# POLITECNICO DI TORINO

**Master's Degree in Electrical Engineering**



**Master's Degree Thesis**

# Implementing an energy trading strategy using forecasting of energy prices and production

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# Summary

Energy production is evolving over time: the number of players involved is increasing and new variables, such as the rate of production from renewable resources, are introducing the influence of uncontrollable events as weather conditions. Consequently, this fact leads to an increasing of the volatility of the production and, as a result, of the price, with more variables to take into account. In previous times, energy production was handled locally, and the energy price was settled daily.

On the contrary, nowadays the interconnection throughout all Europe has created new opportunities for energy traders, particularly with the advent, as anticipated, of the volatile renewable resources. Producers are hence facing the challenge to adapt to this new landscape. The new markets (so-called Cridas "Complementary Regional Intraday Auctions") have been created for enabling them to adjust their position for selling and bidding quantities of energy during the day ahead or the same day of offering. In this way they can maximize the income from the selling or buying energy through all the energy markets.

The aim of this thesis is to find a way to maximize the profit with a proper strategy. First of all, it has shown the current development of the Italian energy markets, the trends of the historical price, the exchange volumes in the markets and then portfolio of energy production in the peninsula and the islands. After that, it is required to forecast the price on the relevant energy markets, and, to do this aim, several models have been implemented, with the target of reducing the error in comparison with the actual data. Later on, a forecasting of energy production in different types of power plants has also been developed. This has allowed to understand the quantity of energy that a producer could sell or bid.

Finally, as anticipated, it is shown how different strategies for selling and bidding energy can change the expected earnings by the end of the negotiation. Different strategies will be shown to understand which of them is the winning one.

# Acknowledgements

**English**

Sometimes one does not realize how many steps one has taken until has reached the top. When I think back on my university journey, it was a strenuous walk, with ups and downs, that brought me this far.

My gratitude extends over many paths: many have accompanied me on this road, some for a short time, some for a long time, some towards the end, some only at the beginning, but all have left me something.

It is right to start my thanks on the Politecnico side, which for years has been my second home, and my first thanks go to my supervisors, Professors Repetto Maurizio and Lazzeroni Paolo, who have assisted me in a masterly manner, both on the human and professional side. Then I would like to pass on to my historical colleagues, or rather friends, in particular Margherita, Matteo, Pietro, Alessio, Rebecca, Fabio and Thomas, in whom we have always supported each other over the years.

Subsequently, my thanks go to Volue, to Alvaro, who in moments of discouragement managed to keep me from giving up, to Andreas, who was always willing to listen to my streams of consciousness and comment them in a helpful way, to Kari and Anja, who first realized my value and hired me, to Erlend, who introduced me to Volue, and to the guys in Oslo, Madrid and Gdansk, as well as Anamaria and Marco, who introduced me to the world of Volue Insight.

Then to my lifelong friends, who have never made me feel lonely on the countless journeys I have undertaken, in particular the Erasmus group (too many to mention, but I am grateful to each and every one of you) and the friends of Pinerolo and the valleys, in particular Camilla, Davide, Fede, Renzo and Umberto, without all of you, I would not have made it.

Last but not least, to my family: to my brother Simone and my parents Rossana and Davide, who, despite the fact that having a son abroad is not easy, have never stopped me from pursuing my dreams, even in the dark times.

Takk

*Stefano*
*Turin 27/11/23*

*"...Ai miei nonni"*
*"...To my grandparents"*

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# Acronyms

**GSE**

Energy Services Operator,
Gestore Servizi Energetici

**GME**

Energy Market Operator,
Gestore Mercati Energetici

**MPE**

Electricity Market at Readiness,
Mercato Elettrico a Pronti

**PUN**

Single national price,
Prezzo Unico Nazionale

**MGP**

Day Ahead Market,
Mercato del Giorno Prima

**ARERA**

Regulatory Authority for Energy Networks and Environment,
Autorità di regolazione per energia reti e ambiente

**ARIMA**

AutoRegressive Integrated Moving Average

**AU**

Sole Buyer,
Acquirente Unico

**RSE**

    Electrical System Research,
    Ricerca del Sistema Elettrico

**CRIDA**

    Complementary Regional Intraday Auctions

**NEMO**

    Nominated Electricity Market Operators

**SIDC**

    Single IntraDay Coupling

**IDM**

    Intra-Day Market

**DAM**

    Day-Ahead Market

**XBID**

    Cross-Border Intra-Day Market

**LSTM**

    Long Short Term Memory

**DNN**

    Deep Neural Network

**MLR**

    Multiple Linear Regression

**TS**

    Time Series

**MAPE**

    Mean Absolute Percentage Error

# Chapter 1

# Introduction

## 1.1 My background

I am an Electrical Engineer student at Politecnico of Turin, enrolled in the specialization course "E-mobility and Smart Grid", and enrolled in the cohort of 2021-2022. I did an Erasmus in the Norwegian city Trondheim for 5 months, at NTNU, from August 2022 to December 2022, in which I have known the company Volue.
After that, with the help of my actually supervisor Repetto Maurizio, I figured an internship out in the same company from January to February 2023 and then came back to Italy in March 2023.
After spending the last semester in Turin, I came back to Oslo in September 2023 to work on this thesis at Volue.

## 1.2 Choice of the project

Volue is working in several fields, such as energy markets, energy trading, energy production, power grid, constructions and water, but during this months my focus has remained the energy production.
During the period in the Trondheim office, I had the opportunity to work with my other current supervisor of the thesis Alvaro, from the Madrid office. We discussed about my study path and interests, and he proposed me the current thesis, and I have happily accepted to handle this work.
Indeed, this is a new field within the Italian energy market, since the goes live of the European Intraday Market was September 2022, hence it is a new area of work. Then I have always been concerned in the data analysis and forecasting, hence it was a concrete opportunity to develop this interest in a skill, in addition to the knowledge of energy market.

## 1.3 Company presentation: Volue

Volue, first of all, is a software company focused on the Green Transition [1].



**Figure 1.1:** Volue's logo

They supply technology to three main sectors: energy, power grid and infrastructures. Hence, their customers are energy utilities, large end consumers, grid operators, or builders of infrastructure; but also municipalities, defense, maritime or transport.

In addition, a slice of Volue, called Insight, is committed in the analysis of data for the energy market, thus covering most of all the European bidding zone. Additionally to the studies of the actual data, they provide forecasting for most of the European energy markets.

Nevertheless, as shown on their website [1], Volue has approximately 800 employees worldwide and owns 30 offices, helping overall more than 2500 customers.

### 1.3.1 History and description

The Company was formerly founded in 2020, after a renovation of the former company Powel, founded in 1996 as an offshoot of the SINTEF group, one of the largest research organizations, settled in Trondheim.

So research and innovation are within their DNA from the beginning, they update products to be always up-to-date to the new outstanding technologies of energy markets.

In summary, the commitments of the Company are about creating the software, insight and systems for enabling the Green Transition and leading also the European markets' transition.

## 1.4 Customer

The type of customer that might be interested in this work, so implementing a strategy for bidding and selling in the various markets, it needs to be a large market operator working in the Italian market. It might be active in the production or trading of energy, but it might want to increase its revenue by investing energy in not only the Day Ahead Market.

### 1.4.1 Portfolio and future objectives

As other European companies, the commitment of producers of energy is the reduction of emission of greenhouse gases, hence be focused on renewable resources, such as hydro or wind, instead of thermoelectric production. The Intraday Markets

have been created indeed for investing the energy from renewable resources, so if the trend stands, would be expected a larger volume traded in these markets. The main point of these markets is to invest properly the surplus of energy already sold in the Day Ahead Market, or on the other hand buy the mismathch energy. This is so as to resolve the volatility of renewable resources, and the energy operator can change its position close to the delivery point, depending on the forecast implemented.

# Chapter 2

# Methodology

## 2.1   Italian electricity market

The modern Italian electricity market [2] was created by the "Decreto Legislativo
n. 79/99" of the 16th of March 1999, also known as "Decreto Bersani". The organs
created are hence under the control of the GSE which has the role of *"management
of the electricity market"* [...] and this has to carry out [...] *"according to criteria
of neutrality, transparency, objectivity and competition between producers"* [2]. The
creation of the electricity market is a milestone for the trade of energy, with the
aim of balancing the generation and the load in the whole Country. In case of the
generation in Italy exceeds or not the load, energy is imported or exported to the
countries that border by sea or land, thus creating a flow of energy through various
kilometers from production and use. It is clear that energy is a product that is
worn out at the same time is produced (storing is not yet economically feasible in
large amounts), differentiating itself from mass products not only for deliveries,
but also for commercialization. So, this markets act like intermediary between the
producers and the customer, settling up at the end of the negotiation the PUN,
the Single National Price (*Prezzo Unico Nazionale*), and in the section 3.3.1 it will
explain the procedures to establish it.
The keystone is to find a middle point between the producers of energy, who want
to sell that at the highest cost possible, and the suppliers, who on the other hand
prefer to buy at the lowest price possible [3]. It is possible to visualize the mismatch
between generation and production from the measurement of the frequency in the
grid. Normally, in Europe the frequency has to be close to 50 Hz, with a bearable
gap of $\pm 50$ mHz standard, and $\pm$ 800 mHz as the maximum deviation [4]. Hence,
if the frequency lowers, this means that the load has overtaken the generation, or
vice versa.
As a result, if the frequency goes beyond this tolerable range, blackouts could occur,

from local ones to catastrophic national ones, as already happened in 2003.

The organization that is responsible for forecasting the national demand for electricity is the TSO, Terna, and then makes a comparison between the production planning from producers and the national power demand (then split in the various bidding zones), supplying or selling the difference quota abroad.

So the electricity market is not only a place for selling and buying randomly an asset, nevertheless, a place where a basic necessity is traded and every citizen of a country might be affected, in positive and negative.

### 2.1.1 Structure

For a better understanding of the offices involved, it is created a list of the various departments, with a scheme of connection in Figure 2.1. First of all, every office performs tasks in accordance with the Government and the Parliament.

The "Decreto Bersani" already quoted, has convened to dismantle the monopoly of energy production, transmission and distribution of Enel, thus creating a competitive market in which Enel is part of it. The "Decreto Bersani" was the milestone for the creation of the actual energy supply chain and markets, with the organizations shown in Figure 2.1 below.
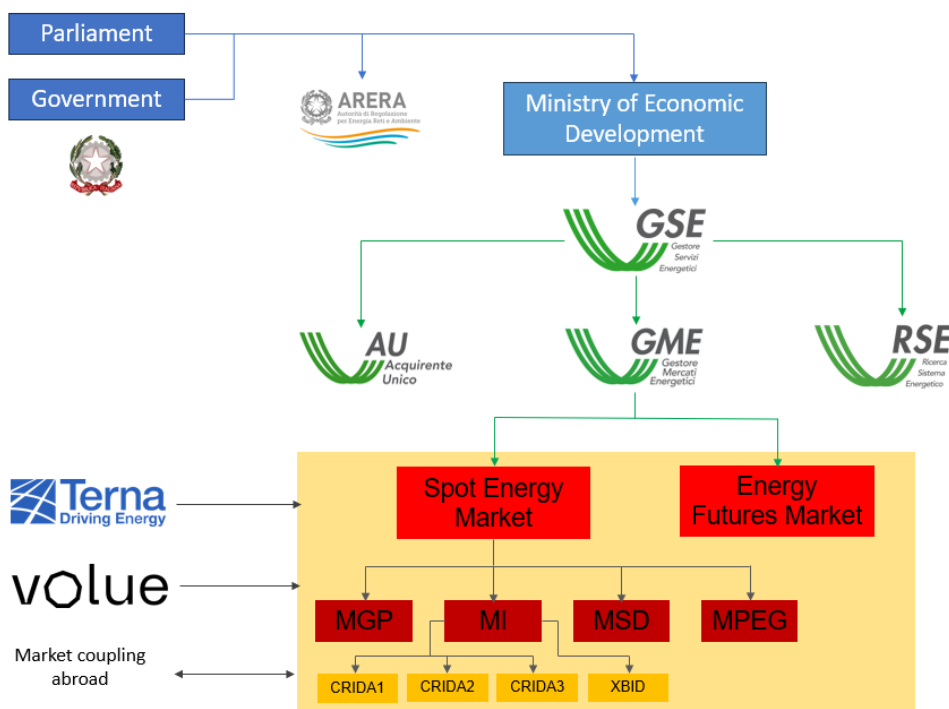


**Figure 2.1:** Scheme of the structure of Italian Market with associated companies

The various organs presented are hence explained below:

- ARERA
  ARERA is the "*Autorità di Regolazione per Energia Reti e Ambiente*" and it is an independent authority that stipulates, every three months, the price of energy and gas in the existing protected market, so outside the negotiation of the free energy market. This price is set by the trend of the feedstock and the energy market. Within of protected market can only access domestic users, and it will work until April 2024. However, their main commitment is to make the market more competitive for energy suppliers and producers.

- GSE
  This is the "*Gestore Servizi Energetici*", or Energy Services Operator, who works below the Ministry of Economic Development. They manage the domestic production of PV solar energy, renewable energy and energy markets. Their commitment remains to promote and support the development of green energy and energy efficiency. The GSE manages also the following offices:

  - GME
    "*Gestore Mercati Energetici*", Energy Market Operator
    It is the Italian NEMO, so the Nominated Electricity Market Operator, that manage the energy markets within the Italian peninsula. The producers and suppliers present their bidding through a telematic platform on the GME's website. After the negotiation, the GME loads all the data used in an FTPS database, accessible from a normal citizen to guarantee transparency and evidence in the managing of data.
    In this paper has been used the data from this FTPS database, from the host *ftps://download.ipex.it/* with username and password provided by GME. In the database the data are split into three parts, Environmental Markets, Electricity Markets and Gas Markets, and then in several subfolders. For instance, it has been used for the Electricity Market:
    * MGP Prezzi - Day-Ahead Market prices;
    * MGP Quantita' - Day-Ahead Market volumes;
    * MI-A1 Prezzi - Intra-Day Market 1 Auction Trading Session prices (CRIDA1)
    * MI-A1 Quantita' - Intra-Day Market 1 Auction Trading Session volumes (CRIDA1)
    * MI-A2 Prezzi - Intra-Day Market 1 Auction Trading Session prices (CRIDA2)
    * MI-A2 Quantita' - Intra-Day Market 1 Auction Trading Session volumes (CRIDA2)

        * MI-A3 Prezzi - Intra-Day Market 1 Auction Trading Session prices (CRIDA3)

        * MI-A3 Quantita' - Intra-Day Market 1 Auction Trading Session volumes (CRIDA3)

    – AU
    "*Acquirente Unico*", Sole Buyer.
    As said before, there are two major markets, one is the free energy market and the other one is the protected market. The responsibilities of the Sole Buyer are to provide the supplying of energy for the customer for the latter market. It therefore buys energy from the MGP at the most favourable market conditions and then sells it to domestic consumers or small businesses, in accordance with the law. [5]

    – RSE
    "*Ricerca sul Sistema Energetico*", Research on the Energy System.
    The Office's activity is committed to innovation and to improving the performance of the electricity system from the point of view of cost-effectiveness, safety and environmental compatibility. The research activity concerns the entire electromagnetic chain for the implementation of the development strategy led by the Italian government or Europe. [6]

- Terna Spa
  Terna is the Transmission System Operator (TSO) in Italy: this company manages the high-voltage National Transmission Grid, it has ownership of 99.9 % of that with a total of 75 thousand km of line handled. In addition, they also guarantee the match between the consumption and production of energy, with also exchanges with foreign countries through borders.
  For the energy market, Terna works in the MSD to provide the necessary resources for managing and controlling the Italian system [7] and the possible mismatch between generation and load.

- Market Coupling Abroad
  The Italian energy market negotiate energy not only through bidding area within the national territory but also abroad. All the bidding zones concerned are shown in the further Table 3.1, but the nations involved are hence Austria, France, Greece, Slovenia, Switzerland, Malta and Montenegro.

## 2.2 Markets

The Italian electricity market is led by the GME, and it is also known as Italian Power Exchange IPEX. It is divided into other sub-markets [2][3] and regulated also by other platforms.

Since every market has its own bidding and offering time, it means that also the deadline for presenting the offers change, as shown in Figure 2.2. "D" is the treated day, as it can be visualized that the submission of offers depends on the type of market, and so also the periods under negotiation.

In any case, these are the various markets:

- *"Mercato Elettrico a Pronti"*, Spot Energy Market: This market includes four main different market:

    - *"Mercato del giorno prima"*(MGP), Day Ahead Market
      As the name suggests, this market is held until the day ahead of the day deemed, and so the producers, the wholesalers and the end customers may negotiate for each hour of the day after, at least one day before. The changes in the price on different days are led by the variation of variable plant costs on one hand, on the other by the transformation of requests on the demand side. It is possible to submit the offers on the MGP from 8 AM of the ninth days before, until the 12 PM of D-1, whereas the bidding time is the whole D. The results are published by the 12.58 PM of the D-1;

    - *"Mercato Infragiornaliero"*(MI), Intraday market
      First of all, the name MI stands for *"Mercato Infragiornaliero"*, so it is one of the Italian electricity markets where the operator can adjust its position for selling and bidding quantities of energy during the same day of offering. This is due to the increasing pace of growth of no-dispatchable resources, such as energy produced by solar panels, run-of-river hydroelectric power plants or wind, so a cheaper energy for the production than for instance thermoelectric run by fossil gas.
      The energy operators faced this trouble with the introduction of the Intraday markets.
      The European context has hence set a Target Model for MIs, like the Single Intra-Day Coupling (SIDC) which works on the basis of continuous negotiating between bidding areas bordering. Within this context the Target Model foresees that the inter-zonal transmission capacity can be allocated in complementary regional implicit auctions, so the so-called CRIDA.
      Furthermore, for implicit capacity auction, it means that electrical energy flows depart from low price area (the one that a surplus) to an high price area, with the limitation of the day ahead transmission capacity, and they reach the price convergence.
      These markets provide three implicit auctions with the participation of not only the Italian bidding zone, but also the foreign ones.
      The main aim of this project is the creation of XBID Market Project

*"with the aim of creating a European intra-day market-based on continuous trading that would allow implicit capacity allocation"* [8] with a central role of the TSOs for the limit of capacity for transmission inter-zonal. Nowadays howevever there are three markets for the CRIDAs and one market XBID.

The offers on CRIDA1 and CRIDA2 start at the same time, 12.55 PM of D-1 (after the closing time of the MGP) but then the closing time changes, respectively until 4 PM and 11 PM of the D-1. However the bidding time is equal to the MGP, so the whole day of the day is treated. In CRIDA3 the operator has the capacity to offer from 4 PM of D-1 until the day of negotiating at 10 AM on the D.

Instead the market of XBID is split in three phases, and everyone has a different offers period. Altogether the first phase opens at 3.30 PM of D-1, and the last one closes in the treated day D, but one hour before the start of each applicable period, so it is a continuous negotiation. Therefore it is the newest market and is supposed to grow in the next years.

– *"Mercato per il servizio di Dispacciamento"*(MSD),
Ancillary Services Market
The MSD is a different type of market from the MGP and the MI since the attendees are not market participants, but rather dispatching users, for balancing the power market. The Italian market Terna procures the amount of energy resources for congestion relief and balances in real-time the system, for keep the frequency in the gap bearable. Nevertheless, the price paid by Terna is the offered price, there is no negotiation, but the MSD market has also the capacity to adjust the position of the operator from the dictation of the TSO. In addition, the data of MSD could be found also in the FTPS on the GME.

– *"Mercato dei prodotti giornalieri"*(MPEG),
Daily Products Market
The only products that it is possible to trade in this market are the one with "unit price differential", with Baseload and Peak Load profiles, hence offers with a price and a bearable gap for the negotiation. Furthermore, the operators need to be also in the platform of PCE (see below in section 2.2.1), otherwise they cannot attend this market.

- *"Mercato a Termine dell'Energia"* (MTE), Energy futures market
In the market of the MTE can negotiate two typologies of contract, one is the *Baseload*, which needs to be delivered in every delivery period, and the other one is the *Peakload*, distributed from the ninth to the twentieth from the delivery day, without counting the Saturdays and Sundays.
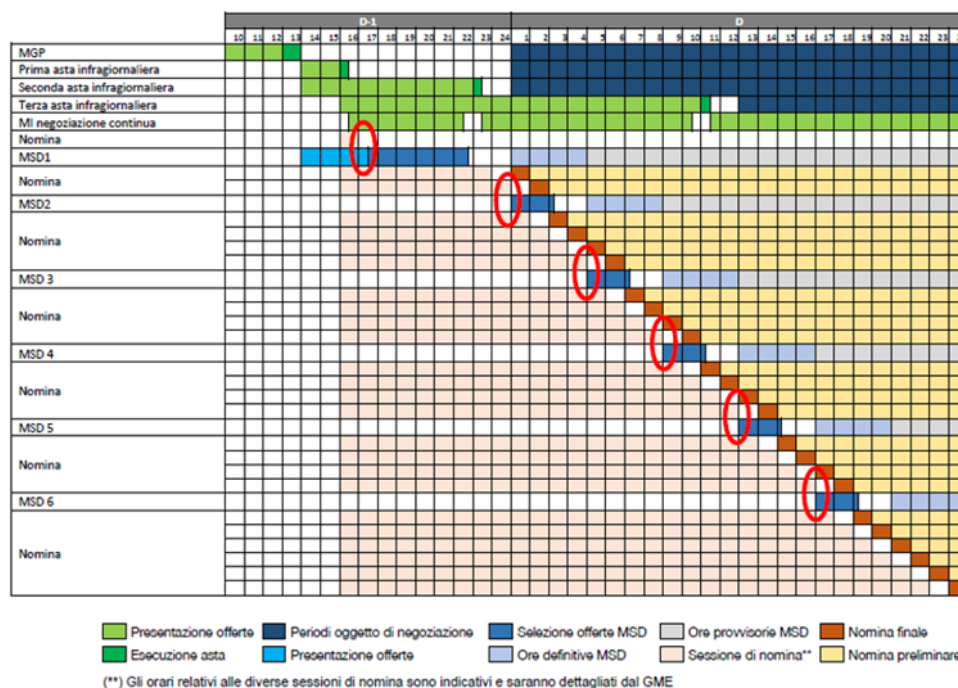
**Figure 2.2:** Scheduling of MGP, MI and MSD, from [9]

Summarising, it is crucial for a market operator to change its position of negotiating since the variables within the formation of price of the markets, and so the bidding, are countless. More it is getting closer to the time that the operator has offered in the past, the more it has security of energy production in that temporal slot.

The fluctuation of the energy price is due to the change of energy source: when the electrical system is fed by a renewable source the price is lower, instead is higher when the main source is the gas, as reported in the next section of 3.4.

The point of the market is to sell the amount of energy at a lower price, according to the energy source, thus the offer might be accepted, but then be remunerated by the price of the bidding zone of the powerplant.

### 2.2.1 Platforms

Nevertheless, the energy market is led by the GME in the IPEX (Italian Power Exchange), but it is possible to find others platforms: [2]

- *"Piattaforma per la consegna fisica dei contatti finanzioari conclusi sull'IDEX"*
  The market of IDEX, so the one of energy derivatives, is not led by the GME, but rather to the Borsa Italiana (Italian stock exchange), and this platform enables operators to join both markets.

- *"Piattaforma dei Conti Energia a Termine (PCE)"*
  Producers and suppliers could buy and sell energy outside the platform of GME through bilateral contracts, so the price and the quantities are chosen by the parties. In any case, these contracts need to respect the network constraints and so is required a validation.

### 2.2.2   Electricity market zones in Italy

The electricity market zones were born to represent the bottlenecks within the grid. Indeed, Italy has an unusual shape and it is necessary to limit the flow of energy between zones, to respect the network constraints, otherwise, some parts of the grid might be overloaded and others unexploited.

Typically, each country has just one electricity market zone, except for Italy and the Nordics, and this is on one side for the geographical conformation, long and narrow, on the other, to influence producers to invest where there is less offering and thus high price.

From the 1st of January 2021 [10] also the SUD zone, was split in two parts: CALA and SUD. This was necessary for an improvement of integration and homogeneity with the European market. The results are possible to be shown in Figure 2.3.

For the records, the suppliers always pay energy at the PUN, meanwhile the producers are remunerated with the price of the bidding zone of the power plant.



**Figure 2.3:** Zones of electricity markets, from [10]

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## 2.2.3   Single Intraday Coupling (SIDC)

Italy exchanges energy not only within its territory but also in the countries that border, not only by land but also with submarine cables. The SIDC's commitment is the creation of a Single EU cross zonal Intraday electricity market. It means that the market participants, so producers and suppliers, might trade electricity across Europe in the same day that the energy is required, for re-establish their position. This is due to the high volatility of renewable resources, so the DAM was not enough for balancing production and consumption, and the XBID was created to fulfill this mismatch in the European context. This has led to an increasing of competition on one hand and the liquidity on the other's.

The goes live of this platform of trading was chosen to be split in more tranches, as possible to see in Figure 2.4, for enable TSOs and NEMOs to a better collaboration. It is reasonable that the NEMO cannot trade electricity without the clearance of the TSOs, and not only with the one of its country (for instance GME and Terna in Italy). Also in this context, there would be a huge quantity of data to be collected and processed, not only the one of its own country.

In this context, Volue Insight [9] is working to collect all the significant data in the power supply chain. For a better understanding of the opportunities of energy traders, it is shown in 2.5 the various link of electricity zones, with the same zones within Italy in Figure 2.3.
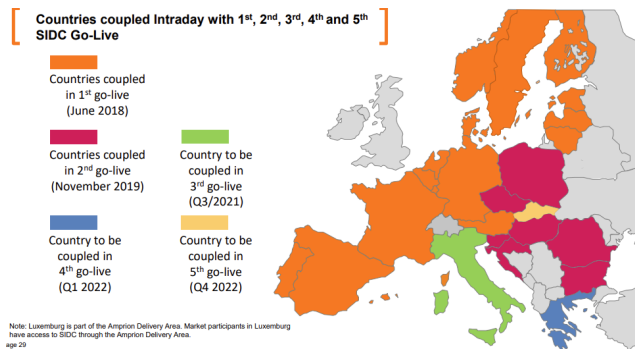


**Figure 2.4:** Zones of goes live market coupling, from [11]



**Figure 2.5:** Coupling of european market, from [9]

# Chapter 3

# Analysis of data

As said in the previous chapter, the amount of data in the Electricity Market is vast: it is enough to consider that for every hour of one specific day it is deemed four markets (MGP, CRIDA1, CRIDA2, CRIDA3) with in addition all the bidding zone, within and outside the Italian borders. The organization appointed that stores those data is the GME, set in Rome, in a FTPS database. All the analysis that follows are hence extrapolation of this data through XML files. However, for further clarification of the import of data, it might be possible to check directly on the GME website, with the explanation on how to get access to the data [12]. However, for a better understanding of how it has managed the data, it has been used the np.convolve function, that gives a discrete, linear convolution of two one-dimensional sequences. The reason for this choice is that the trends of the price change every day, and it is required to implement a moving average (or rolling average) to visualize the data. The concept behind this choice is to visualize the time series data properly, and the trend, without the fluctuation of data. The operation of convolution is describes with:

$$(a * b)_n = \sum_{i,j} a_i \cdot b_j \tag{3.1}$$

$$i + j = n \tag{3.2}$$

$a$ and $b$ are respectively the first and second one-dimensional input array.
For the implementation of the moving average, the $a$ is the vector with all the data, meanwhile $b$ is an input array, with all the terms equal but $\sum_{i=j}^{N} b_j = 1$, hence the sum of all the terms in the vector is one. When it is make the convolution, the $b$ vector is moving step by step, and it is possible to see the data within this time frame, thus taking an average. At the end of the process, it ought to have a uniform version of the original data. In summary, in the Python code the execution of this has been made as follows:

```
1  np.convolve(x, np.ones((N,))/N, mode='valid')
```

With $x$ equals to the input data and the second input is an array of one, with dimension $N$, over $N$. For instance a vector of dimension of three ($N = 3$), would be consisted of three terms of $\frac{1}{N} = \frac{1}{3}$ , so the sums remains one.

