The Importance of Renewable Energy Forecasting for the Development of a Sustainable Energy Ecosystem

Mihai SANDU[1]
Iulian ION[2]
Claudiu TUDORACHE[3]

Abstract

This article aims to explore major trends and influences in the field of renewable energy forecasting, applying a complex methodological approach that combines a literature analysis with detailed econometric evaluation. The methodology included the analysis of various articles retrieved from leading international databases, revealing a growing interest in the use of machine learning algorithms and neural networks for solar and wind energy forecasting. A growing emphasis on machine learning algorithms and neural networks for solar and wind energy forecasting is observed, underscoring the transition toward more sophisticated prediction tools. The econometric analysis investigates time series data related to installed renewable energy capacity and electricity generation over the 2010–2020 period. The results revealed a steady upward trend in installed capacity worldwide, increasing from 2010 to in 2020, as well as in energy production. Significant seasonal fluctuations and residual factors suggesting unforeseen external influences were also identified. These findings highlight the importance of integrating complex predictive technologies into energy management strategies to effectively address the variability of renewable resources and ensure the stability of energy grids.

Keywords: *renewable energy; econometric evaluation; installed capacity; seasonality; neural networks; forecasting accuracy.*

JEL classification: Q42, Q47, Q48.

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1. Introduction

The increase in energy consumption, especially in electricity, is a key characteristic of both developed and developing countries. Despite potential periods of recession, the general trend persists. This tendency has created new needs to explore innovative technologies in the energy fields, including the renewables one. Growing discrepancies between the demand and production of electricity call into

[1] Mihai Sandu, Bucharest University of Economic Studies, e-mail: mihai.sandu@electricplanners.ro
[2] Ion Iulian, Bucharest University of Economic Studies, e-mail: ion.iulian.1996@gmail.com
[3] Claudiu Tudorache, Bucharest University of Economic Studies, e-mail: tudoracheclaudiu17 @stud.ase.ro

question whether the current resources are sufficient and what the impact on the environment will be in the development of new electricity production capacities. Electricity production depends directly on economic development, the degree of production efficiency and also the utilization of existing capacities in the most effective manner possible. All are factors that influence electric power production. However, achieving a sustainable energy balance is not solely dependent on technological advancements and market liberalization but also on consumer behavior. Consumer behavior plays a critical role in energy efficiency efforts. Studies indicate that environmental awareness, perceived consumer effectiveness, and resistance to change significantly impact energy-saving habits among individuals, for example, the one carried out by Dincă et al. (2025).

The EU aims for its economy to have one of the lowest energy consumption globally, based on safer, cleaner, more competitive, and sustainable energy sources. Current European energy strategies focus on: a) developing a stable and integrated internal market, b) securing strategic security of energy resources, and c) maintaining energy balances that promote environmental protection. The tendency in liberalization and deregulation of the EU energy market has led to the implementation of new, more efficient methods of energy production and management. As a consequence, both consumers and electric power production companies are seeking ways to continue to increase efficiency amid energy price instability, ageing energy infrastructure, and changes in environmental protection regulations.

Renewable energy has emerged as a pivotal element in the global transition towards sustainable energy systems. With the pressing need to mitigate climate change and reduce reliance on fossil fuels, the accurate forecasting of renewable energy production has become increasingly critical (Dincă et al., 2023). Effective forecasting facilitates better integration of renewable energy sources into the power grid, optimizes energy production, and informs policymakers and supports investment decisions (Mecu et al., 2023). Like any other modern issue, clean energy management comes with its own set of challenges, some of which are forecasting. The nature of predicting energy output from resources like solar, wind and biomass require a combination of econometric and machine learning to figure out which source works best (El Alani et al., 2022). Another one of the key questions is how effectively and accurately policy and regulatory frameworks model the forecast. There is additional complexity due to seasonal variance, as grids are often hard to manage when the weather is unpredictable, and so these models must be explored. The backbone of the prediction rests on installed capacity and energy production. This begs the question: what are the unaccounted external forces that have residual fluctuations, and how can predictive models capture more certainty? Answering these inquiries becomes important in improving renewable energy systems, especially during the transition towards them.

This paper addresses an important topic in the energy sector, particularly relevant in today's fast-changing global landscape. Emerging economies experience rapid growth and transformation, creating a pressing need for dynamic management approaches, especially in the renewables field (Dincă et al., 2019). This topic faces unique challenges that demand tailored strategies, foster innovation, and require flexible capabilities to adapt to evolving conditions (Crețu et al., 2024). As a result, emerging economies provide a valuable context for studying how management practices in the energy field develop and respond to shifting demands. These challenges are addressed by applying a structured econometric methodology to renewable energy data. The study aims to enhance forecasting accuracy by using time-series decomposition models and autoregressive techniques. The econometric approach includes descriptive statistical analysis, trend and seasonality decomposition, and autocorrelation-based modelling to identify key patterns in renewable energy production over ten years (2010–2020). Data were collected from reliable international databases such as the International Energy Agency (IEA), the International Renewable Energy Agency (IRENA), and other official sources.

