Empirical Mode Decomposition of wind speed signals

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Abstract

Empirical Mode Decomposition of wind speed signals, by Ines PINTO MOLINA. Master's degree in Electromechanical Engineering - Energy specialization. Academic year: 2022-2023.

Empirical Mode Decomposition (EMD) is a powerful signal processing technique with diverse applications, particularly in the analysis of non-stationary data. In this study, we assess the capabilities of EMD for wind data analysis, aiming to uncover its effectiveness in capturing intricate temporal patterns and decomposing data into Intrinsic Mode Functions (IMFs) to identify crucial frequency components. Various methods of sifting have been studied as the imfs and therefore results may vary according to the type. It has been concluded that the Ensemble Empirical Mode Decomposition (EEMD) is the most suitable method for these data. A comparison with Fourier analysis is also conducted to elucidate the strengths and limitations of each method. Furthermore, this investigation examines the Average Diurnal Variation (ADV) and Average Seasonal Variation (ASV) patterns within the wind data. It is found that these patters have a physical significance and interpretation of the IMFs and that it is easier to use EMD than Fourier for wind signals.

Key words: Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD), Intrinsic Mode Functions (IMFs), Fourier, Average Diurnal Variation (ADV), Average Seasonal Variation (ADV), non-stationarity.

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List of Abbreviations

ADV	Average Diurnal Variation
ASV	Average Seasonal Variation
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
CEEMD	Complete Ensemble Empirical Mode Decomposition
DC	Direct Current
DFT	Direct Fourier Transform
EEMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Mode Decomposition
FT	Fourier Transform
FFT	Fast Fourier Transform
HHT	Hilbert Huang Transform
IA	Instantaneous Amplitude
IF	Instantaneous Frequency
IMF	Intrinsic Mode Function
IP	Instantaneous Phase
itEMD	Iterated Masked Empirical Mode Decomposition
MEMD	Multivariate Empirical Mode Decomposition
MHS	Marginal Hilbert Spectrum
PSD	Power Spectral Density
SAWV	Seasonal Average Wind Speed Variations
STFT	Short-Time Fourier Transform

Chapter 1

Introduction

Energy is a vital resource for humanity. However, this need has led to an irrational use of energy due to constant population growth worldwide, industrialisation and rising living standards in places like China and India [8].

The energy crisis that took place in the early seventies was primarily triggered by geopolitical events, including the oil embargo imposed by the Organization of the Petroleum Exporting Countries (OPEC) on several countries. This event led to a sharp increase in oil prices and highlighted the vulnerability of relying heavily on fossil fuels [9]. Thus, it had far-reaching implications, including economic downturns, inflationary pressures, and disruptions in various industries heavily dependent on oil [10].

Beyond these impacts, energy conflicts reshape geopolitical dynamics, influence foreign policy decisions, and impact global energy security. They emphasize the urgency of pursuing sustainable and renewable energy sources to address resource depletion and climate change risks. By understanding these patterns and implications, policymakers and energy stakeholders can work towards promoting energy diversification, increasing renewable energy adoption, and fostering international cooperation to ensure a more stable and sustainable energy future [11].

Traditionally, fossil fuels have been the main sources of energy, but their intensive use has led to environmental problems such as climate change and air pollution and their reserves are becoming limited. As the negative impacts of fossil fuels become more evident, there is a growing need to transition towards cleaner and more sustainable sources of energy [10]. Renewable energy sources, such as solar, wind, hydroelectric, and geothermal energy, offer a viable solution to reduce our dependence on fossil fuels and mitigate their environmental consequences.

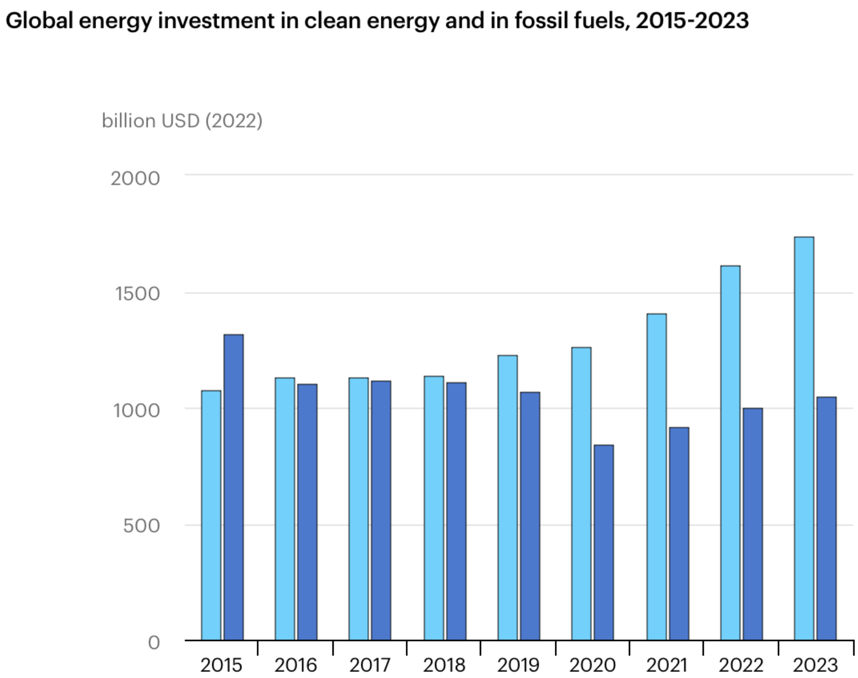

Fig. 1.1: Global energy investment in clean energy and in fossil fuels, 2015-2023 [1]

Moreover, the gas problem in Europe, marked by import dependency and geopolitical conflicts, has given an additional boost the search for more sustainable and resilient energy solutions. The growing demand for gas in Europe has led to increased dependence on external suppliers, exposing European countries to supply risks and price volatility. Political conflicts, such as between Ukraine and Russia, have exacerbated this situation and highlighted the need to reduce dependence on imported gas. [12]. While natural gas has traditionally been considered a cleaner alternative to other fossil fuels, it is important to note that its environmental impact is not negligible. So, this context, renewable energies present a promising alternative [13].

Unlike fossil fuels, renewable sources do not produce significant greenhouse gas emissions during operation, which contributes to combating climate change. They also have the potential for long-term availability, as they rely on naturally replenishing sources. In addition, renewable energy technologies have advanced rapidly, leading to cost reductions and efficiency improvements [12].

The transition to renewable energy requires collective action from governments, businesses, and individuals. It involves investing in research and development, promoting supportive policies, and fostering international collaboration. Renewable energy aligns with sustainability principles and offers a solution to climate change, resource depletion, and environmental degradation. To facilitate the transition, investments in innovation and technology are needed, along with favorable policies and incentives. International collaboration enables the sharing of knowledge and resources and also embracing renewable energy leads to a cleaner and more sustainable energy future [11].

Renewable energy technologies have experienced remarkable advancements and cost reductions in recent years, making them increasingly competitive and economically viable. Technological innovations, research and development, and economies of scale have contributed to substantial reductions in the costs of renewable energy generation, leading to grid parity in many regions. This cost-competitiveness, coupled with supportive policies and incentives, has facilitated the widespread adoption of renewable energies across the globe [14].

Furthermore, exploring and investing in emerging technologies, such as advanced energy storage systems and smart grids, can help address the intermittency and variability challenges associated with renewable energy sources. These technologies can store excess energy for later use and facilitate a more flexible and reliable energy system [13].

Nevertheless, there are different disadvantages and limitations in renewable energies. For instance, their heavy dependence on weather conditions, non-continuity and unpredictability, and the complexity of grid management. Solar and wind power, two major renewable sources, are intermittent and unpredictable, making it difficult to ensure a stable and reliable power grid. This variability can lead to inconsistencies in electricity supply, making it difficult to ensure a stable and reliable power grid [15].

Some renewable sources may have limitations in their ability to produce electricity at scale, such as small-scale hydropower or biomass facilities. Additionally, certain renewable energy conversion processes may exhibit lower energy efficiencies compared to traditional fossil fuel-based power plants, requiring higher resource consumption to generate the same amount of energy [16].

Renewable energy sources also have lower capacity factors, meaning they may not consistently operate at their full potential output, impacting overall energy production efficiency and requiring additional investments in infrastructure. The high cost of electricity production is another common challenge for renewable energy, with operational costs generally lower but initial investment and technology costs higher compared to traditional fossil fuel power plants. The cost of energy production can also vary based on the specific renewable technology and the natural resources available in a region [15].

By embracing renewable energy and reducing reliance on fossil fuels, Europe and the world can mitigate environmental impacts, enhance energy security, and foster a more sustainable and resilient energy future. Continued efforts in research, policy support, and technological advancements are crucial to accelerating the transition and realizing the full potential of renewable energy.

Currently, Belgium is undergoing an energy transition to reduce its reliance on fossil fuels and promote the use of renewable energy sources. While fossil fuels still play a significant role in the country's energy mix, efforts are being made to diversify and adopt cleaner sources [17].

Belgium has traditionally been a net importer of natural gas, relying heavily on imports from neighboring countries such as the Netherlands and Germany. However, the country is working to diversify its supply sources and reduce its dependence on imported natural gas. Investments are being made in storage infrastructure and the development of liquefied natural gas (LNG) terminals to enhance supply flexibility and security [18].

In terms of renewable energy, Belgium has made progress in its development. Wind and solar energy are the prominent renewable sources in the country. Belgium has invested in both onshore and offshore wind farms and has encouraged the installation of solar panels on buildings and public spaces. Additionally, hydroelectric and biomass projects are being pursued to further diversify the energy mix and promote a transition to more sustainable sources [19].

Other energy sources in Belgium include nuclear energy and energy derived from waste. The country has five nuclear power plants that have been a significant part of its electricity supply for decades. However, Belgium has plans to gradually reduce its reliance on nuclear energy and replace it with renewable sources [20].

In terms of policies and regulations, Belgium has implemented measures to incentivize renewable energy, such as feed-in tariffs and green certificate schemes that promote the production and consumption of renewable energy. The Belgian government has also set ambitious targets to increase the share of renewable energy in the country's energy mix [18].

1.1 Content

The remainder of this chapter will focus on analysing the state of the art and where the wind measurements have been obtained from. Chapter 2 explains the methodology of the thesis, which mainly deals with the Empirical Mode Decomposition algorithm and the Intrinsic Mode Functions that will be used to perform the comparison. It also explains the Fourier, Hilbert-Huang Transform, carried out using Python. Then, Chapter 3 describes all the results obtained in the project, dividing the analysis into the different parts analysed. Finally, Chapter 4 shows the conclusions drawn from the elaboration of the thesis and proposes future work to continue the analysis.

1.2 State of art

Wind energy has gained global attention over the years due to its low cost and environmental benefits. Extensive research and engineering efforts have significantly improved various aspects of wind energy, including wind farm management and maintenance, wind resource estimation, layout optimization, and turbine design. The development of offshore wind energy has also been noteworthy, with successful implementation of economically and technically viable wind farms [21].

Globally, wind energy is growing steadily. According to the International Energy Agency (IEA), the world's installed wind power capacity will reach 107 GW at the end of 2023 [22]. Europe is leading the way in wind energy adoption, with countries such as Germany, Spain and the UK at the forefront. China has also experienced rapid growth in the wind sector and has become the country with the largest installed wind power capacity globally [23].

In Belgium, there has been substantial support and focus on wind energy in recent years. The government has implemented policies and incentives to encourage wind energy project development. Onshore and offshore wind farms have been established along the Belgian coastline and in suitable inland areas. Belgium has effectively utilized its favorable wind resources, especially in the North Sea, to expand its offshore wind capacity [24]. Prominent offshore wind farms like C-Power, Thorntonbank, Norther, and Rentel have made significant contributions to the country's wind energy generation [25]. Additionally, onshore wind farms have been developed in various regions of Belgium.

These initiatives align with Belgium's ambitious renewable energy and climate targets, which aim to increase the share of renewable energy and reduce greenhouse gas emissions. The country actively supports research, innovation, and collaboration in wind energy to optimize turbine technology, enhance energy production, and advance wind farm design and operation. Overall, Belgium is making significant progress toward a sustainable and low-carbon energy future through its focus on wind energy and other renewable sources [26].

However, the intermittent and non-stationary nature of wind energy, characterized by fluctuations in wind speed and wind direction presents significant challenges to power system dispatching operations and power quality [27]. These challenges have slowed the growth of wind power. Both effective wind power prediction and forecasting can address these issues by reducing the need for excess capacity and operating costs in the power system. Furthermore, accurate wind power prediction can help mitigate the adverse impacts of wind energy on the power grid, thereby improving the competitiveness of wind generators and increasing the installed capacity of wind power. By utilizing modeling and statistical analysis techniques, short-term and long-term patterns of wind energy generation can be predicted. This assists grid operators in planning the integration of wind energy into the electrical grid, optimizing generation scheduling, and ensuring a reliable and stable energy supply [28].

Non-stationarity in data, reflecting changes over time, is vital for accurate forecasting. Understanding its sources, like economic fluctuations or weather events, helps build adaptable models for more precise predictions. Additionally, the role of synthetic data can bridge gaps in limited historical data or introduce hypothetical scenarios, enhancing our models and enabling more robust forecasts.

Accurate wind measurements play a crucial role in various aspects of wind energy applications, including wind forecasting and wind power generation. To ensure precise input measurements are essential for advanced forecasting models that aid in predicting wind speed and direction, thereby enabling effective grid management and energy production scheduling

1.3 Wind measurements

Wind measurement, both in terms of speed and direction, plays a fundamental role in the field of wind energy. It is especially relevant in work and research focused on this field.

When it comes to measuring wind speed, instruments called anemometers are used to collect data on wind speed and direction at different heights and locations within a wind farm. This is because wind speed and direction can vary depending on the height and the presence of nearby obstacles. Therefore, it is common to take measurements at ground level, at the average height of wind turbines and also at higher altitudes using meteorological towers.

These devices allow the wind speed to be quantified accurately. There are different types of anemometers, from the more traditional ones with cups or pressure transducers, to the more advanced ones using laser technology such as LIDAR. Wind vanes or directional anemometers are used to measure wind direction. These devices help us to determine which way the wind is blowing [29]. This data is used to assess the quality and availability of the wind resource and identify wind patterns to determine the best locations for future installations or to access the performance of wind turbines.

Measurement accuracy and quality are crucial for producing dependable results. This can be impacted by a number of variables, including the terrain in the area, nearby barriers, and bad weather. In order to ensure the measuring equipment's proper operation and the collection of accurate data, it is required to perform routine calibration and maintenance on them.

Fig. 1.2: Types of anemometers [2]

Enhancing the accuracy of wind data prediction has been the focus of extensive research. In the past, wind prediction primarily relied on physical and statistical methods [30] based on numerical weather prediction (NWP) and taking into account the manufacturer's power curves, which could mitigate the lack of historical data [31]. However, with the rapid advancements in computational techniques and machine learning, more sophisticated and intelligent prediction models, including artificial intelligence methods, have emerged.

Nowadays, there is a set of design criteria called IEC 61400 standard and it ensures the robust design and the durability of wind turbines against potential hazards throughout their anticipated lifespan. This standard exerts its influence across a spectrum of turbine life phases, spanning from pre-construction site assessments to the testing, assembly, and operational stages of turbine components [32].

