UNIVERSIDAD PONTIFICIA COMILLAS

ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

OFFICIAL MASTER'S DEGREE IN THE ELECTRIC POWER INDUSTRY

Master’s Thesis

PRICING MODEL FOR THE ITALIAN ELECTRICITY MARKET

Author: Martina Cebollero Burgués
Supervisor: Carlos Ezquerra Pérez

Madrid, July 2018

Official Master's Degree in the Electric Power Industry (MEPI)

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Abstract

This master thesis has as a main objective the prediction of expected zonal prices in the Italian Electricity Market based on a pricing model according to the thermal gap. This objective will enable to obtain appreciated information of the market and to understand the functioning of it. The model can be defined as a deterministic, fundamental and hybrid model. Training data consists of data from 2016 to 2017 while forecasted data covers the period from 2018 to 2019. Within the first months of the forecasted data, the period from January to May will be considered as test data used in the Validation process.

The general methodology is a model based on a stack model, this means the demand shall be estimated and then it is covered with production, ordered according to its marginal cost. In this model, demand is covered until the thermal gap (or thermal production) is left. As supply curves for thermal plants are unknown, an algorithm is developed in order to build these curves based on historical data, therefore these curves will relate the thermal gap with the price. The algorithm abovementioned, replicates the price formation in each bidding zone and has as an output a coefficient for each virtual plant to be added in its cost formula. This coefficient allows to capture the strategy of the different agents and will be different for each day and period classification. Thus, the model is not a formal stack model neither a static one since the strategy of the agents is captured with these coefficients and the cost formula for thermal technologies varies with commodities price in the market.

The validation process provided positive results and showed that the model adjusted its outputs according to actual data. In addition, in this analysis, residuals were close to zero which is a condition for a good accuracy in the forecast.

If results are compared with the expectations of forward markets, it was showed how similar the values were. Therefore, one can conclude that results and the model development were satisfactory, considering that this model was developed from scratch where great scope for improvement exists. Some of the improvements are included in the Section Future Works.

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1 Introduction

1. Motivation

Understanding the market, in this case the Italian electricity market, is essential to start modelling and developing the forecast. For that purpose, before the problem modelling, a study of the market was carried out.

Italian electric power industry has suffered a transformation from a significant thermal production mix to a slightly more varied mix generation, remaining as a mix based on thermal technology. According to GME data, in 2017, in 85% of the hours the marginal technology was thermal based. Italian prices are higher than European average, nevertheless, due to the market overcapacity, the increase on RES installation and the improvement in the interconnections, there has been a trend of heavy price decrease.

Furthermore, the Italian spot market has a unique price method calculation called Prezzo Unico Nazionale (PUN) which calculates the price for the six main geographic zones. This particularity makes the Italian market a challenging, complex and interesting case study. Sicily presents a higher price than the other zones due to capacity constraint in interconnections. For this reason, within the model, zones will be studied separately.

This model is seen as a tool to acquire a general knowledge of the market, to forecast the price and therefore to assist in making sound decisions in forward markets and long term-contracts. Tendency of electricity forward markets can be compared with the output of the model developed whose training data is based on the spot market and its inputs are related to the forward commodity market. Hence, the model may explain changes in the forward market tendency.

2. Objectives

This master thesis has as a main objective the prediction of expected zonal prices in the Italian Electricity market, based on a deterministic, fundamental price model according to the thermal gap. This objective will enable to obtain valuable information of the market and to understand the functioning of it.

The objectives of this Master Thesis are:

1. To forecast expected prices in the Italian market (PUN) covering the period from the start of 2018 to the end 2019.

The main objective implies other secondary objectives, namely:

2. To gain general knowledge of each zone and to study the impact of each one to the final national electricity price, the PUN.
3. To obtain an average daily future price curve. This will help to design a better hourly pricing for Italy, to personalize the offer and to hedge part of the price volatility. Forward markets provide signs for the future, yet not with the granularity needed to obtain a daily curve.
4. To develop a model which can be used by different users. Therefore, the interface should be user-friendly and give visual and fast information without any additional data treatment.

In summary, this preliminary model will help to understand better the Italian market behavior while forecasting expected prices and, therefore, assist as a tool in long term contracts.

3. Structure of the report

The purpose of this section is to introduce the following sections included in the Master Thesis:

2. **State-of-the-art**: The section aims to introduce the main types of electricity price forecasting models which have been used in the literature. After a brief description of each method, some advantages and drawbacks will be presented. Finally, some conclusions are drawn, and the actual model will be established as a hybrid. This means, different theories have been used in the process.

3. **Problem description:** The goal of this section is to provide some general information about the Italian Electricity Markey. This includes a description of the different zones, demand, generation and capacity mix, interconnection and commodities evolution. As one of the main particularities of the Electricity Italian Market is the price calculation method (PUN), a description of the PUN is included. Finally, a last chapter covers the main challenges and constraints faced during the model development, since these constraints will determine the methodology chosen.

4. **Methodology**: This is the section where the model is explained, and all the steps needed to create the model are described. Specifications about: data sources, assumptions and hypotheses will be included.

5. **Results**: The fifth chapter will analyze the obtained forecast and the validation results.

6. **Conclusions:** Last section will comprise conclusions that can be deducted from the obtained results. A summary of the problem, main findings and analysis of the objectives related to the results will be concluded. The report will end with the future works of the model and its possible potential improvements.

2 State-of-the-art

1. Electricity price forecasting's review of the state-of-the-art

Models are usually defined in terms of the decision variable's **time scope**. Short-term models usually consider a time scope up to a week. The objective of short-term models in a liberalized context is the bidding procedure. The scope of medium term models is considered from a few weeks to one year. In the medium term, the main objectives are to compute the market price and the market share. These models aim to estimate the necessary budget and the bidding strategy in the derivatives markets. Finally, long term models can be defined as the models with a time scope from one or two years onward [1].

Secondly, the classification should clarify whether the model handles uncertainty in its variables, as it is the case of **stochastic approach** or if uncertainties are external to the model itself, then a **deterministic approach** is considered.

The third main classification distinguishes between a **fundamental approach** and a **quantitative approach**. Fundamental approach takes into account a representation of the system, in case of electricity market models, the input variables may be: the demand evolution, fuel costs, hydro inflows, capacity and companies' structure. The output would be the price which is obtained as a result of the previous inputs. Models considering a quantitative approach are the ones based on the application of different statistical techniques using data from available historical records [2].

After having introduced the main approaches used in modelling electricity markets, specific kinds of electricity models generally used in the literature are going to be classified.

1. **Production-cost models (PCM):** Production-cost models are also called stack-models. PCM models involve matching the estimated demand to the supply obtained by stacking up generation in ascending order according to their operational cost. The models are capable of forecast hour by hour and bus by bus. However in 2014, *R. Weron* [3] stated they did not capture the different strategic bidding behavior.

   In 2002, *Batlle et al.* [4] introduced a modification of the traditional PCM models called **Strategic Production Costing Model (SPCM).** SPCM capture the agents' strategic bidding, modelling the agents' behavior, the market clearing and liquidation algorithms. Thus, in contrast to traditional PCM, SPCM captures agent's behavior.

2. **Single-firm optimization:** In 2005 *Ventosa et al.* [5] grouped in this category all the approaches based on profit maximization of one firm. These models can be divided as

well in models which represent the price as an exogenous variable and the ones which represent the price as a function of the demand supplied by the firm. As the Master Thesis aims to model the Italian electricity market, single firm optimization is not an appropriate approach.

3. **Multi agent models:**
   In 2005 *Ventosa et al.* [5] considered three main electricity market modeling trends: optimization (explained in the previous point), market equilibrium considering all firms and simulation models:
   - **Market equilibrium models** consider that companies' decisions are mutually dependent and are based on the concept of Nash equilibrium (i.e. market reaches equilibrium when each company's strategy is the best response to the strategy of the opponents). Companies interact with each other and build the price by matching the demand and supply. The two main types of models are the ones based on **Cournot competition**, where firms compete in quantity strategies, and the ones based on **Supply Function Equilibrium (SFE)**, where companies compete in offer curve strategies.
   - **Simulation models** are usually used as an alternative when the problem is too complex to be addressed with a formal equilibrium framework.

4. **Fundamental methods:** Fundamental methods describe the price dynamics by modelling the impacts of important physical and economic variables on the price of electricity, such as the abovementioned ones (fuel costs, demand evolution, wind power, capacity…).

   In 2012, *Carmona et al.* [6] developed a stochastic model of the bid stack and translated demand and fuel prices into spot prices.

5. **Reduced-form:** Reduced-form models usually have a quantitative and stochastic approach which characterize the statistical properties of prices over the time [3].

6. **Statistical:** Statistical models forecast the price by using a mathematical combination of the historical prices and other variables related to consumption, production and weather [3], [7].
   Statistical models can be classified as:
   - **Similar-day:** It is a benchmark model which takes historical data from days with similar characteristics as the predicted one.
   - **Regression models:** One of the most classical form of regression models is multiple regression which assumes the relationship between variables is linear. This method studies the relationship between several variables and a dependent variable.
   - **AR-type time series:** In the **Autoregressive Moving Average model (ARMA)**, the price is expressed linearly in terms of its past values (i.e. autoregressive part) and in terms of previous values of the noise (i.e. moving average part). In the case, a transformation in the time series is needed to stabilize the variance and the mean, the **Autoregressive Integrated Moving Average (ARIMA)** is used. In the case the

time series is seasonal, the **Seasonal Autoregressive Moving Average model (SARIMA)** is used.

- **ARX-type time series**: In the previous models the variable (in this case, price) is studied according to historical data of this same variable. This type of models (ARX, ARMAX, ARIMAX and SARIMAX) are a generalization of the previous models to an exogenous variable. Therefore, exogenous variables (e.g.: load profile or weather conditions) can be included in the time series.

7. **Computational intelligence:** Computational intelligence models combine elements of learning, evolution and fuzziness. Models such as Fuzzy neural models or support vector machines may be included in this classification.

2. Conclusion

Regarding the general classification, the scope of the model is considered between a medium and a long-term one. Furthermore, it has a deterministic and fundamental approach.

Concerning a more specific classification, the approach of the model developed in this Master Thesis can be considered a hybrid solution, since it is a combination of the techniques abovementioned and cannot be only classified with just one procedure. In the following diagram, the approach of the model is represented:

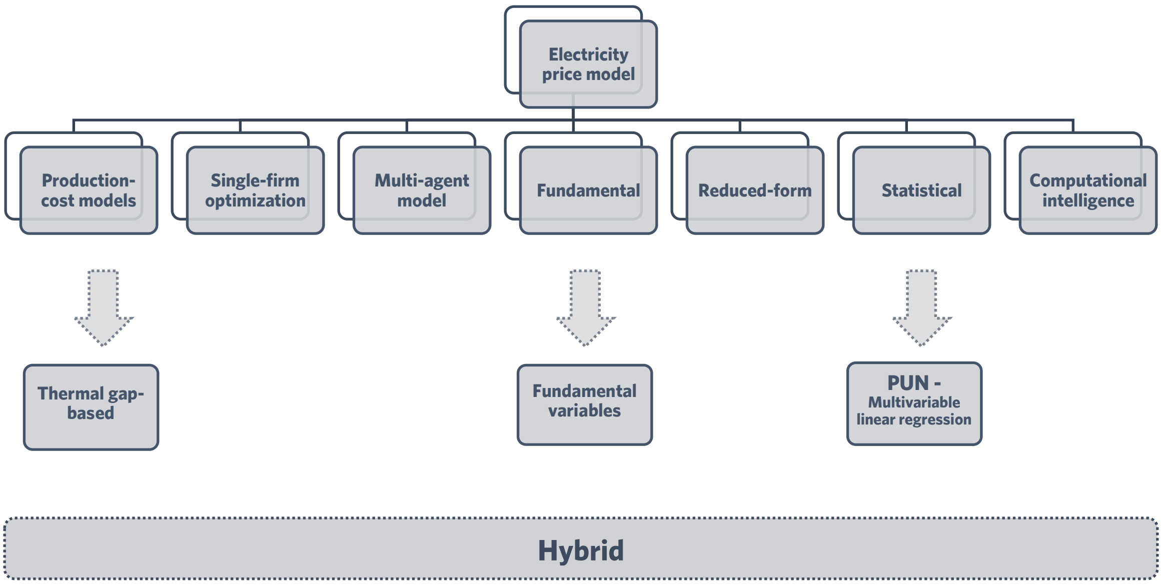

Figure 1: Diagram of the approaches followed in the Master Thesis.

As it can be seen in the diagram, the solution has used mainly three techniques: Production-cost models, Fundamental models and Statistical techniques.

Firstly, the model is based on a Production-cost approach. However, as PCM models do not capture strategic behavior among agents, the model has a particular feature which allows to include a dynamic and strategical approach. Some virtual plants are defined according to the actual capacity of each zone. These virtual plants have been related to thermal gap and spot price from historical data of the years 2016-2017. The model learning process is based on a replication of the market clearing process with the virtual plants above mentioned. In the end, these plants will obtain coefficients which represent the strategy in the bidding procedure and the strategy among different type of days and the zone (the input data is classified among type of day, month and period of the day). The methodology of the model is further explained in later sections.