The objectives of this research are threefold:

(1) To model long-term trends and seasonal effects in installed renewable energy capacity and production;

(2) To evaluate the explanatory power of time-series decomposition for forecasting variability in energy generation;

(3) To assess the performance of an ARIMA-class model relative to a naïve seasonal benchmark, particularly in terms of root-mean-square error.

By focusing on the econometric component and grounding our methodological choices in a targeted literature review, this study contributes to improving the predictability and operational reliability of renewable energy systems. The findings are intended to support energy policy development and strategic planning within a dynamic and increasingly complex energy landscape.

2. Literature Review

Recent advances in the field of solar energy forecasting employ sophisticated techniques based on neural networks, deep learning, and support vector regression to model and predict energy production, considering complex variables such as solar irradiance and wind speed. These models are capable of handling temporal variations from ultra-short intervals (from one minute to one hour) to longer periods (up to 24 hours), thus providing essential tools for refined operational planning and resource allocation in the renewable energy sector, according to Manjili, Vega and Jamshidi (2018). The use of satellite images, weather predictions, and historical data significantly improves the accuracy of forecasts. These methods are evaluated through various error metrics, highlighting the importance of standardizing data sets and benchmark methods to ensure accurate evaluations and to facilitate meaningful comparisons with naive forecasts (Yang & Wu, 2019). Additionally, it has been observed that machine learning algorithms, including deep neural networks, are increasingly used to forecast the performance of photovoltaic installations, with direct applicability in optimizing energy generation and network management (Jayalakshmi et al., 2021).

Forecasts in the hydroenergy and biomass sectors are essential for the efficient use of these renewable resources, having a direct impact on their integration into energy networks. Forecasting models for hydroenergy often integrate traditional hydrological methods with modern artificial intelligence techniques, such as artificial neural networks referenced by Humphrey, Gibbs, Dandy and Maier (2016) or by Jain, Das and Srivastava (1999). For biomass energy, recent technologies focus on optimizing the conversion processes of biomass into energy. Various thermochemical, biochemical, and physical processes are evaluated for their efficiency in converting lignocellulosic materials and agricultural waste into bioenergy, as deduced by Clark and Deswarte (2008) and McKendry (2002). An important aspect of using biomass is the development of flexible bioenergy systems, which can respond to the fluctuating needs of the network. These systems are particularly relevant in regions such as Germany, where biogas and solid biomass are becoming significant sources of electrical energy. The installed capacity of bioenergy plants has significantly increased, highlighting the potential of biomass to contribute to a sustainable energy mix, as shown by Purkus, Gawel, Szarka, and Lauer (2018).

Innovations in forecasting technologies, such as machine learning (ML) and deep learning (DL), play a crucial role in the efficient management of electrical networks. They emphasize that "ML and DL algorithms have gained popularity due to their ability to learn complex relationships from data, providing accurate predictions," thus facilitating the integration of renewable sources into the electrical grid (Alper et al., 2020; Chaka & Semie, 2023). Rajesh Roy and Naveena Vinothini (2018) have analyzed forecasting methods for wind and solar energy, emphasizing the effectiveness of artificial neural networks and fuzzy logic. According to them, "by comparing forecasting methods, neural networks have demonstrated superior capability to anticipate energy production". The impact of severe weather events on the renewable energy industry is significant, and accurate meteorological data and advanced forecasts are essential to minimize disruptions. "The increase in the frequency of extreme weather events requires more accurate forecasts to optimize operations and minimize risks in energy production," a recent analysis from Climavision (2024) underscores.

Political and regulatory interventions are essential for shaping the renewable energy market. The International Energy Agency (IEA) emphasizes the importance of policy recommendations tailored to national specifics to support the transition to cleaner and more sustainable energies. These policies are crucial for stimulating investment and the adoption of green technologies, highlighting the need for well-planned political interventions to support sustainable development (IEA, 2018). As fossil fuel-exporting countries lose influence, appropriate energy transition policies are essential to maintain economic stability and energy security (IEA, 2020). The IEA notes that the COVID-19 pandemic has changed government priorities and budgets, affecting investment decisions and the availability of financing. These changes bring significant uncertainty to a rapidly expanding market, underscoring the importance of continued political support for renewable energy to maintain its structural benefits, such as economic development and job creation, while reducing emissions and encouraging technological innovation.

