

Forecasting techniques for power systems with renewables

16

Paul Arévalo^{1,2}, Darío Benavides^{1,3} and Danny Ochoa-Correa²

¹Department of Electrical Engineering, University of Jaén, Jaén, Spain, ²Faculty of Engineering, Department of Electrical, Electronics and Telecommunications Engineering (DEET), Universidad de Cuenca, Balzay Campus, Cuenca, Azuay, Ecuador, ³Department of Electrical Engineering, University of Málaga, Malaga, Spain

Introduction

The increasing capacity of renewable energy offers a key opportunity to address the growing global energy crisis. Despite reaching 27% for renewable energy and 24% for natural gas in 2019 (Zhu et al., 2022), challenges persist due to the variable nature of renewable energy production. Governments and policymakers advocate for increased penetration of renewables, with projections suggesting that their contribution could reach 85% by 2050, highlighting their crucial role in the future energy landscape (Alkabbani et al., 2021). Global electricity demand rises with population and economic growth, primarily fueled by conventional fossil fuel-based power plants emitting harmful greenhouse gases (Islam & Roy, 2023). To address this, the integration of renewable energy sources (RES) like wind, solar, hydro-power, and biogas is essential for sustainable energy production. Advances in wind and photovoltaic (PV) technologies have significantly increased renewable energy generation (Li et al., 2020). However, the inherent uncertainty of RES requires innovative solutions. Technologies such as smart inverters and machine learning enhance integration, while research in frequency control aims to manage high RE penetrations (Wen et al., 2019). The volatility of renewable energy production underscores the need for advanced forecasting techniques to ensure system balance. Accurate predictions are crucial for informed decision-making in energy system management. This chapter explores energy forecasting concepts, highlighting the importance of precision and introducing advanced techniques to address specific challenges (Alkabbani et al., 2021).

The evolution of RES necessitates robust forecasting methods for efficient grid integration and sustainable energy planning. In a Sicily wind energy study (Cellura et al., 2008), traditional approaches, including statistical analyses and geostatistical interpolation, were employed to estimate wind probability distribution functions, emphasizing the need for reliable tools, such as artificial neural networks (ANNs), for spatial wind speed estimation. In Germany, autoregressive integrated moving average (ARIMA)-based forecasting models have optimized renewable energy generation (Fattah et al., 2023). A hybrid methodology, derived from four years of

data, improved yearly accuracy by approximately 89.5%. The REN4KAST software platform was introduced to address the stochastic nature of renewable energy generation. Examining wind speed forecasts in Karnataka, a weather model with a 3 km resolution identified regions suitable for wind power plants (Gangopadhyay et al., 2019), recommending new locations based on factors like transport facilities and diurnal patterns. The economic viability of a compressed air energy storage (CAES)-PV system was addressed through a novel model-free deep reinforcement learning (DRL) method (Dolatabadi et al., 2023). This approach optimized CAES energy arbitrage using a hybrid forecasting model based on 2-D convolutional neural networks (CNNs) and bidirectional long short-term memory (BLSTM) units.

On the other hand, various techniques and procedures for forecasting generation from random REs exist. A comprehensive review of the study highlighted the importance of tailored forecast products for end-users (Sweeney et al., 2020). Emphasis was placed on integrating blockchain technology for decentralized yet trusted data exchange, addressing uncertainties, and enhancing predictive dispatch tools for system stability with higher renewable energy integration. The dynamic nature of solar and wind energy, subject to fluctuations on various timescales, presents challenges in managing stable and reliable energy supplies. Accurate forecasting becomes imperative for optimal energy production management in intermittent and stochastic RES (Notton et al., 2018). The review emphasizes the cost implications of variability and stochastic variations in REs, highlighting the economic benefits of efficient forecasting. It underscores the role of forecasting in mitigating integration costs, becoming an essential tool for electrical grid managers.

Integrating renewables and the increasing demand for electricity necessitate efficient energy management strategies. Smart grid technology emerges as a solution to enhance energy efficiency, particularly in the context of renewable energy integration (Sharma et al., 2023). The comprehensive overview provided in this survey paper explores various techniques for demand forecasting across residential, industrial, and agricultural sectors. Load forecasting, demand response management, and implementing smart meters are crucial for achieving energy efficiency and green energy goals. Electricity price forecasting is fundamental for grid management and renewable energy integration. Complex generation mix data and heteroskedasticity pose challenges for accurate forecasting, addressed in this study using advanced analytics methods like principal component analysis (PCA) (Nyangan & Akintunde, 2024). The research emphasizes the importance of PCA in improving forecasting accuracy, particularly in highly renewable energy markets like the California independent system operator, contributing to grid stability and optimal resource utilization. Furthermore, the pivotal role of renewable energy in a low-carbon society requires understanding the impact of weather and climate on energy demand and supply. A systematic review of seasonal forecasting for wind and wind power in the Iberian Peninsula and the Canary Islands sheds light on the importance of teleconnection patterns and the stratosphere in predicting wind variability (Bayo-Besteiro et al., 2022). The limited existing literature underscores the need for increased research efforts to enhance the operation and planning of renewables. Integrating variable and nondispatchable renewable power generation requires

assessing variability and accurate forecasting. This review paper surveys previous research on solar, wind, wave, and tidal energy resources, emphasizing the need for coherent studies that analyze variability and forecasting methods consistently (Widén et al., 2015). The conclusion stresses the importance of comparable studies, metrics, and evaluations across different renewable energy resources.

Although the reviewed studies have significantly contributed to the understanding of renewable energies and their forecasts, there is a lack of integration that addresses traditional methods, meteorological models, machine learning, and ANNs in a holistic manner. Most existing approaches focus on specific aspects, without providing a comprehensive and comparative view. For example, the study presented in Sweeney et al. (2020) emphasizes the importance of forecast products tailored to end-users, highlighting the need to integrate blockchain technology for decentralized yet reliable data exchange. However, a greater integration of diverse methods is required to more comprehensively address the challenges associated with variability and stochasticity in REs, as evidenced in previous studies (Bayo-Besteiro et al., 2022; Widén et al., 2015). This lack of global integration underscores the need for future research aimed at developing more unified and comprehensive approaches, leveraging the strengths of different methodologies to improve the accuracy and applicability of forecasts in the context of renewable energies. Zhu et al. (2022) highlighted that the continual increase in renewable energy capacity presents a crucial opportunity to address the growing energy crisis and the ever-rising global demand. Islam and Roy (2023) pointed out that, despite the significant electricity generation by conventional fossil fuel-based power plants, they also emit environmentally harmful greenhouse gases. Alkabbani et al. (2021) mentioned that accuracy in predicting renewable energy generation becomes a crucial factor in addressing challenges associated with the variability and intermittency of these sources.

These findings underline the importance of considering the specific needs of end-users and exploring decentralized solutions for data exchange in forecast management within the realm of renewable energies. The lack of uniformity in renewable energy generation, in contrast to conventional resources, emphasizes the need for broader and more effective strategies to address these challenges and ensure a successful transition to a more sustainable energy matrix. Alkabbani et al. (2021) highlighted the need for improved accuracy in predicting renewable energy generation to address challenges associated with the variability and intermittency of these sources. The projected increase in the contribution of REs to the future energy matrix, as mentioned in the citation from Alkabbani et al. (2021), emphasizes the urgency of developing more advanced and accurate forecasting methods to ensure a successful and sustainable integration of these sources into global energy systems. The lack of uniformity in renewable energy generation, as evidenced in Islam and Roy (2023), poses specific challenges in planning and managing optimal electricity generation, highlighting the need for more comprehensive approaches that address the inherent variability of these sources. Collectively, these studies underscore existing gaps in current research on renewable energy forecasts, emphasizing the need for more integrative reviews and advanced methods that effectively address

the variability and stochastic nature of these energy sources. In summary, to address identified gaps in the literature, this chapter makes a significant contribution by bridging this divide, presenting a unified and in-depth perspective on forecasting techniques for renewable energy integration. The following key contributions are proposed:

- Conducting a comparative and integrated analysis of the uniqueness of the load forecasting problem in integrated energy systems, highlighting its crucial differences compared to conventional electrical systems.
- Thoroughly investigating traditional methods, meteorological models, machine learning techniques, and ANNs, providing a critical understanding of their specific applicability to renewable energy generation.
- Emphasizing the unique contributions of this chapter by offering a critical analysis of case studies and practical applications. The aim is to provide valuable insights for effective implementations in real-world environments.

Fundamentals of forecasting

Basic concepts

In light of the expansive growth within the realm of RES, acquiring an in-depth comprehension of their inherently stochastic nature has become imperative. This understanding is pivotal not only for the seamless dispatch of energy but also for preemptively addressing potential stability challenges within the electrical grid. Consequently, there arises a pressing need for predictive modeling, grounded in historical data and a meticulous analysis of the power outputs from RES (Li et al., 2020). The temporal horizon, denoting the timeframe during which such prognostications are formulated, is contingent upon the specific application at hand. Emphasizing the pivotal role of precision in forecasting becomes paramount, serving as a foundational cornerstone for informed decision-making in the realm of renewable energy systems. The dependability of these prognostications holds direct implications for the efficacy of planning and operation strategies within the energy infrastructure. Armed with a profound understanding of these foundational concepts, we position ourselves to delve into the intricate realm of forecasting techniques, precisely tailored to accommodate the nuances introduced by the variability inherent in RES, thereby addressing the intricate challenge of accurately predicting the dynamics of energy supply and demand (Koltsaklis et al., 2021).

The efficacy of forecasting techniques within renewable energy systems is inherently linked to a meticulous consideration of temporal scales. Categorized into four primary groups, these temporal scales act as a dynamic framework, facilitating the nuanced adaptation of forecasting strategies to the diverse planning requirements dictated by different timescales. In the ultrashort term (0–4 h), the focus of forecasts sharpens to manage near-real-time events, thereby enabling immediate and responsive adjustments to abrupt changes. Extending this temporal window, the short-term scale (0–72 h) emerges as a crucial domain for anticipating variations in

both energy generation and consumption. This extension proves pivotal in optimizing the daily operation of the energy system (Wen et al., 2019).

