UNIVERSITY OF GENOA

PH.D. THESIS: PART III

Forecasting and Risk Measures in Energy Markets

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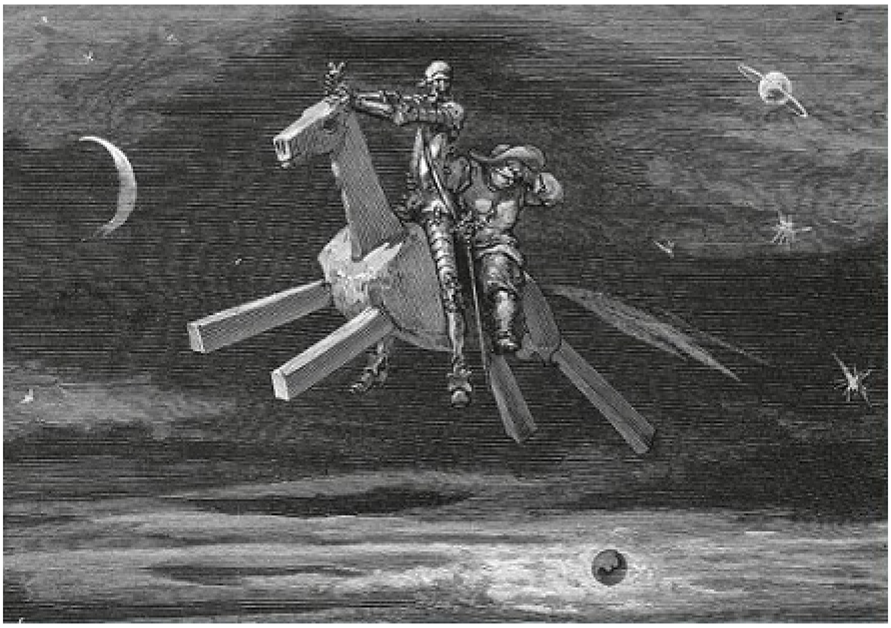

Gustave Dorè, 1868 - Don Chisciotte della Mancia

Undoubtedly there is no Knight who faces his adventures without a trusted horse and a virtuous squire, just as there is no Scientist without suitable measuring instruments for his experiments, or an Engineer without the calculators for his projects or a Mathematician without theorems for his proofs.
Thus, here are my computers through which I have solved all my numerical elaborations in the field of applied mathematics together with the years of their use: *Laplace I* (2003-2006), *Fourier II* (2006-2009), *Ito III* (2009-2013), *Nash IV* (2013-2017) and *Mandelbrot V* (2017), with which I hope to successfully complete this challenge and to be able to dismiss it from its honorable service.

Indubbiamente non c'è Cavaliere che affronta le sue avventure senza un fidato cavallo ed un virtuoso scudiero, così come non vi è Scienziato senza strumenti di misurazione adeguati per i suoi esperimenti, o un Ingegnere senza calcolatori per i suoi progetti o un Matematico senza teoremi per le sue dimostrazioni.
Ecco dunque i miei computer con i quali ho affrontato tutte le mie elaborazioni numeriche nel campo della matematica applicata unitamente agli anni del loro onorato servizio: *Laplace I* (2003-2006), *Fourier II* (2006-2009), *Ito III* (2009-2013), *Nash IV* (2013-2017) e *Mandelbrot V* (2017), con il quale spero di portare a termine con successo questa impresa e poterlo così congedare.

"I do not believe that science per se is an adequate source of happiness, nor do I think that my own scientific outlook has contributed very greatly to my own happiness.
Science in itself appears to me neutral, that is to say, it increases men's power whether for good or for evil.
An appreciation of the ends of life is something which must be superadded to science if it is to bring happiness."

Bertrand Russell - The Scientific Outlook (1931)

"Io non credo che la scienza per sè sia fonte adeguata di felicità, nè credo che la mia mentalità scientifica abbia contribuito granchè alla mia propria felicità.
La scienza di per se stessa mi sembra neutra, essa, cioè accresce il potere degli uomini per il bene come per il male.
Una valutazione dello scopo della vita è cosa che va aggiunta alla scienza se si vuole che essa rechi felicità "

Bertrand Russell - Lo visione scientifica del mondo (1931)

UNIVERSITY OF GENOA

Abstract

Department of Economics

Doctor of Philosophy

Forecasting and Risk Measures in Energy Markets

by Pier Giuseppe GIRIBONE, PhD

The third part of my PhD Thesis deals with Forecasting and Risk Management in Energy Markets. The first chapter introduces the two studies presented in this field through a short literary review and the Regulatory framework.
The second chapter suggests some quantitative methods with the aim of managing the main risks of Guarantees of Origin (Gos). Given that Gos trading is rather recent, it implements an innovative integrated control system in order to handle market and counterparty risks. The following techniques are covered:

- Market Risk: Historical, parametric and Monte Carlo VaR with a special focus on volatility modeling (historical, implied, GARCH, SABR σ).
- Liquidity Risk: Bid-Ask spread analysis.
- Counterparty Risk: Probability of Default estimation starting from: listed CDS premium, traded bond prices and statement analysis (KMV model).

The third part deals with the energy spot prices forecasting problem. The aim of the study is to establish a time-horizon within which it is reasonable to predict prices. The state-of-the-art architectures based on Deep Learning methods are implemented in order to solve this econometric issue. The analyzed techniques are:

- A multi-layered Nonlinear Autoregressive (NAR) network (Endogenous variable: prices).
- A multi-layered Nonlinear Autoregressive with an exogenous variable (NARX) network (Endogenous variable: prices - Exogenous variable: demand).
- A Long Short-Term Memory (LSTM) network with one feature (prices).
- A Long Short-Term Memory (LSTM) network with two features (prices and demand).

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First of all, I would like to thank the Professors of the Ph.D. School in Economics (DIEC) who have constantly followed me during my researches in the economic field, in particular my Supervisor Prof. Marco Guerrazzi. Thereafter, I would like to thank Prof. Ottavio Caligaris, my external Supervisor of the Engineering Department (University of Genoa - DIME).

The Financial Econometric part dedicated to the forecasting models through the use of Dynamic Artificial Neural Networks in application to the Spanish Electricity Market has been conducted jointly with the Department of Electrical Engineering of the University of Genoa and the Engineering Department of the University of León. I would like to thank the whole academic research team made up of: Federico Delfino, Stefano Bracco, Giorgio Piazza (UNIGE), Miguel de Simón Martín and Enrique Rosales-Asensio (Universidad de León).

The work was accepted and presented in the Regulation and Electricity Markets session at the International IEEE-sponsored conference of Electrical and Environmental Engineers that was supposed to be held in Madrid at the Puerta de Toledo Campus from 9th to 12th June 2020. A short Visiting period, with research and teaching purposes was planned for me during that week. Unluckily, due to the COVID19 global pandemic, all these planned activities could not take place physically for safety reasons. As a result, both the conference and the lectures were held on a web platform instead. There will for sure come a time for a meeting in our usual "real" world.

I would like to thank Prof. Dr. Anna Bottasso (Coordinator of the PhD in Economics) & Prof. Dr. Miguel de Simón Martín (Researcher at the University of León, Department of Electrical Engineering, Systems and Automation) for this interesting academic experience. Thanks also to Banca CARIGE (Financial Administration) for allowing me to be part of this professional experience.

A heartfelt thanks to my mother Giuliana who supported (and tolerated) with tenacity and patience me and my father Piero during the hard and long months of quarantine. Smart Working (Virtual meetings, call conferences, lectures, exams), books and papers scattered everywhere, philosophical walks in the corridor, computers everywhere, philatelic documents and music CDs on every table . . . Undoubtedly chaotic scenarios.

A particular thanks to all my co-authors on this topic of research: Anna Bottasso, Stefano Bracco, Federico Delfino, Miguel de Simón Martín, Matilde Martorana, Giorgio Piazza and Enrique Rosales-Asensio.

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In primo luogo desidero rivolgere un sentito ringraziamento ai Docenti Universitari della Scuola di Dottorato in Economia (DIEC) che mi hanno costantemente seguito durante lo studio e l'approfondimento delle materie economiche, in particolare il mio Relatore Chiar.mo Prof. Marco Guerrazzi. Desidero, quindi, ringraziare il Chiar.mo Prof. Ottavio Caligaris, Relatore esterno del Dipartimento di Ingegneria dell'Università di Genova (DIME).

La parte di ricerca econometrica dedicata ai modelli di forecasting mediante l'utilizzo di reti neurali artificiali dinamiche in applicazione al mercato elettrico spagnolo è stata condotta congiuntamente con il Dipartimento di Ingegneria Elettrica dell' Università di Genova e con il Dipartimento di Ingegneria dell'Università di Lèon. È d'uopo rivolgere un ringraziamento a tutto il team di ricerca accademico composto da: Federico Delfino, Stefano Bracco, Giorgio Piazza (UNIGE), Miguel de Simón Martín e Enrique Rosales-Asensio (Universidad de León).

Il lavoro svolto è stato accettato e presentato alla conferenza internazionale degli Ingegneri Elettrici ed Ambientali patrocinata IEEE che si sarebbe dovuta svolgere a Madrid presso Puerta de Toledo Campus dal 9 al 12 Giugno 2020 nella sessione Regulation and Electricity Markets. Durante quella settimana ero stato invitato dall'università spagnola a svolgere un breve periodo di Visiting per scopi didattici e di ricerca. Purtroppo a causa della pandemia globale COVID19, tutte queste attività pianificate non hanno potuto svolgersi nelle consuete modalità in presenza, ma hanno dovuto tenersi in modalità virtuale sul web tramite piattaforme dedicate. Giungeranno sicuramente tempi migliori per poterci incontrare nel nostro usuale mondo "reale".

Per tale interessante esperienza accademica di Visiting desidero rivolgere espressamente un ringraziamento alla prof. Dr. Anna Bottasso, Coordinatrice del corso di Dottorato in Economics, e al prof. Dr. Miguel de Simón Martín, ricercatore presso il Dipartimento di Ingegneria Elettrica dell'Università di León. Un grazie anche all'Amministrazione Finanza di Banca CARIGE per aver acconsentito affinchè potessi svolgere tale esperienza.

Un grazie di cuore a mia mamma Giuliana che ha supportato (ma anche sopportato) con tenacia e pazienza me e mio padre Piero durante i duri e lunghi mesi di quarantena: Smart Working (Virtual Meeting, lezioni, ricevimenti ed esami), libri e paper ovunque sparsi, passeggiate di riflessione nel corridoio, computer in elaborazione, documenti filatelici su ogni tavolo, CD di musica sparsi, ...In effetti scenari a dir poco caotici.

Un sentito ringraziamento quindi a tutti i co-autori dei lavori di ricerca inerenti questa terza parte di tesi: Anna Bottasso, Stefano Bracco, Federico Delfino, Miguel de Simón Martín, Matilde Martorana, Giorgio Piazza ed Enrique Rosales-Asensio.

To our little Imperfections.

Both to those that make us smile, and to those that create a stimulus towards the search for noble ideas, giving us the opportunity to understand ourselves better and therefore to improve ourselves.

Alle nostre piccole Imperfezioni.

Sia a quelle che ci fanno sorridere, sia a quelle che ci creano uno stimolo verso la ricerca di nobili idee dandoci in questo modo la possibilità di comprenderci meglio e pertanto di poterci migliorare.

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Chapter 1

Introduction

"- Is this real? Or has this been happening inside my head?
Dumbledore beamed at him, and his voice sounded loud and strong in Harry's ears even though the bright mist was descending again obscuring his figure.
- Of course it is happening inside your head, Harry, but why on earth should that mean that is not real?"

J. K. Rowling, *Harry Potter and the deathly hallows*, Chapter: King's cross (2007)

"- È vero? O è successo nella mia testa?
Silente gli sorrise raggiante, e la sua voce risuonò forte e chiara nelle orecchie di Harry anche se la foschia luminosa stava scendendo di nuovo oscurando la sua figura.
- Certo, sta succedendo nella tua testa, Harry, ma perchè mai questo dovrebbe significare che non sia reale?"

J. K. Rowling, *Harry Potter e i doni della morte*, Capitolo: La Croce del Re (2007)

In this chapter I introduce the Risk Management and forecasting techniques that can be implemented in order to manage the trading of some particular Energy deals.

1.1 Guarantees of Origin trading

This chapter focuses on the risks arising from the emerging market of Guarantees of Origin (GO). In recent years, in fact, traded volumes of these electronic certifications have increased, although the markets are yet incomplete and rather opaque.

Information is limited and there is no evidence of specific studies nor well-established regulation for risk assessment. For this reason, the aim is to suggest a risk management framework, useful for companies in the new GO trading business.

To achieve this objective, different methodologies for estimating market, liquidity and counterparty risks are proposed. These must be considered as a part of an overall evaluation system and not as stand-alone approaches.

Since the available time series are rather short and characterized by constant prices over long periods, ad-hoc quantitative methodologies are presented to measure and prudently manage risks.

1.1.1 How Guarantees of Origin work

The Guarantees of Origin (GO) are electronic certifications, reserved for electricity producers who use renewable energy sources, used to demonstrate the origin of the energy they sell.

They are issued throughout Europe by national issuing bodies that are part of the AIB - Association of Issuing Bodies. In Italy they are released by the Energy Services Manager (GSE). GOs were introduced in Europe with the Renewable Electricity Directive 2001/77/EC (*Directive 2001/77/CE* 2001), implemented in Italy with Legislative Decree no. 387 - December 29, 2003 (*DL 29/12/2003 n.387* 2003), which imposed an obligation for all Member States to develop a reliable tracking system, providing evidence to the final customer that a given quantity of energy was produced from renewable sources.

GOs are regulated through Directive 2009/72/EC, also known as Internal Electricity Market Directive (*Directive 2009/72/CE* 2009). Directive 2001/77/EC provides the obligation for energy suppliers to disclose once a year in the bill the mix of fuels and energy sources used - Fuel Mix Disclosure (*Directive 2001/77/CE* 2001). This can be fulfilled based on the GO exchanges and not based on the physical production of electricity in the region or country.

The interest in this market is due to the fact that, in recent years, the exchanged volumes of these electronic certifications are increasingly significant also as a consequence of the obligations set by the Renewable Energy Directive for the 2021-2030 period (Drabik, Egenhofer, and Jansens, 2016; Ragwitz, R. Gonzalez, and Resch, 2009).

The data used to conduct the GO risk analysis were provided by the information provider Greenfact, which is considered by the operators one of the most reliable source. The historical time series used in the analysis are the Close, Bid and Ask prices for a period of twelve months between 2017 and 2018 related to four GO categories, differentiated according to technology (i.e. energy source) and years of production (called vintage).

Financial time series are proprietary and they cannot be published or disclosed to third parties, even using aggregated data. As a result, the quantitative methodologies implemented in the risk management system will be illustrated in the discussion, providing, when possible, accurate details.

1.1.2 Guarantees of Origin Trading

In recent decades, limits have been imposed on industrial and domestic polluting emissions in order to protect the environment. These measures reflect the greater sensitivity to the eco-sustainability of resources and the awareness that emissions into the atmosphere, water and soil produce negative repercussions on the overall balance of the planet.

Only recently, more rigid mechanisms for controlling CO2 emissions, such as, for example, the imposition of maximum emission limits, have been joined by more flexible mechanisms (Turner, Pearce, and Bateman, 2015), such as environmental certifications, eco-labels for businesses and above all the Guarantees of Origin. The GO scheme is a system for tracking energy sources: a GO corresponds to 1 MWh of electricity produced with renewable sources and includes detailed information on the origin of energy, the source (technology), age and dimensions of the plants. The three main attributes of the GO are precisely the year of energy production (vintage), the place and technology used for production.

For example, a GO could be related to the production of solar energy from a European plant in 2018. Vintage, in particular, indicates not only the year of production, but also the year for which the obligations associated with GOs must be fulfilled. GOs have a useful life of one year from the end of the production period to which they refer. There is a wide range of GO, which responds to the different preferences and perceptions that consumers have of the concept of ecology and renewability (environmentally friendly).

For some consumers, for example, the term "ecologic" is meant as opposed to non-renewable, that is, different from traditional coal or gas-fired power plants; for others it means products related to environmental objectives, such as the protection of the environment and wildlife. For others, GOs must contribute to the production of other "green" energies: in fact, although this contribution, which is the so-called "Additionality", is not the main purpose of the GO system, it certainly is one of the main reasons why many consumers buy these commodities.

Furthermore, with regard to individual preferences, many consumers prefer GOs on energy produced in local power plants, others prefer GOs from hydroelectric rather than solar plants, still others simply want the cheapest available GO. Finally, some operators require customized GO products. Due to the heterogeneity of the offer for these products, GOs are not traded on the Exchange, but over the counter (OTC). This adversely affects the transparency of the markets and hinders the possibility for end users to compare different products and their respective prices.

GOs are negotiated on a voluntary basis, through two main types of contracts: spot contracts and forward contracts. For both types of contracts, the GO prices are set on the date of the agreement. The main difference concerns the settlement and payment date. However, the concept of spot and forward is a bit different compared to traditional finance: in fact, even if the price of a spot contract is the current price for an immediate delivery, this contract is related to the energy production that took place both during the previous year and during the current year.

In the same way, the price connected to a forward contract is predetermined today for the delivery that will take place in the future, but, compared to the more classical meaning of forward, not only the delivery, but also the energy production underlying the contract is projected forward in time. In particular, the main terms of exchange of the Guarantees of Origin is the bilateral bargaining between those who produce green electricity and those who are willing to pay in order to classify their energy consumption as "renewable".

GOs are traded both on a wholesale market, through intermediaries, trading houses and directly between producers and large companies (end-user markets). In the wholesale market, buyers are generally energy suppliers and large companies, while sellers are energy producers who sell GOs directly through brokers, or hire a portfolio management company, such as ECOHZ, to organize their own trade in GOs. These portfolio management companies, which are very popular on the wholesale market, manage significant volumes of GOs on behalf of small and medium-sized energy producers.

