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Master of Science in Data Analytics for Business

Hedging strategies for value optimization in photovoltaic energy production

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Introduction

In recent years, the need for sustainable energy solutions has become increasingly evident, driven by growing environmental concerns and the global necessity to reduce reliance on fossil fuels. As the world strives to decarbonize its power generation systems, renewable energy sources have gained widespread attention as a critical pathway toward a cleaner energy future.

Photovoltaic (PV) systems, which convert solar radiation into electricity, are now a landmark of this renewable energy revolution. However, renewable energy sources, including solar power, are inherently affected by weather conditions, which exposes these sources to various risks. Therefore, effective risk management strategies for renewable energy are essential to support their promotion and integration into the energy mix.

By offering the potential for large-scale, inexhaustible, and clean energy production, solar power generation is one of the most prominent renewable energy sources, emphasizing the critical importance of managing risks associated with its inherent variability. This variability presents a significant challenge: ensuring the stability and profitability of an energy portfolio that relies heavily on renewable assets. Solar power, being dependent on natural phenomena—specifically solar radiation—makes it inherently difficult to accurately predict energy availability at any given moment. However, the adoption of advanced energy management system (EMS) strategies, leveraging various machine learning regression models for predicting hourly energy production from photovoltaic (PV) systems, has seen a significant rise in recent years, offering bright solutions to this challenge (see [1]).

As a result, energy producers who depend on solar power are exposed to significant risks, particularly in markets where electricity prices are also volatile.

For example, on days when electricity prices are lower than expected and solar energy production is very high, producers may experience financial losses due to an oversupply of energy that cannot be sold at profitable rates.

Risk management is essential for integrating renewable energy into the market while ensuring financial viability. Hedging strategies, in particular, offer a way to stabilize revenues by reducing exposure to the uncertainties of both energy production and the volatility of market prices. These strategies are critical for optimizing an energy portfolio that includes renewable assets, allowing producers to manage production risks while capitalizing on market opportunities.

This thesis, conducted in collaboration with Sorgenia, focuses on developing a hedging strategy tailored to portfolios that combine renewable energy with standard market products. By minimizing the variability in profits and losses, the proposed model aims to address the risks associated with solar power's inherent variability and its interaction with market prices.

The analysis relies on historical data and market insights to develop a model that identifies the optimal approach for balancing production risks and market opportunities. The primary objective is to mitigate the risks associated with the variability of renewable energy production by minimizing the profit and loss fluctuations within the portfolio. This portfolio includes both renewable energy assets and a carefully selected mix of standard market products, ensuring a comprehensive and resilient risk management strategy.

These studies are conducted in collaboration with Sorgenia and aim to address this challenge by developing a hedging strategy that optimizes the management of an energy portfolio, incorporating both renewable assets and standard market products and the outcomes of the research are expected to provide valuable insights for renewable energy producers, enhancing the stability and profitability of their portfolios. Ultimately, this study contributes to the broader goal of creating more resilient and efficient energy markets, supporting the transition to a sustainable energy future.

1. The company: Sorgenia S.p.A.

The development of the analysis is totally supported by the usage of real data about PV, provided by Sorgenia S.p.A.

In Italy, the energy market has evolved significantly since its full liberalization in 2007, allowing new players to enter the industry and drive innovation. One such company at the forefront of this transformation is Sorgenia S.p.A. [2], founded in 1999. As the first non-incumbent company in Italy's liberalized energy market, Sorgenia has played a pivotal role in reshaping the country's energy landscape. Today, it remains one of the key operators in the sector, with over 920,000 customers, as stated in company's profile of 2024 [3].

Sorgenia's business model is heavily centered on innovation and sustainability, a strategy that has positioned it as Italy's first Digital Energy Company. The company's commitment to environmental sustainability is reflected in its focus on energy produced from renewable sources, as well as its reliance on four high-efficiency combined-cycle power plants located across Italy. These plants, in contrast to traditional thermal power stations, significantly reduce emissions and can be activated quickly, ensuring a stable and reliable energy supply for the national grid.

During the last few years, driven by the pressing need for change, particularly in climate action and renewable energy, Sorgenia's strategy has focused on four core vertical businesses: Generation and Energy Management, Renewable Energy Sources, Bioenergy, and Energy Retail. These sectors are integrated to maximize synergies in industrial operations, commercial activities and risk management, combining digital innovations with leading energy technologies.

1.1. Photovoltaic tracker systems

Photovoltaic tracker systems are advanced technologies designed to enhance the efficiency of photovoltaic panels by allowing them to follow the sun's path throughout the day, aiming to optimize solar energy production and improving the overall efficiency of the system. The importance of tracker systems is highlighted by their ability to reduce the levelized cost of energy (LCOE), that measures the lifetime cost of generating electricity from a solar installation, taking into account factors such as the initial investment, operational expenses, and energy output over time; in this way the solar energy becomes more competitive with respect to the traditional energy sources. This technological progress increases not only the efficiency of solar power generation, reducing the LCOE more than the other sustainable energy sources during the last years and aligning with global goals to mitigate climate change by promoting the use of renewable energy.

As Figure 1 illustrates, these systems are classified into single-axis and dual-axis trackers, based on their mechanical orientation and electronic control (see [4]).

Single-axis trackers have one horizontal or vertical rotation axis and in one direction, typically following the sun from east to west, allowing them to track the sun from sunrise to sunset. This system is more reliable and longer-lasting and has a lower complexity so fewer maintenance issues, but at the same time a limited technology upgrade capabilities.

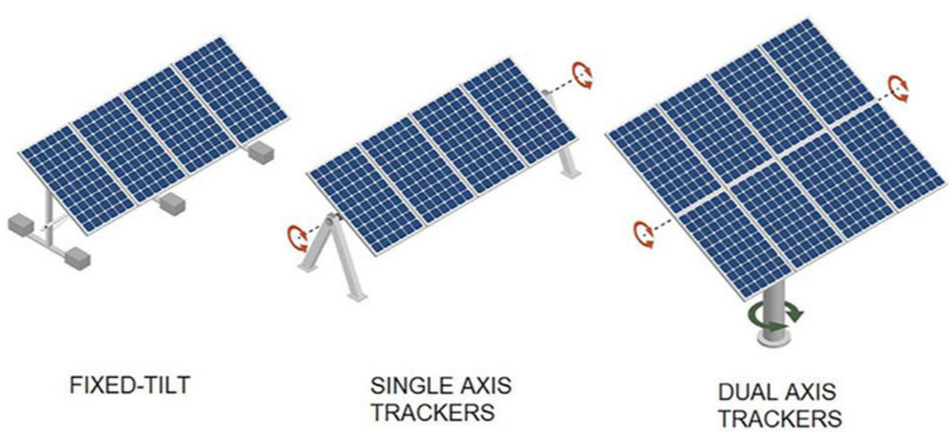

Figure 1: Different types of solar trackers (from [5])

On the other hand, dual-axis trackers are more advanced and flexible, allowing them to follow the sun in all directions, from east to west and from north to south. This advanced capability allows for higher energy production in a smaller land area and helps manage grid power limitations more effectively; nevertheless, they are more complex and costly, requiring higher maintenance efforts and expenses than single-axis systems.

The results in Figure 2, produced by an analysis of Vu Phong Solar Energy Joint Stock Company [5], show that, when compared to the performance of fixed photovoltaic systems, solar trackers demonstrate a significant advantage, with energy production increasing by more than 20% : this improvement is mainly due to the tracker's ability to dynamically adjust the orientation of the panels to follow the sun's path throughout the day, maximizing exposure to sunlight.

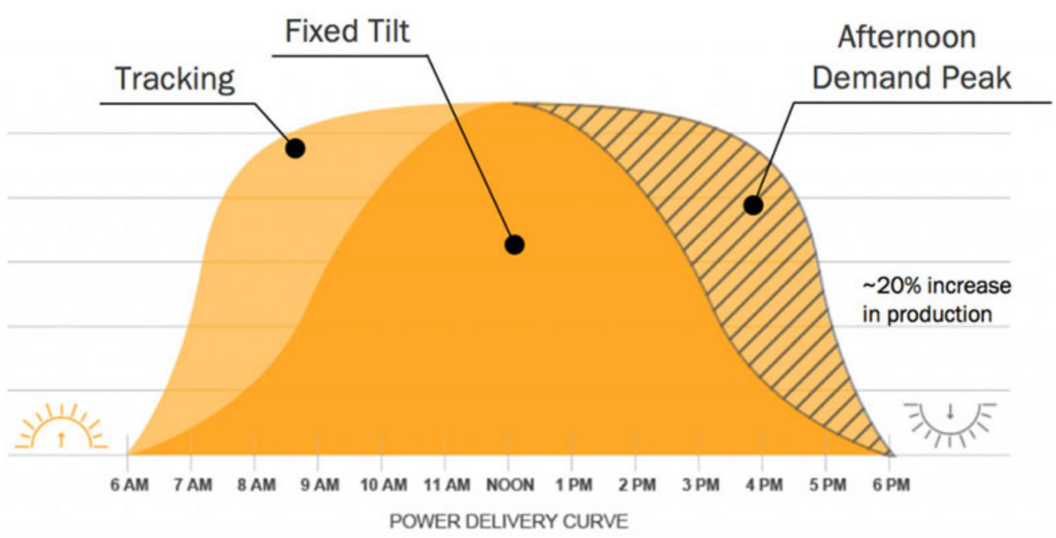

Figure 2: Solar Tracker vs fixed system (from [5])

However, the design and functionality of solar trackers can vary depending on the type of rotational mechanism used: as seen before, each system has its own set of advantages and limitations.

The trade-offs between the two types of PV tracker structure must be carefully evaluated to select the most suitable system for specific geographic and economic conditions: in regions near the equator, single-axis trackers, particularly those with a horizontal rotation axis, are commonly preferred due to their simplicity, ease of installation, and low maintenance requirements. However, as one moves closer to the poles, dual-axis trackers become increasingly effective, as they can better adjust to the more pronounced variations in solar angles throughout the year (see [6] for a comprehensive review).

Furthermore, solar trackers can be classified as active or passive based on how they move to follow the sun.