## 3.1   Differences of price between market

Depending on the energy source that is running the system, the energy price might change for every hour during the day. The causes could be many, such as a sunny day in an area with a high concentration of solar power parks or on the opposite a dry spell on a river full of hydroelectric plants. The energy from renewable resources like run-of-river hydro plants, wind or solar power farms is cheaper than the one from thermal gas power plants, but it is also uncontrollable and no-dispatchable. So energy producers need to be cautious about investment in the energy market because once an amount of energy is sold, they need to respect the contract, otherwise they would buy energy from the market at not a money-worth price, or pay a penalty from the TSO.

As said in the previous section 2.2.2, Italy is split into seven bidding zones, geographical ones, and every zone has its own bidding price, in which the producer is remunerated according to this price, even if the suppliers pay according to the PUN. So for a producer of energy makes sense to invest in a zone in which the price is higher, and so the offer per production is lower in comparison to other zones.

In addition, the treated bidding areas are split into two parts, one geographical, within the Italian borders, and the other one foreign virtual, outside, as shown in Table 3.1 from [13]. In addition in the last column represents the bidding zone devolved for market coupling, with "COUP" representing the interconnections with foreign markets in coupling from NORD bidding zone.

| Geographical | | Foreign virtual | | Foreign virtual coupling | |
|---|---|---|---|---|---|
| Name | Acronym | Name | Acronym | Name | Acronym |
| Central Northern Italy | CNOR | Austria | AUST | France Coupling | XFRA |
| Central Southern Italy | CSUD | Corsica | CORS | Austria Coupling | XAUS |
| Northern Italy | NORD | Corsica AC | COAC | Slovenia Coupling | BSP |
| Sardinia | SARD | France | FRAN | Greece Coupling | XGRE |
| Sicily | SICI | Greece | GREC | Italy Coupling | COUP |
| Southern Italy | SUD | Slovenia | SLOV | | |
| Calabria | CALA | Switzerland | SVIZ | | |
| | | Malta | MALT | | |
| | | Montenegro | MONT | | |

**Table 3.1:** Bidding zones

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So the connections could be made not only by land but also by sea. Terna manages more connections throughout the sea, such as the SACOI (Italy - Corsica - Sardinia), SAPEI (Sardinia - Italy) and it is developing the Tyrrhenian Link (Italy - Sicily - Sardinia), project confirmed and signed in November 2022.

### 3.1.1   MGP

As it is said in the previous chapter 2.1.1, MGP is the market for the Day-Ahead trading, and currently, the European Electricity Market has fully achieved this completeness. In case of the European context, the DAM (Day Ahead Market) is solved with a downward auction, taking into consideration the network constraints provided by the TSOs. Since the cost of energy depends on the type of source used, hence the variable costs of the plant, the price of MGP is set with those variables. In the following section shows the historical data of the Italian MGP, splits in different bidding zones. In details is shown the MGP from 2014 to 2019 in Figure 3.1, then from 2020 to 2021 in Figure 3.4 and in conclusion from 2021 to currently in Figure 3.6, with all the details below to every figures.
Nevertheless in the main figure is shown only the moving average, already explained in the section above, meanwhile in the details figure it can be seen the details of every day, and these are not so human readable.

**2014-2019**
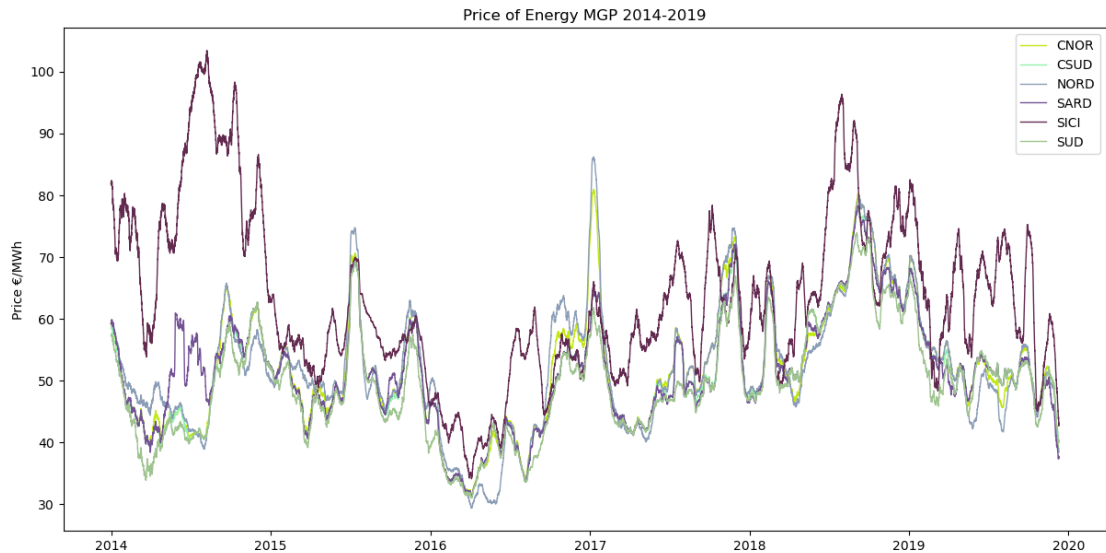


**Figure 3.1:** Price of MGP from 2014 to 2019. N=500

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**(a)** NORD        **(b)** CNOR        **(c)** CSUD



**(a)** SUD        **(b)** SICI        **(c)** SARD
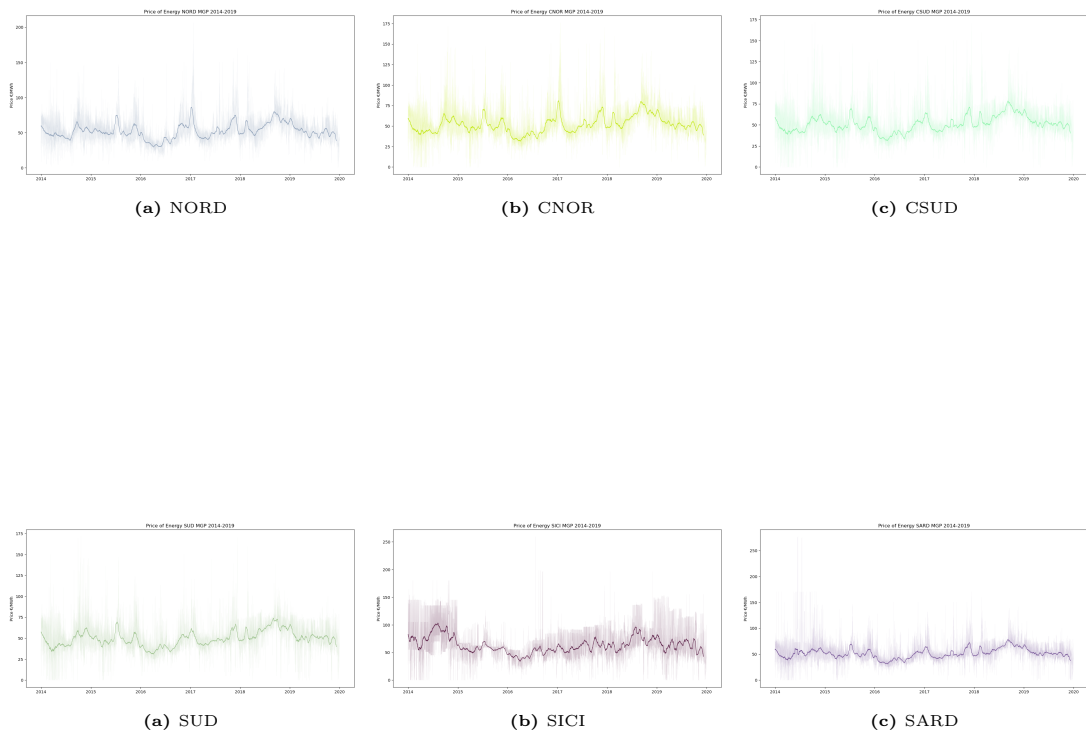
**2020-2021**

The reason why in this section has been developed only two years is due to the
fact that in 2021 has been activated CRIDA1, CRIDA2 and CRIDA3. Since this
data will be compared with this market in the next section, it seems reasonable to
split the data in this way, also for not overload only one graph.

In addition, is of great interest that in the 1st January 2021 has been developed the
bidding zone CALA, as already explained in section 2.2.2, with the split of SUD
zone in two: SUD and CALA, and follows the trends of the others bidding zones.
The price of energy is not set independently to the outer world, but it follows the
crisis, the war, but also the upturn and the recovery. For instance, the tendency
of this graph is led by the wasgoing pandemic session of Covid: the market, not
only the electrical one, is balanced by demand and supply, hence less load (for the
shut factories) means a reduction of energy price. After that it follows the trend
for recovery from the crisis.
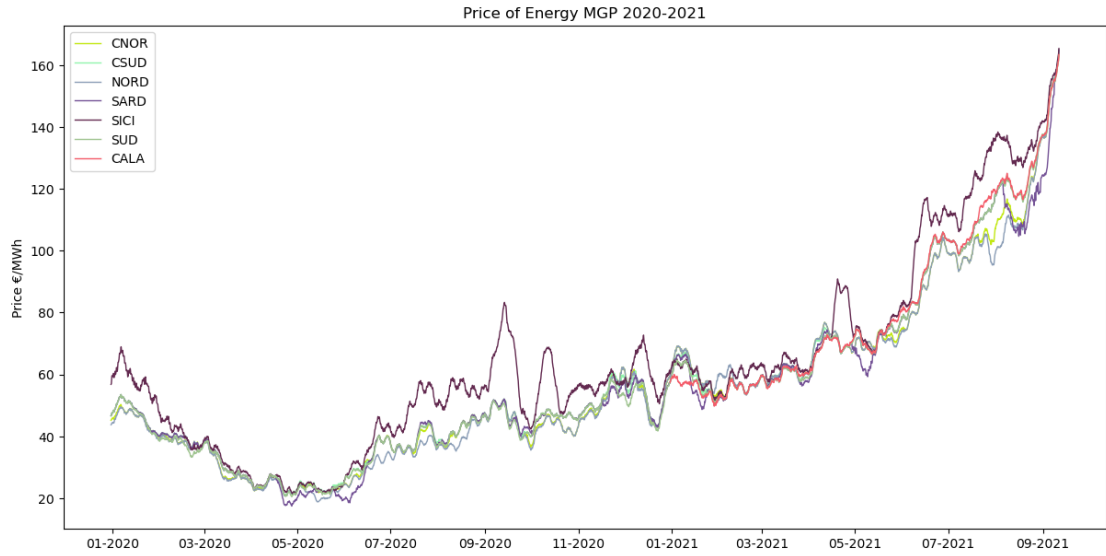
**Figure 3.4:** Price of MGP from 2020 to 2021. N=250
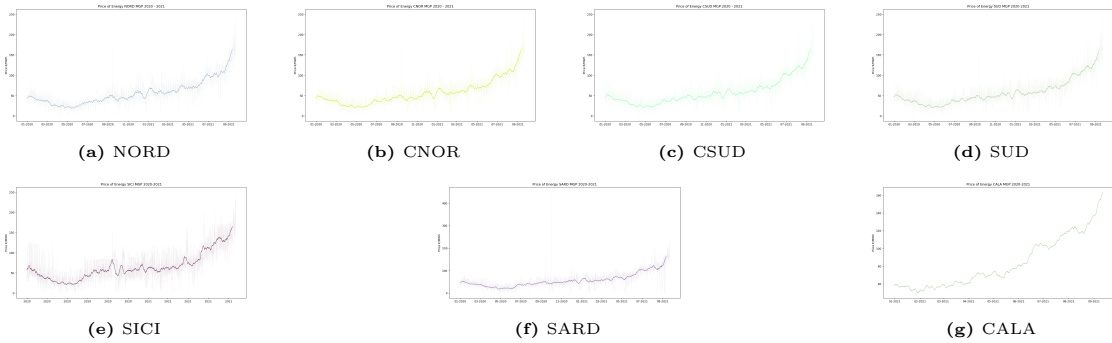


**Figure 3.5:** MGP 2020-2021 in various bidding zone

## 2021-2023

As just said, the price of energy follows the trend of the outer worlds, and the following graph in Figure 3.6 is a demonstration of that. The ongoing war in Ukraine has led to an increase of the price of gas, and since most of the bidding zone are run by thermal fossil gas power plants, has led to an increment of the energy price. This is due to the method of setting of the cost of energy, that paid the producers with the most expensive type of production in a zone.

In the graph, it could be seen the second peak of August 2022 was due to a high demand and a higher cost of the primary source, so it was necessary to use most of the time thermal power plants. Indeed the trend during the times has shown the the price of energy is higher during the summer period, when the request is at the

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maximum point of the year. So the price of gas has increased for a high request of the latter, which has led to greater prices throughout all the markets, falling upon consumers.
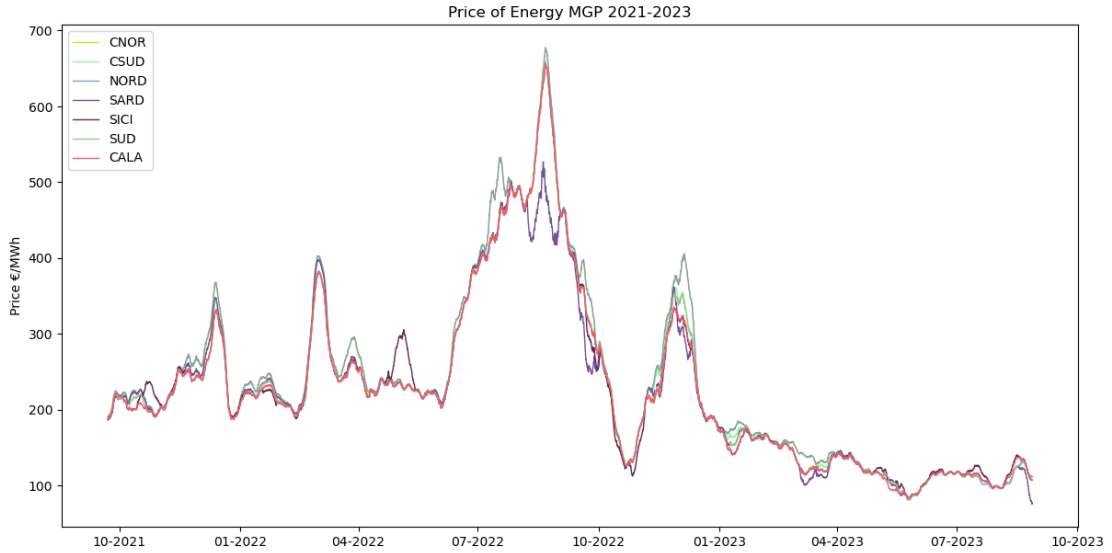


**Figure 3.6:** Price of MGP from 2021 to 2023. N=250
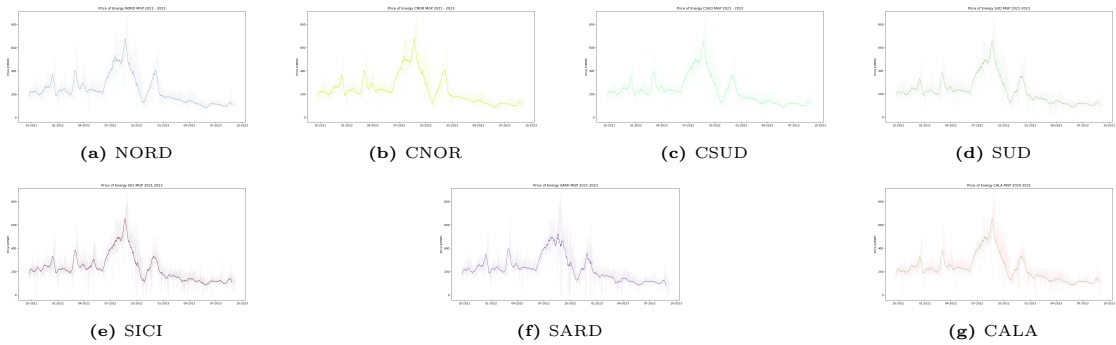


**Figure 3.7:** MGP 2021-2023 in various bidding zone

## 3.1.2  MI

As said in the previous section, the MI is the market for the Intraday auctions, section 2.1.1. The Algorithm of the NEMOs for the Intraday Auction has to respect these criteria, from the guide of the NEMO [14]:

- Intraday Auctions (IDAs) observe the requirements for pricing within the SIDC;

- Taking into consideration the limit of congestion of the grid and the management for the resolutions, with the guarantee of optimal use of the transmission infrastructure;

- It has to guarantee competitiveness in the generation, trading and supply of electricity, in addition to transparency and reliability;

- It does not allow any type of discrimination of offers between market participants.

And it has to produce at least the following parameters for every 15 minutes:

- A single price for each bidding zone in €/MWh;

- The volume of each bidding zone;

- Scheduled exchanges between bidding zone and areas;

- Information used to determine how orders are executed. The acceptance for each block as defined in SIDC product terms and conditions

Furthermore, the following sections show the historical prices for the various CRIDAs from their beginning, so 22nd September 2021 to nowadays, with all the reasonable bidding zones.

## CRIDA1

The trend is equal to the MGP in Figure 3.6, and the prices are almost equal. The offers in this market are only for 2 hours, just after the closing time of MGP, but however it is the first ID market for exchange volume (see Figure 3.15).
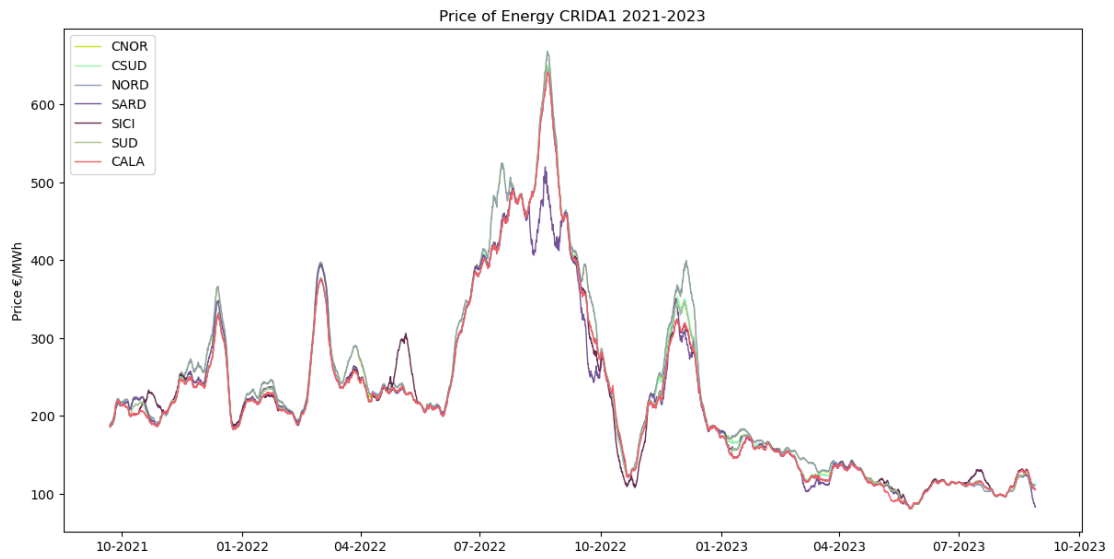
**Figure 3.8:** Price of CRIDA1 from 2021 to 2023. N=250
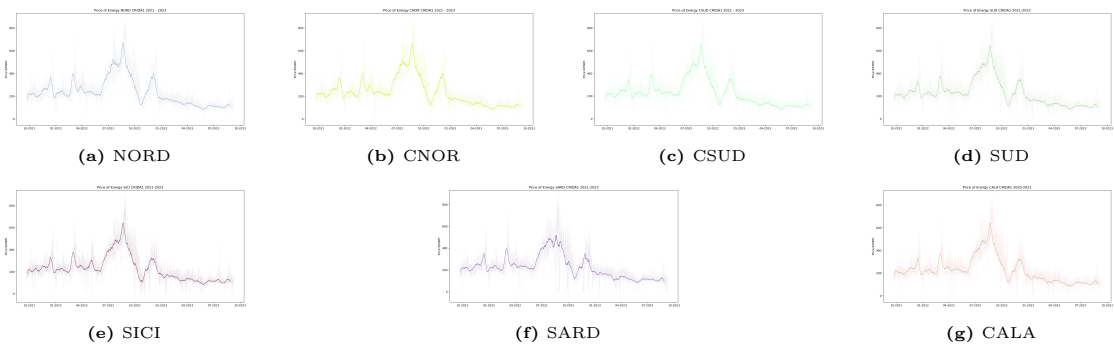


**Figure 3.9:** CRIDA1 2021-2023 in various bidding zone

## CRIDA2

The results obtained are close to the ones in the CRIDA1, with the difference that the offers time is nine hours, instead of the two of CRIDA2. So even if the time is greater and the opening time is the same, at the end of the auctions the volume traded in CRIDA2 is lesser than CRIDA1 (see Figure 3.15).
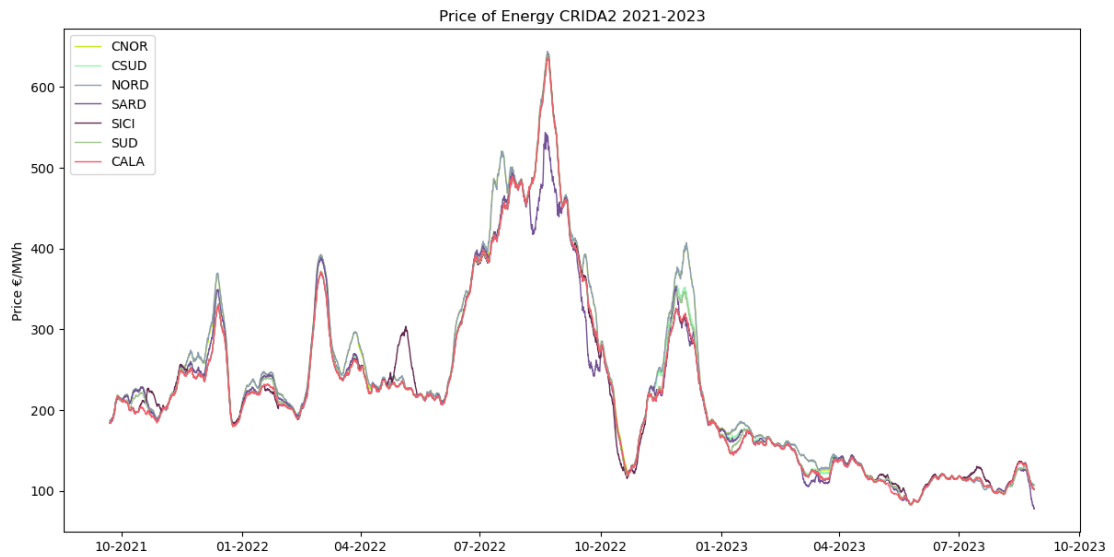
**Figure 3.10:** Price of CRIDA2 from 2021 to 2023. N=250
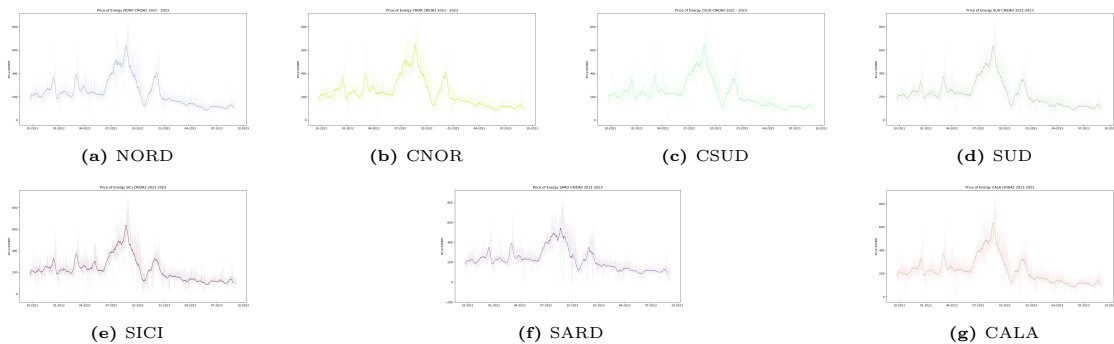


**Figure 3.11:** CRIDA2 2021-2023 in various bidding zone

## CRIDA3

The offering time in CRIDA3 starts from 1 PM to 12 AM and so it is obtained the half of the points than of the others CRIDAs, so the algorithm developed has been different from the other CRIDAs or the MGP. The reason of this change is figuratively explained in Figure 2.2 in which CRIDA3 has half of the points of the other markets and also different deadlines to respect. Furthemore the time of negotiation is larger than CRIDA1 and CRIDA2, 19 hours from 4 PM D-1 to 10 AM D, but the volume traded is the is the lowest of all.

In addition, for a problem internally to the database FTPS of GME, there is a lack of information for the day 3rd October 2021. So the extrapolation of data had to rely on a manipulation of that day: the 3/10/21 was the second Sunday from

the implementation of the CRIDAs system, so the data available were not huge, hence it was considered the only Sunday available, 26/9/21, and it was inserted the same data of that day. The secondary reason was that there were not events attributable to a increase of price.