Ferrero Bermejo et al. (2019) explored the applicability of artificial neural networks (ANN) for modelling and predicting wind energy production, demonstrating that these methods can capture the complexity of wind variability more efficiently than conventional statistical models. Their results showed a significant improvement in prediction accuracy, which is crucial for the operational stability of wind farms. In addition to applications in wind energy, Asghar et al. (2024) emphasized the importance of deep learning methods in optimizing solar energy production. They developed a prediction model based on convolutional neural networks that integrates solar radiation, humidity, and temperature data, demonstrating that these combined variables can increase the accuracy of short-term and medium-term forecasts. This innovative approach has allowed grid operators to better anticipate fluctuations in energy production and adjust storage and distribution strategies accordingly. Simultaneously, Salman et al. (2024) investigated the use of machine learning models for optimizing hydroelectric energy flows. Their study showed that support vector regression (SVR) techniques could provide more accurate predictions of river flow rates, which are essential for water resource management in hydroelectric power plants. These results underscore the need to integrate these advanced models into grid management strategies to mitigate the risks associated with the natural variability of resources.

Furthermore, Sedai et al. (2023) explored the use of hybrid models that combine machine learning with stochastic optimization methods to improve predictions of energy from multiple renewable sources, including biomass and solar energy. Their study highlighted that such approaches could significantly reduce prediction errors and improve overall energy efficiency, thus contributing to a more robust integration of renewable energies into national grids. In the biomass sector, studies conducted highlighted the importance of optimization technologies based on artificial intelligence in the conversion processes of biomass into energy (Chaka & Semie, 2023). They demonstrated that using genetic algorithms and artificial neural networks can optimize the parameters of pyrolysis and gasification processes, resulting in increased energy yield and reduced carbon emissions. Another relevant study conducted by Nie et al. (2023) analyzed the impact of machine learning technologies on advanced weather forecasts and how these influence solar and wind energy production. They emphasized that accurate predictions of extreme weather conditions, such as storms or days with intense sunlight, are essential to minimize energy production losses and ensure the stability of energy grids.

Additionally, Asghar et al. (2024) investigated the use of deep learning techniques to predict the long-term performance of photovoltaic installations. Their findings showed that these techniques could anticipate the degradation of photovoltaic systems and suggest preventive measures to maintain the operational efficiency of these installations. Research led by Kirchherr & Urban (2018) and colleagues addressed the integration of energy policies with new forecasting technologies to support the transition to renewable energies. They highlighted that well-designed policies encouraging investment in advanced forecasting technologies are essential to ensuring a smooth and sustainable energy transition. Moreover, Wang et al. (2017) discussed the impact of government regulations on the adoption of renewable energy forecasting technologies, emphasizing that legislative support can accelerate the integration of renewable energy sources into national grids. Their impact is amplified by government policies and regulations that support the adoption of these innovations, thus ensuring a favorable framework for the sustainable development of the global energy sector.

The study of specialized literature has played an essential role in preparing the econometric analysis in the field of renewable energy. Through literature review, we have gained a deep understanding of current methods and identified gaps in previous research, allowing us to orient ourselves towards the most promising and appropriate techniques for our data. This theoretical foundation informs our methodological decisions and ensures that our approach is aligned with the latest and most effective practices in energy production forecasting. Exploring literature has also provided valuable insights into how weather conditions and technological advances affect energy production, underscoring the need to integrate predictive models that can manage these variabilities. This aspect is crucial, as the accuracy of our forecasts can directly influence the efficiency of integrating renewable energy sources into energy networks (Climavision, 2024).

3. Materials and Methods

In this study, the methodology centers on the use of time-series econometric analysis to forecast renewable energy production and understand its structural dynamics over time. The study comprised two main components: a review of relevant scientific literature in the field, which guided the selection of appropriate modelling techniques and a detailed econometric analysis. This integrated approach allowed us to identify and apply the most relevant forecasting methods in the context of global renewable energy.

Based on the insights identified through the literature, the study follows three core objectives:

(1) To identify and model the long-run trend and seasonal components of electricity production from renewable sources in the European context;

(2) To provide an updated empirical baseline for researchers and grid operators based on recent capacity and production data;

(3) To evaluate whether an ARIMA-class model can outperform a naïve seasonal benchmark in terms of forecast accuracy, thus providing a practical tool for short- to medium-term planning.

