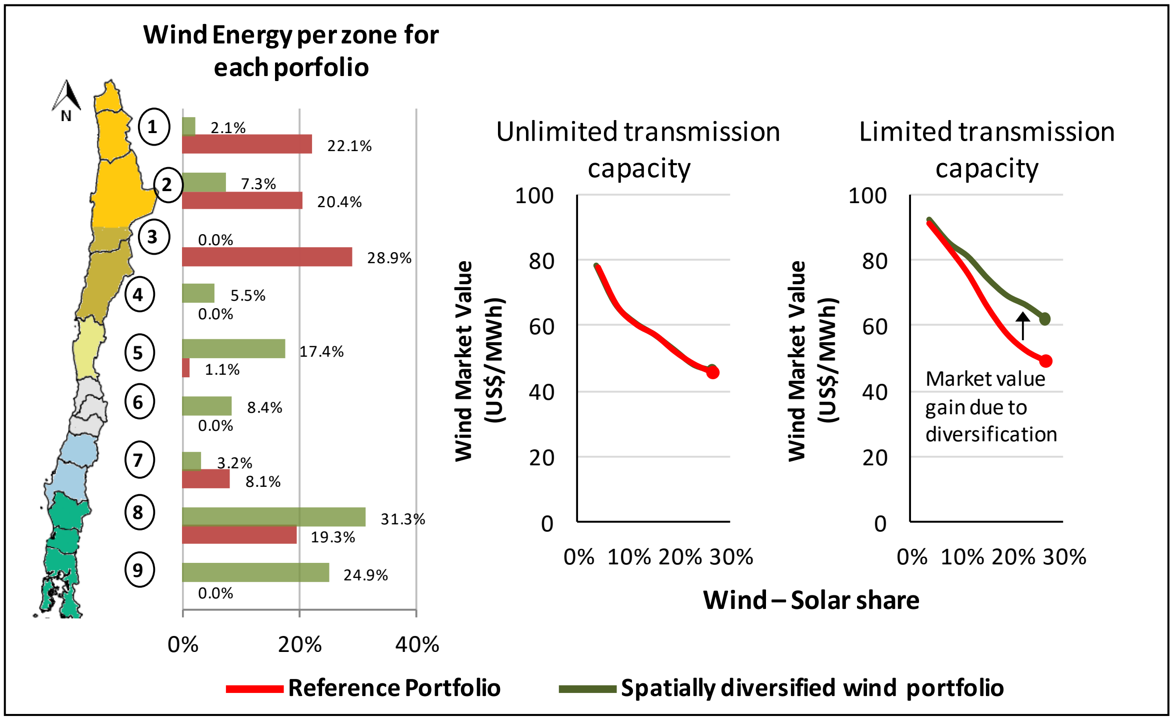

FIGURE 45: WIND MARKET VALUE FOR TWO DIFFERENT PORTFOLIOS (REFERENCE PORTFOLIO AND DIVERSIFIED PORTFOLIO) AND TWO DIFFERENT TRANSMISSION SCENARIOS

In scenarios in which transmission is fully available, the results show that market value does not change much with geographical diversification. This result confirms that diversification is not very useful in scenarios in which the system has a high degree of flexibility, at least when evaluating with an hourly model. Figure 46 shows the convergence of the market value as the transmission capacity of the main corridors increases. As transmission capacity increases, spatially diversified portfolios mitigate the reduction in economic value in a much more effective way than the reference portfolio. Naturally, it is difficult to quantify the benefits because it strongly depends on the topology of the transmission system.

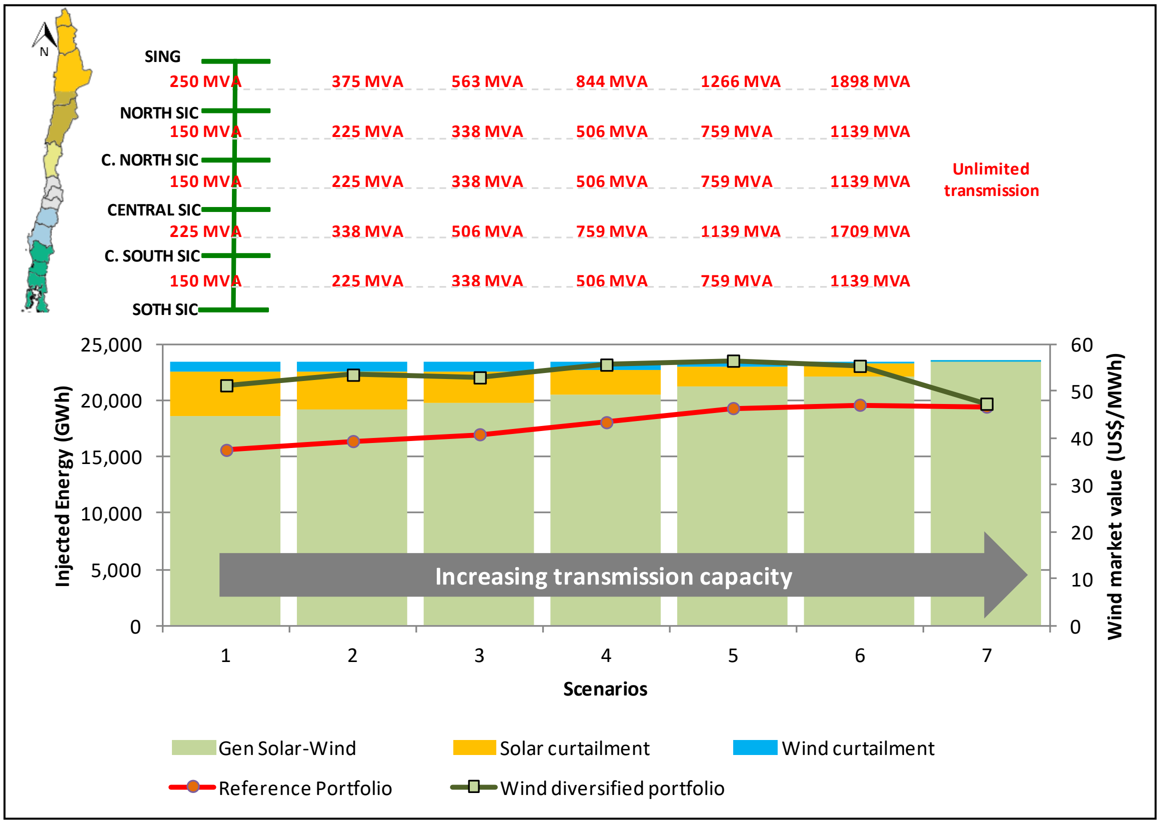

FIGURE 46: WIND MARKET VALUE FOR DIFFERENT LEVELS OF TRANSMISSION CAPACITY

The effects shown in Figure 46 in which the wind market value increases more than US$10 can be explained conceptually because the availability of transmission extends the "relevant market". This is especially important for non-dispatchable renewable generators since there is a greater possibility that demand will absorb their energy production. Moreover, most of the curtailments of wind power are caused by transmission congestion and not by the generator inflexibility (there is nearly no curtailment in the unlimited transmission scenario). Figure 47 shows how the spatial diversification of wind reduces curtailment in a scenario of constrained transmission. This result is consistent with other results presented in the literature (see Novacheck and Johnson [228]).

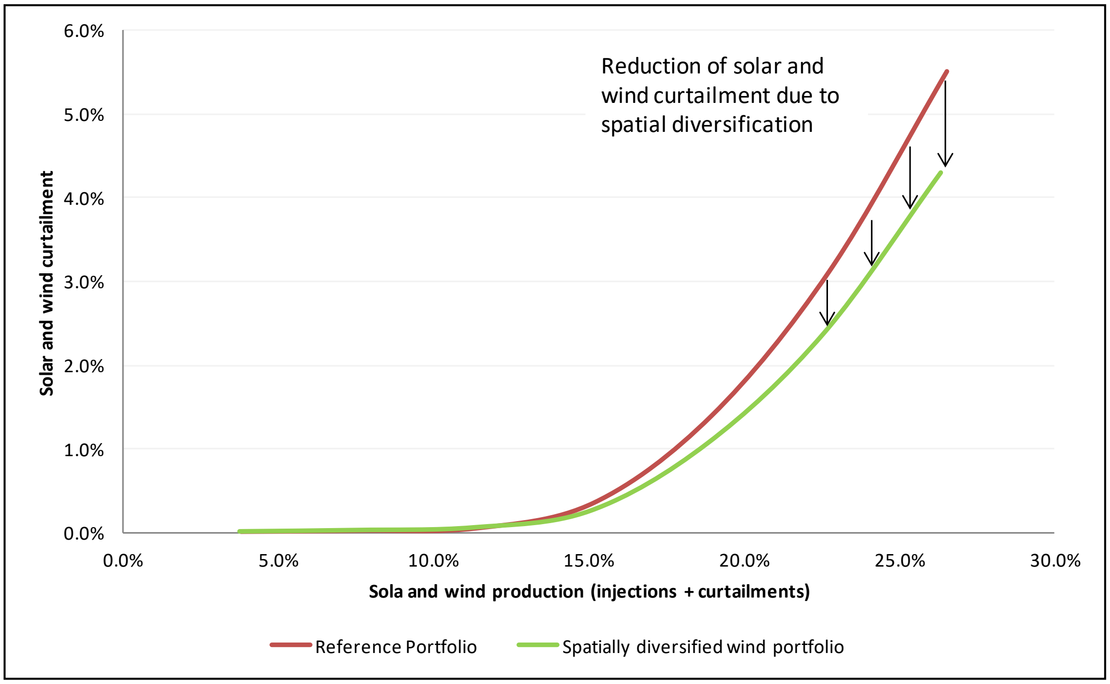

FIGURE 47: SOLAR AND WIND CURTAILMENT FOR THE REFERENCE PORTFOLIO AND LIMITED TRANSMISSION CAPACITY IN THE CHILEAN ELECTRICITY MARKET

Depending on their location and function (base generation, mid generation or peak generation) some technologies will benefit from renewable spatial diversification and others will not. For example, coal-fired and LNG power plants are usually base generation and therefore wind diversification does not affect them too much. Base generation can benefit from renewable diversification since cycling can be avoided (this chapter does not quantify that effect because an hourly model is used). Figure 48 presents the market value for different technologies and the two portfolios (reference and wind diversified) tested in this Chapter. Coal-fired power plants show an increase in market value because in the wind-diversified portfolio, wind power generators are developed farther from the coal plants and therefore local prices goes up. On the contrary, diesel units suffer a decrease in market value with wind geographical diversification, which is mainly explained by the smoothing out of the wind profile and the decreased need for diesel generation to cover spikes in the demand. Hydro reservoirs also suffer from a decrease in market value with wind diversification because a significant part of the value of storage is captured by wind diversification as another important flexibility measure. The price decrease of solar generation is dramatic because its generation is time-coincident. Due to Chile's geography, the production of solar energy at an hourly level, is highly correlated.