Furtherly, since the CRIDA3 start the offering time at 1 PM, the remaining hours of the morning hours has been inserted a not a number, and then interpolate (by using the proper numpy function) the obtaining data into a series of number. It was done like this because it is required for the algorithm of the forecast to be fed by data. Also, it might be exploited the moving average, for make it human-readable.
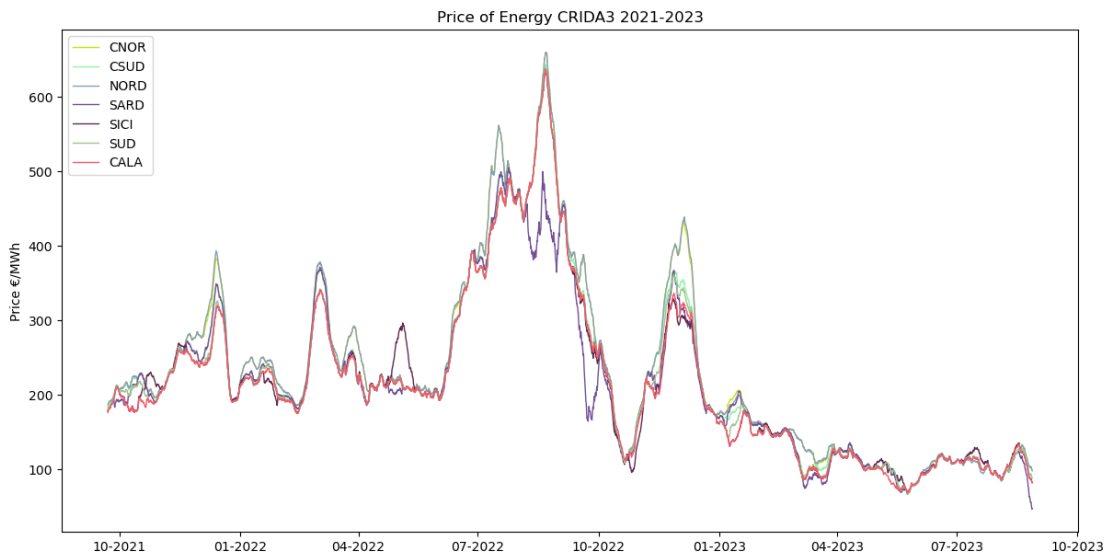


**Figure 3.12:** Price of CRIDA3 from 2021 to 2023. N=250



**(a)** NORD      **(b)** CNOR      **(c)** CSUD      **(d)** SUD

**(e)** SICI      **(f)** SARD      **(g)** CALA
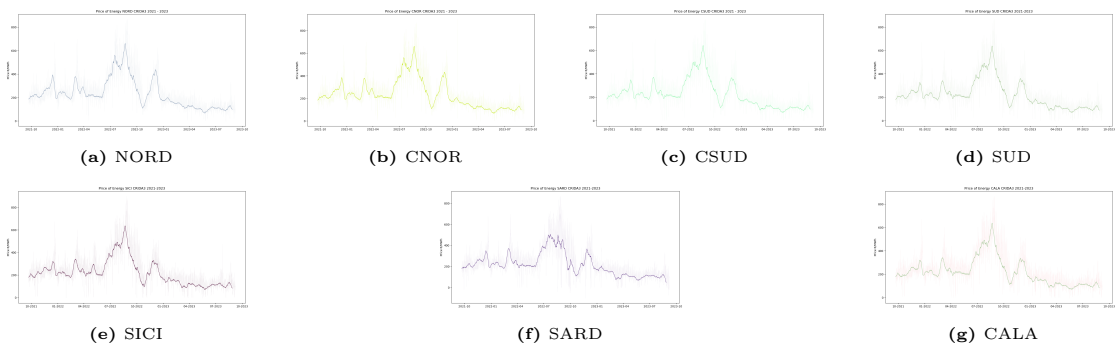
**Figure 3.13:** CRIDA3 2021-2023 in various bidding zone

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### 3.1.3 Traded Volume

Most of the traded volume in the energy market stays below the MGP, indeed as shown in Figure 3.14, it is possible to check an inequality between the markets of the Cridas and the market of the MGP. This is due to the fact that the MGP is a traditional market that has been around for years, in the meantime the CRIDAs are a pretty new type of market, not eradicated in trading. In addition, interestingly is the fact that, even if the traded volume on the Cridas is steady, the MGP's traded volume is variable: with the peak during the summer, but not in August, and valley during the Christmas or Easter holiday. It can be deduced that trading can be preferably done only during the time when factories and cities are working. Meanwhile the trading in the CRIDAs is stable in comparison to the one of the MGP, but relatively speaking, also the CRIDAs have peak and valley, but not such as the ones in the MGP. In addition, for the development of these graphs, it has been used the library Plotly, instead of Matplotlib.
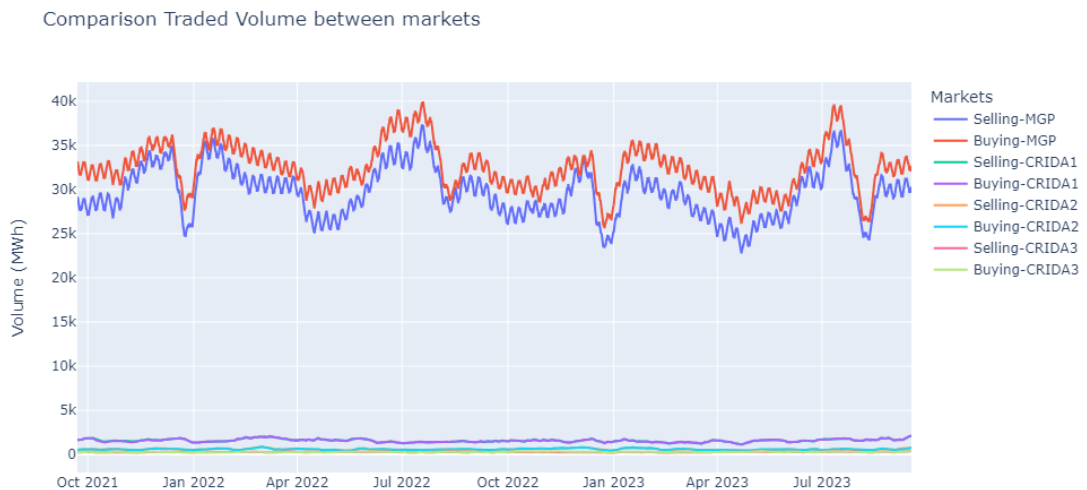


**Figure 3.14:** Comparison of Volume traded throughout the markets

Furthermore, in Figure 3.15 is shown the particulars of the traded volume within the CRIDAs. As expected, the CRIDA1 is the most concerned for the trading volume, at the expense of CRIDA2 and CRIDA3, with an average traded volume respectively of 1.6 GWh, 0.6 GWh and 0.2 GWh.

It means that at state of art, the producer of energy wants more to invest in the traditional markets instead of the new ones. This is also due to the fact that the bidding time of MGP is more extensive than the Intraday Markets; if the forecast

is correct, it is not required to invest in the other markets.
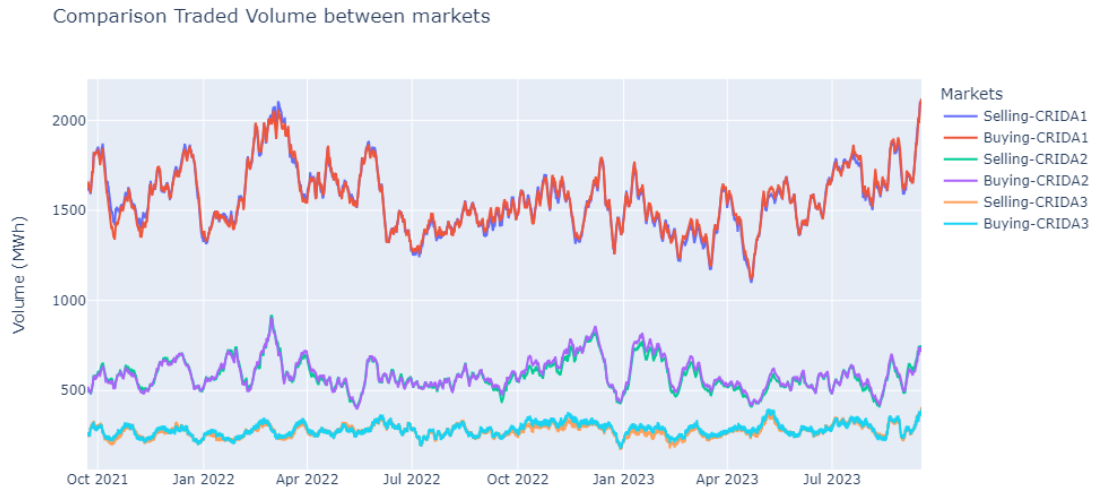


**Figure 3.15:** Comparison of Volume traded throughout the CRIDAs

## 3.2 Historically prices

The trend of the energy price is comparable to the trend of the price of gas, as shown in Figure 3.16. This is due to the large consumption of fossil gas in the Italian production of energy, since it highly relies on this source.
More in detail, the price for the gas operated is the TTF Amsterdam, meanwhile, the other prices are hence the ones already shown in the previous section. As it possible to see, there is a clear correlation between the price of energy and the one of the gas. Furthermore, again as before, has been implemented the moving average for the MGP and CRIDAs, thus resulting as comparable, as expected, but not equal. For instance, in the Figures 3.17 and 3.18 are visualized the various prices in markets: it seems that MGP, CRIDA1 and CRIDA2 follow a ranking in order of the price, meanwhile CRIDA3 is more volatile, indeed in the Figure of 3.17 is the cheapest meanwhile in 3.18 is the most expensive.
That might be an error of how is handled the CRIDA3: the point to be interpolated are like the half, hence it takes the first point of 1 PM and uses this point for the interpolation. When will be developed a forecasting of CRIDA3, it will be forecast the whole day, but for the strategy only the points from 1 PM will be relevant (see section 5.3).

In any case, the algorithm for obtaining this graph is reported in Appendix A

Comparison between average of MGP, CRIDAs and Gas Price
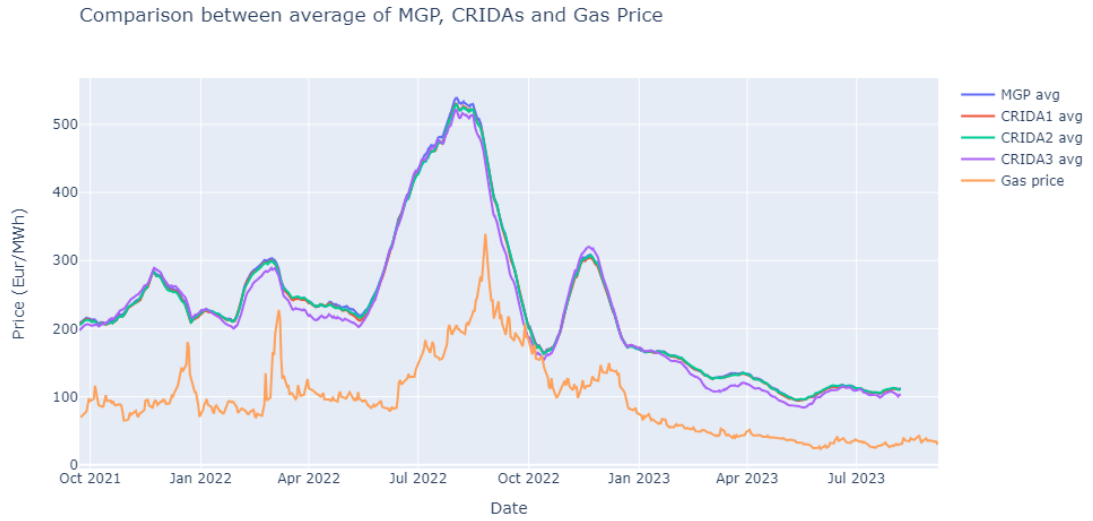


**Figure 3.16:** Prices between markets from the implementation of CRIDA until nowadays N=750 in comparison with the price of Gas (DUTCH TTF)
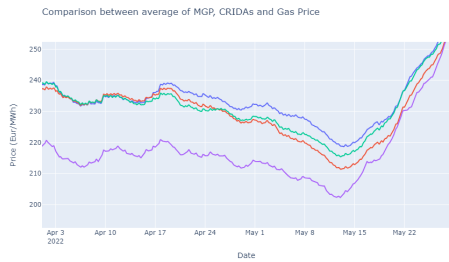


**Figure 3.17:** Detail of comparison May 2022
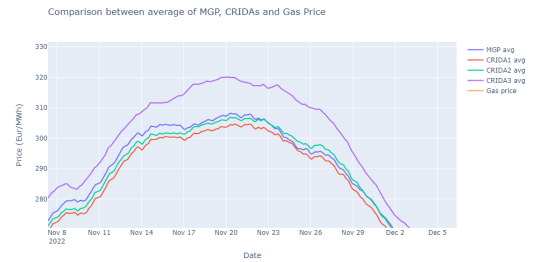


**Figure 3.18:** Detail of comparison November 2022

In any case, the implementation of a strategy for bidding and selling makes sense, since there is a difference in the various price.
So if the various operators invest in a technology for the forecasting of the price, and then a forecasting of the various production, they could manage one day before, the earnings for the next day.

## 3.3   Settling of the price

The parameters counted for settling the price in the markets are [3]:

- For each plant :

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- Cost of fuel for each plant;
- Network constraints;
- Weather;
- Historical data;
- Initial investment.

- For the italian market:

  - Electricity consumption;
  - Historically prices,
  - Total amount of energy produced by renewables;
  - Installed capacity;
  - Import and export.

The most important thing to note is that the total amount of energy produced by renewable depends also on the weather. Indeed the production of hydro relies on dry periods and flood period, solar with solar radiation, and the wind with differences of pressure. Hence a sunny day might produce a cheap amount of energy sold in the energy market, and so might lower the PUN for the consumers. The renewables energy power plants are characterized by a high initial investment per energy produced, but then by an inexpensive primary source. On the other hands, thermal is cheaper for the initial investment, since they might produce a high quantity of energy, but then the cost of the primary source is higher.

### 3.3.1   Price offering

As reported in the previous section 3.3, energy price fluctuates within days and hours, but the producers of energy offer energy depending on the energy source. The PUN stands for "Prezzo Unico Nazionale" and so translated as "Single National Price". This is how in brief it is priced the energy:

1. The producers offer an amount of energy (MWh) with a price ( € / MWh) in the IPEX;

2. The price and quantity are scaled by economic benefit, accepting first lower offers and then increasing, matching then the curve of the customer, see Figure 3.19;

3. Checking for the network boundaries:

   - If every limit is respected, the PUN ( € / MWh) is the meeting point between supply and demand;

- Otherwise, it split the country into two zones, one importer and the other exporter, and the PUN is found again in these two zones, see Figure 3.20.
  - If every limit is respected, the PUN is the average between the two zones;
  - otherwise is split again the zone and the process continues until every limit is respected

The PUN changes in function of the load of the system and the price of the exploited sources, and it represents a national price average taking into account the network constraints, as shown below:

$$PUN = \frac{\sum_i (P_i Q_i)}{\sum_i Q_i} \qquad (3.3)$$

With Q is the load of every zone, i represents one zone and P is the price of that zone.

Summarising, the price of PUN in the IPEX is set by a weighted average of the price set in the downward auctions by the traded volume, if the constrains between zones are not respected. At the end of the process, the producer that offered a lower price is paid with the price of the local bidding zone price. Indeed, a owner of a renewable resource, even if the cost of the primary source is inexpensive, might be paid at the same amount of the expensive energy, Euro per MWh. In the two Figures belows 3.19 and 3.20 are shown how the downward auction is made and then how the price is settled in the various bidding zones.
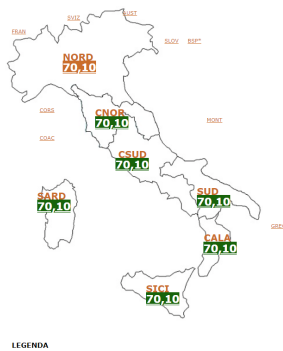


**Figure 3.19:** Detail prices of MGP every bidding zone for 6/11/23 at 12 [12]

**Figure 3.20:** Detail prices of MGP downward auction 6/11/23 at 12

[12]

### 3.3.2   Strategies for buying and selling electricity

The key point of this thesis is to forecast the price of energy in all the markets, and then apply a strategy that maximises the profit of the customer based on investment decisions in which markets. If the gap between predicted price and the real one is closer, and if it is developed a resilient strategy, those can lead to a higher profit. So for the producers, the game is:

- Staying with a lower price, but reasonable, for getting accepted;

- Forecast correctly the turning on of expensive power plant, for getting the income of a higher PUN. This point is done by the forecasting of historical price, since the load might be the same, but the producers might make a plant unavailable;

- Developed a resilient strategy by reducing the error between forecast values and the actual one.

In summary the strategy of electricity sales and purchasing depends on two factors:

- Price of electricity in each market on the one hand;

- Production of a power plant on the other.

## 3.4   Energy production in Italy

After the introduction of electricity market in Italy in the section 2.1 above, it is reasonable to continue the treatment a step forward after the negotiation: energy production within Italy.
The negotiations are indeed before the production of energy, so the parties involved need to understand the amount of energy that would be produced, and the price to be sold, before the actual production. Indeed a producer can also choose to not produce at all for that hour, if the forecast of income does not match the expected one.
This is given by the fact that the supply chain of energy has several infrastructures involved, with more constraints to be respected. In fact energy departs from power plants, usually places far away outside the cities, then is made to flow through the transmission and distribution grid, and finally it could reach the end users. Even though in the last years has been increased the amount of energy from distributed generation, this remains the preferred route for energy production.
In any case, the portfolio of capacity production has changed during the years, also from the drive of the Italian government to replace the older nuclear energy

source, banned in a referendum in 1989, and increase the production from renewable resources. As reported in Figure 3.21, the trend of growth has been in favor of natural gas for years.

The other energy sources, such as hydro, coal, wind and solar have been kept over the years constants, with only a growth for Biofuels and waste. In summary from 1990 to 2021, the sources exploited passed from Oil and Coal to renewable energy and natural gas.
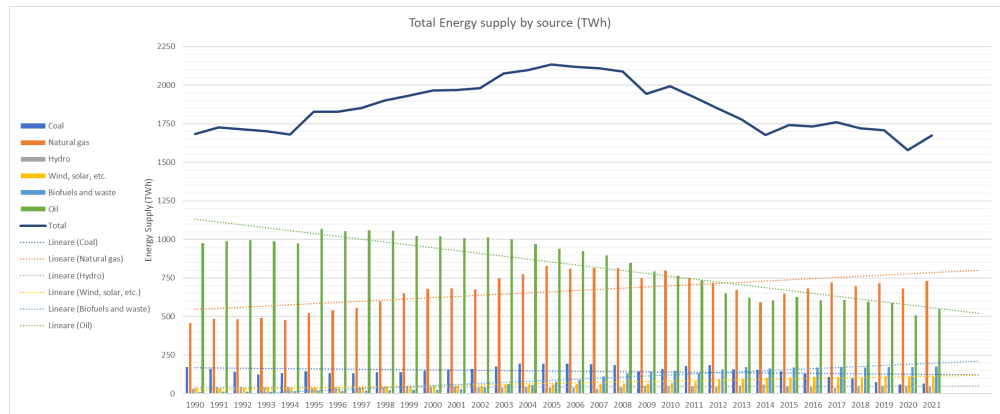


**Figure 3.21:** Energy source by supply, with the trends of single source and total production [15]

Even if the pace of increasing or decreasing of one energy source would change, since the government and Europe ought push in renewables direction instead of polluting plants. The reasons why Italy needs to change its primary resource are multiple [16]:

- it has to reduce the reliance on the natural gas from the Russia [16], reducing the actual energy crisis.

- it has to reach the climate neutrality by 2050

- it has to reach the target Fit for 55 (FF55), which means to reduce greenhouse gases altogether by at least 55 %

In addition, the GME publishes every month a newsletter for the key parameters of the energy market. For the month of July it could be seen an important inhomogeneity between the production in the North and the South for the renewable resources, indeed as shown in the following Figure 3.22 [17]. As said before, the energy production for renewable resources relies on the weather in one bidding zone. In July 2023 indeed there were heat waves, that produced a huge quantity of renewable solar energy.
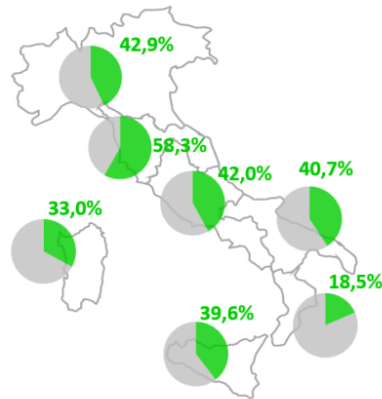
**Figure 3.22:** Amount of Energy from renewables resources in the MGP for July 2023 [17]

### 3.4.1   Total capacity of Italy

The amount of non renewables power is slightly the half of the power installed in Italy. With the actual capacity, the new installation of renewables energy has to be 4 GW yearly [16] to meet the requirements of target set for 2030. Nevertheless in 2022, the new renewable energy installed has been only 2.1 GW: 1.6 GW of PV and 0.5 of wind capacity [16]. To reach the target FF55 of 2030 the capacity of renewable resources of PV needs to be increased to 64 GW and for the wind to 23 GW, so total it needs to fulfill 38.9 GW for solar and 11.2 GW for the Wind, from the total capacity of 2022 shown in Figure 3.23. If it is considered the goes live of power plants such as a linear trend, every year the capacity would be increased of 4.9 GW for PV and 1.4 GW for the Wind; so the actual investments are not satisfactory.
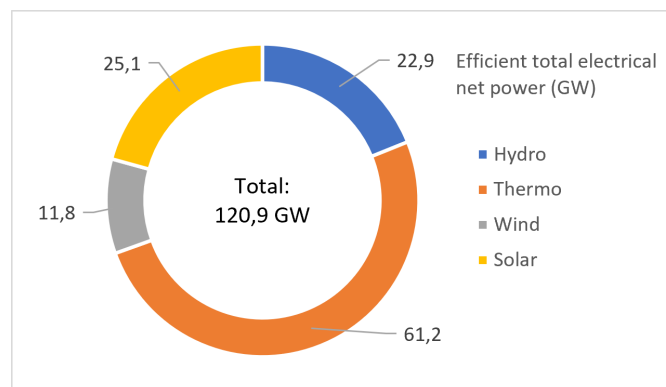


**Figure 3.23:** Efficient total electrical net power (GW) in 2022, from [18]

In the next subsections are shown which parameters are fundamental for each plant and how are spread in Italy. The data of 2023 below are to be considered until the end of October, so they are marked with an asterisk.

## Wind

The wind production is principally concentrated in the southernmost part of Italy, as it is possible to visualize in the following Figures 3.24 and 3.25. It is common that more than one wind turbine is located close to each other, thus exploiting the economies of scale and also all the power given by the wind. They are also linked to each other with an underground cable, and by the end also through a substation linked to the grid. There are three types of wind farm, the on-shore so in the mainland, the near-shore so close to the coastlines, and the off-shore so placed in the sea or lake. The last one is typically located in the North part of Europe (UK, Denmark, Norway,...), and the Italian projects are usually hampered by bureaucracy, but in 2022 has been inaugurated the first off shore Italian wind farm in the bay of Taranto.

These large wind farms are more common than a simple domestic wind turbine, since the former could exploit more the power of the wind, instead of the latter ones. And since the wind acts like an aleatory variable, so difficult to predict, it makes sense to take advantage (also for the height of the infrastructure of the wind turbine) of all the speed available of the wind. The source of the data of the following graphs is Volue Insight [9], but it has been done handling on data. The data collected for 2023 refers to the end of October, this is why it has been inserted an asterisk.



**Figure 3.24:** Wind Production in 2022 [9]



**Figure 3.25:** Wind Production trend [9]

## Solar

The solar production is a key point in the green transition. Currently, it is increasing the small producers of this type of energy, with also the economical benefit that the Italian State has given in these last years, for instance the *"Bonus edilizio 110*

%" (construction bonus 110 %), and the capacity of PV production is expected to increase in the following years, reaching the objective for 2030. Most of the projects under development are settled in the South part of Italy, where the solar irradiation is also higher.

Apart from the big project under development, in the tiny, a single householder that installs in their properties PV panels, and links with the Grid, might sell the surplus of energy to the GSE (section 2.1.1) and get paid for the energy sold. This type of householders are called "Prosumer" (merging words between producer and consumer), and it is expected that in the next years continue to increase. The primary energy source for the prosumer remains solar irradiation, since the installation of PV panels on the roof is a non-invasive and cheap way of producing renewable energy. Typically, the power installed for a domestic user is around from 1 kW to 4 kW, so it might satisfy just the need for the prosumer, with a small amount of surplus energy. On a large scale, a neighborhood of prosumers might sell the surplus of energy to the building in need, thus enabling the development of a Smart Grid, with all the associated problems and opportunities.

As it possible to see in the Figures 3.26 and 3.27, solar production is scattered in every bidding zone. Further even if the data considered for 2023 are not the annual ones, it might be interesting to notice that the heat wave that hit Italy in the summer 2023 is viewable in the production of energy. The source of the data for the following Figures 3.26 and 3.27 is Volue Insight [9], but it has been done handling on data. The data collected for 2023 refers to the end of October, this is why it has been inserted an asterisk.
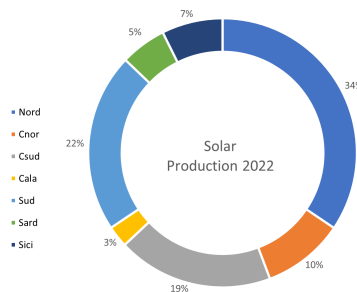


**Figure 3.26:** Solar Production in 2022 [9]
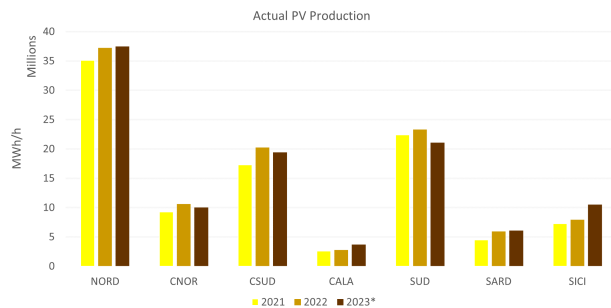


**Figure 3.27:** Solar Production trend [9]

## Hydro

Italy has a long heritage of hydro production, with most of the dams older than 60 years. The trend of the growth of capacity of hydro powerplants has been kept the same for years, with the divestment of medium power plants and the introduction of the small hydro. [19]

There is unevenness of the presence of hydro plants in the Italian territory, with an increased concentration in close to the mountain ranges, like the Alps and the Appennini, as it is possible to see in Figures 3.28 and 3.29. The regions with the highest number of powerplants are Piedmont (in 2018 were counted 930 power plants [19]) and Lombardy (661 powerplants), but the latter counts the larger amount of installed power (27 % in Lombardy in comparison to 14 % in Piedmont). The source of the data for the Figures is Volue Insight [9], with an elaboration on what it is obtained. The data collected for 2023 refers to the end of October, this is why it has been inserted an asterisk.
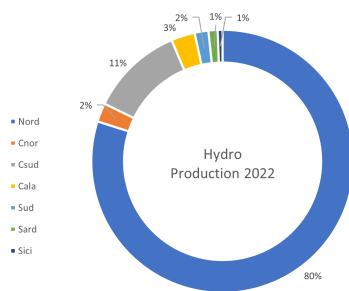


**Figure 3.28:** Hydro Production in 2022 [9]
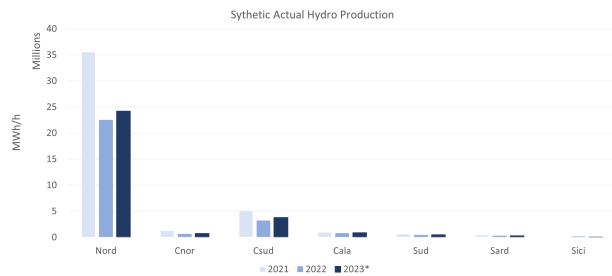


**Figure 3.29:** Hydro Production trend [9]

## Thermal

Most of the energy produced within the Italian territory comes from thermal power plants, with different primary energy supplies. In comparison to other energy production, this is by far the most common in Italy. The thermal power plant with the highest installed capacity in Italy is the "Alessandro Volta" plant, with 3.6 GW of installed capacity, and typically these plants are placed outside the main cities for environmental and cost reasons.

For instance, just to have a point of reference in this scale, the total installed capacity of all wind farms is equal to 14.26 GW ($\approx 120.9 GW * 11,8\%$ from Figure 3.23), but only the sum of the first sixth thermal power plants for installed capacity overlaps the wind capacity.