The first types use electric motors to slowly adjust the position of solar panels, consuming energy in the process; these are further divided into analog, which use sensors to find the optimal sun position, and digital, which use microprocessors to adjust the panels based on stored data.

The second types rely on natural physical phenomena, like the thermal expansion of gas heated by the sun, to move the panels without the need for external energy.

2. The dataset

As mentioned in the introduction, to achieve the objective of this thesis, Sorgenia has provided valuable data regarding the price indices (€/MWh) for both the northern and southern regions of Italy over the last three completed years (2021, 2022, and 2023). In addition, data on the volume of photovoltaic (PV) energy produced, expressed in MWh, has been provided for the same period. The production volume for the year 2023 is relevant, since it can be assumed as a standard or representative figure, given that the energy production from PV sources typically exhibits a similar magnitude year after year, assuming no significant changes in the capacity or operating conditions of the systems.

These historical data were made available through GME (Gestore Mercati Energetici) [7], the organization responsible for the management and regulation of the Italian electricity market. GME plays a crucial role in ensuring the efficient functioning of the electricity market, overseeing the coordination and optimization of electricity transactions, and guaranteeing that the market operates in a fair and competitive manner. Furthermore, GME is responsible for managing Italy's energy reserves, ensuring the availability of adequate energy supplies to meet the country's demand.

In the following sections, a detailed overview of the data will be presented.

2.1. Price index

The price index dataset is formed by combining data from three years and includes two key variables: *pr_idx_nord* and *pr_idx_sud*, both measured in €/MWh on an hourly basis, as shown in Table 1. This dataset contains a total of 26,280 observations, representing each hour over the three years under consideration.

Date	Hour	pr_idx_north	pr_idx_sud	Year	Month	Day	Weekday
2021-01-01	1	50.87000	50.87000	2021	1	1	4
2021-01-01	2	48.19000	48.19000	2021	1	1	4
2021-01-01	3	44.67966	44.67966	2021	1	1	4
2021-01-01	4	42.92193	42.92193	2021	1	1	4
2021-01-01	5	40.39151	40.39151	2021	1	1	4
...							
2022-01-01	1	170.28000	170.28000	2022	1	1	5
2022-01-01	2	155.72000	155.72000	2022	1	1	5

Table 1: Head of price dataset

The dataset includes metadata such as the year, month, day, and weekday for each observation, enabling a comprehensive temporal analysis of price trends. The variables *pr_idx_nord* and *pr_idx_sud* represent the zonal price indices for the northern and southern regions, respectively, providing insights into the spatial variability of electricity prices. These indices are influenced by various factors, including supply-demand dynamics, renewable energy availability, and grid constraints.

	North (€/MWh)	**South (€/MWh)**
Mean	186.93	181.48
Standard deviation	127.47	121.36
Median	146.51	145.00

Table 2: Summary statistics for price indices

The summary statistics for *pr_idx_nord* and *pr_idx_sud* are illustrated by the boxplot in Figure 3 , which provides an overview of their distribution.

It can be stated that there are almost no significant differences in the statistics illustrated in Table 2, with the average price and variability slightly higher in the north compared to the south.

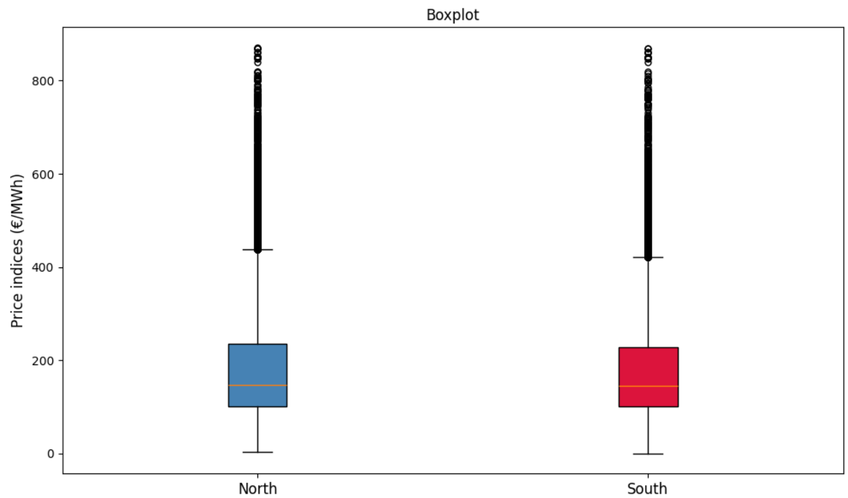

Figure 3: Boxplot of the price indices data

It is important to note the high presence of outliers, particularly above the threshold of 400 €/MWh, which indicates for both regions the occurrence of occasional extreme values: these outliers suggest periods of unusual market behavior, possibly driven by specific events or market anomalies that deviate significantly from typical pricing trends.

It is important to analyze the price index distribution: Figure 4 represents the normalized probability density for the northern and southern regions: the bars of the histogram are calculated proportionally to the relative frequency, ensuring that the total area under the curve is equal to 1.

Both regions exhibit right-skewed patterns, also known as positive skew, where most observations are concentrated at the lower end of the range, with a long tail extending toward higher values.

In this case, most prices are clustered below 200 €/MWh, while higher prices occur less frequently but extend further into the right tail. This suggests that extreme price spikes, though rare, are possible and have a significant impact on the overall distribution.

It is possible to see in the plot two lines that represent the Kernel Density Estimate (KDE), a non-parametric technique used to estimate the probability density function of a continuous random variable. It smooths the histogram and converts the discrete representation into a continuous curve, improving the clarity of the distribution's shape. By providing a smoother visualization, KDE highlights the right skew, making the asymmetry of the data more apparent.

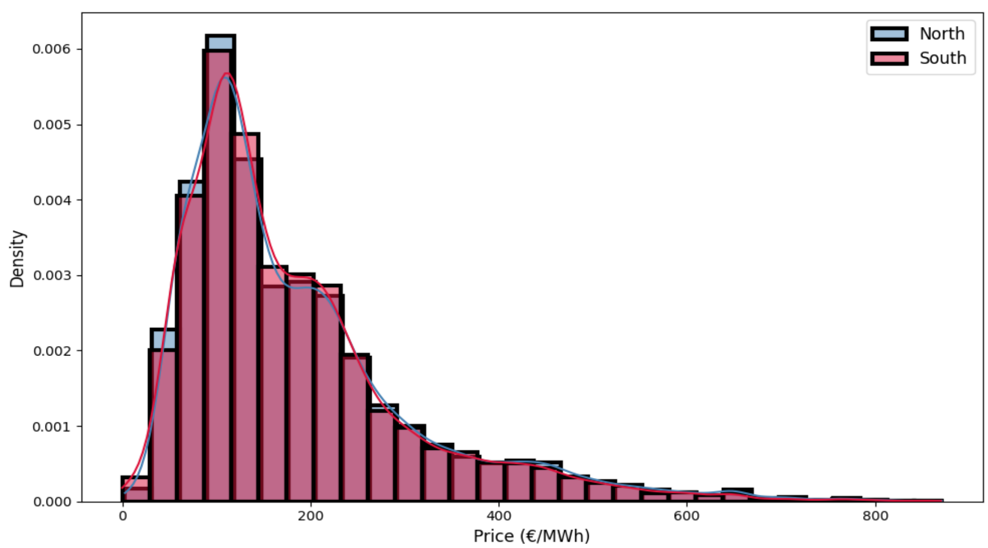

Figure 4: Distribution of price indices

Figure 5 shows the changes during the three years of the price index, expressed in €/MWh. There are no significant differences between north and south in the level of price index, with a range of values between 3 €/MWh and 871 €/MWh for north and between 0 €/MWh and 870 €/MWh for the south.

There has been a significant rise in the price index toward the end of 2022, coinciding with the profound effects of the war in Ukraine [8].

Sanctions on Russia, along with restrictions on gas and oil supplies, have driven a substantial increase in electricity prices across Europe. Additionally, extreme weather events such as heatwaves and droughts have hindered renewable energy production, further contributing to price volatility.

Apart from this exception driven by political and economic factors, the price index remained relatively stable in both 2021 and 2023, following a similar trend. In both years, the average value settled around 125 €/MWh across all regions of Italy.

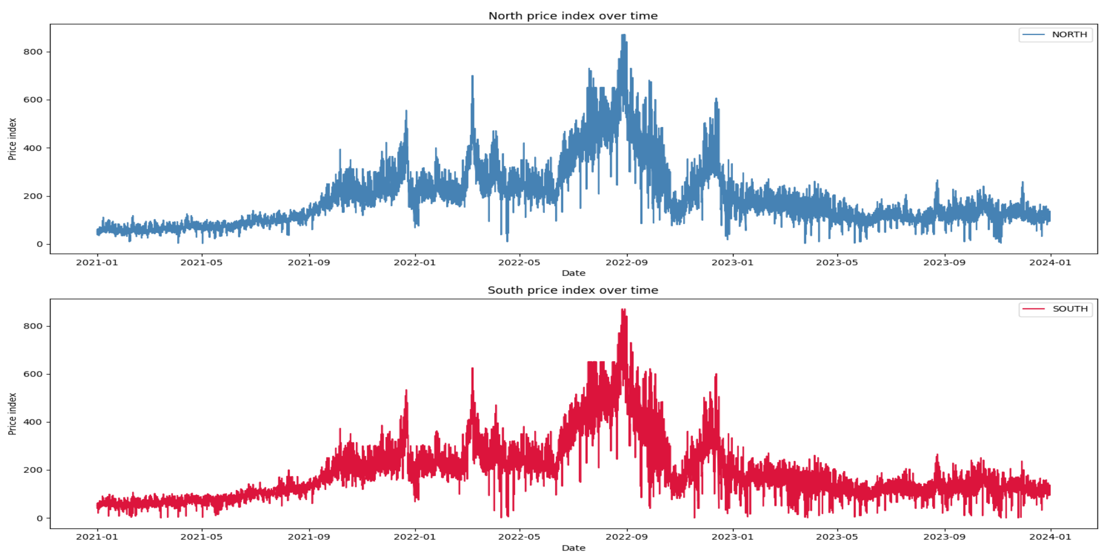

Figure 5: Time series of the price indices

It is also interesting to analyze periods of extreme volatility, showing the two days with the highest and lowest volatility, respectively, offering insights into the behavior of prices during such periods.

