



Modeling the Synergy of Wind and PV Power in Galicia Using Copula Theory

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Abstract. One of the main goals of international sustainability projects is the transition to renewable energy. This study uses copula theory to explore the relationship between wind and photovoltaic (PV) electricity Production in Galicia, Spain. The aim is to analyze the interaction and complementarity between these two renewable energy sources. The research uses copula models to capture the dependency structure between how much wind and PV energy is generated, recognizing that their interactions are complex and not linear. Copula theory allows us to represent how wind and PV energy behave together, enabling the prediction and optimization of energy production. That said, this research shows how to improve the stability and sustainability of energy networks. The methods used in this study can be applied to other regions and energy sources, giving us a flexible way to explore renewable energy systems in the future.

Key words. Copula theory, renewable energy, wind and PV generation, energy forecasting.

1. Introduction

The transition to renewable energy is a key driver of global sustainability efforts, with particular emphasis on diversifying energy sources to enhance reliability, reduce greenhouse gas emissions, and improve energy security. Wind and PV power are among the most prominent renewable sources, offering significant potential for energy generation but facing challenges due to their variable and intermittent nature. In this context, the complementarity between these two sources—wind and PV—has become an important area of study. Specifically, the Galicia region in Spain presents an ideal case for exploring the complementary nature of wind and PV energy, given its unique climate conditions and growing renewable energy capacity [5].

Galicia has established itself as one of Spain's most important regions for renewable energy generation. According to the Red Eléctrica de España (REE) data, Galicia has a high share of wind power in its energy mix, contributing significantly to the national electricity supply. The region's geographical location, characterized by a diverse climate with moderate temperatures, strong winds, and variable sunshine hours, creates a complementary relationship between wind and photovoltaic (PV) electricity Production. Galicia wind energy benefits from the region's coastal position and its exposure to Atlantic

winds, while PV energy is becoming increasingly viable as technology advances and PV radiation intensifies during the summer months [5]. These factors make Galicia an attractive region for studying the potential synergies between these renewable sources and their impact on energy supply stability.

However, the variability of renewable energy generation can challenge grid operators to maintain a consistent energy supply. Wind energy production peaks during specific weather conditions, and PV energy generation is limited to daylight hours, often leading to periods of undersupply or excess generation. In this context, understanding the complementarity between wind and PV power becomes essential to developing strategies that can help balance supply and demand, thus enhancing the reliability of renewable energy systems [1]. By analyzing the temporal patterns and the potential for joint generation, the energy systems can be optimized to maximize the contribution of renewable sources and reduce reliance on conventional fossil fuel-based power.

This study uses monthly data to explore the complementarity between wind and PV photovoltaic generation in the Galicia region from January 2014 to August 2024. The research applies copula theory to model the joint distribution of these energy sources, capturing their dependence structure and generating scenarios to calculate the probability of different occurrences. Copula models allow for a flexible approach to understanding complex dependencies, particularly in cases where variables exhibit non-linear relationships, or the data does not follow standard parametric assumptions [4]. This methodology offers significant advantages over traditional correlation analysis, as it enables the analysis of the tail dependencies and extreme events that are critical in energy production scenarios.

This study's primary goal is to evaluate the possibility of PV and wind power complementing one another in Galicia and so strengthening the region's renewable energy infrastructure. This study will generate data on interactions between these two renewable sources by applying copula theory. This study underscores the significance of diversifying renewable energy sources and the function of sophisticated statistical techniques in energy system optimization. By providing a model that advances the

broader goals of resilient and sustainable energy systems, knowledge of Galicia's wind and PV power complementarity can benefit other regions with similar renewable energy potential. [9].

2. Literature Review

The transition to renewable energy sources has been a priority in Spain, mainly on wind and PV photovoltaic energy. The region of Galicia, located in the northwest of the country, possesses geographical and climatic characteristics that make it particularly suitable for developing these energy sources (Evergreen Eléctrica, 2024).