So even if the commitment in the next years will be the reduction of energy produced by coal, oil and gas, Italy relies mostly on these sources, as it is possible to check in Figure 3.31. Only Sardinia relies only upon 75 % of the thermal energy production on coal, but most of the other bidding zones rely on natural gas from a 60 % to a close 100 %. In any case, the various differences in primary energy might be observed in Figure 3.31, such as the difference in production per year in Figure 3.30.

In addition, as expected the bidding zone with the highest production of thermal

energy remains the NORD, with a quota of 54 % overall.

The source of the data for these Figures is Volue Insight [9], by handling the data obtained. The data collected for 2023 refers to the end of October, this is why it has been inserted an asterisk.
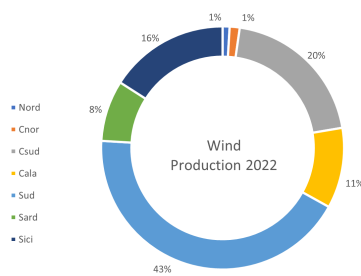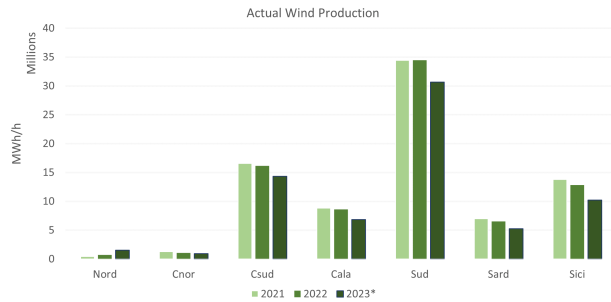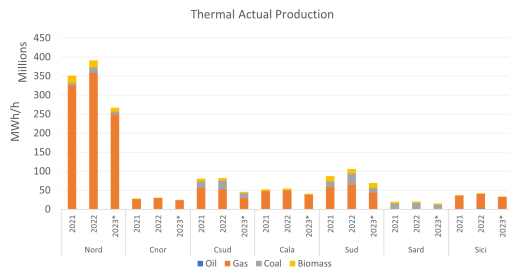


**Figure 3.30:** Thermal Production trend [9]
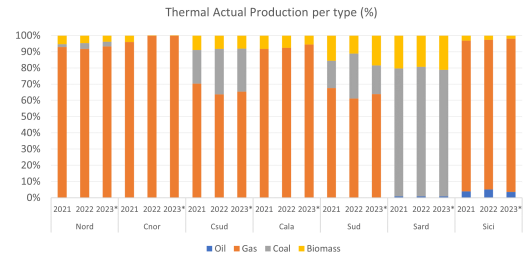


**Figure 3.31:** Thermal production trend in comparison [9]
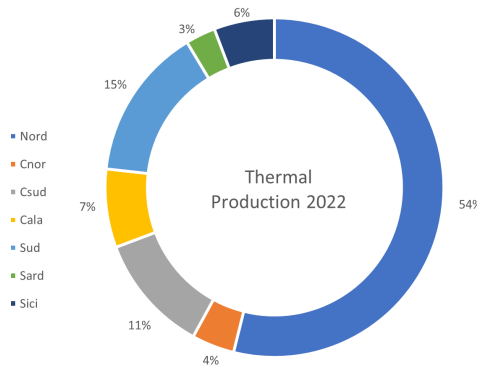


**Figure 3.32:** Thermal Production in 2022 [9]

## 3.4.2 Tipically production

The production of energy relies on the natural resources in the area, for instance mountains, and so reservoirs in the Alps or sunnier or windier in the South.

However the common point throughout every bidding zone is that the most exploited way for producing energy remains the thermal one, and the quota of renewables is still shortened with respect to the thermal.

The source of the data remains Volue Insight [9] but with another visualization respect the previous Figures in section 3.4.1.
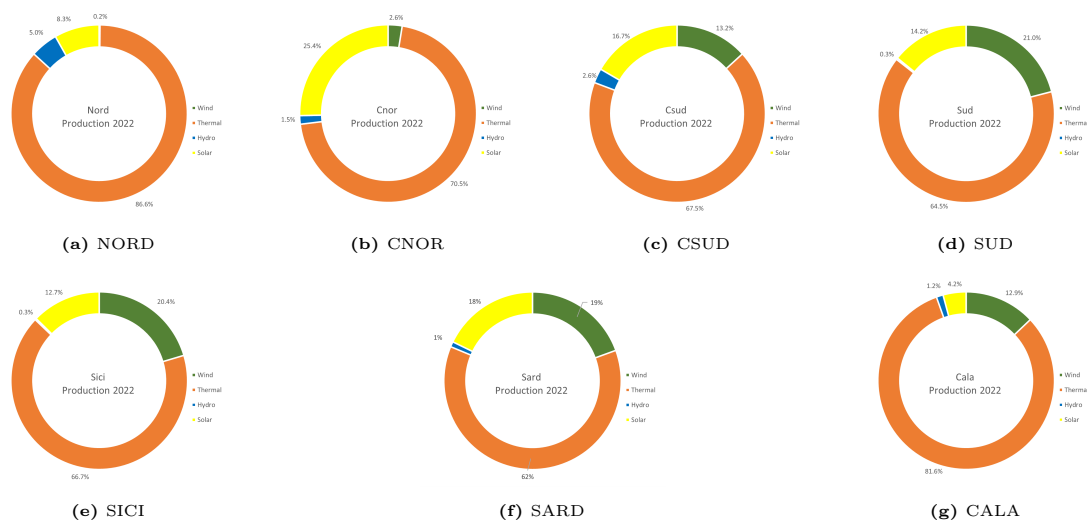
**Figure 3.33:** Production of bidding zone 2022[9]

### 3.4.3 Tipically consumption

One of the aims of Terna is to balance the consumption and the production of energy throughout the whole nation, otherwise the grid will be overwhelmed. In the case of lack of energy, there might be the possibility to import energy from different countries, and in case of a surplus, sell it.

Terna everyday is doing the forecast of the actual production for managing in the best way the constrains of the national grid.

What is relevant in Figure 3.34 is that consumption is concentrated in the North, meanwhile the other bidding zone are lower than NORD. The sum of consumption of the other bidding zone is comparable with NORD, thus showing a huge unevenness also in the consumption. This is due to historical reason: industries are concentrated in the North area, and it leads to a larger consumption of energy. Therefore, energy consumption is an important economical index that represents economic development of a zone, and this parameter has been used largely for typifying countries or cities [20] .

Also it might be interesting to notice how the consumption of energy is greater in the month of July, and the price is also greater in this month (see Figure 3.16), noting that it follows the law of supply and demand.

### 3.4.4 Import and export

Italy borders with many European countries by sea and by land, which means exchanges of energy flow incoming and outgoing, and so trades and negotiation with different parties. The Italian TSO Terna has thus empowered during the
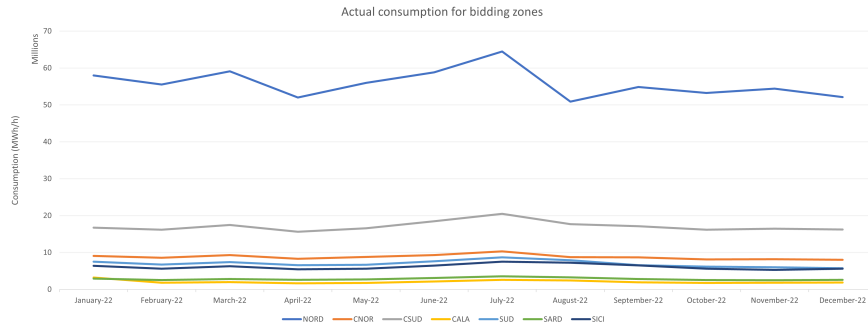
**Figure 3.34:** Consumption in every bidding zone in Italy in 2022 [9]

years the high-voltage network capacity, especially across the borders, crucial for connecting Italy with the rest of Europe.

The price in the abroad markets, as possible to see in the below figures, follows the trend of MGP, CRIDA1, CRIDA2 and CRIDA3. The abroad bidding zones are the ones reported in the Table 3.1, and below are shown the various trend in the MGP and CRIDAs for the foreign virtual, considering also the Italian coupling COUP.



**(a)** AUST    **(b)** SVIZ    **(c)** COAC    **(d)** CORS



**(a)** GREC    **(b)** MALTA    **(c)** MONT    **(d)** SLOV



**(a)** FRAN                    **(b)** COUP
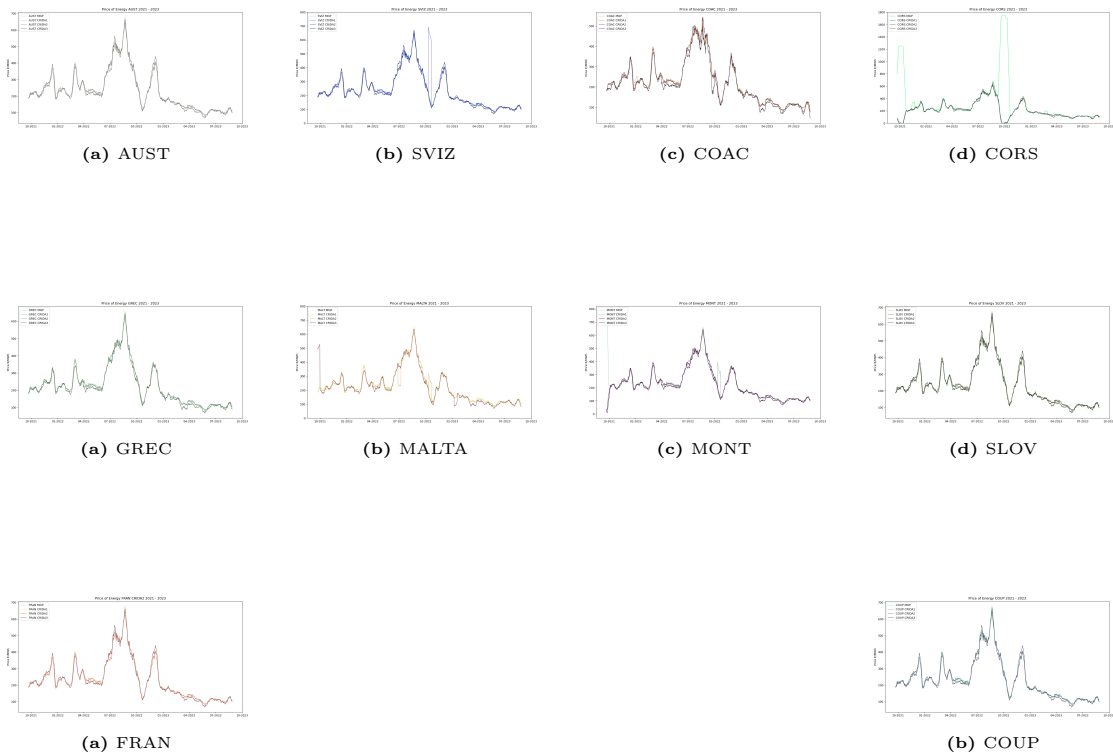
**Figure 3.37:** Trend price of energy bidding zone foreign virtual and coupling

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## 3.5   State of art of the problem

The customer might offer energy on MGP, CRIDA1, CRIDA2 and CRIDA3 indifferently, without any strategy that takes into account the price in each market. For example, they might offer the forecast for the generation of one plant in each market indifferently without considering that investing in one market rather than another makes a difference to the final profit. Two algorithms are developed to address this problem, one for the energy price and another for the quantity of energy to be sold. Finally, it is developed strategies for investing in a proper market.

# Chapter 4

# Development of code

## 4.1 Forecast

The forecast of energy price is a complex operation that requires historical data, from more inputs, and mathematical models that enable to handle huge amounts of data. Hence the forecasting of energy prices need a type of data called Time-Series (TS), that link a value to the equivalent date point, typically a day with an hour. It is followed more steps, such as:

- Data collection,
  Collection of data through different database; the main point is the consistency of data, and even a lack of one point means a mismatch between the data after this point and the time. The data collected and shown in the previous chapter was the basis of this evaluation.


- Data Analysis,
  Some TS are following a trend due to the week, the month, or even the seasonability. It is reasonable to check these parameters.

- Choice of the model,
  This choice is led by the results that it required to obtain, as long as the quality and quantity of the input data.

- Preparation of the data,
  Check the quality of the data, if there is some lack or inconsistency, figure it out how to fix it, such as interpolation between data, or set values. This manipulation has the aim of not changing the nature of input data, but instead making it workable for the model. In addition, sometimes the matrix needs to be reshaped in a different format such as an array, or limited the input value

between a gap (from 0 to 1, or from -1 to 1). Then it might be useful to split the data in training and test for the model.

- Creation of the model,
  After the model crunches the input data (it might requires from some seconds to a lot of minutes, depending on the epochs and the size of the problem), forecast output data.

- Validation of model,
  Check the forecasted output with the actual data, then check the relative error such as the MAPE.

During this work the process has changed during the time, but might be summarized as follows:

- If the data comes from the GME, it means that these are XML file that needs to be converted, as shown in Appendix A and then imported in a csv file;

- Insert the data from Volue Insight with the same time scale in the same excel file of the GME;

- Split data into "test and training", and another one only with the actual data;

- Run the algorithm of the forecasting feeding with only the file "test and training", to be double sure that it cannot read the actual data to be forecasted;

- Export the forecasted data;

- Compare the forecasted data with the actual ones in previous csv file.

## 4.2   Models

The input data are Time Series measurements, from both [9] and [12], which means that are data points recorded through time, with the characteristic that they are measured equally spaced.
When doing a time series forecast, it is important to find the right model that fits the behavior of data throughout time and then use this model to forecast and predict a new time series in the future, without input. The problem is that the forecast both of the price and the production might be difficult, since it is affected to government decisions or natural events, that most of them are unpredictable by a model. As proof of this indeed in the last chapter 3 has shown how the changes of prices are not linear through time and decrease or decrease in function of the supply and demand.

### 4.2.1 ARIMA

The first method used is the one most exploited for forecasting the consumption for a zone [20]. Since the price is related with the consumption, as seen in Figure 3.34, it seems reasonable to forecast the price with the same procedures.

More in detail, the ARIMA model stands for "AutoRegressive Integrated Moving Average" and it is split into three components: the autoregressive part, so the AR, then the integrated average, so IA, and finally the moving average, MA.

The structure of this model follows four steps: identification of the model, estimate the key parameter ($d,p,q$), recognition of the model and then forecasting. [20] For using the ARIMA model, the data needs to be as stationary as possible, and in this way, it is possible to find one of the key value of the model, the $d$, that is the number of no seasonal differences. Others key values are hence the $p$, that is for the numbers of autoregressive terms and $q$ for the numbers of lagged forecast errors. The ARIMA model for $p$ and $q$ could be summarising by these equations [20]:

$$x_k = \sum_{i=1}^{p} A_i x_{k-i} + \sum_{j=1}^{q} B_j v_{k-j} + v_k \tag{4.1}$$

$$E[v_k v_k^T] = R \tag{4.2}$$

Where $v_k$ is the uncorrelated random noise with covariance matrix $R$, $p$ and $q$ are the key values for the ARIMA and it is necessary to know the order of this predictor. Moreover $A_1, ... A_p$ and $B_1, ... B_q$ are respectively the coefficient matrices of $p$ and $q$.

### 4.2.2 DNN

DNN stands for Deep Neural Network and it will be used for the prediction of the price in the CRIDA1 CNOR and the PUN.

Indeed, a linear model sometimes cannot be sufficiently accurate for the task prediction optimally. The DNN model has been created with the aim of abstracting the predictive models into a sequence of layers, in such a manner that each layer applies a linear transformation followed by a simple non-linearity. If the number of layers is increased, then the prediction model will be more accurate and precise. [21]

The difficulty embedded in this problem, nevertheless, come from the neural network representation: multiscaled and distributed. Indeed there might be issues that some neurons might be activated for only few data points, but others are more overwhelmed by the whole system, thus causing an imbalance in the algorithm. So the prediction is the sum of local effects, due to the neurons non tipically activated, and the global effects, creating a non linearity in the system, that other models

cannot handle. Another cause of error is the high depth of some neural network, where it causes a "shattered gradient" so with discontinuity. So if the depth of the model is increased, the number of discontinuities in the gradient grows instead exponentially. [21]

In any case, the predictive model can be approximated as follows, considering that every function is a layer [21]

$$f(x) = f_L \circ \cdots \circ f_1(x) \tag{4.3}$$

### 4.2.3 LSTM

LSTM is the acronym for Long Short Term Memory and it is a type of Recurrent Neural Network (RNN) architecture, commonly used for time series forecasting and sequence modeling.

The main advantage of this algorithm is that it fixes the problem of vanishing gradient, and it do so by ignoring useless data in the network. When several time series are included, the algorithm can choose the information to keep, the one to discard and the one to add. [22]

The network of the LSTM is made up of 4 different components: the Memory cell, the Forget, Input and Output Gates, as shown in Figure 4.1.

The LSTM architecture consists of more layers, that include at least an input layer, an output layer and then more than one LSTM layers.

Every time it is obtained a new input, it goes through this block diagram; it then chooses if a data might be relevant or not for the algorithm. When it is agreed that an input is useless, it is multiplied by zero, and so forgotten by the LSTM.

The Forget Gate is responsible for deciding which input might be forgotten, by a sigmoid layer (so a sort of shaped 'S' function).



**Figure 4.1:** Various components of LSTM's algorithm

Meanwhile the Input Gate determines which new input might be stored in the Memory Cell, and has a sigmoid layer and a *tanh* activation that work in parallel. Finally the Output Gate is made up of a sigmoid layer in series with a *tanh*, thus giving a gate output.

**Multi-Step Multivariate Time-Series Forecasting using LSTM**

The energy price is set through several inputs, as shown in the previous chapter, based on the quantity and type of energy supplied by the used plants.

Hence, it might be an open position for several variability of inputs, and the main commitment remains to correctly choose these values.

LSTM is able to build a Multi-Step Multivariate time series for forecasting, with more independent values of input ( called simply $x$) that predict a dependent variable ($y$). [23]

If there is only a single $x$, it is called Univariate forecasting, otherwise a Multivariate one. In this paper is used indeed the second one, with more $x$ of input.

In addition, if the model predicts only one step in the future, it is called obviously a one-step forecast, otherwise, it is a Multi-step.

With all the methods combined, in the next paragraph in Section 4.3.3 will be predicted the price of CRIDA1 CNOR $y$ with more inputs $x$.

### 4.2.4 MLR

The MLR stands for Multiple Linear Regression, so in comparison with simple linear regression, it involves more independent variables. It is a statistical method that relates a dependent variable with one or more independent variables, and the relationship is assumed to be linear throughout the variables. The commitment of this algorithm, such as every prediction algorithm, is to minimize the distance between the predicted values and the actual, and this one is particularly exploited in economic field.

The first trial has been conducted taking inspiration from the forecasting of the price of corn in China such as dependent variable [24]. In this paper, it has been established first a univariate nonlinear regression, and then deepened with other influencing factors, thus obtaining the MLR. The outcome of the paper is a precisely forecast of the price using domestic and international corn market price, thus estimating the various input independent parameters in the model.

Taking inspiration from this document, it is decided to marking this path. As shown in the below general equations for regression, in 4.4 is the single variable linear regression and 4.5 is the multiple variable linear regression. The $\beta$s are the coefficients (or weight) of the model, $x$s are the equivalent input of the model, independent variables, $\epsilon$ represents the error and finally $y$ is the predicted output, a dependent variable.

[25]

$$\hat{y} = \beta_0 + \beta_1 x + \epsilon \tag{4.4}$$

$$\hat{y} = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p + \epsilon \tag{4.5}$$

The value $\hat{y}$ means that it is an estimations of the value $y$. What might be considerable for the study is the differences in the size of the $x$ and the $\beta$, meanwhile

the $y$ remains the only output of the system.

In the code developed, it is chosen two types of regressive terms: the automatic one, in which is the responsibility of the programmer to select a correct number, and the seasonal ones, inserted like dummy variables in the system. So every time is required to make a forecast, it is of major importance to choose the independent parameter that might forecast correctly instead of them that increase the error.

### 4.2.5 MAPE

For a proper evaluation of a forecast, it is needed to compare these points with the actual data, to understand if the mismatch between the actual data and the forecast is reasonable or not.

One of the most common typologies for evaluating this problem is the MAPE, the Mean Absolute Percentage Error, used mostly for regressive models. It has an intuitive equation, follows below, that is an average of the relative errors for all the values. Since it has done an average of errors, it is used for the application in which is not important the punctual error, but instead to be sensitive to relative variations than absolute. [26]

$$MAPE = \frac{1}{m} \sum_{i=1}^{m} \left| \frac{Y_i - X_i}{Y_i} \right| \tag{4.6}$$

$Y_i$ and $X_i$ are respectively the Actual and Forecasted value a the $i^{th}$ position. If the MAPE is equal to zero, it means that there is a match in all the considered points, and is the best value achievable; otherwise the worst obtainable is infinite, with the actual value $i^{th}$ is zero.

In the code, it will cause a problem, since it will be forecasted the consumption of PV energy, and during the night is a null value. This problem has been avoided easily by excluding the nighttime hours, not relevant in the forecast.

## 4.3 Algorithm for price of energy

The forecast of the price within a market is a crucial parameter since the market participants exploit these data to maximize the profit up to they can. [3] The producers usually enter into the MI to minimize their mismatch and imbalances due to a change in the forecast, and if they produce the same quantity of energy that was sold previously, in the most expensive market, the forecast is correct and the earnings are at a peak. Instead, if is produced a quantity of energy smaller or higher than the amount sold, the producer has to pay a penalty to the TSO or adjust their position in the XBID. The aim of the forecast is the reduction of risk in the energy investments, hence the error (MAPE) needs to be close to zero.

First of all, for the beginning of this forecast, it has been focused only on CRIDA1 for the bidding zone CNOR, and so all the downloaded data refers to this zone. It has been done in this way since the CNOR zone is a small zone, without an abroad connection, and it is logical to begin in the small and then in the complex.

### 4.3.1 Input

Other research has engineered the forecast of the price, as reported in [3]. For instance this paper has demonstrate why is important to forecast the price for Turkey in the DAM and which data has been used such as:

- The changing of production in the Wind Power;

- The changing of production of hydroelectric power;

- The changing of production capacity of natural gas;

- The changing in production capacity of coal;

- The changing of total consumption.

Instead, for this work of thesis it has been used the following parameters, from different sources within the company Volue Insight and outside, such as the GME database, have already been used for the showing of historical data:

- Foreign Exchange;

- Temperature;

- Prices - Natural Gas Forward;

- Hydro production and historical forecast;

- Wind production and historical forecast;

- PV production and historical forecast;

- Traded Volume (acquisition and sales);

- Historical Price MGP and Cridas;

- Residual load.

These inputs were combined for the LSTM multivariable, instead for the other models have only used the historical data.

## 4.3.2   Troubleshooting

As reported in the section 4.1, it is important to keep the data consistent and with high quality.
During this phase of work, it has been faced some troubles with the data from the GME.

- For instance for some days, as shown in Figure 4.2, the price of Crida1 reached a value close to zero, equals to zero, or even negative. The main reason is that in those days coincide with national holidays, such as Easter, and so the data are not reliable. To fix this mismatch, it has been interpolated the data before and after the lack.

| 1 | Data | Num | Historicak price CRIDA1 |
|---|---|---|---|
| 4816 | 4/10/2022 15:00 | 4815 | 0 |
| 4984 | 4/17/2022 15:00 | 4983 | 0.1 |
| 13575 | 4/10/2023 14:00 | 13574 | 0 |
| 13576 | 4/10/2023 15:00 | 13575 | -10 |
| 13577 | 4/10/2023 16:00 | 13576 | 0 |
| 14559 | 5/21/2023 14:00 | 14558 | 0.28 |
| 16407 | 8/6/2023 14:00 | 16406 | 0 |
| 16408 | 8/6/2023 15:00 | 16407 | 0 |

**Figure 4.2:** Problems with the data in CRIDA1

- In addition, for two hours within the 6th of August of 2023 Crida1 the price was 28,02 Eur/MWh at 1 PM, and 24 Eur/MWh at 4 PM, but zero in between of them, as it possible to see in the same Figure 4.2 above. Since it has caused problems in the algorithm (a division for the actual price, so zero, and then so infinite), it was therefore decided to interpolate the lack of data (26,7 Eur/Mwh at 2 PM and 25,4 Eur/MWh at 3 PM). In this way, the algorithm properly works.

- Nevertheless is found another error in the data of the GME, such as a lack of data in the 26th March 2023 at midnight, see Figure 4.3. For avoid this problem it has been created the same value of 11 PM. This error continues in the other markets, so there was not a recording by the GME for this point in any markets.

```
<Prezzi>
    <Data>20230326</Data>
    <Mercato>MI-A1</Mercato>
    <Ora>22</Ora>
    <NAT>130,000000</NAT>
    <CALA>130,000000</CALA>
    <CNOR>130,000000</CNOR>
    <CSUD>130,000000</CSUD>
    <NORD>130,000000</NORD>
    <SARD>130,000000</SARD>
    <SICI>130,000000</SICI>
    <SUD>130,000000</SUD>
    <AUST>130,000000</AUST>
    <COAC>130,000000</COAC>
    <COUP>130,000000</COUP>
    <CORS>130,000000</CORS>
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    <GREC>130,000000</GREC>
    <SLOV>130,000000</SLOV>
    <SVIZ>130,000000</SVIZ>
    <MALT>130,000000</MALT>
    <MONT>130,000000</MONT>
    <XGRE>130,000000</XGRE>
    <BSP>130,000000</BSP>
</Prezzi>
<Prezzi>
    <Data>20230326</Data>
    <Mercato>MI-A1</Mercato>
    <Ora>23</Ora>
    <NAT>104,330000</NAT>
    <CALA>104,330000</CALA>
    <CNOR>104,330000</CNOR>
    <CSUD>104,330000</CSUD>
    <NORD>104,330000</NORD>
    <SARD>104,330000</SARD>
    <SICI>104,330000</SICI>
    <SUD>104,330000</SUD>
    <AUST>104,330000</AUST>
    <COAC>104,330000</COAC>
    <COUP>104,330000</COUP>
    <CORS>104,330000</CORS>
    <FRAN>104,330000</FRAN>
    <GREC>104,330000</GREC>
    <SLOV>104,330000</SLOV>
    <SVIZ>104,330000</SVIZ>
    <MALT>104,330000</MALT>
    <MONT>104,330000</MONT>
    <XGRE>104,330000</XGRE>
    <BSP>104,330000</BSP>
</Prezzi>
</NewDataSet>
```

**Figure 4.3:** Problem 2 with the data in CRIDA1

### 4.3.3 Output

In this part are shown the results for the forecasting of CRIDA1 CNOR with the models explained from the methodology in Section 4.2. The methodology used was of trials and errors, so for intellectual honesty are shown also the less efficient models, but might be skipped to the correct forecast, hence the MLR in section 4.3.4.

**ARIMA**

Since the [20] suggests the ARIMA model as one of the most promising, it is the first model implemented. In Figure 4.4 the results for manual forecasting are shown, by inserting manually the $p$, $d$ and $q$, and then automatic one.