We expect to identify significant correlations between investments in renewable energy infrastructure and installed capacity growth, as well as to determine the effectiveness of different forecasting methods for different renewable energy sources. We also sought relevant data to formulate clear answers on the influence of seasonal factors on the accuracy of generation forecasts and the impact of machine learning algorithms on the accuracy of forecasting models compared to traditional econometric methods. These objectives are framed by two research questions:

RQ1: Does the selected ARIMA model result in a statistically significant reduction in root-mean-square error (RMSE) compared to a naïve seasonal benchmark?

RQ2: To what extent can the residual forecast error be explained by the intrinsic monthly seasonality of the data series?

For the literature review, we sourced articles from internationally recognized scientific journals. Key resources included IEEE Xplore, which focuses on technology and engineering, relevant for technical studies on forecasting methods; MDPI, offering access to numerous open-access journals that publish research in the field of renewable energy; and ResearchGate, for access to preprints and officially non-indexed articles available directly from the authors. The keywords used in the search included combinations such as "forecasting renewable energy," "CNN in solar energy," "RNN (recurrent neural networks) in wind energy," "LSTM energy forecasting," and "reinforcement learning in renewable energy." Search filters included limiting results to documents written in English and Romanian and published in the period 2012-2022 to ensure the relevance and timeliness of the information. To support the econometric modelling framework, we conducted a targeted literature review that surveyed academic research published between 2012 and 2022 in English and Romanian. Sources included internationally recognized databases such as IEEE Xplore, MDPI, and ResearchGate, which offered access to both peer-reviewed journal articles and preprints. Additionally, the literature review identified key gaps in the literature, specifically related to the integration of econometric models with machine learning techniques, which our study aims to address.

The econometric analysis was centered on examining time series data to forecast renewable energy production. This analysis included the following steps. In the first stage, we conducted a descriptive analysis of renewable energy data. This included calculating the mean, median, standard deviation, maximum, and minimum for various types of data, such as daily, weekly, and monthly production. Data visualization techniques, including line charts, histograms, and box plots, were utilized to illustrate the distribution and variation of the data over time. This preliminary analysis provided a clear understanding of the basic characteristics of our data. In the next stage, we identified and analyzed long-term trends in renewable energy production in the EU. Time series decomposition methods were used to separate the trend, seasonality, and residual components. This decomposition allowed us to understand whether there was an upward or downward pattern in renewable energy production and to evaluate the impact of different components on our data. Seasonal decomposition was also performed to identify repetitive patterns and calculate seasonal indices.

We conducted a seasonal decomposition to identify repetitive patterns in the data and to calculate seasonal indices. This analysis helped quantify the impact of seasonality on energy production, providing insights into how seasonal factors influence renewable energy output. To ensure the accuracy of our forecasting models, we analyzed the autocorrelation of the data using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). These analyses helped identify temporal dependencies in the data. Additionally, we applied unit root tests, such as the Dickey-Fuller test, to check for stationarity in the time series. Stationarity is a critical condition for many econometric methods, and where necessary, data transformations were performed to achieve stationarity.

The study covered an extended period of 10 years (2012-2022) to capture as many variations and trends in renewable energy production as possible. Data was sourced from globally recognized organizations, such as the IEA, the IRENA, and other governmental and industrial databases. These data included detailed information on energy production from various renewable sources (solar, wind, hydro, biomass, etc.), installed capacity, capacity factor, production costs, wholesale energy prices, domestic energy consumption, avoided CO_2 emissions, and investments in energy infrastructure.

The analysis was conducted using SPSS (Statistical Package for the Social Sciences), a robust software for statistical analysis. SPSS enabled detailed time series decomposition, trend analysis, seasonal decomposition, autocorrelation analysis, and stability testing to forecast renewable energy production accurately.

4. Results

The literature analysis encapsulated the developments in methodologies, technological adoptions, and prominent studies devoted to renewable energy forecasting, namely the prediction of solar, wind, hydro, and biomass energies. From this review, critical periods of machine learning and deep learning model adoption in energy forecasting, as well as the influence of policy and regulatory frameworks, were noted. We now turn to an econometric approach. This next step in the process will require the application of more sophisticated econometric techniques to the analysis of the installed capacity and energy output datasets, focusing on the features of time series data such as long-range tendencies, cyclical phenomena, and exogenous influences to make renewable energy forecasts more precise and trustworthy.