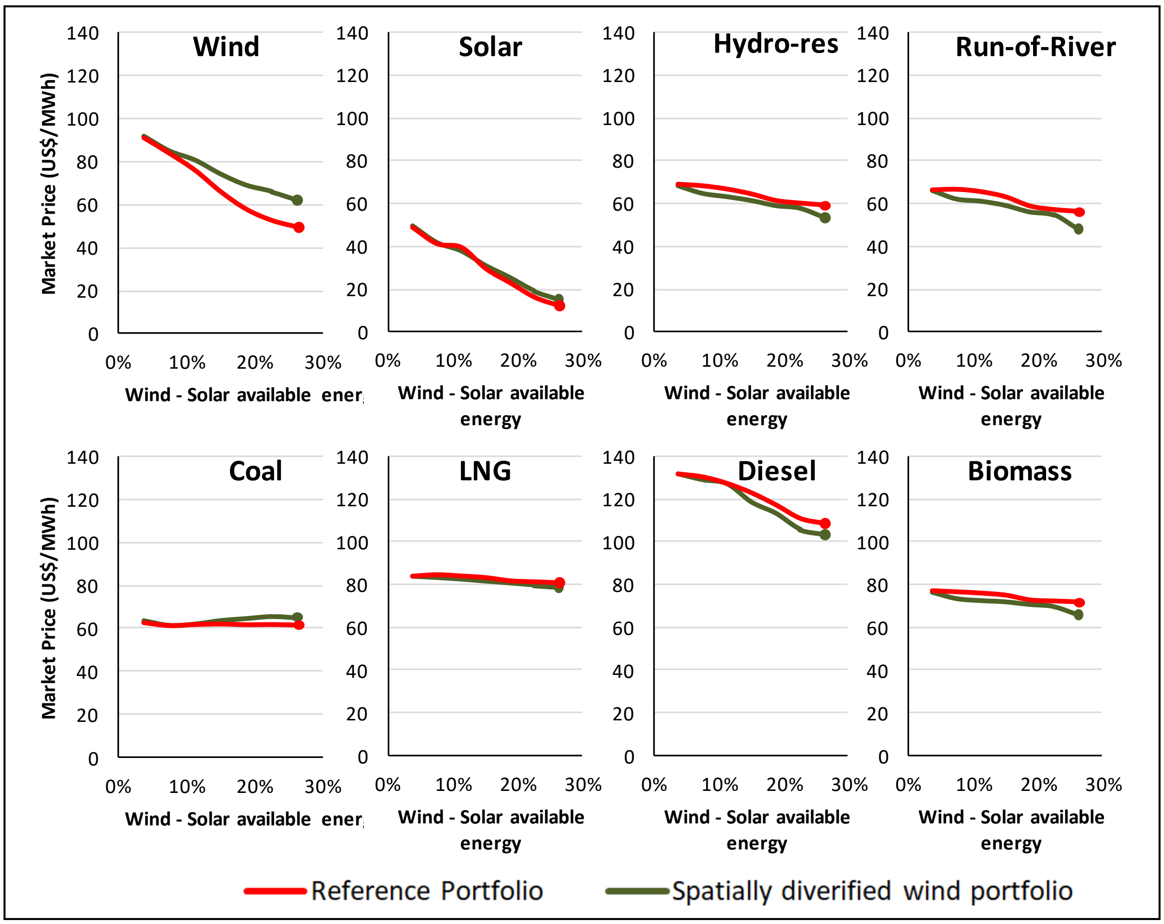

FIGURE 48: MARKET VALUE FOR DIFFERENT TECHNOLOGIES IN THE REFERENCE AND THE WIND-DIVERSIFIED PORTFOLIO IN THE CHILEAN ELECTRICITY MARKET

4.4.2 Interaction of solar and wind market value and hydro storage: location matters

Some studies state that hydropower with storage slows the decrease in the market value of renewable energy as penetration rises [258]. Considering the results presented above, this statement appears to be correct but incomplete in the case of the Chilean electricity market, because hydro resources can rapidly become exhausted and, after a certain renewable penetration, the effect vanishes. In a scenario of massive solar PV, as is expected for Chile, the flexibility of hydro resources would be basically used to absorb solar PV production fluctuations, especially to cover the ramp produced in the afternoon when solar production declines and demand rises. Figure 49 presents wind and solar market values for two simulation variants, one with the hydro reservoirs with their normal storage capacity and the other one without any reservoirs (reservoir hydro power plants are treated as run-of-river plants).Both variants receive the same water flows (same energy inflow). When storage is restricted, and the temporal flexibility is lost, hydro energy will then be immediately used or wasted. As can be seen in Figure 49, a decrease in bulk storage capacity, push down the solar market value, while the opposite is true in the case of wind market value. Note that after a certain wind - solar penetration, the difference of market value between the situation with normal storage and the situation with limited storage remains roughly constant, i.e. after a certain penetration of VRE the effect of current hydro reservoir capacity on solar market value does no longer increase, reaching approximately US$5/MWh.

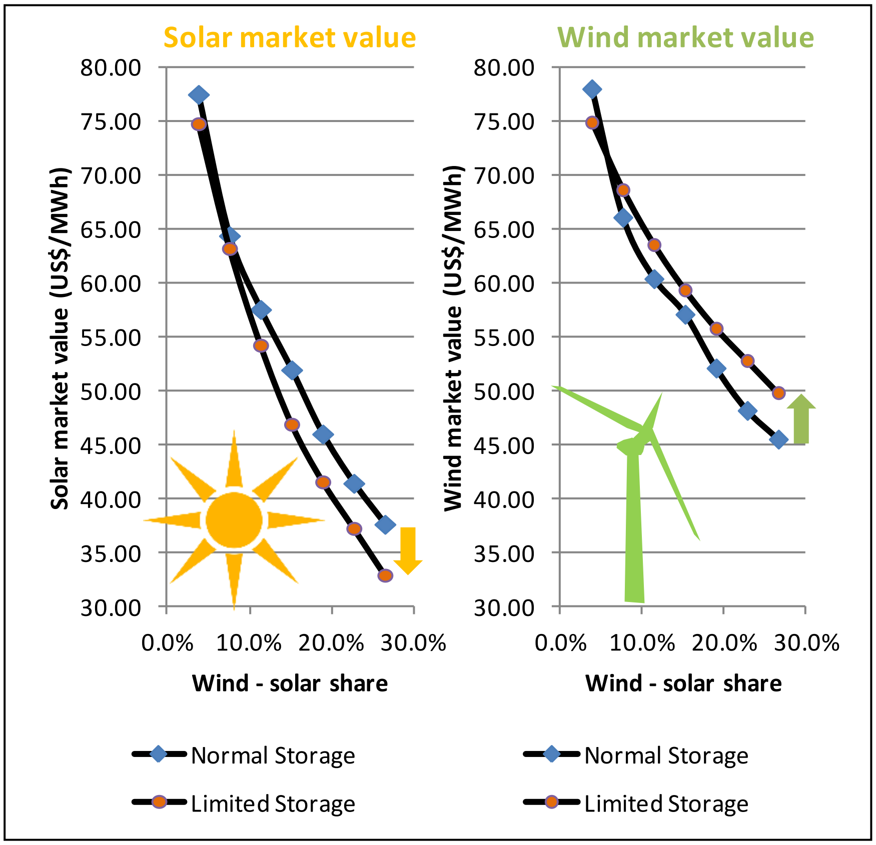

FIGURE 49: WIND AND SOLAR MARKET VALUE FOR NORMAL AND LIMITED HYDRO STORAGE CAPACITIES IN A SCENARIO OF MASSIVE SOLAR PV PENETRATION IN CHILE

Spatial diversification and storage are complementary flexibility measures. Spatial diversification has positive effects when transmission capacity is constrained. In a scenario of constrained transmission, the ability of reducing market value losses when penetration increases is very much conditioned by how close the location of renewable energy generators are to the congested paths of the network. Also, storage cannot help alleviating value loss if there are significant transmission constraints between storage (hydro reservoirs in the case of Chile) and renewable power plants.Bad diversification combined with a congested transmission network can impede the use of the flexibility provided by storage. A very contingent example has occurred in Chile, where solar resources are concentrated in the north, and hydro resources are concentrated in the south, and it has become is imperative to maintain large transmission corridors to take advantage of the flexibility of the hydro reservoirs to diminish the drop of solar market value.

The primary constraint for integrating high shares of VREs, and the most important factor that pushes down their market value, is the limited temporal coincidence of generation profiles with the demand profile of the system. Hydro-storage allows production “to move" when it is more useful, so it is one of the most important sources of temporal flexibility in power systems. Reservoir hydro plants can mitigate the well-known "duck curve" effect (ramps produced in the afternoon when solar production declines and demand rises), because when there is high solar penetration, hydro generation is displaced toward the night and significantly reduces the afternoon ramp of thermal power plants. Figure 50 shows the hourly profile for two cases, one simulating low penetration of wind and solar and the other simulating a high penetration of these technologies. Every case is simulated with two variants, one with limited storage of and the other with normal storage of hydro reservoirs. All the simulation cases assume a transmission system without congestion.

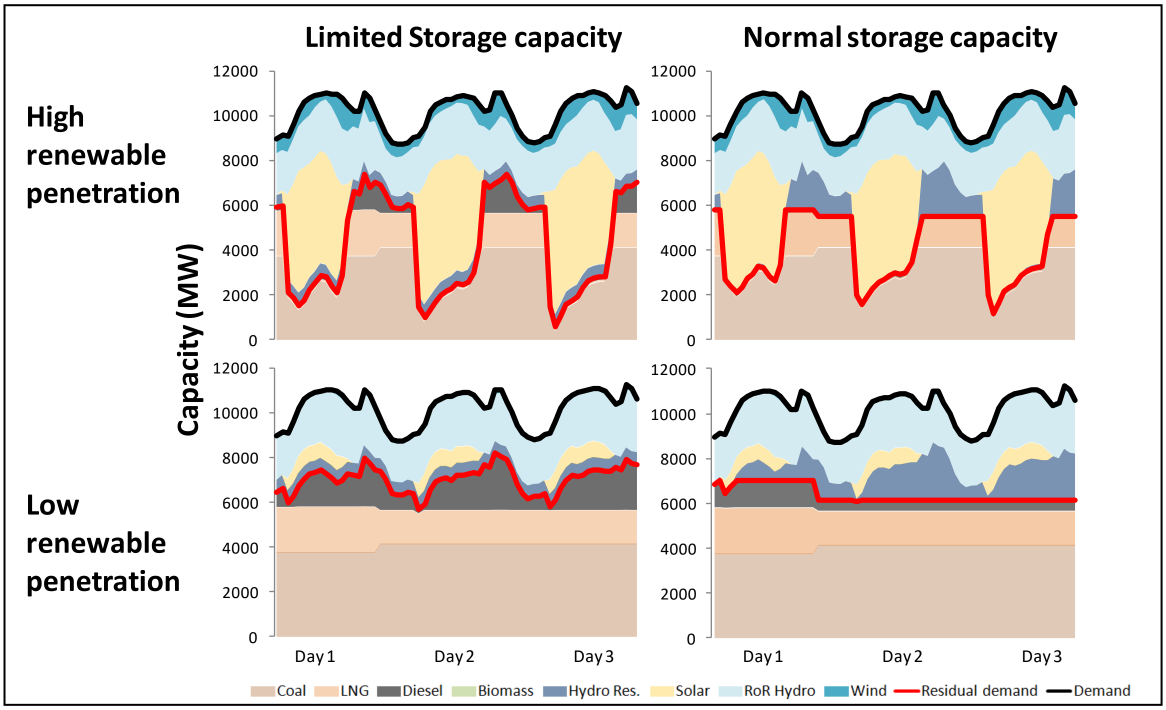

FIGURE 50: HOURLY PROFILE FOR TWO CASES, ONE SIMULATING LOW PENETRATION OF WIND AND SOLAR AND THE OTHER SIMULATING A HIGH SHARE OF THESE TECHNOLOGIES IN THE CHILEAN ELECTRICITY MARKET

As shown in Figure 50 for low penetration of solar and wind energy, the normal reservoir of hydro capacity allows for limiting the cycling of the thermal generation (residual demand is almost flat). However, when renewable penetration is increased, the cycling of coal and LNG generation is also increased. As shown above, hydro reservoirs provide the ability to inject energy when it is needed most: when the solar resource is declining, and demand is rising. In the example above, without the presence of the storage, the afternoon ramp is covered by expensive thermal generators, including diesel generation.