Stepping into the arena of medium to long-term planning (1 month–1 year) necessitates a comprehensive consideration of seasonal factors and trends extending over more extended durations. This temporal domain is indispensable for shaping strategic decisions governing the development of energy infrastructures. Finally, the long-term forecasting horizon (> 1 year) transcends immediate concerns, projecting overarching trends that provide invaluable insights for policymaking and formulating transformative strategies for the evolution of the energy matrix. A nuanced and comprehensive understanding of these diverse temporal scales forms the bedrock for the effective implementation of forecasting techniques, thereby ensuring a precise, adaptive, and sustainable management approach to the intricacies of energy systems (Moret et al., 2016). To further illustrate these concepts, Fig. 16.1 provides a concrete example of a demand prediction system over the course of a day. The graph captures the dynamic interplay between actual and predicted renewable energy generation, offering a visual insight into the accuracy and responsiveness of the forecasting model within this relatively brief temporal window. This visualization serves to underscore the importance of precise short-term predictions in ensuring optimal energy management and grid stability, particularly in the context of RES with inherent variability.

Traditional forecasting methods

The traditional forecasting methods refer to established and conventional approaches used to anticipate future events or trends. These methods are generally based on historical data and observed patterns from the past. Some of the most common traditional methods include MA, ARIMA method, linear regression, time series decomposition, exponential smoothing models, relative index method, and Delphi method.

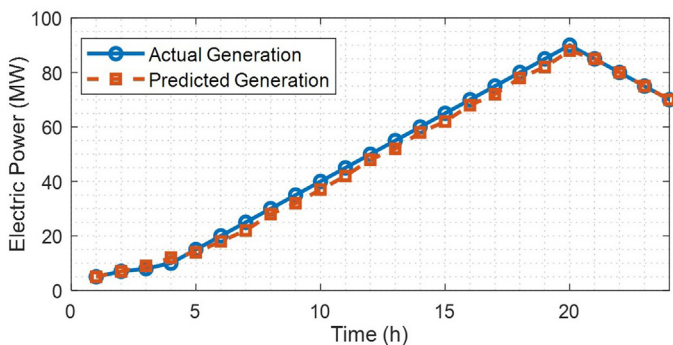


Figure 16.1 Example of renewable energy prediction for a short-term interval (24 hours). Anticipating tomorrow's energy: A 24-hour snapshot of renewable energy prediction.

Moving average and autoregressive integrated moving average methods

The MA method is a fundamental technique in time series analysis and forecasting. It involves calculating the average of a set of past observations to predict future values. In the context of solar irradiance forecasting, the MA model generates a set of random variables using past values of solar irradiance, resembling a random walk with zero mean and constant variance of white noise (Mishra et al., 2017). This method is expressed as MA (q), where “q” represents the order of the process, determining the number of past steps considered for calculating the average along the time series. In the evaluated models, MA contributes to point forecasts within the broader framework of solar irradiance forecasting. The main idea is to smooth temporal fluctuations and highlight general trends.

In recent years, the ARIMA method has emerged as an evolution of MA. Given the inherent uncertainty in predictions, models have been developed to forecast not only the mean but also the associated uncertainty, emphasizing the need for rigorous comparisons to assess their ability and accuracy in the dynamic field of solar energy. David et al. (2018) focused on intraday forecasts with time horizons of 1 to 6 hours, using models that employ only endogenous inputs, specifically past solar irradiance data. The selected models combine three point forecast models (autoregressive and moving average recursive [ARMARls] and coupled autoregressive and dynamic system) with seven probabilistic methods (linear quantile regression model, weighted quantile regression, quantile regression neural network, recursive generalized conditional heteroskedasticity, sieve bootstrap, quantile regression forest, and gradual boosting decision trees), resulting in a comprehensive comparison of 20 model combinations (David et al., 2018).

The ARIMA model is a versatile approach widely used in renewable energy forecasting, known for its simplicity and efficiency. It combines autoregressive, integrated (I), and MA components to capture temporal dependencies and patterns in the data (David et al., 2016; Malhan & Mittal, 2022). The ARIMA model is particularly effective in capturing the persistence of solar irradiance datasets, making it a robust competitor in forecasting scenarios (David et al., 2016). Specifically, ARMARls model, a variant of the ARIMA model, has proven to be robust in predicting renewable energies, demonstrating its effectiveness in providing accurate short-term forecasts of solar irradiance (David et al., 2016). In summary, the comparison of these forecasting methods reveals the complexities of solar irradiance prediction. The MA method, with its simplicity, contributes to the set of models, while the ARIMA model, and its ARMARls variant, demonstrate their effectiveness in capturing the dynamics of solar irradiance in short-term forecasts. The exhaustive evaluation involving various combinations of these methods highlights the nuanced nature of forecasts in the renewable energy domain, shedding light on the strengths and limitations of each approach (David et al., 2016, 2018; Mishra et al., 2017; Zhang et al., 2022). As the renewable energy landscape evolves, these methods serve as essential tools to optimize energy management and network stability, promoting a sustainable energy future.

However, there are some drawbacks, as the MA technique can be sensitive to noisy data or random fluctuations in the time series. Sudden oscillations can affect forecast accuracy, especially in high-variability environments. Additionally, the performance of the MA method depends on the appropriate choice of the moving window size (the number of observations used for the average). In situations where the time series exhibits complex patterns, determining the optimal window length can be a challenge. The MA assumes that the time series is stationary, and the trend is linear. In the presence of nonlinear trends or structural changes in the data, the model may provide inaccurate forecasts. Sensitivity to parameter choice is a key feature of the ARIMA method, similar to the MA. The performance of ARIMA is inherently linked to the appropriate choice of parameters, including autoregression (p), differencing (d), and MA (q) orders. Incorrect determination of these parameters can lead to inaccurate forecasts.

Another significant limitation of ARIMA is its lack of suitability for nonlinear data. The model assumes that the relationship between observations is linear, meaning that it may struggle to capture the complexity of nonlinear patterns present in the time series. The inability to effectively handle irregular seasonality is another challenge associated with ARIMA. If the time series exhibits irregular seasonal patterns or seasonality that changes over time, the model may not fit optimally, affecting forecast accuracy. Additionally, ARIMA works best with stationary time series, where the mean and variance are constant over time. In cases where the series is nonstationary, additional preprocessing, such as differencing, is required, adding complexity to the analysis. Another crucial limitation of ARIMA is its lack of consideration for external effects or exogenous variables in the model. This deficiency can limit its ability to capture external influences that may affect the time series, resulting in less accurate forecasts. Finally, ARIMA's sensitivity to abrupt changes in the time series can impact the reliability of long-term forecasts. Significant changes in series behavior over time can affect the model's effectiveness in accurately predicting future events (Malhan & Mittal, 2022). Fig. 16.2 illustrates an example prediction using an MA for a random signal with a 100-hour interval and a window size of 5. The signal was generated in MATLAB® 2021a using the “movmean” function.

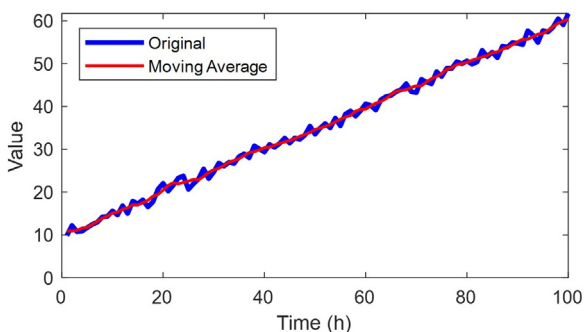


Figure 16.2 Original time series and MA forecast. Analyzing trends: Original time series vs. moving average forecast.

Linear regression in renewable energy prediction

Linear regression analyzes the relationship between two variables, such as time and the magnitude of an event. Through this relationship, the future behavior of the dependent variable can be predicted. Linear regression emerges as a fundamental technique in predicting renewable energy production, particularly in solar energy, where the variability of solar radiation poses challenges for grid management. Various studies have addressed this issue, emphasizing the importance of accurate prediction to ensure system stability and optimal resource allocation. In a study (Hassan et al., 2017), the focus was on predicting solar radiation using linear regression techniques, specifically the least squares regression. The simple linear regression equation is employed to model the relationship between solar radiation and a time-related variable, showing a 32% improvement in prediction accuracy compared to other reference models. Another study (Sharma et al., 2011) addressed solar power generation prediction in distributed systems. Both linear regression and support vector machines (SVM) with different kernel functions were utilized. SVM-based models proved to be 27% more accurate than the existing models, highlighting the effectiveness of these techniques in distributed generation prediction.

In the context of wind energy, Sanusi and Corne (2016) concentrated on wind speed prediction to optimize the integration of this RES. Multivariate linear regression is applied, emphasizing the importance of derived features, such as the gradient in wind speed, to enhance model accuracy. Uncertainty in electricity prices in renewable energy environments is tackled in a fourth study (Minhas et al., 2017). Here, linear regression is applied to forecast electricity prices, leveraging the intermittency of RES. A load control algorithm based on logistic regression is proposed to activate consumer load demands during low-price periods. Subsequently, in a study (Wahbah et al., 2020), a nonparametric model of solar irradiance probability density using local linear regression was proposed. This method surpasses both parametric and nonparametric models in terms of fit and precision. In summary, these studies demonstrate the versatility and effectiveness of linear regression in predicting key variables for renewable energy generation. The combination of linear regression with advanced machine learning techniques offers a comprehensive approach to address the challenges of variability in renewable energy production, contributing to the transition to more sustainable energy systems.