Wind turbines are meticulously designed to withstand specific environmental conditions. During the planning and construction phases, assumptions are formulated regarding the prevailing wind patterns that the turbines will encounter. A measure of the typical wind variability is over a 10-minute span in order to avoid leakage [32].

1.4 Wind forecasting

Wind prediction has undergone significant development over time, driven by advancements in technology, more sophisticated mathematical models, and greater availability of data. From collecting historical wind speed and direction data to state-of-the-art numerical models and the use of statistical and machine learning techniques, wind prediction has evolved to provide more accurate and reliable forecasts [28].

Hence, the incorporation of pre- and post-processing techniques has played a crucial role in improving prediction accuracy. By processing the data before prediction or refining the results afterward, researchers have achieved even higher levels of accuracy [33].

Collectively, all these techniques have significantly increased the accuracy and reliability of wind data prediction. These advances are essential to meet the growing demand for more accurate and reliable wind forecasts.

In the early days, simple mathematical models based on empirical relationships and simplified assumptions were used. However, with advancements in computing power and calculation capabilities, more sophisticated numerical models were developed, capable of simulating atmospheric dynamics and predicting wind behavior with greater accuracy. These models take into account multiple atmospheric variables and utilize complex differential equations [34].

With improved computing capacity, it became possible to increase the spatial and temporal resolution of numerical models, allowing for a more precise representation of local and regional atmospheric phenomena. Additionally, real-time observation data from advanced technologies such as Doppler radars and weather satellites were incorporated to enhance short-term prediction accuracy [28].

In recent years, statistical and machine learning techniques have also been employed to further improve wind prediction accuracy. These techniques enable the identification of patterns and trends in large datasets, contributing to more reliable and precise forecasts.

Since wind changes significantly with time and height, wind resource evaluation, modeling, and forecasting are helpful tools for understanding wind speed fluctuation behavior as well as for calculating the energy yield output of wind turbines. Thus, in order to produce energy at the lowest possible cost, wind speed, and direction predictions must be accurate [35].

Its function in grid management is another important component. Since wind energy is a variable energy source, accurate wind signal forecasts allow grid operators to foresee variations in wind generation and take the necessary action to efficiently balance electricity supply and demand [36].

Infrastructure planning is another aspect to consider. Whether it is determining the optimal locations for wind farms, constructing buildings and structures that can withstand wind forces, or planning transport routes for the aviation and maritime sectors, accurate wind forecasts are essential as they help to assess risks, make informed decisions and ensure the safety and efficiency of these infrastructures [35].

Another reason could be natural disaster management. These serve to better prepare for and respond to events such as hurricanes, tornadoes, and severe storms. This helps minimize risks to life and property, aids evacuation planning, and facilitates effective disaster management [36].

Depending on the prediction period and the main reason, different research has been done on wind speed/power prediction. Numerous scientific publications have reported on various time-scale horizons. The time frames used to predict wind speed span from minutes to days.

The different wind speed and wind power forecasting techniques are grouped into very short, short, medium, and long-term methods, as shown in table 1 [7].

Time Horizon	Range
Very short-term	Few seconds to 30 minutes ahead
Short-term	30 minutes to 6 hours ahead
Medium-term	6 hours to 1 day ahead
Long-term	1 day to 1 week or more ahead

Table 1.1: Wind Speed Prediction Time Scale [7]

- Very short-range forecasting: Its primary use is for clearing the electricity market and taking regulatory action. With this method, wind speed/power values can be predicted from a few seconds to thirty minutes in advance.

- Short-range forecasting: The main goal of short-term wind speed forecasting is to deploy the power output of wind turbines to quickly satisfy customer demand. From a few seconds to thirty minutes in advance, the time scale is available.

- Medium-range forecasting: The forecasting time frame ranges from six hours to one day in advance. It is used for wind generator on/off decisions, operational security, and electric market objectives.

- Long-range forecasting: The long-term forecasting prediction period extends from one day to one week in advance. This kind of wind forecasting is mostly utilized for unit commitment decisions and turn-around maintenance scheduling.

In wind forecast, there are several techniques commonly used. One widely used technique is Numerical Weather Prediction (NWP), which employs mathematical models to simulate atmospheric behavior and forecast weather conditions, including wind patterns. NWP models incorporate data from various sources, such as satellite observations and ground-based measurements. By employing complex algorithms, they can predict wind patterns over a specific time period [28].

Another approach is the utilization of Machine Learning (ML) algorithms, including regression models, decision trees, random forests, support vector machines, and neural networks. These algorithms learn from historical wind data and relevant features to make future wind predictions. They identify patterns and relationships in the data, enabling them to forecast wind behavior accurately [37].

Statistical methods, such as ARIMA, AR, and STL, are also commonly employed for wind prediction. These methods analyze historical wind data using statistical techniques to forecast future wind conditions. They examine the statistical properties of the data and employ fitting and extrapolation methods to make predictions [38].

In addition, time series analysis techniques, such as Fourier analysis, wavelet analysis, and spectral analysis, help identify periodic patterns and frequencies within wind data. These techniques provide insights into the temporal behavior of wind, facilitating predictions based on the identified patterns [38].

Ensemble modeling is another effective approach that combines multiple prediction models or techniques to improve the accuracy of wind forecasts. By combining forecasts generated by different models and weighting them based on their performance or expertise, ensemble models create more robust and reliable predictions [34]..

Physical models, such as Computational Fluid Dynamics (CFD) models and Weather Research and Forecasting (WRF) models, simulate the physics of atmospheric processes and their effects on wind patterns. These models take into account factors such as terrain, atmospheric stability, and boundary conditions to simulate and forecast wind behavior accurately [34].

Furthermore, hybrid approaches integrate multiple techniques, leveraging the strengths of different methods to improve prediction accuracy. For example, combining NWP outputs with machine learning or statistical models can lead to more robust wind predictions [37].

The choice of technique depends on various factors, including data availability, computational resources, application requirements, and the specific characteristics of the wind prediction problem. It is essential to consider domain expertise and ongoing research to advance wind prediction techniques and achieve more accurate forecasts.

Another wind forecasting technique is the Empirical Mode Decomposition. It decomposes the time series of wind data into intrinsic mode functions (IMFs). These IMFs represent different oscillatory components with varying time scales. By analyzing each IMF obtained from the EMD decomposition, it is possible to capture different frequency components of the wind signal and understand various short-term and long-term variations [39].

1.5 Non-stationarity and non-linearity

Non-stationarity and non-linearity are important concepts in the field of signal processing. Both of these properties can significantly impact the analysis and modeling of various types of signals.

Wind exhibits significant variability over time, both on a daily and seasonal basis. Throughout the day, wind speed and direction change due to solar heating and temperature gradients in the atmosphere. Diurnal variations, like sea breezes during the day and land breezes at night, influence the wind energy potential at different times. Additionally, seasonal changes, influenced by the Earth's axial tilt and solar heating patterns, lead to stronger winds in some regions during winter and weaker winds in summer [40].

The temporal variations in wind energy reflect non-stationarity and non-linearity in renewable energy analysis. Non-stationarity arises from dynamic atmospheric conditions and solar heating, causing statistical properties of wind data to vary over time. Non-linearity comes into play when the relationship between wind speed and energy production deviates from a linear pattern due to aerodynamic limitations [41].

To deal with non-stationary signals, various methods have been developed. One commonly employed technique is time-frequency analysis, which provides a representation of how the frequency content of a signal changes over time. This includes methods such as the Fourier Transform (FT) or the Wavelet Transform [42].

Another approach is adaptive filtering, where the filter parameters adjust dynamically to track the changes in the signal. Adaptive filters employ algorithms like the Least Mean Squares (LMS) and Recursive Least Squares (RLS) to update their coefficients based on the input signal's characteristics. These adaptive filters can be useful in applications such as noise cancellation, echo cancellation, and channel equalization, where the signal's properties change over time [42].

On the other hand, non-linearity refers to a system or signal whose output is not directly proportional to its input. In non-linear systems, the output exhibits behaviors such as distortion, amplitude modulation, frequency mixing, and generation of harmonics [43]. Non-linearities can arise due to various factors, including saturation, memory effects, and interactions between different components of the system.

In addition to the methods mentioned earlier, Empirical Mode Decomposition is another powerful technique used to analyze non-stationary and non-linear signals. EMD is a data-driven and adaptive method that decomposes a signal into intrinsic mode functions (IMF's) based on its local characteristics [39].

Moreover, wind signals can exhibit non-linear characteristics due to the complex interactions between air masses, terrain, and atmospheric conditions. Non-linear effects can manifest as amplitude modulation, frequency mixing, and the generation of harmonics in wind signals [44]. EMD is particularly effective in capturing non-linear behavior as it adaptively decomposes the signal into IMF's that can reveal the non-linear dynamics inherent in wind fluctuations [39].

Furthermore, machine learning algorithms, such as artificial neural networks, support the analysis and modeling of non-linear systems. Neural networks can approximate complex non-linear mappings by learning from training data. They have shown promising results in various fields, including speech recognition, image processing, and control systems [45].

Both non-stationarity and non-linearity can occur in a wide range of signals. In audio processing, non-stationary signals may include speech, music, or environmental sounds, where the characteristics of the signal change over time. In image processing, non-stationarity can arise in videos or dynamic scenes. Non-linear systems can be encountered in electronic circuits, communication channels, control systems, and many other domains where non-linear effects play a significant role.

1.6 Synthetic wind dataset

Synthetic data in wind signals refers to artificially generated wind datasets that replicate the statistical and temporal characteristics of real-world wind behavior [46]. It is created to supplement or replace limited or unavailable real wind measurements and is particularly useful for research, modeling, and testing purposes. Moreover, synthetic data can be generated through various methods, including numerical weather models, statistical models, and data-driven simulations. These techniques aim to produce wind signals that closely resemble the behavior of actual wind but provide more flexibility and control over the generated data [47].

On one hand, numerical weather models utilize complex mathematical equations and computational algorithms to simulate atmospheric processes and generate synthetic wind patterns. These models incorporate meteorological variables such as temperature, pressure, humidity, and terrain features to estimate wind speed and direction. By running the model with specific inputs and parameters, synthetic wind data can be generated for desired locations, time periods, and atmospheric conditions [48].

Furthermore, statistical models employ statistical properties and distributions derived from real wind data to generate synthetic wind signals. These models capture the statistical characteristics, such as mean, variance, and correlation, and produce synthetic wind data that exhibits similar statistical properties. They are particularly useful when historical wind data is available and can be used to simulate wind conditions in regions or time periods without recorded measurements [47].

And then, data-driven simulations involve analyzing and extracting patterns from existing wind data and using them to generate synthetic wind signals [48]. Techniques such as time-series analysis, Fourier analysis, or machine learning algorithms can be employed to capture the temporal and spectral characteristics of real wind signals. Based on these extracted patterns, new wind data can be synthesized, either by extrapolating existing data or generating new instances that closely resemble the original behavior [46].

In the pursuit of generating high-fidelity synthetic wind data, a comprehensive understanding and characterization of non-stationarity becomes imperative. This ensures that the synthetic data accurately reflects the dynamic and evolving nature of wind patterns.

1.7 Cabauw Experimental Site for Atmospheric Research

The data analyzed in this study were obtained from the KNMI mast situated on the KNMI meteorological research site near Cabauw in the Netherlands. CESAR, the Cabauw Experimental Site for Atmospheric Research, is the Dutch hub for collaboration on atmospheric research and climate monitoring and is used for studying atmospheric and land surface processes for climate modeling. It serves as a validation site for space-borne observations and atmospheric models, as well as for the development and implementation of new measurement techniques [49].

The KNMI mast at Cabauw is a 213-meter tall structure specifically designed for meteorological measurements. It is operated by the Royal Netherlands Meteorological Institute (KNMI) to collect atmospheric and meteorological data. Equipped with a variety of instruments and sensors, the mast enables measurements of parameters such as temperature, humidity, atmospheric pressure, wind speed, and wind direction, among others [50].

In this context, the collected data on wind measurements are utilized to analyze wind speed and direction within the Cabauw region and its surroundings. This information proves vital for scientists and meteorologists engaged in climate and meteorological studies in the Netherlands, providing them with detailed insights into local and regional wind patterns.

Wind speed and wind direction are measured using specific instruments at multiple levels on the KNMI mast at Cabauw. At six different heights —10 m, 20 m, 40 m, 80 m, 140 m, and 200 m- wind speed is measured using cup anemometers, while wind direction is determined using wind vanes [51]. To avoid interference, special care is taken at specific levels. For levels 40 m, 80 m, 140 m, and 200 m of the KNMI mast, there are three booms for wind direction measurement and two booms for wind speed measurement. The selection of the appropriate boom depends on the prevailing wind direction. At levels 10 m and 20 m, wind direction and wind speed are measured using smaller masts situated near the main KNMI mast. These include the ‘B-mast,’ located 30 m southeast of the KNMI mast, and two ‘C-masts’ positioned 70 m and 140 m northeast of the KNMI mast for wind measurements at 20 m and 10 m heights, respectively. The selection of the specific mast for measurements also depends on the wind direction [3].

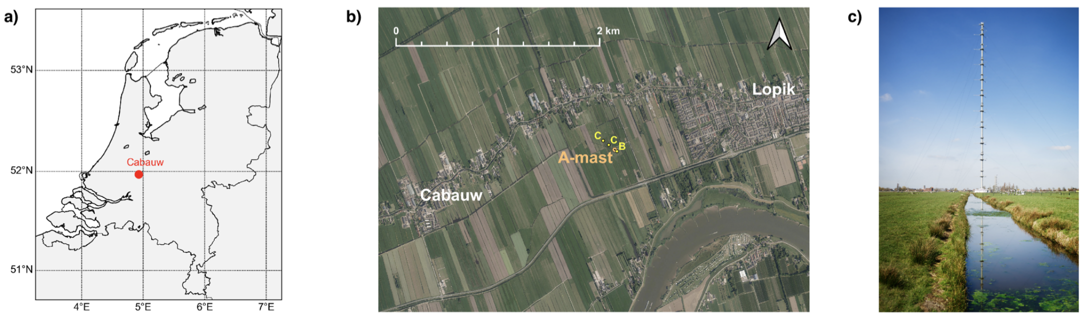

Fig. 1.3: (a) Map of the Netherlands with the Cabauw site indicated. (b) Aerial image of the site indicating the locations of the masts. (c) The 213-m tall A-mast. [3]

These measurement setups and precautions make it possible to collect precise and dependable wind data at various heights, which helps to improve understanding of wind patterns and other meteorological phenomena in the Cabauw region.

The Cabauw area experiences prevailing winds that typically blow from the west to southwest. These winds are influenced by the prevailing westerly winds prevailing in the North Sea region. They are commonly associated with weather systems and frontal activity that originate in the Atlantic Ocean and move towards the European continent [52].

Wind data in the Cabauw area is generally considered to be non-stationary. This means that the characteristics of the wind, such as wind speed and direction, exhibit variability and change over time. The non-stationarity is mainly due to the influence of various factors, including diurnal cycles, seasonal variations, weather systems, and local topography [53].

The wind patterns can vary significantly throughout the day, as well as across different seasons. For example, wind speeds may be higher during certain times of the day or during specific seasons, while they can be relatively calmer at other times. Additionally, the direction from which the wind blows can also fluctuate, influenced by weather patterns and the proximity to the North Sea [54].