They are counterparties to both the seller and the buyer, actively helping the latter to choose, implement and document the consumption of renewable energy according to their needs. These companies sometimes buy GOs to keep them on their own account for speculative purpose, but such speculation is rather infrequent. According to the research done by Oslo Economics (Skaar, 2017), the greatest volume of GOs passes through brokers. Beyond these OTC trades, there were a few attempts to create ad-hoc exchanges for GOs (for example by the EEX Power Exchange) over the years, but they did not succeed, mainly due to higher transaction costs compared to the fees charged by intermediaries. In end-user markets, on the other hand, GOs are sold to enterprises (around 70%) and consumers.

Companies buy GOs because they want to document their demand for renewable energy to customers, investors and other interested parties, but also in order to meet the criteria for environmental standards - Greenhouse Gas Protocol - GHG (Piebalgs and Olczak, 2018) and to achieve their own marketing objectives related to renewable energy. In fact, being compliant with recognized standards can also be a powerful tool for companies to sell their products and attract investors.

An example concerns the over one hundred large multinationals engaged in the most different fields, from the telecommunications sector to the production of cars, which are actively committing themselves to exclusively use renewable energy in their daily needs. This is the so-called RE100 initiative, launched in 2014 by the Climate Group and the Carbon Disclosure Project.

Small-sized electricity consumers do not usually buy GOs directly, but their price is among the many components of electricity tariffs or is included in the price of other "renewable" products and services, such as donations for the protection of forests. In particular, Rhein Energie, based in Cologne, is one of the few companies that supplies GO energy at an explicit premium of 2 EUR / MWh. In most cases the price of GOs is not shown on the bill, but is included together with the other components of the electricity tariff.

There are also many companies, such as BMW, that purchase GOs, to increase the share of renewable energy used in production, without applying additional costs to their customers. With regard to aggregate demand and supply, it is important to underline how the offer depends on the capacity of the plants, on the climatic conditions in a certain period of the year, on the national legal framework and, not least, on any incentive policies. Furthermore, in the long term, the increase in the production of renewable electricity in Europe will impact the offer and consequently the price of GOs.

The demand varies greatly according to the categories of GO and depends on “attributes” such as the position or technology of the production unit, thus generating niche markets with excess demand and higher prices. In general, from 2012 to 2016, the demand for GOs registered a significant average annual growth rate, which stood at 14.3% (Source: ECOHZ). Currently, the GO market is characterized by strong price differentials between the three main products, which are “bulk”, “premium” and “customized” GOs.

The “bulk” GOs are the cheapest and the more basic ones; for example, the general categories Nordic Hydro and European Wind are part of it (the names are consistent with the convention used by the Greenfact information provider to classify GOs). They do not have any further specifications about the country of origin or the type of production plant. They are generally traded at relatively low prices due to the large supply and low local demand.

The “premium” GOs are required by companies that are willing to pay an additional premium in order to purchase local GOs, that is to say those issued to energy producers geographically close to the buyers, or GOs that respect certain ecological quality standards (like Bra Miljöval), connected to the respect for the climate and the environment, particularly appreciated by green customers. For example, the national railway company of the Netherlands, after conducting a survey among its customers that revealed a preference for local energy sources, decided to satisfy their requests by buying GOs from wind power plants located in the territory, with the consequence of a considerable price increase.

Some companies, such as ECOHZ, want tailor-made GO products (“customized” GOs) that meet certain specific needs and preferences, such as, the desire to contribute directly to the financing of new renewable plants (“additionality”), or that concern shorter time intervals in accordance with the end user consumption profile (instead of annual GOs, monthly GOs are preferred). In general, in recent years there has been a generalized increase in demand from end-users of premium GOs at national level, and an increase for customized GOs in more local areas.

1.1.3 Regulatory Aspects

The Guarantees of Origin system was established in the European Union legislation with the Directive 2001/77/EC (Renewable Electricity Directive) for the promotion of electricity produced using renewable energy sources (*Directive 2001/77/CE* 2001). This directive introduced the obligation for all Member States to develop a reliable energy tracking system, providing evidence to end users that a certain quantity of energy was produced from renewable sources. This allowed companies and consumers to meet their demand for environmentally friendly products, services and investments.

GOs are regulated through Directive 2009/72/EC (*Directive 2009/72/CE* 2009), which suggests that the Fuel Mix Disclosure, i.e. the disclosure of the mix of fuels and energy sources used, should be made based on the exchanges of the GOs and not on the basis of the physical production of electricity in the region or country. In particular, according to the Fuel Mix Disclosure, at least once a year, energy suppliers must communicate the energy mix relating to the production of electricity on the bill, in order to allow an informed choice by end customers, who can thus express their environmental awareness. For the purpose of disclosure, domestic and imported GOs are managed in the same way.

Since 2010 many new GO-based products have been developed both for consumers and corporates (CER, 2011). In 2014, however, the German Federal Environment Agency (Umweltbundesamt) still defined the wholesale market as a non completely transparent market. In fact, only in the last two years the trades in this market have seen improvements in the form of a larger share of volumes exchanged by brokers, more contributed prices and a new offer of analytical services. These improvements will be further supported by the changes decided by the Renewable Energy Directive for the period 2021-2030 (RED II), also known as the EU Winter Package, once it is approved.

This directive, proposed by the European Commission in order to review the Renewable Energy Directive (RED) and enriched with the amendments of the European Parliament and the Council of the EU, provides for a series of measures that strengthen the use of these electronic certifications at the expense of other potentially more unreliable and misleading tools, in order to better protect end-users. The agreement for the drafting of the text of the directive was reached on 14th June 2018 and the results were made public in early July. As for the Italian case, after the issuance of the GOs by the GSE, the certifications are traded in platforms supervised by the Energy Market Manager (GME).

In particular, for each MWh of renewable electricity introduced into the network by qualified IGO plants (Plants powered by renewable sources for the purpose of issuing the Guarantee of Origin), the GSE issues a GO certificate, in accordance with Directive 2009/28/CE and Renewable Energy Directive (*Directive 2009/28/CE* 2009). GOs are issued on a monthly basis and can be transferred, within the terms of their validity, from the moment of their issue until the following year from the production of the electricity to which they refer, after which they lose their validity. The transfer takes place electronically, through the web portal and it is recorded in a dedicated register. In countries where GOs are issued, there is a national register containing the traces of all commercial transactions which have taken place. This register makes it possible to track ownership and above all prevents electricity suppliers from selling the same renewable energy twice (*DM 31/07/2009* 2009).

Since it is impossible to accurately monitor the energy source of electricity supplied by a specific power outlet, the purpose of the GO system (which are intangible assets separated from the actual physical distribution of energy) is to keep track of energy production information and of the “attributes” of the generated electricity. Another regulatory obligation connected to GOs, in addition to the Fuel Mix Disclosure, is the so-called GO “cancellation”. Within the EU, operators who hold GOs and want to declare that they have renewable energy instruments in their portfolio, must delete the GOs for the corresponding portion from the register. The same operation must also be carried out by the energy suppliers in order to be able to communicate on the bill that the electricity they offer comes from renewable sources.

Therefore, from the suppliers point of view, these electronic certifications are canceled from the registers once they are used for information purposes for the benefit of the final consumer. In particular, from 1st January 2013, sales companies are obliged to obtain a quantity of GOs equal to the electricity sold, which must then be canceled by March 31th of the following year in which it was provided. In Italy it is only from the beginning of January 2013 that electricity suppliers can sell GOs to their customer companies that wish to acquire energy produced from clean sources.

1.1.4 Market analysis

The Guarantees of Origin are exchanged both on a wholesale market and on end-user markets. Practically there is not a unique wholesale market, but many markets defined by end users, such as the electricity, public transport and household appliances markets,... for which GOs are only one of many components.

Following the approach presented by Oslo Economics in Report 58 of 2017 (Skaar, 2017), it is interesting to evaluate whether GO markets exhibit characteristics similar to perfectly competitive markets. According to the theory of general economic equilibrium, in fact, a perfectly competitive market satisfies several ideal conditions that lead to the equilibrium of perfect competition, therefore to a stable Pareto optimum, in which it is not possible to improve the utility of a player, without worsening the wealth of others. An equilibrium under perfect competition is considered efficient because production and consumption guarantee an efficient allocation of resources.

Producers accept market prices (price takers), trying to reduce their production costs, in order to maximize their profit, as long as the market value equals the marginal cost ($P = MC$). The main conditions that characterize a perfectly competitive market are the presence of many players, the homogeneity of the product, the absence of entry barriers (such as restrictive licenses or high transaction costs), the presence of perfect information and the perfect rationality of the agents. The wholesale market of some GOs is, for high volume products, quite similar to a perfectly competitive market: it is characterized by the presence of many agents and no entry barriers, it is quite liquid, with low transaction costs and enough transparency. As a result, prices promptly reflect the information from the market, even if not all players are able to have this information at the same time.

These considerations cannot be applied in the case of GOs exchanged with less frequency, such as Bra Miljöval Hydro, for which the wholesale market is also much further away from the ideal concept of perfect competition (Skaar, 2017). The end consumer markets, on the other hand, are characterized by insufficient liquidity and transparency, as well as by very imperfect competition which can generate problems of information asymmetry between energy suppliers and end consumers. Barriers to entry often exist on GO markets: for example, Deutsche Bahn is a monopolist on the rail ticket market in Germany, where GOs are included. The wide range of GOs and the fact that they are often merged with other renewable products or services are obstacles to perfect information and negatively affect not only the transparency of the markets, but also the possibility for users to compare different products, favoring hence the persistence of price differentials on the wholesale market.

Always in a perspective of comparison with perfectly competitive markets, information on prices is very difficult to find for those who are outside the market, while most operators generally have access to prices contributed by brokers or other platforms and information providers, such as Montel Online, Greenfact .... It is therefore believed that the issue of transparency represents a central problem for the Guarantees of Origin market, which could affect its future development.

1.1.5 Financial Characterization

A traditional analysis of these particular assets is proposed, in order to better understand the financial characterization of the GOs. This study was conducted in the same period for a total of 265 daily returns. In addition to considering the Guarantees of Origin described above, i.e. NHY, EWD, EUB and EUS for different vintages (17-18-19-20), we consider more popular futures and ETFs linked with the energy sector with the aim of highlighting why these assets could be an interesting form of investment. The traditional asset classes we analyzed together with the GOs are:

- Generic First Futures on Crude Oil (WTI).
  Bloomberg® Ticker: CL1 Cmdty
- Generic First Futures on Natural Gas.
  Bloomberg® Ticker: NG1 Cmdty
- Generic First Futures on Coke.
  Bloomberg® Ticker: KEE1 Cmdty
- iShares Global Clean Energy ETF is an exchange-traded fund incorporated in the USA. The ETF tracks the performance of the S&P Global Clean Energy Index. The ETF holds energy, industrial, technology and utilities stocks that can be predominantly classified as mid cap. The ETF weights these holdings using a market capitalization methodology.
  Bloomberg® Ticker: ICLN US Equity
- Lyxor New Energy DR UCITS ETF is a UCITS compliant Exchange-Traded Fund established in France. The Fund's investment objective is to track the performance of the World Alternative Energy Index SW.
  Bloomberg® Ticker: NRJ FP Equity
- Invesco Wilderhill Clean Energy ETF is an exchange-traded fund incorporated in the USA. The Fund tracks the WinderHill Clean Energy Index which holds US-listed stocks in the Clean Energy sector: specifically, businesses that should benefit substantially from a societal transition towards the use of cleaner energy, zero-CO2 renewables and conservation. The fund is rebalanced quarterly.
  Bloomberg® Ticker: PBW US Equity
- First Trust NASDAQ Clean Edge Green Energy Index Fund is an exchanged-traded fund incorporated in the USA. The fund seeks investment results that correspond to the NASDAQ Clean Edge U.S. Liquid Series Index, which is a modified market capitalization weighted index designed to track the performance of clean energy companies that are publicly traded in the United States.
  Bloomberg® Ticker: QCLN US Equity
- VanEck Vectors Low Carbon Energy ETF is an exchanged-traded fund incorporated in the USA. The Fund seeks investment results that correspond to the price and yield of the Ardour Global Index, which tracks companies primarily engaged in the business of alternative energy.
  Bloomberg® Ticker: GEX1 EU Equity

In Table 1.1 the main statistical measures linked with the time-series are provided: the range of variation in the considered interval (minimum and maximum) and the four moments of the empirical daily return distribution (i.e. Mean, Variance, Skewness and Kurtosis). The range of the price fluctuations for GOs is on average bigger than traditional assets and this phenomenon is also reflected in a bigger volatility. This means that the investment in GOs can be considered riskier than a conventional one: the illiquidity of a new-born market undoubtedly plays a crucial role. Higher risk, higher returns: the average of the daily returns confirms this trading milestone. Furthermore the shape of the empirical returns is right-skewed: a feature that is particularly important especially if compared with the traditional investment which, on average, records a negative value for this shape indicator. There is no such thing as a free-lunch: for the asset for which the positive skew is higher, the kurtosis assumes extreme values. The excess kurtosis, measured as the fourth moment of the distribution minus three (the Gaussian distribution has a theoretical value of Kurtosis equal to 3), shows the presence of fat tails. It is clear that traditional risk management techniques which work with normal assumptions cannot perform well in these cases: as a result, a quantitative monitoring system will be designed ad-hoc in the next chapter.

Asset	MIN	MAX	MEAN	VARIANCE	VOL.	SKEW	KURTOSIS
NHY17	-4.3	11.64	0.54	3.3725	1.8364	0.6712	1.4506
NHY18	-5.38	10.29	0.67	3.2768	1.8102	0.3539	1.1252
NHY19	-4.02	12.23	0.68	3.6499	1.9105	0.3858	1.1488
NHY20	-7.7	13.03	0.69	5.009	2.2381	0.7253	1.526
EWD17	-10.54	16.45	0.5	5.2588	2.2932	1.4084	2.9835
EWD18	-9.03	14.21	0.63	7.7851	2.7902	1.3275	2.7624
EWD19	-5.19	16.59	0.62	5.125	2.2638	1.6173	3.6157
EWD20	-12.41	14.76	0.58	6.4545	2.5406	1.7889	4.2
EUB17	-8.22	21.23	0.58	6.703	2.589	1.7176	3.9501
EUB18	-8.93	22.01	0.69	8.455	2.9077	1.7528	4.0721
EUB19	-7.76	23.8	0.69	6.5282	2.555	2.167	5.6957
EUB20	0	21.6	0.69	5.432	2.3307	2.3212	6.3879
EUS17	-10.54	14.71	0.43	5.5083	2.347	2.695	8.2631
EUS18	-3.32	20.22	0.5	5.7298	2.3937	3.0151	10.0909
EUS19	-1.72	16.37	0.47	5.2467	2.2906	3.3124	11.9723
EUS20	-8.48	17.84	0.45	6.3264	2.5152	3.5494	13.5982
CL1	-5.16	4.53	0.15	2.284	1.5113	-0.2913	3.4576
NG1	-12.79	7.49	-0.03	4.8099	2.1931	-0.5574	7.7955
KEE1	-10.74	14.58	0.091	6.2164	2.4933	0.5042	9.8942
ICLN	-3.16	3.45	0.004	0.82679	0.9093	-0.2452	4.0741
NRJ	-3.06	2.84	0.013	0.98546	0.9927	-0.1478	3.2768
PBW	-3.71	2.79	0.048	1.0732	1.036	-0.3927	3.3799
QCLN	-4.41	2.53	0.026	1.1572	1.0757	-0.5757	4.0395
GEX1	-3.09	3.09	0	1.158	1.0761	-0.1421	3.4935

TABLE 1.1: GOs Financial Characterization of the Daily Returns. Minimum, Maximum, Average and Volatility are expressed in [%] while variance is expressed in [bps]

The second step of the analysis concerns the estimation of the Correlation Coefficients of the 24 analyzed assets. The heatmap of the Correlation matrix is represented in Figure 1.1. In this table negative values are rare: it is reasonable because all the assets belong to the same asset class (energy), but the low positive correlation of GOs compared to traditional assets is worth noticing (the highest coefficient is 0.15). Considering the correlation among GOs, it is interesting to highlight how low the coefficients are compared to a hypothetical portfolio composed of traditional green investments: it is evident comparing the light tone of blue on the top left corner with the dark tone on the bottom right. As a result, GOs can provide a very interesting diversification under a perspective of portfolio diversification.

1.2 Electricity Spot Prices Forecasting

Deregulated power markets take advantage of the high competition between utilities, which results in significant reduction of electricity prices (Kirschen and Strbac, 2019). Electricity is a very special commodity as the power system stability requires a constant balance between production and consumption and it is economically non-storable (Weron, 2014).

In deregulated systems, such as the Spanish one, typically there exist two main instruments for power trading: organized markets for power exchange and bilateral contracts. Among bilateral contracts, the so-called Power Purchase Agreements (PPAs) are getting special attention lately. In the power exchange market (also called power pool), the power trades derive from a process based on auctions where the supply and demand of electricity are matched and the market clearing price (MCP) is determined. In the Spanish system, buyers with bids equal or above the MCP pay that price and suppliers with offers equal or below the MCP are paid the same price: it is a uniform or marginal price auction market.

The organized market for power exchange (which is run by OMIE in Spain) is a day-ahead market that, since mid-2018, allows continuous trading and intra-day trading sessions. Thus, in the day-ahead market, agents submit their bids and offers for the delivery of electricity during each hour of the next day before a certain market closing time, according to the Transmission System Operator (TSO) power demand forecasts. Then, the scheduled program is sent to the TSO who checks if it is technically feasible and falls within transmission constraints. Finally, once the day-ahead program is validated, the hourly MCP can be revised in an intra-day market executed from the day before of the power dispatch up to 15 minutes before the physical power dispatch.

On the other hand, bilateral contracts are negotiated directly between a single utility and a buyer, who decide not to participate in the power exchange market. In this context, derivatives are a sort of bilateral contract where future power trades are negotiated in the present with the aim of moving risks from hedgers to speculators. These power exchanges can be done both in OTC (Over the Counter) markets or in an organized market where a clearing house (OMIP) guarantees that the signed contracts are properly executed. The aim of the participants of the electricity market is to maximize profits while minimizing risks. Thus, accurate forecasts of future electricity prices help traders to optimize their bidding strategies which would lead to higher profits for suppliers and, therefore, to guarantee economic feasibility to the power plants.