Despite its utility in predicting related variables, linear regression has some disadvantages that must be considered. It assumes a linear relationship between variables, which may not accurately reflect the complexity of certain phenomena, leading to inaccurate models in nonlinear cases. Additionally, linear regression is sensitive to outliers, where extreme data points can disproportionately impact results, affecting model robustness. It also lacks automatic handling of categorical variables, necessitating additional transformations for inclusion. Moreover, linear regression may suffer from multicollinearity, where predictor variables are highly correlated, making it challenging to precisely identify individual contributions. It may not be suitable for describing nonconstant relationships over time or in different data segments, as it assumes a constant relationship. In environments with large

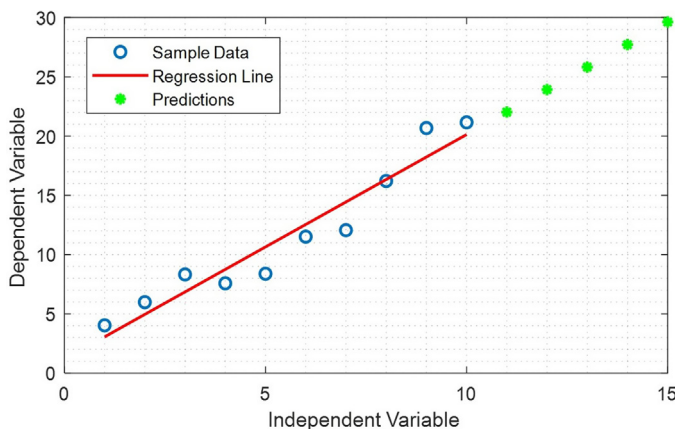


Figure 16.3 Regression prediction illustration, capturing trends and forecasting new data. Unlocking insights: Regression prediction revealing trends and forecasting future data.

datasets, linear regression can become computationally expensive and less efficient compared to more advanced machine learning approaches. In summary, while linear regression offers simplicity and ease of interpretation, its limitations in terms of linear assumptions, sensitivity to outliers, and challenges with nonlinear relationships suggest the need to carefully consider its applicability in specific contexts. Exploring more advanced approaches becomes essential when dealing with complex data. Fig. 16.3 illustrates an example of data prediction using linear regression.

Analysis and decomposition of time series in renewable energy prediction

The analysis of time series and its decomposition are crucial components in the prediction of renewable energy, contributing to understanding and forecasting complex patterns. A widely used approach involves decomposing time series data into components such as trend, seasonality, and residuals. This method enhances the understanding of underlying patterns, enabling more accurate predictions (Pujari et al., 2023). The study (Pujari et al., 2023) on wind energy prediction utilizes the Brock–Dechert–Scheinkman test to detect nonlinearity and the augmented dickey–fuller test to assess stationarity. Long-term dependencies are analyzed using the Hurst exponent. Subsequently, the time series is decomposed into trend, cycle, and seasonal patterns using the seasonal and trend decomposition using loess (STL) method. Furthermore, the study introduces an evolutionary algorithm for neural architecture search (NAS) to efficiently optimize models, comparing nonlinear autoregressive (NAR) models, LSTM neural networks, and wavelet neural networks (WNN) (Pujari et al., 2023). In another study (Malhan & Mittal, 2022), a novel prediction model was proposed for combined wind and hydroelectric power generation. The model consists of three phases: phase-I utilizes ARIMA and BiLSTM and

phase-II integrates forecasts of seasonal and off-season periods obtained through a diligent search algorithm (DSA). Finally, phase-III facilitates the amalgamation of results from phases I and II to construct the proposed prediction model. Seasonal effects are crucial, and DSA identifies hidden seasonality, improving overall performance. This model offers advantages in terms of accuracy, diversity, and uniformity, demonstrating its effectiveness for long-term prediction scenarios.

On the other hand, [Damaševičius et al. \(2024\)](#) presented a novel recurrent neural network (RNN) model based on attention for long-term prediction of renewable energy generation, focusing on wind and solar energy datasets. Decomposition techniques are applied, and a modified metaheuristic is introduced to optimize hyperparameters. The proposed approach demonstrates an improvement in prediction accuracy, especially in addressing challenges related to the storage and management of renewable energy generation. The introduced HHO algorithm proves effective in handling the large number of hyperparameters in RNN-type networks. These studies highlight the importance of time series analysis and decomposition in improving the accuracy of renewable energy prediction models. The proposed methods, such as evolutionary NAS and ensemble prediction, contribute to overcoming challenges in nonlinear and dynamic patterns of renewable energy. The attention-based RNN approach, along with metaheuristic optimization, emerges as a promising strategy for long-term prediction. Like in any research, there are limitations, and future directions include refining optimization algorithms, exploring additional decomposition methods, and examining alternative metaheuristics for further improvements. The continuous evolution of methodologies and models remains essential for advancing the capabilities of renewable energy prediction systems.

[Fig. 16.4](#) illustrates an example of decomposing a time series into its fundamental components using the STL method in MATLAB[®] 2021a. In the first subplot, the original time series is shown, which in this hypothetical example is a combination of a sinusoidal function with random noise. The second subplot presents the trend component of the series, obtained through a smoothing process that highlights long-term variations and eliminates short-term fluctuations. This trend provides information about the overall direction of the time series. The third subplot shows two additional components. The green line represents the seasonal component, capturing repetitive or cyclical patterns in the original series. Obtaining this component involves removing the trend from the original series. The blue line in the third subplot represents the residuals, which are the variations not explained by the trend and seasonality. Residuals are essential for understanding irregularities and unexpected changes in the time series. Together, this STL decomposition allows for a more detailed analysis of the time series, facilitating the identification of seasonal patterns, long-term trends, and unusual events. This approach is crucial for making more accurate forecasts and understanding the underlying structure of temporal data.

Exponential smoothing models

Exponential smoothing models play a crucial role in predicting electricity production, especially from RES. These models assign exponential weights to past values,

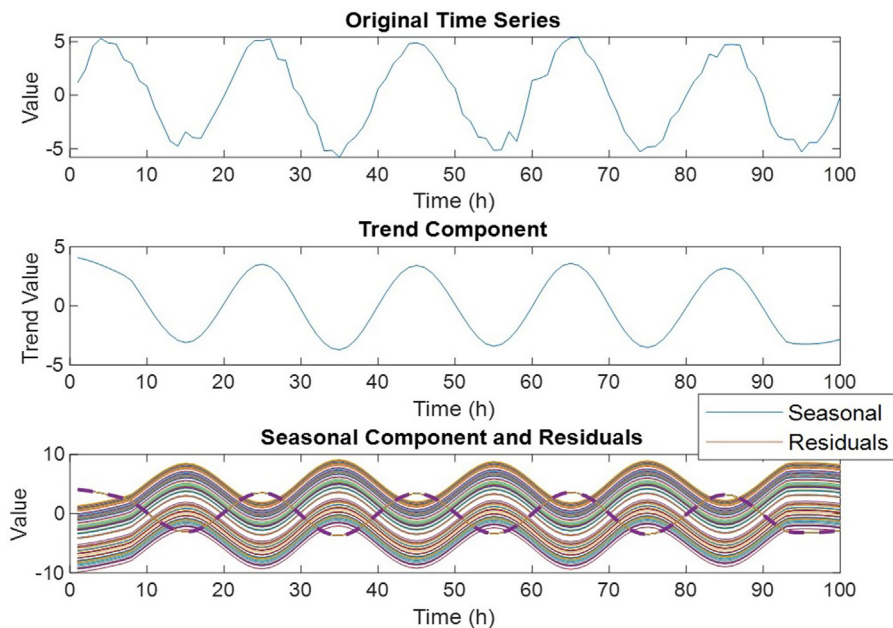


Figure 16.4 Time series decomposition: original, trend, seasonal, and residual components. Decoding time series: Original, trend, seasonal, and residual components unveiled.

giving more importance to recent observations. By adapting to changes in trends over time, they provide valuable insights into future electricity production trends, particularly in the context of renewable energy. The application of exponential smoothing models has been demonstrated in predicting electricity production in various countries, such as China, Japan, and the United States. These models have shown superior prediction accuracy compared to classical versions like error, trend, seasonal models. The ability to estimate and predict electricity production from both coal and RES is essential for informed decision-making and sustainable energy management (Tulkinov, 2023). In a study (Boland & Farah, 2021), the focus was on wind and solar systems connected to the grid in Australia. Accurate prediction of the production of these systems is crucial for increasing renewable energy penetration. Exponential smoothing is explored as an efficient alternative for predicting variance, considering the changing nature of error variance over time. The study emphasizes the importance of constructing prediction intervals, especially in situations where variance is not constant, such as in wind farms with conditional changes or due to diurnal effects in solar parks.

The discussion on predicting the production of wind or solar parks is conducted in the study (Boland & Farah, 2021), introducing two approaches: predicting the resource (wind speed or solar radiation) and using a power conversion model, or predicting directly from historical performance. The latter approach is preferred due to lower model error levels and considerations about the complexity of power conversion models. The study demonstrates the effectiveness of building prediction

interval forecasts for situations where common assumptions for time series prediction may not hold. Despite their advantages, some drawbacks of exponential smoothing models include sensitivity to sudden and extreme changes in data, as well as the need to properly adjust parameters, which can be challenging in dynamic environments (Boland & Farah, 2021). Additionally, these models may not capture highly complex data patterns and are not ideal for datasets with irregular seasonality or pronounced nonlinear trends. The choice of exponential smoothing method may also depend on the specific nature of the data and require adjustments on a case-by-case basis.

In Fig. 16.5, an example of exponential smoothing applied to a time series is presented. The original time series (in blue) exhibits a sinusoidal pattern with random noise. The exponential smoothing process is carried out manually, using a smoothing parameter (alpha) set to 0.8. The dashed red line represents the predictions generated by the exponential smoothing method. This approach weighs past values and assigns more weight to recent observations. The technique aims to adapt to changes in the trend of the time series over time. The visualization of the original time series alongside predictions highlights how the exponential smoothing method smoothens fluctuations and captures the underlying trends of the time series. This approach is useful for generating forecasts that more accurately reflect the evolution of the series as new data is incorporated.