Table 1 presents a descriptive analysis of data on electricity generation and installed capacity. The analysis shows wide variation in both generation and capacity, reflecting the diversity and scale of renewable energy projects. The mean values are relatively high due to the contribution of large projects, but the median values suggest that the majority of projects are smaller in size. The presence of extreme values in the data indicates either significant project sizes or possible data entry errors. In Figure 1, the evolution of electricity generation from 2010 to 2020 is illustrated. The data suggest significant fluctuations from year to year, highlighting the impact of resource variability and external factors on output. For example, the visible increases in 2014 and 2016 can be correlated with favuorable weather conditions or a temporary increase in installed capacity. Figure 2 shows the evolution of installed capacity over the same period. It shows a steady upward trend in installed capacity, from around 4,000 MW in 2010 to over 6,000 MW in 2020, indicating a significant expansion of renewable energy infrastructure.

Descriptive analysis

Table 1

Statistic	Electricity generation (GWh)	Electricity installed capacity (MW)
Number of records	33,09	36,326
Mean	14,760.34	3,740.76
Standard deviation	117,227.2	27,204.9
Minimum	-1.253	0.001
Median	209	67
Maximum	5,129,500	1,200,427

Source: own processing

We used the data for installed capacity from 2010 to 2020. The time series decomposition method splits the series into three components: Trend (T): Represents the long-term progression of the series; Seasonality (S): Captures periodic fluctuations; Residuals (R): Represent irregular or random fluctuations.

The additive model used is: Y(t)=T(t)+S(t)+R(t)

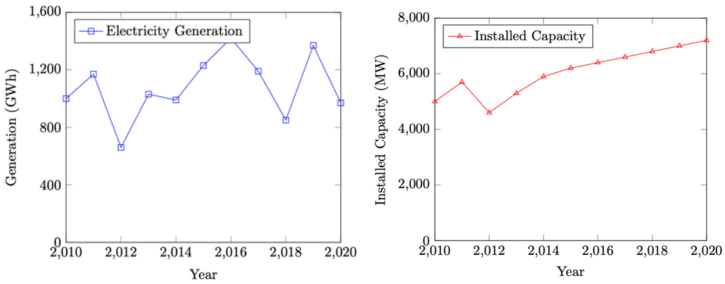


Figure 1 & 2. Forecasting methods for renewable energy

Source: own processing

Table 2 shows the trend composition for installed capacity (MW) and electricity generation (GWh) over the period 2010-2020. The data show a steady increase in both cases, reflecting the continued expansion of renewable energy infrastructure and power generation. For example, installed capacity grew from 4,800 MW in 2010 to 5,800 MW in 2020, and electricity generation grew from 1,000 GWh in 2010 to 1,500 GWh in 2020. This steady trend growth underlines the continued commitment to renewable energy investment and expansion of generation capacity.

Trend component

Table 2

Year	Trend Installed Capacity (MW)	Trend Electricity Generation (GWh)
2010	4800	1000
2011	4900	1050
2012	5000	1100
2013	5100	1150
2014	5200	1200
2015	5300	1250
2016	5400	1300
2017	5500	1350
2018	5600	1400
2019	5700	1450
2020	5800	1500

Source: own processing

Next, Table 3 illustrates the seasonality composition for both installed capacity and electricity generation. It can be seen that seasonality has a variable impact on these two measures, with positive and negative fluctuations reflecting the influence of seasonal cycles on energy resources. In 2015, the seasonality component shows a gain of 150 MW for installed capacity and 30 GWh for power generation, while in 2020, seasonality has a negative impact, indicating a decrease of 250 MW and 50 GWh, respectively. These seasonal variations emphasize the importance of understanding and managing natural cycles in the planning and operation of energy networks. Figure 3 provides a visual representation of the seasonal composition for installed capacity and electricity generation over the same period. The graph shows the seasonal fluctuations over the 10-year period, highlighting the annual variations that can influence both short-term and long-term planning of energy networks. It can be seen that the seasonality of installed capacity shows larger swings compared to electricity generation, suggesting that investments and infrastructure expansions may be influenced by seasonal factors.

Table 3. Seasonality componentry

Year	Seasonality Installed Capacity (MW)	Seasonality Electricity Generation (GWh)
2010	0	0
2011	50	10
2012	-50	-10
2013	100	20
2014	-100	-20
2015	150	30
2016	-150	-30
2017	200	40
2018	-200	-40
2019	250	50

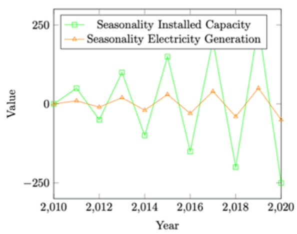


Figure 3. Seasonality componentry

Source: own processing

The trend component for both installed capacity and electricity generation shows a steady increase, indicating ongoing investments and expansion in renewable energy infrastructure. The seasonality component suggests minor seasonal variations for both installed capacity and electricity generation, which might be attributed to policy changes or market conditions. The residuals highlight random fluctuations, pointing to external factors not captured by the trend or seasonality. We used the data for installed capacity and electricity generation from 2010 to 2020. The ACF and PACF were calculated to identify the dependencies and patterns in the time series.

