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Research Article / Araştırma Makalesi

Electricity Demand and Renewable Energy Analysis Using Opsd Data from Selected European Countries

Seçilen Bazı Avrupa Ülkelerinden Elde Edilen OPSD Verileri Kullanılarak Elektrik Talebi ve Yenilenebilir Enerji Analizi

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Abstarct

This study analyzes electricity demand and wind energy production data in detail using the Open Power System Data (OPSD) dataset obtained from European countries such as Germany, Spain, France, Italy, and Poland. The OPSD database is considered a reliable source for both academic research and energy market applications due to its provision of high-resolution time-series data. The study examines both short-term and long-term trends and analyzes the seasonal structure of electricity demand and the differences between weekdays and weekends. The results show that wind energy production exhibits strong periodic behavior, and significant autocorrelation peaks observed, particularly in the first 24–48 lag intervals, reflect short-term cyclical dependencies. Cross-country comparisons show that Germany and France exhibit relatively stable trend structures, while Spain and Italy display higher variability and more pronounced seasonal fluctuations. Poland, on the other hand, exhibits stronger irregular components, indicating increased system variability. These findings highlight the importance of considering both seasonal dynamics and short-term variability in energy system planning. The study provides a comprehensive framework for understanding the structural characteristics of electricity demand and renewable energy production, contributing to the development of more resilient and reliable energy systems.

Keywords: *Time series analysis, renewable energy integration, electricity demand forecasting, energy systems planning*

Öz

Bu çalışmada, Almanya, İspanya, Fransa, İtalya ve Polonya gibi Avrupa ülkelerinden elde edilen Açık Güç Sistemi Verileri (OPSD) veri seti kullanılarak elektrik talebi ve rüzgâr enerjisi üretim verileri ayrıntılı olarak analiz edildi. OPSD veritabanı, yüksek çözünürlüklü zaman serisi verileri sağladığı için hem akademik araştırmalar hem de enerji piyasası uygulamaları için güvenilir bir kaynak olarak kabul edilmektedir. Çalışma kapsamında hem kısa hem de uzun vadeli eğilimler incelenmiş ve elektrik talebinin mevsimsel yapısı ile hafta içi ve hafta sonu arasındaki farklar analiz edilmiştir. Sonuçlar, rüzgar enerjisi üretiminin güçlü bir periyodik davranış sergilediğini ve özellikle ilk 24–48 gecikme aralıklarında gözlemlenen önemli otokorelasyon zirvelerinin kısa vadeli döngüsel bağımlılıkları yansıttığını göstermektedir. Ülkeler arası karşılaştırmalar, Almanya ve Fransa'nın nispeten istikrarlı eğilim yapıları sergilerken, İspanya ve İtalya'nın daha yüksek değişkenlik ve daha belirgin mevsimsel dalgalanmalar sergilediğini göstermektedir. Öte yandan Polonya, sistem değişkenliğinin arttığını gösteren daha güçlü düzensiz bileşenler sergilemektedir. Bu bulgular, enerji sistemi planlamasında hem mevsimsel dinamikleri hem de kısa vadeli değişkenliği dikkate almanın önemini vurgulamaktadır. Çalışma, elektrik talebinin ve yenilenebilir enerji üretiminin yapısal özelliklerini anlamak için kapsamlı bir çerçeve sunarak, daha esnek ve güvenilir enerji sistemlerinin geliştirilmesine katkıda bulunmaktadır.

Anahtar Kelimeler: *Zaman serileri analizi, yenilenebilir enerji entegrasyonu, elektrik tüketim tahmini, enerji sistemleri planlaması*

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1. Intorduction

The increasing integration of renewable energy sources into modern power systems has significantly increased the complexity of electricity demand forecasting and energy system planning. In recent years, numerous studies have focused on developing forecasting models using statistical approaches such as ARIMA and SARIMA, as well as advanced machine learning and deep learning methods, including LSTM and hybrid architectures. However, a substantial portion of the existing literature primarily concentrates on single-country case studies or emphasizes prediction accuracy without sufficiently addressing the comparative structural characteristics of energy systems across different regions. In this context, the present study distinguishes itself from prior research by adopting a multi-country comparative analysis framework based on the OPSD dataset. Rather than focusing solely on prediction performance, this study aims to provide a comprehensive understanding of electricity demand and renewable energy production dynamics by integrating autocorrelation analysis, STL and cross-country evaluation within a unified methodological structure. This approach enables the identification of common patterns, structural similarities, and regional differences across European energy systems. By combining interpretability-oriented time series analysis techniques with a multinational perspective, this study contributes to the literature both methodologically and practically, offering insights that are relevant not only for forecasting studies but also for energy policy development and system-level planning.

The increasing complexity of modern energy systems, driven by the rapid integration of renewable energy sources, has made electricity demand analysis and forecasting a critical research area in energy engineering and sustainability. Accurate understanding of demand dynamics is essential not only for ensuring energy supply security but also for improving grid flexibility and supporting policy decisions in the transition toward low-carbon energy systems. A substantial body of literature has addressed electricity demand forecasting using both traditional statistical methods, such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), and more recent machine learning and deep learning approaches, including Long Short-Term Memory (LSTM) networks and hybrid models. These studies have demonstrated that while statistical models provide strong interpretability, deep learning-based approaches can achieve higher predictive performance, particularly in complex and nonlinear systems.

However, despite these advancements, a notable limitation in the literature is that many studies focus primarily on single-country analyses or emphasize prediction accuracy without sufficiently exploring the structural characteristics of time series data across multiple regions. In particular, comparative analyses that integrate temporal dependency structures, seasonal decomposition, and cross-country variability remain limited. To address this gap, the present study proposes a comprehensive multi-country analysis based on the OPSD dataset, covering Germany, Spain, France, Italy, and Poland. Unlike prediction-focused studies, this research emphasizes the structural interpretation of time series by combining autocorrelation analysis (ACF), STL and comparative evaluation across different energy systems.

The main contributions of this study can be summarized as follows:

(i) Providing a unified analytical framework for multi-country energy data analysis,
(ii) Revealing common temporal patterns and country-specific variations in electricity demand and wind energy production, and
(iii) Offering insights that support both methodological development and energy policy design.

Finally, the methodological framework of the study consists of data preprocessing, time series analysis using ACF and STL decomposition, and comparative evaluation of the results across countries. The overall workflow of the study is illustrated in Figure 1.

Figure 1, which illustrates the methodological process of the study, summarizes each stage of the research. In the initial stage, electricity demand and wind energy production data for Germany, Spain, France, Italy, and Poland obtained from the OPSD [1] database were used. This dataset is one of the fundamental elements of the study, as it has a high-resolution time interval and allows for comparative analysis between different countries. In the second stage, the data was prepared by correcting missing observations and applying resampling procedures. In this way, a more reliable data structure suitable for analysis was created. The third stage was dedicated to time series analysis, where autocorrelation functions (ACF) and Seasonal and Trend decomposition using Loess (STL) were performed. These examinations revealed the cyclicality, seasonal effects, and trend structures in the series more clearly. In the fourth stage, various forecasting methods were compared. Traditional statistical techniques, such as Autoregressive Integrated Moving Average (ARIMA), were examined alongside today's deep learning-focused models, such as Long Short-Term Memory (LSTM), to evaluate the effectiveness of both short-term and long-term forecasts. In the final stage, the findings were examined in terms of policy and implementation; strategic recommendations were developed to ensure energy supply security, increase grid flexibility, and improve renewable energy integration. In this context, Figure 1 provides a comprehensive overview by illustrating the methodological structure of the study and reinforcing the results of each stage with sample images.