While there may be some statistical properties of the wind data that exhibit stationarity over shorter time scales or under specific conditions, the overall nature of wind data in Cabauw is characterized by its non-stationary behavior.

1.8 Objectives

In this study, the aim is to assess the capabilities of Empirical Mode Decomposition for wind data analysis. By applying EMD to the wind signals, we aim to explore its effectiveness in capturing non-stationary patterns and decomposing the data into Intrinsic Mode Functions to identify important frequency components. Additionally, we will compare the results obtained from EMD with those obtained from Fourier analysis to gain insights into the strengths and limitations of each method.

Thus, the work is divided into sub-objectives:

1. Select the appropriate type of sifting method to ensure proper application of Empirical Mode Decomposition for extracting Intrinsic Mode Functions from wind data.
2. Analyze the obtained Intrinsic Mode Function and their associated trend to identify distinct temporal patterns and frequency components in the wind signals.
3. Present a detailed comparison between the results obtained using Empirical Mode Decomposition and those obtained using the Fourier transform.
4. To analyse the characteristics of the diurnal and seasonal mean variations in wind speed signals using EMD.

Chapter 2

Data & Methods

This chapter will explain the whole process of analysis of the Cabauw under the EMD algorithm. Firstly, a case description will be presented, defining wind speed and wind direction. Preprocessing the data using the empirical mode decomposition, with which the data are decomposed into a number of intrinsic mode function components, is the first step. Then, the energy-frequency-time distribution known as the Hilbert Huang spectrum, from which the time locations of events will be retained, is created by applying the Hilbert transform. In addition, Fourier will also be described since the main objective of the work is to compare both methods.

2.1 Case description

The dataset provided contains detailed wind measurements spanning a period of 20 years, from 2001 to 2020, including both wind speed and wind direction, 1 second sampling and averages over 10 minutes (i.e. 600 values) are stored. To carry out the analysis, all the data will be worked with using Python. As the total number of measurements is very large, a table with the total averages per year for each height is proposed.

The KMI-mast used for data collection measured wind characteristics at various heights 10 m, 20 m, 40 m, 80 m, 140 m, and 200 m as is seen at table 2.1. This diverse range of heights allowed us to gain a comprehensive understanding of the vertical profile of wind behavior throughout the entire study period. However, it's important to note that we had to exclude the data recorded at the 2 m height from our analysis due to the lack of valid values.

	wspd200	wspd140	wspd80	wspd40	wspd20	wspd10
time						
2001	8.465	7.829	6.798	5.617	4.775	4.163
2002	8.762	8.112	7.075	5.899	5.038	4.426
2003	8.086	7.509	6.511	5.371	4.513	4.426
2004	8.515	7.914	6.901	5.764	4.904	4.272
2005	8.259	7.702	6.689	5.548	4.669	4.072
2006	8.657	8.023	6.972	5.799	4.944	4.324
2007	8.768	8.103	7.069	5.882	4.968	4.284
2008	8.847	8.133	7.132	5.949	5.056	4.389
2009	8.521	7.851	6.820	5.618	4.742	4.106
2010	7.832	7.291	6.376	5.258	4.429	3.840
2011	8.588	7.936	6.959	5.781	4.917	4.263
2012	8.361	7.702	6.759	5.611	4.774	4.129
2013	8.379	7.779	6.778	5.644	4.805	4.193
2014	8.413	7.798	6.771	5.584	4.740	4.122
2015	8.945	8.275	7.179	6.002	5.109	4.446
2016	8.097	7.535	6.559	5.446	4.593	3.972
2017	8.211	7.609	6.620	5.497	4.623	4.001
2018	8.307	7.722	6.709	5.516	4.659	4.029
2019	8.478	7.904	6.856	5.655	4.774	4.110
2020	8.819	8.204	7.159	5.998	5.120	4.461

Table 2.1: Yearly wind speed average in m/s for each height.

This study has been carried out with data obtained at a height of 80 m. In order to present the average variations of these velocities over the years, figure 2.1 is presented.

Fig. 2.1: Yearly wind speed average in m/s.

The mean and seasonal diurnal variation over the years has also been plotted for the same height.

It can be seen that the diurnal pattern is a function of the hours of the day. From 10 am onwards, the wind speed starts to increase until midday when it remains more or less stable, around 6.9 m/s - 7 m/s until 5 am the following day when it decreases again. This factor could be associated with sunrise, as the wind is lower during the hours when the sun starts to rise. Actually, the differences are not very large as the speed range is between approximately 6.4 m/s and 7 m/s.

When analysing the ADV, pronounced variations in wind speed are observed throughout the day, mainly driven by the diurnal cycle of solar heating and cooling. However, these variations are not perfectly sinusoidal. Instead, they may contain higher frequency components that deviate from a pure sinusoidal shape.

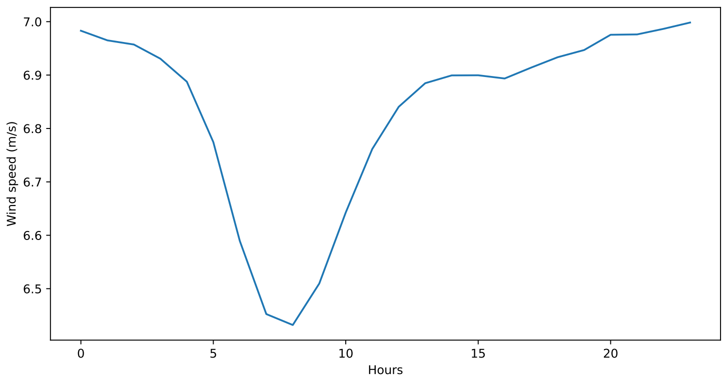

Fig. 2.2: Average diurnal variation of wind speed in m/s at 80 m.

The same happens for seasonal variation. During the winter months wind speeds are higher than in the summer months. One of the factors is that wind speed and solar radiation are interrelated, both of which are influenced by local and regional weather patterns.

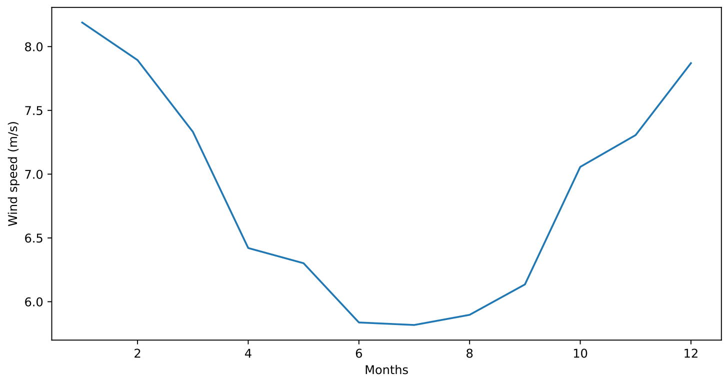

Fig. 2.3: Average seasonal variation of wind speed in m/s at 80 m.

2.2 EMD Algorithm

N.E. Huang [39] introduced the Empirical Mode Decomposition (EMD), a nonlinear analysis tool for complex, non-stationary time series. EMD, when combined with Hilbert spectral analysis, is referred to as Hilbert-Huang Transform (HHT). It decomposes non-stationary time series adaptively and locally into Intrinsic Mode Functions (IMFs), which are zero-mean amplitude and frequency-modulated components. Furthermore, the Hilbert spectral analysis of intrinsic mode functions provides frequency information evolving with time and quantifies the amount of variation due to oscillation at different time scales and time locations [55]. Unlike traditional Fourier or wavelet decompositions, EMD is fully data-driven and does not require a predefined basis system [56].

EMD has the property of perfect reconstruction, meaning that combining all extracted IMFs with the residual slow trend can reconstruct the original signal without loss or distortion of information. However, interpreting the IMFs is not as straightforward as in traditional decompositions. It can be challenging to identify and combine the IMFs in a meaningful way to obtain physically meaningful components.

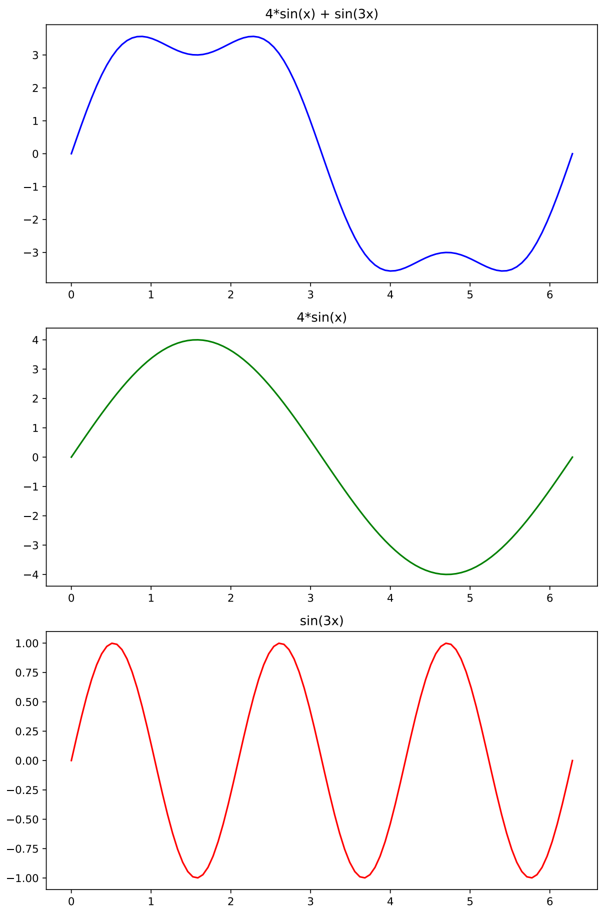

Fig. 2.4: How the EMD works [4].

Additionally, if partial reconstruction is desired, the decision to include or exclude specific IMFs is binary and not based on an optimality criterion [57]. But to be considered valid an IMF, it must meet the following conditions [58]:

a) The number of over shootings and the number of zero crossings in the total data set must be equal or differ by at most one.

b) The mean of the upper and lower envelopes defined by the local maxima and local minima, respectively, must be zero at any point or at least, close to zero.

Considering the signal as $y(t)$ the Empirical Mode Decomposition of any signal can be applied using the following steps [59].

Step 1. Initialize the algorithm.

- Start with $y(t)$ as the input.

Step 2. Perform the sifting proces.

- Apply the sifting process to $y(t)$ to extract the first IMF. It is explained in section 2.3.

Step 3. Obtain the first IMF

- The first IMF is obtained after doing the convergence of the sifting process.

Step 4. Calculate the residual.

- Subtract the extracted IMF from the input signal to obtain a residual signal.
- The residual represents the components of the signal that have not been captured by the extracted IMF.

Step 5. Repeat steps 2-4.

- Repeat the process by applying the sifting process to the residual signal to extract the next IMF.
- Iterate this step until the stopping criterion is met, which can be based on the number of IMFs desired or the characteristics of the residual.

Step 6. Determine the final trend.

- The last remaining component after extracting all the IMFs is considered the final trend of the signal or the residual.
- The trend represents the low-frequency or long-term behavior of the original signal.

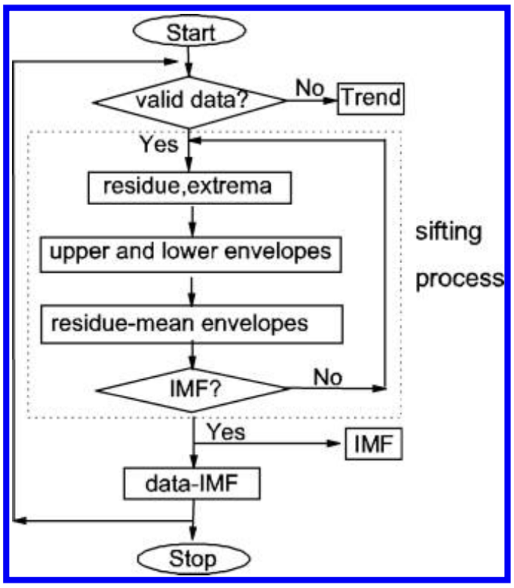

Fig. 2.5: The flow chart of the decomposition process of EMD [5].

This method has become a valuable tool in diverse fields of study, and its application has been the subject of numerous research investigations of complex and non-stationary time series. In engineering and environmental sciences, EMD is used for the analysis of meteorological and air quality data. EMD enables the identification of variability patterns and trends in climate variables such as wind speed, temperature, and pollutant concentrations [60]. These analyses are crucial for understanding atmospheric phenomena, climate modeling, and air quality assessment.

The Empirical Mode Decomposition (EMD) algorithm has undergone several innovations and improvements to enhance its performance and address its limitations. Ensemble Empirical Mode Decomposition (EEMD), Complementary Ensemble Empirical Mode Decomposition (CEEMD), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) are ensemble-based approaches that aim to overcome the limitations of EMD, such as mode mixing and sensitivity to noise [61]. These methods involve generating multiple decompositions by introducing noise or applying complementary operations to improve the accuracy and robustness of the decomposition results [54].

Multivariate Empirical Mode Decomposition (MEMD) extends the concept of EMD to handle multivariate or multidimensional signals. It allows for the decomposition of signals with multiple variables or channels, taking into consideration the interdependencies among them. MEMD provides a way to extract intrinsic modes and their variations in a multivariate dataset [62].

2.3 Sifting process

The main idea behind the method is to iteratively detect the intrinsic mode functions in the data based on their characteristic time scales, and then breakdown the data accordingly [39]. Starting from the fastest and through to the very slowest until only a non-oscillatory trend is left [63]. A systematic way to extract them, designated as the sifting process, is described as follows [64], [39], [65].

Step 1. Identify the local extrema of $y(t)$.

Step 2. Generate the upper and lower envelopes.

- Using all the identified local extrema with an interpolation method, (e.g., cubic spline interpolation) to generate the upper and lower envelope, $y_{\mathrm{up}}(t)$ and $y_{\mathrm{low}}(t)$ respectively.

Step 3. Calculate the mean envelope $m(t)$ from the upper and lower envelopes.

- The mean envelope is obtained by calculating the mean of the upper and lower envelopes, $m(t) = [y_{\mathrm{up}}(t)+y_{\mathrm{low}}(t)]/2$. Then subtract it from the signal to obtain a detailed component $d(t) = y(t)$ - $m(t)$.

Step 4. Stopping criteria.

- A criterion for the sifting process is defined to terminate such that the IMF components preserve sufficient physical awareness of both amplitude and frequency modulations.

- Check whether $d(t)$ is an IMF. If $d(t)$ is an IMF, $c(t) = d(t)$ and meantime replace $y(t)$ with $r(t) = y(t)$ - $c(t)$. Otherwise, replace $y(t)$ with $d(t)$ and repeat steps 1, 2 and 3 until the following termination criteria is satisfied.

$$\sum_{t=1}^{l} \frac{[d_{\text{j-1}}(t) - d_{\text{j}}(t)]^2}{[d_{\text{j}}(t)]^2} \leqslant \delta(j = 1, 2, ...; t = 1, 2, ..., l) \tag{2.1}$$

Being δ a value between 0.2 and 0.3, j the number of iterative calculation and t the length of the signal.