Secondly, the model is a fundamental model and because of that, numerous fundamental variables have been used as fuel prices, demand evolution or capacity evolution. The price is computed considering fundamental variables as inputs.

Thirdly, the approach followed in the computation of the Prezzo Unico Nazionale (PUN) is a multilinear regression, a pure statistical methodology. In fact, the PUN is computed iteratively during the market clearing process in all the zones. However, as the model compute the results of each zone separately, the PUN cannot be computed then during the algorithm process. Because of this fact, once all the zonal prices are obtained, a multilinear regression approach is used to compute the PUN. The regression has as inputs historical prices from 2016 and 2017.

Furthermore, in the model other statistical techniques have been used such as clustering. This is used to classify the thermal gap during the day into peak, shoulder and valley hours or to classify all the data into standard values to then build an hourly profile and extrapolate the data into the future.

The methodology of the problem will be further explained in Section 4: Methodology.

3 Problem description

1. Italian market description

1.1 General description

Italy is a unitary bicameral parliamentary republic and a member of the EU located in Southern Europe. Italy covers an area of 301,338 km^2 and has a population of 61 million inhabitants with a result of being the fourth most populous EU member state [8].

Italian peninsula runs from the Alps to the central Mediterranean Sea. Italy includes Sicily and Sardinia as well as about 70 minor islands. Orography is characterized by the Apennine mountains as a backbone and the Alps as a northern peninsula. This results in a diverse weather such as continental and Mediterranean in the South, coastal areas and Tuscany. Note that the average winter temperatures vary from 0^{o}C in the Alps and 12^{o}C in Sicily and the average temperature in summer 20^{o}C and 25^{o}C, respectively.

In the next figure, the temperature evolution is represented for 2016, 2017 and the beginning of 2018.

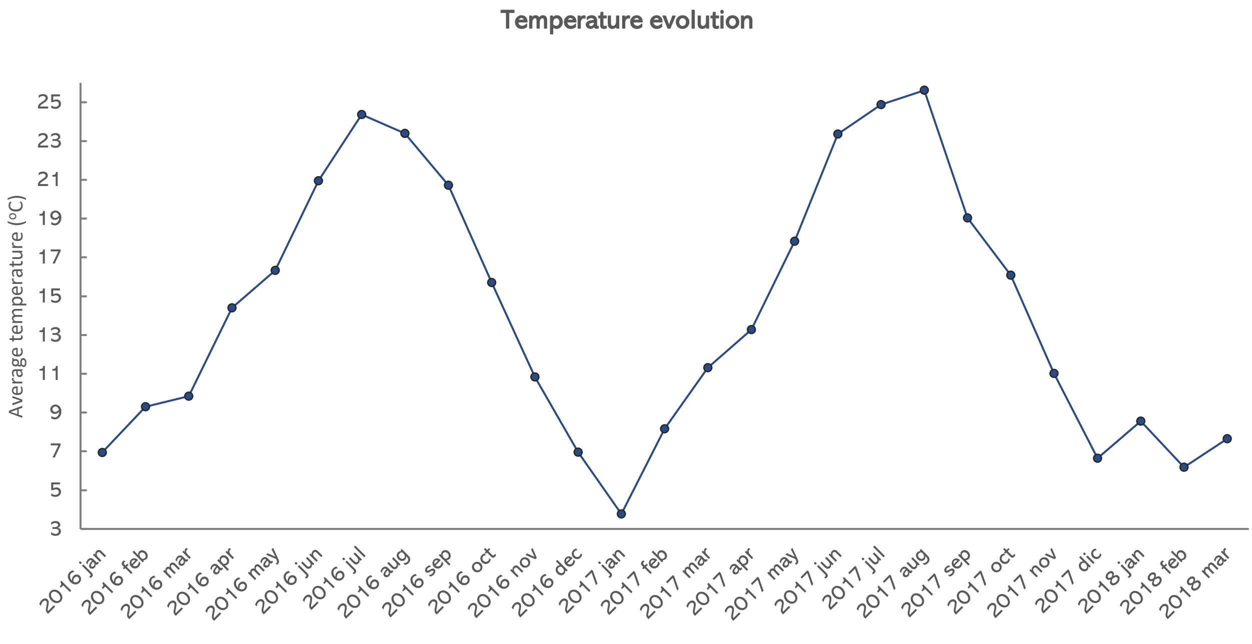

Figure 2: Temperature evolution. Data source: Bloomberg.

The following table indicates the minimum and the maximum temperature in Italy in 2016 and 2017.

	Minimum		Maximum	
	Date	Data (°C)	Date	Data (°C)
2016	19/01/2016	1,97	11/07/2016	26,67
2017	07/01/2017	-1,21	04/08/2017	29,45

Table 1: Temperature data. Data source: Bloomberg.

As it can be seen, both in the table and in the graph, 2017 was a year with more extreme temperatures, resulting in a higher maximum temperature and a lower minimum temperature in comparison with the previous year.

Italy is subdivided into 20 regions; this fact will affect the electric system framework (*see Section: PUN*).

Amongst the main macroeconomic variables, Italian Gross Domestic Product (GDP) of the fourth quarter (Q4) in 2017 reached 449828,5 M€. As it can be seen in the next chart, GDP in 2017 recorded an increase in comparison with the previous year due to economy's recovery. Italy is classified as the third largest nominal GDP in the Eurozone and the eighth largest globally.

Figure 3: Evolution of the GDP in Italy. Data source: Eurostat [9]

1.2 Relevant institutions

Ministry, (Ministry of Economic Development)

The ministry responsible for energy policy is the Ministry of Economic Development (MSE, *Ministero dello Sviluppo Economico*) while the Ministry for the Environment, Land and Sea (MATTM, *Ministero dell'Ambiente e della Tutela del Territorio e del Mare*) has the responsibility for coordinating climate policy issues [10].

Regulatory Authority, (Italian Regulatory Authority for Energy, Networks and the Environment)

The Italian Regulatory Authority for Energy, Networks and the Environment (ARERA, *Autorità di Regolazione per Energia Reti e Ambiente*) is an independent body whose purpose is to protect consumer interests and to promote competition, efficiency and distribution of services with adequate levels of quality. ARERA has also responsibility of preparing the new regulatory framework for European electricity and gas markets according to the Third Energy Package and to this end, it participates in the Agency for Coordination of Energy Regulators (ACER) [11].

Competition authority, (Autorità Garante della Concorrenza e del Mercato)

Another main authority within the regulatory framework is the Competition Authority (AGCM, *Autorità Garante della Concorrenza e del Mercato)*. AGCM is an administrative independent Authority established by Law no. 287 of 1990. AGCM enforces rules against unfair and anticompetitive commercial practices, abuses of dominant position, unlawful advertising or mergers and acquisition, joint ventures which may create or strengthen dominant position [12].

Market operator (Gestore dei Mercati Energetici)

Italy adapted the European Directive on the internal market in electricity (96/92/EC) into the national legislation approving the Legislative Decree no.79 of 16 March 1999. The creation of a market responds of two requirements:

- Promote competition in generation, sale and purchase, under neutrality, objectivity and transparency, creating a market place.
- Ensuring economic management and availability of ancillary service.

Ministry of Economy and Finance wholly owns Gestore dei Servizi Energetici (GSE S.p.A) whose function is to pursue and achieve environmental sustainability through renewable sources and energy efficiency. GSE guides and coordinates Gestore dei Mercati Energetici (GME). GME operates power, gas and environmental markets. Following the approval of the EU Regulation 1222/2015 (CACM), GME has been nominated Nominated Electricity Market Operator (NEMO) for the day ahead and intraday markets in Italy [13].

Italian electricity market consists of:

- Spot Electricity Market (MPE) (also known as Italian Power Exchange) is formed by:
    - Day-Ahead Market (MGP): The MGP, where hourly energy blocks are traded for the next day, holds the highest number of electricity sale and purchase transactions.
    - Ancillary Services Market (MSD): In MSD the System Operator, Terna, presents the quantity needed to face congestions, to create reserves and to balance energy in real time.
    - Daily products Market (MPEG): In MPEG daily products with obligation of energy delivery are traded on a continuous mode.
    - Intra-Day Market (MI): In this platform, agents can modify the schedules defined in MGP by submitting additional offers and demand bids.

Data prices used in the model correspond to the spot market, the Day Ahead Market (MGP).

- Forward Electricity Market (MTE): In MTE forward contracts with delivery and withdrawal obligation are traded on a continuous basis.
- Platform for physical delivery of financial contracts concluded on IDEX (CDE): The CDE is the platform where financial electricity derivatives contracts are executed. These contracts must be concluded on IDEX (i.e. Derivatives segment of Borsa Italiana S.p.A.).

In the next diagram, the structure of the market is represented:

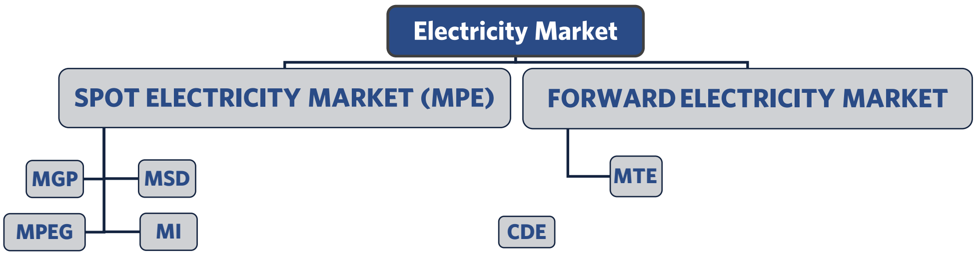

Figure 4: Italian market structure representation.

System operator (Terna)

Terna is the Italian Transmission System Operator (TSO), which is responsible for transmission and management of electricity flows of the Italian high voltage and very high voltage electricity National Transmission Grid. Currently, Terna operates 72900 km of high voltage grid and 5,3 billion € of investments in regulated activities is expected over the period 2018-2022 [14].

1.3 Demand

The evolution of the demand is represented in the following chart. It can be seen that in both years, 2016 and 2017, the highest demand takes place in summer while the lowest demand takes place in April.

Furthermore, the share of each zone in the total demand is represented. Note that the highest demand belongs to the Nord where all the industry is placed, and the second highest takes place in the Central-Southern of Italy, as Rome is located in Lazio (Central-Southern of Italy).

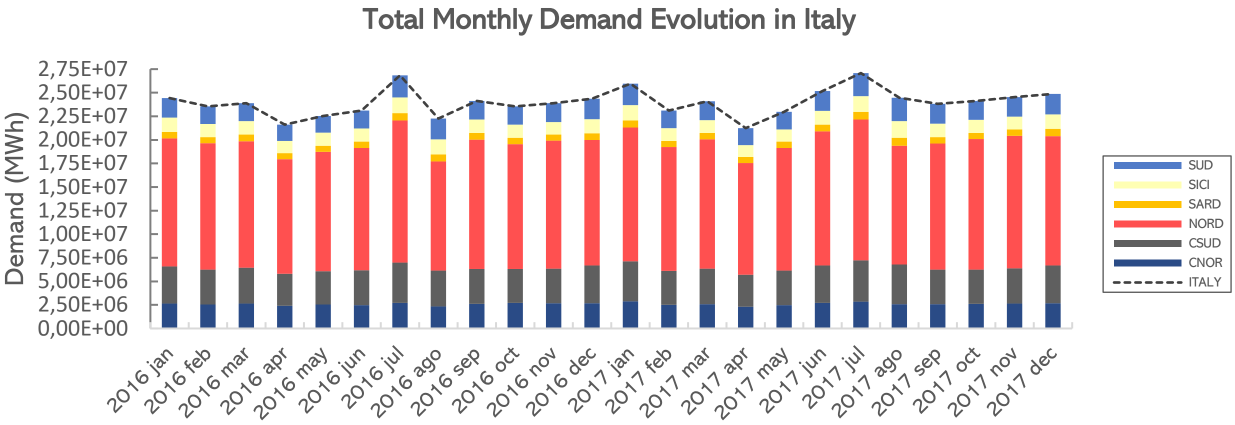

Figure 5: Demand evolution in Italy, 2016-2017. Data Source: Terna.

1.4 Generation and capacity mix

The average generation mix of 2017 is shown in the next figures. Note that in Central-Northern Italy, there is a significant geothermal production, in Northern Italy a significant hydro generation and in the South and Islands a significant wind generation. It is clear as well, that in all the zones, above all technologies, the thermal production has the highest share.