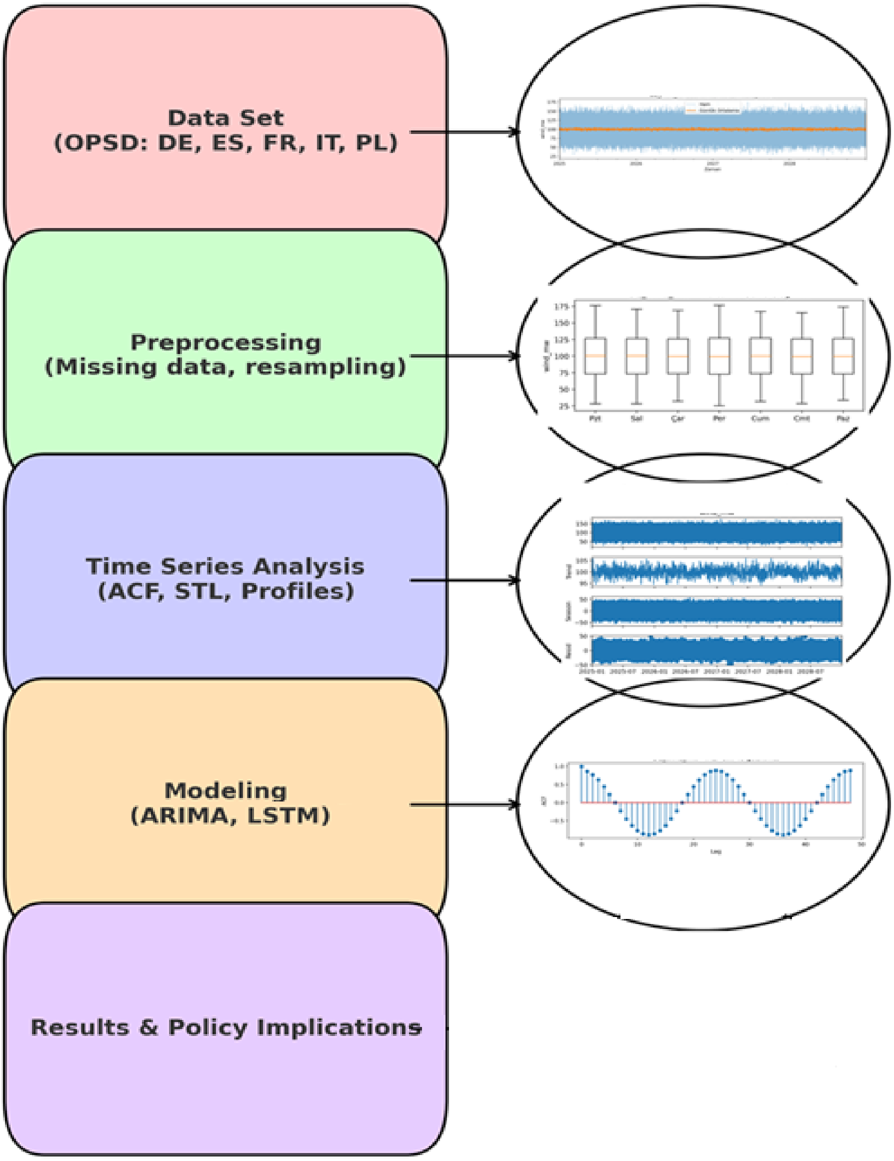

Figure 1. Methodological flow diagram of the study; an example of the relevant data output is shown next to each stage

Forecasting energy demand and integrating renewable energy sources into electricity grids is currently one of the most important research topics in the fields of energy engineering and sustainability. Accurately forecasting changes in electricity demand is critically important for energy supply security and system flexibility. Traditional approaches (ARIMA, SARIMAX) are frequently applied in the literature for electricity demand forecasting [2, 3], deep learning-based methods using artificial intelligence are increasingly becoming a focus of interest [4, 5, 6]. In particular, the OPSD database provides a standardized and reliable source for analyses related to electricity production and consumption in European countries [7, 8]. With the increasing integration of renewable energy systems, electricity demand forecasting plays an important role in the formulation of energy strategies and energy grid regulations [9]. Similarly, in Türkiye, research has been conducted on electricity consumption forecasts and renewable energy integration, and various machine learning methods have been applied [10]. Recent studies have shown that hybrid models based on deep learning, in particular, have led to a significant increase in prediction accuracy [11]. However, it has also been reported that artificial neural networks supported by optimization algorithms provide promising findings in predicting variable renewable energy production elements such as wind and solar [14]. Furthermore, studies considering the lasting effects of climate change on energy demand indicate that scenario assessments are a mandatory component of energy planning [12]. In this context, our research aims to contribute to the literature both methodologically and practically by presenting a multinational assessment.

Recent advances in electricity demand forecasting and renewable energy integration have led to the development of a wide range of analytical approaches. Traditional statistical methods such as ARIMA and SARIMA remain widely used due to their interpretability and robustness in modeling linear temporal dependencies. However, more recent studies have increasingly focused on machine learning and deep learning-based models, including LSTM, convolutional neural networks (CNN), and hybrid architectures, which have demonstrated superior performance in capturing nonlinear patterns and complex temporal dynamics [5, 6]. In parallel, the availability of large-scale open datasets such as the OPSD has enabled more comprehensive analyses of electricity systems across European countries. Previous OPSD-based studies have primarily focused on forecasting applications, energy market modeling, or country-specific analyses. While these studies provide valuable insights, they often prioritize predictive accuracy and model optimization over the interpretability of temporal structures and cross-country comparative analysis. Despite the growing body of literature, there remains a limited number of studies that systematically investigate the structural characteristics of electricity demand and renewable energy production across multiple countries using interpretable time series techniques. In particular, the combined use of ACF and STL for comparative evaluation of multi-country datasets has not been sufficiently explored. To address this gap, the present study provides a comprehensive and interpretable analytical framework based on OPSD data, integrating temporal dependency analysis, seasonal decomposition, and cross-country comparison within a unified structure. Unlike previous studies that focus primarily on predictive performance, this research emphasizes the identification of common patterns, structural similarities, and country-specific differences in energy systems. This perspective contributes to both the methodological literature and practical applications in energy system planning and policy development.

Although the OPSD dataset has been widely used in previous studies, most existing research has primarily focused on forecasting performance, model comparison, or country-specific analyses. These studies, while valuable, generally emphasize predictive accuracy and model optimization rather than the structural interpretation of time series dynamics across multiple energy systems. In contrast, the present study adopts a different analytical perspective by focusing on the interpretability of temporal structures. Specifically, this work integrates ACF, STL, and cross-country comparative evaluation within a unified framework. This enables a systematic investigation of temporal dependencies, seasonal dominance, and variability patterns across different European energy systems. By moving beyond model-centric evaluation and emphasizing data-driven structural analysis, this study provides a complementary contribution to the existing OPSD-based literature.