4.5 Conclusions: relevance of VRE spatial diversification in power markets

Exploiting the best potential sites to integrate them where they provide the highest value to the electricity system is no trivial matter. The spatial diversification of renewable generators, especially wind power generators, reduces the variability and therefore may add value to the system by reducing the needs of operating reserves and flexible traditional generators. Also, spatial diversification may reduce the risk of price depression and low market values in scenarios with active transmission capacity constraints.

This chapter does not focus on the reduced variability of the diversified portfolios, but rather it presents a methodology and analysis to assess the interaction of spatial diversification with the availability of transmission capacities and bulk storage (hydro reservoir storage) for the Chilean electricity market. Unlike most works that evaluate the impact of wind diversity by focusing on minimizing wind variability and the ramping of wind farms, this study models the impact of that spatial diversification of wind on its own market value in scenarios of transmission capacity and storage limitations. The effectiveness of the spatial diversification of wind power plants is measured by comparing its market value within two portfolios under different transmission and storage available capacities. In a scenario of abundant transmission capacity, the value of spatial diversification is produced by the reduced variability of the aggregate wind production (as per the current literature trend). However, few power systems have unlimited transmission capacities. Furthermore, the availability of transmission capacity is dynamic, since construction and connection of renewable projects, especially solar and wind power plants, is extremely fast.

In an ideal world without transmission constraints, market value would be a function of the share of renewable energies, and the variability and co-variability with other resources (a very good theoretical approach is explained by Hirth and Radebach [259]). However, in real power markets the value depends very much on the transmission topology and its availability. The results in this chapter suggest that wind market value in Chile can vary up to US$10/MWh depending on the level of diversification and the spatial and temporal constraints of the system. Hydro storage is also an extremely important source of flexibility that can be used to alleviate the drop in the market value of renewable energy. As presented in Section 4.4.2, the current capacity of Chile's hydro reservoirs may increase value of the solar market up to US$5/MWh (depending on the transmission capacity and the share of variable renewable energy in the system). Even though these results must be observed with caution, because they depend on the assumptions made, they are an additional effect of renewable spatial diversification that have been ignored in the literature.

Expanding the storage capacity of the reservoir will not always increase the market value of a specific renewable generation technology, because it depends upon the presence of other sources of intermittency. In Chile, the massive penetration of solar PV technology exhausts the flexibility of hydro storage in a scenario of abundant transmission availability. To take full advantage of the flexibility of hydro resources to incorporate solar PV, is imperative to develop and maintain transmission corridors that connect solar resources from the north and the hydro resources to the south with the demand centers. In that context, a viable regulatory strategy to promote the development of wind power and increase its market value in Chile could be to incentivize the spatial diversification to reduce the risk of congestion and avoid the "self-cannibalization effect" [191]. It should be noted that in this study, traditional hydro storage was evaluated because it is one of Chile's primary resources for energy generation, however, electrical energy storage (EES) costs are rapidly decreasing [55], thus variable generation technologies will be capable of regulating their own production sooner than later. Accordingly, another methodology, beyond the analysis of this chapter, could be developed to assess the impact of ESS on the market value of wind and solar power plants.

The economic efficiency of generation projects depends upon their location respect to transmission constraints. Understanding the impact of the dispersed aggregation of wind generation and more generally of renewable energy generators on the power market might help policy makers to take these effects into account and change the "technological portfolio" paradigm to a "technological-locational" paradigm. Territory-specific characteristics of renewable energies allow policy makers to point toward much more regional-specific and accurate strategies and consequently to the most effective and cost-efficient measures. The promotion of a zone as a renewable energy supplier may have more benefits for the system than solely the production of energy if it provides temporal and spatial diversity within the generation profile. This research is an argument and reminder that policy designs on siting decisions, especially in Chile, should be made with a system perspective. First, as explained in Section 4.4.1, the diversification of VRE generators solely based on their profiles is useless if there is not enough transmission capacity. Transmission enables diversification and Chile has very good potential to diversify wind resources throughout its territory as presented in Sections 4.2.2 and 4.3.2. Second, while wind market value may increase by diversifying wind generation throughout its territory, the availability of hydro reservoirs provides almost all of its flexibility to solar generation and increases their market value. As mentioned in Section 4.4.2, this interaction only produces benefits if there is enough transmission.

CHAPTER 5: OPTIMAL GENERATION INVESTMENT STRATEGY UNDER UNCERTAINTY OF THE EXPANSION OF TRANSMISSION INFRASTRUCTURE: AN APPLICATION OF REAL OPTIONS THEORY AND RISK-RETURN ANALYSIS

5.1 Introduction: flexibility investments on modular renewable energies

Renewable energy technologies are increasingly being incorporated into electricity markets, not only due to the social and environmental pressure of citizens or as a measure to mitigate emissions, but also because they have reached a technological stage, which allows them to compete on costs with conventional generation technologies. Consequently, the power systems and their planning will have to continue adapting in order to incorporate large amounts of renewable energies in short times [187,188,260–262].

5.1.1 The fast time to market of renewable energies

One of the main features of renewable energy technologies and especially solar PV is its rapid construction, since large civil works are not required and therefore several hundred of megawatts can be developed in few years [263]. Another feature of these technologies, especially intermittent renewable energies, is that it is very difficult to forecast their generation accurately, which can go from zero to full capacity in an instant, therefore they require permanent transmission capacity [238,264].

The fast construction time that characterizes renewable generators that in most countries is decided by the private sector, along with the centrally planned large transmission infrastructure, causes periods of mismatch between the development of the generation and the development of transmission [265]. That is, periods in which installed generation cannot be fully dispatched due to the lack of transmission. This situation can be caused by simultaneous, rapid and uncoordinated installation of new generators that deplete the existing transmission capacity [266]. Transmission congestion, causes a production limitation and strongly affects the income of a generation plant, as it may reduce marginal costs at the point of injection and can even affect long-term contracts [267]. Given that investments in power plants are largely irreversible, since they imply a high degree of sunk costs, the investment evaluation must be carried out with tools that incorporate uncertainty and the flexibility of waiting or developing the project in stages.

5.1.2 The link between transmission, its uncertainty and the effect of its scarcity in the development of renewable projects

As the certainty about the entry of new transmission increases in time, the investments in generation also increase and therefore waiting times for the commissioning of projects may be greater, because all projects simultaneously. request environmental authorizations, building permits and connection requests A longer time to enter the market or "time-to-market" affects the investment return, since the income of the first months has a higher present value than the future income. Therefore, a delay of the project, once the investment has been made, severely affects the profitability of the project. For example, a project that rents 7% and has an economic useful life of 15 years, will approximately lose a point of profitability if, the commissioning is delayed one year after the investment was made.

Both effects, the limitation in production due to the lack of transmission capacity and the delays in the commissioning of generation projects are analyzed in this paper to find a strategy for the investor. Two well-known techniques are used in this paper: the real option theory to consider the flexibility of delaying an investment and the risk-income analysis associated with the portfolio theory to evaluate investment by stages. In this context, the risk is understood as the possibility that the profitability may be lower than expected and the income refers to the expected profitability of the project.

The rest of this work is divided as follows: section 2 presents a review of the literature on real option theory and portfolio analysis; section 3 presents the model developed and the main assumptions, section 4 develops a conceptual example; section 5 shows some results of the application of this model; and section 6 presents the conclusions of this work.

5.2 Real option and portfolio theory and their application on electricity markets: A literature review

The conceptual bases of option theory and portfolio theory are born in the field of finance, the first mainly through the work of Black and Scholes [58] and the second through the work of Markowitz [21].

In the financial sphere, one option is an instrument or contract that gives the right but not the obligation, to buy or sell an asset, subject to specific conditions within a certain period. There are two basic types of options: those that give the right to buy (call) and those that give the right to sell (put). The options are classified as american when the right can be exercised at any time before the expiration date and as european when the right can only be exercised at a specific time [268].

Portfolio optimization theory was a revolution in 1952, since for the first time an investment methodology considered the expected return and the risk of investments. At the same time, there was no need to study individual assets anymore, but rather their contribution to increasing profitability and reducing the risk of an entire portfolio. In fact, the quantification of the diversification concept through the correlations between the assets returns was a great novelty in the financial field [22]. Likewise, the introduction of the efficient frontier that shows all efficient portfolios (maximizing return for a given risk and vice versa) is another of the great contributions of Markowitz's work. Figure 51 presents an example of the portfolio’s efficient frontier.

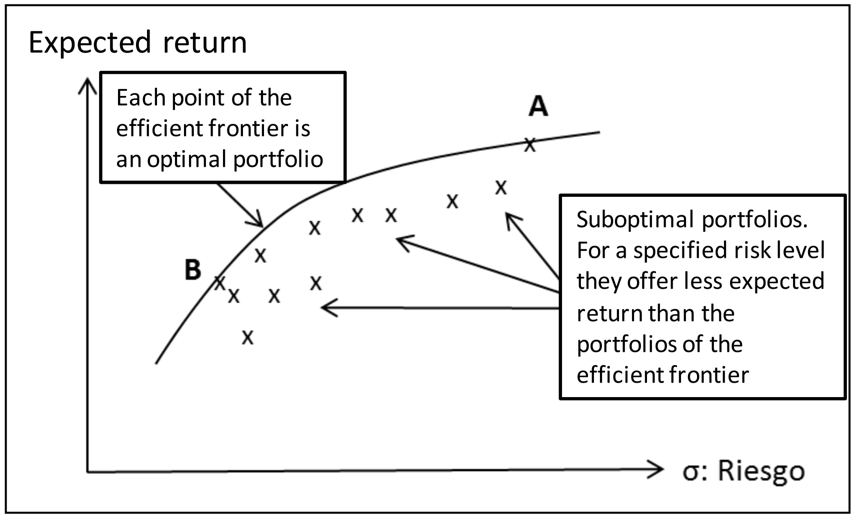

FIGURE 51: EXAMPLE OF AN EFFICIENT FRONTIER

5.2.1 Real option theory in electricity markets: incorporating and valuing flexibilities

A real option can be defined as the right, without the obligation, to make an investment decision that involves a real asset (delay, abandon or modify) [143]. This flexibility, when considered in the economic evaluation of a project can decrease the expected variability of the project's value [143,269]. The real option theory allows to explicitly assess investment flexibility, which makes this technique very suitable for the evaluation of projects that are exposed to great future uncertainty, but that at the same time have some degree of flexibility and this, when considered, can add value to the project.

There are multiple types of real options, but the most common are the following [270]: delaying or deferring, developing by stages, escalating the operation, abandonment, changing the output or input and growing. These different types of options can be applied to multiple projects and the first two options (delaying or deferring and developing in stages) are especially suitable for evaluating infrastructure investment decisions that are normally very rigid and with large volumes of capital, such as electricity infrastructure projects. The sources of value of each of the options are summarized in Table 11.

TABLE 11: MULTIPLE TYPES OF REAL OPTIONS, BASED ON [270]

Option	Source of Value
Delay /defer	Wait for better conditions (higher sales prices, lower costs, have more information and reduce risks).
Develop in stages	Come into the market early, take advantage of high prices and then go on with new stages.
Scale the operation	The firm can increase / decrease its output according to market conditions.
Leave	Operations can be abandoned and capital-intensive equipment can be sold.
Change the output or input	The productive process of the firm allows to change the output product or the output product can be produced with other production factors
Grow	The firm has prior investments, information, knowledge or other vantage points that allows to develop new products or processes.