However, this is not an easy task as the electricity spot prices are characterized by a strong seasonality and volatility, caused by weather changes, power outages, transmission bottlenecks or fuel prices uncertainties. This scenario is getting even more relevance nowadays, and it will be in the future, due to a significantly high amount of non-manageable renewable energy (mainly wind and solar) participation in the market, the imminent decommission of carbon and nuclear power plants and the increase of the power demand due to the electrification of transport and domestic heating and cooling, which is usually called sector coupling (BloombergNEF, EATON, and Statkraft, 2020).

In order to promote market competence and flexibility, two main projects in Europe are being executed for market coupling. On the one hand, the PCR (Price Coupling of Regions) project, which has been launched in 2014, enables the coupling of day-ahead hourly electricity markets between 19 countries in Europe. It is estimated that the participants in this system currently represent over 2800 TWh of yearly consumption. In order to determine the coupled prices, the EUPHEMIA (Pan-European Hybrid Electricity Market Integration) algorithm is used, which considers all generator bids and buyer offers from the participant countries. On the other hand, the XBID project has allowed the coupled continuous intra-day market since 2018.

As expected, the current complexity of energy markets makes it unattractive for investors to participate in new generation projects, especially non-manageable ones, such as solar or wind (Rio Gonzáles, 2008; Barradale, 2010). The high uncertainty on the expected revenues, due to the volatility of the market spot prices, conducts to a difficult evaluation of the payback of the investment.

As a compromise solution, markets for derivative products are arising (Lucia and Schwartz, 2002; Lautier and Simon, 2009). They allow the interchange of power contracts with different time horizons: typically, 1 day, 1 week, 1 quarter or 1 year, with several time delays: from 3 days to 7 years. The negotiation of forward prices, futures, options and swaps increases flexibility in the market and some of the risks for generators and power demand aggregators can be reduced.

When managing future products and open continuous trading markets, several difficulties arise. One of the most relevant is the forecasting of prices and energy volumes, which is fundamental for energy traders if they want to maximize their profits and/or cover their risks. The particular electricity price dynamics observed show seasonality at the daily, weekly and annual level, and abrupt, short-lived and generally unanticipated price spikes (Weron, 2006). Thus, electricity price forecasts have become fundamental for energy companies and investors as costs of over-/under-contracting and then selling or buying power in the balancing market are typically so high that they can lead to huge financial losses (Weron, 2014). Moreover, the extreme price volatility of electricity usually forces market participants to hedge not only against volume risk but also against price movements, which increases the interest and value of price forecasts from a few hours to few months ahead (Weron, 2014).

This study is intended to provide a test on the use of an adequate calibrated Deep Learning Dynamic Neural Network, for point forecasting of electricity prices according to both econometric and statistical considerations, and to evaluate the impact of including or not an exogenous variable. For this purpose, Non-linear Autoregressive (NAR) and Long-Short Term Memory (LSTM) Neural Networks have been evaluated, as they have provided excellent results in other studies. As exogenous variable, the TSO forecasted power demand has been proposed, as observed in the literature, due to the fact that it has the highest correlation with the electricity spot price, followed by the weather temperature, the solar and wind generation, the transmission congestion, the reserve margin and the future options market (Weron, 2014).

The main contributions of this work can be summarized as follows:

- The latest machine learning methods for time series forecasting have been evaluated for the electricity spot prices of the Spanish market (MIBEL). An iterative one-step ahead approach has been considered.
- Dynamic artificial neural networks, with and without exogenous variables, have been compared. The one-week ahead daily updated forecasted power demand by the TSO (volume) has been used.
- An optimal design of the ANNs architectures based both on statistical and econometric tests have been performed, allowing the optimal tuning of the number of layers, the number of neurons for each layer and, in the case of NAR and NARX models, the appropriate number of lags to consider.
- A back-testing methodology for measuring the out-of-sample models' performance has been applied. Thus, the reliability of the forecasting horizon is evaluated.

1.3 Author's research work

This third part of the Ph.D. Thesis is mainly based on the following Author's work:

1. BOTTASSO A., GIRIBONE P. G., MARTORANA M. (2019). Design of quantitative measures for monitoring financial risks in the emerging market of Guarantees of Origin. Risk Management Magazine Vol. 14, N. 2 (Bottasso, Giribone, and Martorana, 2019)
2. DE SIMóN-MARTíN M., BRACCO S., ROSALES-ASENSIO E., PIAZZA G., DELFINO F., GIRIBONE P. G. (2020). Electricity Spot Prices Forecasting for MIBEL by using Deep Learning: a comparison between NAR, NARX and LSTM networks. International Conference on Environment and Electrical Engineering - EEEIC 2020, Technical Area: Regulation and Electricity Markets. (Simón Martín et al., 2020)
3. GIRIBONE P. G. (2020). Prices forecasting using Dynamic Neural Networks: from NAR to LSTM networks. Visiting Lecture Notes (University of Leon). (Giribone, 2020)

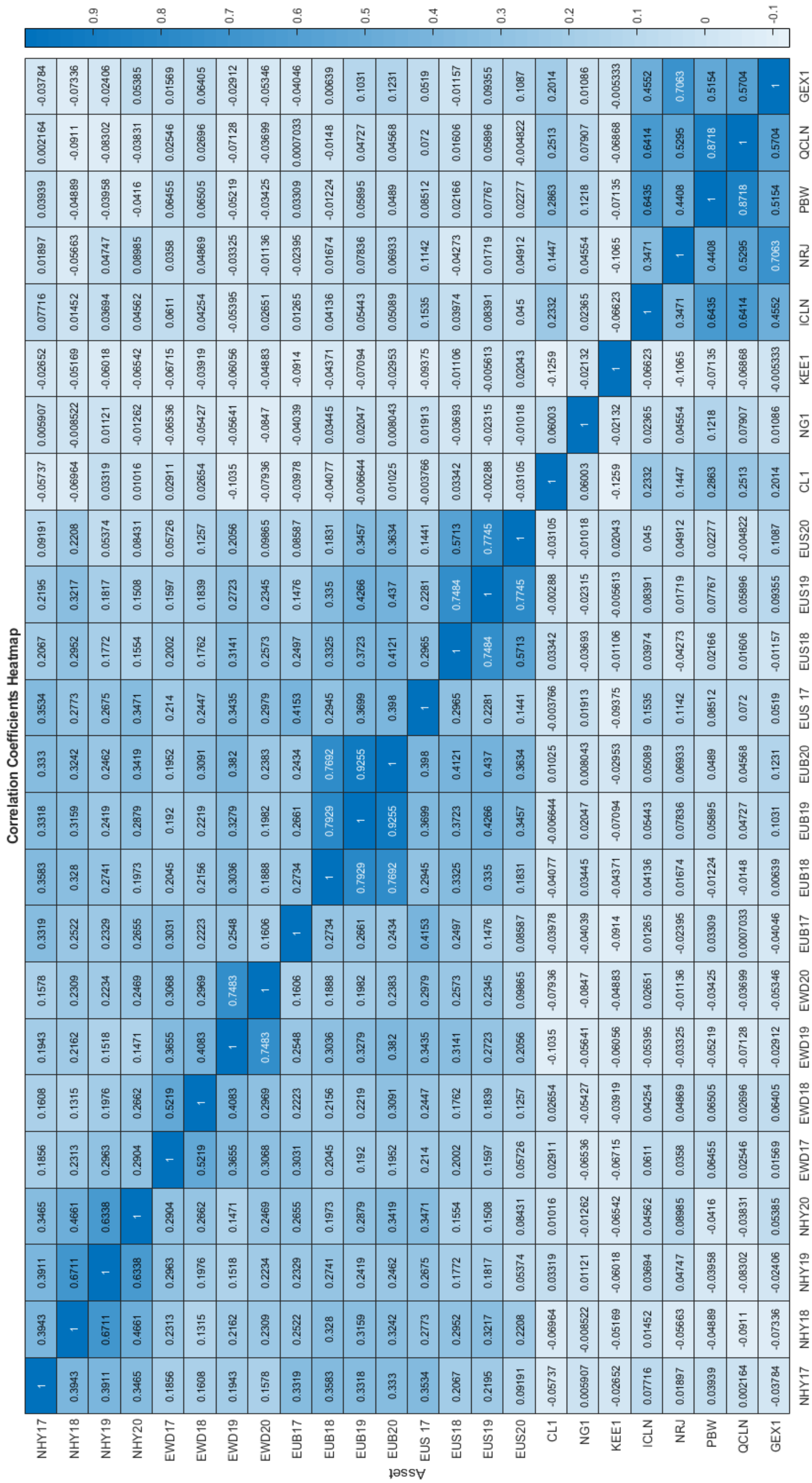


FIGURE 1.1: The Heatmap of GOs Correlation Coefficients

Chapter 2

Risk measures for Guarantees of Origin

"When you are afraid of things you have to measure them."

Daniel Kehlmann, *Measuring the World*, Chapter: The Sea, 2014

"Quando si ha paura delle cose bisogna misurarle."

Daniel Kehlmann, *La misura del mondo*, Capitolo: Il Mare, 2014

2.1 The need for a risk management integrated system

The Guarantees of Origin (GOs) are electronic certifications that allow producers of electricity from renewable energy sources to prove the origin of the energy they sell. The objective is to deepen the knowledge of the emerging GO market, highlighting the risks associated with them (Martorana, 2018). A complete quantitative analysis has never been carried out previously and acquires particular relevance also in light of the fact that there isn't a strict reference legislation for this market. In particular, the aim of this work is to propose different methodologies for estimating market, liquidity and counterparty risks, offering traders the opportunity to choose the method that is most prudential or consistent with their investment objectives. The risk analysis was conducted on some GO historical time series which are characterized by very peculiar features: they are very short (just over a year) and show a trend of continuous growth, characterized by constant prices for many consecutive days (market data: 2017-2018). These characteristics made the analysis particularly challenging; in fact, the constant prices in different periods (more or less protracted) and the presence of zero returns, can in many cases lead to a possible underestimation of the risks. For these reasons, the provided estimates are considered a starting point for the study of this evolving market, for which there are few bibliographical references. A synthetic overview of the emerging market of Guarantees of Origin is provided in the first part: we focus on the peculiarities of their trading, on the main regulatory aspects and on the difference between the markets on which the GOs are traded. The second part focuses on a market risk analysis, with particular reference to Value at Risk - VaR (Artzner et al., 1999), Expected Shortfall (ES) and liquidity risk measures through the analysis of the Bid-Ask spread. In the third part, we provide a traditional Monte Carlo (MC) VaR and some other simulation techniques for both spot and forward contracts. The main methodologies presented for spot contracts are the historical MC and the MC with a GARCH(1,1) volatility. We will also propose a more forward-looking approach to estimate future returns using a MC that implements estimated volatilities implied by traded options written on a similar underlying. Finally, in the fourth part, some methods for the counterparty risk are proposed, analyzing in detail three possible cases: the counterparty has listed credit default swaps (CDS), the issuer has actively traded bonds on the market and those in which it does not have any of these characteristics, therefore the analysis has to be carried out using only statement data. It is important to underline that the risk estimation methodologies addressed in this work must not be considered as alternatives, but they must be considered as an integral part of a risk management system able to handle different types of financial risks.

2.2 Market and Liquidity Risk

Financial historical time series used in the analysis are the closing, the Bid and Ask prices for the period from 18th July 2017 to 3rd August 2018, related to four categories of GOs, differentiated according to technology (or energy source) and considering for each category four different vintage (or years of production). The main problems that emerged from the quantitative analysis, conducted on the initial GO sample of 16 daily prices time series, are represented by their shortness and the fact that they are characterized by increasing trends with constant prices over several days (i. e. zero returns). For these reasons, the quantitative methods proposed to measure and prudently manage the main risks are not always conventional and the estimates must be considered as a starting point for the study of this evolving market. The first approach explored for market risk management is the traditional calculation of historical and parametric VaR (and therefore ES) starting from the returns realized by GOs, using both daily and weekly aggregated data (Manganelli and Engle, 2003). It was decided for the completeness of the analysis to compute the VaR using the variance-covariance approach as well, although the probability distributions of the GO yields are not normal at all, but mostly leptocurtic with fat tails. In fact, in the case of GOs, the quantiles of the empirical distributions are rarely higher than the parametric ones (especially at a confidence level greater than 95%), while more often the opposite occurs, i.e. the VaR calculated with the variance-covariance method is greater than the historical one, both 95% and 99%. However, this could already be deduced from the qualitative analysis of the yield distribution graphs which shows how the normal density curve dominates, in particular on the left tail, the empirical one (Figure 2.1), even if it is not a common feature in all GO distributions.
The heterogeneity of the Guarantees of Origin is one of the reasons why the objective of the study is not to compare the different methods of calculating the Value at Risk with one another, in order to manage to success the "best", but rather that of designing an ad hoc risk management system, using different approaches. The VaR was then estimated, always with the parametric approach, but with the assumption, from a prudential point of view, that the historical average of the returns is zero for all GOs. This choice wants to solve the problem that the short available historical series constantly grow over time. Having analyzed the traditional standard market risk measurement methodologies, we consider a latent risk for the emerging GO market: the liquidity risk. As known, the Guarantees of Origin are exchanged on the wholesale market, through intermediaries, trading houses or directly between

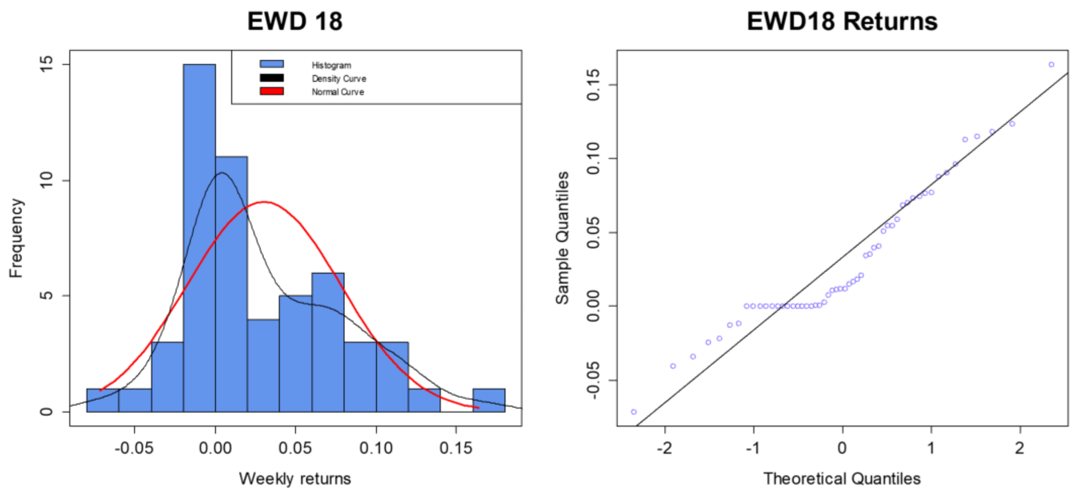


FIGURE 2.1: Weekly yield Histogram and Q-Q plot for the EWD18 GO

producers and large companies or on end-user markets. The GO wholesale market for products with a high volume of trade, such as the category of Large Nordic Hydro GOs is fairly liquid, with low transaction costs and transparent, with the consequence that prices promptly reflect information, which come from the market. Again on the wholesale market, for products traded with less frequency (such as Bra Miljöval Hydro), there are greater price variations compared to high-volume products, mainly due to the lower availability in the offer of the GOs themselves. The end consumer markets, on the other hand, are characterized by insufficient liquidity and transparency, as well as by very imperfect competition. First of all, the heterogeneous demand of GO, mainly due to the fact that consumers have different preferences and perceptions of what represents an "environmentally friendly" status, has led to a wide variety of products, negatively affecting the transparency of the markets and hindering the possibility, for end users, to compare different products and their prices. It can be seen that, in end-user markets, GOs are not normally sold alone, but as one of the many contributions from an electricity tariff. In addition, in some segments of the end consumer markets, such as, for example, that relating to train tickets in Germany, there are both players with wide market power and barriers to entry. This must be interpreted in the light of the fact that, on the contrary, one of the main characteristics of a liquid market is the presence on the market of many buyers and sellers, willing to negotiate at any time. Liquidity in the financial markets is, in fact, defined as the ease of exchange of an asset, which, as the current crisis has highlighted, is often far from high and constant. Liquidity represents a measure of the ability to buy or sell a product without causing a significant change in its price and without incurring significant transaction costs. As regards the measurement of the liquidity risk connected to the GOs of the considered sample, following the suggestion of many authors, the Bid-Ask spread was used (Amihud and Mendelson, 1986). According to the typical conventions of this market, the Bid-Ask spread was calculated as follows:

$$Bid - Ask\ Spread(\%) = \frac{BidPrice - AskPrice}{BidPrice} \cdot 100 \tag{2.1}$$

For example, we analyze the bid-ask differential for the GO NHY 18, which varies in the considered time period from 2.67% recorded in August 2017 to 0.63% at the end of the period (on average 1.27%) and which shows a downward trend, which, however, is not linked to an increase in the traded volumes (Figure 2.2), as one might expect instead.