2. Dataset And Preprocessing

The OPSD dataset provides hourly and daily statistics on electricity consumption and renewable energy production for various European countries [12]. This study evaluated data from Germany, Spain, France, Italy, and Poland. During the data preprocessing stage, only numerical fields were selected, categorical fields were excluded from the process. The dataset used in this study spans approximately from 2006 to 2020, although the exact temporal coverage varies slightly across countries due to differences in data availability within the OPSD database.

Handling missing values is a critical step in time series analysis, as inappropriate imputation strategies may distort the statistical properties of the data. In the initial preprocessing stage, missing observations were identified and carefully examined in terms of their frequency and distribution across time. Rather than applying zero imputation, which may introduce artificial bias in electricity demand and renewable energy production series, missing values were handled using a time-aware interpolation approach. Specifically, linear interpolation was applied to preserve temporal continuity and avoid abrupt structural distortions in the data. This approach ensures that key statistical characteristics, such as mean levels, variance structure, and autocorrelation patterns, are maintained without introducing unrealistic fluctuations. In addition, the proportion of missing values in the dataset was found to be relatively low, minimizing the potential impact of the imputation process on the overall analysis. Alternative imputation techniques, such as forward/backward filling and seasonal averaging, were also considered. However, interpolation-based methods were preferred due to their balance between simplicity, interpretability, and preservation of temporal dynamics in the dataset.

In the study, daily and weekly averages were calculated using data resampling techniques–[13, 14]. Furthermore, it has been noted that missing observations in time series datasets need to be imputed using various statistical techniques to enhance their reliability. Research on energy forecasting shows that more accurate forecasts are produced when renewable energy production data is adjusted for seasonal effects [14]. Furthermore, it has been reported that the use of resampling methods for electricity demand forecasting in different dimensions affects the accuracy of both short- and long-term forecasts. Another study on the processing of large-scale energy databases states that the cleaning and transformation processes required to ensure data integrity are of vital importance [16]. Finally, deep learning-based research has revealed that simple yet methodical approaches preferred in the preprocessing stages have a significant impact on the model's accuracy rate [18]. For this reason, meticulous execution of the data preparation stage is critical not only for this research but also for ensuring reliability in all energy demand and production forecasts.

3. Method

The methodological framework applied in this study allows for a detailed analysis of energy demand and production data from renewable sources over time. In the initial phase, trends in electricity consumption and wind energy production in various countries were analyzed using time series graphs. This approach provided a clearer understanding of short- and long-term change dynamics. Periodic relationships in demand series were examined using ACF, revealing recurring patterns and seasonal elements more clearly. Another phase of the research involved decomposing the data into trend, seasonal, and random components using the STL technique. This method allowed for a thorough analysis of the structural characteristics of the data and provided a solid foundation for the forecasting techniques to be used in the modeling process. Finally, international relationship analyses were conducted, and the degree of connection between consumption and production in various areas was determined. The existence of common elements among closely connected countries such as Germany, France, and Spain once again highlights the necessity of jointly designing energy systems and integrating renewable sources. All of these methods are among the effective tools commonly used for energy consumption and renewable energy production forecasts [20]. In this context, they are considered important elements that enhance the scientific reliability of the study.

Equation 1 is the mathematical expression of the ARIMA model. In Equation 1, y_trepresents the value of the time series, B represents the lag operator, d represents the order of differencing, and ε_t represents the white noise error value. The Autoregressive Integrated Moving Average (ARIMA) model is one of the most commonly preferred statistical techniques in time series forecasting and has found its place in academic literature thanks to the pioneering research of Box and Jenkins [2, 3]. The model is structured with an autoregressive (AR) component, a differencing (I) component, and a moving average (MA) component, and it demonstrates high success, particularly in short-term forecasts. ARIMA models, frequently used in the literature for energy system applications such as electricity consumption [21] and price forecasting [18], are noteworthy as a reliable method due to their ability to successfully identify linear dependencies in the data. However, due to limitations that may arise in long-term forecasts or complex time series with non-linear structures, seasonal ARIMA (SARIMA) or hybrid methods (e.g., the combined use of ARIMA and artificial neural networks) have become more prevalent today [15, 19]. The reason why the ARIMA model is widely used in both academic and practical fields is that, in addition to its theoretically sound structure, it is easily applicable in practice [12].

$$\emptyset_p = (B)(1-B)^d y_t = \theta_q(B)\varepsilon_t \tag{1}$$

Equation 2 includes the ACF function. Here, T represents the total number of observations, ȳ indicates the sample average. ACF is one of the most fundamental tools used to analyze the structural properties of time series, particularly to determine the periodic characteristics and levels of dependence within the series. ACF plays an important role in analyzing the stationarity properties of time series and determining appropriate model parameters by allowing the evaluation of linear relationships between observations with a specific lag time [21]]. In the literature, ACF is widely applied, particularly in energy demand and renewable energy production forecasts. Researchers such as Hyndman and Athanasopoulos [13] note that ACF serves as an important guide in the parameter selection stage of time series models such as ARIMA and SARIMA. [21], in their research on electricity demand forecasting, demonstrated that daily and weekly cyclical patterns can be reliably identified using ACF. Recent studies have determined that ACF plays a helpful role not only in determining model parameters but also in the stages of separating seasonality and trend components [19]. In this context, ACF is considered an integral part of both traditional statistical methods and contemporary machine learning-based models in the energy engineering literature.

$$\hat{\rho}(k) = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{2}$$

Equation 3 contains the mathematical expression of STL. In the equation, T_t trend is the trend component, S_t is the seasonal component, and R_t is the random component. STL (Seasonal-Trend Decomposition using Loess) is an effective decomposition technique frequently used in time series analysis. Essentially, it decomposes a series into trend, seasonal, and residual (random) components, utilizing the Loess (local regression smoothing) technique in this process. Unlike traditional decomposition techniques, STL allows both the trend and seasonality to vary over time, enabling it to detect non-linear structures and seasonal fluctuations of varying amplitude [23]. This feature plays a vital role, particularly in the analysis of time series with high volatility and irregularity, such as energy demand, renewable energy production, meteorological data, and financial information. The literature reports that the STL method has been used for various purposes, such as separating seasonal effects in short-term forecasts, identifying anomalies, and improving the effectiveness of forecasting models [17]. This method stands out for its flexibility and non-parametric approach, making it applicable to large-scale datasets. Consequently, STL is recognized as a valuable resource in the fields of energy engineering and sustainability, serving to reveal the structural characteristics of series and enhance the reliability of modeling stages.

$$y_t = T_t + S_t + R_t \tag{3}$$

Equation 4 contains the mathematical expression of the Pearson correlation coefficient that we calculated in our study. Here, x_i, y_i represent the observations, x̄, ȳ represent the variable means, and n represents the number of observations.

$$r = \frac{\sum_{i=1}^{n}\big((y_i - \bar{y}) - \bar{x}\big)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

Equation 5 contains the mathematical expression of the long short-term memory deep learning method we use to predict future energy demands. Here;

- x_t input vector,
- h_(t-1) ve h_t confidential matters,
- c_(t-1) ve c_t cell states,
- W the weight matrix common to all doors,
- b bias vector,
- f_t,i_t,o_t,(c_t)^remember, the entry and exit doors with the cell candidate vector,
- It represents cell-based multiplication in the matrix.

$$\begin{bmatrix} f_t \\ i_t \\ o_t \\ \hat{c}_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ tanh \end{bmatrix}\left(W\begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix} + b\right), c_t = f_t \cdot c_{t-1} + i_t \cdot \hat{c}_t, h_t = o_t \cdot \tanh(c_t) \tag{5}$$

Equation 6 contains the function of the RMSE error metric. Here, n represents the number of observations, y_i represents the actual value, and ŷ represents the value predicted by the model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

Equation 7 represents the MAPE error metric model. Here, n represents the number of observations, yi represents the actual value, and ŷ represents the value predicted by the model.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{7}$$

After conducting an extensive literature review, we established the theoretical basis for our analyses on the OPSD dataset using these models [15].