Step 5. Repeat the process.

- The sifitng process, including the stopping criteria, is repeated until all the IMFs and the residual are obtained.

Finally, the original series $y(t)$ can be decomposed as follows:

$$y(t) = \sum_{i=1}^{n} c_{\text{i}}(t) + r_{\text{n}}(t) \tag{2.2}$$

Being $c_{\text{i}}(t)$ the different IMFs and $r_{\text{n}}(t)$ the final residual, which can be either the mean trend or a constant.

In the following picture an example of the sifting process and how the IMF's look like is showed.

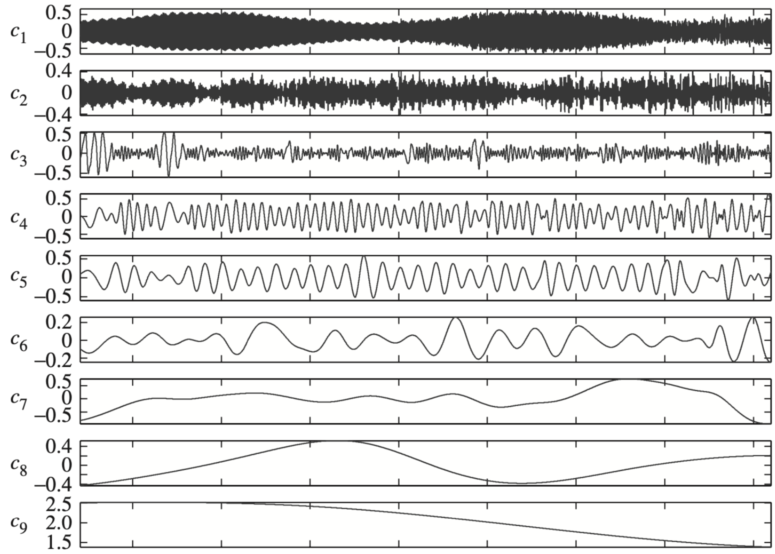

Fig. 2.6: An example of the different Intrinsic Mode Functions from a given signal after the application of the sifting process [6].

Notice that the last component is not an IMF but represents either the mean trend or a constant. In some cases the last resulting component may be a constant, also known as the residual or low frequency component [39]. This residual component typically does not contain significant information and does not contribute substantially to the signal analysis. However, it is important to note that there some cases where the residual component may contain relevant information, particularly when working with complex or noisy signals [6]. In such cases, the residual component might capture certain characteristics or patterns that are of interest for the analysis. Therefore, it is necessary to exercise caution and consider the specific context and characteristics of the signal when deciding whether to discard or retain the residual component. This would be the case for the trend as it is also considered the last component and which represents the part of the signal that shows a smooth and gradual variation over time. This component can be a linear or non-linear function that captures the general direction of the signal [66]. Even though, in some cases, the trend may be significantly larger in magnitude than the fluctuating components, which may cause the trend to dominate the signal and make it difficult to identify more subtle or rapid variations. This can be problematic if the objective of the analysis is to examine and understand the high frequency fluctuations and modulations present in the signal [39].

Mode Mixing

Mode mixing is a significant challenge and has been extensively studied due to its impact on the accuracy of the decomposition. It occurs when an IMF resulting from EMD decomposition contains components of different frequencies which is considered a problem. To be more precise, there are two types. The first one is caused by the frequencies of the signals being too close to each other, while the second type is caused by the excessively large amplitude of the low-frequency signal. Obviously, these different types of mode mixing require distinct solutions [67]. There are several proposed solutions for addressing mode mixing in EMD such as derivation method, frequency sifting method, masking signal method, ensemble EMD and adaptive approaches [67], [68].

2.4 Types of Sifting

Standard Sifting

The regular process without masking is the standard EMD algorithm, which follows the conventional sifting process to extract the IMFs from a signal. However, variations in the sifting process can lead to differences in these IMFs. In some cases, issues may arise when applying the standard EMD algorithm to certain signals. These issues can include the presence of noise, undesired components, or difficulties in separating specific modes or oscillatory patterns [69]. To address these challenges, some different siftings process are created.

Masked Sifting

Masked sifting is a modification of the sifting process in which certain portions of the signal are masked or excluded during the extraction of the IMFs. By masking certain regions, this extraction can be focused on the desired signal components, improving the decomposition quality [70]. The main reasons for using masked sifting are to reduce mode mixing, to address boundary effects, to refine IMF definitions, and to enhance noise suppression. This, in turn, improves the interpretability of the obtained IMFs [69].

Iterated Masked Sifting

And the last one, the iterative mask sifting is an approach to further enhance the decomposition results and address potential limitations of the standard EMD algorithm. It involves repeating the mask sifting process iteratively to refine the intrinsic mode functions and improve their quality. The benefitis of this type of sifting are to reduce the mode mixing, to refine the IMF definitions, artifact suppression, to enhance stability, and to improve signal reconstruction [71].

Ensemble Sifting

Following that, the ensemble EMD (EEMD) has been proposed as a means to improve the robustness and reliability of the decomposition process. It involves performing multiple iterations of the sifting algorithm with different initial conditions or noise realizations. These advantages are realized, facilitating better separation of modes, enhancing noise robustness, enabling stability assessment, quantifying uncertainty, and improving the accuracy of signal reconstruction [61].

2.5 Intrinsic Mode Function

Frequency analysis is a fundamental aspect of signal analysis, as it provides valuable insights into the characteristics of a signal beyond just its time-domain representation. The Fourier analysis, a classic example of frequency analysis, has been widely used since its introduction in 1807 [72]. However, the Fourier analysis has certain limitations, primarily applicable to linear systems and strictly periodic or stationary data. For non-stationary signals, alternative methods are required to analyze them effectively [4].

To address these challenges, researchers have sought adaptive and effective methods for processing and analyzing non-linear and non-stationary data. While many of these methods still rely on the Fourier analysis, the key focus has been on developing intrinsic and adaptive representations for the oscillatory modes present in the signals [73].

Researchers have discovered that complex signals can be decomposed into simpler signals, referred to as 'mono-component signals', which consist of a single oscillatory mode at any given time. The components of the complex signal could sum up to the original signal precisely. [74].

In 1998, Huang et al. [39] introduced a novel model for mono-component signals called the 'Intrinsic Mode Function' (IMF). To be clearer, an IMF serves as a representation of a basic oscillatory mode within a dataset, analogous to the simple harmonic functions utilized in Fourier series analysis and always being ordered from highest to lowest frequency [64]. In addition, the IMFs capture the local oscillatory behaviors present in the data at various scales and time durations and they can provide insights into the underlying oscillatory modes and transient phenomena within the dataset [6].

The IMF is derived using the Hilbert transform and provides instantaneous frequencies as functions of time [39]. This enables the sharp identification of embedded structures within the signal and also, it refers to the frequency content of the IMF at any given point in time. It allows for the identification of frequency modulations, transient events, or any variations in the oscillation behavior throughout the dataset. The culmination of this analysis is represented by the Hilbert spectrum, which presents an energy-frequency-time distribution [74].

2.6 Fourier Transform

The Fourier Transform (FT) is a powerful mathematical tool used to analyze signals and functions in the frequency domain. It decomposes a function into oscillatory functions in the same way that a prime decomposes light into different colours and wavelengths. It provides information about the amplitude and phase of each frequency component as the decomposition of the signal is in the time domain into its constituent frequencies [75].

When dealing with periodic functions, Fourier discovered that it is possible to express them as an infinite sum of sine and cosine functions with different frequencies and amplitudes. This representation is known as the Fourier Series [76]. It provides a way to understand periodic signals in terms of their fundamental frequency and its harmonics.

However, the usefulness of Fourier analysis extends beyond periodic functions. Even non-periodic functions can benefit from Fourier analysis by considering them as periodic with an infinitely long period, effectively treating them as if they repeat over an infinite interval. This approach allows us to examine their frequency content using the Fourier Transform [77].

In engineering and signal processing applications, signals are typically acquired and processed digitally, which means they are sampled at discrete time points. The discrete nature of these signals requires us to adopt a discrete approach to Fourier analysis. The Discrete Fourier Transform (DFT) is used to compute the Fourier coefficients for discrete signals, providing a discrete representation of the signal in the frequency domain.

The direct evaluation of the Discrete Fourier Transform (DFT) typically requires a computational complexity of (n^2) arithmetic operations. However, the Fast Fourier Transform (FFT) algorithm provides a significant improvement by achieving the same result with only (n log n) operations [76]. The essence of the FFT algorithm lies in decomposing the transform into smaller and simpler sub-transforms by dividing the data into even and odd samples. The algorithm process is recursively applied until the transform is reduced to pairs of individual samples, which can be efficiently computed using mathematical operations [4].

One limitation of the Fourier Transform is that it provides a global representation of the signal in the frequency domain but loses the temporal information. It does not reveal the exact times at which specific events occur in the signal. To address this limitation, techniques such as windowing functions and short-time Fourier Transform (STFT) can be employed. These methods allow us to analyze the signal in both the time and frequency domains simultaneously, providing localized information about the time-varying spectral content of the signal [78].

There are also other transforms for more complex signals such as the non-stationary, the Wavelet Transform and the Hilbert-Huang transform to reduce the limitations.

The Wavelet Transform is well-suited for analyzing signals with time-varying frequency content or non-stationary behavior. Unlike the Fourier Transform the Wavelet Transform uses wavelet functions that vary in size and shape, allowing for localized analysis in both time and frequency domains. This adaptability makes it particularly useful for capturing transient phenomena, sharp changes, and variations in frequency over time [79].

On the other hand, the Hilbert-Huang Transform is specifically designed for analyzing non-linear and non-stationary signals, making it an excellent alternative to Fourier analysis in cases where the data exhibits non-linear and non-stationary behavior. The HHT is a two-step approach that involves Empirical Mode Decomposition followed by Hilbert Transform [55]

Spectral Analysis

Spectrum analysis is a fundamental application of Fourier analysis, where the goal is to examine the contributions and characteristics of different frequency components present in a signal [80]. The Fourier Transform, with its ability to convert a signal into its frequency representation, forms the basis for spectrum analysis. By analyzing the magnitudes and phases of the frequency components, insights into the spectral characteristics of the signal are gained [81]. However, the Fourier transform alone does not capture the instantaneous properties of a signal. Thus, it was necessary to implement or improve the existing analysis processes as the Hilbert transform which is specifically concerned with the analytical representation of a signal [82].

Usullay, PSD scales are most often adapted to logarithmic scales in order to better interpret the information. As mentioned before, the x-axis is the frequency [Hz] and the y-axis is the absolute power. When a PSD of a non-stationary signal is plotted, it is observed that appears in the first quadrant ($x > 0$ and $y > 0$). If it is a very large signal with a lot of data, it is more difficult to extrapolate the information as so-called harmonics appear in the plot.

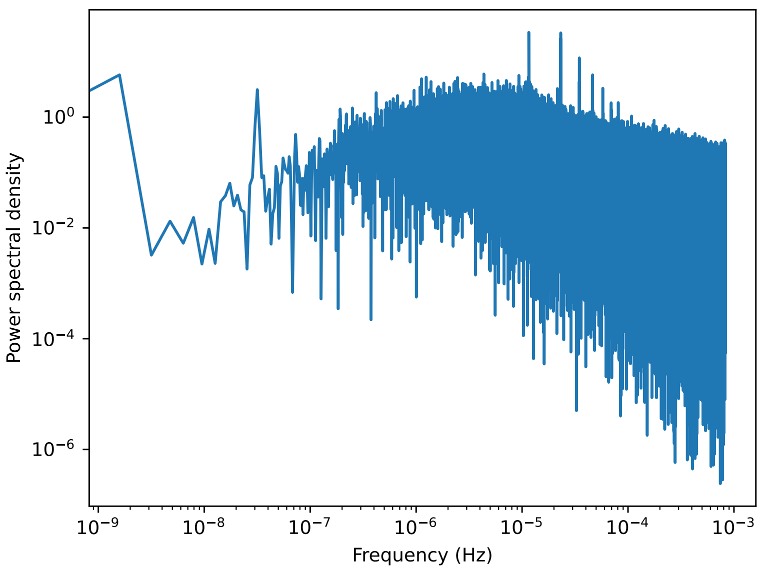

Fig. 2.7: Power Spectral Analysis of a wind speed signal.

In the spectrum you can get information about the frequencies. in this case there are several peaks that stand out on the left side which could mean that they are the diurnal frequencies, although this should be checked.

When a signal is not purely sinusoidal, but contains additional frequency components, it is said to have harmonics. Typically, they are generated by non-linear phenomena and can have undesirable effects on electrical and communication systems for example [83].

The harmonics refer to frequency components that are integer multiples of a fundamental frequency. The fundamental frequency is the lowest frequency present in a periodic signal and determines the periodicity of the signal [84].

In the specific case of wind signals, harmonics can be generated due to different reasons. For example, wind turbine blades may experience aerodynamic imbalances or structural imperfections, which cause the generated wind signal to have additional frequency components. In addition, electronic and electrical components used in wind energy conversion systems can generate harmonics due to non-linear distortion of current or voltage waveforms [85].

2.7 The Hilbert Spectrum

As mentioned above, the signals treated by the EMD algorithm are subject to non-stationarity and non-linearity. This causes frequency and amplitude to vary over time and the concept of frequency needs to be analysed in more detail. N.E. Huang et al. [39] to determine a unique and analytic signal from a real signal to calculate instantaneous properties.

An analytic signal is composed by [55]:

$$z(t) = f(t) + iH\{f(t)\} \tag{2.3}$$

Where $H\{f(t)\}$ is the Hilbert transform of $f(t)$, that is (2.4) being P the Cauchy principal value. The Hilbert transform it is related on the Fourier transform. Its function is to separate effectively the positive and negative frequency components of the signal, producing a complex-valued signal with no negative frequencies. This complex signal, contains both amplitude and phase information [86].

$$H\{f(t)\} = \left(\frac{1}{\pi}\right) \mathcal{P} \int_{-\infty}^{\infty} \frac{x(s)}{t-s}\, ds \tag{2.4}$$

The complex signal can be represented in polar coordinates as (2.5),

$$z(t) = A(t) \cdot e^{i\phi(t)} \tag{2.5}$$

where the amplitude is $A(t)$, the phase is $\phi(t)$ and e is the Euler number.

$$A(t) = \sqrt{f(t)^2 + H\{f(t)\}^2} \tag{2.6}$$

$$\phi(t) = \arctan\left(\frac{H\{f(t)\}}{f(t)}\right) \tag{2.7}$$

Thus, the instantaneous frequency as time varying phase is defined as

$$\omega(t) = \frac{d\phi(t)}{dt} \tag{2.8}$$

In the context of signal analysis, the instantaneous frequency refers to the frequency of a signal at a specific point in time but in the case of monocomponent or narrow-band data, the instantaneous frequency can be represented as a single-value function of time [87].

For a monocomponent signal, e.g. an IMF, which consists of a single oscillatory mode, the instantaneous frequency corresponds to the frequency of that mode. In this case, the instantaneous frequency is a well-defined, single-value function of time.

The instantaneous frequency, amplitude and phase are to be assigned as IF, IA, IP respectively. IF analyses the frequency variations in the signal over time, while IA and IP analyse the waveform and characteristics of the signal at different points in time [88].