The real option theory has been applied in the evaluation of projects for decades. In 1977 Myers [271] was the first to use the option theory in analyzing decisions about real assets and present it as real options, since that publication, several applications have been developed. A review of real options applications in the petroleum and electrical industry and the implementation of environmental policies is presented by Dixit and Pindyck [143]. Also, a more recent review of various applications in the energy field is carried out by Fernandes et al. [133]. In the area of electricity markets, real option theory has been widely used: firstly to value investments facing price uncertainty [272,273] and, more recently, to value environmental policies [153,154,274]. Yang et al. [153] uses real option theory to analyze the effects of the uncertainty in environmental public policies over investment decision in gas, coal and nuclear generators. In other words, the flexibility of delaying the generation projects investment is analyzed in the face of regulatory uncertainty represented by different scenarios of CO_2 prices. Also, there are applications using real option models to investigate the impact of technological progress on investment decisions in the electricity sector [48].

Modeling methods of real options can be classified in three types [133,275]. Modeling through partial differential equations, where the value of the option is mathematically expressed and can therefore be solved analytically or via numerical methods [26]; through decision trees and dynamic programming, where future decisions and their relation with current decisions are explicitly evaluated [153,154] and finally, they can be modeled via Monte Carlo simulations in which multiple evolution scenarios are developed using stochastic parameters and then the optimal investment strategy is decided for each scenario [276,277].

5.2.2 Portfolio optimization applied to electricity markets: literature review

The application of portfolio optimization theory in electricity markets has been widely addressed in the literature, although it has been addressed late after its application in the financial field. Most works applying portfolio optimization to electricity markets are applied to energy planning aiming to define an optimal technological generation mix. A notable exception is the work by Shakouri et al [278] which presents a decision-support model to asses and manage volatility in PV generation projects to assist investors of community-based PV projects in developing optimized investment strategies.

The portfolio energy planning literature started from the work of Awerbuch and Berger [13] that seek to optimize the future technological mix of the European Union, taking into account the levelized system cost and its variability given by the possible trajectories of fuel prices and technologies investment costs. Based on this work, a series of subsequent works of different authors made improvements and applied the methodology to different electricity markets, considering different generation technologies [14,15,74,76,79,81]. Some portfolio applications that go beyond levelized costs, integrate the dispatch optimization to the definitional problem of the optimal technological mix, without assuming pre-established plant factors for generation technologies [88]. Furthermore, other works include the operational constraints, this is the case of the work done by Delarue et al. [72] and Vithayasrichareon and Macgill [100].

5.2.3 Portfolio and real options theories applied electricity markets: literature review

There is very limited literature that combines both methodologies (real option theory and portfolio optimization) to consider the timing of investments due to future uncertainty, as well as the cost-risk profile of investment decisions. The first work to incorporate both methodologies in the context of investments in electricity markets is the work done by Fortin et al. [156]. The authors use real options analysis to find the best timing to invest in carbon capture and storage technologies for coal and biomass generation plants and to invest in wind generation. This analysis is carried out for different electricity and CO_2 price scenarios, using real option theory to obtain different distributions of investment returns. These distributions are used as input for the portfolio optimization to efficiently define a cost-risk profile to invest in these technologies.

The work of Szolgayová et al. [157] takes diversification over time into account. That is, it considers the option to change the portfolio in the future. These authors find that the possibility of adapting the future portfolio has implications in the investment decision of today's portfolio. Another work that uses both methodologies is the work of Fuss et al. [158], that seeks to evaluate the technological mix generation in the face of different socio-economic scenarios considering uncertainty about emission price. They find in their work that uncertainty about the emission price is more significant for the investors than the uncertainty of socioeconomic future scenarios, especially for risk-adverse investors.

5.3 A model to identify the timing of investments based on a portfolio of real options

In this paper, two sources of uncertainty are modeled from the perspective of a firm analyzing to invest in the development of a generation project: the uncertainty regarding the commissioning of a new transmission line and the uncertainty regarding the delay or "time to market" of the generation project. Note that the price of electricity injections are not treated as a random variable, since it is assumed that the generation project will have a Power Purchase Agreement considering a fixed price at its injection point.

Two applications are presented in this work, a conceptual and a numerical application. The conceptual application only considers the uncertainty associated with the commissioning of the transmission line, while in the numerical application both uncertainties are considered. The conceptual application considers the commissioning date of the transmission line as a categorical variable, that is, different probabilities associated with the realizations that the line get into operation at t, t + 1, t + 2, etc. are assumed. The real option analysis is solved using the decision trees method, as detailed in Section 3.1.1. In the numerical application this uncertainty is treated as a random variable with a given distribution, as detailed in Section 3.1.2. Likewise, the uncertainty regarding the delay or "time to market" of the generation project is modeled as a random variable with a specific distribution detailed in Section 3.2.

Both sources of uncertainty have a direct impact on the project's value and its profitability. Since the renewable generation project can be developed in stages, the investment in each stage is evaluated under a cost-risk scheme in order to find the optimal strategy associated with these real options. This is solved in the numerical application through a Monte Carlo simulation, as shown in Figure 52.

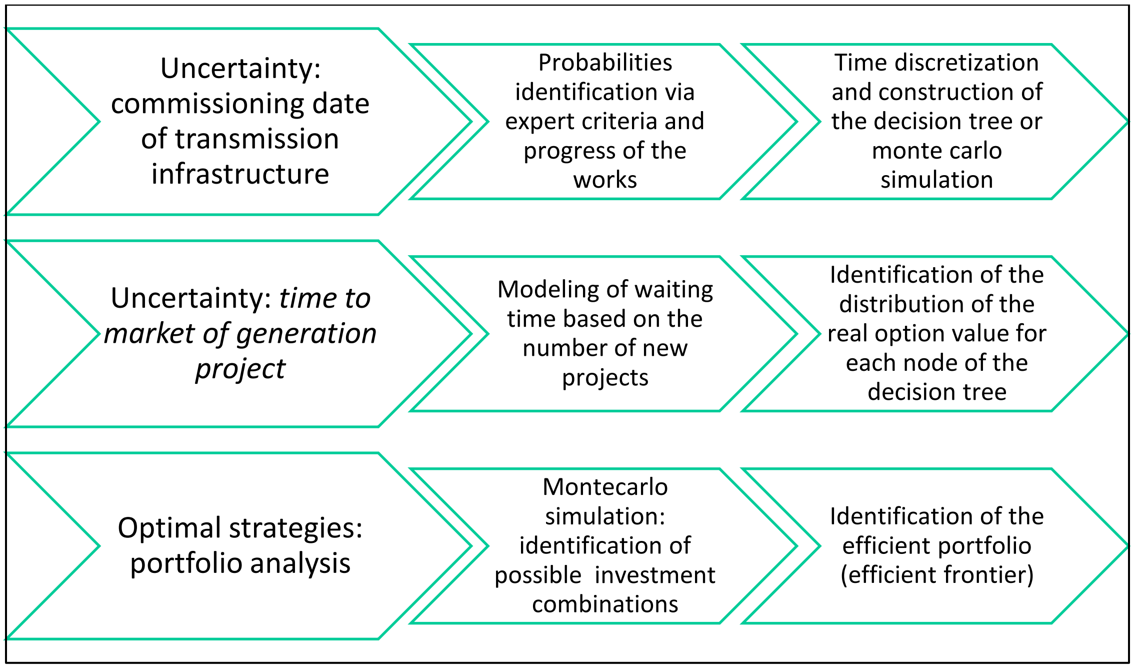

FIGURE 52: STAGES OF THE GENERAL METHODOLOGY APPLIED TO THE NUMERICAL APPLICATION PRESENTED IN SECTION 5

5.3.1 Uncertainty in the commissioning date of the transmission expansion infrastructure

Two resolution methods are used to value the option of delaying the investment. First, in the conceptual application the decision tree method is applied in a very simple but revealing way. On the other hand, in Section 5 the Monte Carlo method is applied, since the presented application is more complex and involves more sources of uncertainty. In both cases, the underlying asset is the present value of the generation project's future flows while the strike price of the option corresponds to the investment cost of the project.

Modeling the uncertainty of commissioning date of the transmission using categorical variables and decision tree method

The only source of uncertainty that is modeled in the conceptual application presented in Section 4 is the commissioning of the transmission line and therefore the basic structure of the decision tree presented in Figure 53 is simple, but it accurately represents such uncertainty.

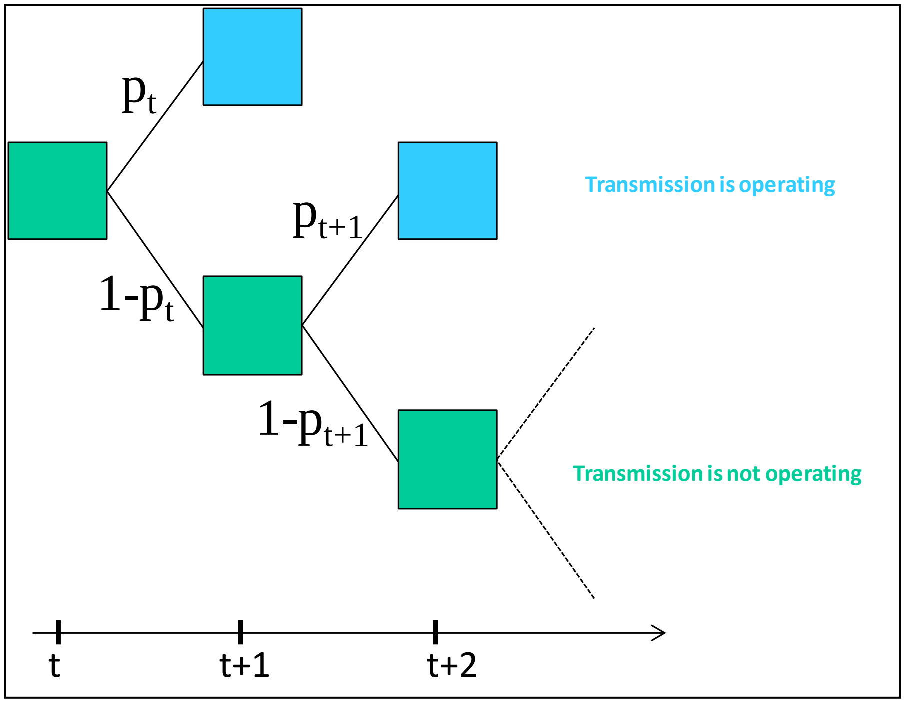

FIGURE 53: DECISION TREE ASSOCIATED WITH THE UNCERTAINTY OF THE COMMISSIONING DATE OF THE TRANSMISSION INFRASTRUCTURE

The probabilities p and 1-p represent the firm's view that the line will be operating or not will be operating in the period t + 1. Therefore, these probabilities should be estimated based on information about the progress of the transmission project and the experts criteria. Just as a financial option to purchase (call), the value of the option represents the value of the flexibility to wait and observe whether the line started to operate or is delayed. Equation (19) represents the value of the option in the intermediate nodes, while in the final nodes the value of the option is represented by the maximum of the difference between the present value and strike price (investment cost) and zero (the option is not used), as presented in equation (20):

$$C_t = [p_t \, C_u^{t+1} + (1 - p_t) C_d^{t+1}] e^{-r\Delta T} \qquad (19)$$

$$C_{t\_max} = max[VP_{t\_max} - K, 0] \quad (20)$$

Where C_t represents the value of the option of the intermediate node at t, C_u^{t+1} is the value of the option of the next node representing when the transmission line starts operating and C_d^{t+1} is the value of the option of the next node when the line does not start operating. C_{t_max} is the value of the option in the extreme nodes, VP_{t_max} is the present value of the project at t_max and K is the strike price or investment cost of the project. Also, the expression $e^{-r\Delta T}$ discounts the flows at a discount rate of r.

The penalty for a generation project that starts operating when the transmission line is not available is estimated by reducing its injected energy and not punishing its sale price. Losing part of its energy production represents lower revenues in the first years of operation and therefore a lower value of the generation project. As explained before a fixed price guaranteed by PPA contract was assumed.