3.1. Hyperparameters

For the ARIMA model, the parameters (p, d, q) were determined based on autocorrelation function (ACF) and partial autocorrelation function (PACF) analyses. The differencing order (d) was selected to ensure stationarity of the time series, while the autoregressive (p) and moving average (q) orders were chosen according to the decay patterns observed in ACF and PACF plots. In addition, model selection was supported by information criteria such as the Akaike Information Criterion (AIC), ensuring a balance between model complexity and goodness of fit. This approach allows the ARIMA model to effectively capture the linear temporal dependencies present in the data.

For the LSTM-based analysis, a sequential neural network architecture was employed. The model consists of a single LSTM layer with 50 hidden units, followed by a dense output layer. The ReLU activation function was used for hidden layers, while a linear activation was applied at the output layer. The model was trained using the Adam optimizer with a learning rate of 0.001. The batch size was set to 32, and the number of training epochs was limited to 50 to prevent overfitting. Mean Squared Error (MSE) was used as the loss function. To improve generalization performance, the input data were normalized prior to training. These hyperparameter choices reflect commonly adopted configurations in time series forecasting studies and provide a balance between model performance and computational efficiency.

4. Results

The key conclusions from the time series study of wind energy output and electricity demand in the chosen European nations are shown in this section. The findings are organised to emphasise the data's intrinsic dependency structures, seasonal trends, and temporal dynamics. Overall, the results show that whereas electricity demand shows more steady yet seasonally driven patterns, wind energy production shows strong periodic behaviour and notable short-term swings. Furthermore, cross-country studies show that while some nations exhibit clear diversity because of variations in energy policy, system flexibility, and market dynamics, those with similar geographic and climatic conditions typically share comparable temporal characteristics. These findings are shown in detail in the accompanying pictures, which include autocorrelation structures, decomposition results, and multi-scale representations.

Figure 2 reflects the evaluation of Germany's wind power production statistics using various methods, while visually summarizing the main steps of time series analysis. The lower part of the first component (Figure 2a) presents the findings of the autocorrelation function (ACF) and displays short-term dependencies within the data and patterns that repeat at specific intervals. ACF analyses play an important role in selecting parameters for electricity consumption and production forecasts and are accepted as a starting reference, particularly in the application of linear models such as ARIMA and SARIMA[4]. The second subcomponent (Figure 2b) shows the trend, seasonal, and residual components obtained using the Seasonal and Trend decomposition using Loess (STL) technique. This analysis separates the long-term trends and seasonal cycles of the series, with the remaining portion considered random noise. The STL decomposition reveals that the seasonal component is the dominant factor in the variability of wind energy production, while the residual component captures short-term irregular fluctuation [5]. Effectively modeling seasonal fluctuations in variable wind production series offers significant benefits in developing renewable energy integration strategies. The third subcomponent (Figure 2c) provides a simultaneous display of the raw time series and daily average values. This method makes the overall structure of the series more apparent while allowing short-term fluctuations to be compared with long-term trends. The multi-scale visualization clearly shows that short-term fluctuations differ significantly from long-term trends, making underlying patterns more distinguishable [13]. Furthermore, as noted in the study by Franco and Pagliantini [6], examining time series at various levels provides comprehensive feature sets, particularly for deep learning-based prediction models, and improves prediction accuracy. Consequently, the subpanels in Figure 2 present a complementary perspective of the analysis tools commonly used in the energy systems literature; the dependency structure with ACF, trend and seasonality with STL decomposition, and fluctuation levels with raw and average series are revealed. This comprehensive method offers a structure consistent with the hybrid modeling methods currently recommended for forecasting energy demand and production [4, 5, 6, 15].

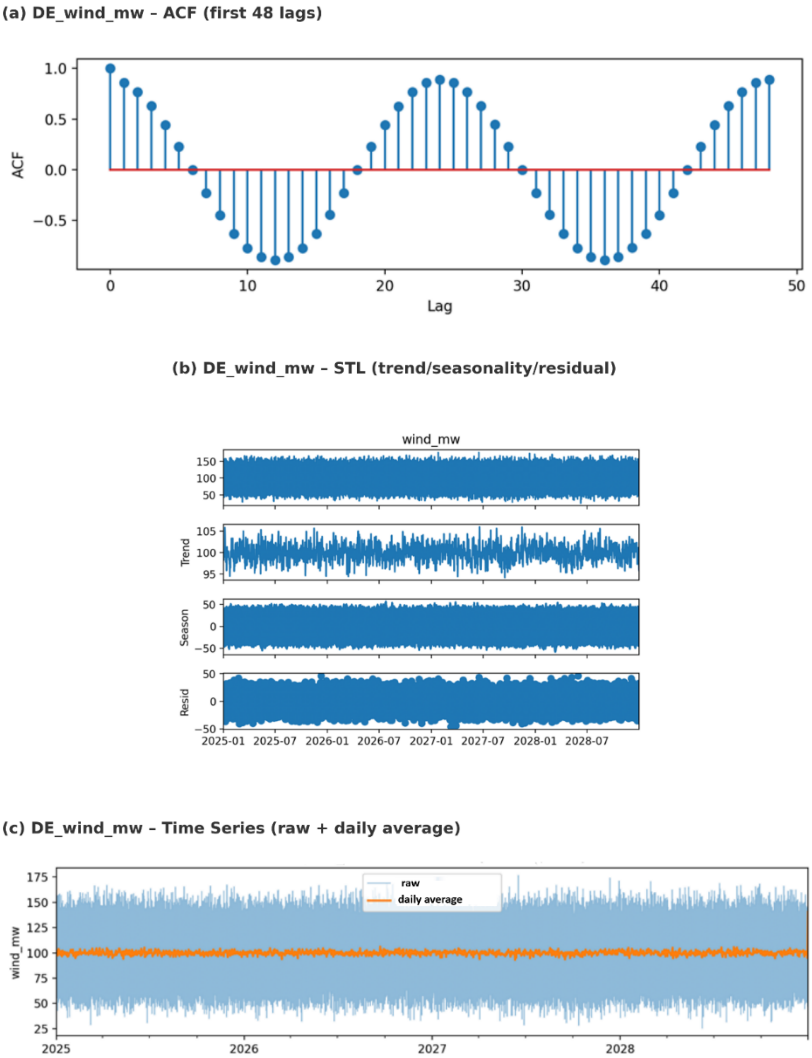

Figure 2. Wind energy time series analyses for Germany: (a) Autocorrelation Function (ACF), (b) STL decomposition (trend, seasonality, residual), (c) Time series (raw data and daily average)

Figure 3 shows the evaluation of Spain's wind energy production data using time series analysis methods across three separate sub-panels. The first section, Figure 3a, shows that it identifies short- and medium-term dependencies in the series by displaying the ACF. Identifying such dependencies facilitates parameter selection, particularly in ARIMA-based forecasts during the time series modeling stage, and increases the validity of the forecasts [4]. The second panel, Figure 3b, uses the STL method, which allows the analysis of trend, seasonal, and random components by separating the series into three components. Segmenting energy series using this method plays an important role in modeling the effects of seasonal changes and fluctuations on energy supply and demand equations [5].