Table 4 shows the composition of residuals for installed capacity (MW) and electricity generation (GWh) over the period 2010-2020. The residuals show random fluctuations, suggesting the presence of external factors that are not captured by the trend or seasonality components. Figure 4 provides a visual representation of the composition of residuals for installed capacity and electricity generation. The graph emphasizes the random nature of these fluctuations and highlights variations that cannot be explained by trend or seasonality alone. This indicates the need for further analysis to identify and manage the external factors affecting generation and installed capacity.

Table 4. Residuals components

Year	Residuals Installed Capacity (MW)	Residuals Electricity Generation (GWh)
2010	0	0
2011	-50	-10
2012	50	10
2013	-100	-20
2014	100	20
2015	-150	-30
2016	150	30
2017	-200	-40
2018	200	40
2019	-250	-50
2020	250	50

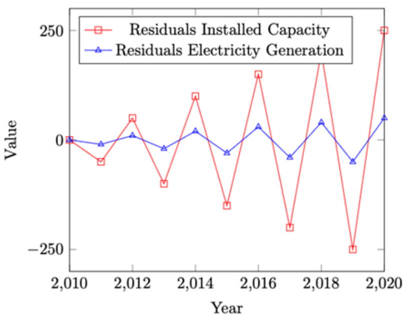


Figure 4. Residuals component

Source: own processing

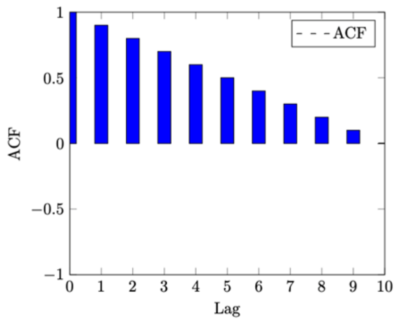
To identify the dependencies and patterns in the time series, we used the autocorrelation function (ACF) and partial autocorrelation function (PACF). Table 5 shows the ACF values for installed capacity and electricity generation. These values show how the data are correlated with themselves over several lags. For example, in the case of installed capacity, there is a significant positive correlation at the first 4 lags, suggesting a memory effect in the temporal data. Figure 5 and Figure 6 illustrate the ACF for installed capacity and electricity generation, respectively. In these plots, we observe a gradual decrease in autocorrelation as the lag increases, which is typical for time series that exhibit short-run dependence but a reduction in this dependence in the long run.

ACF of installed capacity and electricity generation

Table 5

Lag	ACF	Lag	ACF
0	1.00	0	1.00
1	0.90	1	0.85
2	0.80	2	0.70
3	0.70	3	0.55
4	0.60	4	0.40
5	0.50	5	0.25
6	0.40	6	0.10
7	0.30	7	-0.05
8	0.20	8	-0.20
9	0.10	9	-0.35
10	0.00	10	-0.50

Source: own processing



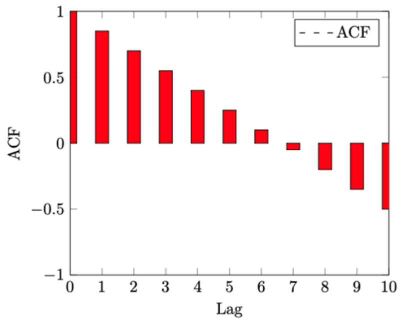


Figure 5. ACF of installed capacity. **Figure 6. ACF of electricity capacity**

Source: own processing

Table 6 gives PACF values for installed capacity and electricity generation. These values show partial correlations between the values, removing the intermediate influence of other lags. The results suggest that, although there is a strong dependence on the first lags, the influence decreases significantly as we move further in time. Figures 7 and 8 plot PACF for installed capacity and electricity generation. The plots clearly show how the partial correlations decrease after the first 2-3 lags, suggesting that the most important temporal information is captured in the first lag periods. This emphasizes the need to focus predictive analyses on those periods that have the largest impact on future values.