Modeling the uncertainty of commissioning date of the transmission using PERT

The analysis through tree model discretizes the uncertainty: the transmission infrastructure will be available at time t, when, the transmission infrastructure could start its operation at any time. In addition, it is necessary to model the delay of the generation project. Therefore, taking these two sources of uncertainty into account, the resolution through the tree method becomes very complex.

To model the uncertainty of the commission time of the transmission line, a Beta distribution is used, obtained from project evaluation techniques or PERT (from the Program Evaluation and Review Techniques) [279,280]. This technique is widely used to model delays for project evaluations [279,280]. Under this methodology, to estimate the activity's duration of the project, a beta distribution is used, calibrated with three parameters that are determined exogenously: a pessimistic time (b), a probable time or mode (m), an optimistic time (a). Thus, the random variable x, which represents the time it would take to complete the construction of the line, would have a distribution function as expressed in (21):

$$f(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(a)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1} \tag{21}$$

Where Γ is the gamma function and the parameters α and β are represented by equations (22) and (23).

$$\alpha = \frac{4m + b - 5a}{b - a} \tag{22}$$

$$\beta = \frac{5b - a - 4m}{b - a} \tag{23}$$

The previous equations represent a distribution that is a case of the Beta distribution, also known as the Pert distribution. The shape of this distribution is presented in Figure 54, where on the left a symmetrical PERT distribution is shown, very similar to a normal one but with finite tails. On the right side of the figure there is an asymmetric distribution where the mode is slightly closer to the upper limit.

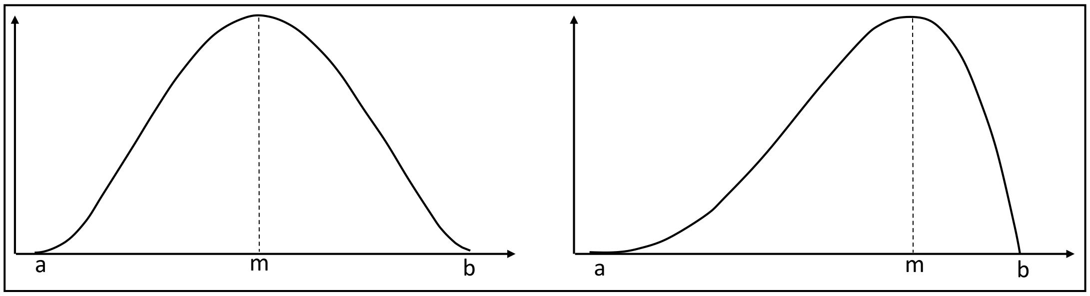

FIGURE 54: SHAPES OF PERT DISTRIBUTION: ON THE LEFT A SYMMETRICAL DISTRIBUTION AND ON THE RIGHT AN ASYMMETRICAL DISTRIBUTION

5.3.2 Modeling the uncertainty of the "time to market" of a generation project

Normally, given the uncertainty of the commissioning date of a relevant transmission line in the system, delaying the investment of a generation project implies greater certainty of the line's commissioning date (the project's progresses), but also a higher probability of a longer waiting time between the investment time of the generation project and its commissioning (time to market). This is because as greater certainty about the line exists, the number of incoming generation projects that will request new connections, environmental impact assessments, sectoral permits, increases. A longer time to market, causes lower returns. One of the main procedures associated with the development of electrical infrastructure projects is the environmental impact assessment of the project, as it is a topic that is increasingly relevant and demanding [281,282]. In Chile, the environmental impact service (SEIA) approved 165 projects between January 1st, 2010 and September 30th, 2017 (93 months) and therefore it had an average attention rate of 1.77 projects per month, furthermore the average processing time for these projects was 10.9 months [283].

Project's waiting modeling by using the queue theory

The process of permitting is modeled in this work as a basic waiting process, based on the classic queuing theory [284]. Specifically, a tail system of type M / M / 1 is modeled, that is, with exponential time between arrivals, exponential service time and one server. In addition, the queue is of FIFO type (First Input, First Output) as shown in Figure 56. These assumptions are traditionally used in queuing theory since times between arrivals distribute exponentially, assuming the number of arrivals distribute Poisson, therefore the projects request is independent from each other. In the case of the generation projects, the three properties of a Poisson process seem to be fulfilled [285]:

1. Requests arrive one at a time.

2. The probability of an application arriving at any time is independent when other requests arrived.

3. The probability that a request will arrive at some point is independent of the moment.

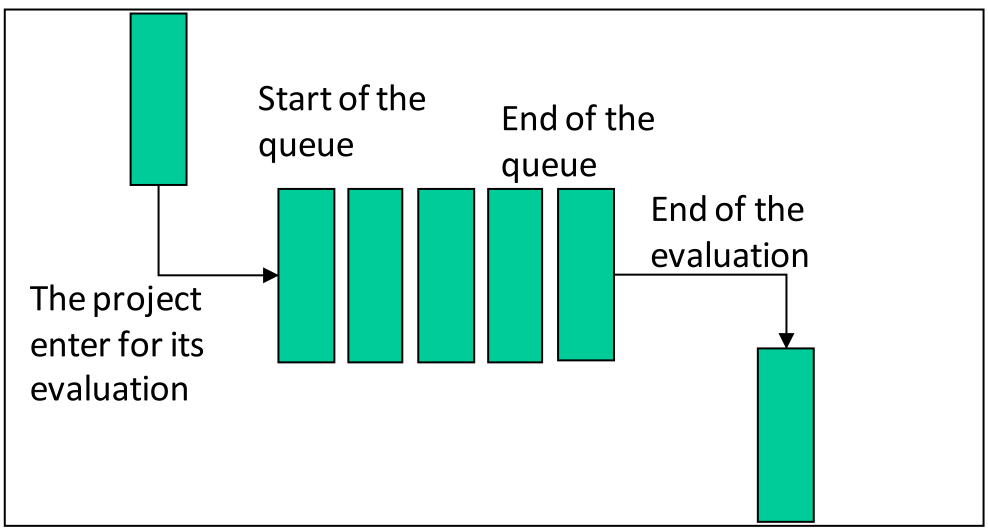

FIGURE 55: REPRESENTAION OF A FIFO QUEUE (FIRST INPUT, FIRST OUTPUT)

If $N(t)$ is the number of requests during the time period T, then the probability of $N(t)$ is expressed in equation (24), where λ represents the average number of projects arrivals per period of time. Therefore, the time between requests distributes as an exponential distribution of rate λ and is represented by equation (25). Finally, it can be inferred that the distribution function of the waiting W or total attention time is represented by the distribution expressed in equation (26):

$$P\,\{N(T) = n\} = \frac{e^{-\lambda T}(\lambda T)^n}{n!} \tag{24}$$

$$P\,\{IA(t) \leq\; T\} = 1 - e^{-\lambda T} \tag{25}$$

$$P\,\{W \leq\; T\} = 1 - \rho e^{-(\mu-\lambda)T} \tag{26}$$

Where μ corresponds to the average attention rate of the system that must be greater than λ (so that the queue does not tend to infinity) and $\rho = \lambda/\mu$ is called the system utilization factor. The total time of attention has an average represented by equation (27).

$$W_a = \frac{1}{\mu - \lambda} \tag{27}$$

Finally, the delay time is estimated as the maximum between the difference between the total processing time and 12 months and zero, as indicated in equation (28). Accordingly, when attention time takes less than 12 months, it is not considered as a delay.

$$D = max(W - 12, 0) \tag{28}$$

5.3.3 Portfolio analysis of the real options: identifying the optimal investment strategy

The real options that the investor faces are varied, being able to postpone his investment or make it in stages as long as the uncertainty is revealed or more information is obtained. Each option represents an expected return together with an expected variability of that return, and therefore a combination of these options should be chosen based on the investor's risk aversion.

To obtain return distributions of what would happen when investing different levels of capital each year and thus obtain the statistical measures that represent expected return and risk, a Monte Carlo simulation is performed for pre-established portfolios. Namely, this methodology does not seek to identify the optimal portfolio or the "perfect" combination of staging investments, since a firm normally has constraints on the use of capital. For this reason, simulation is the most appropriate instrument to solve this problem in order to find the differences in risk-return profiles between different possible investment combinations, as shown in Figure 56.

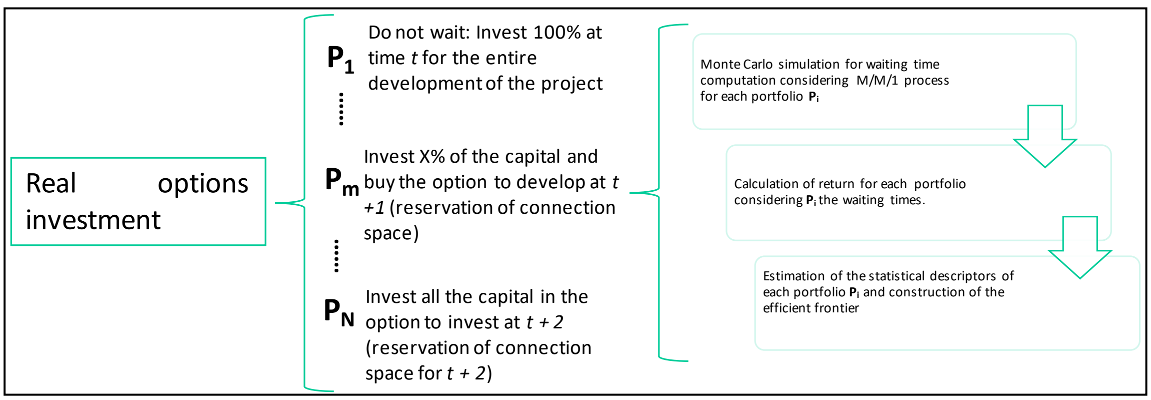

FIGURE 56: SIMULATION METHODOLOGY TO EVALUATE THE REAL OPTIONS

5.4 Real option analysis using the decision tree method: a conceptual application

The transmission capacity's reserve option depends only on three essential parameters: 1) the probabilities assigned to the commissioning line's date, 2) the lower value of the present value associated with its future project flows due to possible reductions of energy injection, and 3) the discount rate or capital cost of the firm that develops the project. This is illustrated in a very simple way when analyzing the following case. Assume that with a certain probability p in year 1 a transmission line starts its operation and on the contrary at year 2 it surely starts its operation. In addition, the following parameters are associated with the generation project:

- Present value of future flows without congestion: a
- Present value of future flows with a year of congestion: $\alpha \cdot a$, where $0 \leq \alpha \leq 1$ and represents a penalty factor of the present value due to congestion of the first year.
- Investment cost of the project: I
- Discount rate: r

The net present value that is expected when investing at year 0 is presented in equation (29). If the investment is made at year 1, when the uncertainty has already been solved (since the line is already operating or it will surely be operating in year 2), the net present value, expressed at year 0, is the one presented in (30).

$$VAN_0 = pa + (1-p) \cdot \alpha a - I \qquad (29)$$

$$VAN_1 = Max(ae^{-r} - I, 0) \qquad (30)$$

When $VAN_0 > VAN_1$ the investment should be done at year 0, since the future flows are greater than the investment. Otherwise, it is convenient to exercise the option of waiting to invest at year 1. Therefore, the inequality (13) represents when it is convenient to invest at year 0.

$$DR = (p + \alpha - p\alpha) > e^{-r} \qquad (31)$$

As can be inferred from the equation above, the decision depends on the probability p, of α and of r. Note that the decision does not depend on the investment value of the project or its future flows. By using this result it is possible to identify the combinations of possible values that would generate one decision or the other. So, for example, if $p = 1$ (the line will surely operate at year 1), then naturally it is never convenient to wait. Otherwise, when $p = 0$ (the line will certainly not start its operation during year 1, but it will do it at year 2), then, it will only be advisable to invest at year 0, if the penalty due to congestion (α) is close to the unit (that is, the congestion produced by the lack of the transmission line does not strongly affect the injections of the project). This analysis is presented in Figure 57 in a more generalized manner for different values of p and α and for a discount rate of r = 10%.