Historically, Galicia has leveraged its wind potential due to favorable wind conditions, especially in coastal and mountainous areas. Starting in the 1990s, the first wind farms were implemented in the region, marking the beginning of significant expansion of this energy source. According to data from the Red Eléctrica de España [6], Galicia's installed wind energy capacity has grown steadily, contributing substantially to the regional and national energy matrix.

In recent years, PV photovoltaic energy has also gained prominence in Galicia. Although the region experiences lower PV radiation levels than southern Spain, technological advances and reduced installation costs have enabled PV projects in Galicia territory. Enel Green Power (2019) reported that new PV plants were inaugurated in Spain in 2019, including projects in Galicia, highlighting the commitment to diversifying renewable energy sources in the region.

Galicia stands out as one of Spain's leading renewable energy producers. The combination of wind and PV energy has enabled the region to meet a significant portion of its energy demand and contribute to reducing greenhouse gas emissions. According to Total HSE (2023), PV photovoltaic energy has reached a significant milestone in Spain, becoming the second-largest technology in installed megawatts, reflecting the growth trend of this source in Galicia as well.

The relevance of renewable energy in Galicia is evident from an environmental and economic perspective. The development of wind and PV projects has generated jobs, driven technological innovation, and strengthened regional energy security. Moreover, the complementarity between wind and PV sources contributes to better stability in energy generation, mitigating the effects of their intermittency [6]; [8].

The evolution of Galicia's wind and PV photovoltaic energy reflects a continuous commitment to sustainability and energy transition. The region exemplifies how favourable public policies and investments in technology and infrastructure can transform the energy landscape, promoting significant environmental and socioeconomic benefits.

2.1. Copula Theory

The theory of copulas has emerged as a powerful and flexible tool for modeling and analyzing the dependence

structure between random variables. Initially introduced in statistical literature by Sklar (1959) [7], copulas provide a mathematical framework separating individual variables' marginal behavior from their joint dependence structure. This makes copulas particularly important in applications where understanding and quantifying dependence between variables is fundamental, such as finance, hydrology, climate studies, and renewable energy analysis.

A copula is defined as a multivariate cumulative distribution function (CDF) with uniform marginals on the interval $[0,1]$. According to Sklar's Theorem, for any joint distribution $F_{X,Y}(x,y)$ with continuous marginal distributions $F_X(x)$ and $F_Y(y)$, there exists a unique copula CC such that:

$$F_{X,Y}(x,y) = C(F_X(x), F_Y(y)), F_{X,Y}(x,y) = C(F_X(x), F_Y(y)), \quad (1)$$

where $C: [0,1] \times [0,1] \rightarrow [0,1]$ is the copula function. Conversely, if the copula CC and the marginal distributions are known, the joint distribution can be reconstructed. This property allows researchers to model marginal distributions independently from their dependence structure, offering greater flexibility in statistical modeling [4].

In research on renewable energy, copulas are especially useful since variables like PV photovoltaic and wind energy generation frequently show asymmetric and nonlinear dependence structures. Because copulas are not limited by linearity or normalcy assumptions like standard correlation-based approaches, they can describe complex dependence patterns, such as tail dependencies that capture extreme co-movements. [3].

The use of copulas relies on a few key premises:

1. Uniform Marginals: Copulas operate on marginal distributions transformed into uniform counterparts via cumulative distribution functions.
2. Flexibility in Dependence Modeling: Copulas can accommodate variables with different distributions or heterogeneous behaviors by separating marginal distributions and dependencies.
3. Tail Dependence Representation: Copulas can model dependence in the tails of distributions, which is particularly relevant for extreme event analysis.
4. Parameter Estimation: Copulas are parameterized by dependence parameters, such as Kendall's tau or Spearman's rho, which quantify the strength of the dependence between variables.

The functional forms of copulas vary widely, with ordinary families including Gaussian, t-Student, Archimedean (e.g., Clayton, Gumbel, Frank), and rotated copulas. The choice of copula depends on the nature of the dependence structure in the data, including symmetry, tail behavior, and degree of correlation.