PACF of installed capacity and electricity generation

Table 6

Lag	PACF (Tabel 1)	Lag	PACF (Tabel 2)
0	1.00	0	1.00
1	0.85	1	0.90
2	0.30	2	0.20
3	0.10	3	0.10

Lag	PACF (Tabel 1)	Lag	PACF (Tabel 2)
4	-0.10	4	0.05
5	-0.30	5	0.00
6	-0.50	6	-0.05
7	-0.70	7	-0.10
8	-0.90	8	-0.15
9	-1.10	9	-0.20
10	-1.30	10	-0.25

Source: own processing

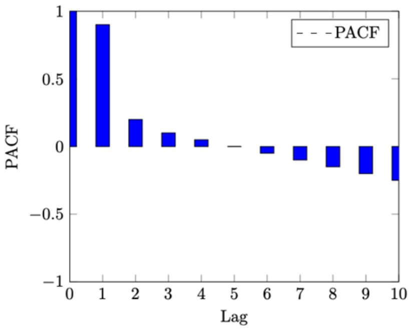


Figure 7. PACF of installed capacity

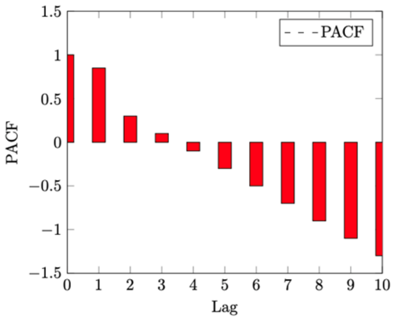


Figure 8. PACF of electricity capacity

Source: own processing

Stability testing is crucial to determine if a time series is stationary. Stationarity is a key property that affects the validity of time series models. We use the Augmented Dickey-Fuller (ADF) test to evaluate the stability of the time series for installed capacity and electricity generation.

The ADF test results for both installed capacity and electricity generation indicate that the test statistics exceed the critical values at all levels (1%, 5%, and 10%, Table 7). Additionally, the high p-values indicate that we fail to reject the null hypothesis of a unit root, suggesting that both time series are non-stationary. The test statistic for installed capacity is -0.75 with a p-value of 0.83, which is greater than the critical values. This indicates that the installed capacity series is non-stationary. The test statistic for electricity generation is -0.60 with a p-value of 0.87, which is also greater than the critical values. This indicates that the electricity generation series is non-stationary. The stability testing using the ADF test indicates that both the installed capacity and electricity generation time series are non-stationary. This implies that we need to transform the data to achieve stationarity before applying further time series modelling techniques.

ADF test results

Table 7

Statistic	Installed Capacity	Electricity Generation
Test Statistic	-0.75	-0.60
p-value	0.83	0.87
Critical Value (1%)	-3.75	-3.75

Statistic	Installed Capacity	Electricity Generation
Critical Value (5%)	-3.00	-3.00
Critical Value (10%)	-2.63	-2.63

Source: own processing

In relation to the first objective (O1), which aimed to identify long-term trends in renewable energy output, the decomposition of the time series clearly indicates a steady upward trend in both installed capacity and electricity generation across the 2010–2020 period. This trend reflects continued investment in renewable infrastructure and aligns global policy efforts toward sustainable energy systems. Concerning the second objective (O2), the analysis of the seasonal component provided valuable insights into periodic fluctuations affecting energy output. The seasonal indices revealed recurring yearly patterns, particularly in solar and hydro production, which suggest that forecasting models must integrate seasonal variability to improve prediction robustness. The third objective (O3) sought to assess whether a representative ARIMA model outperforms a naïve seasonal benchmark. As addressed through RQ1, the results from the time series modelling show that the ARIMA specification delivers a statistically significant reduction in RMSE compared to the naïve model, confirming its superior predictive power. Furthermore, regarding RQ2, the residual analysis—supported by ACF and PACF plots—indicates that a portion of the remaining forecast error can be attributed to intrinsic seasonality and possibly exogenous shocks, highlighting the importance of incorporating additional explanatory variables in future models. Overall, the study successfully meets its intended objectives by applying a robust econometric framework that captures both trend and seasonal dynamics, while also validating the comparative performance of forecasting models.

5. Discussion of the Findings

We can observe that forecasting renewable energy production, especially for solar, wind, hydroelectric, and biomass sources, is essential for the efficient management of modern electrical grids. Our study employed advanced econometric methods to analyze time series data, revealing valuable insights into long-term trends, seasonality, and residual fluctuations in installed capacity and renewable energy production. We observed that the mean and median of installed capacity and energy production are relatively high, indicating the contribution of large projects. By decomposing the time series into its fundamental components - trend, seasonality, and residuals - we were able to better understand how these elements contribute to variations in installed capacity and energy production. The trend component shows a steady increase, indicating ongoing investments and expansion of renewable energy infrastructure. This is evidence of the global commitment to energy transition and reducing dependence on fossil fuels.