This forecast is not acceptable by a market operator, so it is required to change the model: the automatic one is like with a constant slope downwards unreasonable, and the manual one, after few points of decreasing, it is kept flat over the time. Hence, another model is required.
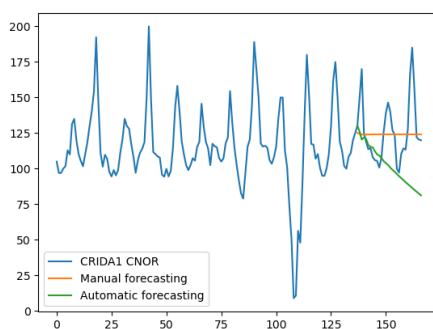
**Figure 4.4:** Arima forecasting CRIDA1 CNOR

## Prediction of the PUN

Consequently the former section, it has been chosen to develop the algorithm for forecasting the PUN in Italy, in a quiet historical moment for the price, such as the time gap between June 2017 and June 2018, as shown all together in the Figure 3.1 and more specific in Figure 4.5, and then continue the handling with CRIDA1 CNOR. The point is wanted to begin with simpler data, stable, and then continue with more complex ones.
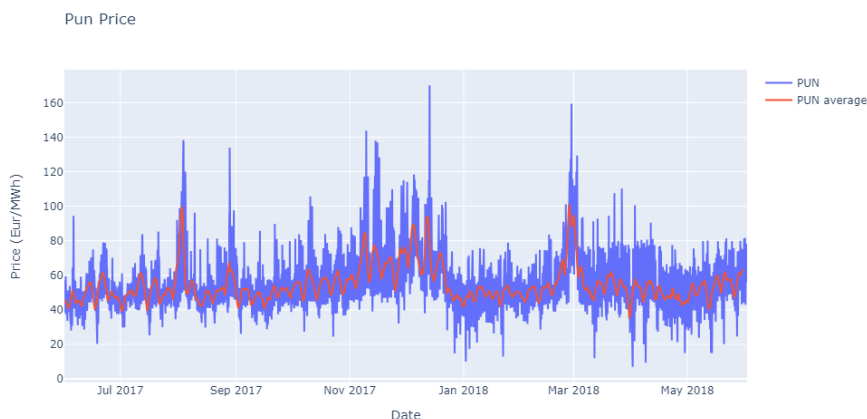


**Figure 4.5:** Trend Price of the PUN

For this first trial, this has been used this repository, with all the modifications for implementing a forecasting of price instead of a load, as reported in [27].
The results are hence shown in the following figures, one is for the LSTM algorithm and the other one is for the DNN, respectively Figures 4.6 and 4.7, with the equivalent MAPE of both. Since the prediction obtain is propitious to be correct, it is then chosen to use these parameters in the CRIDA1 CNOR.
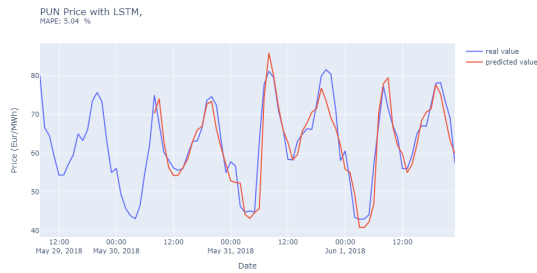
**Figure 4.6:** Forecast LSTM PUN
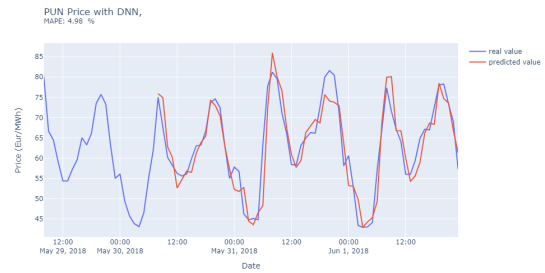


**Figure 4.7:** Forecast DNN PUN

## Prediction of the CRIDA1 CNOR

Since the predictions of the PUN worked, therefore it has continued with the implementation on the CRIDA1 CNOR.

As it possible to check in the previous Figure in 3.8, the data are not stable, so the first point chosen is the 27th of December 2022 and the last one is the 27th of September 2023, as visualized in summary in Figure 4.8, with a downward trend from December to May and then subsequently stabilize in June 2023.

The algorithm for the prediction is the same of the PUN, and the results are shown in Figures 4.9 for the LSTM and 4.10 for the DNN. Both of them have a MAPE below the 9 %, but the LSTM seems to be the most promising for the forecast.
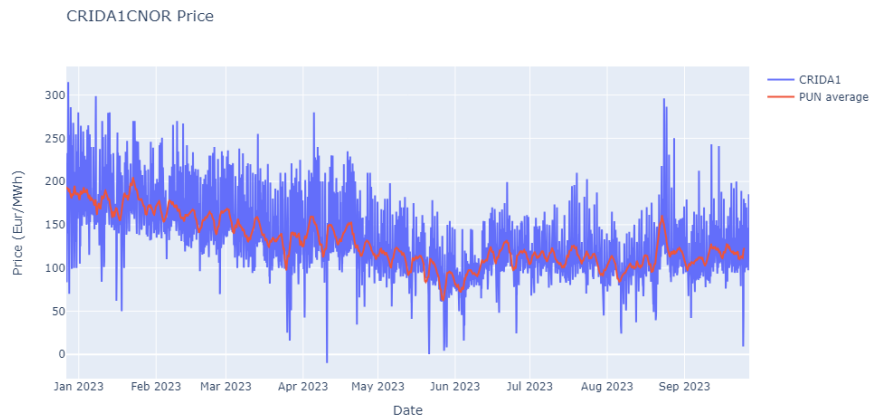


**Figure 4.8:** Trend Price of the CRIDA1 CNOR

## Multi-Step Multivariate Time-Series Forecasting using LSTM

It has been chosen to develop the algorithm of LSTM with several inputs, see section 4.3.1, to understand which data might be useful for the forecasting of the
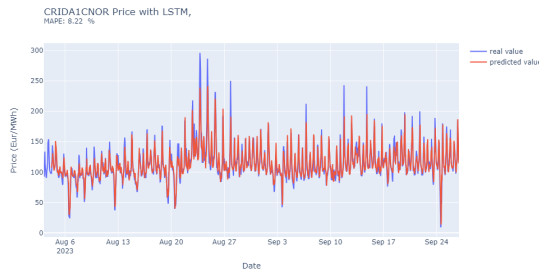
**Figure 4.9:** Predicted LSTM CRIDA1 CNOR
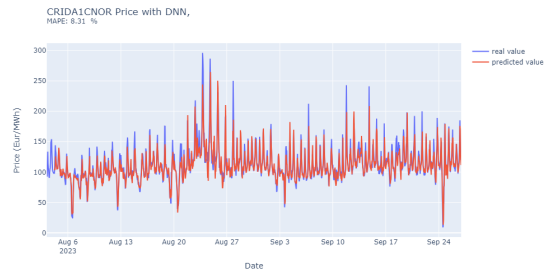


**Figure 4.10:** Predicted DNN CRIDA1 CNOR

price. The sources of the data are the GME and Volue Insight. For instance, it is shown below (Figures 4.11, 4.12 or 4.13) some of the inputs of the algorithm, like the temperature, the energy mix or, as expected, the price in CNOR.

The quantity of data usable is wide, so it is difficult to choose the correct parameters for the forecast of LSTM.
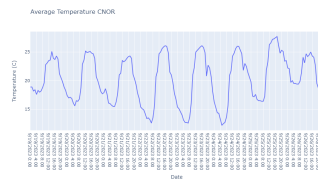


**Figure 4.11:** Temperature CNOR
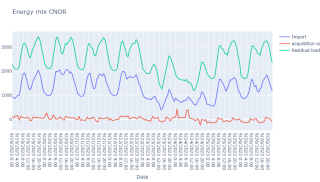


**Figure 4.12:** Energy mix CNOR
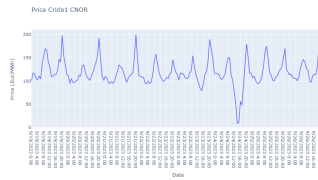


**Figure 4.13:** Price CNOR

In addition, since it has been worked with historical data, it seems reasonable to compare the data forecasted with the actual ones. Then, it is shown the MAPE, already explained in the section 4.2.5. The following results have been obtained through this repository on Github [28]

- **Including Price, Hydro Forecasting, Acquisition-Sales, Temperature, Gas Price, Forecast PV, Forecast Wind**
  In the following Figures 4.14 and 4.15 is possible to visualize the result utilizing the parameters in the subtitle. The result of the MAPE is 14.55 %, with an correct average of the trend, but not of the peak. So even if the average is proper, it is continued with another approach.
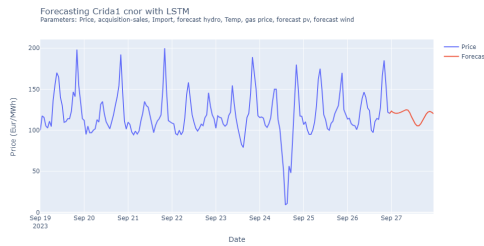
**Figure 4.14:** LSTM forecasting Crida1 CNOR with Price, Hydro Forecasting, Acquisition-Sales, Temperature, Gas Price, Forecast PV, Forecast Wind
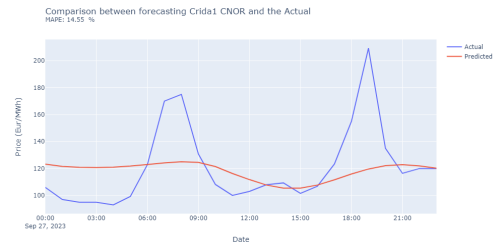


**Figure 4.15:** Comparison Actual and Forecasted value, with MAPE, with Price, Hydro Forecasting, Acquisition-Sales, Temperature, Gas Price, Forecast PV, Forecast Wind considered

- **Including Price, Hydro Forecasting, Temperature, Gas Price, Forecast PV, Forecast Wind**

  Also in this case, as shown in Figures 4.16 and 4.17, there is a difficulty for the peaks and valley of the graph. In addition, the MAPE got worse, with a main result of 15.03 % (instead of 14.55 % before). In any case, the research needs to continue.
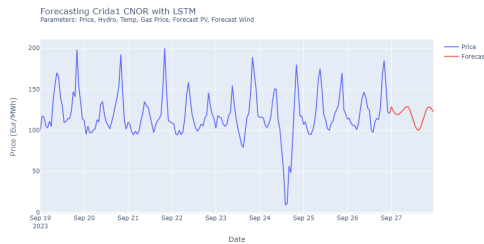


**Figure 4.16:** LSTM forecasting Crida1 CNOR with multiple time series developed, Price, Hydro forecast, Temperature; Gas Price, PV and Wind forecast considered
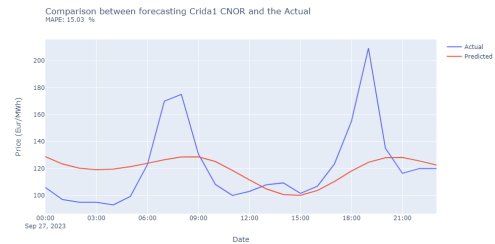


**Figure 4.17:** Comparison Actual and Forecasted value, with MAPE; Price, Hydro forecast, Temperature, Gas Price, PV and Wind forecast considered

- **Including the residual load**

  Since the other trials got worse the results, it was decided to include also the forecasting of residual load of CNOR and removing the "Acquisition-sales". The definition of residual load is the total consumption less the production of wind and solar.

  However, with an error of 14.43 %, this model is the most correct so far.
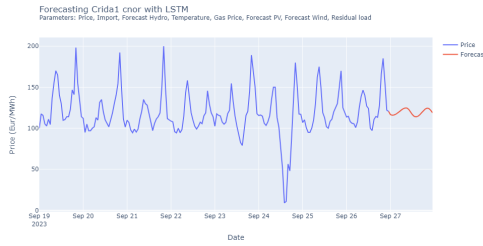
**Figure 4.18:** LSTM forecasting Crida1 CNOR with multiple time series developed: Price, Hydro forecast, Temperature, Gas Price, residual load, PV and Wind forecast considered
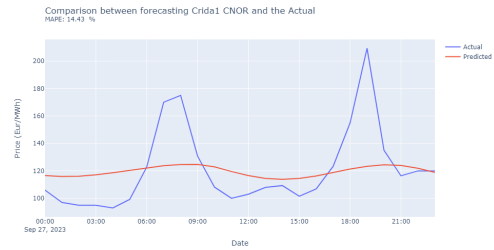
**Figure 4.19:** Comparison Actual and Forecasted value, with MAPE; Price, import, Hydro forecast, Temperature, Gas Price, Residual load, PV and Wind forecast considered

In the previous section in 4.2.3 it has been explained how the LSTM works and how to carry out Multivariate Time-Series forecasting. The error of before might be reduced by processing more data than the ones in the previous section, so another implementation has been put forward. Instead of having more typology of data, since it has been already advanced the difficulty of finding the correct ones, it is therefore preferable to focus on less typology of data but with a larger time scale. In the first section it has been used 10 months of data and the forecasting of 4 days.

For the first trial, it used the actual production of the thermal in CNOR, the residual load in CNOR and after all the price of energy in CRIDA1 CNOR, as shown in the following Figure 4.20, then the results it's possible to visualize in the 4.21.

It is possible to find the repository in the following website [23].
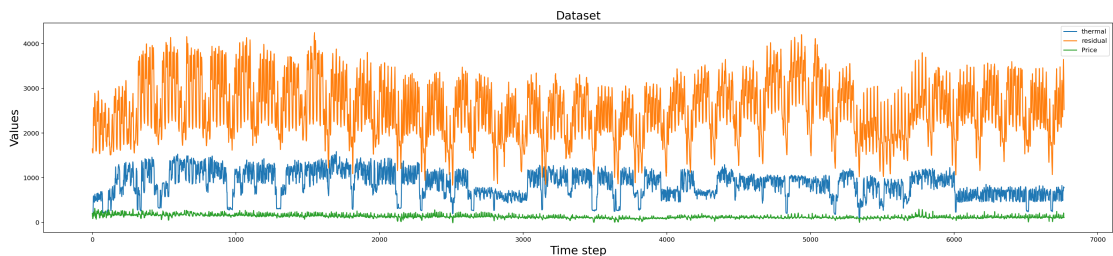


**Figure 4.20:** Dataset multiple forecasting, with price of CNOR, residual and thermal production
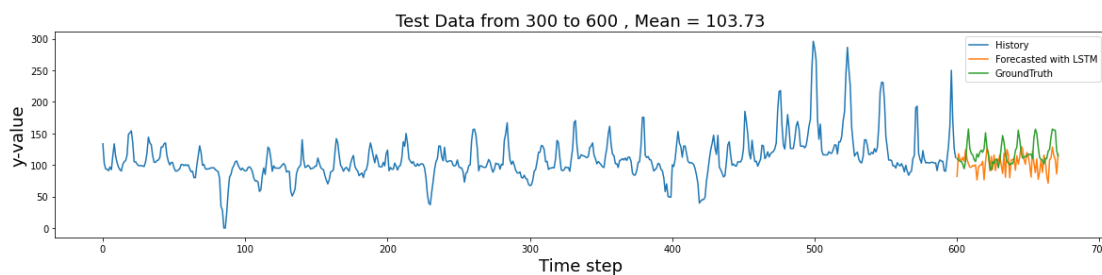
**Figure 4.21:** Forecasting of price with thermal production and residual load, throughout a Multivariables approach using LSTM

Also with this method, it is obtained a correct average of the actual value, but this is not enough using the LSTM method.

### 4.3.4 Using MLR in comparison with other models

Since the previous trials were not satisfactory, it has chosen to use a new methodology, so using more than one model for the forecasting. The repository used is possible to see in the following links [29] and this one [30]. The state of art used by far was the multi variable LSTM, but since the results were not satisfying, it is chosen a single LSTM and after that the repository [30] suggests using MLR, even if all the other research used the LSTM [29] [27]. The total code can be visualized in Appendix B.

So by using the repository of Scalecast [30], it can be studied first the seasonality in the data of CRIDA1 CNOR for the input data, 10 days of input for the first trial, viewable in Figure 4.22. More in details, in the first graph are shown the actual input data, in the second one the Trend, so close to a moving average of the points, then for third the Seasonal, with astonishing equity during the days, and for last the Residual, correlated also with the changing in the trend.
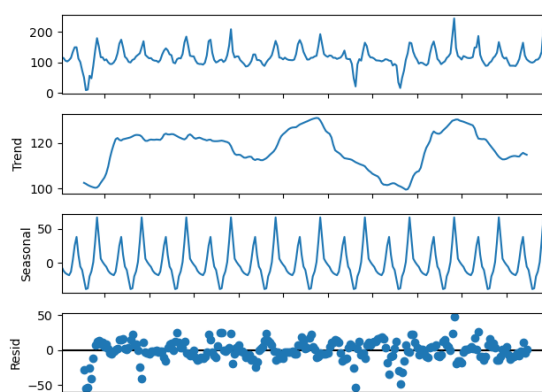


**Figure 4.22:** Seasonality within the data of the CRIDA1 CNOR, from 24/9/23 to 4/10/23

Further, it is decided to keep the treatment as easy as possible, so it is wanted to make a forecast again with LSTM, but only with historical data, as shown in Figure 4.23, with different lags and epoches, but also in this case are not correct.
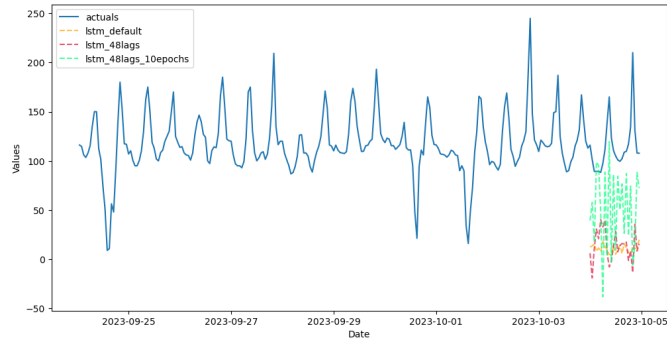


**Figure 4.23:** Forecasting through several model, every trend has an interval of confidence not shown

So the Scalecast repository can change the model easily, so it is decided to use the best LSTM found (by trials and errors) with shuffle, 15 epochs and 48 lags, and the MLR with the dummy variable with hour. In conclusion, the results are shown in Figure 4.24, thus demonstrating that it is possible to make a forecast of the price using MLR.
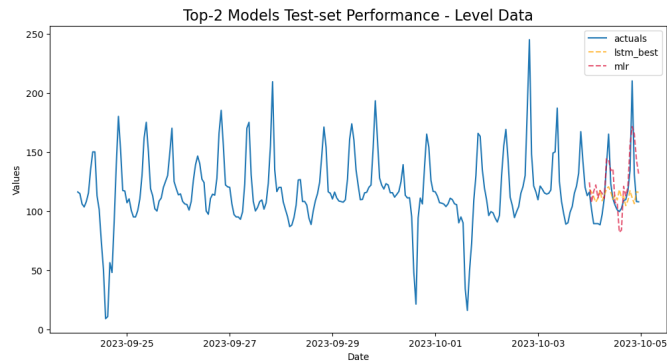


**Figure 4.24:** Forecasting in comparison of the actual data

Hence, it has been done a forecast for one day ahead of the actual data, as shown in Figure 4.25, and also in this case the best option remains the MLR, so the treatment can continue with experiments for a forecasting of more days, or during the weekend, or changing the numbers of autoregressive terms, or changing the dummy variables or insert more input data.
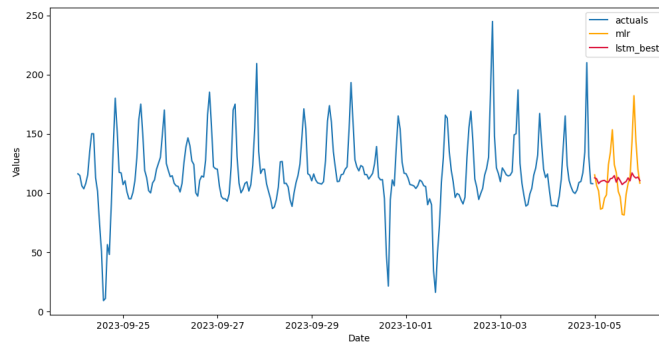
**Figure 4.25:** Forecasting of the day ahead of the actual data given

The code developed is by far the most understandable than all the previous ones, as it is possible to check in the Appendix B, for the Figure 4.34 . The result only with the MLP is hence shown in the below Figure 4.26, with the calculation of the MAPE. The following variables has been used:

```
f.add_ar_terms(48)
f.add_seasonal_regressors('hour', dummy=True)
f.add_time_trend()
```
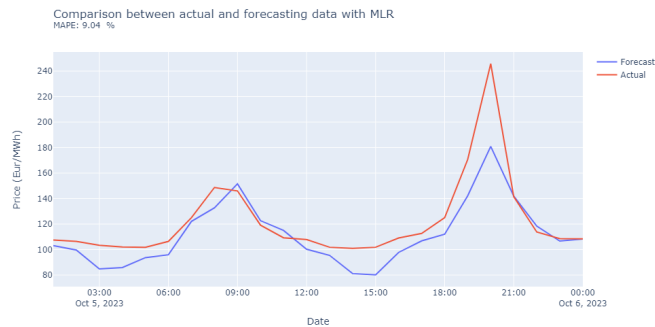


**Figure 4.26:** Comparison and MAPE calculation of forecast values and the actuals

In the second experiment, it has chosen to use more input data, from 1st June 2023 to 4th October 2023, forecasting one day and three days ahead, with the same approach as before of studying the seasonability and the trend of the input. The results are shown below in Figures 4.27 and 4.28, with respectively a MAPE of 6.46 % and 9.74 %.
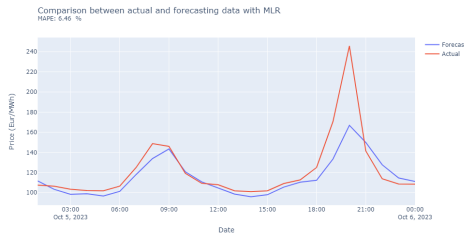
**Figure 4.27:** Forecast one day ahead MLR in weekdays
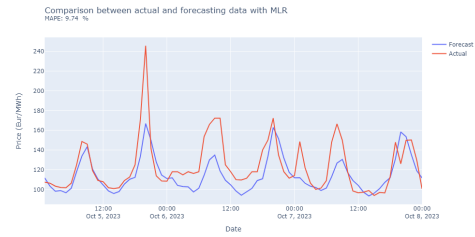


**Figure 4.28:** Forecast three days ahead MLR

Since this way seems promising, it has been chosen to continue with more input data, from the 27th December 2022 to 4th October 2023, and the result are shown below in Figures 4.29 and 4.30, with a MAPE respectively of 6.31 % and 9.59 %. As it is possible to check from the MAPE, even if the input data were twice of before, the result of the forecasting is kept close to the same, so it will not be extended input data.
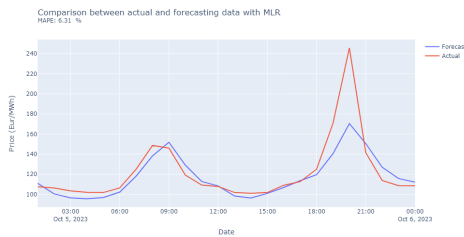


**Figure 4.29:** Forecast one day ahead MLR in weekdays
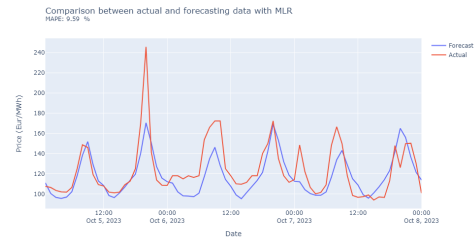


**Figure 4.30:** Forecast three days ahead MLR in weekdays

In addition, it seems reasonable to check the behaviors also during the weekend, when the price is lower.
The results obtained are not satisfactory as shown in Figures 4.31 and 4.33, with a not acceptable MAPE in both. In addition, when the temporal scale is split in this model (weekdays and weekends), the repository cannot recognize the difference in step, so it shatters the rule of time series forecasting, with an illicit manipulation: even if it is only inserted the weekend data in series, the algorithm falls in error.
But instead, it has been chosen to keep this model and add a new regressor in the dummy variables and increase the *ar terms* to 70 instead of the 48 before, as reported below:

```
f.add_ar_terms(70)
f.add_seasonal_regressors(
    'hour',
```

```
4        'dayofweek',
5        dummy=True
6    )
```

Other models might be proposed for fixing this problem (for instance using TimeGPT), but it would be back to the beginning of the analysis of the problem. The results obtained are not only satisfactory, but the forecasting in the three days is even better than the previous one in Figure 4.30.

In Figure 4.32 and 4.34 are respectively shown the correct results for one day ahead and three day ahead using the seasonal regressor of before. The MAPE in Figure 4.34 is 8,58 % during the weekend, in comparison with the previous one in 4.30 of 9.59 % in the weekday, reducing hence the error of 1 % during a forecasting in the weekend. It was supposed to be higher since the MAPE in 4.32 is higher than 4.29, indeed 9.1 % in comparison to a 6.31 %. In any case, at the end of the section are shown the best result in a Table for clarify every doubt.
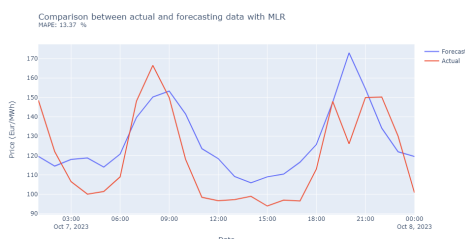


**Figure 4.31:** Forecast one day ahead with MLR in weekend
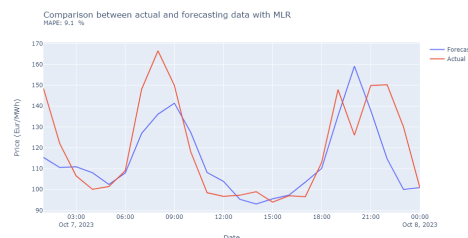


**Figure 4.32:** Forecast one day ahead with MLR in weekend, after implementation dummy and ar terms
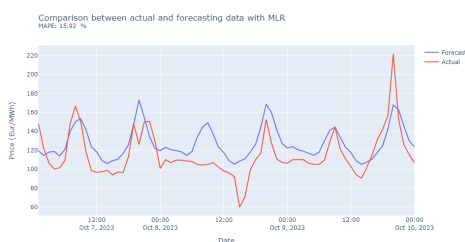


**Figure 4.33:** Forecast three days ahead with MLR in weekend
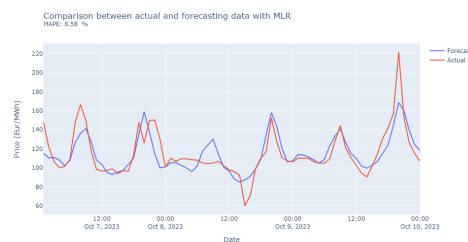


**Figure 4.34:** Forecast three days ahead with MLR in weekend, after implementation dummy and ar terms

It seems reasonable to insert the new parameters in the code of before, with the input parameters from the 27th December 2022 to 4th October 2023, so as to verify if it has been an enhancement or worsening of the error in the MAPE. The

results are shown in Figures 4.35 and 4.34 with indeed a decreasing of the MAPE in both cases, so a successful experiment.
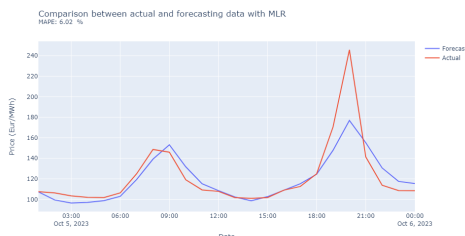


**Figure 4.35:** Forecast one day ahead with MLR in weekday, after implementation dummy and ar terms
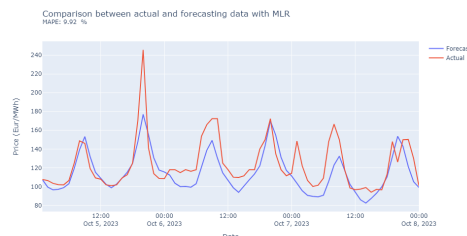


**Figure 4.36:** Forecast three days ahead with MLR in weekday, after implementation dummy and ar terms

For a better understanding of the results, it seems reasonable to show them in a Table 4.1, which are absolutely better of the ones in comparison to the LSTM model.

| MAPE | Weekdays | | Weekend | |
|---|---|---|---|---|
| | Before mod | After mod | Before mod | After mod |
| One day | 6.31 % | 6.02 % | 13.37 % | 9.1 % |
| Three days | 9.59 % | 9.92 % | 15.92 % | 8,58 % |

**Table 4.1:** Differences of errors in MLR before and after the implementation of new seasonal regressor, new trace and dummy variable

# 4.4 Algorithm for energy bidding

## 4.4.1 Dispatchable

The analysis has been focused on the:

- Economy of scale;

- Historic production during seasonability, season or day of week.