Delphi method in time series forecasting

In the context of renewable energy, this approach involves consulting experts anonymously and in a structured manner to gain insights into the future of sustainable energy. Initially, relevant experts in the field of renewable energy are identified. These may be professionals with expertise in specific technologies, energy policies, or any other crucial aspect for understanding the future landscape of RES. Once a representative group of experts is selected, key questions related to the subject are

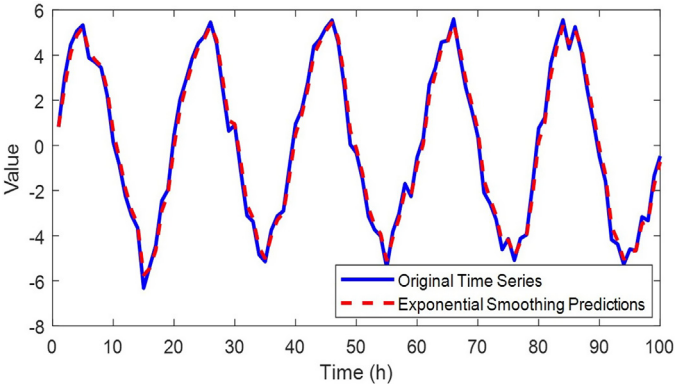


Figure 16.5 Exponential smoothing example. Illustrating smoothing power: A practical example of exponential smoothing.

formulated. These questions often address various aspects such as the expected adoption of renewable technologies, potential challenges, the influence of government policies, or even possible technological advancements in the sector. It is essential that the responses are collected anonymously to encourage honesty and openness from the experts.

The Delphi method has proven to be a valuable tool in predicting and analyzing various aspects related to energy, as evidenced in recent studies. In [Panda et al. \(2023\)](#), a significant transformation of the conventional energy system is highlighted due to the integration of emerging technologies, RES, and storage devices. This analysis proposes a shift toward a decentralized system to address the limited adaptability of traditional energy systems. The effects of privatization and restructuring of the electrical system are explored, along with the integration of distributed generations and consumer-side demand management with information and communication technology protocols. Challenges related to deregulated electricity markets are addressed, and demand management is suggested to handle supply and demand variability in distribution sectors. In [Obrecht and Denac \(2016\)](#), the focus was on the correlation between energy policy and the development of the energy industry with technological prediction. Based on a Delphi survey in Slovenia, the study addressed the importance of energy efficiency and reducing final energy consumption compared to keeping energy prices low. Findings on the future prices of various energy sources, including wood biomass, were discussed, and the feasibility of achieving the 20% renewable energy target in the European Union by 2020 was questioned. Experts emphasize the need for a radical transformation in energy policy toward efficient energy use and local renewable energy production. In another study ([Ribeiro & da Silva, 2015](#)), the Delphi method was used to provide support in strategic decision-making regarding microalgae-derived biofuels. The goal was to determine the prospects of employing microalgae in biofuel production by 2030. The method proved successful in qualitative research for long-term forecasting situations, where expert opinions are the main source of information. Results provide a clear insight into current and future issues in the microalgae-derived biofuel market. These studies illustrate the applicability of the Delphi Method in different energy research contexts, providing valuable insights that influence decision-making, policies, and future development in the field of renewable energy.

While the Delphi Method is valuable in prediction and decision-making, it is not without disadvantages and challenges. Firstly, the quality of predictions heavily depends on the selection of experts, which can introduce biases if the group is not representative. Additionally, there is a risk of conformity, where participants may be influenced by majority opinions or prominent experts, limiting the diversity of perspectives. The process can also be costly and time-consuming, involving anonymous response collection, iterations, and controlled feedback. This temporal and financial limitation can be a barrier in situations with budget or time constraints. Furthermore, the lack of direct interaction among participants may limit the ability to discuss, exchange information, and refine opinions in real time. The dependence on the quality of questions is another critical consideration. Poorly formulated questions can lead to inaccurate or unhelpful responses, compromising the validity of

the results. In rapidly changing areas like renewable energy, long-term predictions can quickly become obsolete due to unexpected technological advancements.

Effective management of feedback also poses challenges, as deciding what feedback to provide to experts and how to balance divergence of opinions requires specific skills. Additionally, in contexts where a deep understanding of market dynamics is sought, the lack of direct interaction and reliance on anonymous responses can limit the thoroughness of the analysis. Despite these limitations, the Delphi method remains a valuable tool for addressing uncertainty and leveraging expert experience in long-term planning. It is crucial to use it consciously, recognizing its challenges and complementing it with other methodologies when necessary to obtain a more comprehensive and accurate perspective.

Fig. 16.6 illustrates the iterative process of the Delphi method applied to the prediction of solar energy growth over five iterations. Each subplot represents the estimates provided by a different expert (expert 1, expert 2, and expert 3) across the iterative consultations. The x-axis denotes the iteration number, while the y-axis represents the evolving estimates of solar energy growth. The markers (“o”) depict the estimated values at each iteration. In the initial iteration (iteration 1), each expert offers their respective random estimates. As the Delphi method progresses, controlled feedback is applied, leading to a convergence of estimates toward a consensus in subsequent iterations (iteration 2 to iteration 5). The legends provide a clear distinction between the estimates contributed by each expert throughout the iterative process. This visual representation showcases how the Delphi method facilitates collaboration among experts, allowing their insights to inform and adjust predictions over successive iterations, ultimately aiming for a refined consensus in long-term forecasting.

Meteorological models

In the realm of renewable energy generation, various types of meteorological models are employed to forecast atmospheric conditions and optimize energy production. Some of the common types include numerical weather prediction, solar irradiance models, wind dispersion models, and data assimilation models.

Numerical weather prediction

Numerical weather prediction (NWP) models play a pivotal role in forecasting wind and solar power output, offering insights into atmospheric conditions critical for renewable energy generation. To grasp the foundations of successful NWP forecasts, a comprehensive understanding of key principles is essential (Haupt et al., 2017). These principles encompass atmospheric motion, observation sources, data assimilation, postprocessing, probabilistic predictions, and validation methods. The NWP model, exemplified by the widely used weather research and forecasting model, discretizes atmospheric equations, enabling numerical approximation crucial

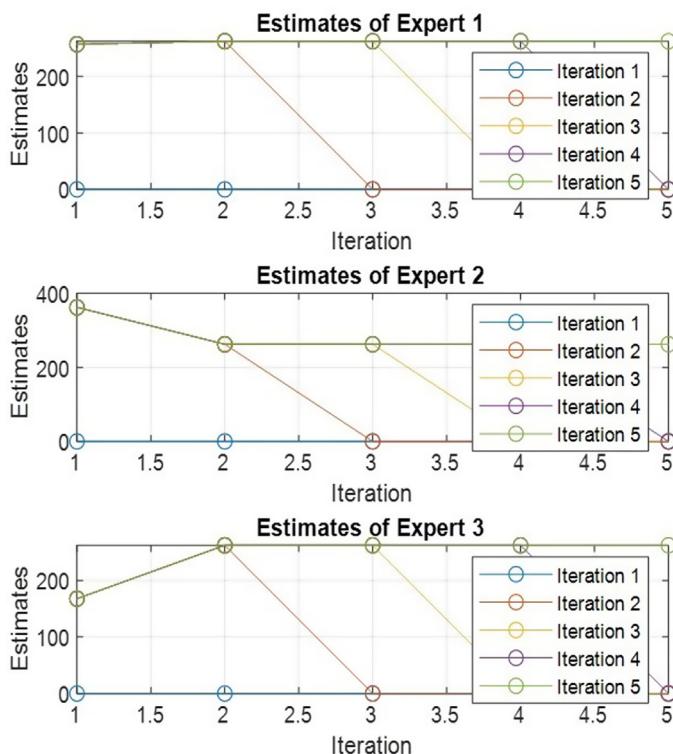


Figure 16.6 Delphi iterative convergence in solar energy growth projections. Navigating Delphi iterative convergence: Solar energy growth projections.

for accurate forecasts (Haupt et al., 2017). At the inception of the 20th century, the conceptualization of NWP was rooted in predicting weather by applying fundamental conservation laws (Haupt et al., 2017). Early attempts involved human “calculators” and grid-based calculations, laying the groundwork for modern NWP models. With the advent of digital computers, pioneering works by visionaries like Richardson and Charney led to the development of successful NWP models (Haupt et al., 2017). In solar energy forecasting, a focus on direct normal irradiance (DNI) for concentrating solar thermal (CST) systems is paramount (Alkabbani et al., 2021). This involves considering various forecasting methods, including numerical weather prediction models, statistical forecasting, and nowcasting. Challenges in immediate forecasting (up to 6 hours) necessitate harmonizing signals for high-resolution spatial-temporal predictions at the plant level (Ramírez & Vindel, 2017).

For PV power systems, accurate forecasting methods are crucial for power supply and demand balancing (Kato, 2016). Forecasting tools, including NWP models, satellite images, and measured PV power output data, contribute to various time horizons, from minutes to days. The evolution of irradiance forecasting demands a nuanced understanding of fluctuation characteristics and the application of

forecasting methods in both power systems and individual energy management systems (Kato, 2016). In the realm of CST systems, forecasting and nowcasting of DNI are critical aspects (Ramírez & Vindel, 2017). The challenges lie in immediate prediction periods (up to 6 hours), requiring harmonization of signals for reliable, high-resolution forecasts. Considerations are presented regarding single versus aggregated or regional forecasting (Ramírez & Vindel, 2017). Wind power generation, characterized by its intermittent nature, demands advanced forecasting techniques (Shirzadi et al., 2023). Traditional NWP models face limitations in long-term forecasting due to computational constraints. A hybrid AI-based approach, integrating deep learning with a probability distribution, enhances wind speed forecast accuracy over a 48-hour horizon. The fusion of this improved model with NWP models further refines accuracy, offering a promising avenue for efficient wind speed forecasting in renewable energy systems (Shirzadi et al., 2023). In summary, integrating NWP models and various forecasting methodologies is crucial for optimizing the performance of renewable energy systems. These approaches provide valuable insights into atmospheric conditions, contributing to more reliable and efficient renewable energy generation.