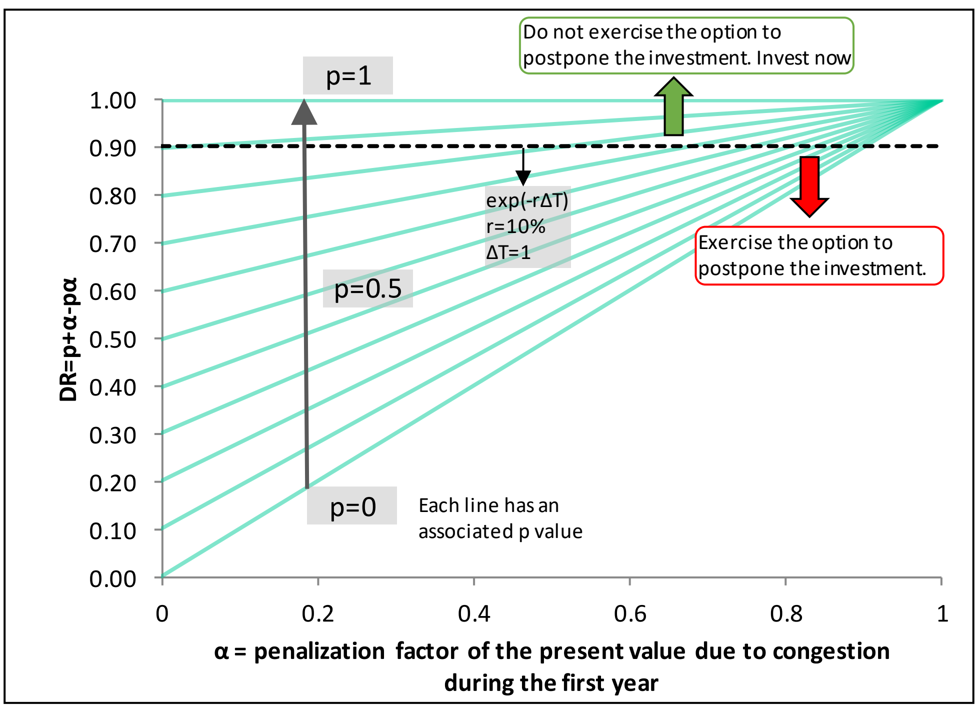

FIGURE 57: GENERALIZED CONCEPTUAL ANALYSIS FOR DIFFERENT VALUES OF P AND Α

Figure 57 shows that for probabilities p approximately higher than 90% it is always advisable to invest in the first year. Also, if the penalty factor is very high (close to 0), then it is only advisable to invest during the first year when the probability that the line starts its operation is greater than 90%, in all other cases it is not advisable to invest in the first year, rather, it is advisable to wait and invest during the second year.

The value of the option to wait to invest is expressed in equation (32) and represents the value that this flexibility has and therefore the maximum amount that a firm would be willing to invest to have this flexibility (e.g.: pay for reserving a connection space).

$$C = a(p + \alpha - p\alpha) - ae^{-r} \tag{32}$$

5.5 Investment decision of a solar PV generation project in the north of Chile considering uncertainty of the commissioning date of the transmission infrastructure

The methodology described in the previous sections is applied to a photovoltaic solar project located in the north of Chile. This case study is not strange in Chile, because it is exactly what has been happening since 2014 with generation projects in the North, first waiting for the interconnection between the SING and SIC systems and still waiting for the 500 kV connection between the Cardones and Polpaico substations, which connect the north, where solar projects are concentrated due to the excellent solar resource, and the center of the country, where a large part of the system's demand is concentrated.

5.5.1 Uncertainty of the commissioning date of the transmission expansion

As mentioned in section 3.1.2, the uncertainty of the commissioning time of transmission expansion, is modeled using the PERT distribution, for which pessimistic, probable and optimistic times must be defined. In this exercise we used an optimistic time of 12 months, a probable time of 30 months and a pessimistic time of 36 months. This means that the parameters of the distribution are the following: α = 3.957 and β = 2.043. These parameters must be chosen with expert criteria and based on the project's progress. This probability distribution is presented in Figure 58.

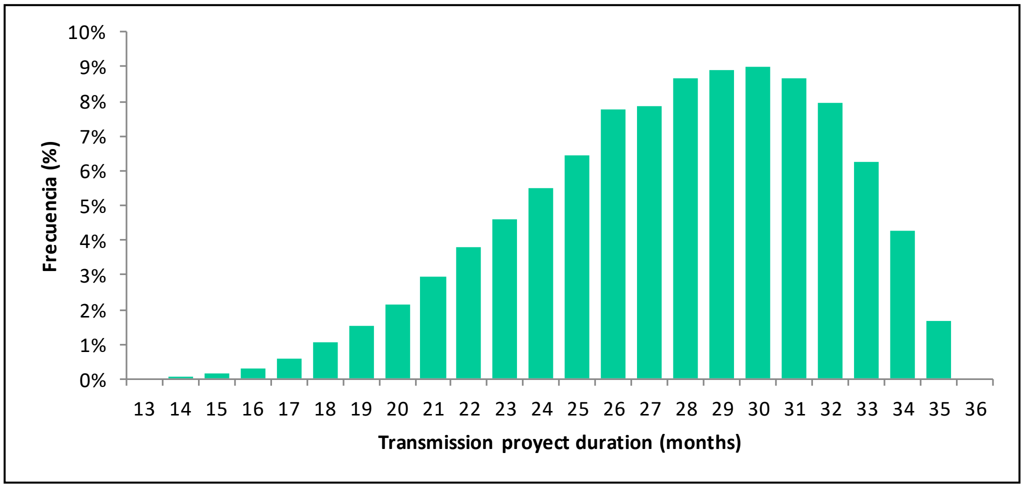

FIGURE 58: BETA DISTRIBUTION ($\alpha = 3.957$ AND $\beta = 2.043$)

5.5.2 Uncertainty of the processing time of the generation project

To model the delay of the generation project, the distribution functions are used with different project arrival rates λ per month, depending on the year in which the investment is made. For the investments of a generation project made in the first years, it is expected that the processing time before its commissioning will be shorter due to the high uncertainty in the commissioning of the line and therefore the lower influx of project requests. In all cases, an attention capacity (μ) of 1.77 projects per month is assumed, as indicated in Section 3.2 in relation to the attention rate of the SEIA. Table 12 presents the parameters of the distribution function and its final column presents the average time of attention resulting for each case.

TABLE 12: PARAMETERS OF THE DISTRIBUTION OF THE WAITING FUNCTION OF THE GENERATION PROJECT

Investment year	Requests (proyect/month) λ	Utilization factor $\rho = \lambda/\mu$	Average waiting time (months) W_a
0	1.678	0.948	10.9
1	1.699	0.960	14.1
2	1.714	0.968	17.9

Finally, it is established that the delay of a generation project will not be longer than 36 months beyond the 12 months after the investment was made. That is, the delay is the minimum time between 36 months and the waiting time indicated in equation (28) and is represented by the expression (33). The representation of the distribution of each of the modeled delays (according to Table 12) is presented in Figure 59.

$$D = min(max(W - 12, 0),36) \quad (33)$$

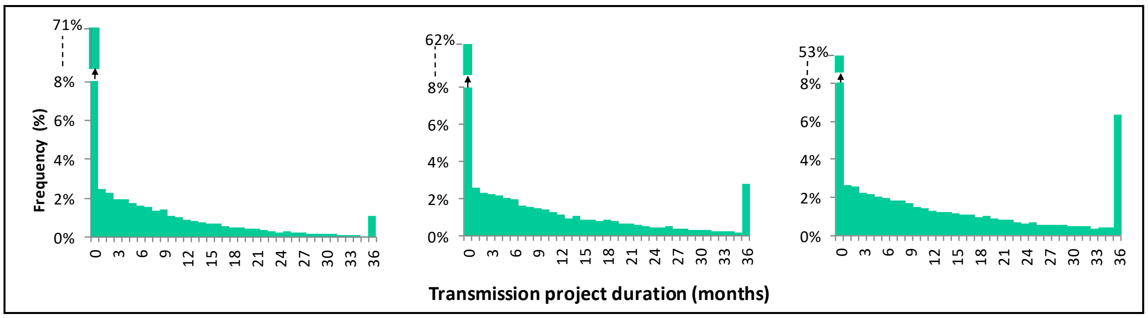

FIGURE 59: DISTRIBUTION OF DELAYS FOR EACH YEAR OF INVESTMENT

5.5.3 Generation project: financial parameters, energy production modeling and reduction of injections due to congestion of the transmission system

The financial parameters of the project, used to perform the NPV calculations, are presented in Table 13. These parameters correspond to the standard costs of a photovoltaic generation project in northern Chile.

TABLE 13: FINANCIAL PARAMETERS OF THE GENERATION PROJECT

Parameter	Value
Investment	1.300 US$/kW
Variable costs	0 US$/MWh
Fixed annual cost	70 US$/kW-año
Sale price (contract)	80 US$/MWh
Debt percentage	80%
Annual debt rate	4%
Debt duration	25 years
Discount rate	10%
Economic life	25 years

For the purpose of determining the monthly injections of the solar generation plant, the simulated production is obtained from the “Explorador Solar del Ministerio de Energía” [207,208] for a 1 MW capacity plant located in Diego de Almagro[12], which results in an annual capacity factor of 28%. The monthly production and plant factors are presented in Figure 60.

The basic production model is used, for a 1 MW plant, panel temperature coefficient (% / ° C) of -0.45, type of arrangement with horizontal tracking (HSAT) and maximum inclination of 45 °, inverter capacity of 1 MW and efficiency of 96% and a losses factor of 14%. The project was located in Diego de Almagro (Latitude -26.3540 and Longitude: -70.0669).

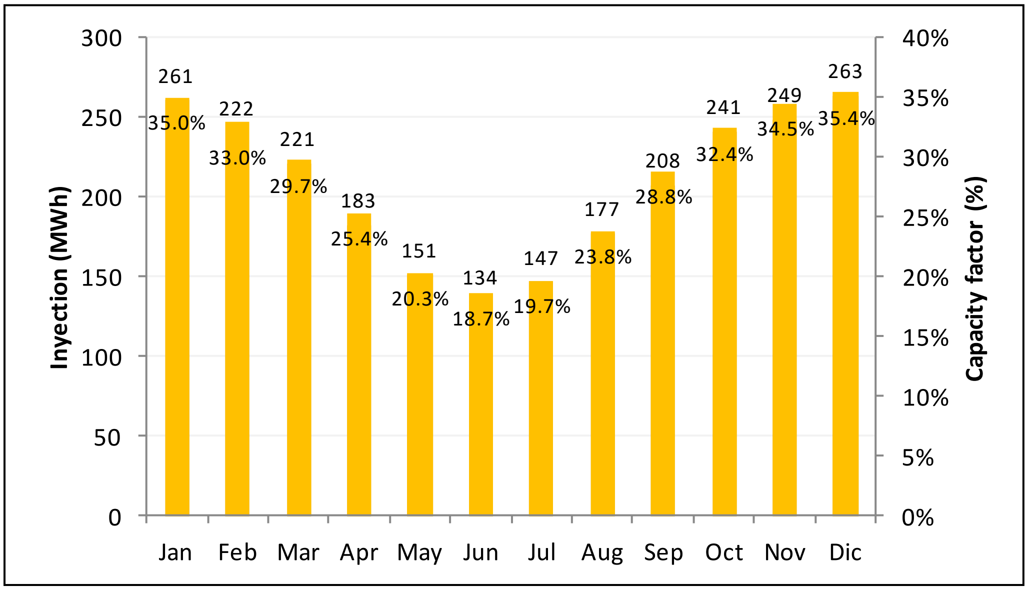

FIGURE 60: MONTHLY GENERATION AND CAPACITY FACTOR FOR A 1 MW POWER PLANT IN THE NORTH OF CHILE

The dispatch cut of the solar plant due to congestion depends on the transmission project and how the injections are affected in the connection point of the generation project due to a delay in its commissioning. Assuming that there are no other operational elements that affect production more than the limitation of the transmission capacity, this study models this as a percentage reduction of the monthly injection. For each month without the additional transmission capacity, the percentage of reduction of the injections increase. For the first year a linear trend is assumed, starting from 20% in January to 39.5% in December, with a total reduction of 30% of the expected injection, that is, the project can inject 70% of its production when there is congestion in the months of the first year. If the line starts operating during the second year, then the injections reductions for the second year increase up to 50%. The monthly reduction of the injections due to congestion is presented in Figure 61.