3. Analysis and Results

This study employs copula theory to model the dependence structure between monthly PV photovoltaic generation and wind energy generation in Galicia from January 2014 to August 2024. Renewable energy sources exhibit distinct temporal and seasonal variations influenced by climatic factors, necessitating a robust methodology to analyze their joint behavior.

The copula-based approach allows for the simulation of realistic scenarios that capture the dependence structure between these variables, aiding in the assessment of complementary energy generation patterns. The analysis involves:

1. **Marginal Distribution Fitting:** Identifying appropriate marginal distributions for wind and PV generation data (Weibull).
2. **Copula Selection:** Selecting the copula family that best represents the observed dependence structure based on goodness-of-fit tests and dependence measures.
3. **Scenario Simulation:** Generating synthetic data to evaluate the joint behavior of the variables under different scenarios.

By modeling the dependence structure, we aim to quantify the probability of high or low energy generation scenarios, demonstrating the complementary nature of wind and PV power. This information is important for energy planners and policymakers in optimizing the energy mix and ensuring stability in the electricity grid.

The joint probability density function (PDF) $f_{X,Y}(x,y)$ of the variables XX (PV generation) and YY (wind generation) can be expressed as:

$$f_{X,Y}(x,y) = c(F_X(x), F_Y(y)) \cdot f_X(x) \cdot f_Y(y), f_{X,Y}(x,y) = c(F_X(x), F_Y(y)) \cdot f_X(x) \cdot f_Y(y)$$

where $c(u,v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ is the copula density, and $f_X(x)$ and $f_Y(y)$ are the marginal densities of XX and YY , respectively.

The dependence parameters of the selected copula are estimated using maximum likelihood estimation (MLE) or inference functions for margins (IFM) methods. We use measures such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to evaluate the goodness-of-fit.

Figure 1 and Figure 2 present the historical time series of wind energy generation and PV photovoltaic generation, respectively, for the region of Galicia. Upon examining these series, it is evident that they exhibit well-behaved patterns characterized by relatively stable trends and clear indications of seasonality. This seasonal behavior can be

attributed to the distinct climatic conditions of Galicia, which influence the temporal distribution of renewable energy generation throughout the year.

As shown in Figure 1, wind energy generation typically experiences higher outputs during the winter months, driven by more substantial and consistent wind patterns associated with seasonal atmospheric dynamics. Conversely, PV photovoltaic generation, depicted in Figure 2, demonstrates peak performance during the summer, when PV radiation levels are at their highest due to longer daylight hours and clearer skies.

These complementary characteristics between wind and PV energy generation are particularly noteworthy. While wind generation tends to dominate during periods of lower PV output in the winter, PV generation compensates during summer when wind activity often declines. This complementarity helps mitigate the intermittency typically associated with renewable energy sources, contributing to a more balanced and reliable regional energy supply.

The observed patterns reflect the advantages of leveraging multiple renewable energy sources in a geographically and climatically diverse region like Galicia. By capitalizing on the complementary nature of wind and PV generation, energy planners can enhance the stability and resilience of the energy system, reducing reliance on non-renewable energy sources and promoting a sustainable energy transition.

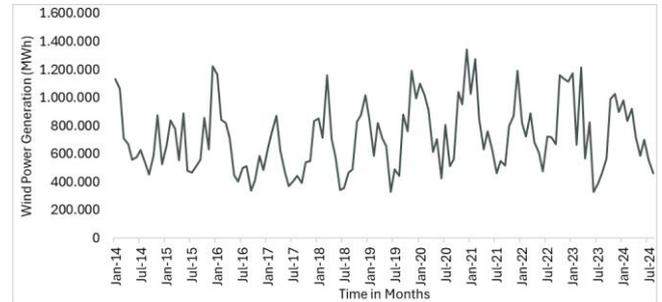


Fig 1 – Wind Generation History (MWh)