Solar irradiance models

Solar irradiance models play a crucial role in the assessment and optimization of PV energy systems, providing essential information about the amount of incident solar radiation on the Earth's surface. In this context, five prominent models stand out: HOMER (hybrid optimization model for multiple energy resources), PVWatts, SOLPOS (solar position and intensity), SMARTS (simple model of the atmospheric radiative transfer of sunshine), and PVGIS (PV geographical information system). Each of these models addresses specific aspects related to solar irradiance prediction and has undergone detailed studies revealing their effectiveness and applicability under various conditions. The following is a brief description of each model followed by citations highlighting their utility and performance in particular contexts.

Hybrid optimization model for multiple energy resources

HOMER is a versatile tool that not only serves as a simulator and optimizer but also incorporates models for predicting solar irradiance. Its use extends to microgrid systems, and a detailed study (Shaikh et al., 2021) on the configuration, operation, and integration of multiple energy sources in microgrid systems emphasized the prominence of HOMER Pro and the particle swarm optimization algorithm. This study provides a comprehensive review of microgrid perspectives, considering adopted technologies, control strategies, existing applications, software tools, and artificial intelligence techniques.

PVWatts

PVWatts, developed by the National Renewable Energy Laboratory (NREL), is an online tool that models the performance of PV solar energy systems. This model uses meteorological data and PV system specifications to estimate solar energy production. In a comparative study (Milosavljević et al., 2022) evaluating 14 PV simulation tools, PVWatts showed lower deviation in simulated results compared to experimental measurements of a 2 kWp PV system in Niš.

Solar position and intensity

SOLPOS, developed by the NREL, focuses on calculating the sun's position and solar intensity at specific locations and times. In a study (Suh & Choi, 2017), methods for converting monthly accumulated irradiation data into hourly data were compared. The research concluded that the SOLPOS algorithm was the most suitable method, as it showed highly similar monthly irradiation patterns to measured values at seven sites in the United States and Korea.

Simple model of the atmospheric radiative transfer of sunshine

SMARTS, an acronym for simple model of the atmospheric radiative transfer of sunshine, developed by NREL, is used to simulate spectral solar irradiance. In a study (Ali & Zhao, 2022), spectral solar irradiance measured by a spectrometer in the black hills area was analyzed, and a data-based model was developed to convert measurements into absolute irradiance. This case study demonstrated that using SMARTS to determine the energy production of PV systems improves accuracy by avoiding absolute calibration of the light spectrometer.

Photovoltaic geographical information system

PVGIS, developed by the Joint Research Centre of the European Commission, provides data and models to evaluate the performance of PV systems. In a study (Lehneis et al., 2020), PVGIS was used to simulate the electricity generation of 1.612 million PV systems in Germany. This model relies on publicly accessible data and offers an alternative for calculating highly resolved electricity generation data from PV systems, demonstrating its applicability in different regions and climatic conditions.

Machine learning and neural networks for renewable energy generation prediction

Machine learning and ANNs emerge as innovative and efficient tools to precisely anticipate energy production from RES. This research field not only addresses the challenges associated with the inherent variability of these energy sources but also

provides advanced solutions that can significantly enhance the planning and management of renewable energy generation. In this section, we will explore the most powerful techniques currently available and present some challenges and future trends.

Recurrent neural networks

The application of RNN in renewable energy generation forecasting signifies a significant advancement in optimizing sustainable energy prediction. RNNs, with their ability to grasp intricate temporal patterns, emerge as ideal tools for addressing the inherent variability in RES. This technique enables the modeling of dynamic relationships among climatic variables, past generation patterns, and other relevant factors, thereby achieving more accurate forecasts. In this section, we will explore how RNN, particularly the well-recognized techniques of LSTM and gated recurrent unit (GRU), offer a promising perspective to enhance prediction accuracy in the context of renewable energy generation.

Long short-term memory

LSTM stands out as a robust model for solar forecasting, adept at addressing challenges such as hyperparameter tuning and the consideration of meteorological parameters. The optimized stacked Bidirectional LSTM/LSTM model, introduced in the referenced study, integrates stacked LSTM layers, dropout architecture, and Bayesian optimization to augment performance. The model exhibits exceptional accuracy in forecasting global horizontal irradiance (GHI) and observed plane of array (POA) irradiance, achieving R^2 values of 0.99 for univariate and multivariate models using GHI data. [Michael et al. \(2022\)](#) underscored the model's flexibility, achieved through Bayesian optimization and the choice between BiLSTM and LSTM architectures. The conclusions highlight the efficacy of the LSTM model in delivering superior solutions for univariate and multivariate solar forecasting, surpassing benchmark models in terms of error metrics. The incorporation of POA data and the model's successful application to PV power forecasting further emphasize its versatility. The study acknowledged the LSTM model's prowess in handling extensive time series data and proposed future efforts to mitigate errors in solar irradiance forecasting under nonlinear weather conditions.

On the other hand, some studies ([Shirzadi et al., 2023](#); [Rangelov et al., 2023](#)) discussed the hurdles posed by the unpredictable nature of RES, particularly wind and solar power. They proposed innovative AI-based solutions to enhance the precision of energy generation forecasts. In [Shirzadi et al. \(2023\)](#), the emphasis was on wind power, revealing the limitations of traditional numerical weather prediction models due to computational constraints. The study introduced a hybrid AI approach that integrates wind speed probability distribution with a deep learning model, showcasing improved accuracy in a 48-hour forecast for Montreal. Results indicate a substantial reduction in the root mean squared error, highlighting the efficacy of combining AI techniques for enhanced wind power prediction. Similarly, [Rangelov et al. \(2023\)](#) delved into challenges related to the integration of PV

systems into the grid, emphasizing the volatile and intermittent nature of RES. The paper evaluates three AI methods—random forest, deep neural network, and long short-term memory network—for short-term PV output power forecasting in Berlin, Germany. The study underscores the significance of accurate PV power output forecasts in reducing disruptions, refining capacity planning, and cutting operational costs. The successful performance of the random forest and deep neural network models underscores their ability to generate precise solar power forecasts and navigate abrupt changes in PV power output. Collectively, these studies underscore the pivotal role of AI in overcoming challenges tied to renewable energy integration and refining the dependability of forecasting models.

Gated recurrent unit

GRU, as another variant of RNN, has demonstrated effectiveness in renewable energy forecasting and energy management. In a study exploring a demand-supply matching approach for renewable energy forecasting, DL models, including GRU, were employed to enhance energy management for futuristic cities with 100% renewables (Almalaq et al., 2021; Kim et al., 2021). The use of GRU in this context aligns with its ability to capture dependencies in time series data, which is crucial for forecasting intermittent RES. Furthermore, the study proposing a data-driven bidding strategy for a DER aggregator in the day-ahead power market emphasizes the role of GRU in the precise modeling of renewables and local load, showcasing its superiority over LSTM, RNN, and SVR (Kim et al., 2021). The GRU model, optimized using the ELPSO algorithm and IMI feature selection technique, outperformed other models in terms of forecasting accuracy, contributing to reduced penalty costs and improved bidding strategies in the face of uncertainties. In summary, LSTM and GRU, as sophisticated RNN variants, play crucial roles in addressing the complexities of renewable energy forecasting. The cited studies provide compelling evidence of their efficacy in capturing temporal dependencies, handling uncertainties, and outperforming traditional models. The versatility of these models, demonstrated across various scenarios and datasets, positions them as valuable tools for advancing the accuracy and efficiency of renewable energy prediction, thereby contributing to the sustainable evolution of energy systems.

Despite their notable advantages, RNN models, such as LSTM and GRU, are not without challenges and limitations in predicting renewable energy generation. One key challenge is the need for high-quality data for training, as the accuracy of these models heavily depends on the quality and representativeness of historical data. Additionally, the computational complexity associated with deeper architectures, such as deep neural networks, may require significant resources. The interpretation of results can also be challenging, especially for models based on deep learning, which may lack transparency. Moreover, extreme climatic variability and unpredictable weather conditions pose additional challenges, as models must adapt to sudden changes in environmental variables. These challenges underscore the importance of continuously addressing data quality, computational efficiency, and model interpretability to optimize accuracy in renewable energy generation prediction.

Convolutional neural networks

CNNs, commonly associated with computer vision, have found innovative applications in predicting renewable energy generation, particularly in scenarios such as wind speed maps. This discourse delves into the advancements achieved by various studies in employing CNNs for renewable energy prediction, emphasizing their potential to overcome challenges linked to the intermittent nature of renewables. In [Schreiber et al. \(2021\)](#), the ComPonentNet (CPNet) family of architectures utilizes CNNs for wind speed prediction. The study introduces three architectures, illustrating that processing wind components separately, as in the bottom-fused CPNet (BF-CPNet), significantly enhances forecasting accuracy. The results underscore the promising nature of CNNs in addressing the stochastic elements introduced by renewable energy, highlighting potential cost reductions for power systems. Similarly, [Schreiber et al. \(2021\)](#) introduced a temporal convolutional network (TCN) for day-ahead power forecasts, improving forecast accuracy by considering the diurnal cycle. The study demonstrated a notable improvement (up to 25%) compared to traditional multilayer perceptrons in renewable power forecasts. The proposed TCN architecture exhibits adaptability for multitask learning, inductive transfer learning, and even zero-shot learning, indicating its potential to overcome challenges associated with renewable power prediction. In [Bastos et al. \(2021\)](#), the U-Convolutional model employs CNNs for hourly wind speed prediction, displaying competitive performance against advanced CNN architectures, fully connected neural networks, and univariate models. The proposed architecture, combining U-Net and Convnet, proves promising for spatiotemporal wind speed prediction. The results underscore the importance of advanced models in supporting power systems grappling with the increasing penetration of intermittent renewables.