**Hydro**

The aim of this section is to find a correct forecasting in one hydropower plant.
First of all, it is chosen a bidding area, from the previous Figure 3.28 it seems sensible to choose, for this first example, the area with more hydro production, indeed NORD.
Then it is imported from Volue Insight [9] the total historical data of the production

of hydro power plants in the Nord bidding zone, using training and test data from 5/10/21 0:00 AM to 4/10/23 11:00 PM, with totally 17521 points. The Volue's database is able to lend data with a 15-minute frequency, but since the data from the GME are 1 hour of frequency, it has hence chosen to sum the 4 data of energy produced in 15 minutes in one data of 1 hour.

With the available actual data, it has been used the forecasting method of MLR (see Appendix B), already implemented for the CRIDA1 CNOR, changing the input data and the dummy variables.

This time, the dummy variables used were two: *day of year* and *month*, thus obtaining an error of 7.05 %. But, even if the result is acceptable in the weekdays, it is not for the weekend, hence in addition to that dummy variable, it is inserted also *dayofweek*, that in one hand increased the MAPE (i.e. 8.18 %), but it gives a reasonable forecast for every day.

Nevertheless, it is obtained only the forecast for the bidding zones, but not for one plant. It could be useful to use directly the production of a real power plant, but these data are sensitive, so it is then chosen to manage that differently. It makes the assumption that each plant produces a quantity of energy through the weighted average of its installed capacity.

For instance, from the Terna website [31] the total net capacity of hydro on the bidding zone NORD can be visualized, as shown below in Figure 4.37 is 14400 MW. After that, it is chosen one reasonable powerplant in NORD bidding zone, it is chosen the hydropower plant of Grosio, in Lombardia, with a capacity installed of 431 MW [32], and it is supposed that this capacity is the net one, not the gross. What is possible to achieve is that this powerplant participates for the 3 % ($= \frac{431}{14400}$) on the production of energy in the NORD bidding zone, so this value will multiply the result obtained in Figure 4.38 resulting in Figure 4.39, so the forecast of one powerplant. Just to be sure that the assumption made makes sense, it has used one data of forecasted energy produced, and it has been multiplied for 8760 hours in one year, obtaining an outcome close to the one shown in A2A's website in [32]. In addition the results obtained in Figure 4.39 stay in the tolerance threshold of the powerplant (below the installed capacity of 431 MW), thus confirming the results.

**Thermo**

With the same approach as before, it is analyzed the production of energy in NORD, since is the bidding zone that offers more data points, focused only in the plants supplied by gas.

The forecasting of total production is shown in Figure 4.40, but in comparison of before, a new approach has been used: the *ar terms* are 300 and the *seasonal regressor* are "day of week", "quarter" and "week".

Nevertheless it can be seen from the TSO's website [31], that the total net capacity
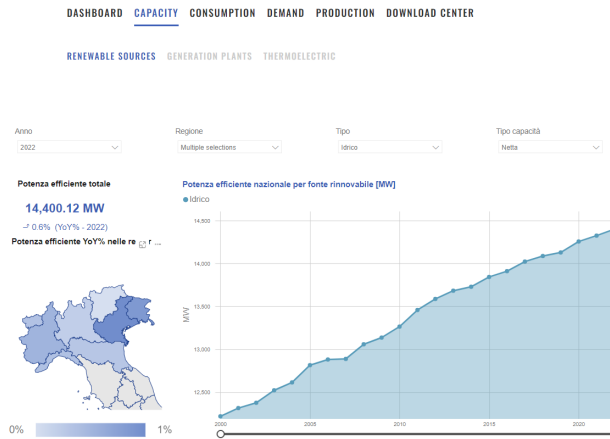
**Figure 4.37:** Capacity of hydro power plants in NORD
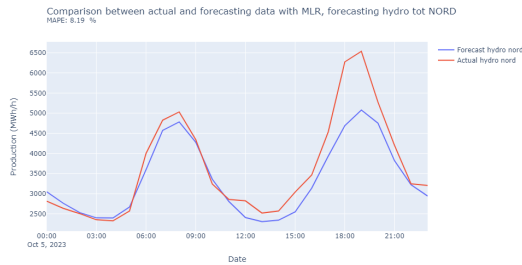


**Figure 4.38:** Forecast one day ahead with MLR, NORD tot hydro power plants
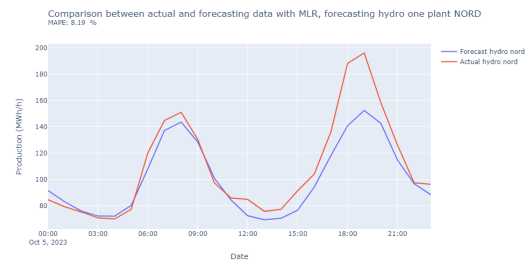


**Figure 4.39:** Forecast one day ahead with MLR, NORD one hydro power plant

for NORD thermal powerplant is 29041 MW, but Terna cannot show the capacity split by resources.

In any case, it could be calculated easily, since in the previous chapter has studied the percentual for every type of natural resources split by bidding zone (see Figure 3.31). Hence it could be deducted that the total percentual of gas source is 91.7 % of the total, and so the total capacity for the gas is $= 29041 * 91.7\% = 26630 MW$. After that, it is chosen a powerplant in the italian portfolio of gas powerplant in NORD, for instance the one of Cassano d'Adda, with 848 MW of installed capacity, as reported in the website of A2A in [33]. For instance, altogether this power plant might supply the NORD of the $\frac{848}{26630} = 3.18\%$, and so the result for one plant is shown in Figure 4.41. In contrast to the last section of the hydro power plant, the results obtained are not satisfactory, with an overtaking during the peaks of the threshold tolerance of 848 MW, so it has been multiplied for a corrective factor to match the threshold.
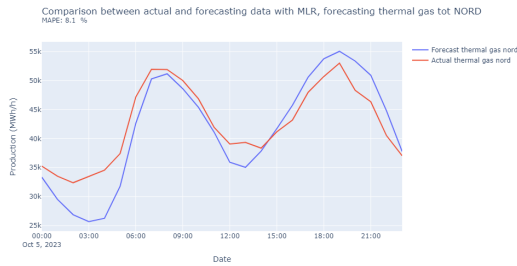
**Figure 4.40:** Forecast one day ahead with MLR, NORD tot thermal power gas plants
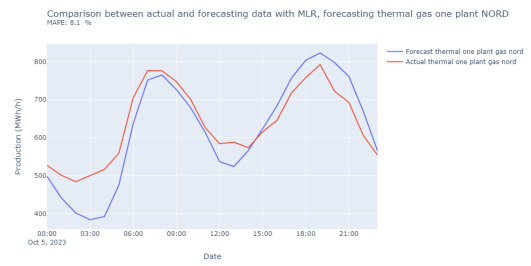


**Figure 4.41:** Forecast one day ahead with MLR, NORD one thermal power gas plant

## 4.4.2 Dispatchable

**Solar**

Solar production is a key element in the green transition, as reported in the previous chapter. It focuses for a large part in NORD bidding zone, as shown in 3.33a, so it is studied the NORD bidding zone. It is, as expected, dependent on solar irradiation, so during the night hours the production is zeroed out. This causes a problem in the calculation of the MAPE (Section 4.2.5) with a division over zero, so not reasonable. So to have an idea of this value, the calculated MAPEs refer only to the daytime, so when the actual data are over the zero value.

In this way, the forecast obtained is reasonable, even if during the night it is supposed that there might be an unreasonable production, as it possible to be seen in 4.42.

Following the analysis, from Terna's website in [31], the net solar capacity in NORD is 11523 MW, and it takes as reference the power plant in Poggio Renatico, the solar park Malvezzi by Enel [34], with a capacity of 17 MW and so $\frac{17}{11523} \approx 0.1\%$
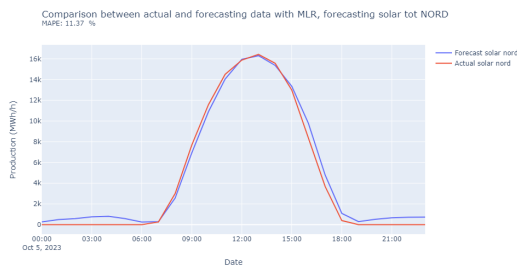


**Figure 4.42:** Forecast one day ahead with MLR, NORD tot solar plants
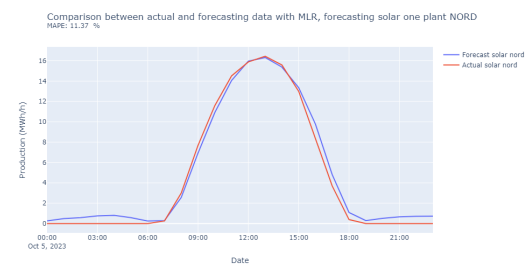


**Figure 4.43:** Forecast one day ahead with MLR, NORD one solar one plant

**Wind**

In comparison to the other resources studied, wind power plants are located in the SUD bidding zone (Molise, Puglia and Basilicata), as reported in Figure 3.33d with a total net capacity equals to 4873.62 MW, from [31]. It is hence considered the offshore wind farm of the Taranto's bay of 30 MW overall capacity, hence a 0,61 % of the production in the area ( $= \frac{30}{4873,62}$ ).

As it possible to see from the Figures 4.44 and 4.45, the volatility of this renewable source is reflected on a unsatisfactory forecast, even if it is considered a macro area such as SUD. This is the reason why it has been deployed the Intraday Market, this source of energy is highly dependent on weathers condition.

Neverthless, the changing of *dummy variables* and *ar terms* has lead to a reduction of the error of 150 %, and consequently in an improvement in the following actual trend, but it is not enough. Compared to others approach, a more sophisticated approach is required, not over the total bidding zone but in the single power plants. These data are owned by the producer, so these are not published.
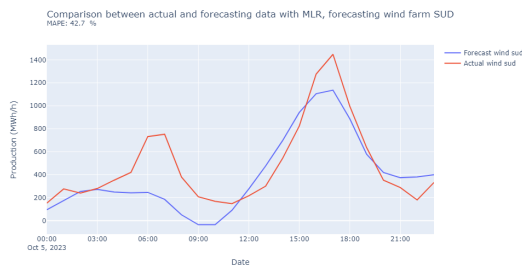


**Figure 4.44:** Forecast one day ahead with MLR, SUD tot wind farms
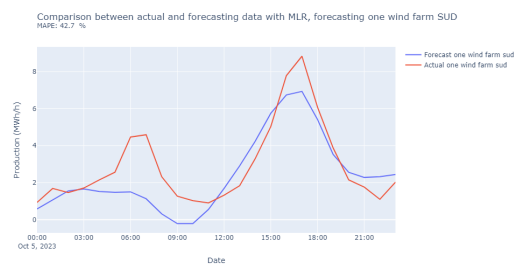


**Figure 4.45:** Forecast one day ahead with MLR, SUD one wind farm

# Chapter 5

# Comparison of strategies

In this chapter, it is shown the various strategies for bidding and selling energy in the energy markets. As reported in the Figure 2.2, every market has a deadline for presenting the offers for the negotiation. So it is the producer's responsibility to respect these deadlines.

In any case, every strategy has been reported in a flowchart scheme in Appendix C, hence even if the explanations might be tough only by words, the flowchart might give a clear explanation on what has been developed.

It is important to note that every quantity and price refers only to an hour. Hence in the algorithm has defined all the strategies first, then it has been forecasted every price and quantity of one hour, and then finally run all the hours in one day. For every point, it is computed all the output of every strategy, and then saved only the one that maximizes the profit. In addition, it is of relevance to note that the Crida3 starts the negotiation after 1 PM, hence in case of balancing of the quantity before this hour, this has been done in the Crida2 instead, but in the flowcharts, this is clearly viewable.

In any case, the full code might be found in Appendix D, thus once the strategies are understood, it can be visualized the code.

## 5.1   Risk and penalties

It is a common behavior by producers to underestimate the quantity of energy, selling less energy than the one forecasted, to be able to join the trading session. Hence, every forecasting is multiplied by a value called "Secure", which is nothing more that $Secure = 1 - \frac{Risk}{100}$, so the quantity at least sure to produce

In addition to the risk, it is developed also the penalty that the producer has to pay for not having respected the quota sold, either in surplus or in deficiency. For

the penalties, it has been an average of 15 minutes of the data obtainable by Terna in [35], thus obtaining an array of 24 elements, corresponding of every hour of the day. Even if the penalty is set to zero, for instance, the algorithm suggests to use different strategies, not only the traditional, thus proving again that makes sense to invest in different markets.

## 5.2 Strategies

The strategies implemented are in total six, from 0 (the traditional one) to 5 (the most promising), and in the output in the code (see Figure 5.9 and Appendix D) can be seen the number of the strategy involved.

### 5.2.1 Traditional strategy - Zero strategy

It is made the supposition that the customer invests all the production of energy in the DAM market, hence the MGP, without considering the others market.
Indeed, after the forecasting of the price and the quantity, it is calculated the profit during one hour in the MGP merely by multiplying the quantity forecasted in the MGP with the price forecasted also in the MGP.
At the end of the process, the profit net is calculated with the previous earning by multiply the difference of the actual quantity and the one sold in the MGP with the penalty of TSO for unbalancing.

### 5.2.2 Market trend - First strategy

This strategy has been built with the commitment of following the trend of the markets, without any criteria of choice in which of them it is better to invest. Indeed, after the calculation of the forecast values, it is calculated the gain in MGP, with the total quantity predicted in this market. Then it is sold/bought quantity of energy in Crida 1, depending if the forecast is lower or boosted the forecasted value. In case of purchasing quantity of energy, so the quantity is lower than the one already sold, with this calculation it is obtained a negative gain. Then the method continues in the other markets.
At the end of the strategy, the total profit is made up of the sum of all the earnings of all the markets, so it makes sense to have a negative value for the purchasing, subtracting thus by the total.

### 5.2.3 MGP and relocating - Second strategy

In this strategy, it starts again with the selling in the MGP, but the other markets are not considered for repositioning the offers, except the ones for rebalancing:

Crida3 after 1 PM or Crida2 otherwise. This might be the easiest possibility for trading energy, since it is considered the first market in the Day Ahead, and then the relevant market for repositioning the offers.

### 5.2.4   Sell initial minimum quantity in MGP - Third strategy

This strategy has immediately begun with the split of the hours to differentiate the hours with Crida3 and the others without.
Hence, if the hours are below 1 PM, the first quantity sold is the minimum value among MGP, Crida1 and Crida2, otherwise is after 1 PM, it is included in the comparison of values. The market in which is sold this quantity is the MGP, at the MGP's price. Subsequently, it is repositioned in Crida2 or Crida3, thus calculating the total earnings by subtracting the penalty of the TSO.

### 5.2.5   Sell as much as possible - Fourth strategy

As the title of the subsection suggests, it has done the trial to sell as much as possible, for then relocating in the last market available. Hence it starts to sell in the MGP, then it proceeds to the other markets: if the quantity already sold is less than the one forecasted, it is sold the difference, if it is less however the code does not buy anything. Then it is relocating in the last market, so or Crida2 or Crida3.

### 5.2.6   Invest in the most lucrative market - Fifth Strategy

This strategy has been developed with the aim of using the maximum price available in all markets and the quantity associated with them. Subsequently is made the rebalancing in the Crida2 or 3, depending on the time, if there are not the maximum price in the system, otherwise the rebalancing matches with the offering. For this part is recommended to see in detail the Appendix C, Figure C.6 for a better understanding of the process. Indeed, even if the concept behind is easy to understand, and the code is also easy, in practice it is needed to address the code in the right direction, with more values to handle properly.

## 5.3   Example of strategy

The evaluation of the data with different deadlines might be interesting for the forecast, since it gives a chance for the algorithm to be fed by more data input, and so could be close to the actual data, or differently lead to a major error. Indeed as soon as it is getting close to the offering time, it is collecting more data to improve the forecast.

For this example, it has been chosen to implement a strategy for an hydro plant in the bidding zone NORD for the 5th of October 2023. It is necessary to insert a point to stop the values, and this day is in the middle of the week in the fall season, hence in a stable moment for the production.

In the below Figures (from 5.1 to 5.8) are hence inserted in comparison on the left the forecasting of the price and on the right the one for the production.

For the price the data are from the GME, with the manipulation mentioned in the 4.3.2.

In this example is of considerable importance that for every market, and so the price and production of that market, the data fed are only the ones before the deadline for showing the offers:

- for MGP stops at 12 PM of D-1, with 36 points forecasted, then only 24 relevant (the ones of D);

- for CRIDA1 stops 3 PM of D-1, with 33 points forecasted, then only 24 relevant (the ones of D);

- for CRIDA2 stops 10 PM of D-1, with 26 points forecasted, then 24 relevant (the ones of D);

- for CRIDA3 stops 10 AM of D, with 14 points forecasted and 12 relevant (the points from midnight, 11 AM and 12 PM are not considered in this market either).

In the Figures below (from 5.1 to 5.8) are only shown the relevant points for the bidding. Also the MAPEs has been calculated with this relevant points. Indeed the points not relevant has been excluded by the calculation, since they are not relevant for the treatment, but necessary for the forecast.

Furthemore, for the production it has been chosen the same powerplant used in the previous chapter, with a capacity of 848 MW.

The results are shown below in Figures 5.9 and 5.10, with a clear representation on how much energy has been invested and which strategy has been developed for every hour. The output desired has remained the one for maximizing the earnings of the energy producer.

For this case indeed, if it is chosen a risk of 10 %, by the end of the day of production (D), the producer could earn a 253.524 Euro in one day, in comparison to 252.339 Euro of the previous strategy, thus gaining a net of 1.185 Euro, as it possible to see in Figure 5.10. The strategies exploited by the code in this example are the traditional one, then the first or the fifth, as it possible to see in Figure 5.9. If it has been used only the traditional one, the gain would have been lower, so the experiment has been conducted successfully.
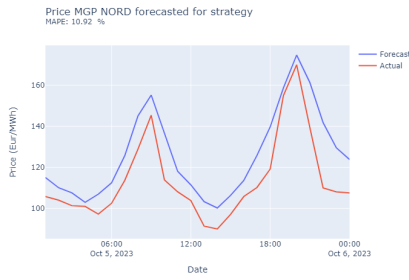
**Figure 5.1:** Forecast price MGP
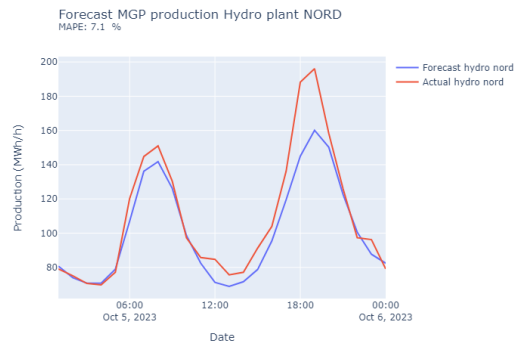


**Figure 5.2:** Forecast production MGP
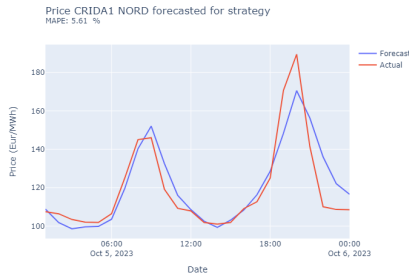


**Figure 5.3:** Forecast price CRIDA1
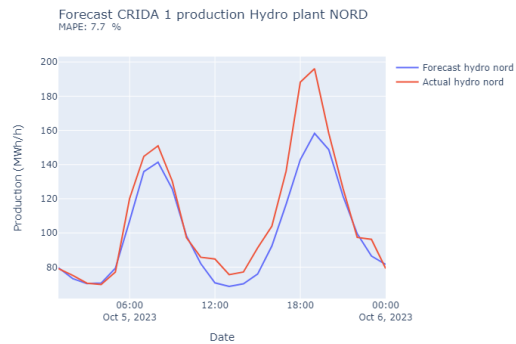


**Figure 5.4:** Forecast production CRIDA1

# 5.4 Discussion and result

The results obtained show how it is possible to trade quantity of energy in different markets, increasing thus the profits of energy producers.

Even if for a powerplant of this dimension is not worth it in the short term, in one year might be half a million, just by investing energy in different markets.

In conclusion of this treatment, is made a prediction on how much energy producers might save by the end of the year, with the assumption that it depends on the installed capacity of the hydro power plants. This last analysis refers only to the hydro assets of a producer of energy and it is possible to visualize in Table 5.1. This last analysis has been conducted with the assumption that every production day is equal to the one on the weekday, so the results are been approximated through a net reduction of the savings, approximately cutting a 10 %.

The same result are also applicable in the other types of powerplants, with the same price developed for this example.
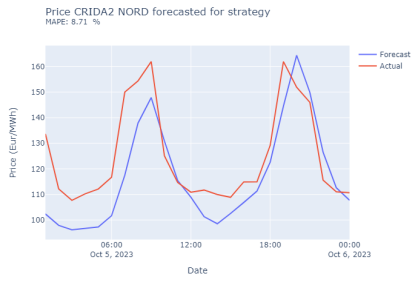
**Figure 5.5:** Forecast price CRIDA2
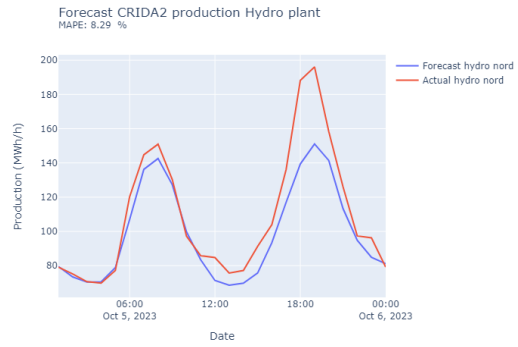


**Figure 5.6:** Forecast production CRIDA2
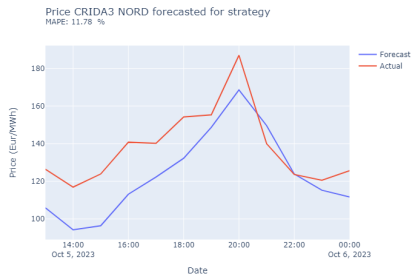


**Figure 5.7:** Forecast price CRIDA3
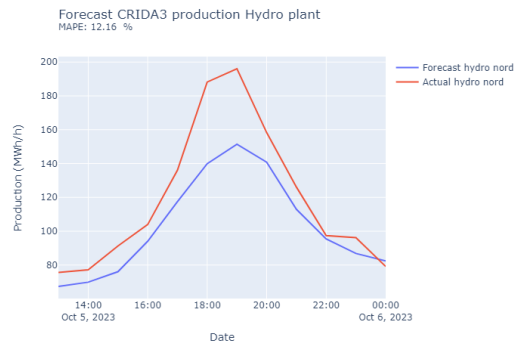


**Figure 5.8:** Forecast production CRIDA3



**Figure 5.9:** Result in table format
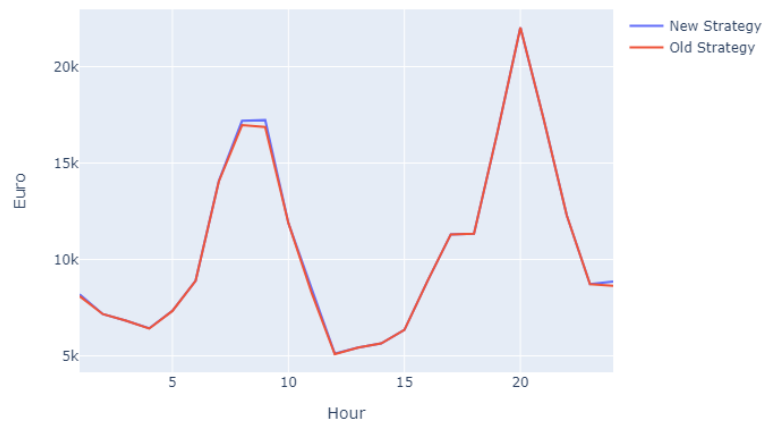


**Figure 5.10:** Gain in comparison

67

| Producers | Hydro capacity MW | Daily saving Euro | Yearly saving Euro |
|:---:|:---:|:---:|:---:|
| *enel* | 2540 | ~3500 | ~1.200.000 |
| *a2a* | 2000 | ~2700 | ~1.000.000 |
| *Dolomiti energia* | 1400 | ~2000 | ~700.000 |
| *eDISON* | 1100 | ~1500 | ~500.000 |
| *CVA* | 934 | ~1300 | ~470.000 |
| *iren* | 600 | ~838 | ~300.000 |

**Table 5.1:** Potential saving for a hydro producer in one day and yearly

# Chapter 6

# Conclusion

This research has investigated how the Italian market works, which institutions lead it and how the various trends of prices were.

Then the visualization of productions, from type and bidding zone, and consumption has finally given to the reader a clearly vision on how the Italian electricity is produced and where.

It has sought to be as clear as possible on how the process for the algorithm for the forecasting is made up, both in price and production, with the MLR.

In conclusion, it is clear that for an energy producer is worth an investment in this type of technology, which might increase its revenue day per day. Hence, the forecast and the exploitation of more than one correct strategy lead to be ready in every tendency of the market such as also in production. This technology might be available for every type of energy power plant, so a producer might save more money than the only hydro assets.

## 6.1 Further work

During an analysis with a quantity of data not negligible, it is important to work with high-quality of data, otherwise it could happen a mismatch between the actual data and the point to which it refers.

Since the data used were imported manually, for instance or from the GME or from Volue Insight, it seems reasonable to make the process automatic, directly with a python code. It is hence possible to exploit the API that these system offers, to make the process automatic. In summary, during this work, the process was not automatic, as reported in section 4.1.

Furtherly, in the code might be inserted the Italian holidays like a dummy variable, not only the ones of the weekend.

Instead, for the part of the strategy, it will be useful to check the behaviour of

the strategies also for other type of energy production, and optimize the existing strategies for the hydro plant. Furtherly it has limited the point to just one day in the fall season, it might be interesting to develop tools for check the behaviour in other seasons or months.