In Figure 6, the day with the highest volatility in the north occurs toward the end of July 2022 and is characterized by significant price fluctuations throughout the day, with a notable peak in the early afternoon, consistently ranging between 600 and 700 €/MWh.

Conversely, the lowest volatility day, observed in mid-November 2023, exhibits a remarkably stable price trend around 120 €/MWh, with minimal variation throughout the hours.

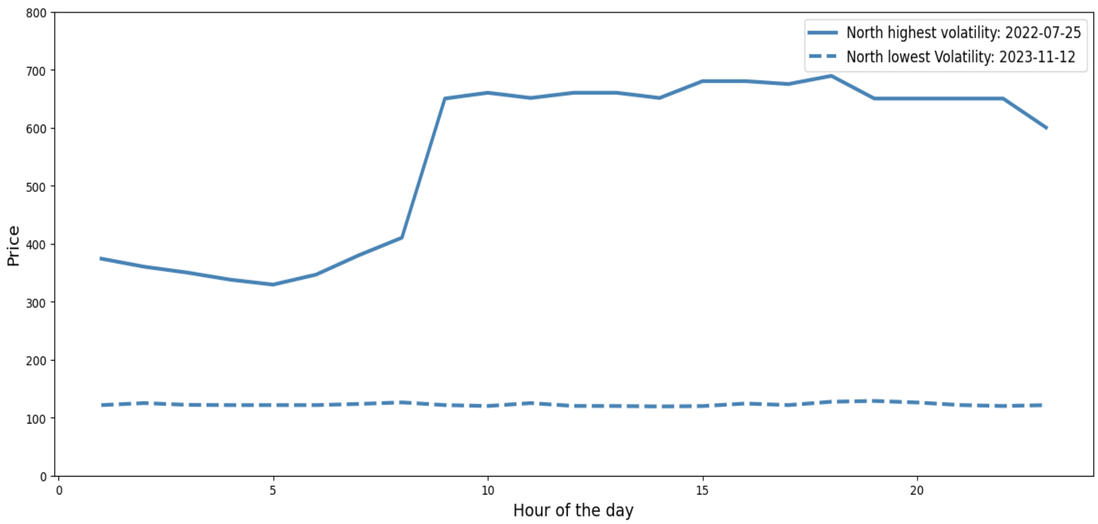

Figure 6: Volatility of north price index

Similarly, Figure 7 shows that the day with the lowest volatility in the south coincides with the lowest volatility day in the north. On the other hand, the day with the highest volatility in the south, observed at the end of September 2022, features sharp price changes throughout the day, with significant fluctuations peaking at 620 €/MWh around 8 PM and dropping as low as 40 €/MWh during the early afternoon. This behavior possibly indicates a delayed market reaction in the south compared to the north.

The analysis of extreme volatility days reveals key challenges in integrating photovoltaic (PV) energy into the market, particularly due to sharp price spikes during periods of high volatility. These price variations underscore the need for targeted hedging strategies to mitigate financial risks.

One effective strategy is the use of energy storage, which can buffer supply fluctuations and decouple production from market price spikes.

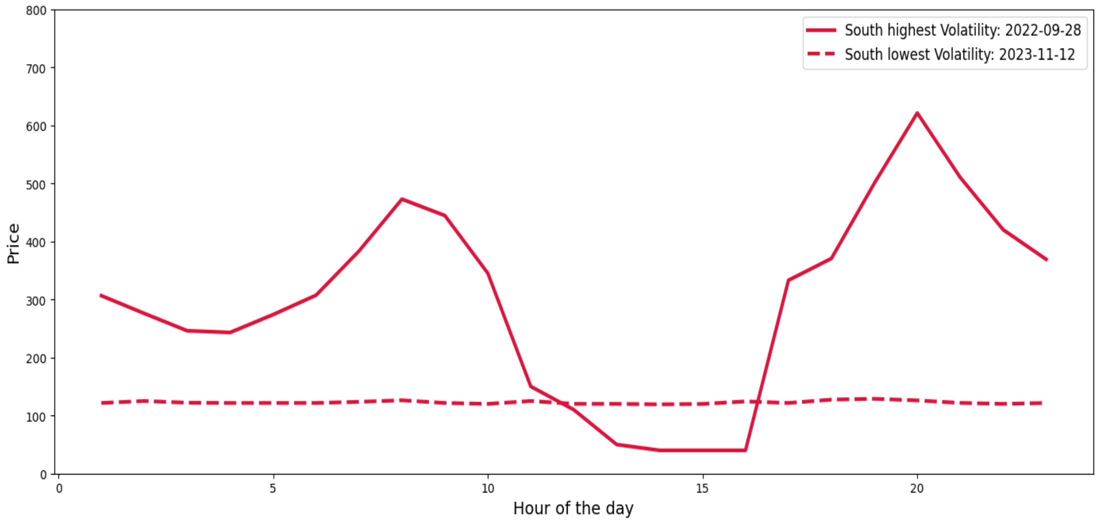

Figure 7: Volatility of south price index

Additionally, diversifying production across regions with less correlated volatility patterns can reduce exposure to localized price dynamics.

Another solution is offered by tailoring financial instruments like forward contracts and power purchase agreements (PPAs) to align with high-volatility periods offers: these contracts help stabilize revenues by locking in prices during expected volatility, ensuring more predictable cash flows.

2.2. Volume

The dataset containing volumes of energy produced by the tracker system is displayed in Table 3. As anticipated, these data are based on the sample year 2023.

The two primary variables, *TRACK_NORD* and *TRACK_SUD*, represent the hourly energy output for the northern and southern regions, respectively, expressed in megawatt-hours (MWh). The dataset spans the whole 2023, providing a comprehensive overview of hourly production patterns across the year, so a total of 8,760 hourly observations are available for each region, covering both daylight and nighttime periods.

TRACK_NORD	TRACK_SUD	date	Month	Day	Hour	Weekday
0.0	0.0	2023-01-01 01:00:00	1	1	1	6
0.0	0.0	2023-01-01 02:00:00	1	1	2	6
0.0	0.0	2023-01-01 03:00:00	1	1	3	6
...						
0.261617	0.275819	2023-01-01 12:00:00	1	1	12	6
0.265387	0.282107	2023-01-01 13:00:00	1	1	13	6
0.273641	0.295508	2023-01-01 14:00:00	1	1	14	6

Table 3: Head of volume data

To gain deeper insights into the dataset, the boxplot of Figure 8 provides a summary of key statistics for the energy production volumes in the north and south regions: these statistics help capture the similarity in production patterns and variability between the two regions.

	North (MWh)	**South (MWh)**
Mean	0.167	0.218
Standard deviation	0.215	0.269
Median	0.0039	0.0059

Table 4: Summary statistics for energy production volumes

The summary statistics in Table 4 further confirm that the northern and southern regions exhibit comparable trends. However, the southern region shows a slightly higher mean hourly production (0.218 MWh) compared to the north (0.167 MWh), as the standard deviation does, indicating a little higher degree of variability in energy production.

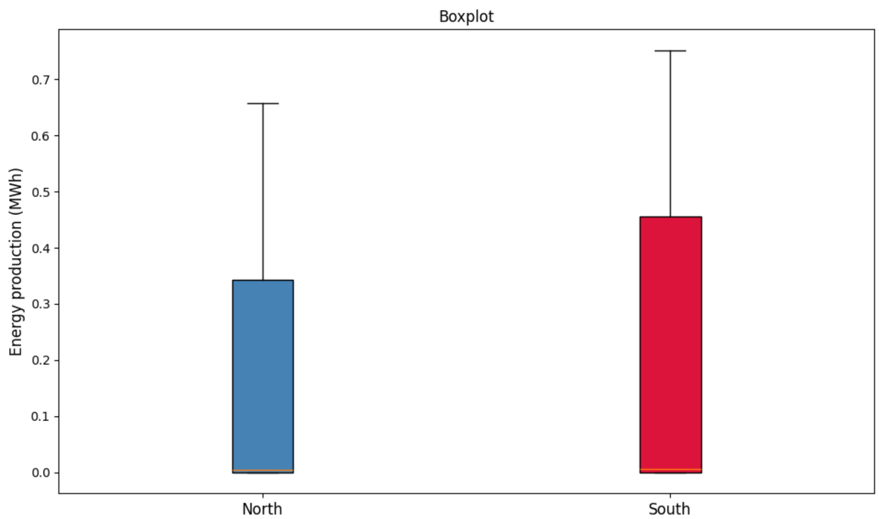

Figure 8: Boxplot of the energy production data

Additionally, data on produced volume are heavily concentrated around zero, primarily due to the numerous instances recorded during nighttime hours when solar irradiation is absent, resulting in no energy generation from photovoltaic (PV) systems: this pattern is inherent to solar energy production and underscores its reliance on sunlight availability. During the daytime, energy production fluctuates based on various factors, including solar incidence angle, weather conditions, and seasonal variations.

As done for the price index variable, the normalized probability density of energy production is analyzed in Figure 9, which highlights that energy production in both regions is predominantly concentrated at very low levels, with a marked spike near zero: indeed, in most instances, energy production remains very low for both the regions and this can be attributed to the large number of nighttime hours in the dataset, during which, energy production often drops to zero.

The tails of the density curves also suggest an interesting distinction: while both regions show low probabilities of very high energy production, the south has a slightly broader tail, implying that it occasionally achieves higher energy production values more often than the north.