[Dolatabadi et al. \(2023\)](#) addressed the economic optimization of a CAES-PV system using DRL and a 2D-CNN-BLSTM hybrid forecasting model. By tackling the intermittent nature of solar power production, the study demonstrates the effectiveness of CNN-based forecasting in enhancing the profitability of the CAES-PV system in energy markets. Lastly, [Wu et al. \(2023\)](#) introduced the unrolled spatiotemporal graph convolutional network (USGCN) for distribution system state estimation and forecasting. The model, incorporating complex spatiotemporal correlations of RES, outperforms traditional methods and achieves at least a 16.42% improvement in state estimation accuracy. The USGCN's ability to efficiently capture spatiotemporal correlations highlights its potential to address challenges posed by high renewables.

The discussed studies illustrate the diverse applications of CNNs in predicting renewable energy generation. From wind speed maps to day-ahead power forecasts and distribution system state estimation, CNNs have demonstrated their effectiveness in enhancing accuracy and overcoming challenges associated with the intermittent nature of renewables. These advancements not only contribute to more reliable renewable energy predictions but also hold the potential to reduce operational costs and support the integration of renewables into modern power systems. Future work may further refine

these CNN-based approaches, exploring additional features, analyzing errors in-depth, and incorporating confidence intervals to enhance spatiotemporal forecasts even further. Despite the notable progress in the application of CNNs in renewable generation prediction, challenges and limitations exist that must be addressed to optimize their utility in practical settings. Firstly, the computational intensity of CNNs, especially in handling large datasets and complex models, can lead to high processing power requirements and prolonged training times. Additionally, the need for extensive training datasets can be a drawback in areas with limited availability of high-quality data.

Generative adversarial networks

Generative adversarial networks have become pivotal tools in the domain of renewable energy prediction, particularly when confronted with limited historical data. Their primary role lies in generating synthetic data to train models effectively, and the following summaries encapsulate insights from five relevant studies. In a collaborative initiative, the Korea electrotechnology research institute and Korea Institute of energy research introduced a renewables management system for large-scale grids. Leveraging a 12-hour-ahead solar irradiance forecast model and a generative adversarial network (GAN) for generating future RES penetration scenarios, the study underscored the potential of GANs in comprehensive grid management (Song et al., 2023). To address the uncertainties of renewable energy, another study introduced normalizing flows, a deep learning technique, for scenario-based probabilistic forecasts in power systems. This novel approach competes with other generative models, including GANs, showcasing its efficacy in generating accurate weather-based scenarios (Dumas et al., 2022). The Fed-LSGAN, an innovative federated deep generative learning framework, offers a privacy-preserving solution for renewable scenario generation in power systems. By combining federated learning and least square GANs, this model outperforms centralized methods, emphasizing the versatility of GANs in overcoming privacy concerns (Li et al., 2022).

Shifting the focus to short-term cloud coverage forecasting through sky image prediction using GANs, a study employs a deep CNN topology with adversarial loss. This method aids in estimating available solar resources by providing realistic images, evaluated using a cloud coverage metric (Andrianakos et al., 2019). In the realm of wind park power modeling, various methods to estimate probability distributions for individual turbine powers are explored. Comparisons between variational Bayesian inference models, GANs, and others reveal that Bayesian models generally outperform GANs in terms of mean absolute errors (MAE) (Bentsen et al., 2022). While GANs offer significant advantages in renewable energy prediction, it is crucial to acknowledge certain disadvantages and future challenges. Computational intensity poses challenges, particularly in handling large datasets and complex models, leading to high processing power requirements and prolonged training times. Additionally, interpreting decisions made by GANs can be complex, hindering their adoption in critical environments where explainability is crucial. Sensitivity to hyperparameter configuration underscores the importance of careful selection to avoid suboptimal performance or overfitting.

Looking ahead, improving the interpretability of GANs and developing techniques for transparent decision-making stand out as key priorities. The adaptability to scenarios with limited data presents a crucial challenge, where strategies like transfer learning may play a pivotal role. Enhancing computational efficiency through exploring more efficient architectures and techniques will be essential for real-time applications. Integrating measures of uncertainty into GAN predictions is vital for informed decision-making, especially in renewable energy generation characterized by variability. Lastly, addressing the generalization of GANs to diverse geographical contexts and climatic conditions remains a significant challenge, requiring considerations of data variability and location-specific conditions for effective applicability in different regions. Overcoming these challenges will unlock the full potential of GANs in renewable energy prediction, supporting a more efficient and sustainable transition to clean energy sources.

Deep learning

Deep learning, a transformative paradigm in predicting renewable energy generation, leverages intricate architectures like deep neural networks to discern complex and nonlinear patterns within data. The following summaries encapsulate insights from five significant studies applying deep learning to renewable energy prediction. In the realm of solar energy, the traditional encoder single deep learning method proves effective for short-term forecasts. The integration of this method into the power grid addresses challenges posed by the irregular and uncontrollable nature of power generation from renewables, showcasing a 27% improvement in accuracy over conventional methods ([Chang et al., 2021](#)). For accurate short-term PV power forecasts, a novel model, transformer neural network (TransNN), integrated with CNN and utilizing variational mode decomposition, outperforms benchmark models with MAE values under 1 kW ([Nguyen Trong et al., 2023](#)).

Addressing the intermittent and irregular nature of wave energy, an optimized deep learning neural network, guided by the moth-flame optimization algorithm, excels in forecasting wave energy flux. This approach, surpassing statistical and physics-based methods, exhibits robust performance, especially over short-term horizons ([Bento et al., 2021](#)). Climate change mitigation necessitates a transition to wind energy, but the nonlinear nature of wind poses forecasting challenges. LSTM networks, NAR models, and WNN emerge as efficient models for accurate wind forecasting. An evolutionary multiobjective strategy for NAS optimally designs these models, balancing computational cost and prediction accuracy ([Pujari et al., 2023](#)). In the context of wind farm prediction, a deep, multilayered neural network demonstrates efficacy in estimating wind farm generation 24 hours in advance. Trained and validated with data from a wind farm, this model outperforms existing predictors, highlighting the prowess of deep learning in enhancing predictive generation models for wind farms ([Torres et al., 2018](#)). While deep learning offers remarkable advancements, challenges and future endeavors persist. Computational intensity, model

interpretability, and hyperparameter sensitivity emerge as notable disadvantages. Future efforts should prioritize enhancing model interpretability, adapting to scenarios with limited data, improving computational efficiency, and addressing model generalization across diverse geographical and climatic conditions. Overcoming these challenges will usher in a new era of accurate and sustainable renewable energy predictions.

Reinforcement learning

RL techniques offer promising avenues for real-time optimization in the renewable energy sector. Let us delve into the application of RL in various scenarios. One innovative application involves CAES combined with PV systems. A novel DRL method is employed to optimize CAES energy arbitrage, considering the intermittent nature of solar power production. A hybrid forecasting model, integrating 2-D CNNs and BLSTM units, enhances solar irradiance predictions. The proposed framework demonstrates effectiveness in real-time scheduling and profitability, showcasing its superiority over state-of-the-art methods (Dolatabadi et al., 2023). In the domain of building energy management, a decision tree-based RL approach is introduced for accurate electricity consumption forecasting. The decision tree identifies different contexts, and a multiarmed bandit algorithm guides the selection of the most suitable forecasting algorithm. The study, validated in building and industrial contexts, highlights the methodology's adaptability and efficacy in enhancing prediction accuracy (Ramos et al., 2022). Addressing challenges in electrification and decarbonization, RL techniques are applied to demand response scenarios. Transfer learning, leveraging existing domain knowledge, is explored to mitigate sample complexity and enhance the performance of machine learning and optimization algorithms.

Despite progress, challenges such as the lack of benchmarks and consensus on techniques for avoiding negative transfer persist in the application of RL to demand response (Peirelinck et al., 2022). Virtual power plants (VPPs) offer the potential to increase power system reliability and efficiency. RL is utilized to formulate profit-maximizing strategies for a VPP aggregating solar systems and electric vehicle (EV) chargers with vehicle-to-grid support. Two-stage stochastic optimization, combining linear programs and RL techniques, optimizes energy trading decisions in day-ahead and imbalance electricity markets. The study evaluates the proposed strategies using real market data and emphasizes the potential profitability of VPPs with EV integration (Rahman et al., 2022). While RL exhibits promising applications in renewable energy prediction, challenges persist. Model interpretability, high sample complexity, and potential negative transfer in demand response scenarios are notable disadvantages. Future endeavors should focus on improving interpretability, addressing data limitations, and establishing benchmarks to overcome the identified challenges. Additionally, research must extend into real-world experiments for a more comprehensive understanding of RL's effectiveness in renewable energy applications.

Transformer neural networks

These networks, initially designed for natural language processing, have proven adaptable to various domains, including the prediction of renewable energy generation. A groundbreaking study in wind power forecasting explores the application of a Transformer coupled with a CNN using attention mechanisms. This novel approach, evaluated across different periods and time intervals, outperforms existing models for ultrashort-term and short-term forecasting. By effectively capturing complex patterns and dependencies in wind power data, the transformer algorithm, in conjunction with CNN and attention mechanisms, demonstrates superior accuracy, enhancing the integration of wind power into the grid (Mulewa et al., 2023). Similarly, the spatial-temporal graph transformer network (STGTN) is proposed for short-term wind speed forecasting. This model incorporates a transformer with an external attention mechanism and a graph convolutional layer, enabling the extraction of both temporal and spatial features. The STGTN outperforms benchmark methods in terms of MAE, root mean square error, and mean absolute percentage error, showcasing its effectiveness in capturing wind speed fluctuations and spatial dependencies (Pan et al., 2022).