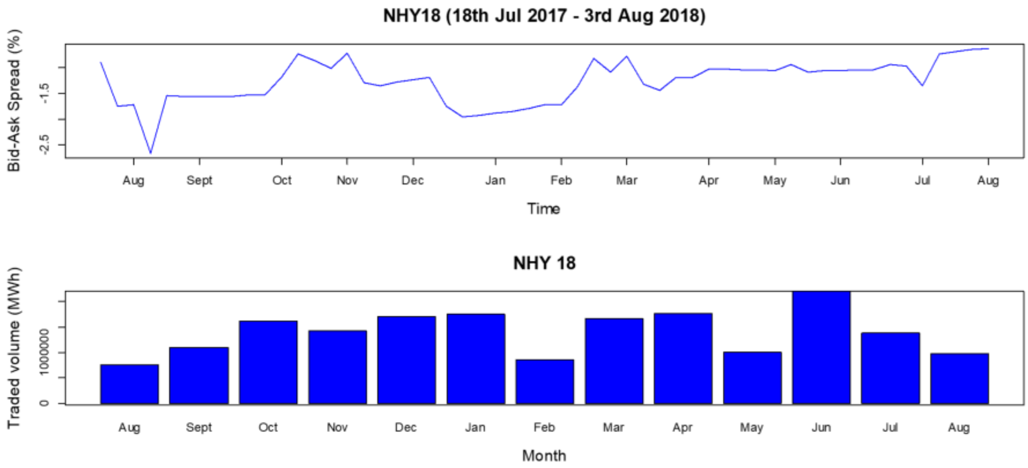


FIGURE 2.2: Comparison between Bid-Ask Spread and monthly traded volumes of the NHY18 GO

Compared to other commodity markets and the current EUA market, therefore, the spreads of the GO market are considerably greater, being on average between 1.27% and 2.5%. Consider, for example, that in 2017, the gold market had an average spread of 0.17% and the EUA market of 0.20% (Marcu et al., 2018). However, the average bid-ask spreads of the GOs are quite in line with what the EUA presented in 2006, equal to around 1.21% (Brouwers, 2006), when the time series available was only one year, just like that of GOs today. One reason why the overall spread is so high could be related to the fact that GO trading takes place outside of any Exchange (i.e. OTC). What emerges from this analysis is an illiquid GO market and the volatility associated with GOs has proven to be higher than that of other commodities, such as gold, wheat and cotton (Tiotto, 2017). From the comparison between market liquidity, represented as Bid-Ask spread, and the volatility of a GO, this correlation may partly emerge. In fact, where the variance has very low or very high values (which happens in November 2017 and in July 2018; red points in Figure 2.3), the Bid-Ask spread also assumes the minimum and maximum values respectively. However, the correspondence between liquidity and market volatility is not perfect: at the beginning of May (green points in Figure 2.3), for example, against a Bid-Ask spread, which has remained constant since the beginning of April, there is a variance, which increases considerably.
At present and from the analysis conducted with the available time series available, it is very difficult to make reliable considerations about the liquidity risk associated with the GO market, because it is an emerging market, which has started to be significant in terms of traded volumes only since the summer of 2018.

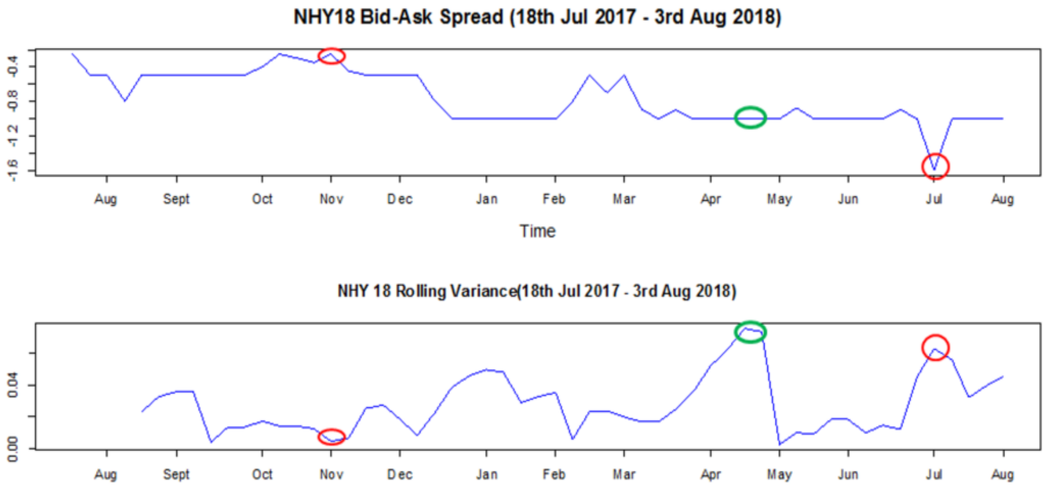


FIGURE 2.3: Comparison between variance and liquidity of the NHY18 GO

2.3 Advanced Monte Carlo methods for Market Risk management

In addition to the methods described in the previous paragraph, it is possible to calculate Value-at-risk through the Monte Carlo method. This methodology allows for greater design flexibility and provides the opportunity to take into account prospective financial data, if any (Huynh, Lai, and Soumare, 2008). The basic designed stochastic integration engine interprets the traditional dynamics of financial asset pricing:

$$dS_t = a(S,t)dt + b(S,t)dW_t \tag{2.2}$$

Setting $a(S,t) = \mu S_t$ and $b(S,t) = \sigma S_t$, we get the traditional Geometric Brownian motion:

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2.3}$$

where:

- μ is the slope of the stochastic process, which, in the case of GOs, can be set equal to the historical trend or equal to the risk-free rate or, in the most prudent valuation, set to zero.
- σ is the volatility and, in function of the available market data, it can be the historical volatility, GARCH, implied or modelized using the SABR (Stochastic Alpha Beta Rho) framework.
- dW_t is the Wiener stochastic process.
- S_t is the spot price at time t.

According to the stochastic calculus theory, Eq. 2.3 can be integrated:

$$S + dS = S \cdot \exp\left[\left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dW_t\right] \tag{2.4}$$

Eq. 2.4 can be discretized and implemented in R software:

$$S + \Delta S = S \cdot \exp\left[\left(\mu - \frac{1}{2}\sigma^2\right)\Delta t + \sigma \epsilon_t \sqrt{\Delta t}\right] \tag{2.5}$$

where ϵ_t is the random extraction from a $NID(0, 1)$.

Starting from Eq. 2.5, we extend the process in the case of multiple assets constituting the portfolio through the Cholesky decomposition, which allows to take into consideration the correlation between the assets.

Let ε and α $1 \times N$ be column vectors, with N the number of the considered GO, then $\alpha = M\varepsilon$, where M is a inferior triangular matrix $N \times N$ such that $MM^\top = R$ with $M^\top$ transposed matrix of M and R the positive-defined correlation matrix of the assets in the portfolio (Giribone and Ligato, 2011).

The estimated $\alpha_{i,t}$ can be used for the simulation of the $i - th$ asset, according to:

$$S_i + \Delta S_i = S_i \cdot \exp\left[\left(\mu_i - \frac{1}{2}\sigma_i^2\right)\Delta t + \sigma_i \alpha_{i,t} \sqrt{\Delta t}\right] \tag{2.6}$$

This simulation engine is able to generate prospective price levels, in accordance with financial best practice, and, consequently, the returns for a generic time t. Once the distribution of returns at the desired time has been generated (typically one day, one week and one month), the same estimation routines for VaR and ES can be used. The advantage of implementing a Monte Carlo approach compared to the traditional historical one is that the former, thanks to its design flexibility, allows to estimate the VaR and the ES by using all known prospective market information, consequently generating simulated yields in a more coherent way with the future financial expectations. Having defined the main simulation framework, the next paragraphs focus on choosing the parameter that represents volatility of the stochastic differential equation (σ). Typically, if there are no reliable market data available, a historical approach is used based on the standard deviation of the logarithms of past performances. This approach is formally described in paragraph 2.3.1, which contains the formulas for estimating the standard deviation based on the past market prices available for the GO (close prices). A more advanced and statistically more reliable historical approach is to model σ through a volatility term structure obtained from a GARCH(1,1). After briefly describing the null hypothesis tests conducted for the presence of heteroscedasticity effects, Section 2.3.2 focuses on how to estimate the model parameters using the maximum-likelihood principle together with the concepts of the Response Surface Methodology (RSM) theory. If the analyst has reliable market information regarding options premiums, he could replace the historical volatility estimate with the implicit market one. Section 2.3.4 describes the more traditional method used by traders to derive σ, which consists in the use of a solver in order to numerically reverse the Black-Scholes-Merton pricing formula. A further refinement of this last approach, particularly suitable for forward contracts, can be considered the SABR model discussed in paragraph 2.3.5. It allows to take into account the volatility smiles observed on the market, that is, it allows to consider how volatility varies, for a fixed tenor, as the exercise price of the option varies. Although the SABR model provides a more truthful and complete estimate of σ, it requires many options market premiums, which are hardly available on the GO market. Section 2.3.3 describes a variant for the traditional Monte Carlo dynamics:

the stochastic differential equation implemented in this case is a Ornstein-Uhlenbeck process. Thanks to this model, the mean-reversion effect, typical phenomenon observed for many commodities, can be taken into account. The code allows, first, the verification of this feature using a statistical null-hypothesis significance test and then the estimation of the dynamics parameters, in accordance with the maximum likelihood principle. Therefore, the numerical integration engine allows to simulate the returns, inputs for the estimation of VaR and ES measures.

2.3.1 Monte Carlo VaR using historical volatility

In the literature there are different ways of calculating volatility, starting from the prices variations in a historical financial time-series (historical volatility). Based on the available financial data, volatility can be estimated using one of the following approaches (Haug, 2007):

Close-to-Close Volatility

$$\sigma_{HIST} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} \ln\left(\frac{Close_i}{Close_{i-1}}\right)^2 - \frac{1}{N(N-1)}\left[\sum_{i=1}^{N} \ln\left(\frac{Close_i}{Close_{i-1}}\right)\right]^2} \tag{2.7}$$

High-Low Volatility proposed by Parkinson (1980)

$$\sigma_{HIST} = \frac{1}{2N\sqrt{\ln(2)}}\sum_{i=1}^{N+1} \ln\left(\frac{High_i}{Low_i}\right) \tag{2.8}$$

High-Low-Close Volatility proposed by Garman and Klass (1980)

$$\sigma_{HIST} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\left[\ln\left(\frac{High_i}{Low_i}\right)\right]^2 - \frac{1}{N}\sum_{i=1}^{N}\left[2\ln(2)-1\right]\cdot\left[\ln\left(\frac{Close_i}{Close_{i-1}}\right)\right]^2} \tag{2.9}$$

where:

- $Close_i$: close price of the asset in the time window i
- $High_i$: highest price of the asset in the time window i
- Low_i: lowest price of the asset in the time window i

For the majority of GOs, the lack of data in the time series led to the use of the Close-to-Close methodology.

2.3.2 Monte Carlo VaR using GARCH volatility

In order to understand if the hypothesis of the constant variance was too strong in the implemented Monte Carlo framework, we carried out statistical hypothesis tests on different time lags (Ljung-Box and ARCH LM Test). Some historical time series of the guarantees of origin certifications have shown heteroscedasticity effects mainly concentrated on the first lag. For this reason, it was decided to implement a GARCH(1,1) model in the risk management system (Engle, 1982). In a GARCH process of order (p, q), the conditional variance depends on its most recent p values, on a long-term average volatility rate and on the square of the last q past returns. Mathematically:

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^{q} \alpha_i u_{n-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{n-j}^2 \tag{2.10}$$

where:

- σ_n^2: variance at time n
- γ: weight for the long-term volatility
- V_L: Long-run average variance
- α_i: weight for the $i - th$ past yield
- u_{n-i}^2: square of the last $n - i$ logarithmic yield
- β_j: weight for the $j - th$ past estimation of the conditional variance
- σ_{n-j}^2: Last $n - j$ conditional variance values

Hence, the equation, which represents the conditional variance according to a GARCH of order (1,1) is:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{2.11}$$

Starting from Equation 2.11, using the Maximum Likelihood (ML) method, we are able to estimate ω,α, β and $\gamma = 1 - \alpha - \beta$. In fact, OLS (Ordinary Least Squares) estimates cannot be used, because their asymptotic properties are based on the hypothesis of homoscedasticity. In particular, by setting $\nu_i = \sigma_i^2$ the estimated variance for day i and assuming that the probability distribution of u_i conditioned by the variance is normal, the maximum likelihood function to be maximized with respect to the three free parameters of the model is Hull, 2018:

$$\mathcal{L} = \prod_{i=1}^{m} \frac{1}{\sqrt{2\pi\nu_i}} \exp\left(-\frac{u_i^2}{2\nu_i}\right) \tag{2.12}$$

where u_i is the $i - th$ logarithmic yield.

Applying the natural logarithm, Equation 2.12 becomes the following target function which is characterized by the same point of maximum:

$$\ln(\mathcal{L}) = \sum_{i=1}^{m} \left[-\ln(\nu_i) - \frac{u_i^2}{\nu_i} \right] = \sum_{i=1}^{m} \ln(\mathcal{L}_i) \tag{2.13}$$

where $\mathcal{L}_i$ is the log-likelihood related to the $i - th$ day.

Maximize Eq. 2.13 is an optimization problem in three independent variables, under the constraints that ω, α and β are positive and the process is stationary ($\alpha + \beta < 1$). In the case of GOs, having short historical time series with many constant data, some shrewdness have been coded, in order to make the solver more robust. First of all, we have adopted the so-called variance targeting which consists in fixing the long-term average variance V_L equal to the sample variance of the considered GO and therefore setting $\omega = V_L \cdot (1 - \alpha - \beta)$. In this way we decrease the dimension of the problem: only α and β have to be estimated. After eliminating a dimension from the numerical maximization problem and correctly setting the constraints that guarantee the existence of a real value for $\mathcal{L}_i$, we found the technical problem that the solution provided by the solver was highly dependent on the initial guess of the optimizing routine (Giribone, 2018). In most cases, Design of Experiment (DOE) techniques had to be used, such as the Response Surface Methodology (RSM), in order to choose a reasonable starting point of the algorithm for subsequent iterations (Bendato et al., 2015). Once the parameters were estimated, a residual normality test, $\epsilon_i = u_i/\sigma_i$, was implemented, which confirmed that the variance was modeled correctly (Tsay, 2010). The volatility term structure, directly implementable in the Monte Carlo engine, can be estimated from the relation:

$$\sigma_{GARCH}(T) = \sqrt{252\left(V_L + \frac{1-\exp\left(-aT\right)}{aT}\right)\left[V(0) - V_L\right]} \tag{2.14}$$

where:

- V_L is set equal to the sample variance
- $V(0)$ is the estimated variance using a GARCH(1,1)
- $a = \ln\left(\frac{1}{\alpha+\beta}\right)$
- 252 are the trading days in a year

2.3.3 Monte Carlo VaR with mean reversion

Both Academics and Professionals often recognized the so-called mean-reverting phenomenon in the dynamics associated with commodities (Lutz, 2010). Experimentally, observing the past time series of the traditional commodities, we are able to detect this kind of behaviour (Chaiyapo and Phewchean, 2017). As for the new GO market, this effect is, in certain cases, confirmed, even though, as it is not yet a mature market and therefore does not allow for robust econometric analyzes or empirical checks, it was possible to confirm it using only some statistical tests with null hypotheses on the time series of the spot values of some Guarantees of Origin (Zivot and Wang, 2006). Therefore, if there is a positive response from the statistical test, a mean reverting Monte Carlo VaR is also computed in the integrated risk management system. The implemented stochastic differential equation is an Ornstein-Uhlenbeck process (also called, with particular reference to interest rates, Vasicek model). Its mathematical representation is:

$$dS_t = \Theta\left(\mu - S_t\right)dt + \sigma dW_t \tag{2.15}$$

where:

- Θ is the mean reversion speed
- μ is the long term average
- σ is the volatility

- dt is the time interval
- dW_t is a Wiener process

Before performing the numerical integration, the routine estimates the parameters through the maximum likelihood method - MLE (Brigo and Mercurio, 2006).

The maximum likelihood function, $\mathcal{L}(\mu, \theta, \sigma)$, is defined:

$$\mathcal{L}(\mu, \theta, \sigma) = -\frac{n}{2}\ln(2\pi) - n\ln(\sigma) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\left[S_i - S_{i-1}\exp(-\Theta\delta)\right]^2 \tag{2.16}$$

By resetting the First Order Conditions (FOC), the stationarity points, which maximize the function, are found:

$$\begin{gathered}\begin{cases}\frac{\partial\mathcal{L}(\mu,\Theta,\sigma)}{\partial\mu} = 0\\ \frac{\partial\mathcal{L}(\mu,\Theta,\sigma)}{\partial\Theta} = 0\\ \frac{\partial\mathcal{L}(\mu,\Theta,\sigma)}{\partial\sigma} = 0\end{cases}\\ \downarrow\\ \begin{cases}\mu = \frac{S_y S_{xx} - S_x S_{xy}}{n\left(S_{xx} - S_{xy}\right) - \left(S_x^2 - S_x S_y\right)}\\ \Theta = -\frac{1}{\delta}\ln\left(\frac{S_{xy} - \mu S_x - \mu S_y + n\mu^2}{S_{xx} - 2\mu S_x + n\mu^2}\right)\\ \sigma^2 = \sqrt{\left(\hat{\delta}\frac{2\Theta}{1-\alpha^2}\right)}\end{cases}\end{gathered} \tag{2.17}$$

where:

$\hat{\sigma}^2 = \frac{1}{n}\left[S_{yy} - 2\alpha S_{xy} + \alpha^2 S_{xx} - 2\mu(1-\alpha)\left(S_y - \alpha S_x\right) + n\mu^2(1-\alpha)^2\right], \alpha = \exp(-\Theta\delta)$, $S_x = \sum_{i=1}^{n} S_{i-1}$, $S_y = \sum_{i=1}^{n} S_i$, $S_{xx} = \sum_{i=1}^{n} S_{i-1}^2$ $S_{xy} = \sum_{i=1}^{n} S_{i-1}S_i$, $S_{yy} = \sum_{i=1}^{n} S_i^2$ and δ is the sampling frequency of the spot level.

2.3.4 Monte Carlo VaR with implied volatility

If you have available listed options on Guarantees of Origin, it is reasonable, in order to provide with a more forward-looking simulation, to use the implied volatility, σ_{IMPL}. This measure is estimated by numerically inverting the Black-Scholes closed formula (Haug, 2007).

$$c = S\exp(-qT)\mathcal{N}(d_1) - X\exp(-rT)\mathcal{N}(d_2) \tag{2.18}$$

with:

$$d_1 = \frac{\ln(S/X) + \left(r - q + \sigma^2/2\right)T}{\sigma\sqrt{T}} \text{ and } d_2 = d_1 - \sigma\sqrt{T}$$

For illustrative purposes, an estimation of σ_{IMPL} is proposed starting from the volatility market surface of the ETF (Exchange-Traded Fund) Invesco Solar (Figure 2.4), an asset that has shown a positive correlation with certain GOs considered of interest.