Localized information can be extracted in the frequency domain using the Hilbert transform after decomposing a signal into IMFs with EMD, keeping any local properties in the time domain. This allows us to spot any hidden local structures that were originally incorporated into the signal. The Hilbert spectrum, which represents amplitude and instantaneous frequency with respect to time, can be used to express local information [55]. In fact, the Hilbert spectrum is a weighted non-normalized joint amplitude–frequency–time distribution. The weight assigned to each time–frequency cell is the local amplitude [39]

With the Hilbert transform, the IMFs yield instantaneous frequencies as functions of time that give sharp identifications of embedded structures. The final presentation of the results is an energy-frequency-time distribution, designated as the Hilbert spectrum [55].

Hilbert-Huang Transform

The Hilbert-Huang transform (HHT) is NASA's designated name for the combination of the empirical mode decomposition (EMD) and the Hilbert spectral analysis (HSA) [89]. The development of the HHT is motivated precisely by such needs: first, because the natural physical processes are mostly nonlinear and non-stationary, there are very limited options in data analysis methods that can correctly handle data from such processes. Second, a special consideration must be given to nonlinear processes [90].

To perform the HHT, first the EMD algorithm is applied to the signal and then the Hilbert transform is applied to each IMF. The Hilbert transform calculates the analytical representation of the signal, providing information about its amplitude and phase as a function of time. This transform allows extracting the instantaneous frequencies, which indicate how the frequency content of each IMF changes over time [91]. Hence, the Hilbert-Huang transform provides a description of how the energy or power within a signal is distributed across frequency.

This method is an empirical approach, and has been tested and validated exhaustively but only empirically. In almost all the cases studied, HHT gives results much sharper than any of the traditional analysis methods in time-frequency-energy representation [39]. Additionally, it reveals true physical meanings in many of the data examined.

Chapter 3

Results and discussion

This chapter discusses the different the results obtained from the Empirical Mode Decomposition (EMD) analysis. The EMD technique has been compared primarily with the Fourier analysis method. The analysis is focused on examining the average diurnal variation, average seasonal variation, frequency characteristics, detailed analysis of Intrinsic Mode Functions (IMFs), power spectrum comparison using Hilbert Huang Transform (HHT) and Fourier analysis, the summation of IMFs representing the signal, and the identification of the last IMF as the signal trend.

3.1 Initial interpretation of the Intrinsic Mode Functions

The EMD algorithm decomposes the signal into several IMFs. As the signal has countless values, the maximum number of IMFs to be obtained is set at 20, although the algorithm itself, with this indication and its own function, optimises it to the appropriate number. Therefore, in figure 3.1 19 IMF's are obtained and the top one is the sum of all of them, which corresponds to the whole signal. The resulting IMFs can be analyzed to better understand the variability and characteristics of the wind speed signal. This analysis helps uncover patterns or components, transient phenomena, and frequency content within a signal that are not easily observable in the original signal itself.

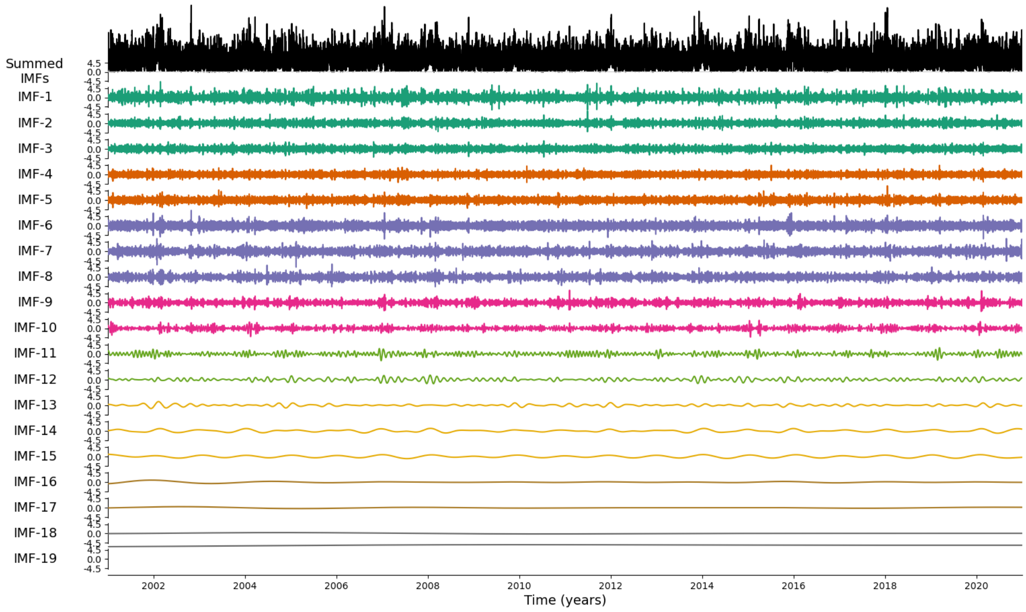

Fig. 3.1: Decomposition of the signal into the Intrinsic Mode Functions using the masked sifting.

When applying EMD to wind data, the decomposition process aims to separate the high-frequency fluctuations or variations from the lower-frequency trends or periodicities. As a result, the high-frequency components, which represent rapid changes or fluctuations in wind speed or direction, tend to be captured in the first few IMF's. In addition, by examining the properties of individual IMF's, such as amplitude, frequency, and phase, a comprehensive understanding of the signal components can be achieved.

According to the graph above, the first IMFs from the first to the 13th IMF correspond to these frequencies that are less than a year, so high frequencies. From IMF 14 to 18 they already encompass low frequencies, i.e. longer periods of time. It is worth noting that the last IMF (IMF 19) is a constant function over time and with a high amplitude; it corresponds to the continuous component of the signal. As can also be seen in the graph, the IMFs 17 and 18 are similar to IMF 19 but with an amplitude practically equal to zero, so they do not influence or provide almost no information in the signal.

Once the EMD process is completed, the next step is to apply the Hilbert-Huang Transform to further analyze the frequency characteristics and extract additional information from the IMFs. The HHT computes the instantaneous phase, frequency, and amplitude for each IMF. These quantities provide insights into the oscillatory behavior and spectral content of the signal at different scales. The instantaneous frequency and amplitude obtained from the HHT are used, along with predefined frequency bins, to calculate the spectrum. The resulting Hilbert spectrum is then plotted using a logarithmic scale on the x-axis to represent frequency in Hz and the y-axis to represent power. The plot visualizes the power distribution across different frequencies, providing information about the frequency content and energy distribution within the IMFs.

The graph showed below, it represents each Intrinsic Mode Function with its instantaneous frequency and amplitude. The extraction of each frequency helps to define the diurnal and seasonal components of the signal.

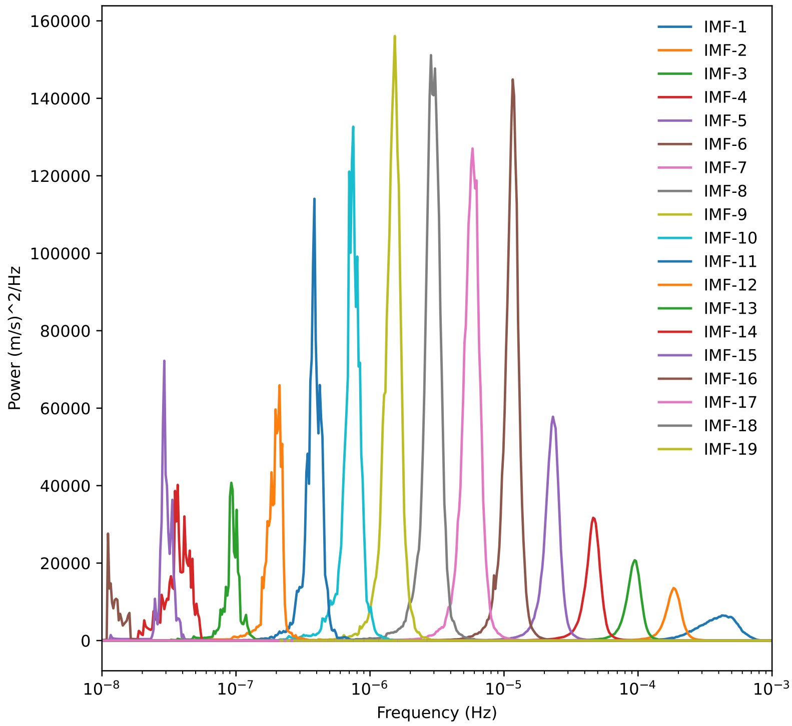

Fig. 3.2: Decomposition of the signal into the Intrinsic Mode Functions.

The frequencies extracted through the Hilbert Huang transform are valuable in identifying which Intrinsic Mode Functions correspond to the diurnal and seasonal components of a signal.

Upon examining the table, a distinct pattern emerges among the first five IMF's, where the frequencies display a clear evolution in powers of 2. This pattern can be crucial in distinguishing the IMF's that capture the diurnal and seasonal variations within the data.

Intrinsic Mode Function	Frequency [Hz]	1/day
IMF 1	4.353E-04	37.61
IMF 2	1.852E-04	16.00
IMF 3	9.435E-05	8.15
IMF 4	4.594E-05	3.97
IMF 5	2.340E-05	2.02
IMF 6	1.192E-05	1.03
IMF 7	5.805E-06	0.50
IMF 8	2.827E-06	0.24
IMF 9	1.506E-06	0.13
IMF 10	7.334E-07	0.06
IMF 11	3.736E-07	0.03
IMF 12	2.082E-07	0.02
IMF 13	9.266E-08	0.008
IMF 14	3.604E-08	0.003
IMF 15	2.878E-08	0.0025
IMF 16	1.119E-08	0.0010
IMF 17	1.023E-08	0.0009
IMF 18	1.023E-08	0.0009
IMF 19	1.023E-08	0.0009

Table 3.1: Frequencies obtained with the Hilbert Huang Transform

Due to the pattern of powers of 2, it was decided to carry out the same procedure but with different sifting, as the one used may not be ideal.

3.2 Intrinsic Mode Functions with different methods

The function in Python is designed to perform the Empirical Mode Decomposition. It takes three input parameters: the sample rate, which indicates the sampling rate of the signal; the input signal; and the option, which determines the specific variant of EMD to be applied. Four options are provided: 'standard', 'masked', 'iterated masked', and 'ensemble'.

Standard Sifting

First, the EMD is applied using the standard sifting By default, 15 Intrinsic Mode Functions are displayed. At first sight, the IMFs obtained seem to be correct as they have the trend in the last IMF and the diurnal and seasonal components.

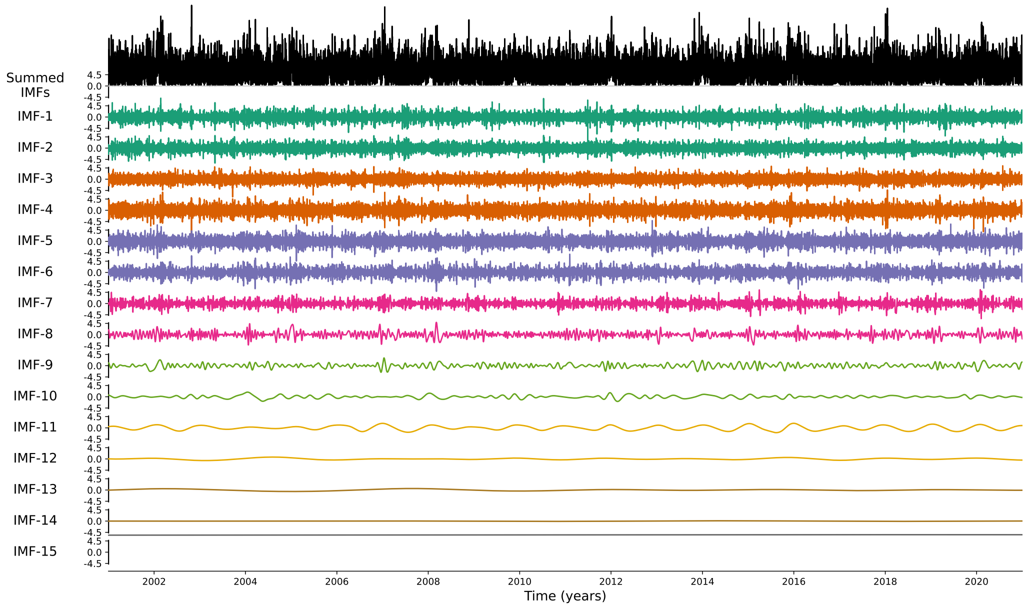

Fig. 3.3: The IMF components from data through the EMD method using the standard sifting.

When applying the Hilbert-Huang transform, which combines the instantaneous frequency and the amplitude of the IMFs to calculate the Hilbert spectrum, yields *Nan* values. It can be seen graphically in the marginal Hilbert spectrum.

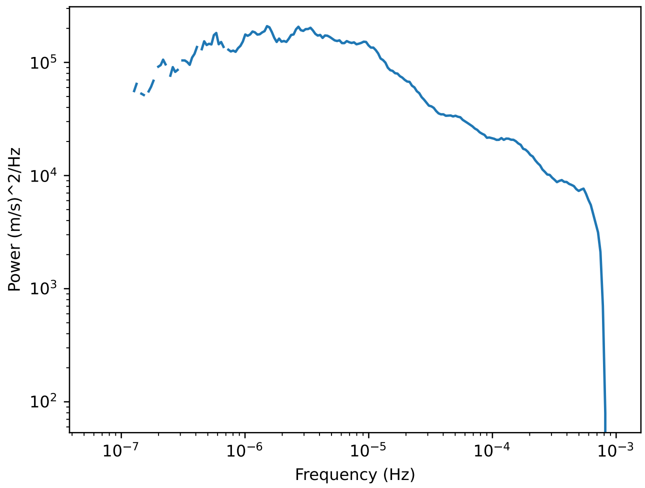

Fig. 3.4: Marginal Hilbert Spectrum using the standard sifting.

By modifying both the resolution and the defined frequency bins, these values persist. Hence, the standard sifting is discarded.