Extending the application of transformers to solar energy, a study utilizes the transformer deep neural network model for solar irradiance prediction. By combining features based on spatiotemporal properties, the transformer model, typically applied in NLP or vision problems, demonstrates remarkable accuracy with a maximum worst-case mean absolute percentage error of 3.45% for one-day-ahead predictions. The model's ability to utilize space–time bonds between features and regional data proves advantageous for solar irradiance forecasting (Pospíchal et al., 2022). Expanding the scope to include VPPs, a study proposes a hybrid system for renewable energy forecasting, integrating the traditional seasonal ARIMA with a transformer neural network. Named H-transformer, this hybrid model outperforms other single models and hybrid approaches across various datasets of wind speed and solar energy. The study emphasizes the importance of accurate forecasting for the profitability and stability of renewable energy systems (Padilha et al., 2022). The integration of CNN, LSTM networks, and transformers is explored for solar energy production forecasting. This hybrid model, outperforming existing models, proves effective in providing accurate forecasts, facilitating the integration of solar energy into grids. The combination of spatial and temporal features extracted by CNN, LSTM, and transformer enhances forecasting accuracy (Al-Ali et al., 2023).

For wind speed and wind energy forecasting, a transformer-based deep neural network-integrated with wavelet transform is proposed (Liu et al., 2023). This model, evaluated in various regions in Bahia, Brazil, outperforms the LSTM baseline, demonstrating effectiveness in forecasting wind speed and power generation. The integration of the transformer model with wavelet decomposition further improves forecast accuracy (Nascimento et al., 2023). While transformer ANNs exhibit promising capabilities, challenges and areas for future research persist. Some of the identified limitations include the complex training process, the need for extensive computational power, and the scarcity of open multivariate renewable

energy datasets. Future endeavors should focus on mitigating these challenges, exploring long-term forecasting, incorporating seasonal factors, and enhancing the models’ robustness across different weather conditions. Additionally, efforts should be directed toward developing interpretable models, addressing optimization complexities, and fostering broader applicability in various forecasting tasks.

Challenges and future research lines in renewable generation prediction

Table 16.1 provides a concise overview of the challenges and future research directions associated with various methods employed in renewable energy prediction. The methods encompass traditional time series forecasting approaches, meteorological models, and cutting-edge machine learning techniques. The challenges highlighted include issues related to adaptability, linearity assumptions, nonlinear patterns, model sensitivity, and the need for substantial data and computational resources. Additionally, future research

Table 16.1 Challenges and future research lines in renewable energy prediction methods.

Method	Challenges	Future Research Lines
Moving average and autoregressive integrated	Sensitivity to outliers and abrupt changes.	Improvements in adaptability to sudden changes in energy generation. Integration of more advanced methods to handle variability.
Linear regression	Linearity assumptions may not capture the complexity of variability.	Development of more sophisticated nonlinear models. Integration of additional variables for improved accuracy.
Analysis and decomposition of time series	Difficulty in handling nonlinear patterns and nonstationary trends.	Research on more advanced decomposition techniques. Adaptation to complex seasonal patterns.
Exponential smoothing models	Sensitivity to parameter and model structure choices.	Development of optimization methods for automatic parameter selection. Improvements in predictive capability.
Delphi method	Dependence on experts and subjectivity in data collection.	Incorporation of methods to manage uncertainty and enhance objectivity. Evaluation of method robustness.
Meteorological models	Specific challenges for each type of meteorological model.	Research on improving the accuracy of specific models. Integration of multiple models for more robust forecasts.

(Continued)

Table 16.1 (Continued)

Method	Challenges	Future Research Lines
Machine learning and neural networks	Need for large datasets and computational resources.	Development of learning techniques with limited data. Research on more computationally efficient models.
Recurrent Neural Networks	Vanishing/exploding gradient problems in long sequences.	Research on more advanced and efficient architectures. Handling longer temporal sequences.
Convolutional Neural Networks (CNNs)	Challenges in capturing temporal relationships in sequential data.	Exploration of hybrid architectures to combine temporal and spatial features. Improvements in interpretability.
Generative Adversarial Networks (GANs)	Generation of realistic data in low generation scenarios.	Research on enhancement techniques for generation in low data availability situations. More robust validation.
Deep learning	Interpretability and explainability of complex models.	Development of methods to increase the interpretability of models. Research on explainability techniques.
Reinforcement Learning (RL)	Need for efficient algorithms for continuous adaptation.	Development of more efficient and adaptable RL algorithms. Integration with traditional approaches to improve robustness.
Transformer Neural Networks (TNNs)	Need for large amounts of data for training.	Research on training techniques with small datasets. Exploration of more computationally efficient architectures.
Federated learning (FL)	Challenges in collaboration between distributed models.	Improvements in security and efficiency of distributed collaboration. Research on more robust federated methods.
Transfer learning (TL)	Effective transfer of knowledge between domains.	Development of transfer learning techniques specific to renewable energy forecasts. Evaluation of generalization.
Ensemble methods	Effective integration of heterogeneous models for improved accuracy.	Research on more sophisticated ensemble methods. Evaluation of ensemble robustness and reliability.

lines are outlined, suggesting potential improvements, advanced techniques, and specific areas for exploration within each method to enhance the precision and reliability of renewable energy predictions.

Conclusions

In this comprehensive analysis of renewable energy generation prediction methods, a wide spectrum of approaches has been explored, ranging from classical methods to advanced techniques in machine learning and ANN. The review of fundamental concepts and traditional methods highlights their historical significance but also reveals their limitations in the face of the increasing complexity of current energy landscapes. The inclusion of meteorological models demonstrates the critical relevance of understanding and predicting atmospheric conditions to optimize renewable energy production. However, specific challenges are evident in terms of accuracy and adaptability to changing conditions. The section dedicated to machine learning techniques and ANNs reveals the innovative potential of these approaches to address the inherent variability of RES. Despite their significant contributions, challenges such as the need for large datasets and substantial computational resources are noted.

As a result of this analysis, future research directions are highlighted to advance renewable energy generation prediction. Adapting traditional methods to changing energy landscapes, improving accuracy in meteorological models, and exploring more resource-efficient approaches emerge as key areas for future investigations. In conclusion, this study provides a comprehensive overview of the current state of renewable energy generation prediction, identifying challenges and pointing towards promising directions to advance this crucial field in the transition toward a sustainable future.

References

- Al-Ali, E. M., Hajji, Y., Said, Y., Hleili, M., Alanzi, A. M., Laatar, A. H., & Atri, M. (2023). solar energy production forecasting based on a hybrid CNN-LSTM-transformer model. *Mathematics*, 11(3). Available from <https://doi.org/10.3390/MATH11030676>, <https://www.mdpi.com/2227-7390/11/3/676>.
- Ali, A. J., & Zhao, L. (2022). Solar spectral irradiance analysis and modeling: A case study in The Black Hills Area. In *North American power symposium, NAPS 2022*, <https://doi.org/10.1109/NAPS56150.2022.10012211>.
- Alkabbani, H., Ahmadian, A., Zhu, Q., & Elkamel, A. (2021). Machine learning and metaheuristic methods for renewable power forecasting: A recent review. *Frontiers in Chemical Engineering*, 3. Available from <https://doi.org/10.3389/FCENG.2021.665415/BIBTEX>.
- Almalaaq, A., Alshammmary, A., Alanzi Bader Alharbi, F., & Alshudukhi, M. (2021). Deep learning applied on renewable energy forecasting towards supply-demand matching. In *20th IEEE international conference on machine learning and applications, ICMLA 2021* (pp. 1345–1349). Institute of Electrical and Electronics Engineers Inc. Available from <https://doi.org/10.1109/ICMLA52953.2021.00218>.

- Andrianakos, G., Tsourounis, D., Oikonomou, S., Kastaniotis, D., Economou, G., & Kazantzidis, A. (2019). Sky image forecasting with generative adversarial networks for cloud coverage prediction. In *10th International conference on information, intelligence, systems and applications, IISA 2019*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/IISA.2019.8900774>.
- Bastos, B. Q., Cyrino Oliveira, F. L., & Milidiú, R. L. (2021). U-Convolutional model for spatio-temporal wind speed forecasting. *International Journal of Forecasting*, 37(2). Available from <https://doi.org/10.1016/J.IJFORECAST.2020.10.007>.
- Bayo-Besteiro, S., García-Rodríguez, M., Labandeira, X., & Añel, J. A. (2022). Seasonal and subseasonal wind power characterization and forecasting for the Iberian Peninsula and the Canary Islands: A systematic review. *International Journal of Climatology*, 42(5). Available from <https://doi.org/10.1002/JOC.7359>, <https://rmets.onlinelibrary.wiley.com/doi/10.1002/joc.7359>.
- Bento, P. M. R., Pombo, J. A. N., Mendes, R. P. G., Calado, M. R. A., & Mariano, S. J. P. S. (2021). Ocean wave energy forecasting using optimised deep learning neural networks. *Ocean Engineering*, 219. Available from <https://doi.org/10.1016/J.OCEANENG.2020.108372>.
- Bentsen, L. Ø., Warakagoda, N. D., Stenbro, R., & Engelstad, P. (2022). Probabilistic wind park power prediction using bayesian deep learning and generative adversarial networks. *Journal of Physics: Conference Series*, 2362(1). Available from <https://doi.org/10.1088/1742-6596/2362/1/012005>, <https://iopscience.iop.org/article/10.1088/1742-6596/2362/1/012005/meta>.
- Boland, J., & Farah, S. (2021). Probabilistic forecasting of wind and solar farm output. *Energies*, 14(16). Available from <https://doi.org/10.3390/EN14165154>, <https://www.mdpi.com/1996-1073/14/16/5154>.
- Cellura, M., Cirrincione, G., Marvuglia, A., & Miraoui, A. (2008). Wind speed spatial estimation for energy planning in Sicily: Introduction and statistical analysis. *Renewable Energy*, 33(6). Available from <https://doi.org/10.1016/J.RENENE.2007.08.012>.
- Chang, R., Bai, L., & Hsu, C. H. (2021). Solar power generation prediction based on deep Learning. *Sustainable Energy Technologies and Assessments*, 47. Available from <https://doi.org/10.1016/J.SETA.2021.101354>.
- Damaševičius, R., Jovanovic, L., Petrovic, A., Zivkovic, M., Bacanin, N., Jovanovic, D., & Antonijevic, M. (2024). Decomposition aided attention-based recurrent neural networks for multistep ahead time-series forecasting of renewable power generation. *PeerJ Computer Science*, 10, e1795. Available from <https://doi.org/10.7717/PEERJ-CS.1795>, <https://peerj.com/articles/cs-1795>.
- David, M., Luis, M. A., & Lauret, P. (2018). Comparison of intraday probabilistic forecasting of solar irradiance using only endogenous data. *International Journal of Forecasting*, 34(3). Available from <https://doi.org/10.1016/J.IJFORECAST.2018.02.003>.
- David, M., Ramahatana, F., Trombe, P. J., & Lauret, P. (2016). Probabilistic forecasting of the solar irradiance with recursive ARMA and GARCH models. *Solar Energy*, 133. Available from <https://doi.org/10.1016/J.SOLENER.2016.03.064>.
- Dolatabadi, A., Abdeltawab, H., & Mohamed, Y. A.-R. I. (2023). Deep reinforcement learning-based self-scheduling strategy for a CAES-PV system using accurate sky images-based forecasting. *IEEE Transactions on Power Systems*, 38(2). Available from <https://doi.org/10.1109/TPWRS.2022.3177704>.
- Dumas, J., Wehenkel, A., Lanasepe, D., Cornélusse, B., & Suter, A. (2022). A deep generative model for probabilistic energy forecasting in power systems: Normalizing flows. *Applied Energy*, 305. Available from <https://doi.org/10.1016/J.APENERGY.2021.117871>.