Using the following market data (28th September 2018), Source: Bloomberg:

- S (spot price): 20.70 USD
- X (strike price): 20.57 USD
- T (time to maturity): 0.0583 years
- r (risk free): 2.259%
- q (dividend yield): 0%
- Option Value: 0.5725 USD

Starting from the formula 2.18, we get an implied volatility value of 28.04%. Once this measure is obtained, it can be plugged in the Monte Carlo framework, obtaining an MC VaR and an MC ES in accordance with the market view of highly-correlated assets.

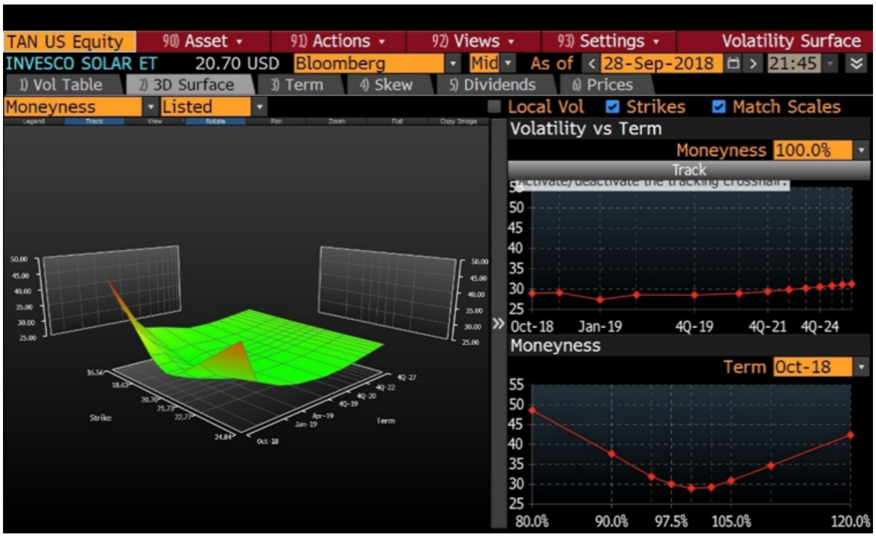


FIGURE 2.4: ETF Implied volatility surface. Source: Bloomberg

2.3.5 Monte Carlo VaR with SABR approach

On the GO markets, a spot contract relates to the production of energy that took place both during the previous and the current year, while a forward contract concerns the production of energy, which will take place in the future. The Stochastic Alpha Beta Rho (SABR) model is a Monte Carlo simulation methodology designed for forward contracts. It implements the following dynamics:

$$\begin{cases} dF = \alpha F^{\beta} dz \\ d\alpha = \nu \alpha dw \end{cases}$$

in which the two processes are correlated, according to:

$$dzdw = \rho dt \tag{2.19}$$

where:

- F is the value of the forward
- α is the volatility of the forward price
- ν is the volatility of volatility
- β is the constant, which influences the distribution of the asset price
- dz and dw are two correlated Wiener processes

Under these assumptions regarding the future evolution of the forward price, F, in accordance with Hagan's studies (Hagan et al., 2002), it is possible to plug in the Monte Carlo VaR simulation engine, σ_B able to take into account the market volatility smile:

$$\sigma_B = \frac{\alpha}{(FX)^{\frac{(1-\beta)}{2}}\left(1+\frac{(1-\beta)^2}{24}\ln\left(\frac{F}{X}\right)^2+\frac{(1-\beta)^4}{1920}\ln\left(\frac{F}{X}\right)^4\right)}\frac{z}{\chi(z)}\cdot \tag{2.20}$$

$$\cdot\left[1+\left(\frac{(1-\beta)^2}{24}\frac{\alpha^2}{(FX)^{1-\beta}}+\frac{1}{4}\frac{\rho\beta\nu\alpha}{(FX)^{\frac{1-\beta}{2}}}+\frac{2-3\rho^2}{24}\nu^2\right)\right]T$$

with:

$z = \frac{\nu}{\alpha}(FX)^{\frac{(1-\beta)}{2}}\ln\left(\frac{F}{X}\right)$ and $\chi(z) = \ln\left(\frac{\sqrt{1-2\rho z+z^2}+z-\rho}{1-\rho}\right)$

Most of the Go markets are not so complete thus have no reliable option prices. But if more data can be retrieved from different contributors for various maturities and strike prices, this model can be implemented for using all the available information. For illustrative purposes, the estimation of σ_B is proposed starting from the volatility smile of the Invesco Solar ETF, an asset that has shown a good correlation with certain GOs.

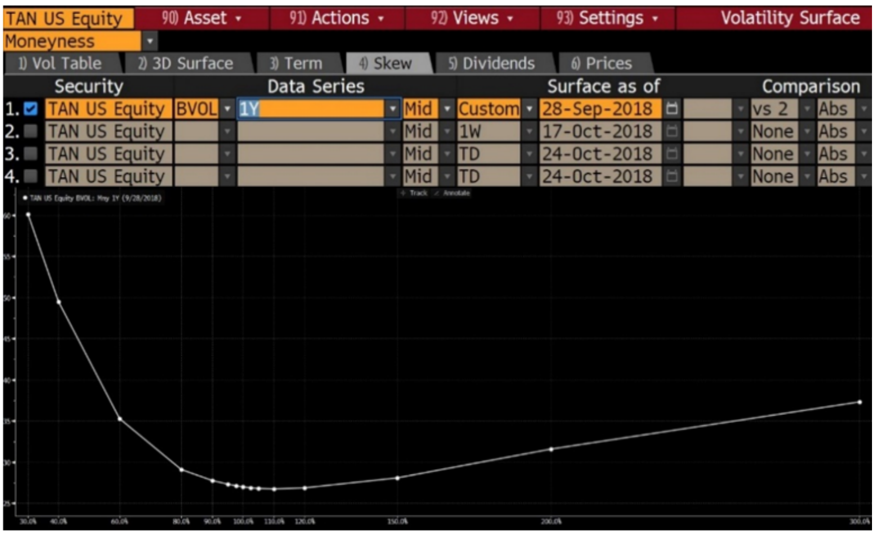


FIGURE 2.5: ETF Implied volatility skew. section for $T = 1$. Source: Bloomberg

Table 2.1 shows the calibration with the market data of the parameters of the SABR, α, β, ρ and ν, and the volatility adjusted for the market smile. This value can be directly used in the Monte Carlo engine for the estimate of the Var of a forward contract with an underlying Guarantee of Origin.

α	β [bps]	ρ	ν	σ_B
5.32	0.143	0.215	0.774	25.7%

TABLE 2.1: SABR parameter estimation and the adjusted smile volatility

2.4 Counterparty Risk

In this paragraph we deal with the counterparty risk. In particular, three different methodologies were implemented according to the available market data and information. The most reliable approach is the one presented in paragraph 2.4.1, since it allows the counterparty probability of default (PD) to be estimated based on the CDS (Credit Default Swap) premiums. The reliability of the method is attributable to the fact that, being a strongly market-based approach, the information related to the credit quality of the issuer is instantly reflected in the CDS quotation and, consequently, in the PD estimation. The second method, described in paragraph 2.4.2, is based on the calculation of the probability of default starting from the calculation of the implicit spread (Z-spread) in the listed bonds of the counterparty. This approach is also to be considered market-oriented, but, if the counterparty has listed CDS, the inference of the PD using the latter method is normally preferable, since the implicit spread obtained from the market price could depend on factors not directly attributable to pure counterparty risk (such as, for example, the illiquidity of the instrument). If there is no market information, you can always, in the last resort, use financial statements information. Section 2.4.3 describes how the probabilistic model of Kealhofer, Merton and Vasicek (KMV model) can be used to estimate the one-year probability of default for a generic counterparty.

2.4.1 Counterparties with listed CDS

If the counterparty has listed Credit Default Swaps (CDS) on active markets, from the premiums (S), typically expressed in basis points, the probability of default can be calculated, according to (Hull, 2018):

$$PD = 1 - \exp\left(-\lambda T\right) \tag{2.21}$$

where:

- $\lambda = \frac{S}{1-RR}$ is the hazard rate
- T is the time to maturity, expressed in years
- RR is the recovery rate, usually $RR = 40\%$
- S is the spread

As an example, Figure 2.6 shows the probability of insolvency, estimated for a company operating in the GO sector starting from the CDS actively traded on the market at the end of September 2018.

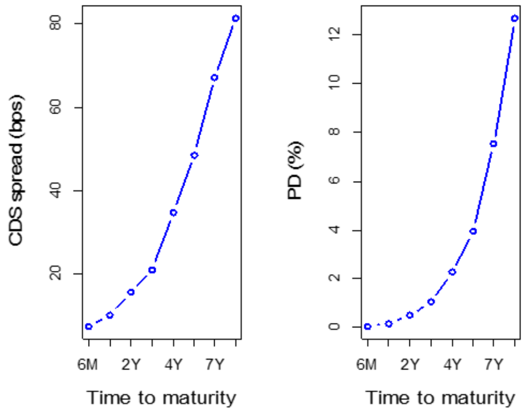


FIGURE 2.6: PD estimated using CDS premium

2.4.2 Counterparties with listed bonds

In the case that the counterparty has listed or actively traded bonds on the secondary market, the implicit Z-spread can be estimated as issuer's risk proxy (Hull, 2018). In the case of the developed risk management system, the term structure of the probability of default for a well-known counterparty operating in the GO sector was estimated (Figure 2.7).

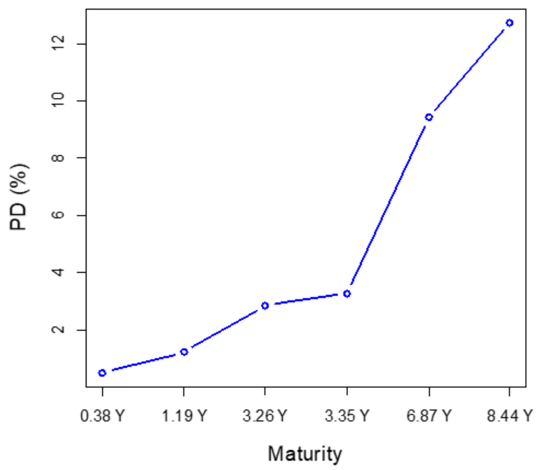


FIGURE 2.7: PD estimated using traded bonds

2.4.3 KMV model

If no financial data are available, the one-year probability of default can be obtained from the balance sheet data analysis, using the model proposed by Kealhofer, Merton and Vasicek (Tetereva, 2015 and Zielinski, 2013). Based on this approach, a company's own resources (V_E) can be seen as a call option on the value of the company's assets (V_A). The value of the equity at maturity $V_E(T)$ can be seen as the payoff of a long position on a call option:

$$V_E(T) = \max\left[0; V_A(T) - D\right] \tag{2.22}$$

where the debt, D, is considered as the strike price of the European option.

It is assumed that the asset value, V_A, evolves according to a Geometric Brownian motion:

$$dV_A = \mu_A V_A dt + \sigma_A V_A dW_t \tag{2.23}$$

where:

- μ_A is the drift of the Stochastic Differential Equation, generally and prudentially set equal to the risk free rate (r).
- σ_A is the annualized volatility of the underlying
- dW_t is the Wiener stochastic process

The following nonlinear system must be solved using a numerical procedure like the Newton-Raphson routine in order to obtain the estimation for $V_A(t)$ and σ_A:

$$\begin{cases} V_E(t) = V_A(t)\varphi\left(d_1\right) - D\exp\left[-r\left(T-t\right)\right]\varphi\left(d_2\right) \\ \sigma_E = \frac{V_A}{V_E}\frac{\partial V_E}{\partial V_A}\sigma_A \end{cases}$$

$$d_1 = \frac{\ln\left(\frac{V_A(t)}{D}\right) + \left(r - \frac{1}{2}\sigma_A^2\right)\left(T-t\right)}{\sigma_A\sqrt{T-t}}, d_2 = d_1 - \sigma_A\sqrt{T-t} \tag{2.24}$$

where:

- $\varphi\left(\circ\right)$ cumulative normal distribution function of a standardized variable
- r is the risk-free rate
- t is the valuation time
- T is the time to maturity
- σ_E is the annualized volatility of the Equity

Once V_A and σ_A have been obtained, it is possible to calculate the distance to default (DD) and consequently the PD:

$$DD(t) = d_1 = \frac{\ln\left(\frac{V_A(t)}{D}\right) + \left(r - \frac{1}{2}\sigma_A^2\right)\left(T-t\right)}{\sigma_A\sqrt{T-t}} \tag{2.25}$$

$$PD(t) = P\left[V_A \leq D\right] = 1 - \varphi\left(DD\right) = \varphi\left(-DD\right) \tag{2.26}$$

As an example, this approach was followed for the estimate of the probability of insolvency of a Norwegian company operating in the GO sector, as shown in Table 2.2.

V_E	σ_E	D [NOK]	r	$V_A[NOK]$	σ_A	PD
992252 MM	38%	71075 MM	1.22%	162478.9 MM	21.51%	0.75%

TABLE 2.2: PD estimation using KMV model. Statement: 31th December 2017

2.5 Validation

Quantitative methodologies for handling financial and counterparty risks have been described in the previous paragraphs. In addition to the working principles, techniques aimed at optimal tuning of the model parameters with reference to a specific scenario were addressed and numerical examples were provided where it was possible to disclose the data. The next step, in order to empirically validate the control system, was to conduct quality tests, to assess the degree of reliability of the designed measurement system. For this purpose, a new sample of quotes was used (sample 2), for a period of three months following that relating to the initial analysis. This new data set was useful to verify whether the analyzes conducted on the first price sample, treated in paragraph 2.3 and related to the four categories of GO in the time period, which runs from 18th July 2017 to 3rd August 2018 (sample 1), were confirmed. The statistical characteristics of the two samples are summarized in Tables 2.3 and 2.4.

GO	Mean(Sample 1)	Mean(Sample 2)	Std(Sample 1)	Std(Sample 2)
NHY18	0.0323	0.0322	0.0408	0.0405
NHY19	0.0329	0.0337	0.0407	0.0430
NHY20	0.0327	0.0325	0.0394	0.0387
EWD18	0.0301	0.0319	0.0475	0.0456
EWD19	0.0296	0.0317	0.047	0.046
EWD20	0.0279	0.0295	0.0511	0.0492
EUB18	0.0337	0.0343	0.0524	0.0503
EUB19	0.0335	0.0343	0.0447	0.0432
EUB20	0.0330	0.0338	0.0441	0.0424

TABLE 2.3: First and Second Moments of the time series

GO	Skewness(1)	Skewness(2)	Kurtosis(1)	Kurtosis(2)
NHY18	1.1271	1.0114	0.4914	0.3174
NHY19	1.1048	0.9993	0.3119	0.0782
NHY20	1.0084	0.9761	0.3061	0.2411
EWD18	0.6433	0.5746	-0.0572	0.0182
EWD19	1.6244	1.4894	3.1641	2.8154
EWD20	1.9413	1.8701	5.4605	5.5038
EUB18	0.8265	0.7850	0.0306	0.1353
EUB19	1.3943	1.3668	1.2794	1.3022
EUB20	1.4275	1.3866	1.4308	1.5300

TABLE 2.4: Third and Fourth Moments of the time series

As regards the liquidity risk, measured by (Eq. 2.1), the Bid-Ask spread values continue to settle also for the new verification sample around 2%. This result is perfectly aligned with the inferential analysis presented in the previous paragraphs: the oscillation, considered normal for these kind of assets, was, in fact, included in the 1.27% - 2.5% interval.

As regards the reliability of the results for the market risk indicators, the following statistical test was carried out, conducted for the traditional methodologies presented (historical and parametric VaR), and, if it would have been possible to find reliable market data, for advanced Monte Carlo data, based on historical price series (paragraphs: 2.3.1 - 2.3.2 - 2.3.3). In order to perform a statistical check on the reliability of the results provided by the analysis, the following test procedure has been defined. Let X_t a dummy variable such as:

$$X_t = \begin{cases} 1 \text{ if } R_t < Var_t \\ 0 \text{ otherwise} \end{cases}$$

where R_t is the logarithmic return at time t.

If the VaR at the confidence level α actually represents the quantile α of the yield distribution, then the random variable X_t assumes the value 1 with probability α and the value 0 with probability $1 - \alpha$, i.e. it is distributed as a Bernoulli distribution with parameter α:

$$X_t \approx Bern(\alpha) \tag{2.27}$$

Knowing that the sum of M Bernoulli variables of parameter α, independent from one another, follows the binomial distribution, we arrive at:

$$Y_t = \sum_{m=1}^{M} X_t \approx Bin\left(M, \alpha\right) \tag{2.28}$$

where M and α are the binomial distribution parameters.

The expected number of outliers, so that the methodology can be considered statistically robust, depends on the number of times the condition $R_t < VaR_t$ occurs and is therefore equal to:

$$E\left(Y_t\right) = T\alpha \tag{2.29}$$

Performing the test at a $1 - \alpha = 95\%$ confidence level and considering the cardinality of the additional test sample, we get $E(Y_t) = 1.7$, while at a confidence level $1 - \alpha = 99\%$, we get $E(Y_t) = 0.34$. Practically, this means that the number of times in which the realized return exceeds the estimated VaR must be less than $E(Y_t)$. This verification, conducted for all the methodologies, led to satisfying results: only in two cases and for a GO with an $\alpha = 0.05$ the occurrence was such that $R_t < VaR_t$ occured, remaining however below the threshold of $E(Y_t) = 1.7$. As regards the VaR calculation engines, which employ a forward-looking Monte Carlo approach (paragraphs: 2.3.4 - 2.3.5), a validation was also carried out using the OV (Option Valuation) Bloomberg pricing module. Moreover with regard to counterparty risk, the results of the implemented models were verified, comparing them with the Bloomberg DRSK (Default Risk)and YAS (Yield and Spread Analysis) modules. In particular, as regards the probabilities of default (PD) implied by the CDS (Figure 2.6), the results were replicated, obtaining an average error on the single PD less than 3 basis points. The average error approaches 10 basis points, if the method for the probability of default estimation from bond prices is used (Figure 2.7). This observed widening of the error, albeit limited, can be justified by the greater number of parameters of the valuation model: interest rate term structure specification (tenor), compounding rates convention, illiquidity spread, fixed income seniority ... When it comes to the validation of the KMV model, it was considered reasonable to replicate the indicators in Table 2.2, using the Bloomberg DRSK module. For this type of model, the validation of the results is rather easy, as the graphical user interface allows the user to enter directly the input parameters used to synthesize the PD. For this reason the computed outputs are perfectly coincident.