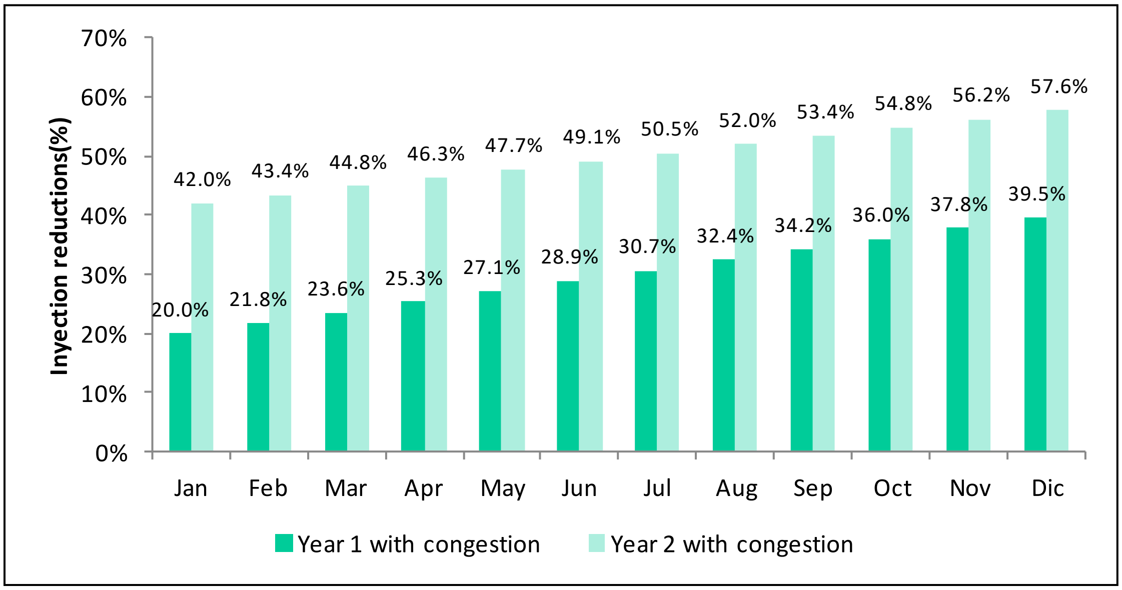

FIGURE 61: MONTHLY INYECTIONS CUTS DURING THE FIRST AND SECOND YEAR IN CASE OF CONGESTION

This reduction rule, as the percentage of the injection is reduced, is the same used by the operator system in Chile, which in cases of congestions limits the injection of all generators in proportion of their injections before the congestion. With the reductions presented above, the energy that would be injected by the project for each installed MW would be the one presented in Figure 62.

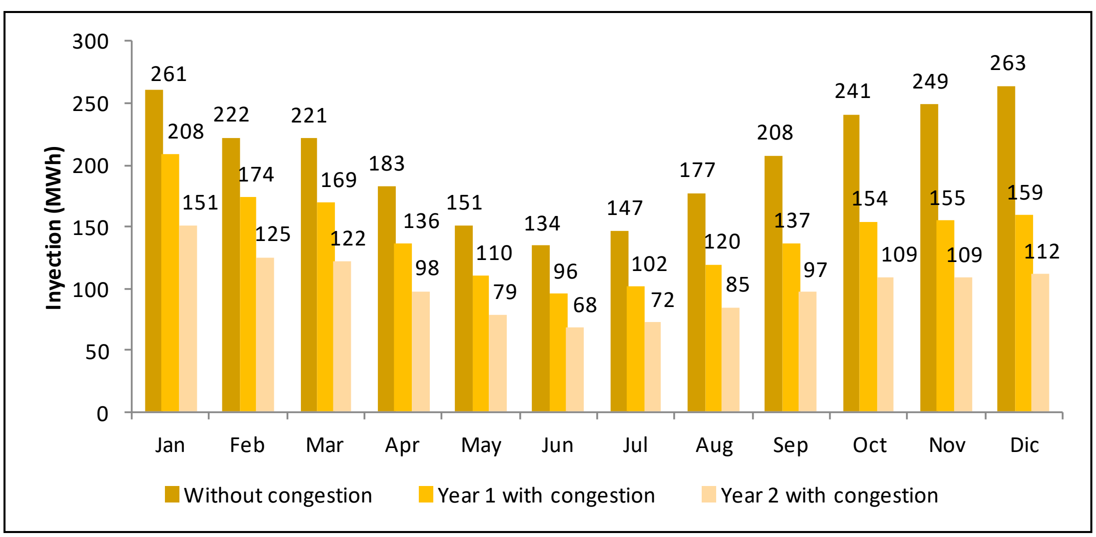

FIGURE 62: MONTHLY INJECTIONS WITHOUT CONGESTION, WITH CONGESTION IN THE FIRST YEAR AND WITH CONGESTION IN THE SECOND YEAR OF A 1 MW PROYECT

5.5.4 Construction of a real investment options portfolio

For investment purposes it is assumed that the firm can invest only at the beginning of each year, that is, it can invest at year 0 or alternatively use the option of delaying the investment and invest at year 1 or at year 2. Also, taking advantage of the modularity feature of photovoltaic projects the option to invest by stages is also considered. Specifically, the following "assets" are evaluated:

Invest at year 0: The investment is made independent of what may happen with the transmission and the delay of the generation project. In this case the value of the project depends on the month of entry of the transmission and the waiting of the generation project, which in this case has an average, of 10.9 months from the time of the investment, (i.e., few possibilities of delay, since the project assumes a construction delay of the project of 12 months).

Wait one year: waiting one year to invest implies that a large part of the uncertainty about the commissioning date of the transmission line will have already been lost at the starting time of operations of the generation plant. However, waiting to invest for the first year (and not investing at year 0) implicates a greater possibility of waiting for the processing of the generation project, whose processing average time is 14.1 months and therefore a delay over the initial 12 months since investment is likely.

Wait two years: waiting for two years to invest implies that the uncertainty about the commissioning date of the transmission line has already been completely lost (it will surely be operating at year 3, when the generation project begins to inject). However, in this case there is a great probability of a high processing time of the generation project with an average of 19.2 months.

Depending on the risk aversion of the firm, it can choose a combination of the three alternatives presented above to configure a portfolio with the desired parameters of net present value and risk. For this analysis, 141 pre-established portfolios are evaluated, whose investment percentages vary in steps of 5% as a minimum. Figure 63 presents each of the combinations analyzed. The fact that the portfolios are previously defined allows to evaluate the true alternatives that a firm has to decide about its capital according to the restrictions of its directors (ex .: minimum and maximum percentage of investment in a stage, requirement of a particular use of capital in a stage, requirement to not invest in a stage, etc.)

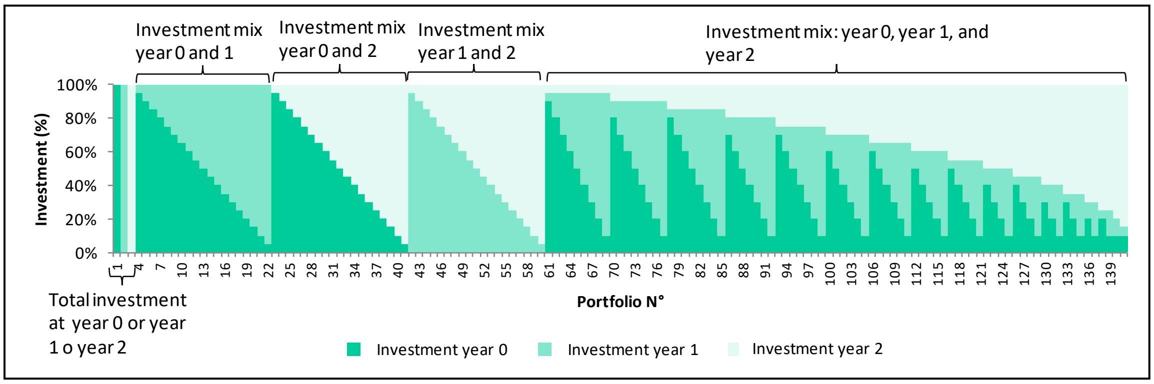

FIGURE 63: PREDETERMINED PORTFOLIOS OF REAL OPTIONS

5.5.5 Net present value of the different investment options: identifying the efficient portfolios

The histograms associated with the investment "assets" presented in the previous section are presented below and as shown in Figure 64, each of these alternatives' present different statistical parameters.

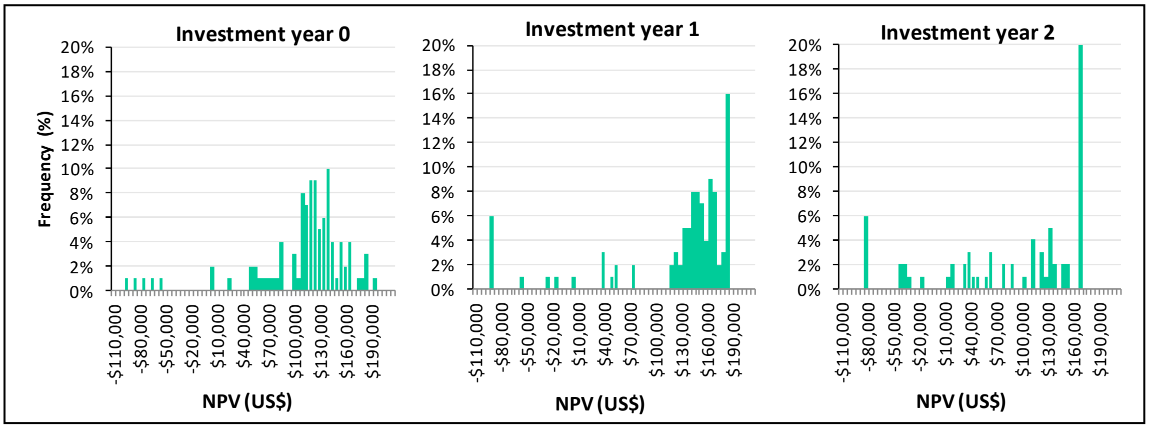

FIGURE 64: HISTOGRAMS OF THE NPV OF THE DIFFERENT INVESTMENT OPTIONS

Figure 65 presents, for each portfolio, the expected net present value against its variability, measured as its standard deviation and against CVaR at 5%. The efficient frontier (highlighted with red) presents the efficient portfolios, that is for a given risk, those portfolios maximize the expected net present value.