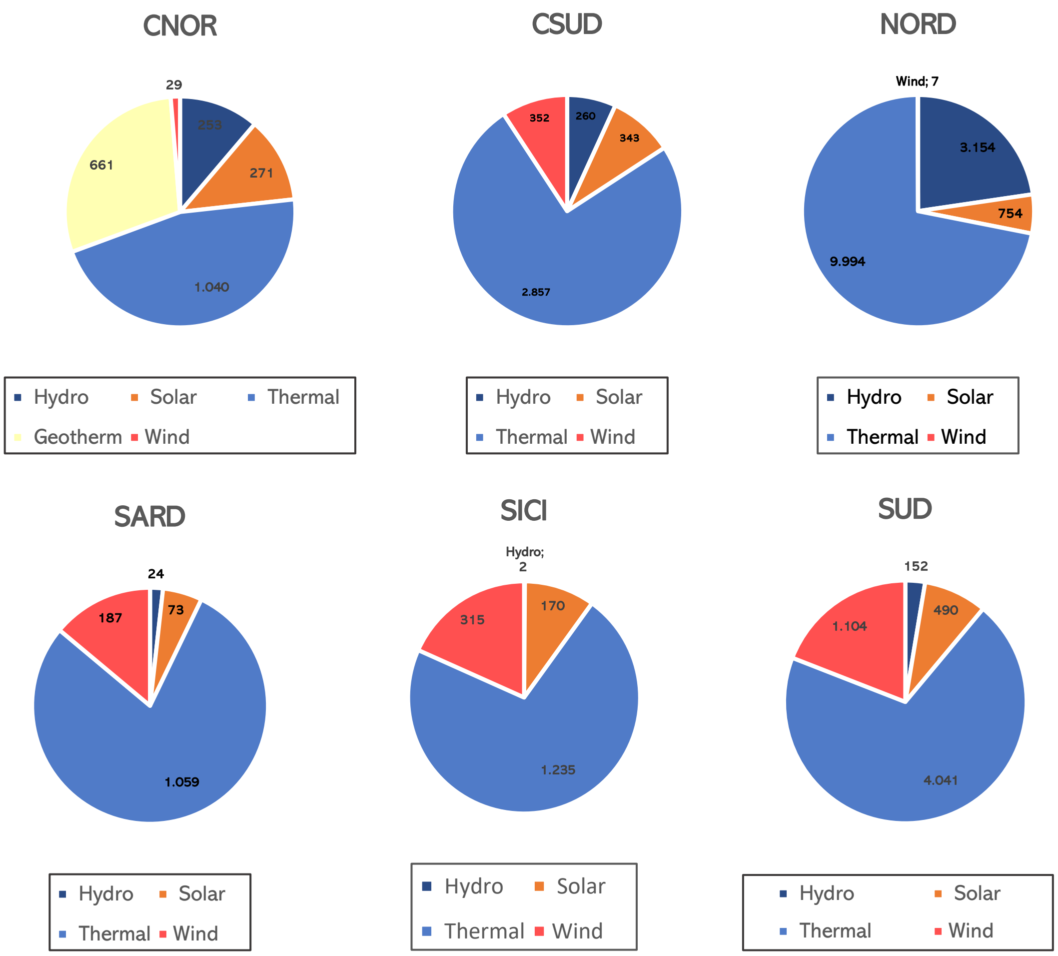

Figure 6: Average generation mix in 2017 (MWh). Reference: own elaboration. Data source: Terna.

In this case, the installed capacity per technology and per zone is represented in the following figure. As it can be seen, the islands and the Southern part are the only ones owning a significant capacity in fuel plants. As it was also shown in the generation mix figure, Northern Italy owns a lot of hydro capacity.

Regarding thermal plants, it can be concluded that:

- Central-Northern Italy: Owns gas, coal and oil plants.
- Central-Southern Italy: Owns gas and coal plants.
- Northern Italy: Owns gas and oil plants, although oil plants represent a really small part of the share.
- Southern Italy: Owns gas, coal and oil plants.
- Sicilia: Owns gas, coal and oil plants.
- Sardinia: Owns oil and coal plants.

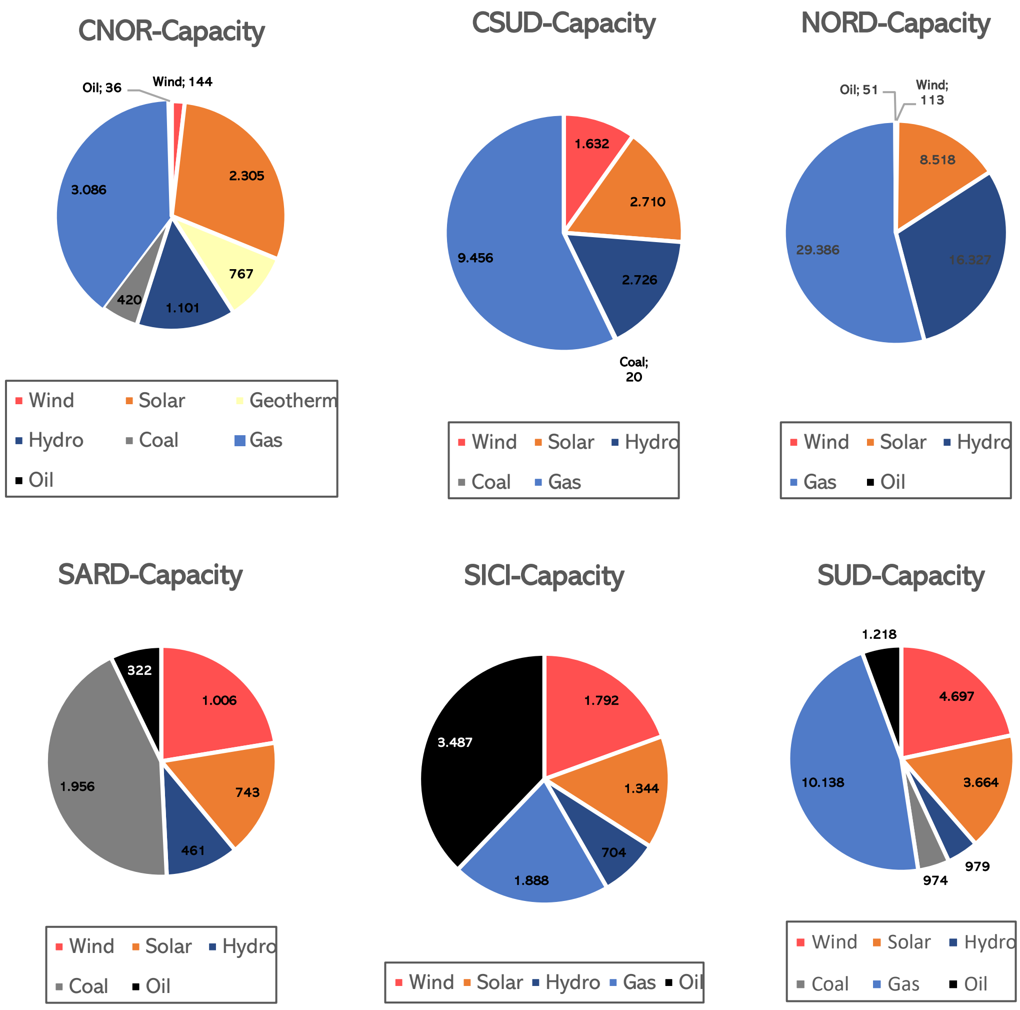

Figure 7: Capacity mix (MW). Reference: own elaboration. Data source: Terna.

1.5 Interconnections

In the following chart, a zonal map with the different international interconnections is represented. In addition, a graph representing the average flow of international interconnections is included.

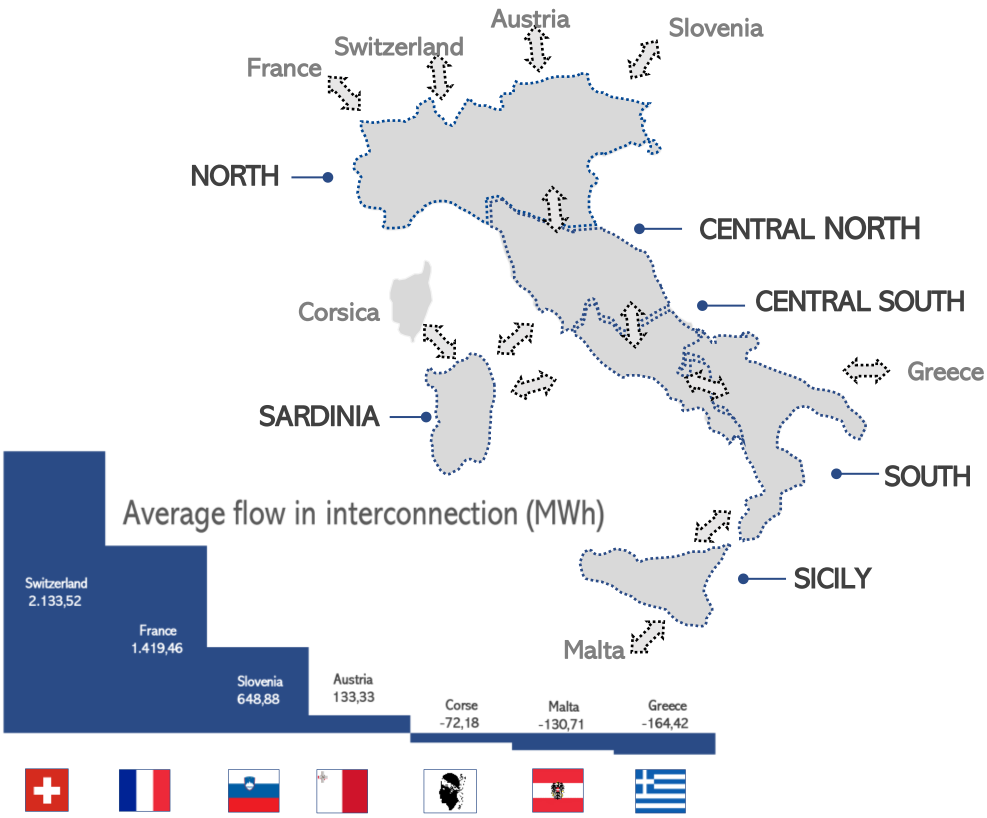

Figure 8: Average flow in interconnection and interconnection diagram. Reference: own elaboration. Data source: Terna.

Northern Italy is the most internationally connected zone. Currently, it owns interconnections with France, Switzerland, Austria and Slovenia, being the French and Swiss interconnection the most significant.

New international interconnections have been commissioned by Terna ,within them two projects are at an advanced-stage of construction: Montenegro-Italy interconnection and a new France-Italy interconnection [15].

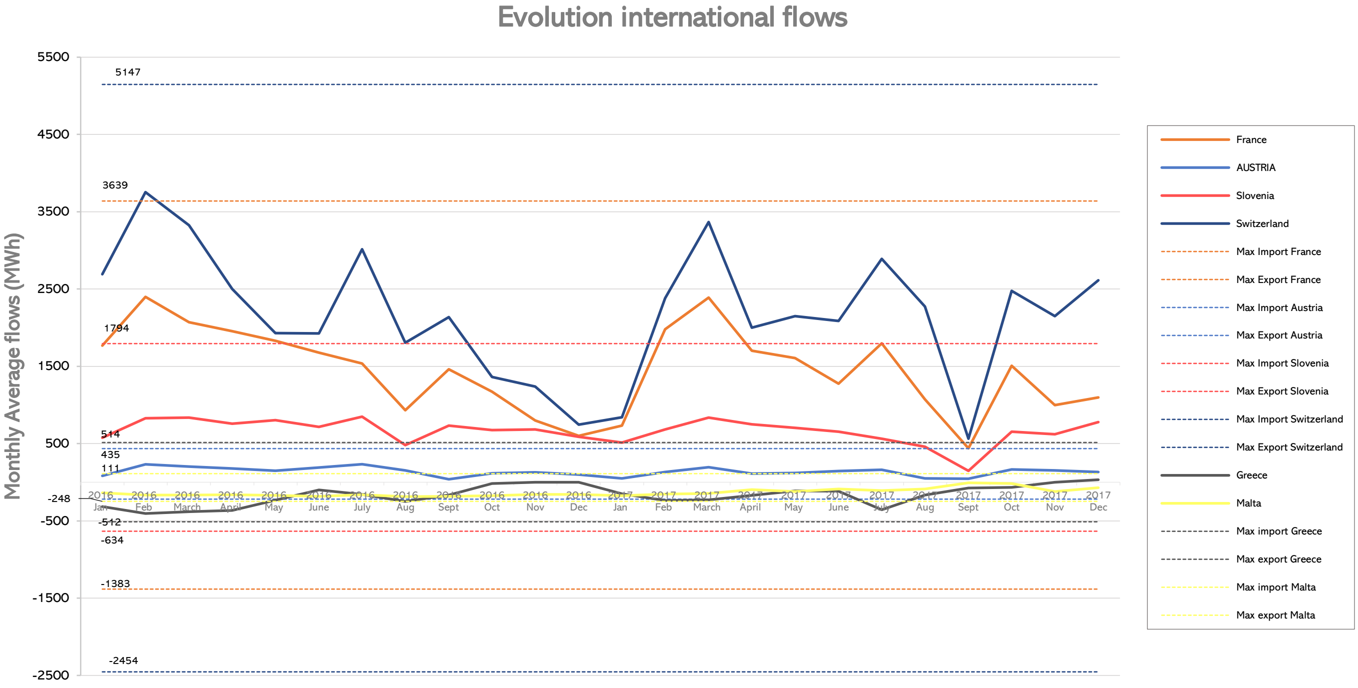

Figure 9: International interconnection flows monthly average. Reference: Own elaboration. Data source: Terna.

As it can be seen in the previous graph, Northern of Italy behaves as an importer from Continental Europe while Southern Italy and Sicily export to Malta and Greece. Furthermore, in the next table, maximum imports and exports are numerically specified.