# Appendix A

This appendix has the aim to show the reader how to read properly the file from the GME. First of all, it is required to save the files from the GME's FTPS in a folder, for instance in the code called 'MGPprezzi2021-2023'.

```python
#######################################
############## MGP ##############
#######################################

""""
@author: stefano.sala
"""
import os
import xml.etree.ElementTree as ET
from bs4 import BeautifulSoup
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px

cartella = 'C:\MGPprezzi2021-2023'

elenco_file = os.listdir(cartella)

# Filtrare xml
file_xml = [f for f in elenco_file if f.endswith('.xml')]

#inizializzo i vettori
b_cnor_tot = []
b_csud_tot = []
b_nord_tot = []
b_sud_tot = []
b_sard_tot = []
b_sici_tot = []
b_cala_tot = []
valori_numerici = np.array([])
val = np.array([])

# Lettura
for file in file_xml:
    percorso_completo = os.path.join(cartella, file)

    try:
        albero = ET.parse(percorso_completo)
        radice = albero.getroot()
        Bs_data = BeautifulSoup(ET.tostring(radice), "xml")

        # ANALIZZO CNOR
        elemento_valore_CNOR = Bs_data.find_all('CNOR')

        for x in elemento_valore_CNOR:
            # estraggo il valore
            valore_float_str_CNOR = x.text
            # converto e rimpiazzo divisore numerico
            valore_float_CNOR = float(valore_float_str_CNOR.replace(',', '.'))
            # inserisco nel vettore di cnor
```

```python
                b_cnor_tot.append(valore_float_CNOR)

             # ANALIZZO CSUD
            elemento_valore_CSUD = Bs_data.find_all('CSUD')
            for x in elemento_valore_CSUD:
                valore_float_str_CSUD = x.text
                valore_float_CSUD = float(valore_float_str_CSUD.replace(',', '.'))
                b_csud_tot.append(valore_float_CSUD)

            # ANALIZZO NORD
            elemento_valore_NORD = Bs_data.find_all('NORD')
            for x in elemento_valore_NORD:
                valore_float_str_NORD = x.text
                valore_float_NORD = float(valore_float_str_NORD.replace(',', '.'))
                b_nord_tot.append(valore_float_NORD)

            # ANALIZZO SUD
            elemento_valore_SUD = Bs_data.find_all('SUD')
            for x in elemento_valore_SUD:
                valore_float_str_SUD = x.text
                valore_float_SUD = float(valore_float_str_SUD.replace(',', '.'))
                b_sud_tot.append(valore_float_SUD)

            # ANALIZZO SARD
            elemento_valore_SARD = Bs_data.find_all('SARD')
            for x in elemento_valore_SARD:
                valore_float_str_SARD = x.text
                valore_float_SARD = float(valore_float_str_SARD.replace(',', '.'))
                b_sard_tot.append(valore_float_SARD)

            # ANALIZZO SICI
            elemento_valore_SICI = Bs_data.find_all('SICI')
            for x in elemento_valore_SICI:
                valore_float_str_SICI = x.text
                valore_float_SICI = float(valore_float_str_SICI.replace(',', '.'))
                b_sici_tot.append(valore_float_SICI)

             # ANALIZZO CALA
            elemento_valore_CALA = Bs_data.find_all('CALA')
            for x in elemento_valore_CALA:
                valore_float_str_CALA = x.text
                valore_float_CALA = float(valore_float_str_CALA.replace(',', '.'))
                b_cala_tot.append(valore_float_CALA)

    except ET.ParseError as e:
        print(f"Errore nell'analisi del file {file}: {str(e)}")

#converto come un numpy array
y_cnor = np.array(b_cnor_tot, float)
x = np.arange(1, y_cnor.size + 1, 1)
y_csud = np.array(b_csud_tot, float)
y_nord = np.array(b_nord_tot, float)
y_sard = np.array(b_sard_tot, float)
y_sud = np.array(b_sud_tot, float)
y_sici = np.array(b_sici_tot, float)
y_cala = np.array(b_cala_tot, float)


media_MGP = (y_cnor + y_csud + y_nord + y_sard + y_sud + y_sici + y_cala)/7
```

Then it is the same procedures for CRIDA1, CRIDA2 and CRIDA3, and for obtaining the graph

```python
    def moving_avg(x, N=30):
    return np.convolve(x, np.ones((N,))/N, mode='valid')

start_date = datetime(2021, 9, 23)
end_date = datetime(2023, 9, 8)
date_list = [start_date + timedelta(hours=i) for i in range(int((end_date - start_date).
    total_seconds() / 3600))]
date_series = pd.Series(date_list)
date_list_2 = [start_date + timedelta(hours=i) for i in range(int((end_date - start_date).
    total_seconds() / 3600)-749)]
date_series_2 = pd.Series(date_list_2)

plt.figure(figsize=(12,6))
```

```
13  plt.plot(date_series_2, moving_avg(media_MGP, 750), color='#A5E6BA', label = 'MGP', linewidth =
        1)
14  plt.plot(date_series_2, moving_avg(media_CRIDA1, 750), color='#9AC6C5', label = 'CRIDA1',
        linewidth = 1)
15  plt.plot(date_series_2, moving_avg(media_CRIDA2, 750), color='#7785AC', label = 'CRIDA2',
        linewidth = 1)
16  plt.plot(date_series_2, moving_avg(media_CRIDA3, 750), color='#7785AC', label = 'CRIDA3',
        linewidth = 1)
17
18  plt.legend(loc=2)
19  plt.tight_layout()
20  plt.gca().xaxis.set_major_formatter(plt.matplotlib.dates.DateFormatter('%m-%Y'))
21
22  plt.ylabel('Price over MWh')
23  plt.title('Differences of prices between markets')
```



Comparison between average of MGP, CRIDAs and Gas Price
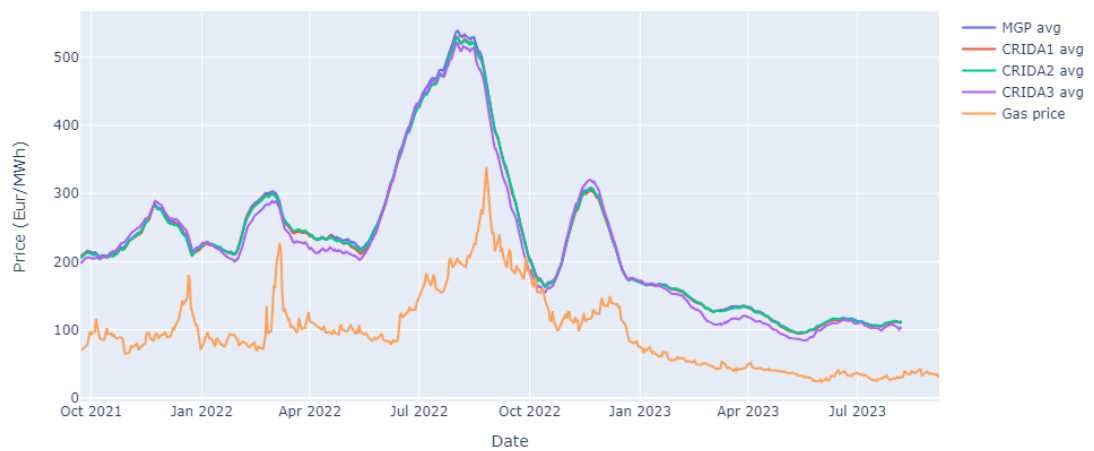
# Appendix B

This appendix shows the procedures implemented in the forecasting, using only the MLR method.

```
1  import pandas as pd
2  import numpy as np
3  import pickle
4  import seaborn as sns
5  import matplotlib.pyplot as plt
6  from scalecast.Forecaster import Forecaster
7  import plotly.express as px
8  import plotly.graph_objects as go
9  # import scalecast
10
11 ####I have saved my historical series in a csv document #####
12 df = pd.read_csv("C:\Esperimento-weekend\multiseries_experiment.csv")
13 print(df['date'])
14
15 f = Forecaster(
16 current_dates = df['date'],
17 y= df['price']
18 )
19 f
```

Forecaster( DateStartActuals=2023-06-01T01:00:00.000000000
DateEndActuals=2023-10-07T00:00:00.000000000
Freq=H
N actuals=3072
ForecastLength=0
Xvars=[]
TestLength=0
ValidationMetric=rmse
ForecastsEvaluated=[]
CILevel=None
CurrentEstimator=mlr
GridsFile=Grids
)

For this forecasting has been used the data from 1/6/23 1:00 AM to 7/10/23 12:00 AM. It also tried to extend this period from the 27th of December 2022, but the error increased.

```
1  f.plot_pacf(lags=26)
2  plt.show()
3  f.seasonal_decompose().plot()
4  plt.show()
```
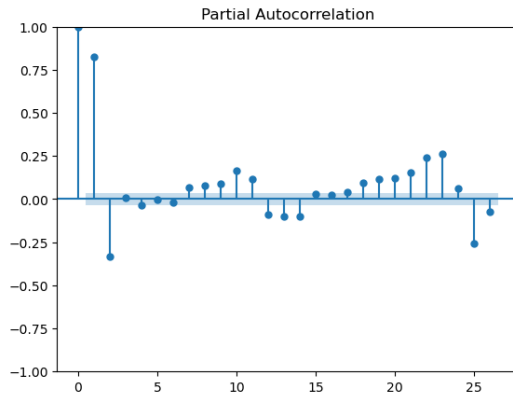


**Figure B.1:** Partial autocorrelation in the data used
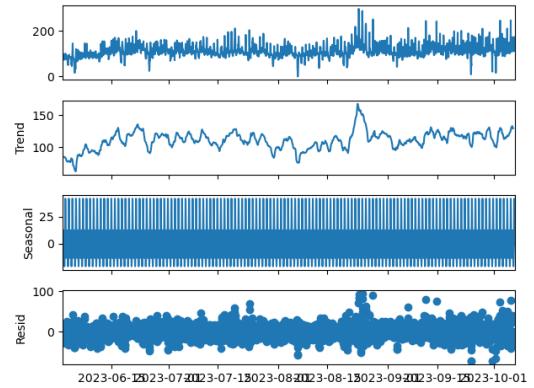


**Figure B.2:** Seasonability of data used

```
1       stat, pval, _, _, _, _ = f.adf_test(full_res=True)
```

stat = -5.178230298690685
pval = 9.737869425085611e-06

pval«0.005 so the series is stationary

```
1   f.set_test_length(615)        # 1. how many point  I want for testing
2   #f.generate_future_dates(24) # 2. how many points I want for forecasting (24 means one day)
3   f.generate_future_dates(72) # 2. how many points I want for forecasting (72 means 3 days)
4   from scalecast.SeriesTransformer import SeriesTransformer
5
6   transformer = SeriesTransformer(f)
7   f = transformer.DiffTransform()
8
9   ####Adds 70 Adds auto-regressive terms #####
10  f.add_ar_terms(70)
11  ###### Adds seasonal regressors######
12  f.add_seasonal_regressors(
13      'hour',
14      'dayofweek',
15      dummy=True
16  ) # dummy vars
17  #f.add_seasonal_regressors()
18  f.add_time_trend()
19  print(f)
```

Forecaster( DateStartActuals=2023-06-01T02:00:00.000000000
DateEndActuals=2023-10-07T00:00:00.000000000
Freq=H
N actuals=3071

ForecastLength=72

$Xvars = ['AR1',' AR2',' AR3',' AR4',' AR5',' AR6',' AR7',' AR8',' AR9',' AR10',' AR11'|$
$,' AR12',' AR13',' AR14',' AR15',' AR16',' AR17',' AR18',' AR19',' AR20',' AR21',' AR22',|$
$'AR23',' AR24',' AR25',' AR26',' AR27',' AR28',' AR29',' AR30',' AR31',' AR32',' AR33',|$
$'AR34',' AR35',' AR36',' AR37',' AR38',' AR39',' AR40',' AR41',' AR42',' AR43',' AR44',|$
$'AR45',' AR46',' AR47',' AR48',' AR49',' AR50',' AR51',' AR52',' AR53',' AR54',' AR55',|$
$'AR56',' AR57',' AR58',' AR59',' AR60',' AR61',' AR62',' AR63',' AR64',' AR65',' AR66',|$
$'AR67',' AR68',' AR69',' AR70',$
$'hour',' hour0',' hour1',' hour10',' hour11',' hour12',$
$'hour13',' hour14',' hour15',' hour16',' hour17',' hour18',' hour19',' hour2',' hour20'$
$,' hour21',' hour22',' hour23',' hour3',' hour4',' hour5',' hour6',' hour7',' hour8',' hour9',|$
$'dayofweek',' dayofweek0',' dayofweek1',' dayofweek2',' dayofweek3',' dayofweek4',|$
$'dayofweek5',' dayofweek6',' t']$

TestLength=615

ValidationMetric=rmse

ForecastsEvaluated=[]

CILevel=None

CurrentEstimator=mlr

GridsFile=Grids

)

```
]
f.set_estimator('mlr')
f.manual_forecast($call_me$='mlr')
f = transformer.DiffRevert(
    $exclude_models$ = [m for m in f.history if m != 'mlr']
)   #only mlr

$f.plot_test_set$(models=['mlr'])
plt.title('Prediction')
plt.show()
f.plot(
    models=['mlr']
)
```
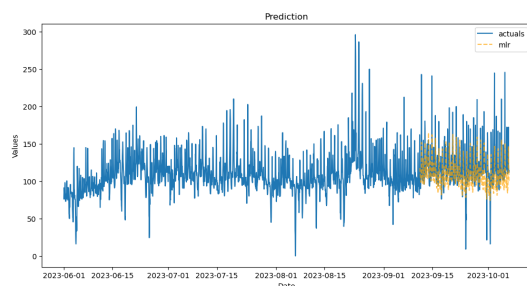


**Figure B.3:** Partial autocorrelation in the data used
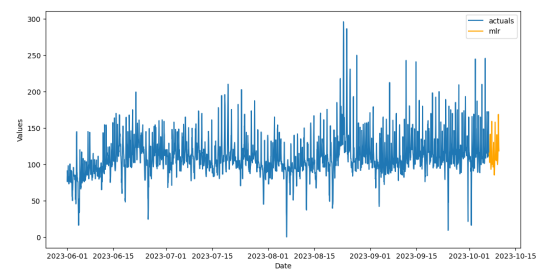


**Figure B.4:** Forecast of 3 days in the weekend

In order to compare the forecast data with the actual, I need to export these

```
1    forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
2    forecast['mlr']
3    ####I read the actual data (another excel created to be double sure)
4    df = pd.read_csv("C:\Esperimento-weekend\Forecast_actual.csv")
5    actual=df['price']
6
7    ######Calculation of MAPE############
8    def calculate_mape(actual, predicted) -> float:
9
10    # Convert actual and predicted
11    # to numpy array data type if not already
12    if not all([isinstance(actual, np.ndarray),
13               isinstance(predicted, np.ndarray)]):
14        actual, predicted = np.array(actual), np.array(predicted)
15
16    # Calculate the MAPE value and return
17    return round(np.mean(np.abs((
18        actual - predicted) / actual)) * 100, 2)
19 actual     = df['price']
20 predicted = forecast['mlr']
21
22 print("MAPE :", calculate_mape(actual, predicted), "%")
23 MAPE= calculate_mape(actual, predicted)
24
25 fig = go.Figure()
26 fig.add_trace(go.Scatter( x = forecast['DATE'], y = forecast['mlr'], mode="lines", name='
        Forecast'))
27 fig.add_trace(go.Scatter( x = forecast['DATE'], y = df['price']  , mode="lines" , name='Actual'
        ))
28 fig.update_layout(
29     title=go.layout.Title(
30         text=f"Comparison between actual and forecasting data with MLR <br><sup>MAPE: {MAPE}  %
        ",
31         xref="paper",
32         x=0
33     ),
34     xaxis_title="Date",
35     yaxis_title="Price (Eur/MWh)"
36 )
```
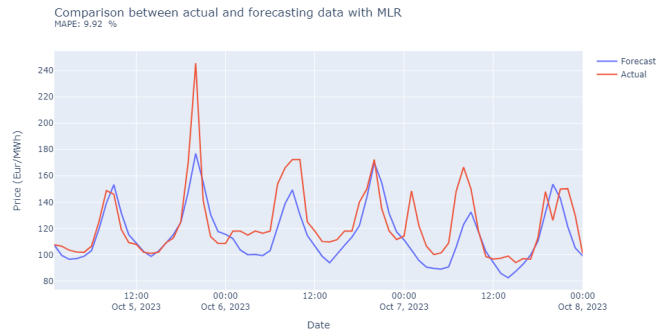


**Figure B.5:** Comparison forecasting with actual data

# Appendix C

In this part the flowcharts of the various strategies are shown, meanwhile, the code will be shown in the next Appendix D. For the construction of the flowchart has been used the software "Miro", useful for the visualization graphically schemes and mental maps