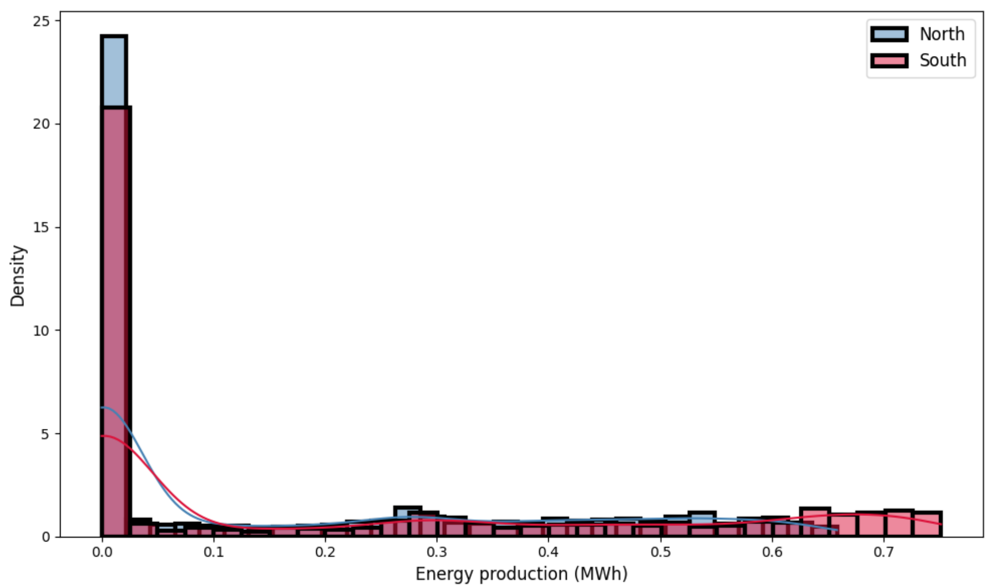

Figure 9: Distribution of energy production

Due to the significant proportion of null observations, which constitute approximately half of the total data for both regions, Figure 10 illustrates the energy production distribution after excluding these values, enabling a clearer visualization of the data: indeed, the exclusion of null values redistributes the density, reducing the y-axis scale and altering the bin distribution.

Without the dominance of zero values, the histogram more accurately captures the variability of non-zero energy production, with the density spread more evenly across the intervals.

The most notable improvement in the bin distribution lies in its increased uniformity and the significant reduction of the right tail, resulting in a less skewed pattern. This adjustment offers a more balanced and interpretable representation of the data.

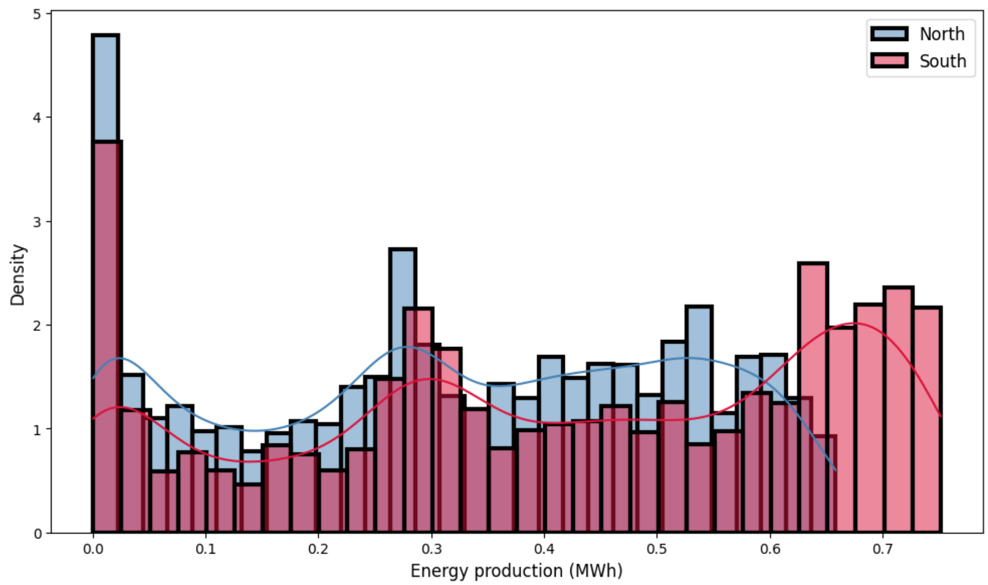

Figure 10: Distribution of energy production without zero values

Figure 11 shows the photovoltaic energy output patterns, analyzed on both daily and weekly intervals, based on the average hourly production for 2023, expressed in MWh. As anticipated before, this year can be considered representative because the production curves remain virtually identical across different years. As a result, the energy output values observed in 2023 are typical and can reliably represent the production levels expected in any given year. Particularly, the plot on the left in shows a bell-shaped distribution, typical of daily solar energy generation.

The energy output for both *TRACK_NORD* (blue) and *TRACK_SUD* (red) starts increasing between 6 and 8 AM, peaks between 12 PM and 2 PM, and decreases to nearly zero by 7 or 8 PM.

This pattern, observed in both production curves, reflects the characteristic performance of solar tracker systems that depend on sunlight and typically produce energy following a bell curve throughout the day.

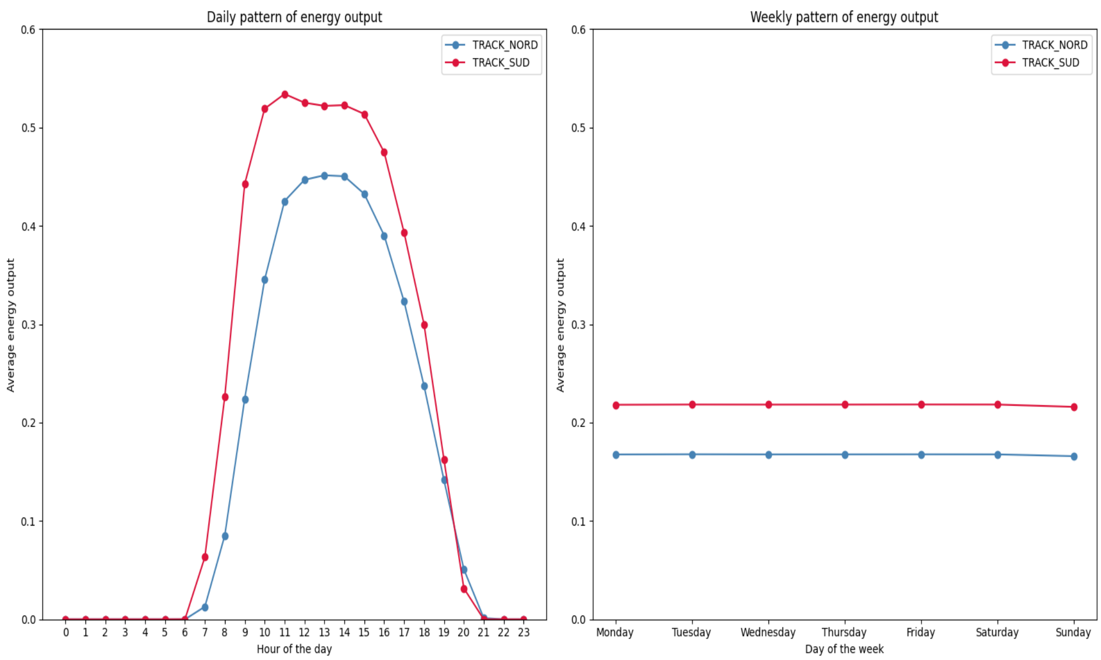

Figure 11: Daily (left plot) and weekly (right plot) patterns of solar energy generation

Instead, the plot on the right, depicting the weekly pattern, reveals that the energy output remains relatively consistent across the week. *TRACK_SUD* averages around 0.22 MWh, while *TRACK_NORD* produces approximately 0.16 MWh, with minimal fluctuations between different days. This consistency indicates a stable and predictable production pattern over the week, which is essential for optimizing energy generation.

3. Ideal production curve

The concept of an ideal production curve is depicted as a typical representation of the energy production pattern, highlighting its shape and characteristics.
The energy portfolio of a PV system could be outlined in the following way:

$$\text{Energy portfolio} = A - \alpha B,$$

where:

- $\boldsymbol{A}$ stands for the energy produced from PV plants, which typically has a bell-shaped profile (see Figure 11, on the left) since there is no energy production during night hours, and the peak occurs around midday: this pattern closely resembles the characteristics of a normal distribution, as it is symmetric and centered around a specific time of day, reflecting the natural variation in solar intensity.

- $\boldsymbol{B}$ represents the market exposure associated with the volume of electricity generated that is subject to market price fluctuations (see Figure 5 above): this can denote either the amount of electricity sold in the market or the monetary value tied to those sales, both of which are influenced by the variability of market prices.

- $\boldsymbol{\alpha}$ represents the hedging coefficient, reflecting the level of coverage or protection the company seeks to implement against these risks.

- $\boldsymbol{\alpha B}$ accounts for the exposure to risks due to fluctuations in electricity market prices.

Due to the absence of products in the market that exhibit a profile akin to the bell-shaped function represented by A, it is essential to implement hedging strategies to mitigate the financial impact of variability in both energy production and market prices. The primary objective of these strategies is to stabilize the company's revenue streams by adjusting the hedging coefficient α, optimizing it to balance potential profits and losses. By carefully optimizing α, the company seeks to achieve a stable financial outcome, minimizing the risks associated with fluctuations in both energy production and market prices, ultimately ensuring a more predictable and resilient energy portfolio, achieving a zero profit/loss balance.

By employing effective hedging techniques, the aim is to offset potential losses that arise from fluctuations in market prices, which are often influenced by external factors such as demand shifts, regulatory changes, and supply chain disruptions. This proactive approach allows the organization to manage its exposure to risks associated with the inherent variability of renewable energy production, ultimately fostering greater financial stability and predictability.

Through careful analysis and strategic implementation of these hedging strategies, the energy portfolio can be aligned more closely with market dynamics, ensuring that the organization can maintain its financial objectives despite the uncertainties associated with energy generation and market behavior.

The energy production from PV systems is inherently variable due to factors like sunlight intensity and weather conditions; this leads to fluctuations in the amount of electricity generated at different times of the day and across different months.

3.1. Comprehensive analysis of monthly production

The ideal production curve captures this variability by representing the average hourly energy production over each month. Figures 12 and 13 display the monthly volume trends for northern and southern regions, respectively. Each subplot represents a specific month, illustrating how PV systems perform on a typical day within that month.