France		Austria		Slovenia		Switzerland		Greece		Malta	
Max Import	Max Export	Max Import	Max Export	Max Import	Max Export	Max Import	Max Export	Max Import	Max Export	Max Import	Max Export
3639	1383	435	219	1794	634	5147	2454	514	512	111	248

Table 2: Maximum importations and exportations of each interconnection (MWh). Data Source: Terna.

2. PUN

Demand is submitted to a single purchase price (PUN) regardless its location, whereas suppliers are submitted to the zonal clearing price. PUN considers the weighted average of zonal prices in Day-Ahead Market, however, it is solved iteratively in Euphemia.

Some aspects have to be considered concerning the Euphemia's procedure:

- The price must ensure that total revenues from the consumers cover the payments to the producers, subject to a tolerance. This is called PUN imbalance constraint and can be defined as:

$$\text{Total Revenues from Consumers} = \text{Total Payments} + \text{Imbalance Tolerance}$$

$$\text{PUN} \sum_{z} Q_z = \sum_{z} Q_z \, P_z \pm \Delta$$

Where:

Q_z is the volume consumed in each zone z.

$P_z$is the market clearing price of bidding area z.

Δ is the PUN imbalance tolerance, this variable will be used in the optimization.

- In order to prevent paradoxically accepted PUN orders, Euphemia determines PUN in an iterative process during the computation of the zonal prices, and not as an ex post procedure. Paradoxically accepted PUN orders could be orders that are accepted considering the clearing zonal price but not with respect to the PUN price (i.e. The price of the accepted demand bid is higher than the clearing zonal price but lower than the PUN price).
- Euphemia shall consider restrictions due to complex bids (e.g. Minimum Income Conditions).

Considering these aspects, Euphemia is structured the following way [17]:

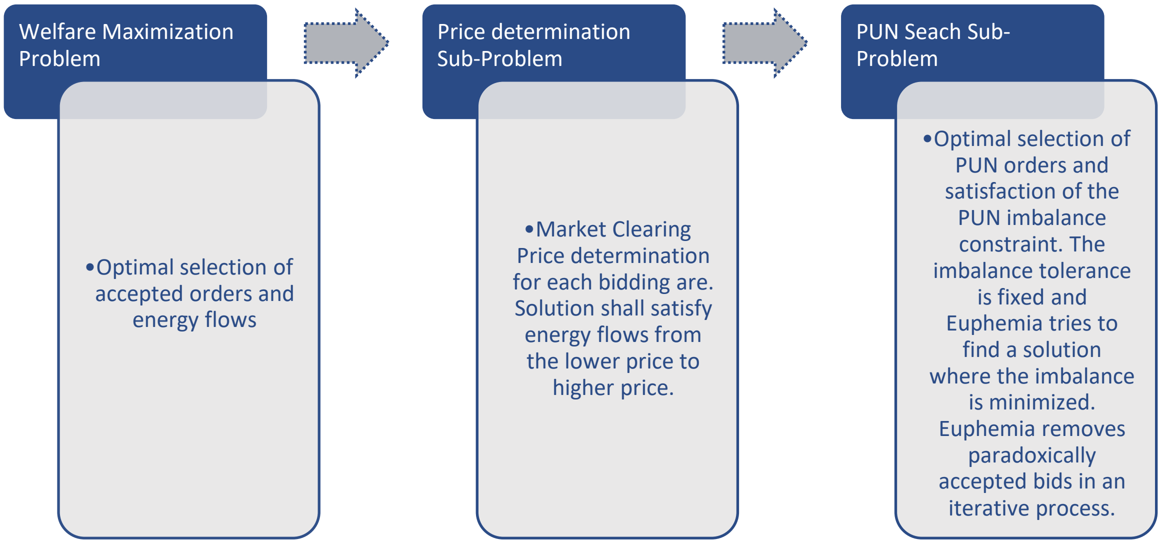

Figure 10: Euphemia's structure.

Italian electricity system is comprised of six main geographical zones and four poles of limited production [18]. Poles of limited production consist in generating units whose interconnection capacity with the grid is smaller than their installed capacity [10]. The six geographical zones are composed of the following regions:

- Central-Northern Italy: Toscana, Umbria and Marche.

- Central-Southern Italy: Lazio, Abruzzo and Campania.
- Northern Italy: Val D'Aosta, Piemonte, Liguria, Lombardia, Trentino, Veneto, Friuli Venezia Giulia and Emilia Romagna.
- Southern Italy: Molise, Puglia, Basilicata and Calabria.
- Sicilia
- Sardinia

Pole of limited production are:

- Brindisi.
- Foggia.
- Monfalcone.
- Priolo G.
- Rossano.

In the next graph, an evolution of the zonal prices is represented. Having the greatest renewable resources in Southern Italy, prices are the lowest. Sicily is the zone with the highest prices in Italy. Note that high prices in commodities in 2017 led to an increase in electricity prices.

Figure 11: Evolution of the price. Reference: Own elaboration. Data source: GME [19].

In the next graph, the congestion cost by zone is represented. Congestion cost by zone is defined as the difference by the Zonal Price and PUN.

$$\text{Congestion Cost } (€/\text{MWh}) = \text{ Zonal Price} - \text{ PUN}$$

Representing this variable, it can be seen how congestion problems in Sicily improved between 2014 and 2015. Northern Italy's price is similar to the final PUN since it is the zone with the highest weight in PUN calculation.

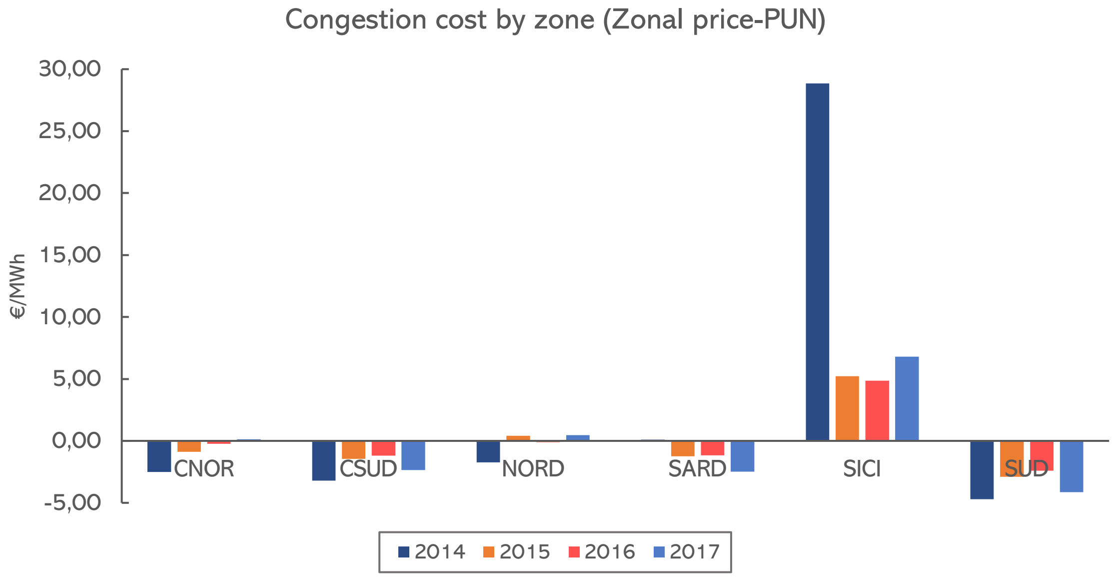

Figure 12: Congestion cost by zone.

3. Commodities evolution

The main four model inputs are commodity prices of thermal plants' fuel: coal, gas, oil and CO_2.

3.1 Coal

Regarding coal, API 2 is the standard reference price for coal imported not northwest Europe, for this reason, API 2 was used in the model as a signal and input to coal plants variable cost [20].

In the next figure, the evolution of API 2 is represented:

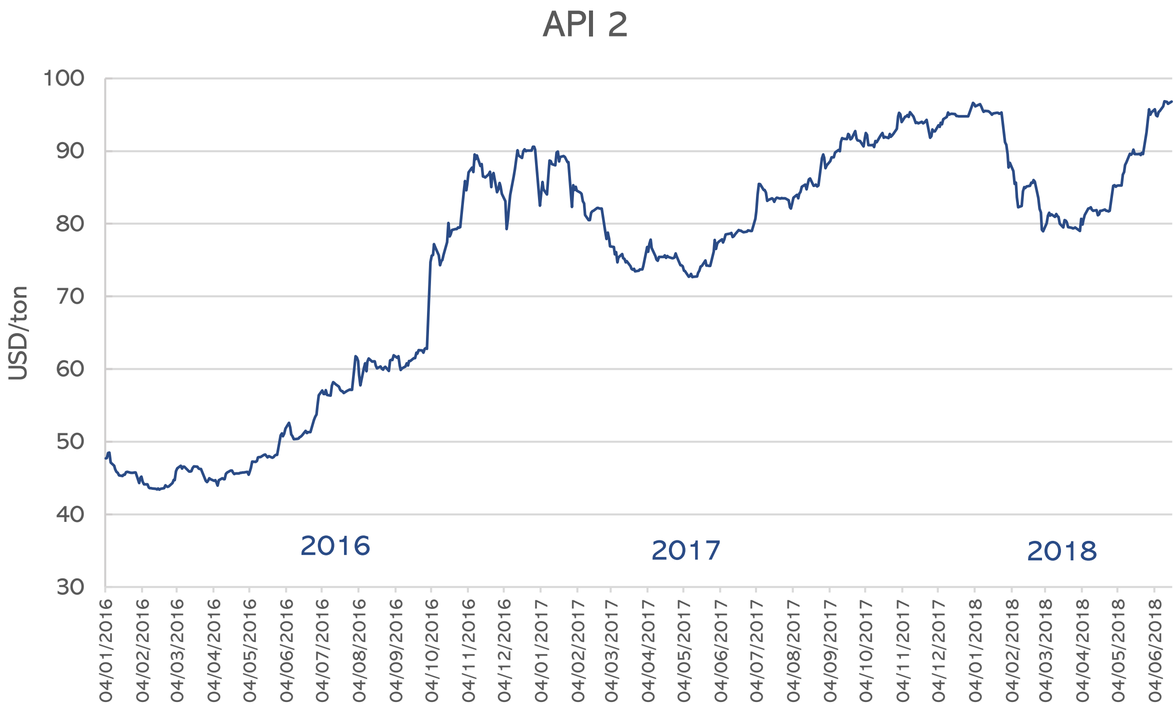

Figure 13: API 2 evolution (2016-2018). Source data: Bloomberg.

The market had several years with an excess of supply and with prices at minimum levels. At the beginning of 2016, Chinese authorities decided to reduce domestic coal production, causing an increase in the country's imports and therefore causing a strong price rebound from approximately 40 USD/ton to prices at more than 80 USD/ton. However, after a mild winter with lower demand, the price was reduced to around 75 USD/ton.

In Q3 and Q4 of 2017, prices have picked up again due to an increase of Chinese demand and a structural reform of Chinese coal Industry. In summary, all these issues are pushing prices up to 90 USD/ton.

The latest data from China show lower imports at the end of 2017. China is still looking to replace its domestic coal with other cleaner energy sources due to environmental problems. Some approved targets agreed by regulation are eliminating coal boilers and replacing coal heating systems with gas or electricity in millions of residences. Even so, the demand is still high when the winter season starts [21].

3.2 Gas

Relative to **gas**, the Italian Virtual Hub, Punto di Scambio Virtuale (Virtual Trading Point, PSV) was used as a reference for gas price used in the gas plants variable cost [22]. In this graph, it is represented both the Dutch Gas Virtual Hub, Title Transfer Facility (TTF) (a market with a higher liquidity) and the PSV.

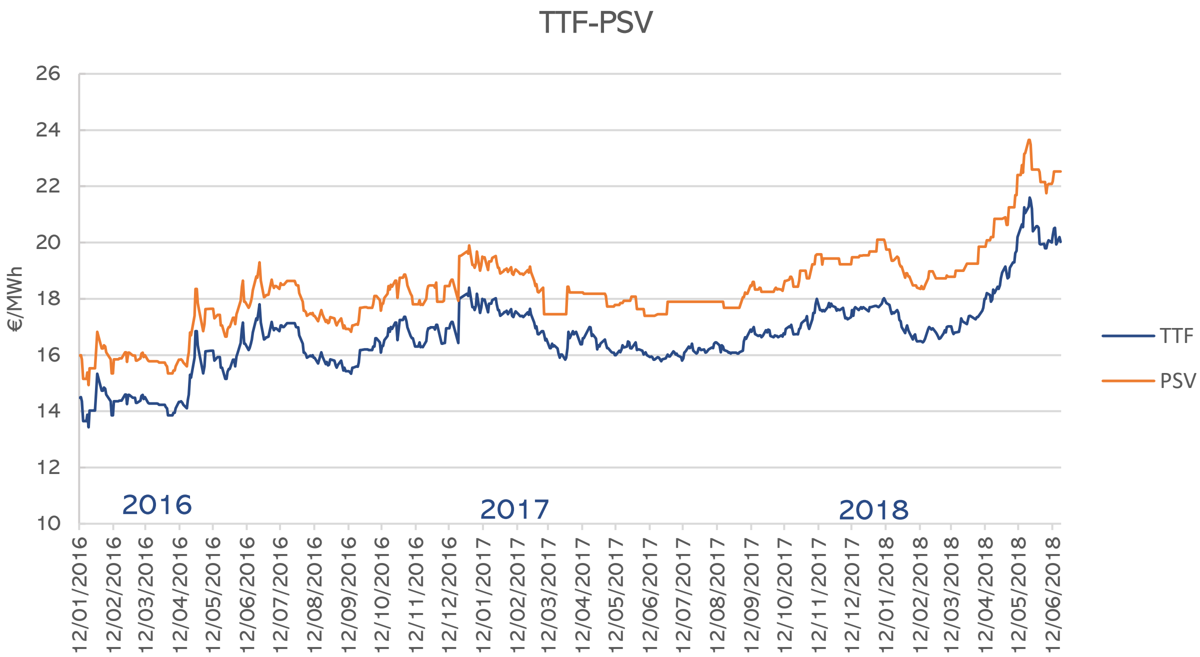

Figure 14: TTF and PSV evolution (2016-2018). Source data: Bloomberg.