Source: Prepared by the authors

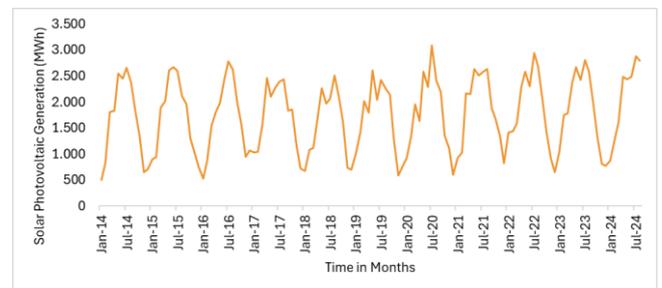


Fig 2 – PV Photovoltaic Generation History (MWh)

Source: Prepared by the authors

Using the Kolmogorov-Smirnov test, we identified that the marginal distributions for the wind energy generation and PV photovoltaic generation variables are best modelled by

the Weibull distribution. This result highlights the suitability of the Weibull distribution in capturing the unique characteristics and variability inherent in the respective datasets, given its flexibility in modeling skewed and non-negative data often observed in renewable energy generation.

Having established the appropriate marginal distributions, the next step in our analysis involves modelling the dependency structure between the two variables. To achieve this, we employ copula theory, which provides a robust framework for describing the interdependence between random variables. Specifically, using the method of maximum likelihood estimation, we will identify the copula function that best represents the dependency structure between wind and PV energy generation data in the region of Galicia for the period from January 2014 to August 2024, analyzed monthly (Figure 3).

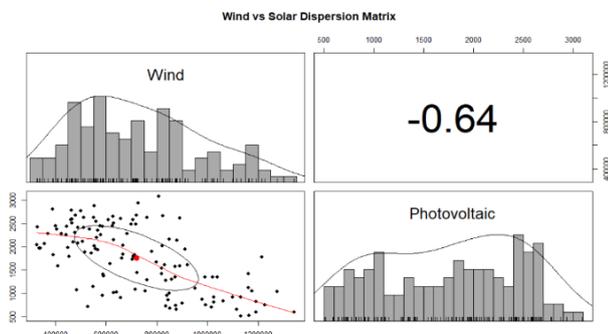


Fig 3 - Correlation between wind and PV sources
Source: Prepared by the authors

Using the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), the 270-degree rotated BB8 copula best represents the dependency structure between wind energy generation and PV photovoltaic generation. This selection is based on its superior performance in balancing model fit and complexity compared to alternative copula models.

The Rotated BB8 copula is a bivariate Archimedean copula known for its flexibility in capturing symmetric and asymmetric dependency structures. The estimated parameters for the selected copula are (par = -3.39) and (par2 = -0.85), which define the copula's shape and tail dependencies. The Kendall's $\tau = -0.43$ indicates a moderate negative dependence between the two variables, further supporting their complementary relationship during certain months.

The Rotated BB8 copula is particularly well-suited for this study because it can accommodate non-linear and asymmetric dependencies often observed in renewable energy datasets. Its ability to capture tail dependencies allows for a more accurate representation of extreme events, such as simultaneous low wind and PV generation, which are critical for energy system planning and reliability analysis.

The choice of this copula highlights the importance of selecting a model that fits the data well and reflects the underlying physical and operational dynamics of the system under study. Using the Rotated BB8 copula, we ensure that

the dependency structure between wind and PV generation is modelled accurately, providing information about their joint behaviour and enabling more reliable scenario generation for resource management and energy integration planning.

One thousand pairs of simulated observations for wind and PV energy generation were generated using the selected marginal distributions and copula. These simulations were performed to capture the joint dependence structure and the individual behaviour of each energy source over the specified period. As presented in Figure 4, the simulated data closely mirrors the historical data, demonstrating a similar pattern of variation and seasonal behaviour observed in the original dataset.

The simulated pairs of wind and PV generation exhibit comparable characteristics to the historical observations, affirming that the chosen model accurately reflects the underlying dynamics and dependency structure between the two energy sources. The matching of the simulated data with the historical data supports the robustness of the copula model, indicating its suitability for representing the joint behaviour of wind and PV generation in the Galicia region.