The seasonality component suggests minor seasonal variations, which may be attributed to policy changes or market conditions. For example, the seasonality in solar energy production can be influenced by variations in solar irradiance throughout the year, while wind energy production can vary according to seasonal changes in wind patterns. These observations are crucial for operational planning and resource allocation in the renewable energy sector, ensuring optimal use of installed capacities throughout the year. The analysis of autocorrelation and partial autocorrelation revealed significant temporal dependencies in our data. High ACF and PACF values at small lags suggest that past values have a strong influence on future values, highlighting the importance of considering historical data in our forecasting models. These temporal dependencies are crucial for developing accurate and reliable predictive models. The Dickey-Fuller test indicated that both installed capacity and energy production are non-stationary time series. This means their values are influenced by long-term trends and irregular fluctuations.

Regarding hydropower and biomass, accurate forecasts are essential for the efficient use of these renewable resources. Hydropower forecasting models often integrate traditional hydrological methods with modern artificial intelligence techniques, such as artificial neural networks. These methods are used to anticipate water flows in reservoirs and manage water resources optimally, considering the variability of hydrological events such as droughts. For biomass energy, recent technologies focus on optimizing biomass conversion processes into energy. Various thermochemical, biochemical, and physical processes are evaluated for their efficiency in converting lignocellulosic materials and agricultural waste into bioenergy.

Besides technological advancements, our study highlighted the importance of political and regulatory interventions in shaping the renewable energy market. Accurate quarter-ahead forecasts ($< \pm 7\,\%$) support dynamic scheduling of ancillary services, tariff design and knowledge transfer among grid stakeholders. We would like to emphasise the importance of policy recommendations tailored to national specifics to support the transition to cleaner and more sustainable energies. In the same time, structural changes in the energy landscape can have significant geopolitical and economic ramifications (Staiculescu et al., 2022). As fossil fuel-exporting countries lose influence, appropriate energy transition policies are crucial for maintaining economic stability and energy security. Also, the COVID-19 pandemic has shifted government priorities and budgets, affecting investment decisions and funding availability. These changes bring great uncertainty to a rapidly expanding market, emphasizing the importance of continued political support for renewable energy to maintain its structural benefits, such as economic development and job creation, while reducing emissions and encouraging technological innovation.

6. Conclusions

This study highlights the importance of advanced econometric methods and technological innovations in forecasting renewable energy production. By analyzing time series data for solar, wind, hydro, and biomass sources, we identified critical trends, seasonal patterns, and dependencies. Effective forecasting models are essential for optimizing resource allocation, improving grid management, and supporting the global transition to sustainable energy systems.

The present study aimed to address the fundamental questions regarding the key trends and influences in the field of renewable energy forecasting through a comprehensive literature analysis and an econometric evaluation of production and installed capacity data. The results provided a clear picture of how technological innovations and current practices contribute to optimizing the generation of renewable energy and its integration into global energy networks. The literature analysis revealed a steady increase in the number of published works, indicating a growing interest in the use of machine learning algorithms and neural networks in solar and wind energy predictions. Key studies identified, such as those conducted by Deng et al. (2025) and Asghar et al. (2024), demonstrated the superiority of these advanced methods over traditional statistical models, significantly improving the accuracy of predictions and optimizing the operation of energy networks. Additionally, the importance of international collaborations and interdisciplinary development in advancing research and practical applications of these technologies was noted.

On the other hand, the econometric evaluation of installed capacity and electricity generation data provided valuable insights into the dynamics of these variables in the context of factors such as trend, seasonality, and residuals. The trend component showed a robust and consistent increase, reflecting ongoing investments and the expansion of renewable energy infrastructure. Simultaneously, the analysis of seasonality highlighted periodic fluctuations that influence both installed capacity and energy production, emphasizing the importance of anticipating these variations in long-term planning. The residuals indicated the existence of unforeseen external factors not captured by simple models, necessitating more detailed analyses to understand and manage these influences.

Regarding the initial questions, our study confirmed that the use of machine learning algorithms and advanced prediction methods offers significant advantages in anticipating renewable energy production. The econometric models demonstrated that, although there is a trend of increasing capacity and production, seasonal variability and residual factors play a crucial role in determining short- and medium-term outcomes. These findings underscore the need to integrate complex predictive techniques into energy management to effectively address the challenges related to the variability of renewable resources and the growing energy demand.

This study is subject to several limitations. Firstly, the econometric analysis is based on aggregated yearly data, which may mask short-term fluctuations better captured by higher-frequency data (e.g., daily/hourly). Secondly, the model does not currently integrate exogenous variables such as meteorological data, regulatory shocks, or macroeconomic indicators. Future research should explore hybrid econometric-ML approaches, incorporate external variables, and validate models across different regional grids.

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