Chapter 3

Electricity Spot Price Forecasting using Deep Learning

"Stop attending the past, try to attend the future."

Antonio Tabucchi, *Pereira mantains*, Chapter: 20, 1994

"La smetta di frequentare il passato, cerchi di frequentare il futuro."

Antonio Tabucchi, *Sostiene Pereira*, Capitolo: 20, 1994

Lately, power markets in Europe, including the Spanish one called MIBEL (Mercado Ibérico de Electricidad), are being deregulated and coupled. As a result, electricity can be easily purchased and sold across further areas and countries. On the other hand, trying to guarantee renewable projects profitability, Power Purchase Agreements and Options contracts are arising as a feasible solution. The problem arises when the power plant owners have to negotiate the purchase of electricity price in order to optimize risks and profits, as well as make future plans. Thus, several methods for Electricity Price Forecasting (EPF) have been developed and presented, showing different results, as market spot prices suffer from strong seasonality, spikes and high volatility. In this study, three methods, based on Deep Learning Dynamic Neural Networks (NAR, NARX and LSTM) applied to forecast MIBEL electricity spot prices are discussed in order to evaluate their adequacy, accuracy and reliable horizon.

3.1 The Electricity price forecasting problem

The EPF problem has been faced widely by many authors in the literature. Existing techniques can be classified according to the forecasting horizon, the type of forecasting and the modelling approach. According to the forecasting horizon, although no consensus in the literature is found, short-term forecasting is usually referred to a few minutes up to few days ahead, medium-term forecasting goes from a few days to a few months ahead and long-term forecasting leads with several months, quarters or even years ahead (Weron, 2014). Forecasting can be evaluated as point forecasting or probabilistic forecasting. While the former is referred to just forecasting values of the time series for a given horizon, probabilistic forecasts try to provide prediction intervals and densities, i.e. intervals which contain the true values of future observations with a specified probability (Weron, 2014; Tahmasebifar, Sheikh-El-Eslami, and Kheirollahi, 2017). Moreover, both forecasting modes can be one-step ahead, when just the next value is forecasted, or multiple steps ahead, when a set of future values are forecasted simultaneously. Finally, the modelling approaches can differ significantly. If we consider individual modelling, we can classify existing methods into three main categories:

- Statistical models: which include econometric and reduced-form models. These models characterize the statistical properties of electricity prices over time and usually consider load forecasting or power market implementations of econometric models. This set of models include the moving average method (Hyndman and Athanasopoulos, 2019), naïve methods (Hyndman and Athanasopoulos, 2019; Ugurlu et al., 2018; Chhetri et al., 2018), regression models, decomposition models, exponential smoothing, ARIMA models, dynamic regression models, GARCH models or VAR models (Zhang, Tan, and Wei, 2020; Siddiqui, 2019;Karabiber and Xydis, 2019; Hubicka, Marcjasz, and Weron, 2019; Monica, Botero, and Jaime, 2018;Yang et al., 2020; Singh and Mohanty, 2015). They are based on statistical methods which can achieve great results but they are limited to model non-linearities.

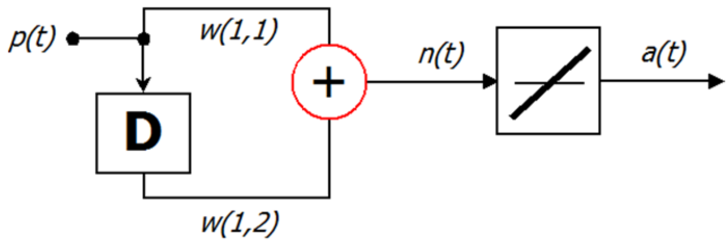
- Machine learning methods: based on artificial computation techniques, they refer to artificial neural networks (perceptron, recurrent, fuzzy, extreme learning or deep learning) and support vector machines. Although they have demonstrated high ability to model complex systems with non-linearities and show great flexibility, they are considered black-box models (system dynamics information is missed) and can suffer from overfitting to the training data (Zhang, Tan, and Wei, 2020; Siddiqui, 2019; Yang et al., 2020; Oksuz and Ugurlu, 2019; Ibrahim et al., 2019).

- Multi-agent methods: these models simulate the operation of a system of heterogeneous agents and the impacts of physical and economic factors by building the price-forming process. Multi-agent simulation, equilibrium, game theoretic and structural methods can be found in this set (Weron, 2014; Weron, 2006).

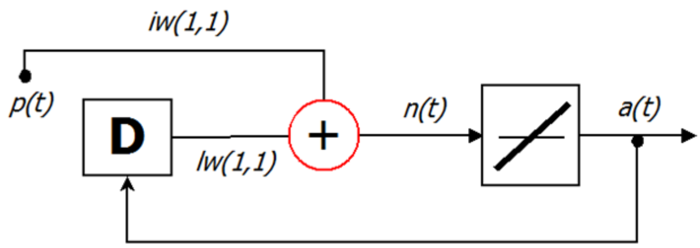
Due to the complex features of the electricity price time series, some authors focus their attention on the pre-treatment of the time series data by decomposition algorithms to detect seasonality and stochasticity (Zhang, Tan, and Wei, 2020; Yang et al., 2020; Qiao and Yang, 2020; Marcjasz, Uniejewski, and Weron, 2019a; Chang, Zhang, and Chen, 2019; Peng et al., 2018; Kim and Won, 2018). Thus, several hybrid models, where first the time series is decomposed and then each component is forecasted with specific methods (usually trend and seasonal components are forecasted by statistical models, while machine learning methods are applied for the stochastic behaviour) have been developed. For the time series decomposition, wavelet transformations (Qiao and Yang, 2020; Chang, Zhang, and Chen, 2019; Capizzi et al., 2018) or variational mode decomposition (VMD) [14], [21] are generally proposed. Moreover, these hybrid methods are complemented with optimization algorithms, such as genetic algorithms (GA) or Particle Swarm Optimization (PSO) techniques to optimize their calibration or their input features selection. Properly configured, hybrid models show impressive accuracy in its results, but, on the other hand, they suffer from extreme sophistication, complexity and high sensitivity to the models' configuration.

3.2 Architecture of the models

In contrast to static neural networks, dynamic neural networks are characterized by the presence of feedback or delay. Consequently, outputs at time t do not depend only on inputs, but also on outputs and state variables related to previous instants. Therefore, the dynamics are characterized by different memory levels and so neural networks, which can be trained with time dependent data, are suitable to be used as forecasting tools (Giribone, 2018).
Dynamic neural networks can be classified into two categories: feed-forward and recurrent (Rojas, 1996). Referring to single-layer neural networks with single-neuron, some considerations can be drawn. In the diagram depicted in Fig. 3.1 (a), related to a feed-forward dynamic neural network with single-delay, the output $a(t)$ depends only on inputs $p(t)$ and $p(t-1)$, whereas older inputs (such as $p(t-2)$, $p(t-3)$, etc.) do not have influence on the output, thus proving the network limited memory. On the contrary, in the case of a recurrent dynamic neural network, as the one shown in Fig. 3.1 (b), the presence of feedback connections enable the network memory to be theoretically unlimited. Indeed, the output $a(t)$ depends on both the input $p(t)$ and the previous output $a(t-1)$. Moreover, $a(t-1)$ depends in turn on both $p(t-1)$ and $a(t-2)$, and so on. In other words, moving backwards, it derives that the output $a(t)$ depends on all the input past values.



(a)



(b)

FIGURE 3.1: Feed-forward dynamic neural net with single-delay, single-layer and single-neuron (a), recurrent dynamic neural net with single-delay, single-layer and single-neuron (b)

A recurrent dynamic neural network is typically characterized by: a set of weight matrices (the number of which depends on the number of both network layers and delays) that can be associated with inputs or layers (IW and LW); a bias vector for each layer (b); a function combining inputs (or layer outputs) with biases, and usually expressed as a weighted sum for each neuron (adder block $\oplus$); a transfer function for each neuron (f); a variable number of delays, which can be applied to the inputs and/or the outputs of the layers. The outputs of Tapped Delayed Layers

(TDL) can be reintroduced into the network in other layers (Beale, Hagan, and Demuth, 2019).

3.2.1 Non-linear Autoregressive (NAR and NARX) Models

NAR dynamic neural networks are widely used for forecasting; they are able to predict future values of a time series through the past values of the same series. If the time series is called $y(t)$, it is possible to write: $y(t) = f(y(t-1), y(t-2), \ldots, y(t-n))$, where the regressors $y(t-1)$, $y(t-2)$,…, $y(t-n)$ are the past values of the time series [33].

A generalization of NAR models is represented by Non-linear Autoregressive Networks with eXogenous variables (NARX), which consider the time series $y(t)$ depending on its past values as well as on the past values of one or more exogenous covariates. It derives that $y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u))$, where $u(t)$ is the exogenous variable, whereas n_y and n_u indicate the number of delays respectively applied to inputs and outputs; both n_y and n_u, as well as the number of layers and neurons, can be changed during the training phase in order to have a coefficient of determination R^2 as close to 1 as possible. A very high value of R^2 indicates that the developed neural network model fits the time series reasonably well without showing error autocorrelation. Just as in static networks, the training phase is based on a gradient descent algorithm which calibrates the network parameters (IW, LW and b) in order to minimize a loss function (e.g. Sum of Squared Errors – SSE or Mean Squared Error – MSE) which measures the error (estimated outputs vs. training values) observed during the training (Jesus, Horn, and Hagan, 2001). In the present study, as shown in Fig. 3.2, a NARX network with two hidden layers has been implemented.

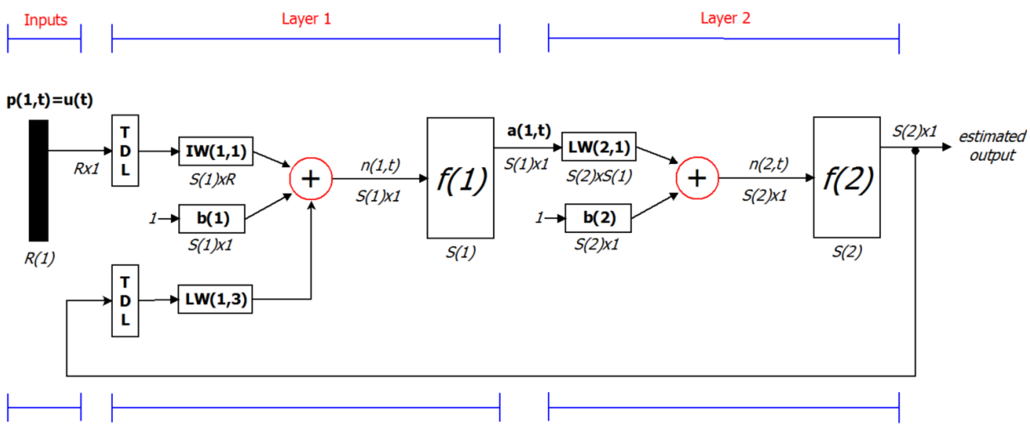


FIGURE 3.2: A two layer NARX network structure

3.2.2 Long Short-Term Memory Model (LSTM)

Long short-term memory (LSTM) networks are architectures able to learn long-term relationships between the time intervals of a time series, without therefore the need to pre-set the number of time lags, as occurs in NAR and NARX (Hochreiter and Schmidhuber, 1997). A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

Intuitively, the cell is responsible for keeping track of the dependencies between the elements in the input sequence. The input gate controls the extent to which a new value flows into the cell, the forget gate controls the extent to which a value remains in the cell and the output gate controls the extent to which the value in the cell is used to compute the output activation of the LSTM unit. The activation function of the LSTM gates is often the logistic sigmoid.
Figure 3.3 shows how the flux of a data sequence Y with C features (or channels) of length S has been processed into a LSTM layer (Beale, Hagan, and Demuth, 2019). In the block diagram, h_t and $c(t)$ are, respectively, the output (also known as hidden state) and the cell state at time t.

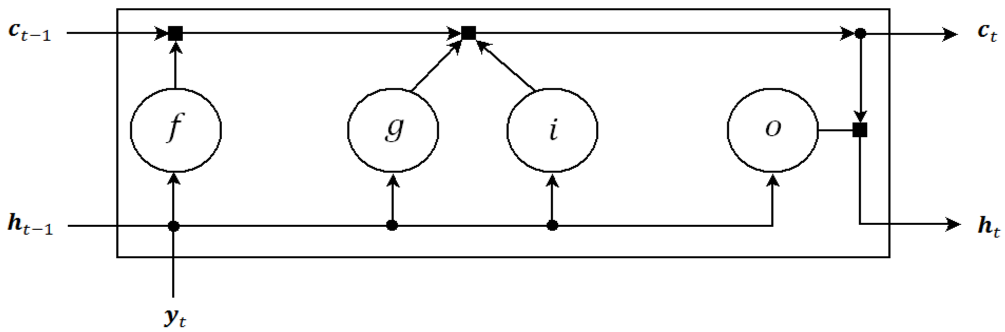


FIGURE 3.3

The first LSTM block uses the initial state of the network and the first time-step of the sequence in order to compute the first output and the first update of the cell state. At the time t, the block uses the current state of the network (c_{t-1}, h_{t-1}) and the next step of the sequence for estimating the output and updating the current state of the cell, c_t.
The layer state is characterized by the hidden state (also known as the output state) and the cell state. The hidden state at time step t contains the output of the LSTM layer for the current time step. The cell state contains the information learnt in the previous steps. For each time step, the layer adds or removes information from the cell state. The layer controls these updates using gates.
The following components control the cell state and the hidden state of the layer:

- Input gate (i): Control level of cell state update.
- Forget gate (f): Control level of cell state reset (forget).
- Cell candidate (g): Add information to cell state.
- Output gate (o): Control level of cell state added to hidden state.

Figure 3.4 shows how the gates (i, f, g, o) process the signal at time t.
In a LSTM, the parameters that are subjected to calibration are: the input weights (W), the recurrent weights (R) and the biases (b). W, R and b are the arrays built through the concatenations of such parameters for each component:

$$W = \begin{pmatrix} W_i \\ W_f \\ W_g \\ W_o \end{pmatrix} \quad R = \begin{pmatrix} R_i \\ R_f \\ R_g \\ R_o \end{pmatrix} \quad b = \begin{pmatrix} b_i \\ b_f \\ b_g \\ b_o \end{pmatrix} \tag{3.1}$$

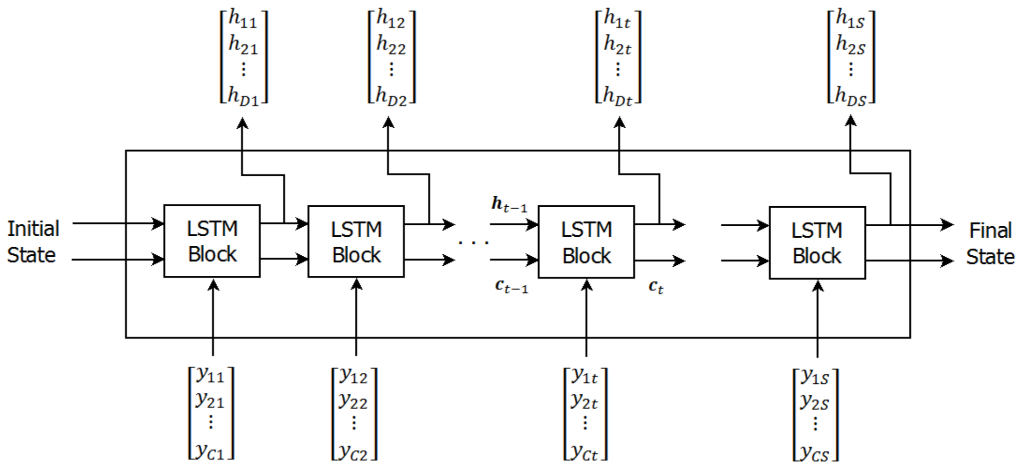


FIGURE 3.4: Cell structure in an LSTM network

where i, f, g and o denote the input gate, the forget gate, the cell candidate and the output gate, respectively.
At time step t, the cell state is given by:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{3.2}$$

where $\odot$ is the Hadamard product operator.
At time step t, the hidden state is given by:

$$h_t = o_t \odot \sigma_c (c_t) \tag{3.3}$$

where σ_c is the activation function of the state (typically a $\tanh(\circ)$).
The following equations define the components at the time step t:

- Input gate (i)
$$i_t = \sigma_g (W_i y_t + R_i h_{t-1} + b_i) \tag{3.4}$$
- Forget gate (f):
$$f_t = \sigma_g \left(W_f y_t + R_f h_{t-1} + b_f\right) \tag{3.5}$$
- Cell candidate (g):
$$g_t = \sigma_c \left(W_g y_t + R_g h_{t-1} + b_g\right) \tag{3.6}$$
- Output gate (o):
$$o_t = \sigma_g (W_o y_t + R_o h_{t-1} + b_o) \tag{3.7}$$

σ_g is the activation function of the gate, which is typically a sigmoid.

3.3 Case Study

3.3.1 Dataset Description

To verify the performance of the optimal tuned forecasting models, an electricity price dataset collected from the Spanish TSO, through its open data platform called e-SIOS, has been used. The dataset is composed of both the average hourly power demand for the Spanish area of the Iberian Peninsula and the final hourly electricity spot prices for the Spanish market. It must be highlighted that the considered spot price includes, not only the daily market price, but also the intra-day market corrections and deviations. The considered period for tuning the models goes from October 2017 to September 2018, both included. The time resolution of the dataset is 1 hour and the descriptive statistics of the dataset are shown in Table 3.1, while Fig. 3.5 reports the histograms of both power demand and prices.