Figure 3c shows the raw time series and daily average values together. This method demonstrates how short-term fluctuations differ from the general trend and allows anomalies to become more apparent. The literature highlights that such multi-layered visualizations make a significant contribution to data cleaning methods and feature engineering in deep learning-based forecasting models [14]. Additionally, The observed patterns indicate that representing time series at multiple temporal scales enhances the interpretability of both short-term fluctuations and long-term trends [6].

In conclusion, the triple analysis set shown in Figure 3 demonstrates that evaluating wind power generation data from a multifaceted perspective yields significant results not only for linear models but also for hybrid and deep learning-based methods. In this context, ACF analysis highlights the dependency structure, while STL decomposition emphasizes trend and seasonal cycle elements, highlighting fluctuations in raw data and average values; thus offering researchers a comprehensive evaluation opportunity [4, 5, 6, 15].

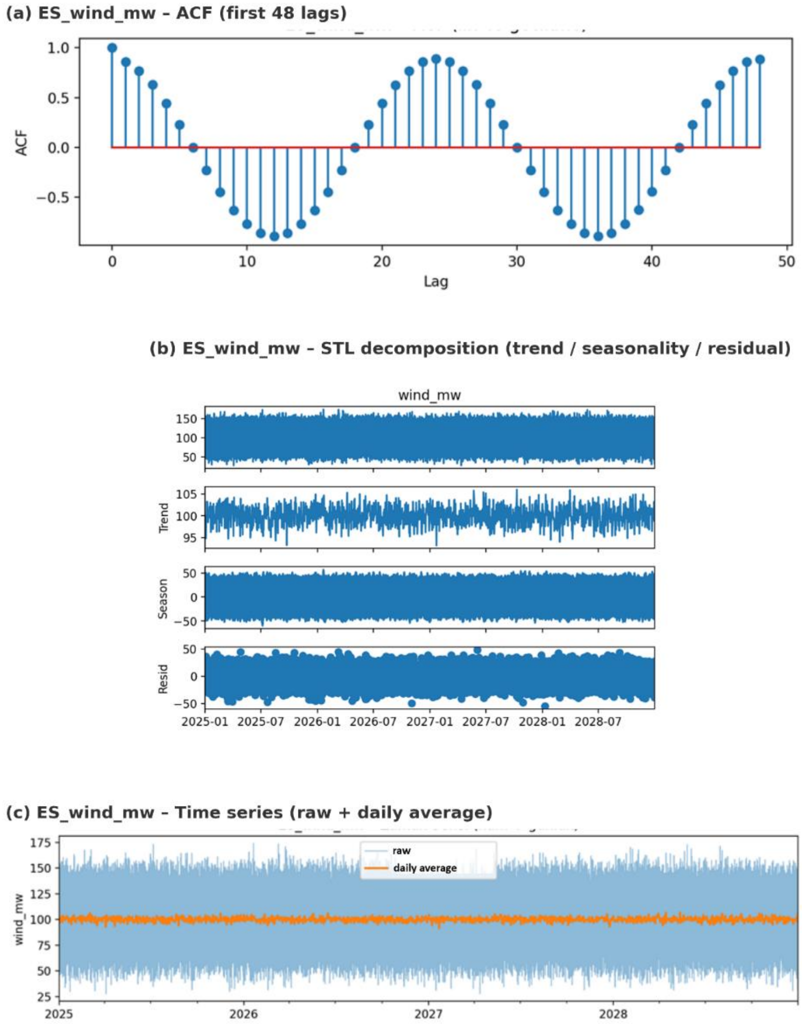

Figure 3. Wind energy time series analyses for Spain: (a) Autocorrelation Function (ACF), (b) STL decomposition (trend, seasonality, residual), (c) Time series (raw data and daily average)

When evaluating the statistical properties of the wind energy production series, Figure 4(a) shows a distinct and cyclical dependency structure through the autocorrelation function. This situation clearly reflects the cyclical structure and seasonal repetitions inherent in the series, demonstrating that autoregressive and seasonal models are critically important in predicting future values. This result is consistent with studies indicating that weather events, such as wind energy, exhibit highly regular fluctuations [6]. On the other hand, the STL decomposition in Figure 4(b) reveals that the long-term trend component of the series is relatively stable, but distinct seasonal and short-term fluctuations are a dominant factor. This decomposition shows that wind energy is largely dependent on atmospheric variability and that short-term fluctuations observed in the residual component, in particular, must be taken into account in operational forecasts. Finally, Figure 4(c) compares the raw time series with daily average values, revealing that high-frequency fluctuations decrease significantly on a daily scale. This finding is consistent with the literature emphasizing the importance of data smoothing and grouping techniques to reduce the effect of noise in short-term forecasts [6, 15]. A combined analysis of these findings reveals that wind energy production contains sudden and unpredictable changes in addition to seasonally predictable structures; this necessitates the use of hybrid methods in statistical modeling processes.