The figure clearly illustrates both the overall range and the distribution of the simulated data align with the historical values. Furthermore, the seasonal fluctuations, as well as the complementary characteristics between wind and PV generation, are preserved in the simulated data. This alignment suggests that the copula and marginal distributions effectively capture the central tendencies, tail dependencies, and extremes important for reliable energy system modelling and forecasting.

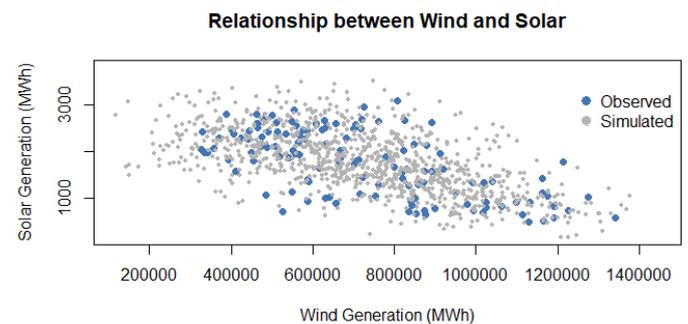


Fig 4 – Relationship between Wind and PV
Source: Prepared by the authors

To assess the goodness-of-fit of the selected copula model, the BiCopGofTest was applied to the simulated data using the Rotated BB8 270-degree copula. This test evaluates the adequacy of the copula model by comparing the empirical copula of the observed data with the copula model that was fit to the data. The test was conducted using the Kendall method, with the parameters set to family 40 (which corresponds to the Rotated BB8 270-degree copula), and the parameters of the copula. The test was performed with a maximum of 30 degrees of freedom and 1000 bootstrap replicates.

The goodness-of-fit test results, presented through the Cramér-von Mises (CvM) and Kolmogorov-Smirnov (KS) statistics, yielded p-values of 0.55 and 0.44, respectively. These p-values are relatively high, indicating no significant difference between the simulated and observed data under the selected copula model. The Cramér-von Mises (CvM) statistic measures the difference between the model's empirical distribution function and cumulative distribution function, quantifying how well the model fits the data across the entire distribution. The CvM statistic obtained here was 0.046, which is small and suggests that the model does a good job of approximating the observed distribution.

On the other hand, the Kolmogorov-Smirnov (KS) statistic is a non-parametric test that measures the maximum distance between the empirical distribution function and the model's cumulative distribution function. It is particularly sensitive to differences in the distribution's tails. The KS statistic obtained here was 0.615, indicating that the largest discrepancy between the observed and simulated distributions occurs within the tail regions. However, the p-value still supports the model's adequacy.

The CvM and KS statistics and their corresponding p-values are consistent with the null hypothesis that the copula model provides a good fit to the data. The non-rejection of this null hypothesis implies that the selected copula effectively captures the dependency structure between the wind and PV generation variables. Therefore, the goodness-of-fit test indicates that the Rotated BB8 270-degree copula is an appropriate model for describing the joint behavior of the wind and PV generation time series.

As shown in Figure 5, a visual comparison between the distributions of the simulated and observed data further supports the findings of the statistical test. The figure clearly illustrates that the distributions of the simulated data align with those of the observed data, confirming that the copula model accurately reproduces the observed joint behavior of the wind and PV generation time series. This visual agreement, coupled with the statistical results, provides strong evidence that the chosen copula model appropriately represents the dependency structure between the two energy sources, validating the reliability of the simulations for subsequent analysis and scenario generation.

In conclusion, the goodness-of-fit test and the visual comparison of the simulated and observed data distributions confirm the adequacy of the Rotated BB8 270-degree copula model. This result enhances confidence in the model's accuracy and robustness for capturing the joint behavior of wind and PV generation in the Galicia region.