Masked Sifting

The same procedure is carried out but with masked sifting and 15 IMFs. Masked sifting is an extension of the standard sifting process, where additional masks are applied to individual IMF's during the decomposition process. This change of IMFs is due to two reasons, the first one because when performing the marginal Hilbert spectrum it appears also *Nan* values the same as with the standard and because by default, 15 is the number that the algorithm offers and considers correct. These masks can either emphasize or suppress certain frequency components within the IMF's, allowing for better control over the decomposition

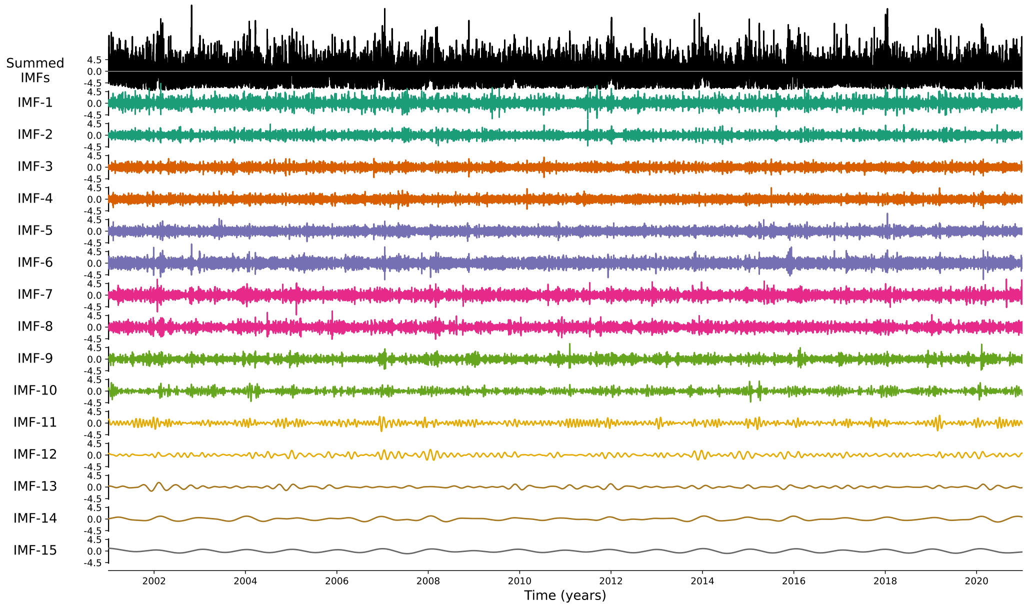

Fig. 3.5: The IMF components from data through the EMD method using the masked sifting.

When observing the different IMF's and comparing it with the same graph but with 19 IMFs, the last IMF in each method is different i.e. IMF 15 vs. IMF 19. In this case, the sifting with 15 IMFs falls short because the trend representing the DC component does not appear and therefore the decomposition is incomplete. Nevertheless, it is true that in this case the *Nan* values disappear as its Marginal Hilbert Spectrum is complete. Even so, this method is not valid either.

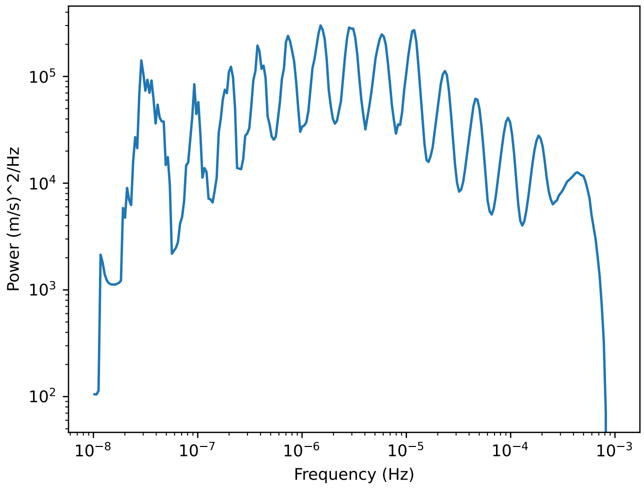

Fig. 3.6: Marginal Hilbert Spectrum using the masked sifting with 15 IMFs.

Iterated Masked Sifting

Iterated Masked Sifting takes the idea of masked sifting further by introducing an iterative approach to the decomposition. This method aims to refine the decomposition process by repeatedly applying masks and sifting to the Intrinsic Mode Functions in an iterative manner. Unlike standard EMD, where masks are applied only once, iterated masked sifting goes through multiple iterations to enhance the stability and accuracy of the decomposition.

In each iteration, itEMD applies new masks to the existing IMFs, modifying their frequency characteristics. The modified IMF's are then re-sifted to obtain new sets of IMFs for the next iteration. This iterative process continues until convergence is achieved, where the IMFs stabilize, and further iterations do not significantly change their features.

While itEMD can lead to a reduction in the number of IMFs, in this case to 13 IMF's, which might enhance decomposition stability, it comes with its limitations. One notable drawback, as observed in the provided context, is the emergence of a zero trend in the final result. This zero trend implies that the long-term behavior or diurnal and stationary variations in the signal are not accurately captured.

Due to this limitation, iterated masked sifting may not always produce satisfactory results, especially when precise identification of diurnal and stationary variations is crucial for specific applications. Thus, alternative decomposition approaches need to be explored.

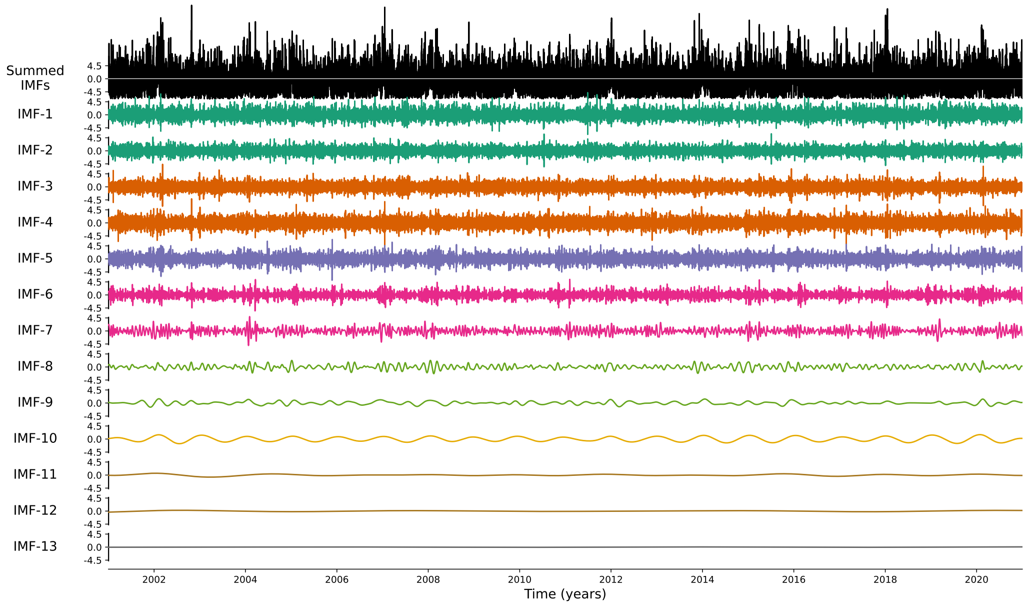

Fig. 3.7: The IMF components from data through the EMD method using the iterated masked sifting.

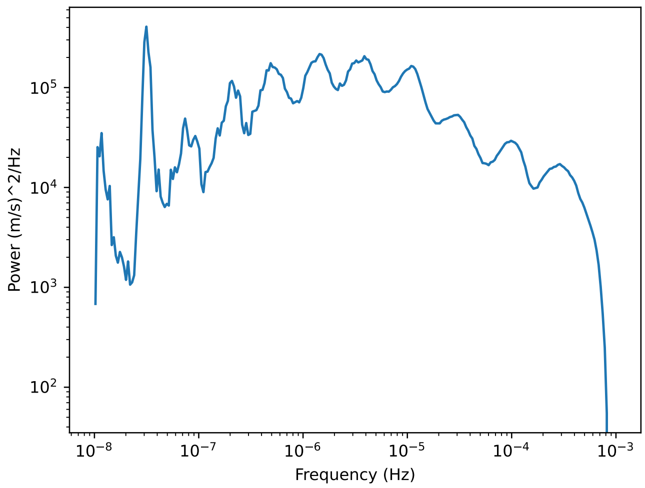

Fig. 3.8: Marginal Hilbert Spectrum using the iterated masked sifting.

It should be noted that the maximum number of IMFs has been limited to 13, as any more than this cause the code to loop and become unresponsive.

Ensemble Sifting

The last method proved is the Ensemble Sifting. This method is a modification of the standard EMD algorithm. It is designed to improve the decomposition results and enhance the stability of the Intrinsic Mode Functions extraction. Additionally, EEMD improves the robustness of the decomposition with respect to noise.

In this case, Ensemble Sifting has produced 15 intrinsic Mode Functions, a reduction from the 19 obtained with Masked Sifting. This suggests that Ensemble Sifting has iteratively refined the decomposition process and arrived at a more optimal number of IMF's by simplifying its subsequent analysis. Moreover, the resulting trend is clearly distinguishable, indicating that the decomposition accurately captures the long-term behavior of the signal.

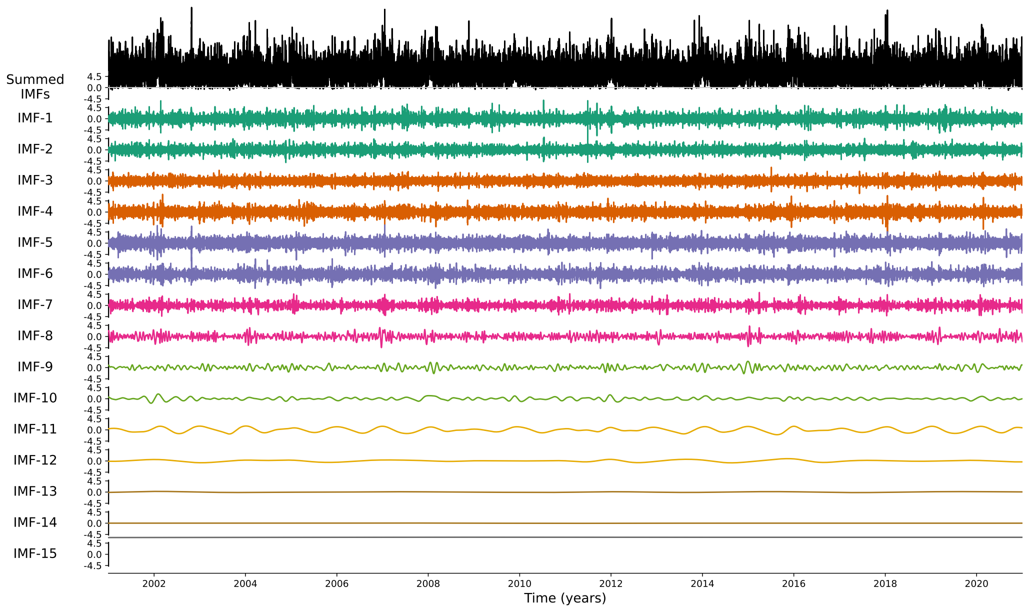

Fig. 3.9: The IMF components from data through the EMD method using the ensemble sifting.

By plotting the Marginal Hilbert Spectrum, it is observed that there are no discontinuities present and it is checked in the table of code values that there are no *Nan*-type values.

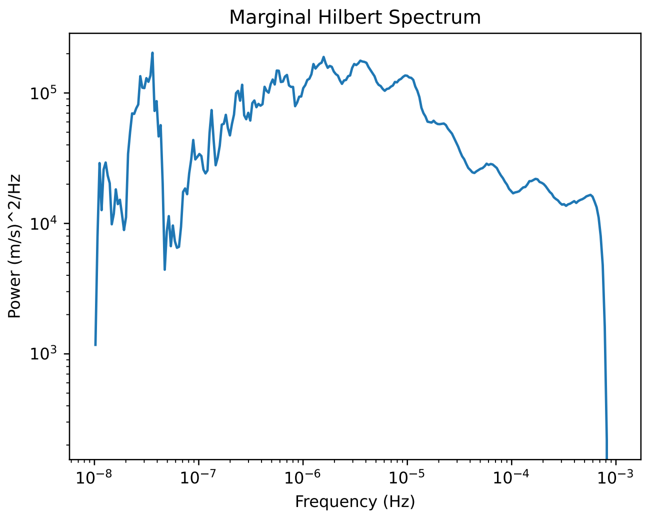

Fig. 3.10: Marginal Hilbert Spectrum using the ensemble sifting.

To confirm that this sifting is correct, the frequencies are also analysed to check whether the powers of 2 that initially appeared have disappeared.

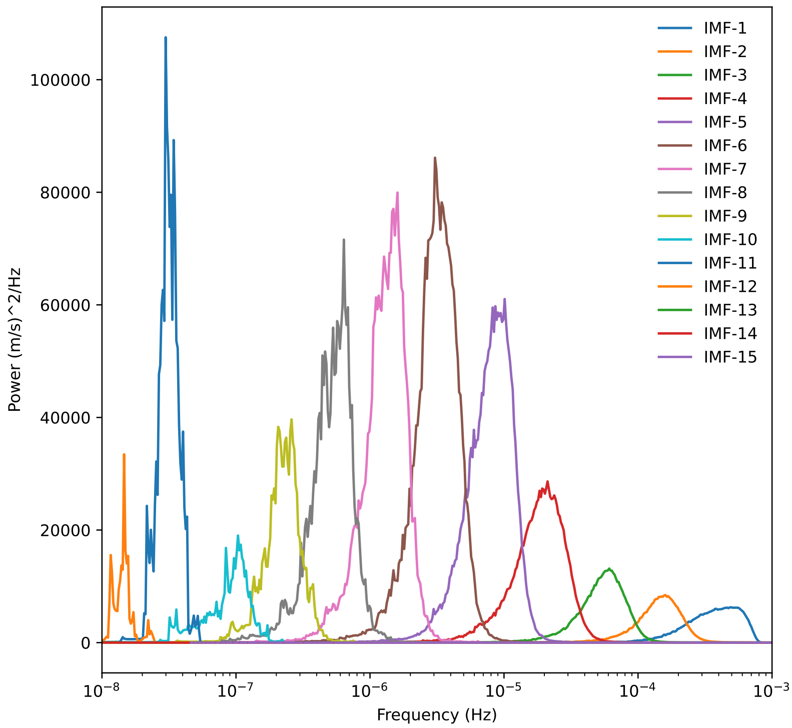

Fig. 3.11: Frequencies of each Intrinsic Mode Function obtained with the ensemble sifting.

The frequencies are captured in a table. As can be seen, the frequencies are random and do not follow any pattern. Considering that the iterative masked sifting is a good method too, the ensemble sifting is also considered first, as it also considers the trend of the signal represented in the last IMF, unlike the iterative masked sifting.

Thus, based on these evidences, the comparison between the EMD and Fourier will be performed using the ensemble sifting.

Intrinsic Mode Function	**Frequency [Hz]**	**1/day**
IMF 1	4.884E-04	42.1954
IMF 2	1.626E-04	14.0529
IMF 3	6.184E-05	5.3428
IMF 4	2.119E-05	1.8313
IMF 5	1.068E-05	0.9231
IMF 6	3.438E-06	0.2970
IMF 7	1.425E-06	0.1231
IMF 8	5.939E-07	0.0513
IMF 9	2.578E-07	0.0223
IMF 10	8.938E-08	0.0077
IMF 11	3.748E-08	0.0032
IMF 12	1.509E-08	0.0013
IMF 13	1.044E-08	0.0009
IMF 14	1.003E-08	0.0009
IMF 15	1.003E-08	0.0009

Table 3.2: Frequencies obtained with the Hilbert Huang Transform

3.3 Comparison between Empirical Mode Decomposition and Fourier

The objective of this study is to compare the effectiveness and performance of Empirical Mode Decomposition and Fourier Analysis in characterizing the frequency components of non-stationary signals. The comparison aims to shed light on the strengths and limitations of each method concerning their ability to accurately identify and represent varying frequency components in the data.

Power spectra of the signal

To assess the power distribution across different frequency components, the power spectra obtained from both Hilbert Huang Transform and Fourier analysis are compared. This comparison allows for a comprehensive analysis of the spectral characteristics and provided insights into the energy distribution in the dataset.