## C.1   Strategy 0
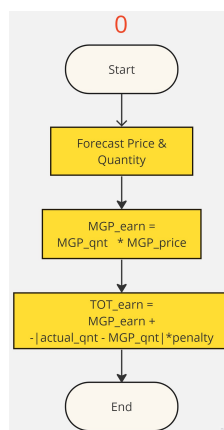


**Figure C.1:** Strategy0

## C.2 Strategy 1
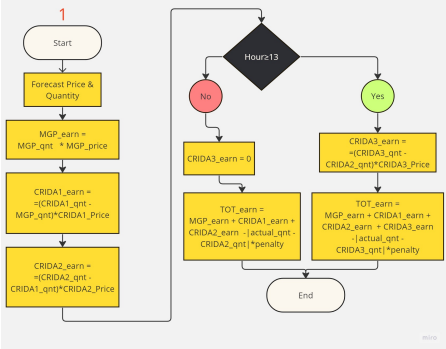


**Figure C.2:** Strategy1

## C.3 Strategy 2
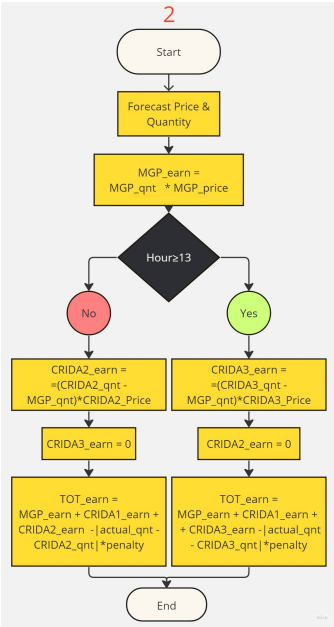


**Figure C.3:** Strategy2

# C.4 Strategy 3
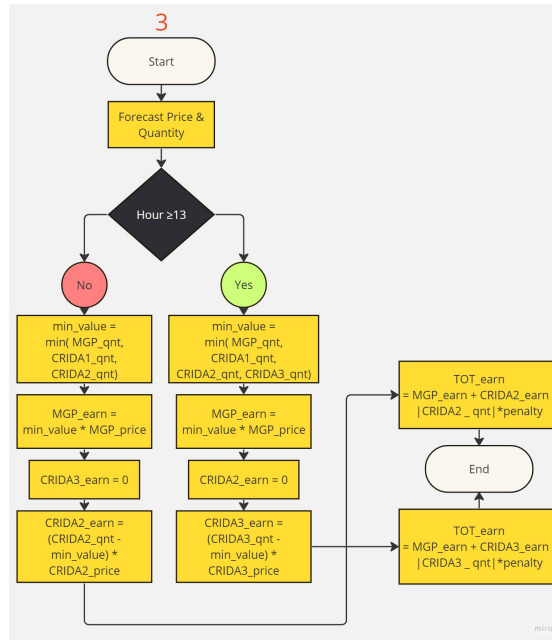


**Figure C.4:** Strategy3

# C.5 Strategy 4
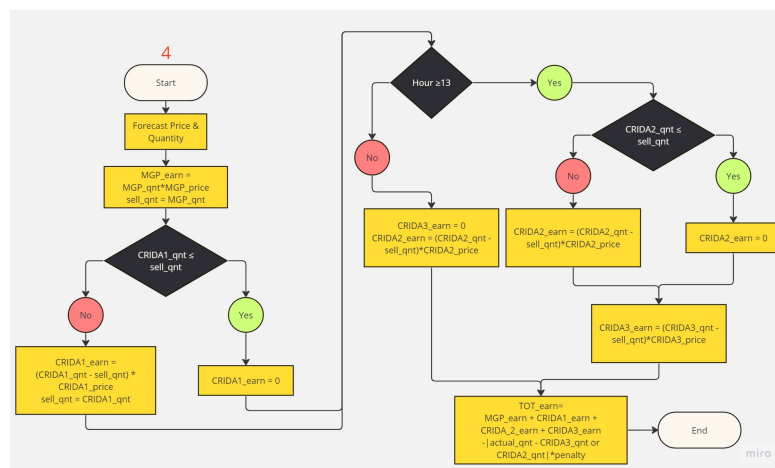


**Figure C.5:** Strategy4

# C.6 Strategy 5
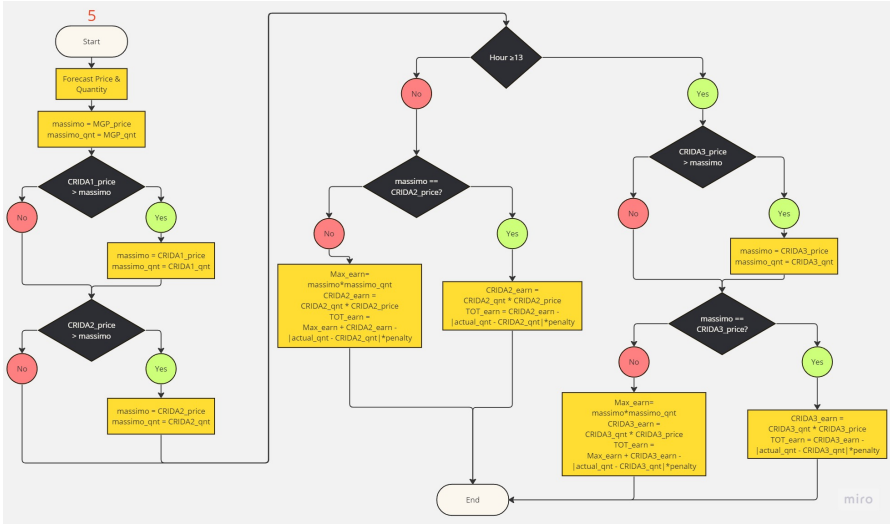


**Figure C.6:** Strategy5

# Appendix D

```python
# -*- coding: utf-8 -*-
"""
Created on Fri Nov 10 12:15:05 2023

@author: stefano.sala
"""


import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
import pickle
import seaborn as sns
from scalecast.Forecaster import Forecaster
from scalecast.SeriesTransformer import SeriesTransformer


#########Manual input###########

Risk = 10 #in %
penality_tab = pd.read_csv("C:\strategia\Prezzi_Giornalieri_Quarto_Orari_20231005.csv")   #from
    TSO, Eur/MWh

#######calculated input########
Secure = 1- (Risk/100)
#Quantity
earn_fin=np.full(24, 0)
strategy_fin=np.full(24, 9999)
hours_1day= np.arange(1, 25)


#Penality
penality_connan = np.array(penality_tab['Price'])
penality= penality_connan[~np.isnan(penality_connan)]

############################QUANTITY#########################

#Definition MAPE
def calculate_mape(actual, predicted) -> float:

    # Convert actual and predicted
    # to numpy array data type if not already
    if not all([isinstance(actual, np.ndarray),
                isinstance(predicted, np.ndarray)]):
        actual, predicted = np.array(actual), np.array(predicted)

    # Calculate the MAPE value and return
    return round(np.mean(np.abs((
        actual - predicted) / actual)) * 100, 2)



df = pd.read_csv("C:\Forecast Produzione - STRATEGIA\MGP\Production_input.csv")

#-----------------MGP----------------
```

```python
57  f = Forecaster(
58      current_dates = df['date'],
59      y= df['hydro nord']
60  )
61  #f.seasonal_decompose().plot()
62  f.seasonal_decompose()
63  #plt.show()
64  f.set_test_length(3504)        # 1. how many point  I want for testing
65  f.generate_future_dates(36)
66
67  transformer = SeriesTransformer(f)
68  f = transformer.DiffTransform()
69
70  f.add_ar_terms(70)
71
72  f.add_seasonal_regressors(
73      'dayofyear',
74      'month',
75      'dayofweek',
76      dummy=True
77  ) # dummy vars
78
79  f.add_time_trend()
80  f.set_estimator('mlr')
81  f.manual_forecast(call_me='mlr')
82
83  f = transformer.DiffRevert(
84      exclude_models = [m for m in f.history if m != 'mlr']
85  ) # exclude all lstm models from the revert
86
87  #f.plot_test_set(models=['mlr'])
88  #plt.title('Prediction')
89  #plt.show()
90  #f.plot(models=['mlr'])
91  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
92
93  df = pd.read_csv("C:\Forecast Produzione - STRATEGIA\MGP\Production_output_only510.csv")
94  actual=df['hydro nord']
95
96  actual    = df['hydro nord'][12:36]
97  predicted = forecast['mlr'][12:36]
98
99  MAPE= calculate_mape(actual, predicted)
100
101 fig = go.Figure()
102 fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = forecast['mlr'][12:36], mode="lines"
        , name='Forecast hydro nord'))
103 fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = df['hydro nord'][12:36]   , mode="
        lines" , name='Actual hydro nord'))
104 fig.update_layout(
105     title=go.layout.Title(
106         text=f"Forecast MGP production Hydro plant <br><sup>MAPE: {MAPE}  %",
107         xref="paper",
108         x=0
109     ),
110     xaxis_title="Date",
111     yaxis_title="Production (MWh/h)"
112 )
113
114 actual    = df['hydro nord'][12:36]*0.03
115 predicted = forecast['mlr'][12:36]*0.03
116
117 MAPE= calculate_mape(actual, predicted)
118
119 fig = go.Figure()
120 fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = predicted , mode="lines",  name='
        Forecast hydro nord'))
121 fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = actual   , mode="lines" , name='
        Actual hydro nord'))
122 fig.update_layout(
123     title=go.layout.Title(
124         text=f"Forecast MGP production Hydro plant NORD <br><sup>MAPE: {MAPE}  %",
125         xref="paper",
126         x=0
127     ),
128     xaxis_title="Date",
129     yaxis_title="Production (MWh/h)"
130 )
131 fig.show(renderer="png")
132
133 Quantity_MGP = (forecast['mlr'][12:36]*0.03).to_numpy()*Secure   # MWh/h
```

```
134
135  Quantity_actual =(df['hydro nord'][12:36]*0.03).to_numpy()*Secure   # MWh/h
136
137
138  #————————————CRIDA1————————————
139  df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA1\production_input.csv")
140  f = Forecaster(
141  current_dates = df['date'],
142  y= df['hydro nord']
143  )
144  #f.plot_pacf(lags=26)
145  f.seasonal_decompose()
146  f.set_test_length(3504)         # 1. how many point  I want for testing
147  f.generate_future_dates(33) # 2. how many points I want for forecasting (72 means 3 days)
148
149  transformer = SeriesTransformer(f)
150  f = transformer.DiffTransform()
151
152  f.add_ar_terms(70)
153
154  f.add_seasonal_regressors(
155      'dayofyear',
156      'month',
157      'dayofweek',
158      dummy=True
159  ) # dummy vars
160  f.add_time_trend()
161  f.set_estimator('mlr')
162  f.manual_forecast(call_me='mlr')
163
164  f = transformer.DiffRevert(
165      exclude_models = [m for m in f.history if m != 'mlr']
166  ) # exclude all lstm models from the revert
167  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
168
169  df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA1\Production_output_only510.csv")
170  actual=df['hydro nord']
171
172  actual    = df['hydro nord'][9:33]
173  predicted = forecast['mlr'][9:33]
174
175  MAPE= calculate_mape(actual, predicted)
176
177  fig = go.Figure()
178  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = forecast['mlr'][9:33], mode="lines",
          name='Forecast hydro nord'))
179  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = df['hydro nord'][9:33]   , mode="lines
          " , name='Actual hydro nord'))
180  fig.update_layout(
181      title=go.layout.Title(
182          text=f"Forecast CRIDA1 production Hydro plant  <br><sup>MAPE: {MAPE}  %",
183          xref="paper",
184          x=0
185      ),
186      xaxis_title="Date",
187      yaxis_title="Production (MWh/h)"
188  )
189  actual    = df['hydro nord'][9:33]*0.03
190  predicted = forecast['mlr'][9:33]*0.03
191
192  MAPE= calculate_mape(actual, predicted)
193
194  fig = go.Figure()
195  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = predicted , mode="lines",  name='
          Forecast hydro nord'))
196  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = actual   , mode="lines" , name='Actual
          hydro nord'))
197  fig.update_layout(
198      title=go.layout.Title(
199          text=f"Forecast CRIDA 1 production Hydro plant NORD <br><sup>MAPE: {MAPE}  %",
200          xref="paper",
201          x=0
202      ),
203      xaxis_title="Date",
204      yaxis_title="Production (MWh/h)"
205  )
206  fig.show(renderer="png")
207
208  Quantity_CRIDA1 = (forecast['mlr'][9:33]*0.03).to_numpy()*Secure   # MWh/h
209
210  #————————————————CRIDA2————————————————
```

```
211
212  df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA2\production_input.csv")
213  f = Forecaster(
214  current_dates = df['date'],
215  y= df['hydro nord']
216  )
217  f.seasonal_decompose()
218  f.set_test_length(3504)          # 1. how many point  I want for testing
219  f.generate_future_dates(26) #
220
221  transformer = SeriesTransformer(f)
222  f = transformer.DiffTransform()
223
224  f.add_ar_terms(70)
225
226  f.add_seasonal_regressors(
227      'dayofyear',
228      'month',
229      'dayofweek',
230      dummy=True
231  ) # dummy vars
232
233  f.add_time_trend()
234
235  f.set_estimator('mlr')
236  f.manual_forecast(call_me='mlr')
237
238  f = transformer.DiffRevert(
239      exclude_models = [m for m in f.history if m != 'mlr']
240  ) # exclude all lstm models from the revert
241
242  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
243  df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA2\Production_output_only510.csv")
244  actual=df['hydro nord']
245
246  actual    = df['hydro nord'][2:26]
247  predicted = forecast['mlr'][2:26]
248
249  MAPE= calculate_mape(actual, predicted)
250
251  fig = go.Figure()
252  fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = forecast['mlr'][2:26], mode="lines",
         name='Forecast hydro nord'))
253  fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = df['hydro nord'][2:26]  , mode="lines
         " , name='Actual hydro nord'))
254  fig.update_layout(
255      title=go.layout.Title(
256          text=f"Forecast MGP production Hydro plant , forecasting hydro tot NORD <br><sup>MAPE:
         {MAPE}  %",
257          xref="paper",
258          x=0
259      ),
260      xaxis_title="Date",
261      yaxis_title="Production (MWh/h)"
262  )
263
264  actual    = df['hydro nord'][2:26]*0.03
265  predicted = forecast['mlr'][2:26]*0.03
266
267  MAPE= calculate_mape(actual, predicted)
268
269  fig = go.Figure()
270  fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = predicted , mode="lines",  name='
         Forecast hydro nord'))
271  fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = actual   , mode="lines" , name='Actual
          hydro nord'))
272  fig.update_layout(
273      title=go.layout.Title(
274          text=f"Forecast CRIDA2 production Hydro plant  <br><sup>MAPE: {MAPE}  %",
275          xref="paper",
276          x=0
277      ),
278      xaxis_title="Date",
279      yaxis_title="Production (MWh/h)"
280  )
281
282
283  Quantity_CRIDA2 = (forecast['mlr'][2:26]*0.03).to_numpy()*Secure   # MWh/h
284  fig.show(renderer="png")
285
286  #————————————————CRIDA3————————————————————————
```

```python
df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA3\production_input.csv")
f = Forecaster(
current_dates = df['date'],
y= df['hydro nord']
)
f.seasonal_decompose()
f.set_test_length(3504)          # 1. how many point  I want for testing
f.generate_future_dates(14)
transformer = SeriesTransformer(f)
f = transformer.DiffTransform()
f.add_ar_terms(70)
f.add_seasonal_regressors(
    'dayofyear',
    'month',
    'dayofweek',
    dummy=True
) # dummy vars
f.add_time_trend()
f.set_estimator('mlr')
f.manual_forecast(call_me='mlr')

f = transformer.DiffRevert(
    exclude_models = [m for m in f.history if m != 'mlr']
) # exclude all lstm models from the revert
forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
df = pd.read_csv("C:\Forecast Produzione − STRATEGIA\CRIDA3\Production_output_only510.csv")
actual=df['hydro nord']
actual     = df['hydro nord'][2:14]
predicted = forecast['mlr'][2:14]

MAPE= calculate_mape(actual, predicted)

fig = go.Figure()
fig.add_trace(go.Scatter( x = forecast['DATE'][2:14], y = forecast['mlr'][2:14], mode="lines",
        name='Forecast hydro nord'))
fig.add_trace(go.Scatter( x = forecast['DATE'][2:14], y = df['hydro nord'][2:14]  , mode="lines
" , name='Actual hydro nord'))
fig.update_layout(
    title=go.layout.Title(
        text=f"Forecast CRIDA3 production Hydro plant  <br><sup>MAPE: {MAPE}  %",
        xref="paper",
        x=0
    ),
    xaxis_title="Date",
    yaxis_title="Production (MWh/h)"
)

actual     = df['hydro nord'][2:14]*0.03
predicted = forecast['mlr'][2:14]*0.03

MAPE= calculate_mape(actual, predicted)

fig = go.Figure()
fig.add_trace(go.Scatter( x = forecast['DATE'][2:14], y = predicted , mode="lines",  name='
        Forecast hydro nord'))
fig.add_trace(go.Scatter( x = forecast['DATE'][2:14], y = actual   , mode="lines" , name='Actual
        hydro nord'))
fig.update_layout(
    title=go.layout.Title(
        text=f"Forecast CRIDA3 production Hydro plant  <br><sup>MAPE: {MAPE}  %",
        xref="paper",
        x=0
    ),
    xaxis_title="Date",
    yaxis_title="Production (MWh/h)"
)
fig.show(renderer="png")
Quantity_CRIDA3 = np.append(np.full(12, 0), (forecast['mlr'][2:14]*0.03).to_numpy())*Secure  #
        MWh/h

#########################PRICE############################
#————————————————MGP————————————————————————

df = pd.read_csv("C:\Forecast MGP − STRATEGIA\multiseries_experiment − STRATEGIA.csv")
f = Forecaster(
current_dates = df['date'],
y= df['price']
)
f.seasonal_decompose()
f.set_test_length(500)          # 1. 12 observations to test the results
f.generate_future_dates(36) # 2. 12 future points to forecast
```

```
363  transformer = SeriesTransformer(f)
364  f = transformer.DiffTransform()
365  f.add_ar_terms(70)
366  f.add_seasonal_regressors(
367      'hour',
368      'dayofweek',
369      dummy=True
370  ) # dummy vars
371  f.add_time_trend()
372  f.set_estimator('mlr')
373  f.manual_forecast(call_me='mlr')
374
375  f = transformer.DiffRevert(
376      exclude_models = [m for m in f.history if m != 'mlr']
377  ) # exclude all lstm models from the revert
378
379  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
380  df = pd.read_csv("C:\Forecast MGP - STRATEGIA\Forecastsolo510 - STRATEGIA.csv")
381  actual=df['price']
382  actual     = df['price'][12:35]
383  predicted = forecast['mlr'][12:35]
384
385  MAPE= calculate_mape(actual, predicted)
386
387  fig = go.Figure()
388  fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = forecast['mlr'][12:36], mode="lines"
          ,  name='Forecast'))
389  fig.add_trace(go.Scatter( x = forecast['DATE'][12:36], y = df['price'][12:36]  , mode="lines" ,
          name='Actual'))
390  fig.update_layout(
391      title=go.layout.Title(
392          text=f"Price MGP NORD forecasted for strategy <br><sup>MAPE: {MAPE}  %",
393          xref="paper",
394          x=0
395      ),
396      xaxis_title="Date",
397      yaxis_title="Price (Eur/MWh)"
398  )
399  fig.show(renderer="png")
400
401  MGP  = (forecast['mlr'][12:36]).to_numpy() #Eur/MWh
402
403  #----------------------------CRIDA1----------------------------------
404
405  df = pd.read_csv("C:\Forecast CRIDA1 - STRATEGIA\multiseries_experiment - STRATEGIA.csv")
406  f = Forecaster(
407  current_dates = df['date'],
408  y= df['price']
409  )
410  f.seasonal_decompose()
411  f.set_test_length(500)
412  #f.generate_future_dates(72)
413  f.generate_future_dates(33)
414  transformer = SeriesTransformer(f)
415  f = transformer.DiffTransform()
416  f.add_ar_terms(70)
417  f.add_seasonal_regressors(
418      'hour',
419      'dayofweek',
420      dummy=True
421  ) # dummy vars
422  f.add_time_trend()
423  f.set_estimator('mlr')
424  f.manual_forecast(call_me='mlr')
425
426  f = transformer.DiffRevert(
427      exclude_models = [m for m in f.history if m != 'mlr']
428  ) # exclude all lstm models from the revert
429  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
430  df = pd.read_csv("C:\Forecast CRIDA1 - STRATEGIA\Forecastsolo510 - STRATEGIA.csv")
431  actual     = df['price'][9:33]
432  predicted = forecast['mlr'][9:33]
433
434  MAPE= calculate_mape(actual, predicted)
435
436  fig = go.Figure()
437  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = forecast['mlr'][9:33], mode="lines",
          name='Forecast'))
438  fig.add_trace(go.Scatter( x = forecast['DATE'][9:33], y = df['price'][9:33]  , mode="lines" ,
          name='Actual'))
439  fig.update_layout(
```

```
440        title=go.layout.Title(
441            text=f"Price CRIDA1 NORD forecasted for strategy <br><sup>MAPE: {MAPE}  %",
442            xref="paper",
443            x=0
444        ),
445        xaxis_title="Date",
446        yaxis_title="Price (Eur/MWh)"
447 )
448 fig.show(renderer="png")
449
450 Crida1 = (forecast['mlr'][9:33]).to_numpy()
451
452 #————————————CRIDA2————————————
453 df = pd.read_csv("C:\Forecast CRIDA2 - STRATEGIA\multiseries_experiment - STRATEGIA.csv")
454 f = Forecaster(
455 current_dates = df['date'],
456 y= df['price']
457 )
458 f.seasonal_decompose()
459 f.set_test_length(500)
460 f.generate_future_dates(26)
461 transformer = SeriesTransformer(f)
462 f = transformer.DiffTransform()
463
464 f.add_ar_terms(70)
465 f.add_seasonal_regressors(
466     'hour',
467     'dayofweek',
468     dummy=True
469 ) # dummy vars
470 f.add_time_trend()
471 f.set_estimator('mlr')
472 f.manual_forecast(call_me='mlr')
473
474 f = transformer.DiffRevert(
475     exclude_models = [m for m in f.history if m != 'mlr']
476 ) # exclude all lstm models from the revert
477 forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
478 df = pd.read_csv("C:\Forecast CRIDA2 - STRATEGIA\Forecastsolo510 - STRATEGIA.csv")
479 actual=df['price']
480 actual    = df['price'][2:26]
481 predicted = forecast['mlr'][2:26]
482
483 MAPE= calculate_mape(actual, predicted)
484
485 fig = go.Figure()
486 fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = forecast['mlr'][2:26], mode="lines",
         name='Forecast'))
487 fig.add_trace(go.Scatter( x = forecast['DATE'][2:26], y = df['price'][2:26]   , mode="lines" ,
         name='Actual'))
488 fig.update_layout(
489     title=go.layout.Title(
490         text=f"Price CRIDA2 NORD forecasted for strategy <br><sup>MAPE: {MAPE}  %",
491         xref="paper",
492         x=0
493     ),
494     xaxis_title="Date",
495     yaxis_title="Price (Eur/MWh)"
496 )
497 fig.show(renderer="png")
498
499 Crida2 = forecast['mlr'][2:26].to_numpy()
500
501 #————————————CRIDA3————————————
502 df = pd.read_csv("C:\Forecast CRIDA3 - STRATEGIA\multiseries_experiment - STRATEGIA.csv")
503 f = Forecaster(
504 current_dates = df['date'],
505 y= df['price']
506 )
507 f.seasonal_decompose()
508 f.set_test_length(500)        # 1. 12 observations to test the results
509 f.generate_future_dates(24) # 2. 12 future points to forecast
510 transformer = SeriesTransformer(f)
511 f = transformer.DiffTransform()
512
513 f.add_ar_terms(150)
514 f.add_seasonal_regressors(
515     'hour',
516     'dayofweek',
517     'month',
518     dummy=True
```

```python
519  ) # dummy vars
520  f.add_time_trend()
521  f.set_estimator('mlr')
522  f.manual_forecast(call_me='mlr')
523  f = transformer.DiffRevert(
524      exclude_models = [m for m in f.history if m != 'mlr']
525  ) # exclude all lstm models from the revert
526  forecast=f.export(dfs=['lvl_fcsts'], models=['mlr'])
527  df = pd.read_csv("C:\Forecast CRIDA3 - STRATEGIA\Forecastsolo510 - STRATEGIA.csv")
528  actual=df['price']
529  actual    = df['price'][12:24]
530  predicted = forecast['mlr'][12:24]
531
532  print("MAPE :",  calculate_mape(actual, predicted), "%")
533  MAPE= calculate_mape(actual, predicted)
534
535  fig = go.Figure()
536  fig.add_trace(go.Scatter( x = forecast['DATE'][12:24], y = forecast['mlr'][12:24], mode="lines"
         ,  name='Forecast'))
537  fig.add_trace(go.Scatter( x = forecast['DATE'][12:24], y = df['price'][12:24]  , mode="lines" ,
         name='Actual'))
538  fig.update_layout(
539      title=go.layout.Title(
540          text=f"Price CRIDA3 NORD forecasted for strategy <br><sup>MAPE: {MAPE}  %",
541          xref="paper",
542          x=0
543      ),
544      xaxis_title="Date",
545      yaxis_title="Price (Eur/MWh)"
546  )
547
548  Crida3 = np.append(np.full(12,0), (forecast['mlr'][12:24].to_numpy()))   #Eur/MWh
549  fig.show(renderer="png")
550
551  #######################################################################
552  ######################Definition of strategy######################
553  #######################################################################
554
555
556  #Strategy only MGP
557  def traditional_strategy(qnt_MGP_1hour, price_MGP_1hour, qnt_actual, penality):
558      index = 0
559      earn_MGP = qnt_MGP_1hour*price_MGP_1hour
560      earn_tot = earn_MGP - abs(qnt_actual-qnt_MGP_1hour)*penality
561      return earn_tot, index
562
563  #First strategy
564  def first_strategy(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour,
         qnt_actual, price_MGP_1hour, price_CRIDA1_1hour, price_CRIDA2_1hour, price_CRIDA3_1hour,
         penality, hour):
565      index = 1
566      earn_MGP = qnt_MGP_1hour*price_MGP_1hour
567      earn_CRIDA1 = (qnt_CRIDA1_1hour - (qnt_MGP_1hour))*price_CRIDA1_1hour
568      earn_CRIDA2 = (qnt_CRIDA2_1hour - qnt_CRIDA1_1hour)*price_CRIDA2_1hour
569      if hour >=13:
570          earn_CRIDA3 = (qnt_CRIDA3_1hour - qnt_CRIDA2_1hour)*price_CRIDA3_1hour
571          earn_tot = earn_MGP + earn_CRIDA1 + earn_CRIDA2 + earn_CRIDA3 - abs(qnt_actual-
         qnt_CRIDA3_1hour)*penality
572      elif hour < 13:
573          earn_tot = earn_MGP + earn_CRIDA1 + earn_CRIDA2 - abs(qnt_actual-qnt_CRIDA2_1hour)*
         penality
574      return earn_tot, index
575
576  def second_strategy(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour,
         qnt_actual, price_MGP_1hour, price_CRIDA1_1hour, price_CRIDA2_1hour, price_CRIDA3_1hour,
         penality, hour):
577      index = 2
578      earn_MGP = qnt_MGP_1hour * price_MGP_1hour
579      if hour >=13:
580          earn_CRIDA3 = (qnt_CRIDA3_1hour - (qnt_MGP_1hour))*price_CRIDA3_1hour
581          earn_tot = earn_MGP  + earn_CRIDA3 - abs(qnt_actual-qnt_CRIDA3_1hour)*penality
582      elif hour < 13:
583          earn_CRIDA2 = (qnt_CRIDA2_1hour - qnt_MGP_1hour)*price_CRIDA2_1hour
584          earn_tot = earn_MGP + earn_CRIDA2 - abs(qnt_actual-qnt_CRIDA2_1hour)*penality
585      return earn_tot, index
586
587  def third_strategy(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour,
         qnt_actual, price_MGP_1hour, price_CRIDA1_1hour, price_CRIDA2_1hour, price_CRIDA3_1hour,
         penality, hour):
588      index = 3
589      ###compro e riassetto su crida3 o 2
```

```python
        if hour >=13:
            min_value= min(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour)
            earn_MGP = min_value*price_MGP_1hour
            earn_CRIDA3 = (qnt_CRIDA3_1hour - min_value)*price_CRIDA3_1hour
            earn_tot = earn_MGP + earn_CRIDA3 - abs(qnt_actual-qnt_CRIDA3_1hour)*penality
        elif hour < 13:
            min_value= min(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour)
            earn_MGP = min_value*price_MGP_1hour
            earn_CRIDA2 = (qnt_CRIDA2_1hour - min_value)*price_CRIDA2_1hour
            earn_tot = earn_MGP + earn_CRIDA2 - abs(qnt_actual-qnt_CRIDA2_1hour)*penality
        return earn_tot, index


def fourth_strategy(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour,
     qnt_actual, price_MGP_1hour, price_CRIDA1_1hour, price_CRIDA2_1hour, price_CRIDA3_1hour,
     penality, hour):
        index = 4
        ###compro e riassetto su crida3 o 2
        earn_MGP = qnt_MGP_1hour * price_MGP_1hour
        qnt_sell = qnt_MGP_1hour
        #passo a crida1

        if qnt_CRIDA1_1hour <= qnt_sell:
            earn_CRIDA1 = 0
        elif qnt_CRIDA1_1hour > qnt_sell:
            earn_CRIDA1 = (qnt_CRIDA1_1hour - qnt_sell)*price_CRIDA1_1hour
            qnt_sell = qnt_CRIDA1_1hour
        else:
            print("Errore")

        #passo a crida2
        # non mi preoccupo di crida 3 tanto devo resettle position alla fine in ogni caso
        if hour >=13:

            if qnt_CRIDA2_1hour < qnt_sell:
                earn_CRIDA2=0
            elif qnt_CRIDA2_1hour >= qnt_sell:
                earn_CRIDA2 = (qnt_CRIDA2_1hour - qnt_sell)*price_CRIDA2_1hour
                qnt_sell = qnt_CRIDA2_1hour
            else:
                print("Errore")

            ##riposiziono su crida 3 in ogni caso
            earn_CRIDA3= (qnt_CRIDA3_1hour-qnt_sell)*price_CRIDA3_1hour

            earn_tot = earn_MGP + earn_CRIDA1 + earn_CRIDA2 + earn_CRIDA3 - abs(qnt_actual-
        qnt_CRIDA3_1hour)*penality

        # mi riposiziono su crida2
        elif hour < 13:
            earn_CRIDA2= (qnt_CRIDA2_1hour-qnt_sell)*price_CRIDA2_1hour
            earn_CRIDA3=0
            earn_tot = earn_MGP + earn_CRIDA1 + earn_CRIDA2 + earn_CRIDA3 - abs(qnt_actual-
        qnt_CRIDA3_1hour)*penality

        return earn_tot, index


def fifth_strategy(qnt_MGP_1hour, qnt_CRIDA1_1hour, qnt_CRIDA2_1hour, qnt_CRIDA3_1hour,
     qnt_actual, price_MGP_1hour, price_CRIDA1_1hour, price_CRIDA2_1hour, price_CRIDA3_1hour,
     penality, hour):
        index=5
        massimo =price_MGP_1hour
        massimo_qnt = qnt_MGP_1hour

        if price_CRIDA1_1hour > massimo:
            massimo = price_CRIDA1_1hour
            massimo_qnt = qnt_MGP_1hour

        if price_CRIDA2_1hour > massimo:
            massimo = price_CRIDA2_1hour
            massimo_qnt = qnt_CRIDA2_1hour

        if hour < 13:
            if massimo==price_CRIDA2_1hour:
                earn_CRIDA2 = qnt_CRIDA2_1hour*price_CRIDA2_1hour
                earn_tot = earn_CRIDA2  - abs(qnt_actual-qnt_CRIDA2_1hour)*penality

            else:
                #cosi capisco quanto ho guadagnato in passato
                earn_max = massimo*massimo_qnt
                #vedo cosa mi manca per sbilanciamento
                earn_CRIDA2= (qnt_CRIDA2_1hour - massimo_qnt)*price_CRIDA2_1hour
```

```
665              #vedo cosa ottengo sottraendo il balore attuale
666              earn_tot = earn_max + earn_CRIDA2 - abs(qnt_actual-qnt_CRIDA2_1hour)*penality
667
668      elif hour >=13:
669          # faccio check qual e prezzo piu alto
670          if price_CRIDA3_1hour > massimo:
671              massimo = price_CRIDA3_1hour
672              massimo_qnt = qnt_CRIDA3_1hour
673
674          if massimo==price_CRIDA3_1hour:
675              earn_CRIDA3= qnt_CRIDA3_1hour*price_CRIDA3_1hour
676              earn_tot = earn_CRIDA3  - abs(qnt_actual-qnt_CRIDA3_1hour)*penality
677
678          else:
679              earn_CRIDA3= (qnt_CRIDA3_1hour-massimo_qnt)*price_CRIDA3_1hour
680              earn_tot = massimo*massimo_qnt + earn_CRIDA3 - abs(qnt_actual-qnt_CRIDA2_1hour)*
        penality
681
682
683
684      return earn_tot, index
685
686 #########Calculation one day##############
687
688 print("Implementation an energy trading strategy using forecasting of energy prices and
        production")
689 print("Hour   #Strategy    Profit (Eur)")
690
691 earn_tot_0_fin = []
692
693 for hour in hours_1day:
694
695     ##traditional
696     earn_tot_0, index_0 = traditional_strategy(Quantity_MGP[hour-1], MGP[hour-1],
         Quantity_actual[hour-1], penality[hour-1])
697     earn_tot_0_fin.append(earn_tot_0)
698     #assign the value in the first position as reference
699     earn_fin[hour-1] = earn_tot_0
700     strategy_fin[hour-1] = index_0
701
702     ##1 strategy
703     earn_tot_1, index_1 = first_strategy(Quantity_MGP[hour-1], Quantity_CRIDA1[hour-1],
         Quantity_CRIDA2[hour-1], Quantity_CRIDA3[hour-1], Quantity_actual[hour-1], MGP[hour-1],
         Crida1[hour-1], Crida2[hour-1], Crida3[hour-1], penality[hour-1], hour)
704     #check if it is better
705     if earn_fin[hour-1] < earn_tot_1:
706         earn_fin[hour-1] = earn_tot_1
707         strategy_fin[hour-1] = index_1
708
709     ##2 strategy
710     earn_tot_2, index_2 = second_strategy(Quantity_MGP[hour-1], Quantity_CRIDA1[hour-1],
         Quantity_CRIDA2[hour-1], Quantity_CRIDA3[hour-1], Quantity_actual[hour-1], MGP[hour-1],
         Crida1[hour-1], Crida2[hour-1], Crida3[hour-1], penality[hour-1], hour)
711     #check if it is better
712     if earn_fin[hour-1] < earn_tot_2:
713         earn_fin[hour-1] = earn_tot_2
714         strategy_fin[hour-1] = index_2
715
716     ##3 strategy
717     earn_tot_3, index_3 = third_strategy(Quantity_MGP[hour-1], Quantity_CRIDA1[hour-1],
         Quantity_CRIDA2[hour-1], Quantity_CRIDA3[hour-1], Quantity_actual[hour-1], MGP[hour-1],
         Crida1[hour-1], Crida2[hour-1], Crida3[hour-1], penality[hour-1], hour)
718     #check if it is better
719     if earn_fin[hour-1] < earn_tot_3:
720         earn_fin[hour-1] = earn_tot_3
721         strategy_fin[hour-1] = index_3
722
723     ##4 strategy
724     earn_tot_4, index_4 = fourth_strategy(Quantity_MGP[hour-1], Quantity_CRIDA1[hour-1],
         Quantity_CRIDA2[hour-1], Quantity_CRIDA3[hour-1], Quantity_actual[hour-1], MGP[hour-1],
         Crida1[hour-1], Crida2[hour-1], Crida3[hour-1], penality[hour-1], hour)
725     #check if it is better
726     if earn_fin[hour-1] < earn_tot_4:
727         earn_fin[hour-1] = earn_tot_4
728         strategy_fin[hour-1] = index_4
729
730
731     ##5 strategy
732     earn_tot_5, index_5 = fifth_strategy(Quantity_MGP[hour-1], Quantity_CRIDA1[hour-1],
         Quantity_CRIDA2[hour-1], Quantity_CRIDA3[hour-1], Quantity_actual[hour-1], MGP[hour-1],
         Crida1[hour-1], Crida2[hour-1], Crida3[hour-1], penality[hour-1], hour)
```

91

```python
        #check if it is better
        if earn_fin[hour-1] < earn_tot_5:
            earn_fin[hour-1] = earn_tot_5
            strategy_fin[hour-1] = index_5


    print(hour, "        ", strategy_fin[hour-1], "      ", f'{earn_fin[hour-1]:,}', "Euro")

print("TOT income:", f'{sum(earn_fin):,}', "Euro in one day")

diff= (earn_fin - earn_tot_0_fin )
new_income = sum(earn_fin)
old_income = int(sum(earn_tot_0_fin))
tot_new_gain = sum(diff)
tot_new_gain_2 = new_income - old_income

fig = go.Figure()
fig.add_trace(go.Scatter( x = hours_1day, y = earn_fin, mode="lines",  name='New Strategy'))
fig.add_trace(go.Scatter( x = hours_1day, y = earn_tot_0_fin, mode="lines" , name='Old Strategy'))
fig.update_layout(
    title=go.layout.Title(
        text=f"Gain with strategies <br><sup>eveNew gain per day: {new_income} - {old_income} = {tot_new_gain_2} Euro",
        xref="paper",
        x=0
    ),
    xaxis_title="Hour",
    yaxis_title="Euro"
)
fig.show(renderer="png")
```

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