The price recorded minimum levels in 2016, standing at around 14 €/MWh. However, during 2017 and mainly in 2018, the gas price has increased. Amongst all the causes of the increase in prices the main are: higher prices in all the commodities, higher demand in combined cycles, higher LNG demand from Asian buyers (Japan and Korea are the main LNG importers) and a lower level of gas storage. The latter cause has a particularly importance in the increase in prices of the last months [23].

3.3 Oil

In Italy, some parts of the country still have **oil** plants, mainly isolated places for instance in Sicily. The reference used for pricing the oil was Brent. Brent is the reference most used for oil. The result is that up to two thirds of the world's oil is priced relative to the Brent reference [24]. In addition to this, Brent reference usually affects other commodities prices.

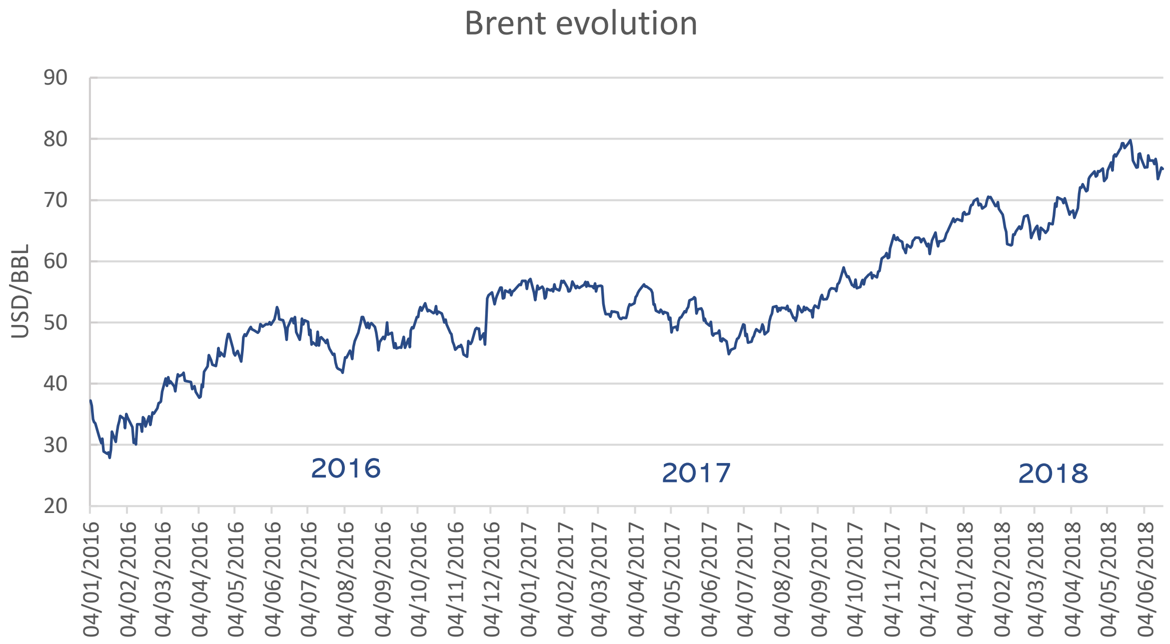

Figure 15: Brent evolution (2016-2018). Source data: Bloomberg.

Oil demand tendency remains growing driven by developing countries in Asia and by the growth in petrochemical sector.

After a sharp fall in prices to 30 USD/bbl in early 2016 due to Saudi Arabia's change of strategy of not adjusting its production and the return of Iran's volumes after the end of the sanctions, the price has been recovering until stabilizing above 50 USD/bbl at the beginning of 2017.

In January 2017 the OPEC agreement and other producing countries that include Russia represented the first crude cut of the last 8 years. It was later agreed to extend the cut until December. The reason for this was to continue balancing supply and demand in order to boost prices. In addition to maintain the limitation of production until December, production quotas were imposed on Libya and Nigeria, countries that have so far been exempt from compliance. This fact, coupled with political instabilities of influential countries (Saudi Arabia, Iran and Venezuela), have contributed to raise the price of crude oil to values over 60 USD/bbl [25].

3.4 CO_2

Price of CO_2 emissions traded in the Emissions Trading System (ETS) is included as an input in thermal plants' variable cost.

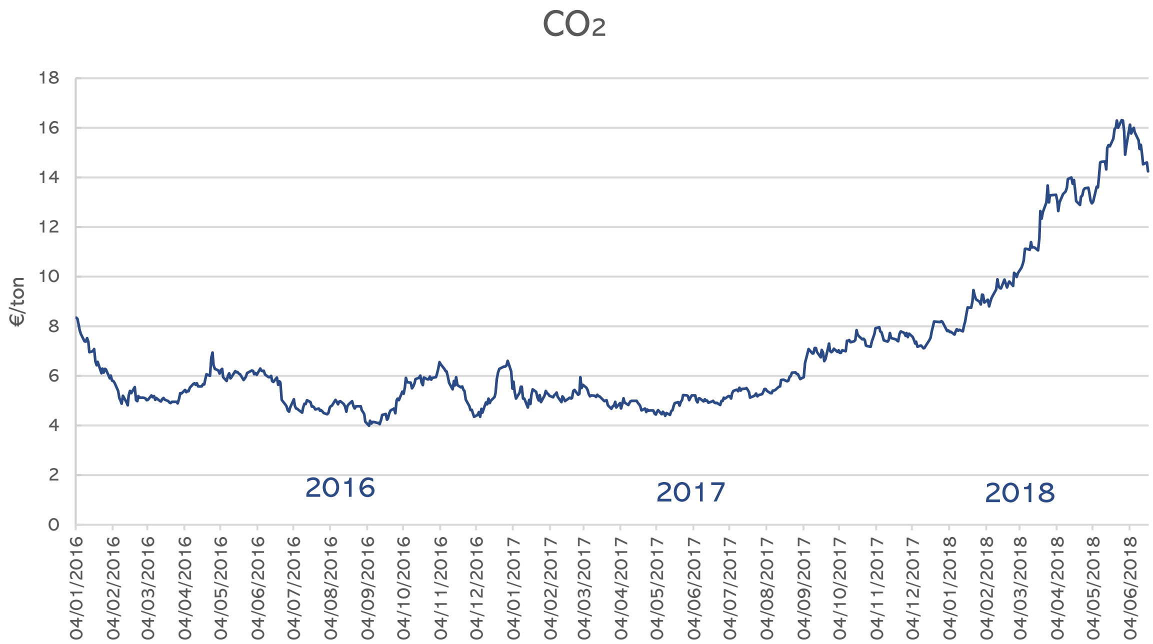

Figure 16: CO_2 price evolution (2016-2018). Source data: Bloomberg.

During 2018, there has been a boost in CO_2 price due to the fact European Parliament has officially supported a reform of the CO_2 trading system with the purpose of limiting emissions.

4. Main challenges

The main challenges which this Master Thesis involved were:

- The difficulty to find accurate data and on a zonal basis.
- There was not any information in the company about thermal plants in Italy. Thus, an algorithm was needed to develop thermal supply curves.
- There was not any model for medium term for Italian Electricity Market in the company. Therefore, the model was developed from scratch.
- The big amount of data needed in this Master Thesis led to the use of statistical techniques such as clustering.

4 Methodology

1. Model description

1.1 Description

Models are usually defined in terms of the time scope of the decision variable involved, in this case, this model is adjusted between medium and long term, as the solution will be given for 2018 and 2019. The model is defined as a hybrid model (explained in Sec. State of the Art), deterministic and fundamental.

The general methodology is a model based on a stack model, this means the demand shall be determined and after this, will be covered with production according to its marginal cost. In this model, this is covered until the thermal gap is left.

The thermal gap is forecasted as the difference between the demand and non-thermal production (renewables and net imports). As supply curves for thermal plants are unknown, an algorithm is developed to build these curves based on historical data, therefore the thermal gap will be related to a price. This model replicates the price formation in each bidding zone and has as an output a coefficient for each virtual plant to be added in its cost formula. This will be further developed in the following sections.

1.2 First step: Thermal gap prediction

Thermal gap is forecasted for each zone as the difference between forecasted demand and non-thermal production. Non-thermal production varies depending on the mix installed on each zone. In summary, variables predicted in this step are:

- Geotherm production.
- Solar production.
- Wind production.
- Hydro production.
- Zonal Net Imports Flows: Net imports from other bidding zones in Italy.
- International Net Imports Flows.

It is important to remark that in this step, the source of all the data is Terna (System Operator).

The first step considered is the **demand** forecast. For that purpose, demand is hourly profiled with historical data updated with the base scenario in Terna Outlook: a yearly increase of 0,48% [26].

After the demand is forecasted, the non-thermal technology production shall be forecasted.

The building profile procedure is the same for all the variables related to the thermal gap prediction (demand and non-thermal production). The historical demand (or non-thermal production) in 2017 is clustered taking into account as well the classification of the date and hour, since standard values for the different types of days and hours are needed to then build an hourly profile. When the variable is profiled for the next year, the profile will include the variation in comparison with the previous year for the forecast (in the case of the demand an increase of 0,48%). This increase will affect the mean of the profile but keeping constant the hourly shape of the curve.

An example of the process is shown in the next figures:

1. **Clustering:**

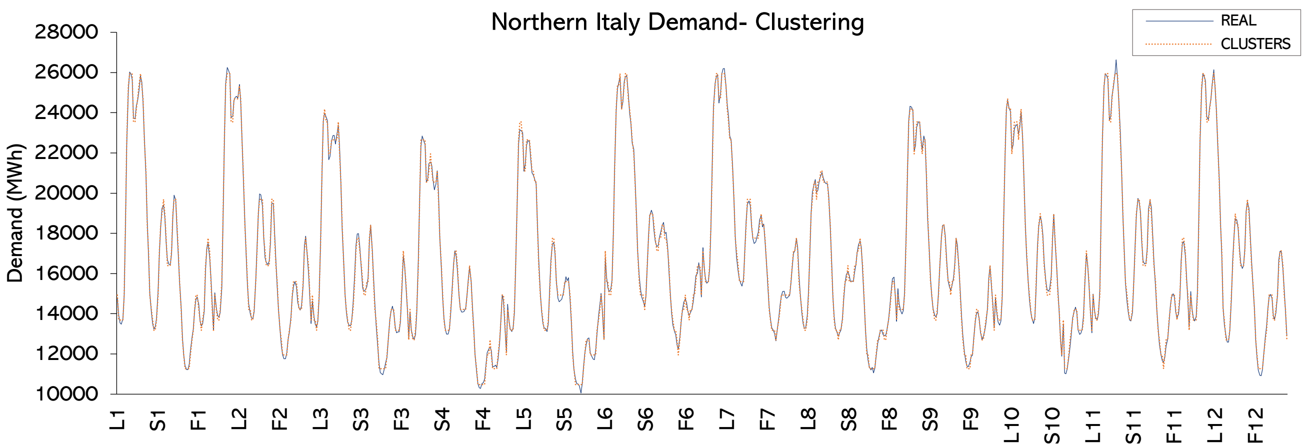

Figure 17: Example of demand clustering for Northern Italy.

The method used in the clustering consists in a centroid-based clustering. In this method, the value of each cluster is the centroid where the squared distances from the variable to the centroid value is minimized. Therefore, the following formula is minimized for each variable:

$$\text{Quadratic Error} = (\text{Actual value} - \text{Centroid value})^2$$

A cluster value is assigned for each of the classification considered (i.e. type of day, month and hour). The classification consists of:

- Type of day: Three groups are considered:
  - Weekdays: This group is composed of days from Monday to Friday which not coincide with a bank holiday.
  - Saturdays: Saturdays which not coincide as well with a bank holiday.
  - Sundays and bank holidays.
- Month
- Hour
- Zone

An example of part of the resultant matrix is represented (Northern Italy, Weekday and January):

Type of day + Month	Hour	Demand	Cluster
L1	1	14.925,87	8,00
L1	2	13.690,28	6,00
L1	3	13.690,28	6,00
L1	4	13.690,28	6,00
L1	5	13.690,28	6,00
L1	6	14.925,87	8,00
L1	7	18.417,03	13,00
L1	8	22.644,41	19,00
L1	9	25.341,50	23,00
L1	10	25.944,45	24,00
L1	11	25.944,45	24,00
L1	12	25.944,45	24,00
L1	13	23.546,41	20,00
L1	14	23.546,41	20,00
L1	15	24.184,21	21,00
L1	16	24.683,79	22,00
L1	17	25.341,50	23,00
L1	18	25.944,45	24,00
L1	19	25.341,50	23,00
L1	20	24.683,79	22,00
L1	21	22.644,41	19,00
L1	22	21.100,08	17,00
L1	23	18.417,03	13,00
L1	24	17.122,87	11,00

Table 3: Part of the clustering result.