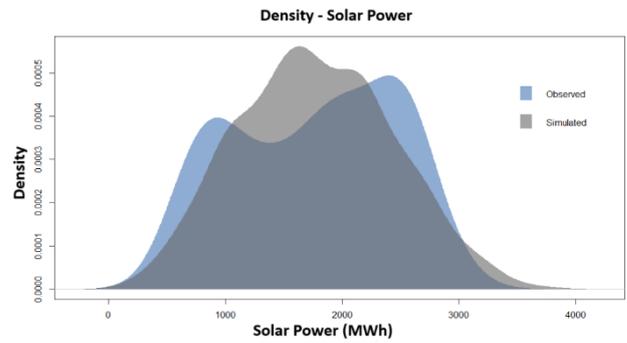


Fig 5 - Density of Observed and Simulated Data
Source: Prepared by the authors

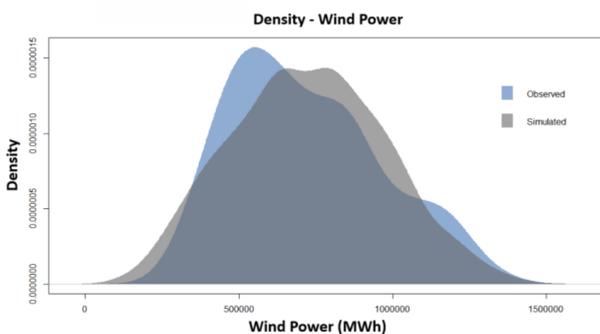
The comparison of the statistical metrics between the observed and simulated data for both wind and photovoltaic energy generation reveals that the discrepancies are minimal, indicating a substantial similarity between the two datasets. Specifically, the average observed value for wind energy generation was 719 MWh, while the simulated value was 720 MWh, resulting in a discrepancy of only 0.1%. The median for the observed data was 690 MWh, and for the simulated data, it was 715 MWh, showing a slight discrepancy of 3.6%. The standard deviation for the observed wind generation was 244 MWh, while for the simulated data, it was 248 MWh, resulting in a discrepancy of 1.8%. Finally, the coefficient of variation for the observed wind generation was 0.34, while for the simulated data, it was 0.35, with a discrepancy of 1.7% (Table 1).

Similarly, for photovoltaic energy generation, the observed average was 1,759 MWh, and the simulated average was 1,763 MWh, resulting in a discrepancy of 0.2%. The median for the observed data was 1,832 MWh, while for the simulated data, it was 1,749 MWh, resulting in a 4.5% discrepancy. The standard deviation for the observed photovoltaic generation was 698 MWh, while the simulated standard deviation was 685 MWh, with a discrepancy of 1.8%. The coefficient of variation for the observed photovoltaic generation was 0.40, while the simulated value was 0.39, with a discrepancy of 2.0% (Table 1).

These results show that the discrepancies between the observed and simulated data for both energy generation types (wind and photovoltaic) are minimal, especially considering the average and standard deviation. The discrepancies in the median and coefficient of variation are also relatively small, suggesting that the simulated data closely approximate the observed data. This indicates that the simulation process has successfully modelled the key statistical characteristics of the observed energy generation, and the results support the validity and robustness of the simulation. Therefore, the simulation provides a reliable representation of the energy generation patterns in both wind and photovoltaic sources, demonstrating high accuracy and a good fit for the historical data.

Table 1 - Discrepancy between observed and simulated data

Variables (MWh)	Average	Median	Standard Deviation	Coefficient of Variation
Wind	719	690	244	0.34



Sim Wind	720	715	248	0.35
Discrepancy	0.1%	3.6%	1.8%	1.7%
Photovoltaic Sim	1,759	1,832	698	0.40
Photovoltaic	1,763	1,749	685	0.39
Discrepancy	0.2%	4.5%	1.8%	2.0%

Source: Prepared by the authors

The link between wind and photovoltaic generation is explained in depth in Table 2. It specifically highlights the probability of photovoltaic generation exceeding its average based on different levels of wind generation. The table shows the probability of photovoltaic generation being greater than or equal to 1,759 MWh under two distinct intervals of wind generation.