Parameter	Power Demand [MWh]	Spot Price [Euro/MWh]
Number of samples	8784	8784
Maximum	40698.50	116.80
Minimum	18697.50	10.66
Median	29261.42	64.48
Mean	29138.48	62.62
St. dev.	4664.44	12.72

TABLE 3.1: Descriptive Statistics of the Dataset

The described dataset is randomly divided into a training set (70% of the data), a validation set (15% of the data) and a test set (remaining 15% of the data). In the training set, the optimization is carried out with respect to its loss function (MSE/RMSE) only. On the other hand, in order to avoid overfitting of the models, in the validation set, the weights that minimize the MSE on this set are saved and updated with respect to the MSE results of the training phase. Finally, the forecasted power demand used in the experiments is one-week with one-step ahead prediction, starting from 1st October 2018 and ending on 7th October 2018 (included). This means that 168 spot price values are forecasted. In the case of using the volume as exogenous values, one week ahead, daily updated, hourly power demand forecasts from the TSO have been used. As can be seen in Fig. 3.6, a strong correlation can be found.
Thus, in NARX and LSTM with exogenous variables, for spot price forecasting at time step $t+1$, the above mentioned power demand forecasting values are used, and then replaced by real power demand values for the next forecasting step.

3.4 Networks tuning and training procedures

In order to obtain valid models for forecasting purposes we have conducted statistical and econometric tests for the design of the dynamic neural networks. During the design of the network architectures, the number of layers, neurons on each layer and, in the case of NAR and NARX models, the number of lags, have been properly chosen by carrying out two in-sample tests:

- An optimal fitting of the time-series values ($R^2 \rightarrow 1$) avoiding over-fitting through statistical techniques applied on the dataset, including random sampling and training-validation-testing data partition.

- Checking absence of autocorrelation error so that the model error is unstructured and the predicted values can be econometrically reliable.

Thus, to calibrate the optimal number of hidden layers (or blocks in the case of LSTM models) and the optimal number of neurons per layer/block, several tests have been performed for each model considering as search space the range from 1 to 4 hidden layers and 1 to 100 neurons, respectively. Moreover, for NAR and NARX models, the optimal number of lags according to an autocorrelation analysis concluded that 48 lags optimize the forecasting results. The calibration results for each model can be seen in Table 3.2.

Parameter	NAR	NARX	LSTM 1 feat.	LSTM 2 feat.
Hidden layers or blocks (LSTM)	2	2	2	2
Neurons per each layer/block	25	25	75	73
Lags	48	48	N/A	N/A

TABLE 3.2: Calibration Parameters

Fig. 3.7 shows that the auto-correlation error for the tuned models (only LSTM-1 has been represented for brevity) has been kept, with a confidence interval equal to 95%, under an acceptable threshold (represented in red dotted lines). Thus, the validity of the models has been checked.

Results for the four tested models can be seen in Fig. 3.8, where it is possible to highlight a good statistical fitting for the complete evaluated period (1 year) for the four models. Moreover, Fig. 3.9 shows the in-sample results of the models' residuals against the realized prices, while Table 3.3 shows the main statistical indicators for the four models, considering the training set. It can be observed that, in the training phase, NAR and NARX models show higher homoscedasticity against the realized prices than the LSTM models, which show a marked biased heteroscedasticity. On the other hand, both LSTM models show better results for the statistical indicators, the most accurate being the LSTM-2 model, but with a very slight difference to the others.

Parameter	NAR	NARX	LSTM-1	LSTM-2
R-squared [-]	0.6745	0.6735	0.9785	0.9753
MAE [Eur/MWh]	10.18	10.24	10.10	10.09
MSE [Eur^2/MWh^2]	165.4	167.7	164.0	163.4
RMSE [Eur/MWh]	12.86	12.95	12.80	12.78

TABLE 3.3: In-sample performance result

3.5 Back-testing and Out-of-Sample Performance

Despite the significant efforts of some authors for providing a standard error benchmark, there is no consensus yet (Weron, 2006). In this case, models' performances have been evaluated through an out-of-sample testing methodology. Thus, we have compared the realized hourly prices with the obtained forecasted values taking the well-known MAPE (Mean Absolute Percentage Error) (Zhang, Tan, and Wei, 2020) as the performance indicator averaged through one week (168 values), which is the evaluation interval.

3.6 Forecasting

Fig. 3.10 plots NAR (green) and NARX (blue) forecasted prices versus the realized ones (red) for the prediction interval (1 week). It can be compared with Fig. 3.11, where results of the LSTM model without (purple) and with (orange) exogenous

variable are shown. At first sight, two main conclusions can be drawn: (i) LSTM models show general better accuracy than NAR/NARX models, and (ii) NARX models and LSTM-2 show better performance than their correspondent NAR and LSTM-1 models. Thus, the impact of accounting with the power demand as exogenous variable is highlighted.
Comparing LSTM results with the predictions of the NARX models, it can be observed that an endogenous, automatic and more flexible modeling of the lags leads to a significant improvement. Fig. 3.12 compares the dynamic MAPE results for the four models along the evaluation period. As expected, the MAPE increases as the forecasted period enlarges, showing the highest increment for the 12 steps ahead (hours) in the four cases. Then, the MAPE tends to stabilize over time.
Out-of-sample performance results are summarized in Table 3.4. Obtained results are in the same order of magnitude as those from other studies (Marcjasz, Uniejewski, and Weron, 2019b; Hubicka, Marcjasz, and Weron, 2019; Qiao and Yang, 2020; Marcjasz, Uniejewski, and Weron, 2019a; Chang, Zhang, and Chen, 2019; Peng et al., 2018; Kim and Won, 2018; Ugurlu, Oksuz, and Tas, 2018; Ruiz et al., 2016) (obviously they cannot be compared directly if they are not tested in the same market, the same out-of-sample period and using the same in-sample periods).

MAPE	NAR	NARX	LSTM-1	LSTM-2
Min. [%]	0.995	0.518	0.199	0.147
Max. [%]	5.438	4.012	2.256	1.857
Mean [%]	4.301	3.086	1.837	1.487
St. de. [%]	0.947	0.701	0.292	0.292

TABLE 3.4: Out-of-sample performance results

Despite not performing a time-series decomposition or applying sophisticated optimized calibration techniques, the accuracy of results is extremely high. As already observed in Fig. 3.11, MAPE statistics for LSTM models are better than for NAR and NARX models.

3.7 Commitment Machine implementation

After the training-validation-test procedure described in the previous paragraphs and having checked the overall performance of the forecasters, it is reasonable to question if the technology which performs better in the considered dataset, will mantain the same higher accuracy than the other networks for other samples too. There is no possibility to generalize this statement using a formal theoretical proof, therefore it is a good idea to implement an algorithm which is able to choose the network that had the best historical performance for each time-step. In scientific literature this automatic procedure able to dynamically choose a forecaster is called Commitment Machine. The coding of this meta-heuristic allows to:

- enhance the prediction of the system
- give only the most reliable output value to the user
- be easily scalable for other forecasting customized techniques (same neural networks but varying the set of exogenous variables or different architectures) or more traditional econometrics methods (ARIMA-GARCH).

Together with the other engineers of the Spanish research group, we have deployed and tested a Commitment Machine composed of six forecasters: three of them rely on the working principles of Non-Linear Auto-Regressive (NAR) Networks and the other three are based on Long Short-Term Memory (LSTM) principles. In detail, the forecasting battery has been designed using the following architectures:

- NAR network using only the prices information (i.e. the endogenous variable) in order to estimate the next one-step ahead value.
- NARX network also using an exogenous variable, in addition to the endogenous variable (the prices time-series), is able not only to consider the endogenous variable information, but also to add the information coming from the demand to the prediction.
- The third typology of Non-linear networks works using both the demand and the Renewable Energy percentage as exogenous variables. In this case, three time-series have been combined with the aim of increasing the price forecasting accuracy.
- LSTM network with 1 feature: prices.
- LSTM network with 2 features: prices + demand.
- LSTM network with 3 features: prices + demand + Renewable Energy percentages.

The Commitment Machine is firstly initialized by performing a full-training for all the six forecasters, according to the so-called memory transfer procedure. This is an essential step for the next phases: it guarantees that all the architectures were properly tuned according to the procedure described in the previous paragraphs. This is the part that typically requires a large amount of computational time, but it is usually only required for the first one-step ahead prediction.

The following forecasting values are predicted using a partial training made by a very low number of epochs. As a result, the automatic system does not use the same pre-trained network, but it implements the weights which were trained before as a starting configuration instead. The low number of epochs can be easily justified considering that the tuning is carried out using the same time-series and adding only the last realized value at the end. Despite this consideration, statistical and econometric tests will be performed as well in order to be secure of the reliability of the prediction.

The Commitment Machine is able to automatically choose the best technology for making the one-step ahead prediction implementing a logic based on the statistical and econometric results performed time after time.

For each time step and for each forecaster, three performance measures are calculated:

- R^2 and MSE are ordinary statistical tests used for testing the goodness of fit.
- the absence of autocorrelation error in the generated outputs.

Based on these outcomes, the Commitment Machine is able to compare the forecasters and choose the best one that will be able to generate the more reasonable prediction.

First of all, the automatic system computes the statistical measures (R^2 and MSE), consequently, the meta-heuristic chooses the indexes that are related to the more performing architectures. If the returned indexes correspond to the same methodology and this forecaster has no autocorrelation error, we are in the best optimal choice and the one-step ahead value is predicted using the absolutely optimal architecture.

If the statistical test does not lead to the same response, the prediction will be carried out using the methodology characterized by the absence of auto-correlation error.

If both methodologies passed the econometric test, the forecasting will be done using the architecture with the lowest MSE. In this case we can say it constitutes a sub-optimal condition because not all of the three performance measures lead to the same choice.

If both methodologies do not pass the econometric test, we are unable to consider the out-of-sample estimation reliable despite the goodness of statistical measure. In this case, the Commitment Machine has to select the forecaster which corresponds to the minimum regret.

As a result, we have to repeat the described steps excluding the two already examined forecaster from the poll. In this case the procedure will be repeated until the system is able to find a forecaster that respects the minimum guaranteed performance in terms of R^2, MSE and absence of error auto-correlation otherwise the system will stop and make a full-retrain of all six networks.

In this last critical occurrence, the system will generate a warning and a full-retraining of all the networks is required. This procedure will go on until it finds a stop criteria: the number of predictions that we want to perform or a pre-set amount of time that we want to dedicate to this process. The described logical steps are represented in the Flow-chart 3.13.

Using the Commitment Machine with six architectures the average out-of-sample $MAPE$ decreases to 1.339% with a standard deviation of 0.287%

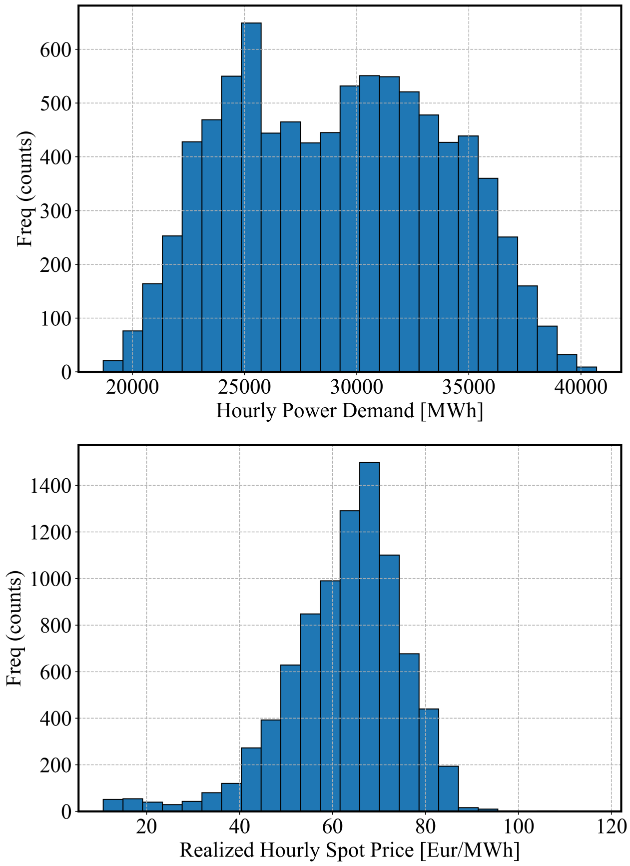


FIGURE 3.5: Histograms of the power demand data (top) and the hourly spot prices (bottom)

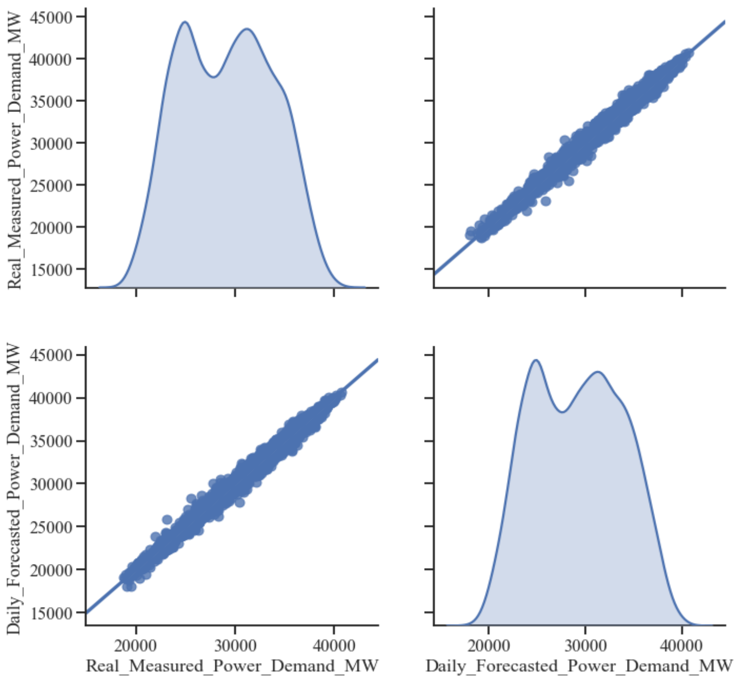


FIGURE 3.6: Correlation matrix between forecasted values and real measured power demands

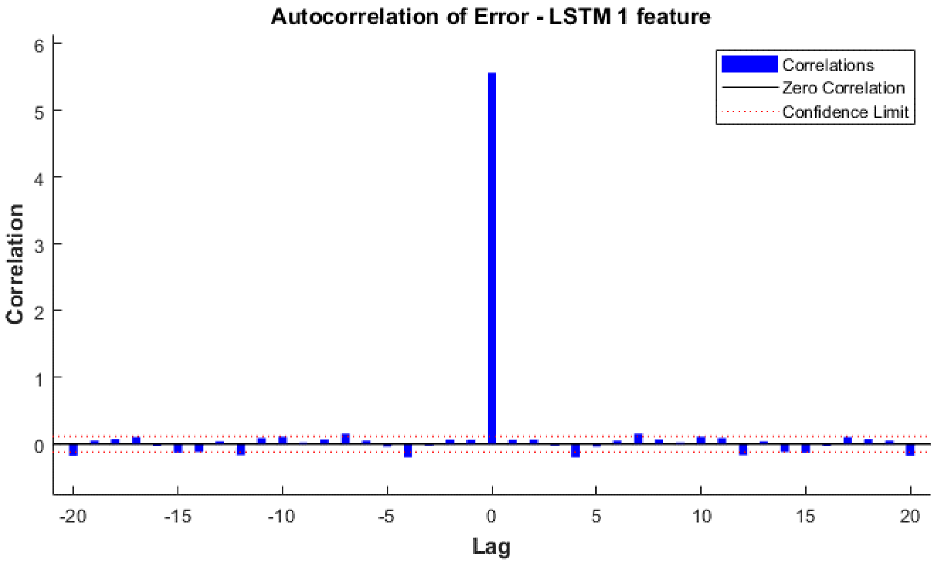


FIGURE 3.7: Test on autocorrelation error. Results for LSTM model with 1 feature

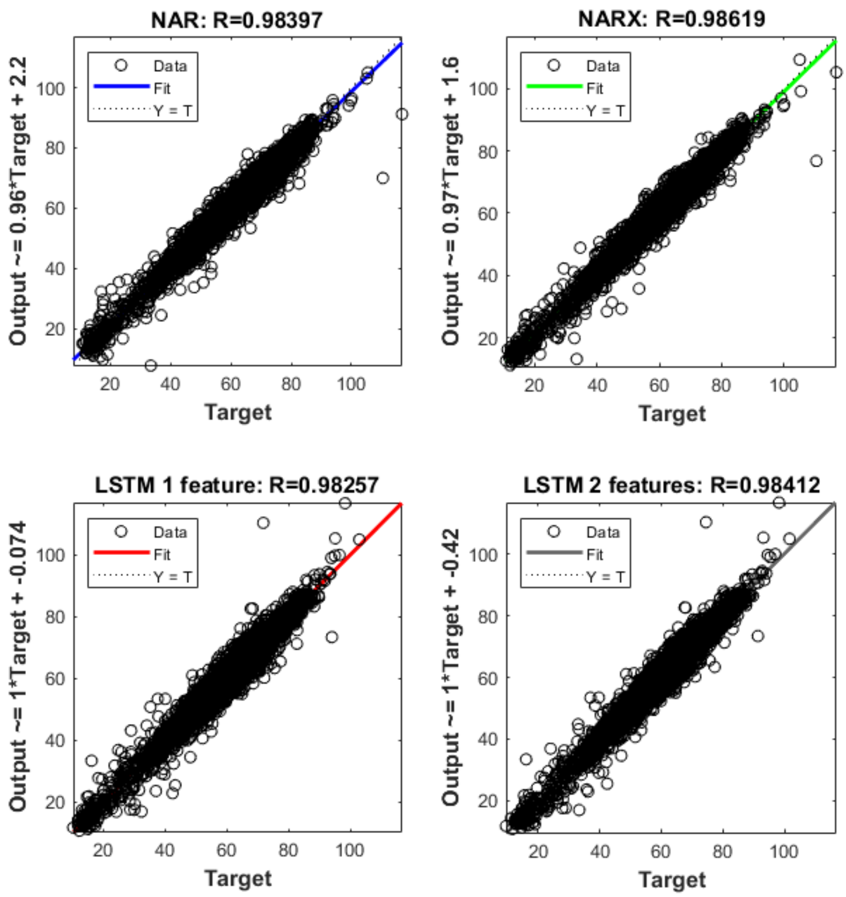


FIGURE 3.8: Test on Statistical Fitting based on Regression plot (training dataset)