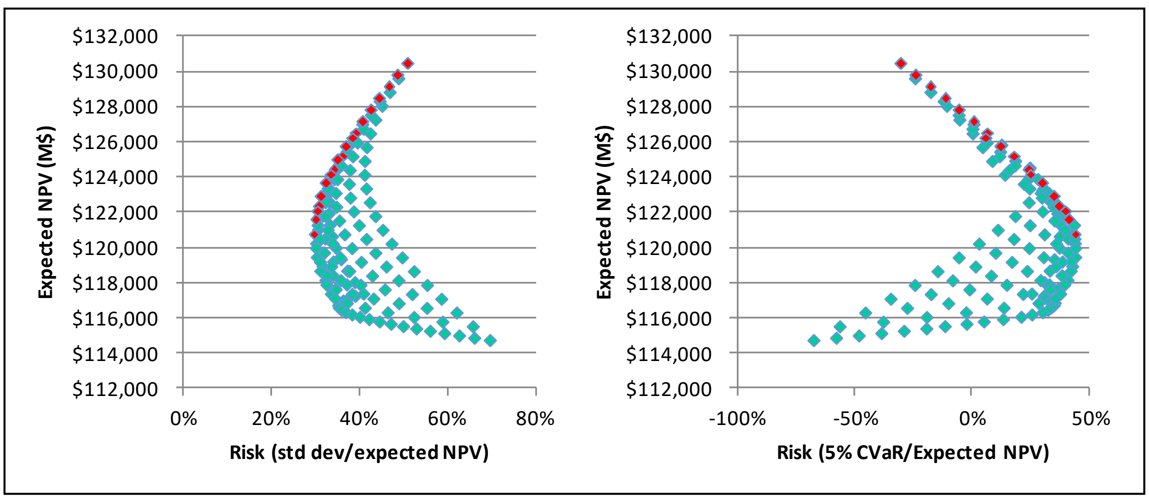

FIGURE 65: EFFICIENT FRONTIER- RISK AS STANDARD DEVIATION (LEFT) AND RISK AS 5% CVAR (RIGHT). IN RED THE EFFICIENT PORTFOLIOS

The maximum expected return portfolio is the one obtained from investing all the capital in the first year, when the risk of delay of the commissioning date of the line has already decreased, but the risk of delay of the generation project has not increased too much. This portfolio has a NPV of US $ 130,389 and a deviation coefficient of 50.9% (US $ 66,388).

On the other hand, the minimum risk portfolio is obtained when investing a 50% at year 0, a 30% at year 1, and 20% at year 2, presenting a NPV of US $ 120,756 and a deviation coefficient of 29.7% (US $ 35,851). Unlike the standard deviation, the 5% CVaR allows to measure the expected losses for the worst cases (5% worse) and therefore, it is a measure that could be more useful than the standard deviation for decision makers that are risk averse and therefore want to avoid great situations of losses. Table 14 presents the portfolios of the efficient frontier with their respective characteristics.

TABLE 14: CHARACTERISTICS OF THE EFFICIENT PORTFOLIOS

Id	Expected NPV (US$)	Standard deviation (US$)	Variation coefficient Std / VAN	5% CVAR (US$)	Investment per year (%)
P1	130,389	66,388	50.9%	-38,913	0% ; 100%;0%
P2	129,738	63,287	48.8%	-30,674	5%; 95%; 0%
P3	129,088	60,285	46.7%	-22,662	10%; 90%; 0%
P4	128,438	57,399	44.7%	-14,402	15%; 85%; 0%
P5	127,787	54,645	42.8%	-6,323	20%; 80%; 0%
P6	127,005	51,514	40.6%	806	20%; 75%; 5%
P7	126,487	49,623	39.2%	8,892	10%; 70%; 20%
P8	126,222	48,738	38.6%	7,889	20%; 70%; 10%
P9	125,704	46,603	37.1%	16,019	30%; 65%; 5%
P10	125,186	45,428	36.3%	22,862	40%; 60%; 0%
P11	124,922	43,716	35.1%	30,533	45%; 55%; 0%
P12	124,404	42,600	34.2%	30,704	40%; 55%; 5%
P13	124,139	41,866	33.7%	30,825	30% 55%; 15%
P14	123,621	40,248	32.6%	37,301	40%; 50%; 10%
P15	122,839	38,460	31.3%	43,324	40%; 45%; 15%
P16	122,321	37,806	30.9%	45,510	50%; 40%; 10%
P17	122,056	37,316	30.6%	48,853	40%; 40%; 20%
P18	121,538	36,473	30.0%	50,499	50%; 35% 15%
P19	120,756	35,851	29.7%	53,205	50%; 20%; 20%

As shown in Figure 65, for the application presented in this paper, both risk measures (standard deviation and CVaR) result in the same efficient portfolios. Moreover, all efficient portfolios found using CVaR are in the efficient frontier while using the standard deviation measure. However, the reverse situation does not occur. This happens, precisely, because CVaR strongly penalizes the portfolios that have greater possibility of high losses.

The fact of being able to postpone the investment has a value and with the obtained results it is possible to estimate it, as well as its variability. For a risk adverse investor, the fact of having the possibility of delaying his investment and carrying it out in stages adds great value, given the uncertainty. The value of this flexibility could be interpreted, for example, as the maximum value that a firm would be willing to pay to reserve a connection space and thus ensure its connection and reduce its waiting time for the following years.

5.6 Conclusions: the value of flexibility under the growing of electricity markets

In this chapter, a review and application of the real options theory and portfolio optimization has been presented to valorize the option of delaying and developing a photovoltaic plant by stages. The uncertainty in the date of commissioning of a new transmission line required to evacuate the generation and the probable delays in the start-up of the photovoltaic plant have been considered. The literature review shows that both techniques have been used for different objectives in the electricity sector. The real option theory has been used, in general, to value projects in the face of fuel prices uncertainty as well as uncertainty in environmental policies and CO_2 costs. Portfolio theory has been used mainly to determine generation mixes considering the uncertainty in the cost of fuels, their variability and correlation of prices. There are very few applications where these techniques have been used together to address the problem of postponing or investing by stages.

The value of the option to postpone the investment, while isolating the effects of energy and power sale prices, depends essentially on the commissioning of the transmission line that will evacuate its injection, as well as the discount rate or capital cost associated with the firm, as shown in the conceptual application presented in Chapter 4.

Given the uncertainty in the commissioning date of the transmission line and the possible delay in a generation project, it is convenient to have the flexibility to postpone the investment and invest in stages depending on the risk aversion of the investor. The option to postpone an investment adds value in the evaluation of the project, that is, a project is more valuable when it has the option of delaying its associated investment, as long as the cost of that flexibility is less than the expected benefit of having it.

This work has assumed that there is always available connection capacity (free and open access to the transmission system), but in practice that does not happen, therefore the value of the investment flexibility is relevant as the only way to ensure the connection space is establishing a capacity reserve mechanism. The methodology presented in this paper to value the flexibility represents the maximum value that a firm would be willing to pay for having such reserve option.

CHAPTER 6: GENERAL CONCLUSIONS

The electric power industry is very dynamic and in constant search of efficiency, especially in a world full of uncertainties. Today more than ever, the electric power industry faces a high degree of uncertainty in every dimension, from operations to investments. Part of this uncertainty is caused by renewable energy technologies that have been experiencing a rapid progress and wide deployment, producing a sharp drop in its investment and deployment costs and reducing the energy price at which they can supply electricity competitively. Indeed, more fundamental changes in the industry are expected over the next years. A boost in electricity demand due to electric vehicles, as well as an increase in distributed generation, massive storage, and the deployment of smart grids are some of the sector’s upcoming challenges. Large investments will be required to address these new challenges, and that is why agents need protection and are constantly looking for risk management tools. To contribute to this task, this work presents a selection of applications, issues, and opportunities for further research on portfolio optimization from different perspectives. Some of the main finding that can be found along this work are summarized below:

- From a private perspective, the “correct” return of a portfolio of projects is the result of the return on individual projects plus the “interaction” among them. This “interaction” is key in portfolio optimization; interaction among projects allows for diversification and the cancellation of risks.
- The literature places little emphasis on the value of waiting or deferring a project or a set of projects within the context of a portfolio. Decision makers who are unwilling to take risks in the face of insufficient information might be well advised to consider the option of waiting.
- Given the radical changes and uncertainties in energy markets, structural-based methods are required to model future behavior of prices, instead of statistical approaches which may produce poor prediction of price behavior.

- Geographical diversification can significantly decrease variability in different time frames, especially of wind power production [46,47,107,108,111,184].
- The most significant absence in the portfolio literature is the lack of spatial representation when power system is modeled. Unlike some planning models, most portfolio models do not consider the constraints of the transmission system as well as the difference and complementarities among renewable profiles at different sites.
- Unlike most papers that evaluate the impact of wind diversity by focusing on minimizing wind variability and the ramping of wind farms, this work use an scenario-approach model to analyze the impacts of spatial diversification of wind projects on its own market value in scenarios of transmission capacity and storage limitations in the Chilean electricity market.
    - Due to the model does not optimize the generation-transmission infrastructure, the scenarios used are variations from the projected scenarios by the planner.
    - Renewable market value depends very much on the transmission topology and its availability. The results in this work suggest that wind market value in Chile can vary up to US$10/MWh depending on the level of diversification and the spatial and temporal constraints of the system.
    - The current capacity of Chile's hydro reservoirs may increase value of the solar market up to US$5/MWh (depending on the transmission capacity and the share of variable renewable energy in the system).
    - Even though these results must be observed with caution because they depend on the assumptions made, they are additional effects of renewable spatial diversification which usually are not taken into account.
- Renewable market value is very important for regulators or policy makers because the development of renewable energy technologies, as well as their market integration and support policies depend on their market value. Territory-specific characteristics of renewable energies allow policy makers to point toward regional-

specific strategies and consequently to effective and cost-efficient measures to mitigate their market value drop.

- Smart signaling the siting of renewable power plants, considering the diversification of the aggregated profile as well as the transmission availability, may provide an opportunity to improve system efficiency, and at the same time, improve the market value of renewable generators.
- Uncertainty on the commissioning date of transmission projects greatly affects the evaluation of generation projects: those who have the flexibility to postpone the investment and invest in stages have advantages.

Some of the research opportunities found in this work and described along the document are briefly described next:

- Future work should study the coordination between network expansion and generation projects. The role of the transmission expansion process is fundamental for diversifying the energy matrix and efficiently using the country's limited geographic space.
- Future studies could contribute by identifying how renewable diversification policies may be used as an option to defer transmission investments.
- Storage technologies are still not considered to be a solution for preventing or mitigating risks in portfolio analysis, although their costs are decreasing quickly, and they are becoming commercially feasible. Research in this area is slowly being integrated into the planning framework.
- An excellent opportunity for research lies in analyzing the impact of the new small and distributed energy systems with the active participation of the demand side of the portfolio, changing its composition, or becoming a component of the optimal portfolio as an energy resource.

- Further work should be done to consider forecast errors in the modeling. Forecasting errors are important because unpredictability of VRE affects unit commitment decisions and long-term hydro generation decisions, therefore forecast errors may have an impact on the system operation. The complementarity of generation profiles also has an impact on forecast errors because the aggregated generation of different renewable projects may be more predictable, so with enough transmission capacity, a centralized forecast model may improve the performance of the operation.
- The benefits of complementarity of renewable generation profiles should be evaluated in a sub-hourly model to account for the benefits on the system reserves, on the reduced cycling of thermal power units and more generally, on the operational level of the system in that time scale.
- For the investor perspective, including the electricity price as other source of uncertainty, in addition to the commissioning date of relevant transmission projects, would be an additional step to going further in understanding the interactions of these two sources of risk and the possibilities of mitigation.
- Future works should study short-term connection reserve mechanisms to facilitate investments in modular and rapidly building renewable energies (such as solar and wind projects), establishing the necessary safeguards to avoid speculation.

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