2. **Profiling:** Once data is classified, profiling is done hour by hour. To do this, it is necessary to specify the date for future bank holidays and the yearly increase or decrease with respect to the previous year. As it was previously mentioned, the hourly shape of the curve is kept constant.

This methodology is repeated with the other variables related to the thermal gap computation.

In the case of the flows, hydro and geotherm technology, the profile is built without any increase in comparison with the previous year.

In the case of PV technology and Wind Technology, Terna expects a yearly increase in capacity of 1,9% and 3,9%, respectively. A simplification was made to compute the increase in production in each zone. The increase of capacity was related through the capacity factor to compute then the increase of production. The capacity factor was computed according to the zone and the month. Therefore, there are different production increase values for each zone and each month.

Once all the variables are profiled, hourly thermal gap is determined as the difference of the demand.

1.3 Second step: Supply curves of thermal technology

Once the thermal gap is determined, in order to determine the zonal price, it is necessary a relation between the thermal gap and the price.

Since variable costs were unknown, an algorithm was developed to replicate real behavior based on historical data. Stack models may not be dynamic enough, however in this case, the model replicates real behavior with a classification of the type of day, period and month, therefore the strategy of the different units is captured.

In addition, commodity prices are embedded in the cost computation, both in the supply curve determination and in the forecast process. Thus, it is possible to capture a much richer and realistic dependency in the structure.

The process has mainly the following steps:

1. **Variable classification:** The first step is to collect all the data and classify the data. Data is first classified according to:
    - Month
    - Zone
    - Type of the day: Same classification as in the previous case.
    - Hours: Peak hours, Shoulder hours and valley hours.

    In order to classify the hours, historical thermal gap is clustered in third clusters. In this case, instead of computing the clusters on a zonal basis, it is done on a national base. Yet, the type of day and the month are considered. By doing the cluster directly in the thermal gap and not in the demand, the effect of the solar energy can be captured among other effects. An example of this cluster is shown in the next figure where the cluster of the thermal gap for July and a Weekday is computed:

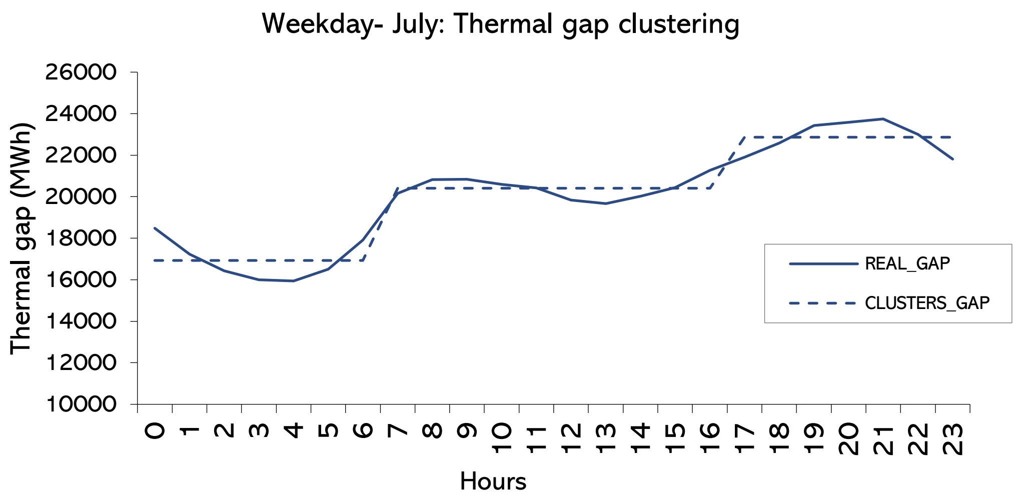

Figure 18: Thermal Gap cluster.

In this case the effect abovementioned is clear, since midday is considered shoulder and not peak hours.

2. **Building the thermal plants supply curve:** When all the data is classified and collected, an algorithm is developed in MATLAB to build the thermal plants supply curves based on historical data.

INPUTS OF THE ALGORITHM

Training data consists of data from 2016 to 2017 (daily commodity prices, hourly thermal gap and spot price). This data is classified as it was explained in the previous section. An example of the input data is showed in the next figure:

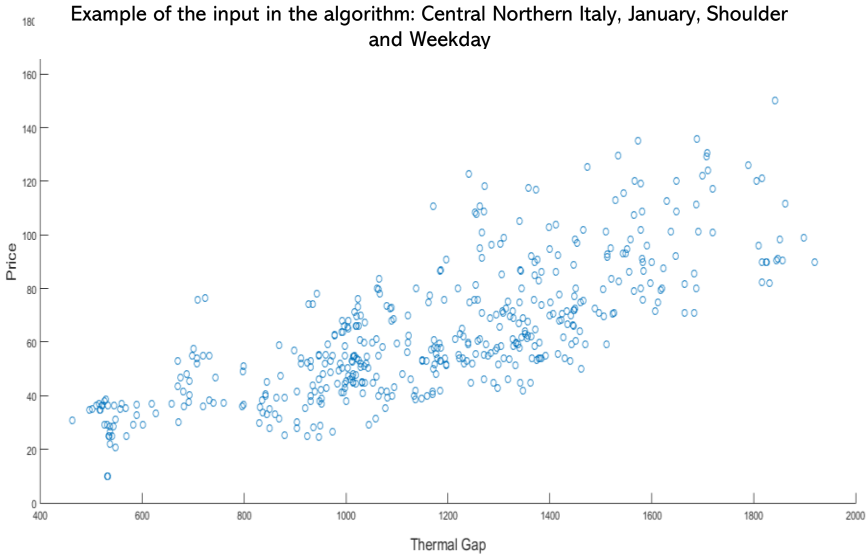

Figure 19: Example of input

FUNCTIONING OF THE ALGORITHM

The algorithm consists in the replication of the price formation in the spot market based on the thermal gap. For that purpose, virtual plants are determined. The total capacity of the virtual plants of each zone is equal to the actual total capacity of the zone and the capacity needs to respect the mix of each zone (oil, coal or gas).

The algorithm within an iterative process, processes hour by hour all the training data. For each day, the algorithm computes the cost of the virtual plants taken into account commodity prices of that day and the different efficiency allocated to each virtual plant. The cost of each technology is determined as follows:

$$C_{coal} = Coal_{\ price}(API2\ price,\ logistics\ costs) \times\ Efficiency\ + CO_2 + O\&M$$

$$C_{gas} = Gas_{price}(PSV\ price,\ logistics\ costs)/\ CCGT\ efficiency\ + CO_2 + O\&M$$

$$C_{oil} = Oil_{price}(Brent\ price,\ logistics\ costs) \times\ Efficiency + CO_2 + O\&M$$

The fuel price is determined with the commodity price and a logistic factor. This price is modified for each virtual plant with its efficiency term (each virtual plant has a different efficiency to allow the ordering process for the dispatch). After this, the cost of emissions is added. This cost is dependent of the price of the emissions allowance in the market and how pollutant the technology is. Finally, a cost term due to operation and maintenance is included. In some cases, a currency exchange rate may be also needed.

After the cost is determined, the plants are ordered in ascending price and the marginal plant is assigned where the sum of capacity covers the thermal gap. For the marginal plant, a coefficient is computed as the difference between the actual price in the spot market and the cost previously computed (i.e. expected cost of the plant):

$$\varepsilon = \text{Actual price spot market} - \text{Cost previously computed}$$

OUTPUT OF THE ALGORITHM

After the algorithm computes the process described in the previous step for all the hours from 2016 to 2017 and all the zones, ε is determined for each virtual plant and all the possible classification of the period. This means each virtual plant for each zone will have a correction in its cost for the different classification of the day and hour. Therefore, the different strategy of the agents on their bids is captured thanks to this coefficient. With the resultant ε ,the determination of the supply curves is achieved. Note that these curves are dynamic since they vary depending on the price. In the next figure, an example of this curve is shown particularized for a specific date:

Date	API2	GAS-PSV	CO_2	Oil-Brent
04/08/2017	68,63	17,15	5,39	52,42

Table 4: Commodities data.

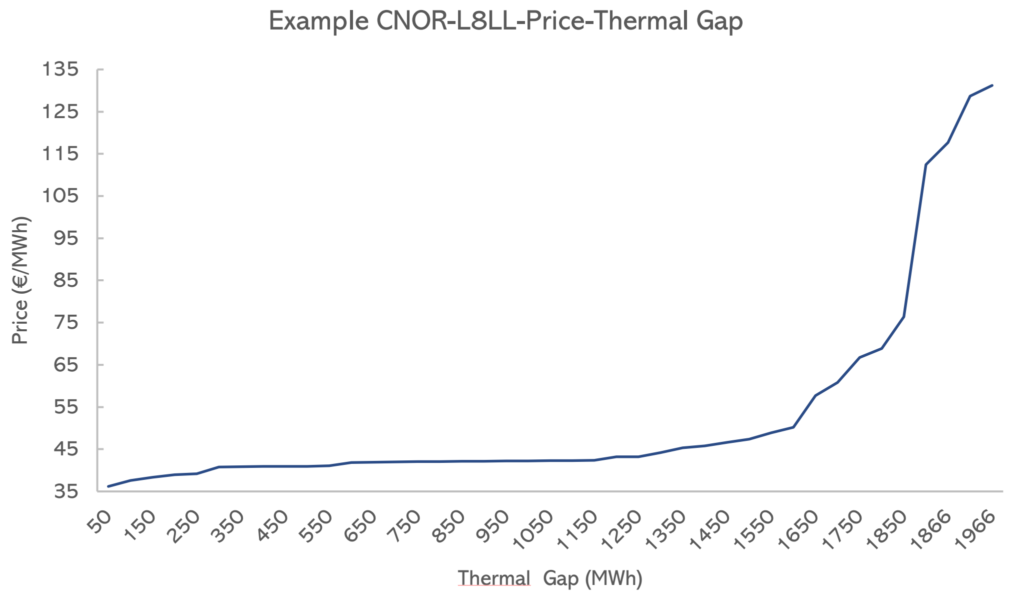

Figure 20: Example supply curve.

In summary, each virtual plant will have a coefficient ε for each type of classification (Type of day, Month and type of hour). With this coefficient, a dynamic curve can be built, where all the thermal technologies are included. This means, that for each zone, there will be 108 types of thermal supply curves (12 months, 3 type of day and 3 type of hour). The order of the virtual plants on the dispatch will vary depending on the commodity prices and the efficiency assigned to each plant.

1.4 Third step: Determining the price

The price is determined with a combination of the output of the first step (Thermal gap forecast) and the output of the second one (Supply Thermal Curves). The structure of this algorithm is similar than the previous one.

INPUTS OF THE ALGORITHM

In this case the inputs are mainly the outputs of the previous steps: Thermal Gap forecast and Thermal Plants Supply Curve. In this algorithm, thermal plants supply curves are computed with commodities' forward prices. For this reason, the result of the model is a dynamic result which changes whenever commodities' forward prices change.

FUNCTIONING OF THE ALGORITHM

The functioning of the algorithm is similar to the previous one. However, the computation cost of each virtual plant is updated with the coefficients obtained in the previous step. In summary, the cost is computed as follows:

$$C_{coal} = Coal_{\,price}(API2\,price,\ logistics\ costs) \times\ Efficiency\ + CO_2 + O\&M\ + \boldsymbol{\varepsilon}$$

$$C_{gas} = Gas_{price}(PSV\ price,\ logistics\ costs) /\ CCGT\ efficiency\ + CO_2 + O\&M + \boldsymbol{\varepsilon}$$

$$C_{oil} = Oil_{price}(Brent\,price,\ logistics\ costs) \times\ Efficiency + CO_2 + O\&M + \boldsymbol{\varepsilon}$$

The dispatch is done hour by hour taking into account the thermal gap and updating the cost of the virtual plants with the commodity price.

OUTPUT OF THE ALGORITHM

The output of the model is the expected hourly zonal price for 2018 and 2019. Although the result is in an hourly basis, a monthly basis or a quarter basis have more interest in forward markets. Therefore, these prices can be processed in order to change the basis.

1.5 Fifth step: PUN calculation

After zonal prices are computed, the last step of the model is to compute the PUN.

As it was explained before, the PUN is not an ex-ante calculation but rather an iterative process during the calculation of zonal prices in Euphemia. Because of the design of the model, zonal prices are calculated separately and therefore it is not possible to use an iterative process.

As a simplification, PUN is calculated ex-post. 2016 and 2017 zonal prices and PUN are statistically related through a linear multiple regressive analysis. 17544 observations constitute the sample of the analysis with the result of a multiple correlation coefficient of: 0,9996.