Initially, the spectral density has been plotted using the fast Fourier transform to observe to identify dominant frequencies, oscillatory patterns or recurring patterns that may be important to understand the phenomena affecting the signal.

Note that use has been made of the window function in Python to reduce spectral leakage effects when analysing the frequency content of a signal using the Fourier transform. Spectral leakage occurs when the analysed signal does not have an integer number of cycles within the window, which causes a 'leakage' of energy into neighbouring frequency ranges and distorts the frequency domain representation. By applying the 'hann' window to the wind-speed data before calculating the PSD, the function helps to improve the accuracy of frequency analysis and provides a valuable tool for characterizing the spectral characteristics of the wind-speed time series. The axes of the graph represent the frequency in Hz on the x-axis and the power on the y-axis.

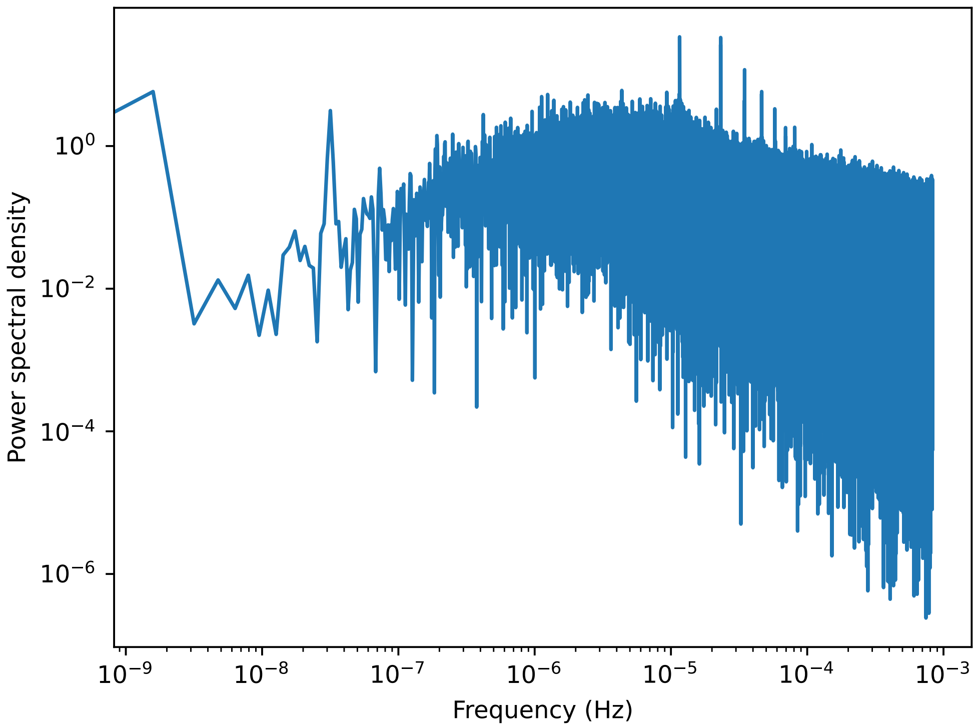

Fig. 3.12: Power spectra of the whole signal

As can be seen from the graph, the power concentration is higher at higher frequencies. A first hypothesis of this fact could indicate that the wind signal contains intense and short-lived bursts. However, in some situations, a higher power concentration at higher frequencies may indicate the presence of turbulence in the wind signal. Also, another option could be the existence of seasonal patterns or daily changes in wind speed. In addition, PSD can reveal dominant frequency components in the signal.

It is noticeable that there are specific frequency components that have a greater presence in the wind signal, and are shown as prominent peaks. So, from frequency 10^{-5} to 10^{-4} it can be seen that there are several prominent frequencies which may contain important information. Therefore, this range is zoomed in without logarithmic scales on the axes and the unit of the X-axis is changed to 1/day.

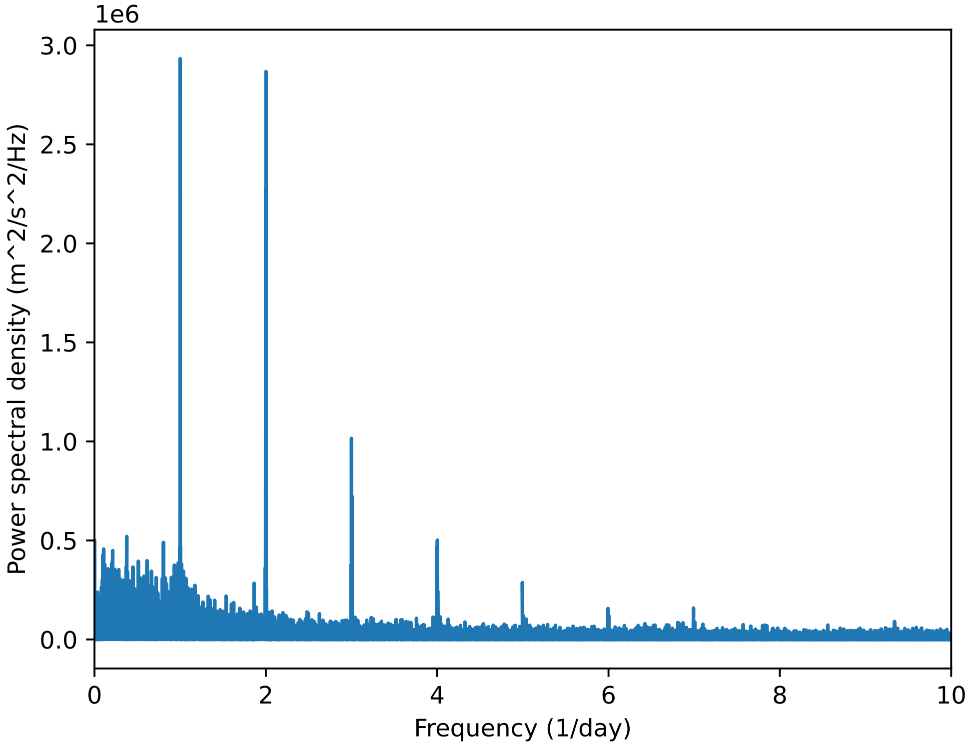

Fig. 3.13: Zoom of the power spectra of the whole signal

These dominant frequencies are extracted and it can be clearly seen that there is a pattern between them. Approximately the values of these frequencies correspond to 1/day, 2/day, 3/day, 4/day, 5/day, 6/day and 7/day. In fact, the frequency 1/day corresponds to the diurnal component while the following are its harmonics. This pattern is reminiscent of the diurnal component of a signal, which is usually of great importance in wind signals.

If these frequencies are compared with those extracted with EMD above, it can be seen that they are more graphically accurate. However, for EMD in principle the diurnal component would be the one corresponding to IMF 5 as the frequency is the one that most resembles 1 while the previous ones would be its harmonics. It is also important to check the seasonal component as wind speed also varies depending on the time of year.

It can be said that it is clearer to extract the frequencies with Fourier although they are not obtained directly by plotting the graph, but rather the axes must be modified and adjusted correctly. While with EMD, the mechanism is much easier but it can be a bit more difficult to find the diurnal component, as the seasonal component for both cases is not trivial.

Intrinsic Mode Functions with Fourier

By performing Ensemble Sifting on the non-stationary signal, a set of IMF's and trend components can be obtained. Simultaneously, Fourier Analysis is applied to these Intrinsic Mode Functions and compared to them to examine their frequency content. The Fourier spectra of all the IMFs exhibit a similar shape as the Power Spectra Density of the original signal. At higher frequencies more power is concentrated whereas in lower frequencies the power is less intense.

Fourier Transform is applied individually to each IMF obtained through EMD. This step allows to examine the frequency content of each specific IMF and assess how well EMD captures the varying frequency components.

It is worth mentioning that the visualization of the power spectra divided into individual IMF's provides valuable insights, particularly in identifying the diurnal component in purple and its harmonics, which follow sequentially. Even though applying Fourier Analysis individually to each IMF involves additional computational steps, it provides a detailed examination of the signal's frequency content.

In addition, it is also clear that there is a component that is below the others. It corresponds to the last IMF and represents the trend or DC component of the signal, i.e. the stationary or offset value of the signal, around which the signal fluctuates.

This level of analysis can be challenging to achieve by directly analyzing the original signal without first decomposing it using EMD. This enables the separation of different frequency bands, represented by the IMFs. Therefore, despite the extra steps involved, the use of EMD in conjunction with Fourier Analysis facilitates a more comprehensive characterization of the signal's frequency components.

When representing each IMF individually, it can be challenging to extract significant insights or interpret the frequency components directly. Nevertheless, the trend looks very good as it is represented by a single line so it confirms the above mentioned.

In conclusion, visualizing the power spectra of all IMFs together allows for a more comprehensive analysis.

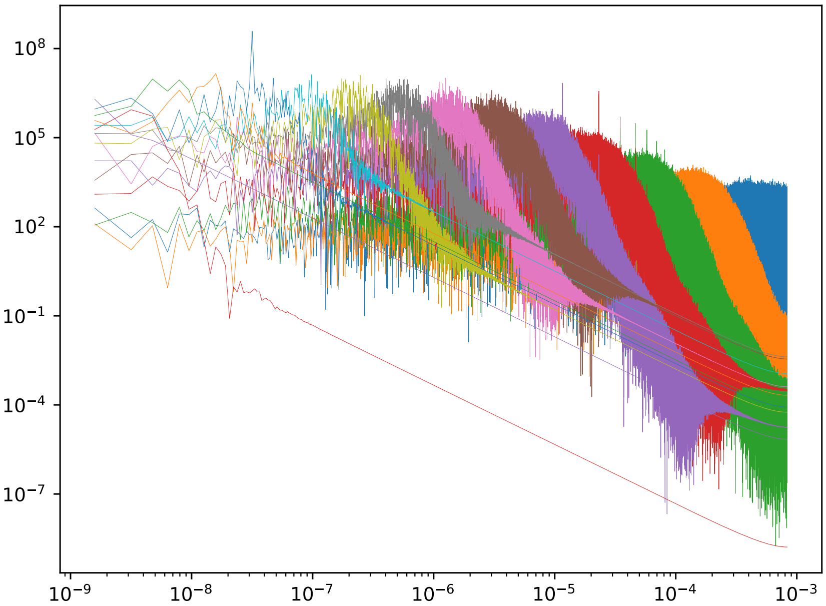

Fig. 3.14: Fourier Spectra of all the Intrinsic Mode Functions.

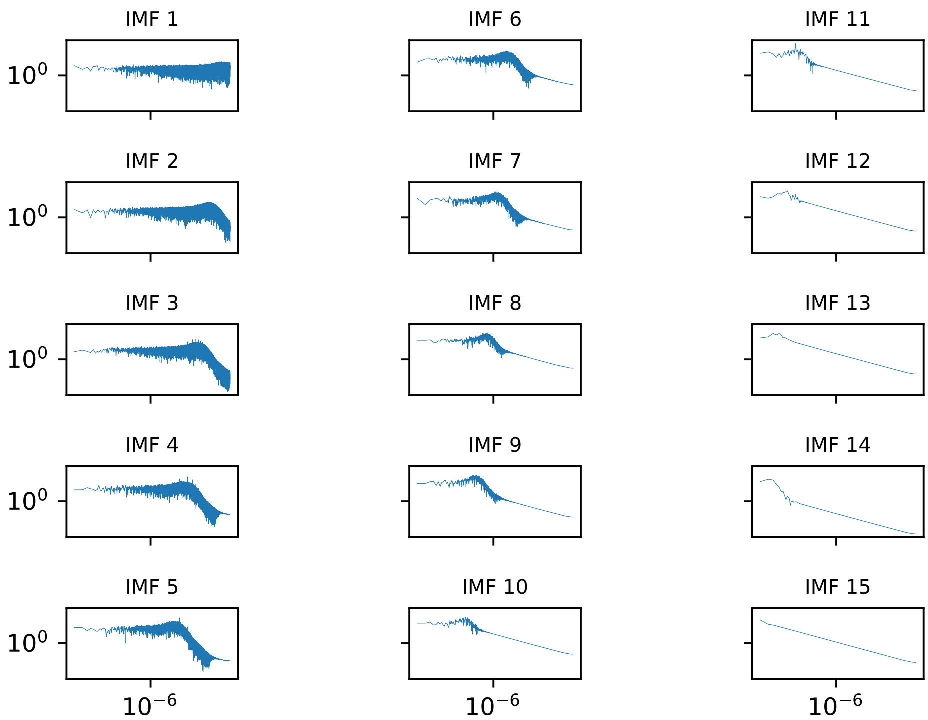

Fig. 3.15: Fourier Spectra of each Intrinsic Mode Function.

Additionally, the Fourier spectra of the original signal and the Marginal Hilbert Spectrum are compared to gain deeper insights into the signal's oscillatory modes in Figure 3.16. To enhance clarity, the values of the spectra are staggered, with the top line representing the Hilbert spectrum, and the bottom line representing the Fourier spectrum.

Upon inspection, both the Hilbert and direct Fourier spectra display rich frequency contents. However, a noticeable distinction arises in the representation of high harmonics. The absence of high harmonics in the Hilbert spectrum can be attributed to either nonlinear or non-stationary effects.

In fact, the marginal spectrum each peak of the curve represents the sharp peaks of the Fourier spectra. It is true that obtaining the frequencies with the Hilbert spectrum is simpler and you can obtain them directly without doing anything else while with Fourier they are obtained in the same way but with more steps in the procedure (see figure 3.11).

This comparison supports the notion that the Hilbert spectrum is a more accurate method for portraying energy-frequency relationships in cases where nonlinear or non-stationary effects are present.

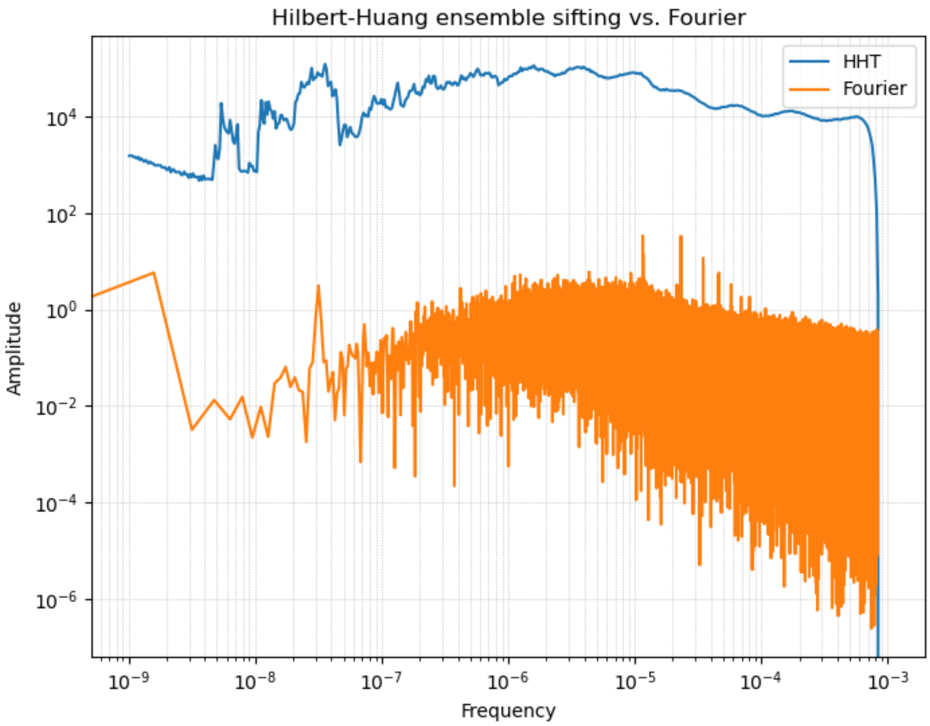

Fig. 3.16: The comparison of the Fourier (the bottom line) and marginal Hilbert spectra (the middle line).