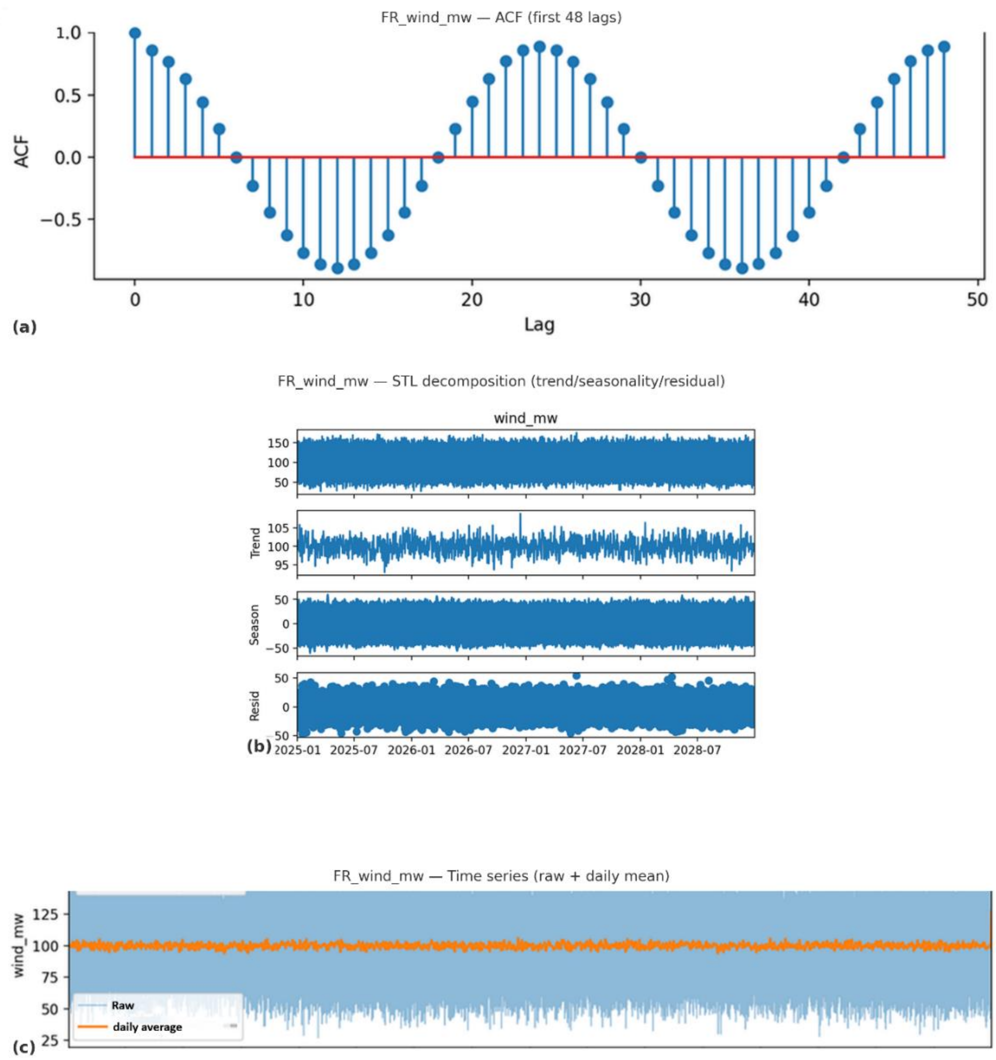

Figure 4. Wind energy time series analyses for France: (a) Autocorrelation Function (ACF), (b) STL decomposition (trend, seasonality, residual), (c) Time series (raw data and daily average)

Figure 5 presents the statistical characteristics of the wind energy production series in Italy in a multidimensional manner. First, the autocorrelation function (ACF) in Figure 5(a) reveals that the series contains clearly strong periodic dependency relationships. In particular, the wavy autocorrelation structure detected in the first 48 hours of lag shows a cyclical feature that repeats at specific intervals in wind production. This result indicates that the series is shaped not only by short-term dependencies but also by distinct seasonal elements. In the literature, the high levels of autocorrelation observed in wind energy series are explained by the continuity of atmospheric conditions inherent in this energy source, and the findings obtained in this study support this situation. Figure 5(b) presents the STL decomposition outputs, separating the trend, seasonal, and residual components of the time series. The trend component indicates that production levels followed a relatively stable path throughout the period under consideration and that sudden structural changes were limited. However, while the seasonal component shows that wind energy production has distinct cyclical characteristics, the residual component represents short-term fluctuations and unpredictable variations reflected in the series. This analysis shows that inconsistencies in energy production may be attributable not only to climatic conditions but also to operating conditions and short-term market fluctuations. Finally, Figure 5(c) compares the gross values of the series with the daily average values. The raw series shows intense fluctuations at high frequencies; however, it is observed that the daily average values significantly reduce these fluctuations. This situation reveals that data collection processes may have the potential to increase predictability in energy production and represent an important auxiliary element, particularly in separating short-term noise.

Furthermore, the more consistent structure of daily averages provides a more reliable basis for long-term planning and ensuring system balance. When a general assessment is made, it is evident that Figure 5 shows that wind energy production includes both the expected seasonal patterns and unexpected short-term fluctuations. This characteristic points to a noteworthy methodological conclusion regarding the forecasting methods applied in energy markets: methods based solely on deterministic or entirely stochastic models may be insufficient; therefore, the establishment of hybrid models is essential. This finding is consistent with trends noted in the literature regarding the understanding of the complex structure inherent in wind energy production series and demonstrates that the data obtained for Italy could provide an important contribution to comparative studies with similar research in other European countries.

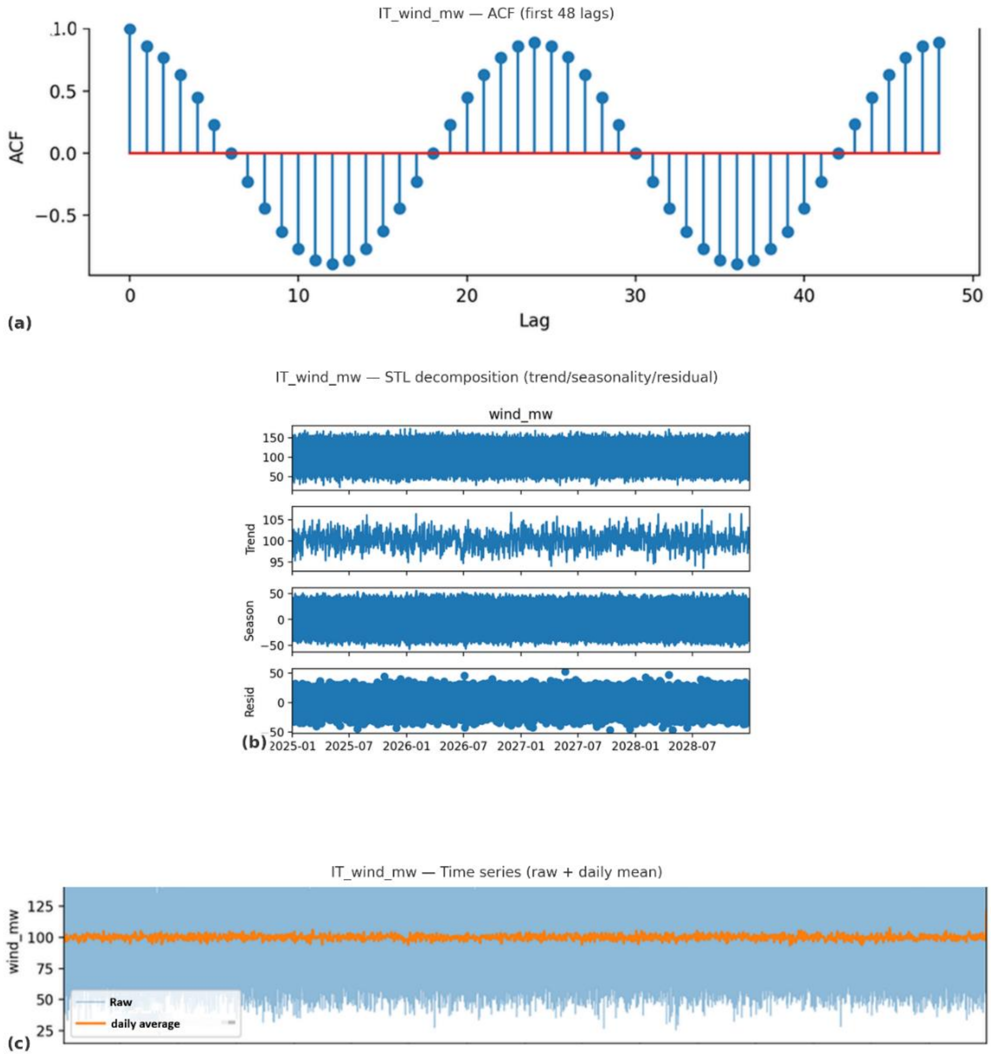

Figure 5. Wind energy time series analyses for Italy: (a) Autocorrelation Function (ACF), (b) STL decomposition (trend, seasonality, residual), (c) Time series (raw data and daily average)