As a result of the analysis, PUN was computed as follows:

$$\mathbf{PUN} = 0{,}0709535 + \mathbf{Price\ CNOR} \cdot 0{,}13436903 + \mathbf{Price\ CSUD} \cdot 0{,}14279306 + \mathbf{Price\ NORD} \cdot 0{,}54717704 + \mathbf{Price\ SARD} \cdot 0{,}03584445 + \mathbf{Price\ SICI} \cdot 0{,}05782892 + \mathbf{Price\ SUD} \cdot 0{,}08395718$$

Note that Northern Italy has the highest weight in the final price due to the high demand of the zone while Sardinia has the lowest weight.

2. Model validation

With the purpose to estimate how accurate the model is predicting the price, data was divided into training data (i.e. data used in the development of the model) and test data (i.e. data used to validate the model.

Training data is used to build thermal plants' supply curve. These curves relate thermal gap with price.

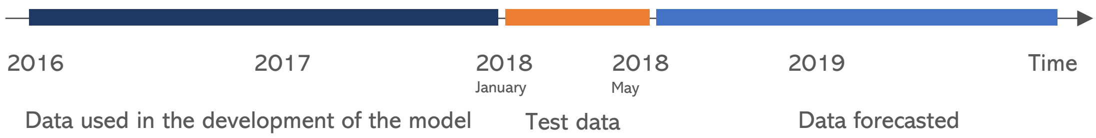

Figure 21: Scheme data model.

After the computation of the results, some statistical analyses are performed.

Residuals are defined as the difference between the actual prices and the resulting price of the model [27].

$$e_t = p_t - \widehat{p_t}$$

Residuals are a useful tool to check whether the model have adequately forecasted the prices. For that purpose, some analyses shall be performed, namely:

- Residuals have approximately a zero mean.
- Residuals are normally distributed and Root Mean Squared Errors and Mean Average Errors are checked.

Results of this analysis are shown in the chapter 5 (*5.1. Validation results*).

5 Results

1. Validation results

As it was explained in the previous sections, the model was developed with inputs from 2016 and 2017, whereas the test data comprised a period from January 2018 to May 2018 May.

In the following graph, the resulted PUN from those dates and the results from the model are compared. Note that, in general, the model captures the behavior and the tendency of the spot prices.

At the end of February 2018, there was a peak in the spot price provoked by a strong increase in the gas prices all around Europe. It can be seen that when the prices are outside the usual range, the model has more difficulties to predict the actual prices.

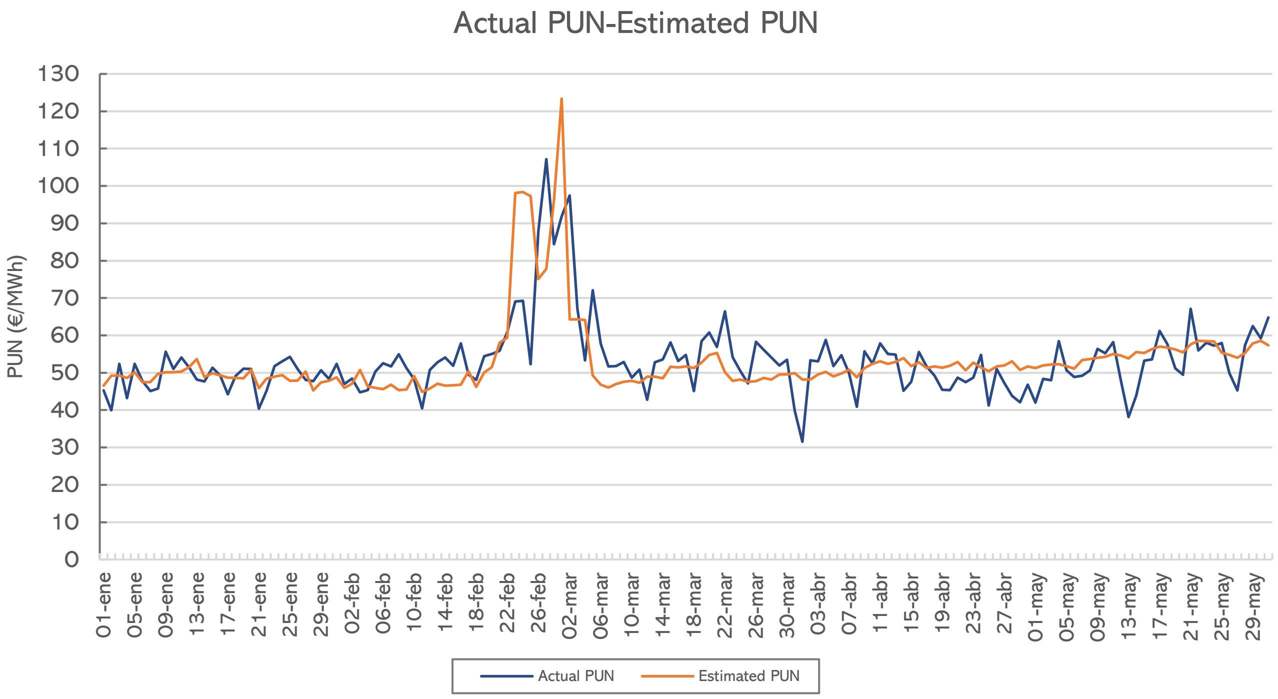

Figure 22:Results validation.

In the following graph, residuals of the test data (i.e. difference between the actual prices and the resulting price of the model) are represented. The biggest difference, as it was seen in the previous graph, resulted at the end of February.

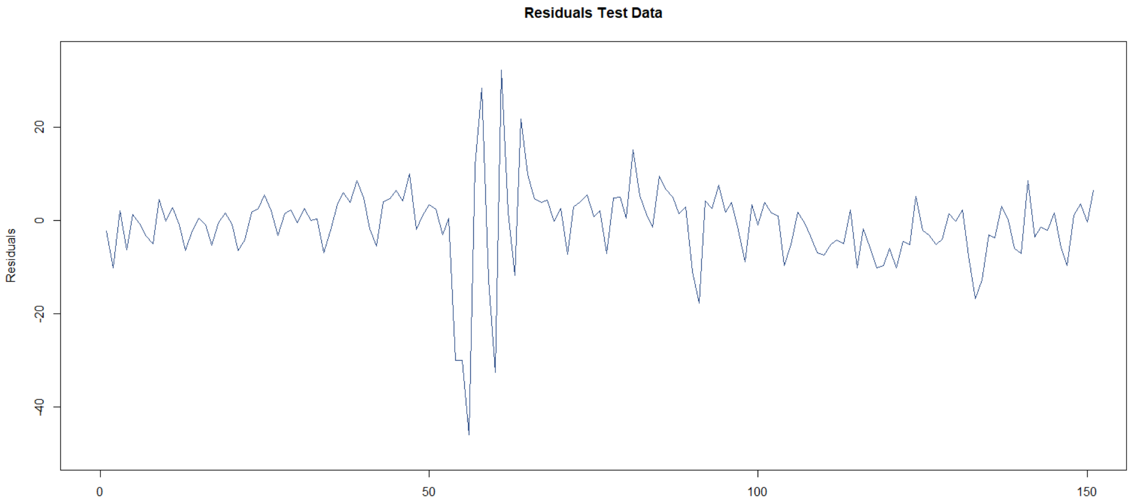

Figure 23:Residuals evolution of the test-data.

The mean of the residuals represented in the graph is: $\mathbf{Average(Residuals)} = \mathbf{-0,9381783}$. The ideal average should be zero, however the resulted average has not a representative difference regarding the ideal value.

Because of the possible effect of the outliers in the final result, the outliers are going to be analyzed. For this purpose, a univariate approach is followed. This means that outliers are defined as the data that lies outside 1,5*Inter Quartile Range or in other words 1,5 multiplied by the difference between 75^{th} and 25^{th} quartiles.

This analysis is performed in the software R with the result of 7 discarded points. After discarding the outliers from the sample data, the average of the residuals is closer to zero: $\mathbf{Average(Residuals)} = \mathbf{-0,5956.}$

In the next graph, a histogram of the residuals is represented.

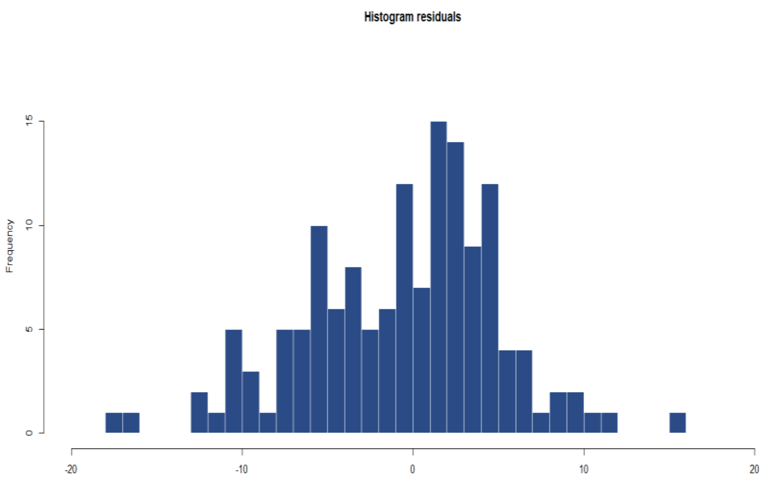

Figure 24: Histogram of the residuals.

In addition to the histogram, a Quantile-Quantile (Q-Q) plot is represented. This graph will help to assess if the residuals set of data came from a Normal distribution.

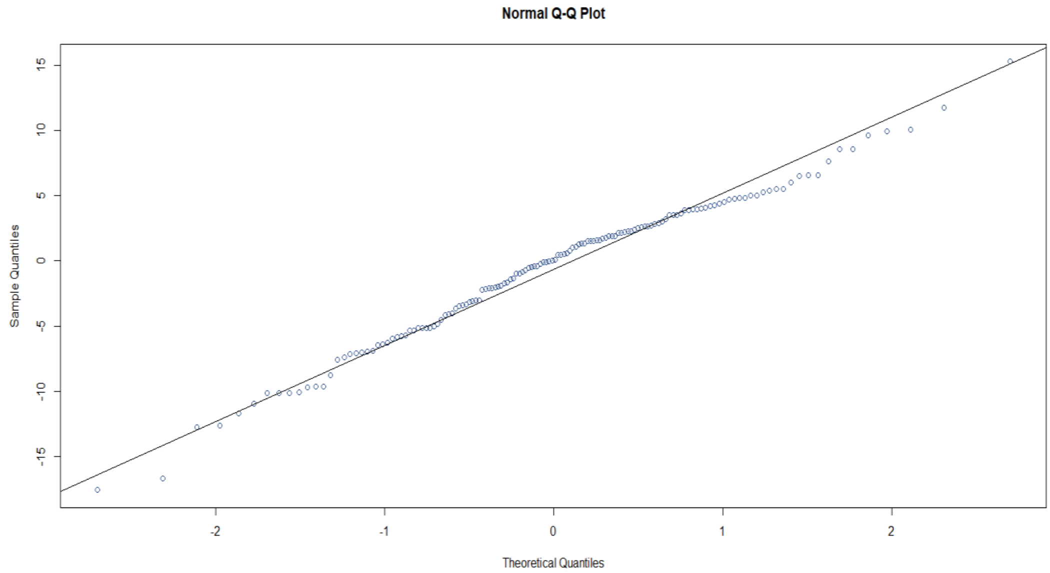

Figure 25: Q-Q plot.

If Shapiro-Wilk normality test is performed, next variables are obtained: W = 0,98488, p-value = 0,1153. With the assumption of the significance level at 0,05, then p-value>α (0,1153>0,05) and null hypothesis about the normal distribution cannot be rejected.

Next, in the next figure, the histogram of the absolute residuals is represented. Note, that residuals with smallest values are the most frequent.

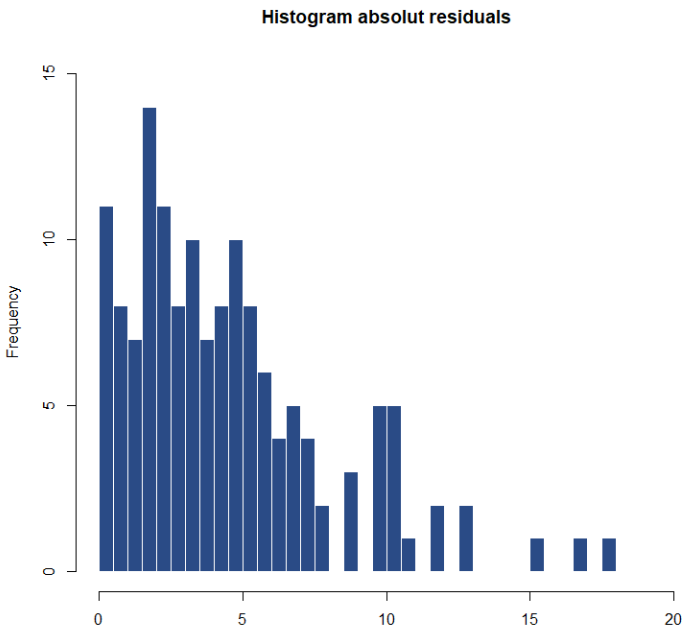

Figure 26: Histogram of absolute residuals.

Finally, some statistical calculations are computed[27]:

- **Mean Absolute Error (MAE):** MAE measures the accuracy of the predictions by measuring the average magnitude of the residuals in absolute terms.