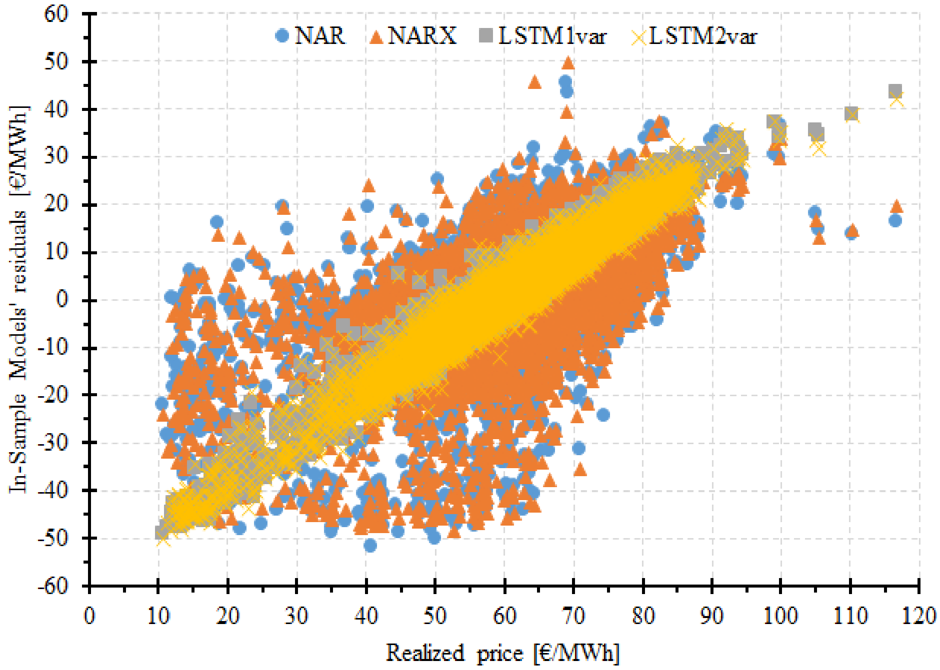


FIGURE 3.9: In-sample residuals versus realized prices

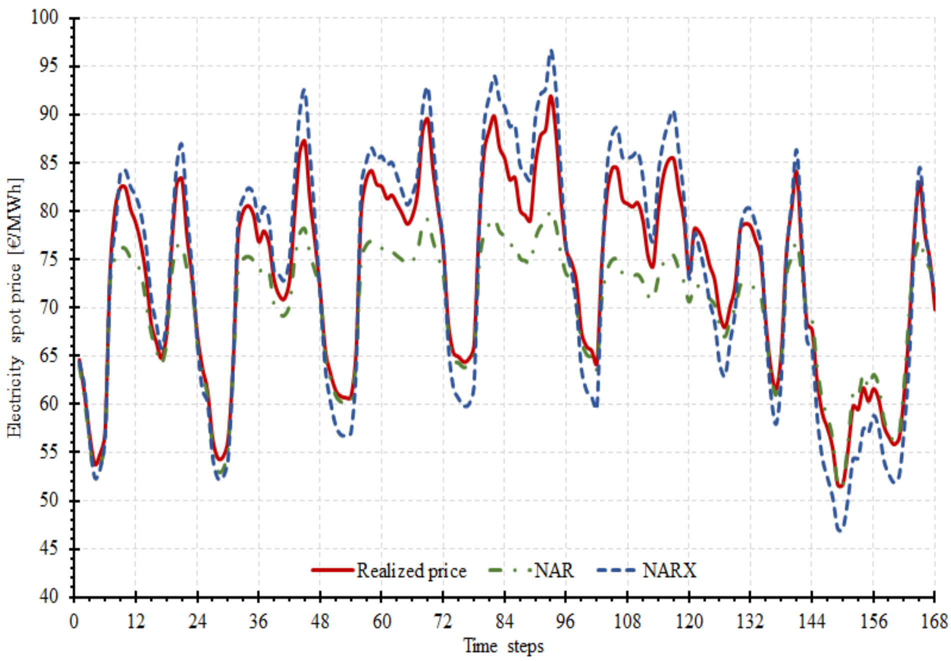


FIGURE 3.10: NAR and NARX models' results versus realized prices

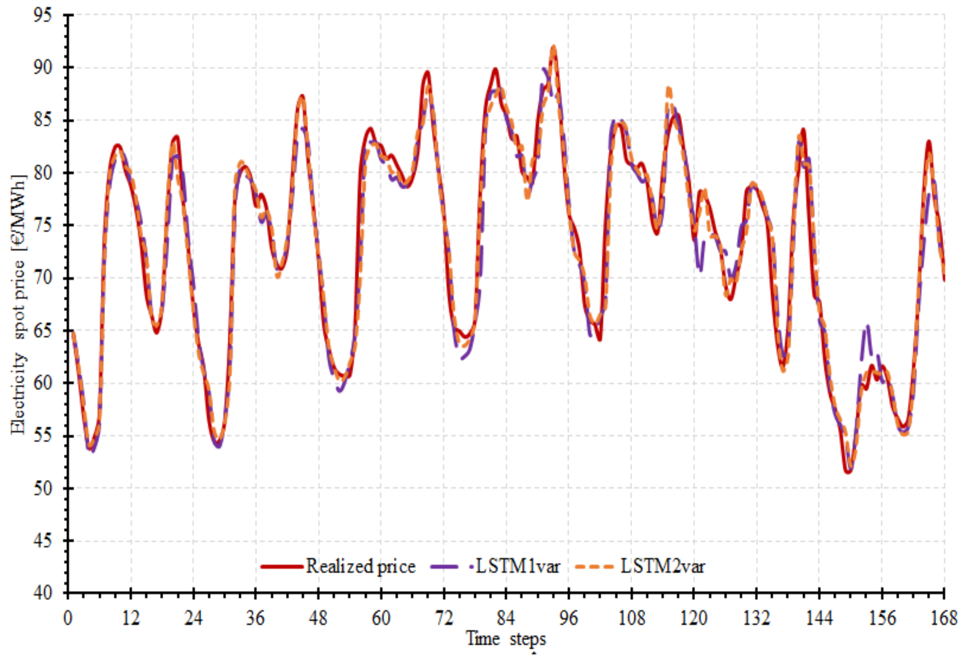


FIGURE 3.11: LSTM-1 and LSTM-2 forecasting results versus realized prices

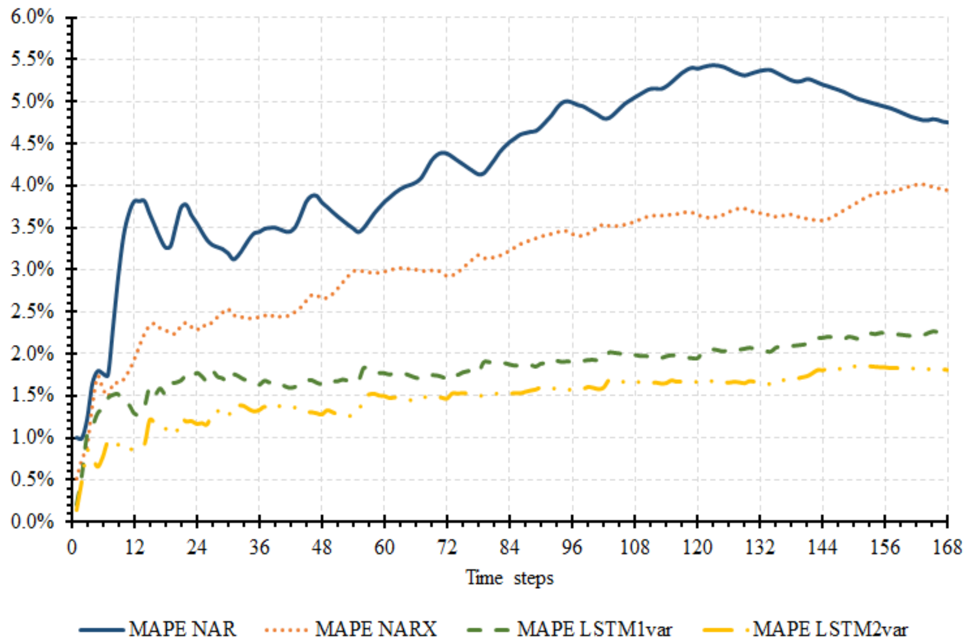


FIGURE 3.12: Dynamic out-of-sample MAPE results for the evaluation period

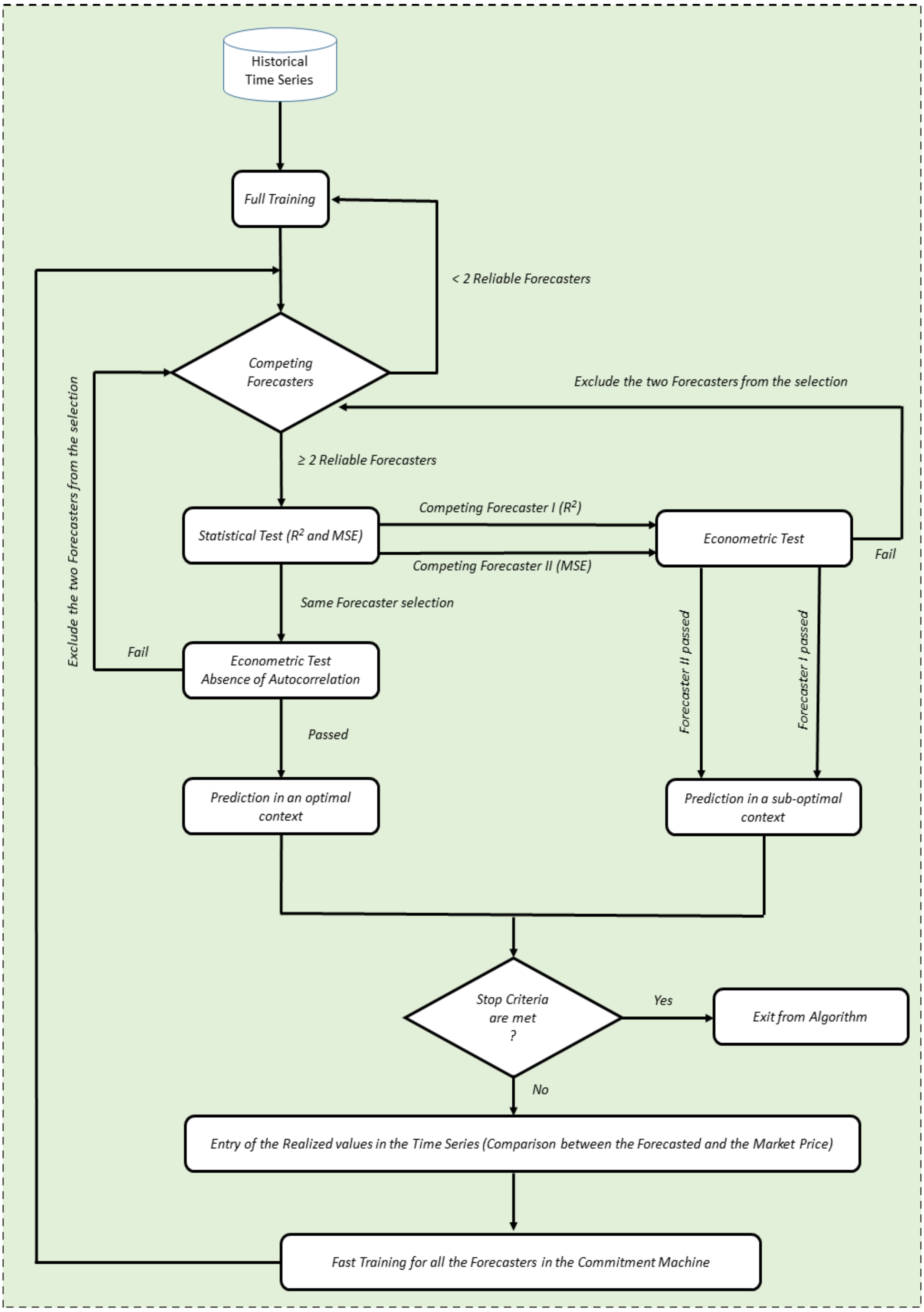


FIGURE 3.13: Commitment Machine logical steps

Chapter 4

Conclusions

"I leave to the various futures (but not all) my garden of forking paths"

Jorge Luis Borges, *Fictions*, The Garden of Forking Paths, 1941

"Lascio ai diversi futuri (ma non a tutti) il mio giardino dei sentieri che si biforcano"

Jorge Luis Borges, *Finzioni*, Il Giardino dei Sentieri che si biforcano, 1941

This chapter concludes the two studies regarding the energy markets.

4.1 Guarantees of Origin Risk Measures

In the first part, the aim was to analyze the emerging market for guarantees of origin, focusing the attention on the various risk components associated with them. In the analysis, a very wide range of approaches was proposed for the assessment and estimation of market, liquidity and counterparty risks, for a market still unripe and unexplored, characterized by the scarce availability of data and the lack of reference literature.

As regards the estimation of market risk, numerous methodologies have been proposed. Using the historical data of the spot contracts of the Guarantees of Origin, we calculate the historic VaR, the parametric VaR, the Monte Carlo (MC) VaR with historical mean and standard deviation of the returns, the MC VaR using the estimated volatility starting from a GARCH(1,1) and the MC VaR which includes mean reversion.

By adopting a more forward-looking perspective, a MC simulation was implemented using implied volatilities derived from traded options.

For forward contracts, on the other hand, although it is possible to use all the methodologies already described for spot contracts, a more innovative approach has been proposed, based on the Stochastic Alpha, Beta, Rho (SABR) model which allows to insert an adjusted volatility to take into account the volatility smile within the simulation motion.

A Bid-Ask spread analysis was made in order to analyze the liquidity risk associated with the GO. This study revealed, as expected, a poor liquidity for the market on which these commodities are traded.

Finally, three methods for estimating counterparty risk have been proposed: the first is suitable if the counterparty has listed credit default swaps (CDS), the second in the case it does not have CDS premium, but the counterparty is a bond issuer with fixed income instruments traded on the secondary market and the third in the case that there is no market information, therefore the only way to carry out an analysis is starting from the statement data.

All the methods for estimating different risk types must not be considered alternatives, but they must be considered part of an integrated approach.

Due to the scarce availability of data and the presence of almost always growing historical series and zero returns for many consecutive days (and weeks), the proposed risk estimates are of an innovative nature, although they do not claim to be a totally comprehensive proposal.

With this implemented system, we want to propose, at least at a methodological level, a possible path to follow in order to face the exploration of this emerging market and manage the risks deriving from it using quantitative tools.

The hope is that in a few years, having longer time series available, the appropriateness of the proposed measures may be verified, as well as carrying out further more traditional analyzes.

It is likely that the Guarantees of Origin market will become mature, transparent and liquid within a few years, also as a consequence of the entry into force of the RED II Directive which will make GOs mandatory for the Renewable Electricity Disclosure, thus favoring the systematic use of these electronic certifications.

4.2 Electricity Spot Prices Forecasting

Electricity price forecasting is a very interesting topic which is getting special relevance due to the high volatility on deregulated markets and the recent high penetration of renewable energy sources and coupling sectors.

Very sophisticated methods can be found in literature in order to properly analyze each component of the price time-series. In the present study two approaches of Dynamic Deep Learning Neural Networks (NAR and LSTM, with and without exogenous variables) have been tested for the mid-term final spot prices Spanish market (MIBEL) obtaining high accuracy results according to the classical MAPE, evaluated out-of-sample through a back-testing technique.

The calibration of the model results of the utmost importance for each performance and generalization. Thus, not only statistical but also econometric criteria must be considered. Then, out-of-sample MAPE results in the range between 0.147% and 5.438% can be obtained, being the best average MAPE (LSTM-2 model) 1.487%.

The different seasonality periods of the data (semi-daily, daily, weekly and monthly) conducted to better results for LSTM models in comparison to both NAR and NARX, while the addition of the TSO forecasted power demand as exogenous variable improved both models' families.

Future research must be conducted in several ways:

- to test the impact on the forecasting performance from different exogenous variables, such as renewable participation or available reserve,
- to evaluate the statistical significance of the decomposition of the timeseries and the application of specific models for each component; and
- extend the point forecasts to probability forecasts.

- Stop with this comedy, Master.
I know the secret.
Bad stuff.
So much studying, hours and hours on the books and then ...
I don't even exist.
- You are a baol ...
an immortal and fascinating idea ...
You are a thought about somewhere else,
magic,
adventure,
freedom,
utopia and
rock-and-roll ...
I stand here and listen to the pianist.
I am at the last table on the far left.
If you don't like the spirit of the time, come.
You will recognize me immediately.
I will stay here until the pianist keeps playing.
And as long as I am there he will play.

Stefano Benni, Baol (1990)

- Basta con questa commedia, Maestro.
Conosco il segreto.
Bella roba.
Tanto studiare, ore e ore sui libri e poi ...
non esisto neanche.
- Ma sei un baol ...
un'idea immortale e fascinosa ...
sei il pensiero dell'altrove,
magia,
avventura,
libertà,
utopia e
rock-and-roll ...
Sto qua e ascolto il pianista.
Sono all'ultimo tavolo a sinistra in fondo.
Se non vi piace lo spirito del tempo, venite.
Mi riconoscerete subito.
Starò qui fino a quando il pianista suonerà.
E finchè ci sono io, suonerà

Stefano Benni, Baol (1990)

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