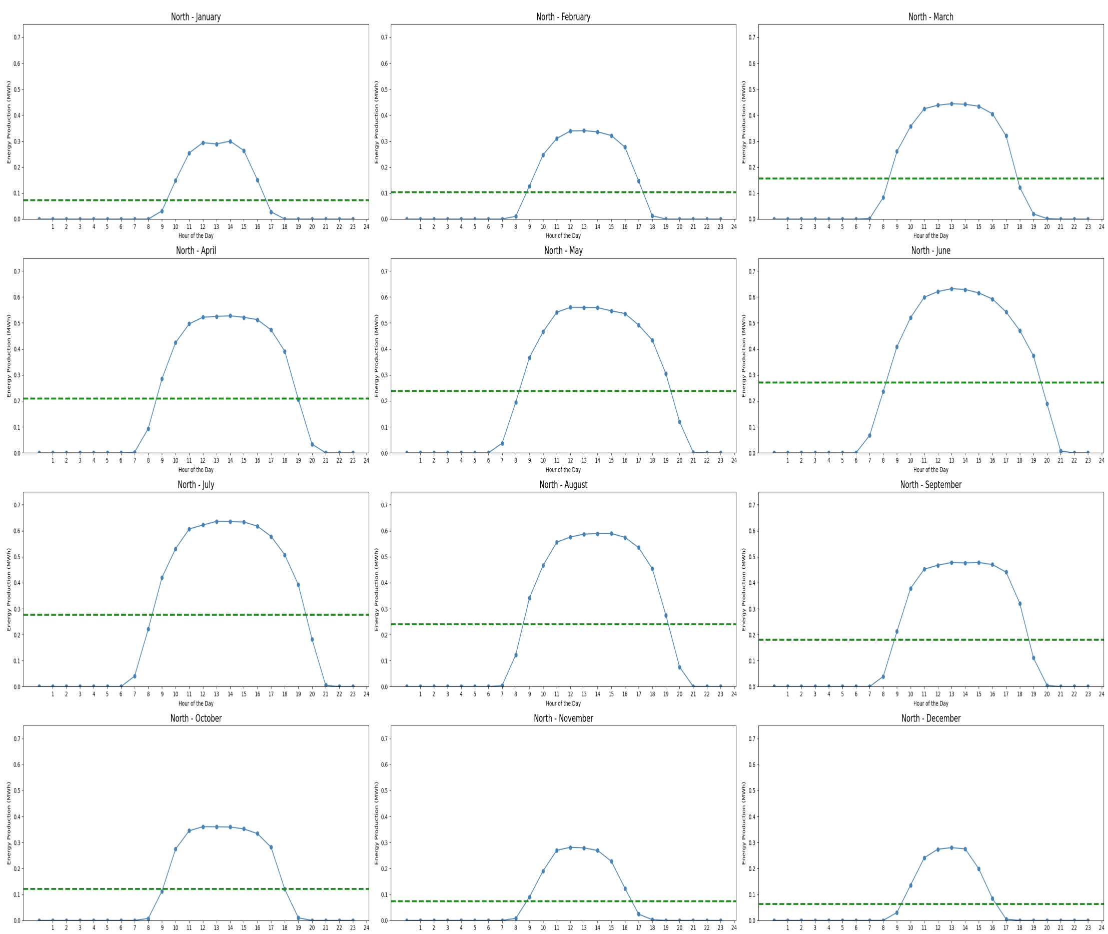

Figure 12: Monthly volume trends for north

The markers, in blue for northern regions and in red for southern regions, indicate the average production per hour of each month. The green line in each plot shows the average of these hourly productions for a specific month, providing a representative value of the monthly average production and corresponds to the average volumes represented in the following tables.

This line serves as a critical reference point, allowing for a comparison between hourly production values and the average output across all hours of the month. By identifying hours that exceed or fall short of this benchmark, the hedging strategy aims to provide a consistent amount of energy that can be reliably sold every hour, thus stabilizing revenue and mitigating risks associated with production variability. Ultimately, this approach ensures more predictable revenue streams by effectively managing fluctuations in energy production and aligning them with market dynamics.

Month	Average volume (MWh)	Max volume (MWh)	Peak hour
January	0.07	0.30	14
February	0.10	0.34	13
March	0.16	0.44	13
April	0.21	0.53	14
May	0.24	0.56	12
June	0.27	0.63	13
July	0.28	0.64	13
August	0.24	0.59	15
September	0.18	0.48	15
October	0.12	0.36	12
November	0.07	0.28	12
December	0.06	0.28	13

Table 5: Monthly energy production (north)

Figure 12 and Table 5 reveal that energy production exhibits notable seasonal fluctuations in the northern region. Peak production is relatively low during the winter months, ranging from approximately 0.28 MWh to 0.34 MWh, while the summer months witness a substantial increase, with peak values reaching up to 0.64 MWh.

In general, for the north region the peak production hours fluctuate significantly throughout the year, ranging from 12:00 PM to 3:00 PM, indicating that the optimal time for energy production varies monthly due to changing daylight hours and weather conditions. This pronounced seasonal variability underscores the necessity for adaptive strategies to address the lower production in winter and the heightened output during summer.

In comparison, the southern region demonstrates consistently higher and more stable energy production throughout the year, as noted in Figure 13 and Table 6. Even during winter, production levels remain moderate, with peak values between 0.31 MWh and 0.40 MWh, occurring consistently around 11:00 AM. During the summer months, energy production significantly escalates, with peak values reaching 0.74 MWh, with peak production hours that are attained up to 1:00 PM. The southern region exhibits a more consistent pattern of peak production, likely due to more predictable and favorable solar conditions. This sustained high production suggests a more efficient utilization of solar energy, potentially leading to a more straightforward risk management approach compared to the northern region.

Month	**Average volume (MWh)**	**Max volume (MWh)**	**Peak hour**
January	0.09	0.33	11
February	0.13	0.40	11
March	0.20	0.53	12
April	0.27	0.64	13
May	0.31	0.66	11
June	0.35	0.73	11
July	0.36	0.74	13
August	0.31	0.70	11
September	0.24	0.60	11
October	0.16	0.45	11
November	0.10	0.31	11
December	0.08	0.31	11

Table 6: Monthly energy production (south)

The analysis reveals a consistent trend in average energy production throughout the year for both the northern and southern regions, characterized by similar patterns of increase and decrease. However, a significant distinction lies in the magnitude of production between the two areas. Specifically, while both regions experience fluctuations in energy output corresponding to seasonal variations, the southern region consistently demonstrates higher overall production levels compared to its northern counterpart.

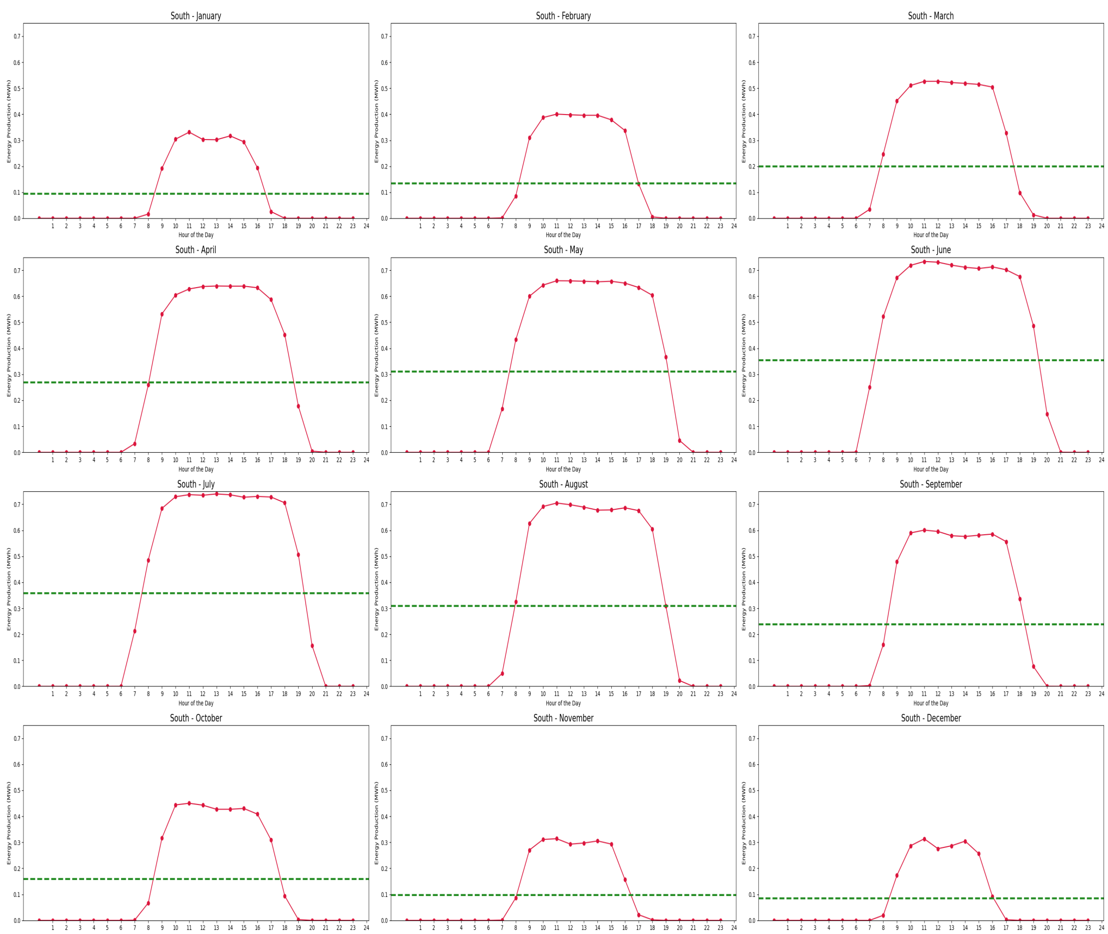

Figure 13: Monthly volume trends for south

This difference in production levels can be attributed to several factors, including geographical location, solar illumination, and climatic conditions, which favor more efficient energy generation in the south. As a result, the southern region not only showcases a comparable seasonal trend in average production but does so at a higher scale. This information is crucial for understanding regional energy dynamics and for developing tailored strategies that consider both the amplitude of energy production and its variability throughout the year.

3.2. Some further indicators

Understanding the behaviour of the energy production across each month, also highlighting the differences between the two regions, could offer valuable insights for energy portfolio management. Table 7 provides a comparative view of standard deviation and skewness for the northern and southern regions. These two statistical indicators help to quantify the spread and asymmetry of energy production.