In the first interval, where wind generation is between the minimum and the average (≤ 719 MWh), the probability of photovoltaic generation exceeding its average (1,759 MWh) is 78%. This suggests a strong likelihood that during periods of lower wind generation, photovoltaic generation has a higher chance of producing above-average output. This is consistent with the complementary nature of wind and PV energy, where lower wind energy is often associated with higher PV energy.

On the other hand, in the second interval, where wind generation is between the average and the maximum (> 719 MWh and $\leq 1,342$ MWh), the probability of photovoltaic generation exceeding its average drops to 48%. This indicates that as wind generation increases, the likelihood of PV energy generation exceeding its average decreases, further reinforcing the complementary relationship between the two energy sources. PV generation tends to be lower when wind generation is high, and vice versa.

This table underscores the utility of the copula methodology for capturing and quantifying the dependency structure between wind and PV energy generation. The ability to calculate conditional probabilities for different intervals allows for a more granular understanding of how these two sources of energy interact across varying levels of generation. This feature of methodology is significant, as it enables the exploration of different intervals and reveals deeper information about wind and PV energy dynamics. Furthermore, this flexibility in analyzing the relationship at different generation levels adds robustness to the study, offering a more comprehensive view of the complementarity between wind and PV power, which is for optimizing energy production and integration into the grid.

Table 2 - Probability of occurrence

Wind	Photovoltaic $\geq 1,759$
326 > Wind Generation ≤ 719	78%
719 > Wind Generation $\leq 1,342,334$	48%

Source: Prepared by the authors

4. Conclusion

This study used the copula theory to analyze the joint dependence structure between PV PV and wind power generation in the Galicia region of Spain from January 2014 to August 2024. The chosen approach captured the

complementary nature of these sources, influenced by distinct climatic conditions and seasonal patterns.

The study followed a three-step process: (i) fitting marginal distributions, (ii) selecting the most appropriate copula to represent the dependence structure, and (iii) simulating scenarios to generate synthetic data and evaluate the joint behaviour of the power generation variables. The Weibull distribution was the most suitable for modelling the marginal distributions of wind and PV power generation due to its ability to capture the asymmetry and non-negative characteristics typical of renewable energy data.

Regarding copula selection, the study identified the BB8 copula rotated by 270 degrees as the most appropriate model to capture the dependence structure between wind and PV power generation. The copula parameters were estimated by maximum likelihood estimation, with a moderate negative dependence, which was expected between these sources, suggesting a complementary relationship during some months. This dependence was modelled using the BB8 copula, known for its flexibility in capturing symmetric and asymmetric dependences, particularly in the distribution's tails. This aspect is important to understand extreme events, such as periods of low power generation in both sources, and this is an important point for reliability analysis in power systems. The model performance was validated through goodness-of-fit tests (Cramér-von Mises and Kolmogorov-Smirnov tests), resulting in the simulated data matching the behaviour of the observed data. Furthermore, visual comparisons of the statistical distributions and metrics showed minimal discrepancies, reinforcing the adequacy of the model. In this way, copula modelling is validated and demonstrates the reliability of the simulation in capturing the joint behaviour of wind and PV generation. This study's relevance lies in its contribution to the understanding of how wind and PV energy, despite their variability and dependence on climate factors, can be modelled jointly to improve energy forecasting and grid integration. The results gained from this study are important for energy system planners, as they provide a robust methodology for evaluating power generation patterns, increase the accuracy of renewable energy integration models, and facilitate the development of more resilient energy systems.

In conclusion, applying copula theory in this study proved an effective tool for modelling the dependence between PV and wind power generation, providing reliable information on their joint behaviour. Calculating probabilities through copulas is particularly significant as it allows a more accurate understanding of the probability of various power generation scenarios, which is important for risk assessment and decision-making in energy management. This methodology is helpful for future forecasting and assists in optimizing the integration of renewable energy into existing power grids, contributing to the sustainability and stability of the energy sector in Galicia. For future research, this approach can be applied to other regions and energy sources, such as hydropower and biomass, to broaden the scope of renewable energy integration studies and increase the generalizability of the results.

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