3.4 Signal Trend Identification

The last Intrinsic Mode Function obtained through EMD decomposition is identified as the signal trend. It represents the constant or average value of the signal over time. It is a fundamental component that does not vary with time and corresponds to the lowest frequency component of the signal's spectrum.

In the context of EMD, the last Intrinsic Mode Function, i.e. IMF 15 in this case, represents the trend component of the signal, which is equivalent to the DC component in many cases. The DC component is essential as it provides critical information about the baseline or mean level of the signal. However, there can be differences between the mean of the signal and the IMF 15 in certain situations. This is because EMD is a data-driven method and the trend component is extracted based on the local extrema of the signal. In some cases, the trend component obtained through EMD may not perfectly align with the mean, especially if the signal has non-stationary or nonlinear characteristics.

If the signal wind speed is averaged and compared with the last IMF, it can be seen that the difference between them is minimal. The orange line represents the trend which is the 15 IMF whereas the blue line is the mean of the signal.

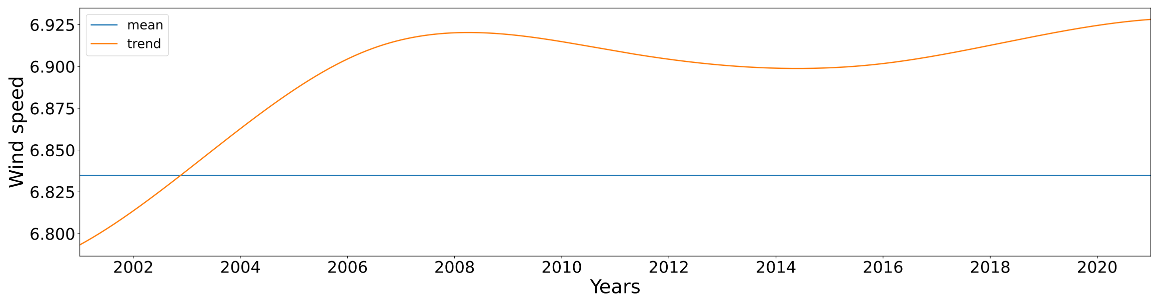

Fig. 3.17: Trend and mean of the signal.

Although in figure 3.17 it looks different to the naked eye, if you look at the y-axis, it only looks at values between 6.79 and 6.93 while the mean wind speed signal is approximately 6.84 m/s. As these values are so similar, it can be said that the trend is the DC component as it is the one that provides magnitude to the signal.

If the energy of the trend component is added to the fluctuating components, the overall energy of the signal will indeed become more levelled or evenly distributed across frequencies. This increase in the overall energy can lead to a higher energy density, which makes it difficult to clearly visualise the individual energy density of the fluctuating components.

In figure 3.18, the fluctuating components and the trend can be seen. The latter is above, so if both are added together, the energy density would increase.

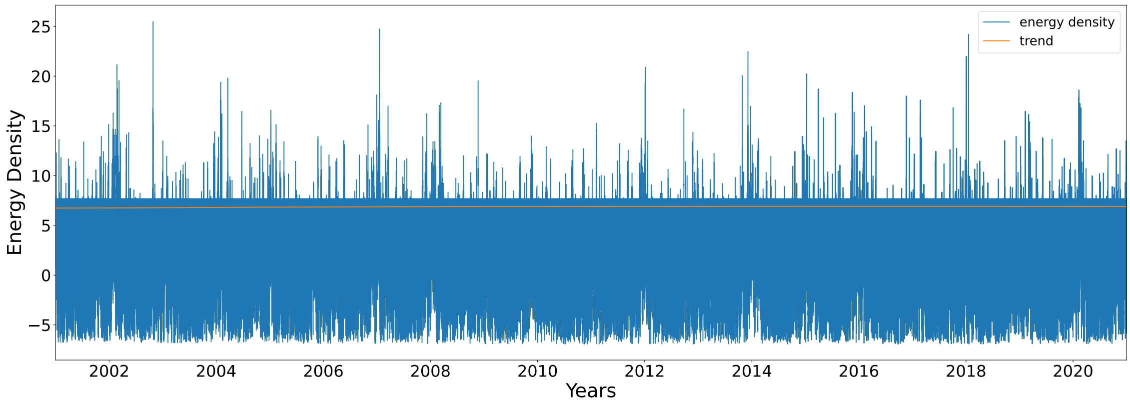

Fig. 3.18: Energy density of the signal and the trend.

3.5 Average Diurnal Variation

The average diurnal variation refers to the regular changes that occur in a signal throughout the day due to weather patterns, such as solar radiation, temperature gradients or local effects. It is a representation of how the value of the signal changes regularly and predictably with the different hours of the day, usually following a 24-hour cycle. For instance, it is common to observe an increase in wind speed during the day due to the generation of thermal breezes and a decrease during the night.

This phenomenon can be seen in figure below, which shows the mean diurnal variation of the signal. To prove that EMD is a good method to analyse wind signals and to extract important information, this variation is checked with the IMFs. One way to check this is to plot the ADV with the IMFs and identify which IMF is the diurnal component.

To know which IMF is the diurnal component exactly, IMF 5 is taken as a reference because of its frequency. Then from the diurnal component and more imfs the ADV can be taken out. In this case the previous IMFs (IMF 4, IMF 3, IMF 2, IMF 1) and the DC component (IMF 15) have been taken and summed. In addition, for each component (IMF) its harmonics are also considered as they influence the ADV composition. The specific combination of IMFs that reconstruct the ADV varies depending on factors like the signal's complexity and the chosen sifting method.

Thus, the sum of all the above-mentioned components should give a result almost identical to the average diurnal variation of the original signal. This comparison can be seen in figure 3.19 where the orange line corresponds to the sum and the blue line to the signal.

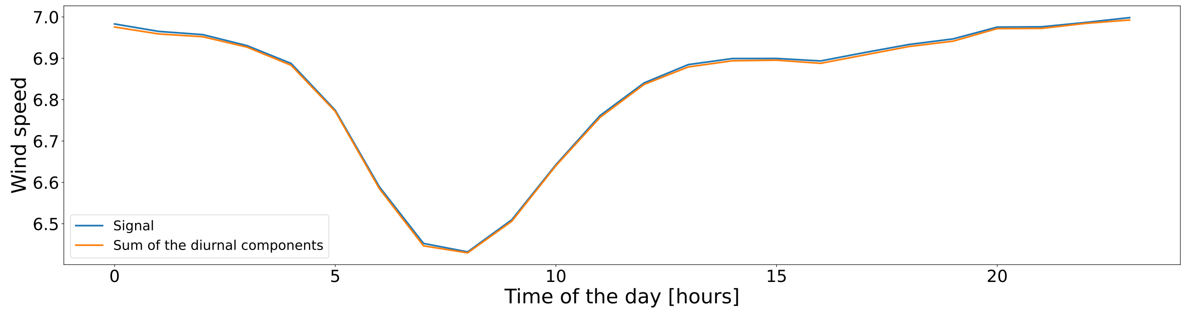

Fig. 3.19: Comparison between the signal and the diurnal component.

The shape is almost identical although there are small differences so it can be confirmed that the EMD method can capture the diurnal pattern of the signal.

3.6 Average Seasonal Variation

The same methodology is applied to extract the Average Seasonal Variation (ASV). The combination of IMFs 1 to 11 and the DC component (IMF 15) is taken into account, where IMF 11 is considered as the annual component.

By summing these components, the ASV can be effectively reconstructed. The effectiveness of this approach relies on the fact that these IMFs and their harmonics collectively capture the seasonal patterns present in the wind signal. The comparison between the summed components and the original signal's ASV can be observed in a similar graphical representation in figure 3.20.

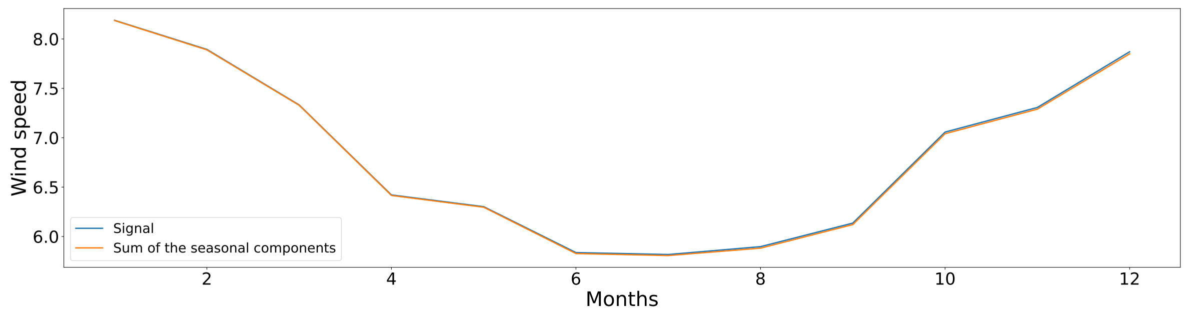

Fig. 3.20: Comparison between the signal and the seasonal component.

In the same way as in ADV, the orange line corresponds to that sum while the blue line is the ASV of the original signal. It can be seen that the difference between them is practically null, so it can be stated that EMD also captures seasonal patterns with the IMFs.

3.7 Physical meaning of the Intrinsic Mode Functions

The Intrinsic Mode Functions hold a significant physical meaning as they correspond to distinct underlying physical drivers within the wind signal. By their frequency content, the IMFs capture specific oscillatory modes inherent in the signal. For instance, the six IMFs that collectively form the Average Diurnal Variation hold the physical interpretation of collectively describing the diurnal pattern of wind speed. Each of these IMFs represents a unique diurnal component. Together, they combine to depict the intricate daily fluctuations in wind behavior.

Similarly, the Annual Seasonal Variation comprises thirteen IMFs, each corresponding to a particular frequency that contributes to the overall seasonal trends observed in wind signals. These IMFs encapsulate the diverse influences shaping the wind behavior over longer time scales, as it could be changes in climate, weather patterns, and environmental conditions across different seasons. The presence of multiple IMFs within the ASV underscores the complex interplay of various physical drivers contributing to the observed yearly variations in wind speed.

3.8 Signal Reconstruction

The signal reconstruction is a fundamental concept in Empirical Mode Decomposition. The original signal can be approximately reconstructed by summing all the Intrinsic Mode Functions and the trend component. The reconstruction is given by:

$$\text{Original Signal} = \text{Fluctuating Components (IMF 1 to IMF N-1)} + \text{Trend (IMF N)}$$

If EMD successfully decomposes the signal into meaningful and physically interpretable IMFs, the reconstruction can be quite accurate.

Considering figure 3.11, as mentioned above, the decomposition of the IMFs from the original signal is observed. At the top of the figure 3.11, the sum of the IMfs is shown.

If the summed IMfs are compared to the signal the difference is minimal. It can be seen that if both graphs overlap, the difference is the blue area of the original signal.

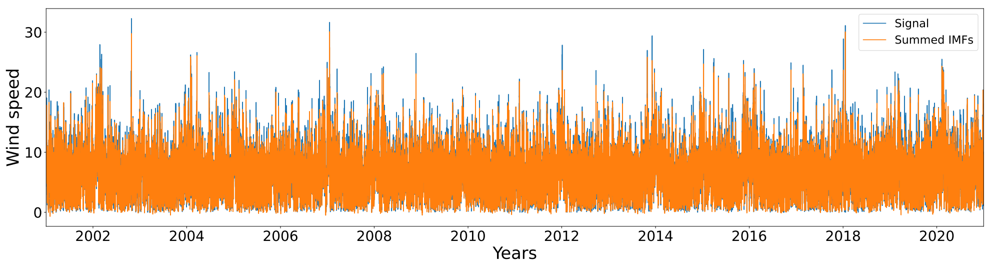

Fig. 3.21: Summed IMFs vs. Signal.

Chapter 4

Conclusions and future developments

In conclusion, the application of Empirical Mode Decomposition (EMD) has been developed for analyzing non-stationary data, exemplified by wind speed signals. First of all it has been analysed which type of sifting should be applied as not all of them provide the correct analysis. Ensemble sifting has proved to be the correct one although iterative masked sifting should provide similar results as well. In this case, the lack of the trend was the key to discard this method and choose EEMD.

Furthermore, with the comparison of Fourier and EMD it can be concluded that both methods are valid for the analysis of wind speed signals. It is true that Fourier is not very recommendable for non-stationary data in contrast to EMD which is specific for this type of data. This is already the first advantage of EMD over Fourier. Additionally, the studies with each of them are different since with EMD it is simpler to obtain the results and to draw conclusions. The frequencies are obtained earlier and physical meanings can be obtained from them whereas with Fourier they are not.

Another significant advantage of the EMD-based analysis lies in its potential to unravel the physical significance of the IMFs with respect to distinct patterns. These IMFs represent distinct oscillatory modes and scales inherent in the signal, allowing for the isolation and analysis of specific frequency components. For example, the diurnal pattern of wind speed is collectively described by the first five IMFs and its trend forming the Average Diurnal Variation. Each of these IMFs represents a unique diurnal component, contributing to the intricate daily fluctuations in wind behavior and being the IMF 5 the diurnal component (1/day). Similarly, the use of thirteen IMFs allows us to understand how wind speed changes throughout the year and to capture the effects of different seasons and weather conditions. These sums have been compared with the average diurnal variation and the average seasonal variation of the original signal and the differences are minimal. EMD is more flexible in this respect, and this is one of the strengths of the method, as Fourier could not be analysed due to its sinus decomposition.

The trend also plays an important role as it provides the amplitude of the signal. Without it, only the analysis of the IMFs could be carried out to obtain the results mentioned above by comparing with the shape, but thanks to the trend, the values of the original signal are obtained.

As a prospect for future research, the exploration of multi-variable analysis is promising. Combining wind signals with additional environmental variables, such as solar radiation, could provide a more comprehensive understanding of the interplay between different climatic factors.

In the realm of future studies, an intriguing avenue lies in the prospect of delving deeper into capturing the Average Diurnal Variation with even greater precision. This endeavor could involve exploring diverse sifting methodologies, refining the techniques employed within the Empirical Mode Decomposition, and dedicating more comprehensive efforts to the analysis. By undertaking these approaches, there exists a plausible yet uncertain opportunity to come remarkably close to encapsulating the ADV within a single Intrinsic Mode Function.

A parallel avenue of research could also be extended to the Average Seasonal Variation. Similar to the prospective study on the capture of ADV, there is the possibility of conducting the same study in order to define ASV with a single IMF. This future research effort could offer valuable insights into the complex factors shaping the ASV and provide a more complete understanding of the underlying mechanisms driving annual wind speed variations.

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