Standard deviation is a measure of the dispersion of the measured values around the average. A high standard deviation indicates more fluctuation in production, suggesting lower predictability and stability, while a low standard deviation reflects a steadier, more consistent energy output.

Skewness, on the other hand, measures the asymmetry of the production distribution. Positive skewness implies that the distribution has a long tail to the right, indicating that while average production may remain relatively low, with occasional instances of higher production that deviate significantly from the mean.

This skew is particularly relevant for PV systems, where production depends heavily on sunlight availability and varies substantially with atmospheric conditions.

When considering the average values of standard deviation and skewness across the year, the north region shows an average standard deviation of 0.20 and skewness of 0.70. In contrast, the south exhibits a slightly higher average standard deviation of 0.24 but a lower skewness of 0.48. These annual averages provide a general indication of variability and asymmetry between the two regions.

However, averages do not fully capture the complexity of monthly production patterns, which reveal seasonal differences in variability that have important implications for energy portfolio management.

As for the monthly trends, both regions exhibit similar patterns in terms of standard deviation and skewness. Notably, the southern region consistently shows a higher standard deviation compared to the north, likely due to its higher absolute production levels.

Month	North		South	
	Std Dev	**Skewness**	**Std Dev**	**Skewness**
January	0.12	1.21	0.14	0.89
February	0.14	0.85	0.18	0.71
March	0.19	0.60	0.24	0.51
April	0.23	0.39	0.29	0.30
May	0.25	0.24	0.31	0.09
June	0.27	0.20	0.34	0.01
July	0.28	0.20	0.34	0.03
August	0.26	0.34	0.33	0.21
September	0.21	0.50	0.27	0.41
October	0.16	0.69	0.20	0.59
November	0.11	1.11	0.14	0.82
December	0.11	1.34	0.13	1.02
Average	0.20	0.70	0.24	0.48

Table 7: Monthly indicators

This increased variability is more pronounced in the summer months, where both regions show elevated standard deviations, reaching up to 0.34 in south and 0.28 in north; this suggests that, during summer, both regions experience a higher degree of fluctuation in production, potentially due to variations in sunlight hours, weather conditions, and other seasonal factors.

In contrast, the winter months stand out with very low standard deviations, indicating that production is relatively more stable during this period, with respect to the warmer months. However, these months also feature exceptionally high skewness values, especially in the north, where skewness peaks at 1.34 in december and 1.21 in january. High skewness values in winter indicate a distribution with a long right tail, meaning that, although average production tends to be lower, occasional spikes in production can occur, creating a more unpredictable and volatile pattern. These spikes may be influenced by less frequent but intense weather events or occasional sunny periods during the winter months. So, while both regions exhibit distinct seasonal trends, the southern region, with its higher degree of variability, can be considered more variable compared to the north.

3.2.1 Extreme production months

Now, the examination will focus on the months that exhibit the highest and lowest average production levels for both the northern and southern regions.

Figure 14 illustrates that July stands out as having the highest average production for both regions. This can be attributed to the longer daylight hours and increased solar insolation that characterize the summer season, which significantly enhance solar energy generation.

In contrast, December shows the lowest average production in both regions. The reduced sunlight and shorter days during this winter month contribute to lower energy output, reflecting the seasonal variability inherent in solar energy production. Notably, the seasonal difference between the highest and lowest production months is less pronounced in the northern region, likely due to regional climatic and daylight-hour variations.

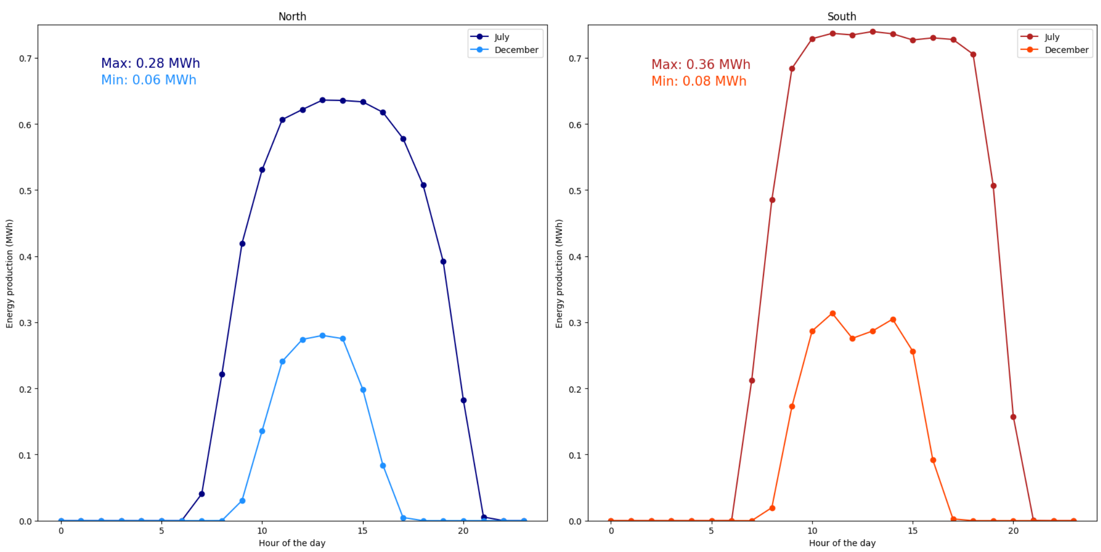

Figure 14: Max vs min monthly energy production

These observations highlight the importance of seasonality in solar energy production and the need for effective energy planning. By accounting for seasonal fluctuations, energy systems can optimize production, efficiency, and risk management, ensuring more stable and reliable output year-round.

Additionally, understanding these patterns also supports better operational strategies, including improved storage and distribution, enhancing overall system resilience.

Other statistics about the ideal production curve are presented below.

First of all, the average weighted price is crucial because it reflects the actual price paid for energy, adjusted by the volume produced.

$$\text{Average Weighted Price} = \frac{\sum(\text{price} \times \text{volume})}{\sum \text{volume}}$$

This weighted price takes into account the varying volumes of energy production, providing a more accurate picture of the cost of energy relative to output. This helps in understanding how price fluctuations correlate with production levels and market demand, offering a clearer financial perspective for energy producers and consumers.

Month	**North**		**South**	
	Average weighted price	**P-V correlation**	**Average weighted price**	**P-V correlation**
January	66.81	0.24	58.86	0.03
February	58.99	0.07	55.42	0.04
March	58.81	-0.10	56.61	-0.19
April	67.56	-0.10	63.47	-0.23
May	68.94	-0.04	67.24	-0.21
June	84.91	0.16	86.28	-0.04
July	104.12	0.27	105.98	0.12
August	107.56	0.09	114.35	-0.24
September	156.81	-0.05	154.50	-0.10
October	218.35	0.00	205.19	-0.13
November	237.31	0.14	227.70	0.07
December	310.73	0.17	262.73	-0.02

Table 8: Other indicators

Looking at Table 8, it can be noticed a distinct upward trend in energy prices during the latter part of the year, culminating in a peak in November and December. This price increase can be attributed to higher energy demand during the colder months, when consumption typically surges.

Specifically, December shows the highest average weighted prices for both regions: 310.73 € in the north and 262.73 € in the south. The sharp increase of the prices at the end of the year reflects this increased demand, coupled with potentially lower production capacity during the winter, further driving prices upward.

Another important metric is the Price-Volume correlation, which provides valuable insights into how production volumes relate to market prices across different regions and times of the year. In the north, positive correlations are observed in January and July, with values of 0.24 and 0.27, respectively.

These months are characterized by higher energy production that corresponds with increased market prices and this trend suggests a seasonal rise in demand during these periods, where boosting production to meet this demand aligns with elevated prices, providing an opportunity for producers to maximize revenue.

Conversely, during the middle months, such as March and April, the north exhibits negative correlations around -0.1.

This indicates an inverse relationship, where higher production volumes result in lower prices; this decline during these months can be attributed to oversupply in the market, as demand typically moderates: when production exceeds demand, it creates downward pressure on prices, which can be dangerous to profitability if not managed properly.

In the south, the situation reflects a similar but more pronounced trend of negative correlations, especially in the mid-year months. In April and August, for example, the correlations drop to -0.23 and -0.24, respectively. This stronger inverse relationship compared to the north suggests that the southern region may experience more significant seasonal fluctuations in demand. These variations in correlation during certain months imply that production adjustments are even more crucial to prevent substantial price reductions in the southern markets.

The differing patterns between the north and south highlight the importance of region-specific production strategies. In months with positive correlations, increasing production can be highly beneficial, particularly in the northern region during periods of peak demand. However, during months with negative correlations, such as the middle of the year, careful management can help avoid price declines caused by oversupply, especially in the more volatile southern region.

4. Hedging Strategy

4.1. Long and short positions in energy market

The results of descriptive analysis conducted so far revealed that energy markets exhibit significant price and production variability, necessitating robust hedging strategies to manage financial and operational risks.

Additionally, the concepts of *long* and *short positions*, which are fundamental in financial markets, have direct applications in the energy sector: actually, this section delves into these concepts and examines their relevance in managing Sorgenia's energy portfolio and reducing price risks in its operations.

In financial terms, as explained by Leslie Kramer in an article of Investopedia [9], a *long position* refers to the ownership of an asset, where an investor purchases the asset with the expectation that its value will increase. The investor benefits when the asset's price rises, as they can later sell it at a higher price than they initially paid, realizing a profit.

In contrast, a *short position* involves selling an asset that the investor does not own, with the expectation that its price will fall. The investor borrows the asset, sells it at the current market price, and aims to buy it back at a lower price in the future to return it to the lender. The goal is to profit from the difference between the price at which the asset was sold and the price at which it is repurchased. However, if the price rises instead of falling, the investor may incur significant losses and could be required to deposit additional funds to meet margin requirements.

In the context of energy production, a *long* position occurs when a producer generates more electricity than required to meet contracted commitments, resulting in surplus energy that can be sold on the spot market, where transactions are immediate with short-term delivery, or the day-ahead market, where market participants purchase and sell electric energy at financially binding day-ahead prices for the following day.

Conversely, a *short* position arises when production is insufficient to fulfill these commitments, necessitating the purchase of additional energy at prevailing market prices to cover the deficit.