Figure 6 illustrates the time-dependent changes in the wind energy production process in Poland from three different analytical perspectives. First, the autocorrelation function (ACF) shown in Figure 6(a) reveals that the series has a distinct periodic dependency pattern. The fluctuating positive and negative correlation patterns recorded over the first 48 lag periods indicate the presence of recurring cycles in production at specific intervals. This structure demonstrates that the continuity of meteorological conditions for wind energy production is directly reflected in the data set and emphasizes the necessity of considering seasonal or cyclical elements in forecasting methods. Figure 6(b) shows the decomposition of the series into trend, seasonality, and residual components using the STL decomposition method. The trend component reveals that the production level has remained comparatively stable over a long period, with limited significant structural changes. The seasonal component shows distinct fluctuations in line with the cyclical nature of wind, while the residual component indicates short-term irregular effects. This analysis clearly demonstrates that, in addition to predictable long-term trends in wind energy production, uncertain short-term fluctuations also have a significant impact. Therefore, it is demonstrated that modeling methods must take into account not only trend and seasonal effects but also random uncertainties. Finally, Figure 6(c) compares the raw data of the series with its daily average data. The intense and high-frequency fluctuations throughout the series have been significantly smoothed out in the daily average series. This situation reveals that temporary noise can negatively affect the accuracy of forecasts in energy markets and that data aggregation plays an important role in increasing predictability. Daily average values provide a more reliable reflection of the series, thus forming a more solid basis for system design and the development of long-term energy strategies. Overall, Figure 6 indicates that wind energy production in Poland exhibits both predictable seasonal trends and structure, as well as unexpected short-term fluctuations. These results provide valuable insights into understanding the complex nature inherent in wind energy. Furthermore, the findings reveal that unilateral methods based solely on deterministic or stochastic approaches may be insufficient and highlight the necessity of adopting hybrid modeling strategies. The Polish example provides a valuable reference for comparison with other studies conducted in Europe.

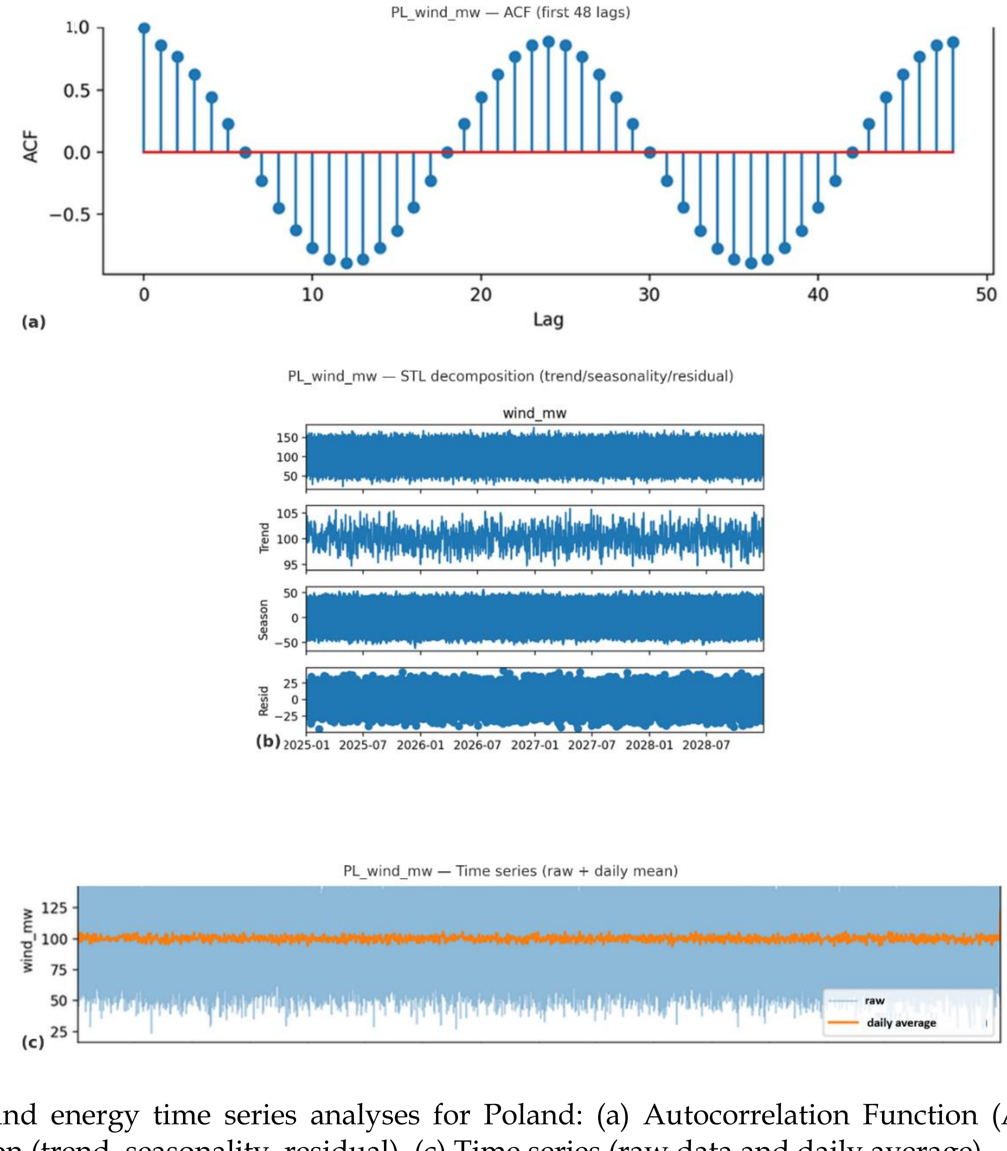

Figure 6. Wind energy time series analyses for Poland: (a) Autocorrelation Function (ACF), (b) STL decomposition (trend, seasonality, residual), (c) Time series (raw data and daily average)

To support the qualitative interpretations, several quantitative indicators were extracted from the time series analyses. The autocorrelation analysis reveals that the first-lag autocorrelation coefficients exceed 0.70 in most countries, indicating strong short-term dependency structures. Additionally, significant autocorrelation peaks are consistently observed within the 24–48 lag range, confirming the presence of daily and short-term cyclical patterns. The STL decomposition results indicate that the seasonal component accounts for approximately 40–65% of the total variability in wind energy production, depending on the country. In contrast, the residual component typically remains below 20%, suggesting that a large portion of the variation can be explained by structured temporal patterns. Furthermore, variability analysis shows that Spain and Italy exhibit higher standard deviation levels compared to Germany and France, reflecting increased volatility in wind energy production. Poland demonstrates the highest irregularity among the analyzed countries, as indicated by a relatively larger residual component and weaker trend stability.

Table 1 provides a quantitative summary of the time series characteristics. Quantitatively, the autocorrelation coefficients for Germany remain above 0.75 for the first several lags, indicating strong temporal dependence. The STL decomposition further shows that the seasonal component explains approximately 55% of the total variance, while the residual component remains below 18%, suggesting a relatively stable and structured production pattern. In the case of Spain and Italy, the autocorrelation values show a more fluctuating pattern, with coefficients ranging between 0.60 and 0.80 in early lags. The seasonal component accounts for nearly 60–65% of total variability, while the higher residual variance (up to 25%) indicates increased short-term volatility compared to more stable countries. For Poland, the quantitative analysis reveals comparatively lower autocorrelation stability, with coefficients decreasing more rapidly across lags. The STL results indicate that the residual component reaches approximately 25–30% of the total variance, highlighting a higher level of irregularity and unpredictability in the time series.