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}|p_t - \widehat{p_t}| = 4{,}4553\ €/\mathrm{MWh}$$

- **Root mean squared error (RMSE):** RMSE is another calculation to measure the accuracy of the prediction. It measures the square root of the average of squared residuals.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(p_t - \widehat{p_t})^2} = 5{,}664\ €/\mathrm{MWh}$$

  RMSE gives a relatively higher weight of large errors as the residuals are squared before they are averaged.

2. Evolution of the prices according to the model

It should be noted that the model is dynamic since the inputs are also dynamic, i.e. Forward commodity prices change in every market session, therefore the prediction of the forward market will change as well. In this section, this fact is analyzed.

The model is run for different periods, therefore as the forward commodity market prices change, the inputs of the model change as well. The output of the model (future electricity price for different periods) is compared with the result of the forward market price.

For this analysis, the result for 2019 and the result for all the quarters in 2019 are analyzed.

In the next figure, the analysis for 2019 is represented.

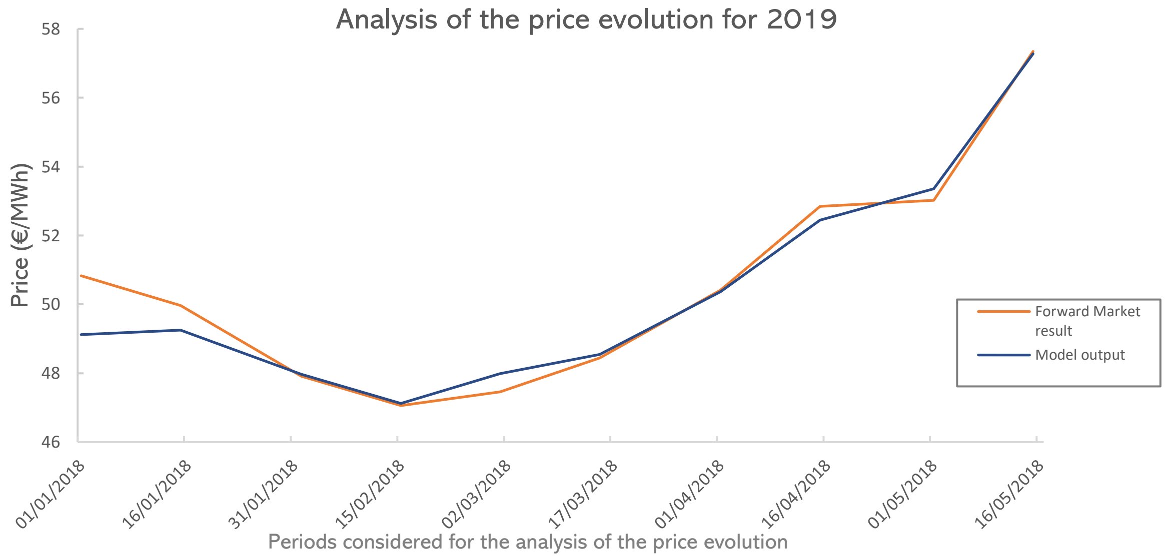

Figure 27: Analysis of the price evolution for 2019.

Note that the difference between the price set by the market and the forecast of the output is small. The average of the difference between the model out and market price is -0,185 €. Therefore, it can be concluded that prices forecasted in the model and forward prices for 2019 are almost equal. In addition, it can be seen that the model converges in the course of the year. It is possible that at the beginning of the year the risk premium was higher due to the low French nuclear capacity. The model is not able to capture this market behavior and consider a base scenario where the net importing from France is positive which means Italy is importing from France.

In the next figure, the results of all the quarters for 2019 is represented.

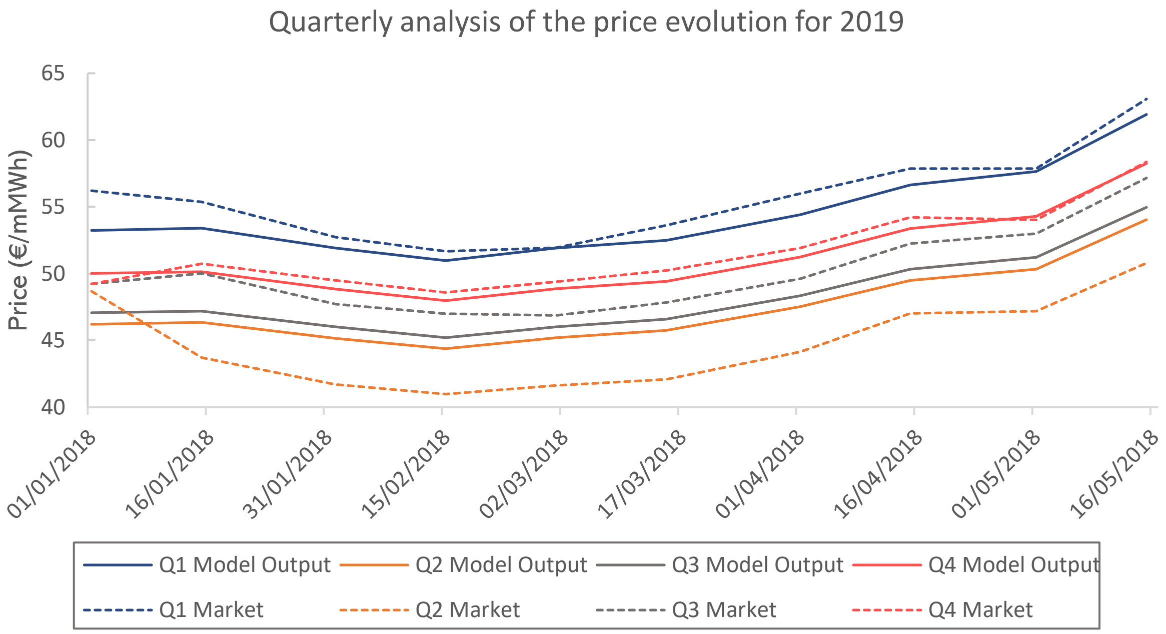

Figure 28: Analysis of the price evolution for all the quarters in 2019.

When the output of the model and market prices are analyzed with more granularity than in the previous case, it can be concluded that in this case there are differences between the two variables. Depending on the quarter, the difference between the two variables is higher and the value is different. In the figure, it can be seen that prices in Q1 are the highest between all the periods while in Q2 the lowest. Regarding the difference between the two values for all the periods, in the next figure is represented the average.

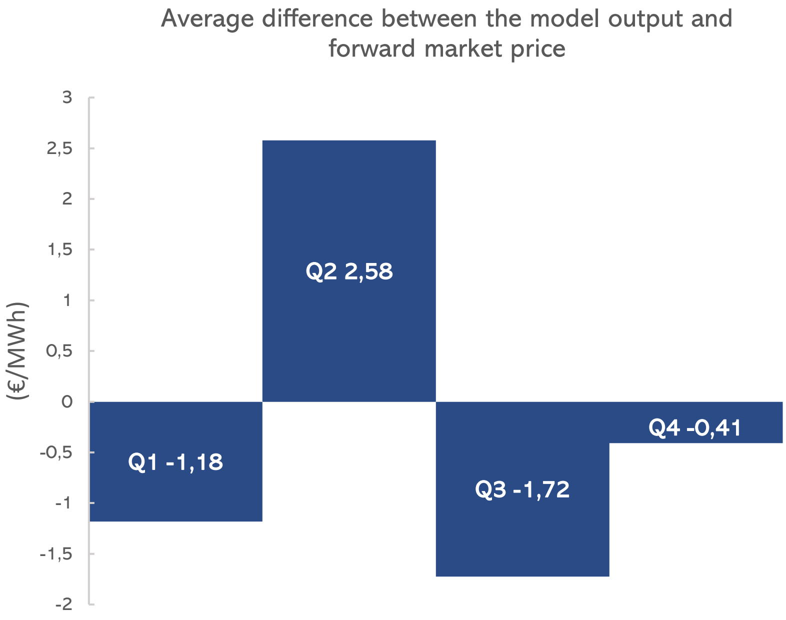

Figure 29: Average of the difference between the output of the model and forward market price.

Note, that in Q2 the model provides higher values than the market prices and the other way around for the rest of the quarters. This fact makes that the yearly comparison abovementioned, presents values which are almost equal.

3. Comparison forward market prices

In this section, the output of the model is shown when the model is run once, in this case with inputs from the date: 21/5/2018. As it has already been explained, the output of the model is dynamic as the input is dynamic as well. For that reason, a date was chosen to show an example of the model results.

The next graph represents the tendency of the estimated prices and the forward market price. Note that the estimated prices are slightly lower than the forward markets except in the second quarter in 2019.

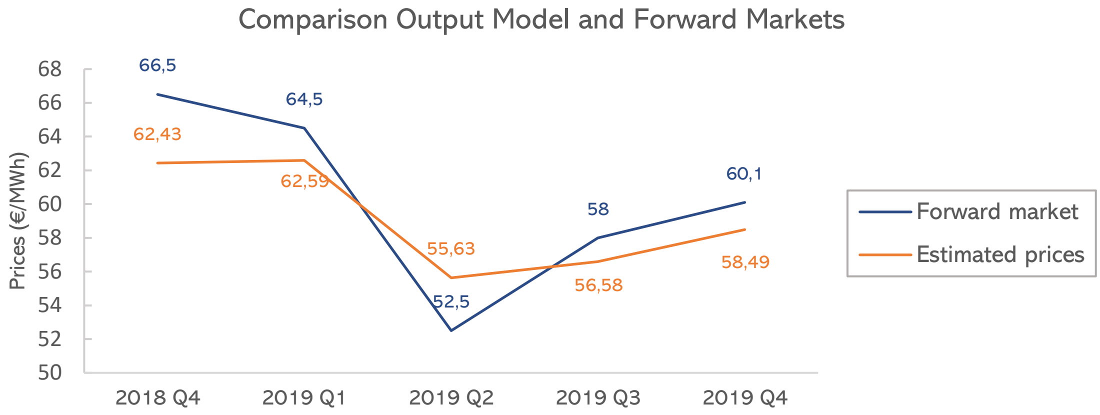

Figure 30: Comparison estimated prices and forward price markets.

Concerning the price for 2019, price estimated, and market price are almost equal:

	Market Price (€/MWh)	Estimated Price (€/MWh)
2019	58,6	58,31

Table 5: Comparison results 2019

6 Conclusions

1. Conclusions

1.1 Summary of the problem

The aim of the Master Thesis was to forecast electricity prices in Italy for 2018 and 2019. For that purpose, a deterministic, fundamental model was developed which can be defined as a hybrid model since different techniques are used. Mainly, the hybrid model can be defined as a production cost model in which different strategies have been captured with an algorithm whose training data is based on the thermal gap and spot prices from the period of 2016 and 2017.

During the Master Thesis development, the main problems were related to difficulties in finding reliable data and in a zonal basis. In addition, one of the main problems as well was the large number of data used in the model. In order to process all the data, clustering analysis was used and databases' tools like SQL and Access were necessary.

1.2 Main findings and discussion

The validation process provided positive results and showed that the model adjusted its outputs according to actual data. In addition, in this analysis residuals were close to zero which is a condition for a good accuracy of the forecast.

Nevertheless, results in the validation showed that when prices were out of the usual range, the model had more difficulties to forecast the price.

If results are compared with the expectations of forward markets, it was showed how the results were almost equivalent. Therefore, one can conclude that results and the model development were satisfactory, taking into account that the model can be improved in future works.

1.3 Objective analysis

In this section, it is going to be analyzed whether the objectives proposed in the first section were fulfilled or not.

The main objective of the Master Thesis was fulfilled as it was explained in the previous section. The results have been validated and compared with the forward market with acceptable results.

Regarding secondary objectives, during the process of the model development, the market was studied. In the section: Problem description, main facts of the Italian market have been introduced. Some of the key aspects which have been concluded are explained in this section, such as the importance of Northern Italy and the Central South of Italy in the final price, main interconnections (first Switzerland and second France) or that the production is based on thermal technologies.

The output of the model is a daily future price curve. Therefore, the objective related to this issue has been positive fulfilled and the curve will result useful for an hourly pricing design.

The last step of the model has been developed in VBA and Access. Thus, any person with a general knowledge in Office can manage the model. In addition to this, if the model has to be modified, only the inputs should be modified and not the code, therefore the functioning of the model will not change.

2. Future works

As this model was started from scratch, there is more room for positive steps and reasonable improvements which can be made to enhance the model.

Firstly, the design of the model is suitable and is prepared for a machine learning methodology. The actual model cannot be considered so far a machine learning model, as there is not an automatic process which updates the input data. However, if a bot is performed to link Bloomberg with MATLAB and Access, databases can be daily updated and then the process will be considered as machine learning. If the inputs are updated, thermal supply curves will be modified and will be continuously improved. The more the model is trained, the more accurate the results will be.

Furthermore, one of the assumptions made in the Master Thesis which should be firstly improved is that the dispatch is done considering economic variables and that flows are based on historical data. However, this could be improved adding an optimization in the dispatch which considers the flows and constraints between zones.

Moreover, variables have been simplified to deterministic ones. Nonetheless, variables such as demand or RES production are not deterministic, and some stochasticity may be added in future works.

Finally, future works might involve extending the model to other countries such as Germany or France, which may also be interesting for the company. In those cases, the model could be simplified as there are not bidding zones within the country.

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