As outlined in the analysis, solar energy producers like Sorgenia often face cyclical variations in their positions due to the nature of photovoltaic production.

During nighttime hours, when solar generation is negligible, Sorgenia typically finds itself in a short position: in such cases, the company must purchase energy from the market to meet its baseload obligations, hoping for lower market prices to minimize costs.

On the other hand, during peak solar production at midday, Sorgenia can find itself in a long position, producing more energy than needed to satisfy contracts: in this scenario, Sorgenia aims to sell the surplus energy on the market, benefiting from higher prices to maximize revenue.

These dynamics highlight the critical role of market price fluctuations in balancing positions and optimizing financial outcomes. To address the risks associated with price volatility in energy markets, a hedging strategy involving the calculation of a baseload quantity offers a practical solution. Instead of actively engaging in the spot market with long or short positions, this approach aims to stabilize financial exposure by establishing a fixed production or purchase level that aligns with a predictable average of energy needs or production.

The development of the model and the results of this hedging strategy will be discussed in the next section.

4.2. Model formulation and approach

The purpose of the hedging strategy is to determine the optimal coverage volume for energy production by aligning the ideal production profile, denoted as A, with market index prices, which are variable over the time. In this study, this alignment is carried out on different temporal bases to achieve a stable financial outcome.

As explained at the beginning of the third chapter, the core objective is to optimize the hedging coefficient α, which involves identifying a *baseload* quantity that ensures the total value of energy sold is equivalent to the value that would be obtained if the energy were sold at the average zonal price over the entire period.

This process involves two main steps: determining a single baseload quantity for the entire year, and then calculating a baseload quantity for each month, resulting in twelve distinct values.

By consistently selling the same volume of energy throughout a certain period (a year or a series of months), this strategy seeks to maintain a “zero profit/loss” scenario, where the generated revenues precisely balance the losses; this choice of energy production allows to analyze deviations and understand the reasons why higher or lower values are obtained in certain months, ultimately optimizing the hedging strategy to stabilize financial outcomes.

The baseload represents a constant quantity of energy that, if sold at a fixed average price over a given period, yields the same revenue as the actual production sold at varying prices throughout that period.

In financial terms, the baseload represents a stable and predictable financial foundation, well-suited to market contexts where consistency is prioritized over the volatility of prices and production levels. It acts as a benchmark for estimating the potential revenue an energy facility could achieve under stable market conditions.

However, as highlighted by Klaus Prommersberger and Thomas Weber in [10], hedging in the energy markets introduces complexities due to the need for managing collateral in volatile environments. As energy prices fluctuate sharply, collateral requirements, such as initial and variation margins, become essential in securing hedging transactions. Initial margins are required at the start of a transaction and are adjusted over time to reflect market conditions, while variation margins are paid daily to address changes in the market value of the positions.

These margins serve as a safeguard, especially in the face of price fluctuations, protecting market participants from the risks of defaults and credit exposure, thus allowing energy producers like Sorgenia to navigate the financial volatility while securing stable revenue streams through hedgingessential to recognize that, given the inherent variability in energy production and the fluctuations in market prices, the baseload quantity discussed is purely theoretical.

Indeed, there is no existing product in the energy market that exhibits this precise form or possesses the ability to maintain such a constant production level over time.

Actually, energy generation is influenced by numerous factors, including weather conditions, patterns in market demand, and operational constraints, which result in significant variations in output. Additionally, market prices are subject to constant change based on supply and demand dynamics, regulatory influences, and other economic factors.

Therefore, while the concept of a baseload serves as a useful benchmark for understanding potential revenue and production stability, it does not correspond to any tangible product or service currently available in the energy sector. This theoretical nature highlights the complexities and challenges faced by energy producers, like Sorgenia, in achieving reliable and consistent output in an ever-changing market landscape.

Mathematically, it can be assumed that the baseload is the constant energy quantity defined by E_{baseload}, that meets the following condition:

$$E_{\text{baseload}} \cdot P_{\text{avg}} \cdot T = V_{\text{tot}},$$

where $V_{\text{tot}} = \int_0^T E(t) \cdot P(t)\, dt$ represents the total value of energy produced at variable prices, and P_{avg} is the average price over the period T. Starting from this, it can be easily obtained that

$$E_{\text{baseload}} = \frac{V_{\text{tot}}}{P_{\text{avg}} \cdot T}$$

To determine the baseload quantity, the following steps are performed for each temporal basis, separately for the north and south zones:

1. Calculate the total production value: the total production value, expressed in euros, is obtained by summing the product of price and volume for each period.
$$\text{Total production value } (€) = \sum(\text{price} \cdot \text{volume})$$

2. Calculate the average price: the average price, in euros per megawatt-hour (€/MWh), is calculated by dividing the sum of prices by the number of days.
$$\text{Average price } (€/\text{MWh}) = \frac{\sum \text{price}}{\text{number of days}}$$

3. Determine the energy-equivalent quantity: this quantity, in megawatt-hours (MWh), ensures equivalence between the actual energy value and the hypothetical value at the average price; it is calculated by dividing the total production value by the average price. It
$$\text{Energy-equivalent quantity (MWh)} = \frac{\text{Total production value}}{\text{Average price}}$$

4. Calculate the baseload (MW): at the end, the baseload, expressed in megawatts (MW), is found by dividing the annual or monthly quantity by the respective number of hours in the year or month.
$$\text{Baseload (MW)} = \frac{\text{Energy-equivalent quantity}}{\text{number of hours}}$$

By performing these calculations, a comprehensive understanding of the required baseload quantities is obtained to achieve financial stability across different timeframes and geographical zones.

4.3. Model outcomes

4.3.1 Yearly basis

The baseload for each year is represented in Table 9.

Year	North baseload	South baseload
2021	0.15	0.19
2022	0.18	0.23
2023	0.15	0.19

Table 9: Yearly baseload values

In the north zone, the baseload remains consistent at 0.15 in both 2021 and 2023, with a slight increase to 0.18 in 2022, indicating a temporary rise in energy production during that year.

At the same time, the south zone shows a similar trend with a steady baseload of 0.19 in both 2021 and 2023, but an increase to 0.23 in 2022. This temporary elevation suggests that either production or the baseline energy demand in the south zone was higher in 2022: this is totally influenced by the reasons explained already in the first chapter of this thesis.

These annual figures smooth out the monthly variations and offer a stable baseline for long-term planning.

The higher annual baseload values in the south zone reflect its higher year-round energy demand due to its warmer climate, whereas the north zone is lower and more variable values indicate a moderate overall energy consumption pattern influenced by seasonal heating and cooling requirements.

In terms of business implications, Sorgenia can optimize energy production by prioritizing this robust strategy in the south, such as investing in sustainable energy sources and storage solutions to handle peak loads, while adopting a flexible approach in the north to adapt to seasonal demand variations.

4.3.2 Monthly basis

The monthly baseload values in Table 10 illustrate distinct seasonal fluctuations across the north and south zones from 2021 to 2023, with a consistent trend of higher values in the south: this regional difference reflects the higher and more consistent energy demand in the south, as exposed in the previous section.

In both zones, the baseload values peak during the summer months, particularly in July, where the north reaches up to 0.27 and the south peaks at 0.35, underscoring the increased energy consumption for cooling. Conversely, winter months like December display the lowest baseloads, with values of 0.06 in the north and 0.08 in the south, correlating with a reduced energy demand typical of the cooler season.

Month	**North Baseload**			**South Baseload**		
	2021	**2022**	**2023**	**2021**	**2022**	**2023**
January	0.08	0.10	0.08	0.10	0.08	0.10
February	0.11	0.14	0.10	0.13	0.10	0.13
March	0.15	0.19	0.15	0.18	0.14	0.16
April	0.20	0.26	0.19	0.24	0.19	0.23
May	0.24	0.30	0.23	0.30	0.23	0.29
June	0.28	0.35	0.28	0.35	0.26	0.34
July	0.29	0.36	0.29	0.35	0.27	0.35
August	0.24	0.30	0.23	0.30	0.22	0.29
September	0.18	0.23	0.18	0.23	0.17	0.22
October	0.12	0.15	0.12	0.15	0.12	0.15
November	0.08	0.10	0.07	0.10	0.07	0.09
December	0.07	0.08	0.07	0.08	0.06	0.08

Table 10: Monthly baseload values

The pattern shows that while cooling needs significantly raise the baseload in summer, especially in the south, there is a great influence on smaller price indices during winter in both regions.

Furthermore, 2022 exhibits a noticeable increase in baseload values across most months for both zones, repeating a pattern already observed in the previous analysis: this increase is especially clear in the spring and summer months.

These insights underscore the influence of both seasonal and regional factors on energy production needs. The south's consistently higher baseload highlights the role of climate in driving energy demand, while the seasonal peaks suggest a need for a strategic hedging approach that anticipates these summer demand surges. Particularly in the south, where variability is more pronounced, this approach to hedging can support stable financial outcomes by addressing the unique patterns of energy consumption across both regions.

Year	**North monthly mean**	**South monthly mean**
2021	0.17	0.21
2022	0.21	0.16
2023	0.17	0.20

Table 11: Mean of monthly baseload values

After highlighting the baseload values obtained on both temporal bases, it is possible to draw initial conclusions about the performance of the values obtained from the hedging strategy. Indeed, looking at Table 11, the most striking observation is that the mean of the monthly values never aligns with the corresponding yearly value, besides, it will always be greater. This is due to several factors:

- Monthly values reflect seasonal or periodic fluctuations that the yearly average smooths out, such as higher consumption during certain months due to weather conditions or available solar energy.

- Monthly baseload values are influenced by short-term spikes or peaks in demand that do not appear in the yearly ones.

- The larger number of data points in the yearly calculation smooths out highs and lows, while the monthly averages, based on smaller periods, are more sensitive to these variations, leading to a higher average when compared to the annual figure.

Moreover, exactly half of the months exhibit a higher baseload quantity compared to the average, and the other half has a lower one: this trend is consistent for both the northern and southern regions and it is observed every year. As an example, the year 2022 for the northern region is shown in Figure 15.

The observed pattern reveals that summer months consistently exhibit higher baseload quantities compared to winter months. This outcome reflects the interplay between prices and volumes, which tend to reach higher levels during warmer months in both regions. As a result, the optimized value for baseload quantities is significantly greater during the summer period.