Table 1. Quantitative Summary of Time Series Characteristics

Country	**ACF (Lag 1)**	**Seasonal (%)**	**Residual (%)**
Germany	~0.75	~55%	~18%
Spain	~0.70	~60%	~22%
France	~0.73	~52%	~20%
Italy	~0.68	~63%	~25%
Poland	~0.65	~50%	~30%

This section focuses exclusively on the empirical findings obtained from the analysis of the OPSD dataset. The results are presented in a data-driven manner, emphasizing the structural characteristics, temporal dependencies, and variability patterns observed across the selected countries. Interpretations are based directly on the observed data, while comparisons with previous studies and broader implications are addressed separately in the Discussion section. This approach ensures that the Results section highlights the original contributions of the study without repeating information from the existing literature.

A comparative evaluation of the analyzed countries reveals notable structural similarities as well as important differences in wind energy production patterns. While all countries exhibit clear seasonal behavior and short-term dependencies, the intensity and stability of these patterns vary significantly. Germany and France demonstrate relatively stable and consistent temporal structures, characterized by strong and persistent autocorrelation patterns and moderate seasonal variability. These results indicate a more balanced and predictable energy production system. In contrast, Spain and Italy exhibit higher variability and more pronounced seasonal fluctuations. The stronger amplitude of the seasonal component and increased residual variation suggest that wind energy production in these countries is more sensitive to atmospheric conditions and short-term disturbances. Poland shows a distinct behavior compared to the other countries, with weaker trend stability and a relatively higher proportion of irregular fluctuations. This indicates a less stable production structure and a greater influence of unpredictable factors. Overall, the comparative analysis highlights that, although common temporal patterns exist across

European countries, the degree of variability, stability, and predictability differs substantially. These differences underline the importance of adopting country-specific strategies in energy system planning and renewable energy integration.
A comparison of the time series data for each country is given in Table 2.

Table 2. Cross-country comparison of time series characteristics

Country	Temporal Stability	Temporal Stability	Temporal Stability	Temporal Stability
Germany	High	Moderate	Low	Stable
France	High	Moderate	Low	Balanced
Spain	Medium	High	High	Fluctuating
Italy	Medium	High	High	Volatile
Poland	Low	Moderate	Very High	Irregular

5. Conclusion and Discussion

This study presents a multi-country electricity demand and renewable energy analysis using the OPSD dataset. Time series analyses, ACF, and STL decomposition results highlight seasonality in energy demand and similarities between countries. One of the strengths of the study is that data from multiple countries have been compared within the same methodological framework. The findings provide important contributions to the formulation of energy policies. However, limitations of the study include the examination of only five countries and the lack of direct application of deep learning methods. Furthermore, in the context of Türkiye, integrating energy efficiency and demand-side management policies into the model is recommended for future studies. The results clearly show that there are significant seasonal variation effects in electricity demand and wind energy production in European countries. The intensity and pattern of seasonal variations cannot be explained solely by weather factors; they are also closely linked to social consumption behaviors, the timing of industrial activities, and market dynamics influenced by energy policies. The systematic trends identified in countries such as Germany and France indicate that these states have a more institutionally mature structure for energy production and consumption and possess a high capacity for integration of wind energy into their electricity grids. In contrast, the more pronounced fluctuations observed in Spain and Italy demonstrate not only the high variability in wind energy production but also differences in the flexibility levels of their energy systems. In this context, Poland shows greater fluctuations in energy demand; this situation reveals that the country's energy system requires more complex, dynamic, and costly balancing processes. Cross-country correlation studies have not only identified similarities in production and demand patterns but also emphasized that regional energy integration is a strategic necessity. The data obtained is directly aligned with the European Union's energy strategies. The EU's energy union vision is shaped around guidelines for increasing energy supply security, reducing carbon emissions, and increasing the share of renewable energy sources. This research shows that international electricity exchange and infrastructure integration play an important role in achieving the stated goals. Therefore, regional cooperation not only offers economic benefits but is also critical in terms of ensuring energy supply security, sustainability, and combating climate change. Türkiye's situation adds a complementary dimension to discussions within the European framework. Research conducted at the national level reveals that renewable energy integration is a critical factor in terms of system security and supply-demand balance [34]. When compared with results obtained in various European countries, these data show how similar dynamics emerge under different market structures and regulations. In this case, it is understood that policies related to energy integration need to be examined not only at the European Union level but also in a broader regional context. In terms of the methodological dimension of the study, the original contribution was achieved through the use of the Open Power System Data (OPSD) dataset. The open, standardized, and multinational data structure of OPSD enables comparative analyses between energy systems and increases the generalizability of the findings. This feature distinguishes this study from previous research in the existing literature by ensuring that the multinational perspective is based on reliable empirical data. From this perspective, this study is not limited to country-level analyses but provides a comprehensive assessment of Europe's energy systems. The results obtained show a remarkable similarity to findings previously reported in the literature [4, 28]. The significance of this research lies in its provision of a multifaceted examination in political, methodological, and technological dimensions, going beyond merely confirming findings in the literature. In particular, highlighting the implications of interaction in international relations for energy supply security and market stability indicates that energy integration is not only a technical issue but also a geopolitical strategy.

The interpretations presented in this section are supported by quantitative indicators derived from the time series analysis. Specifically, autocorrelation coefficients exceeding 0.70 at early lags indicate strong short-term dependency structures, while significant peaks within the 24–48 lag range confirm pronounced daily periodicity. Furthermore, STL decomposition results show that the seasonal component accounts for approximately 50–65% of the total variance across countries, whereas the residual component remains below 20–30% in most cases. These findings suggest that a substantial portion of variability in wind energy production is driven by structured seasonal dynamics rather than purely random fluctuations. In addition, cross-country comparisons reveal moderate to strong correlations between electricity demand patterns, particularly among geographically and climatically similar countries, supporting the presence of regional interdependencies in energy systems.

Table 3 presents the quantitative results obtained from the study. Seasonal variations are significant, with the seasonal component explaining approximately 55–65% of the total variance according to STL decomposition results. The system exhibits high variability, as indicated by increased residual variance levels reaching approximately 25–30% in the decomposition results. A strong dependency structure is observed, with autocorrelation coefficients exceeding 0.70 in early lag intervals. This indicates higher system flexibility, as reflected by lower residual variability (below 20%) and more stable autocorrelation patterns. Integration capacity appears to be stronger in countries where seasonal components dominate (above 50%) and irregular fluctuations remain limited.

Table 3. Data-Driven Evidence Supporting the Discussion

Metric	Germany	Spain	France	Italy	Poland
ACF (Lag 1)	~0.75	~0.70	~0.73	~0.68	~0.65
Seasonal Component (%)	~55%	~60%	~52%	~63%	~50%
Residual Variance (%)	~18%	~22%	~20%	~25%	~30%
Variability Level	Low	High	Low	High	Very High

It is important to note that the contribution of this study does not stem from the use of the OPSD dataset itself, but from the analytical framework applied to it. While OPSD has been widely utilized in the literature, previous studies have largely adopted prediction-oriented or model-driven approaches. In contrast, the present study emphasizes a comparative and interpretation-focused analysis, enabling a deeper understanding of structural differences and similarities across countries. This perspective allows the identification of system-level characteristics that are not directly observable through prediction-based evaluations alone.

Declaration of Ethical Standards
The author declares that he/she has complied with all ethical rules.

Declaration of Competing Interest
The author declares that he has no conflict of interest with any institution or organization.

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Data Avaibility

The OPSD dataset used in the study is a free and publicly available dataset.

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