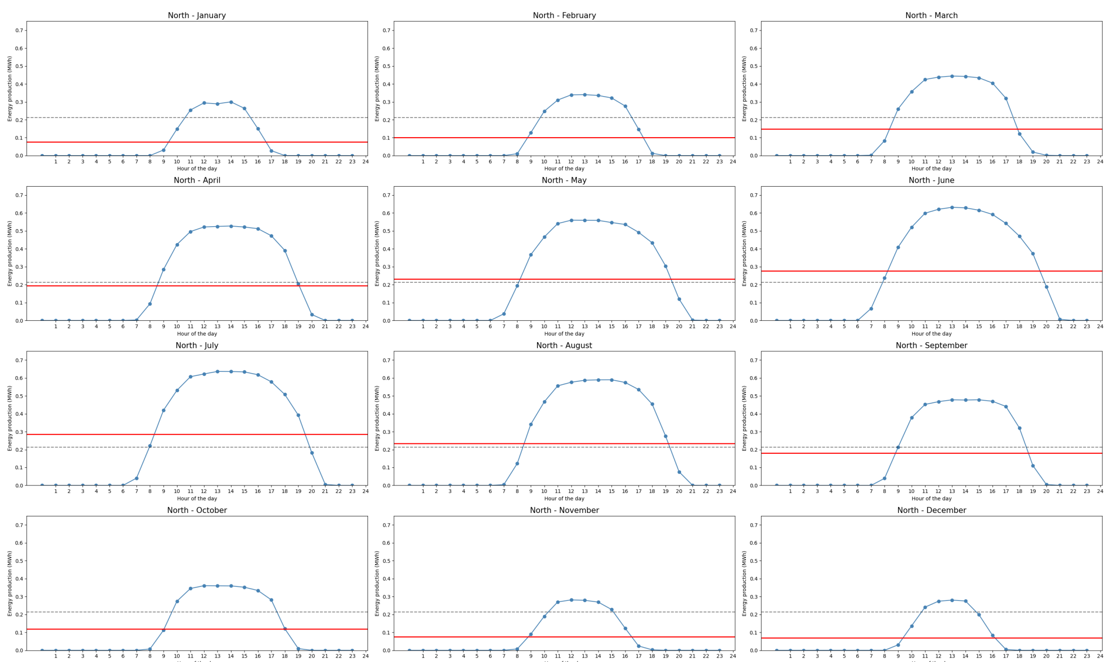

Figure 15: Monthly baseload values

4.3.3 Trends and deviations

Analyzing the deviations of the baseload values found above is crucial for uncovering the factors behind values that diverge from the average. This investigation highlights fluctuations in the data and reveals patterns or anomalies driving these variations.

Another key metric is the weighted average of the baseload, with volumes used as weights: this is given by the sum of the product between the price and the corresponding volumes, over the total sum of the volumes. This provides a more nuanced view of the baseload distribution, accounting for the variation in energy volumes across different months and offering a more accurate reflection of the overall energy consumption patterns for the year.

Several interesting trends emerge from Table 12: in 2021 and 2023 the weighted average of the baseload is relatively similar between the two regions, with the north averaging 110.05 and the south at 107.52, indicating minimal disparity and highlighting a very similar pattern for these two years. In contrast, 2022 saw a significant spike in prices for both regions, with the north reaching 331.24 and the south climbing to 308.84. This sharp increase aligns closely with the events and circumstances of that year, as highlighted in the introduction: it has been a unique anomaly in the pricing trends and, while the general pattern of the north having higher prices remained consistent, external factors in 2022 led to a deviation from this trend.

Year	**Weighted average baseload north**	**Weighted average baseload south**
2021	110.05	107.52
2022	331.24	308.84
2023	115.57	111.19

Table 12: Weighted average of baseload

After that, it could be interesting to observe other measures such as the range and the standard deviation in order to consider the variability of the monthly baseload values.

Table 13 reveals that there were some fluctuations in baseload ranges over the three-year period: as noticed for the weighted average baseload, 2022 stands out as an exceptional year for the north with a greater value of range, indicating more pronounced variability, which could influence operational reserves, and cost management, as unpredictable production spikes must be carefully managed.

The same pattern is evident by looking at the standard deviation, which is higher in 2022 with respect to the other two years, despite the difference is rather narrow.

Conversely, the south, looking at both the statistics, shows its highest variability in 2021 and 2023: again, this is completely consistent with the results founded before.

Year	**North**		**South**	
	Range	**Std Dev**	**Range**	**Std Dev**
2021	0.22	0.08	0.27	0.10
2022	0.28	0.10	0.21	0.07
2023	0.22	0.08	0.27	0.10

Table 13: Range and standard deviation of monthly baseload values

4.4. A possible solution: quarter basis

The comparison between yearly and monthly baseload values has yielded interesting results. However, to enhance the hedging strategy, it could be useful to examine how these values vary on a quarterly basis, dividing each year into broader time periods compared to the monthly intervals.

Therefore, by applying the same calculations as described earlier, the values are presented in Table 14.

Quarter	North Baseload			South Baseload		
	2021	**2022**	**2023**	**2021**	**2022**	**2023**
Q1	0.11	0.11	0.11	0.14	0.14	0.13
Q2	0.24	0.23	0.22	0.30	0.30	0.29
Q3	0.24	0.23	0.22	0.30	0.29	0.29
Q4	0.09	0.09	0.08	0.11	0.11	0.11

Table 14: Quarterly baseload values

Both regions show similar results, as happened in the other measures: the Q1 and Q4 values are consistently the lowest, with the north region maintaining 0.11 in Q1 and even reaching a value of 0.08 in Q4 of 2023; the south region stays around 0.14 in Q1 and remaining at 0.11 throughout the three years. In Q2 and Q3, there is a noticeable increase in values, with the south region consistently showing higher baseload values compared to the north, particularly in Q2 where it peaks at 0.30. This indicates an increased energy demand during the warmer months, particularly in the south, which is consistent with the earlier findings.

Overall, these data reflect again typical seasonal patterns, with a clear increase during the middle of the year and a reduction toward the end, stressing the fact that for all the three years, the quarterly baseload values are higher than the average during the summer and lower during the winter, as happened in the monthly basis.

Year	**North quarterly mean**	**South quarterly mean**
2021	0.17	0.21
2022	0.16	0.21
2023	0.16	0.21

Table 15: Mean of quarterly baseload values

Observing the Table 15, a remarkable result is obtained: once again, there is no match between the mean of the quarterly baseload values and the corresponding value for each year.

Additionally, the mean of the quarterly values is consistently lower than, or at most equal to, the mean of the monthly values. This highlights that monthly averages result in the highest overall baseload values, for the reasons explained in paragraph 4.2.

Given these results, the quarterly basis could be considered a possible solution since it strikes a balance between the monthly and yearly calculations.

Indeed, it offers a compromise between the flexibility of adjusting quantities on a monthly basis, which improves efficiency but also increases costs and time consumption, and the simplicity of the yearly calculation, which lacks the ability to fine-tune production quantities.

This approach mitigates the high costs and time demands associated with monthly adjustments while still allowing for some level of optimization.

Conclusions

This study addresses the challenges associated with the variability of photovoltaic (PV) energy production and its financial implications within the energy market. The hedging strategy proposed by the model developed in this thesis offers a significant solution to managing both the variability of production and the continuous changes in market conditions.

An initial descriptive analysis of hourly data from the northern and southern regions of Italy, covering price indices from 2021 to 2023 and energy production from a sample year (2023), reveals key insights into production trends and price dynamics. These results were instrumental in the subsequent development and implementation of the model.

Energy production follows a bell-shaped daily curve and is notably influenced by significant seasonal fluctuations. The southern region generally exhibits slightly higher overall production levels compared to the north, due to more favorable solar conditions. However, the two regions show similar patterns in terms of both peak production and energy production variability.

As far price indices are concerned, significant volatility is observed, particularly during periods of geopolitical instability, such as in 2022: this volatility is a little higher in the north and underscores the critical importance of hedging strategies in effectively managing financial risks.

A detailed analysis of the ideal production curve detects how the fixed energy production profile is heavily influenced by seasonal variations, with sharp production peaks in the summer and minimal output in the winter. The southern region shows lower variability, but its production peaks are higher compared to the north.

The purpose of the hedging strategy developed in this study is to optimize the hedging coefficient, denoted as α, by identifying a baseload quantity.

This objective has been successfully accomplished by utilizing two time frames: annual and monthly. Each time frame offers distinct advantages and drawbacks.

Annual baseload values are simpler to calculate and less costly, providing a more straightforward solution; however, they lack the flexibility to account for seasonal fluctuations and variations in market conditions. On the other hand, monthly baseload values allow for finer adjustments to reflect these variations, offering more precise alignment with actual production and market prices.

The results show that when comparing the average of the 12 monthly baseload values with the annual baseload value, they will never be identical. Indeed, the monthly baseload values are consistently higher: this is because the monthly values are more sensitive to fluctuations, reflecting the impact of seasonal variations on energy demand and production.

In order to address the trade-offs between the annual and monthly time frames, the most effective solution identified is to adopt a quarterly basis.

This approach provides a balanced compromise, providing the necessary flexibility to adjust for market and seasonal variations, while keeping costs and complexity at manageable levels. It proves to be the most efficient and cost-effective strategy.

This study establishes a framework for managing the risks associated with photovoltaic (PV) production, while also identifying potential areas for future research.

One promising direction would be to extend the analysis over multiple years to gain a deeper understanding of long-term trends in solar irradiation and their impact on production variability.

Additionally, further work could involve developing more advanced hourly simulation models to enhance the efficiency and precision of the existing strategy. This study focused exclusively on price and volume variables, but many other factors, such as weather conditions, geographical variations and technological advancements, also influence PV energy production. Incorporating these factors could complicate the model but would provide a more comprehensive approach to managing production risks.

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List of Tables

List of Figures

Scan here to see the Python script.

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Giunto alla conclusione del mio elaborato, è necessario dedicare alcune parole a coloro che mi hanno aiutato a diventare ciò che sono oggi, 24 anni e due lauree dopo.

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