- Fattah, R., Malik, H., Basmadjian, R., & Shaafieyoun, A. (2023). Assessing ARIMA-based forecasts for the percentage of renewables in Germany: Insights and lessons for the future. *Energies*, 16(16). Available from <https://doi.org/10.3390/EN16166005>, <https://www.mdpi.com/1996-1073/16/16/6005>.
- Gangopadhyay, A., Kanase, R., Mohan, G., Halder, M., Deshpande, M., Mukhopadhyay, P., & Srinivasan, J. (2019). Use of a weather forecast model to identify suitable sites for new wind power plants in Karnataka. *Current Science*, 117(8). Available from <https://doi.org/10.18520/CS/V117/I8/1347-1353>.
- Hassan, M. Z., Ali, M. E. K., Ali, A. B. M. S., Kumar, J. (2017). Forecasting day-ahead solar radiation using machine learning approach. In *4th Asia-Pacific world congress on computer science and engineering, APWC on CSE 2017* (pp. 252–258). <https://doi.org/10.1109/APWCONCSE.2017.00050>.
- Haupt, S. E., Jiménez, P. A., Lee, J. A., & Kosović, B. (2017). *Principles of meteorology and numerical weather prediction. Renewable energy forecasting: From models to applications*. Woodhead Publishing. Available from <https://doi.org/10.1016/B978-0-08-100504-0.00001-9>.
- Islam, S., & Roy, N. K. (2023). Renewables integration into power systems through intelligent techniques: Implementation procedures, key features, and performance evaluation. *Energy Reports*, 9. Available from <https://doi.org/10.1016/J.EGYR.2023.05.063>.
- Kato, T. (2016). Prediction of photovoltaic power generation output and network operation. In *Integration of distributed energy resources in power systems: Implementation, operation and control*. Available from <https://doi.org/10.1016/B978-0-12-803212-1.00004-0>.
- Kim, H. J., Kang, H. J., & Kim, M. K. (2021). Data-driven bidding strategy for der aggregator based on gated recurrent unit-enhanced learning particle swarm optimization. *IEEE Access*, 9. Available from <https://doi.org/10.1109/ACCESS.2021.3076679>.
- Koltsaklis, N., Panapakidis, I. P., Pozo, D., & Christoforidis, G. C. (2021). A prosumer model based on smart home energy management and forecasting techniques. *Energies*, 14(6). Available from <https://doi.org/10.3390/EN14061724>.
- Lehneis, R., Manske, D., & Thrän, D. (2020). Generation of spatiotemporally resolved power production data of PV systems in Germany. *ISPRS International Journal of Geo-Information*, 9(11). Available from <https://doi.org/10.3390/IJGI9110621>, <https://www.mdpi.com/2220-9964/9/11/621>.
- Li, Y., Li, J., & Wang, Y. (2022). Privacy-preserving spatiotemporal scenario generation of renewable energies: A federated deep generative learning approach. *IEEE Transactions on Industrial Informatics*, 18(4). Available from <https://doi.org/10.1109/TII.2021.3098259>.
- Li, Y., Wang, C., & Li, G. (2020). A mini-review on high-penetration renewable integration into a smarter grid. *Frontiers in Energy Research*, 8. Available from <https://doi.org/10.3389/FENRG.2020.00084/BIBTEX>.
- Liu, J., Zang, H., Cheng, L., Ding, T., Wei, Z., & Sun, G. (2023). A Transformer-based multi-modal-learning framework using sky images for ultra-short-term solar irradiance forecasting. *Applied Energy*, 342. Available from <https://doi.org/10.1016/J.APENERGY.2023.121160>.
- Malhan, P., & Mittal, M. (2022). A novel ensemble model for long-term forecasting of wind and hydro power generation. *Energy Conversion and Management*, 251. Available from <https://doi.org/10.1016/J.ENCONMAN.2021.114983>.
- Michael, N. E., Hasan, S., Al-Durra, A., & Mishra, M. (2022). Short-term solar irradiance forecasting based on a novel Bayesian optimized deep long short-term memory neural network. *Applied Energy*, 324. Available from <https://doi.org/10.1016/J.APENERGY.2022.119727>.
- Milosavljević, D. D., Kevkić, T. S., & Jovanović, S. J. (2022). Review and validation of photovoltaic solar simulation tools/software based on case study. *Open Physics*, 20(1). Available from

- <https://doi.org/10.1515/PHYS-2022-0042/MACHINEREADABLECITATION/RIS>, <https://www.degruyter.com/document/doi/10.1515/phys-2022-0042/html>.
- Minhas, D. M., Khalid, R. R., & Frey, G. (2017). Demand response load management price forecasting regression models. In *5th IEEE international conference on smart energy grid engineering, SEGE 2017* (pp. 373–378). Institute of Electrical and Electronics Engineers Inc. Available from <https://doi.org/10.1109/SEGE.2017.8052828>.
- Mishra, S., Leinakse, M., & Palu, I. (2017). Wind power variation identification using ramping behavior analysis. *Energy Procedia*, 141. Available from <https://doi.org/10.1016/J.EGYPRO.2017.11.075>.
- Moret, S., Bierlaire, M., & Maréchal, F. (2016). Robust optimization for strategic energy planning. *Informatica (Netherlands)*, 27(3). Available from <https://doi.org/10.15388/INFORMATICA.2016.103>.
- Mulewa, S., Parmar, A. M., & De, A. (2023). Attention based Transformer coupled with convoluted neural network for ultra-short- and short-term forecasting of multiple wind farms. *International Journal of Green Energy*. Available from <https://doi.org/10.1080/15435075.2023.2244589>, <https://www.tandfonline.com/doi/abs/10.1080/15435075.2023.2244589>.
- Nascimento, E. G. S., de Melo, T. A. C., & Moreira, D. M. (2023). A transformer-based deep neural network with wavelet transform for forecasting wind speed and wind energy. *Energy*, 278. Available from <https://doi.org/10.1016/J.ENERGY.2023.127678>.
- Nguyen Trong, T., Vu Xuan Son, H., Do Dinh, H., Takano, H., & Nguyen Duc, T. (2023). Short-term PV power forecast using hybrid deep learning model and variational mode decomposition. *Energy Reports*, 9. Available from <https://doi.org/10.1016/J.EGYR.2023.05.154>.
- Notton, G., Nivet, M. L., Voyant, C., Paoli, C., Darras, C., Motte, F., & Fouilloy, A. (2018). Intermittent and stochastic character of renewable energy sources: Consequences, cost of intermittence and benefit of forecasting. *Renewable and Sustainable Energy Reviews*, 87. Available from <https://doi.org/10.1016/J.RSER.2018.02.007>.
- Nyangan, J., & Akintunde, R. (2024). Principal component analysis of day-ahead electricity price forecasting in CAISO and its implications for highly integrated renewable energy markets. *Wiley Interdisciplinary Reviews: Energy and Environment*, 13(1), e504. Available from <https://doi.org/10.1002/WENE.504>, <https://wires.onlinelibrary.wiley.com/doi/10.1002/wene.504>.
- Obrecht, M., & Denac, M. (2016). Technology forecast of sustainable energy development prospects. *Futures*, 84. Available from <https://doi.org/10.1016/J.FUTURES.2016.09.002>.
- Padilha, G. A. G., Ko, J., Jung, J. J., De Mattos Neto, P. S. G., Foresta, F. L., Gao, J., & Afonso, G. (2022). Transformer-based hybrid forecasting model for multivariate renewable energy. *Applied Sciences*, 12(21). Available from <https://doi.org/10.3390/APP122110985>, <https://www.mdpi.com/2076-3417/12/21/10985>.
- Pan, X., Wang, L., Wang, Z., & Huang, C. (2022). Short-term wind speed forecasting based on spatial-temporal graph transformer networks. *Energy*, 253. Available from <https://doi.org/10.1016/J.ENERGY.2022.124095>.
- Panda, S., Mohanty, S., Rout, P. K., Sahu, B. K., Parida, S. M., Samanta, I. S., Bajaj, M., Piecha, M., Blazek, V., & Prokop, L. (2023). A comprehensive review on demand side management and market design for renewable energy support and integration. *Energy Reports*, 10. Available from <https://doi.org/10.1016/J.EGYR.2023.09.049>.
- Peirelinck, T., Kazmi, H., Mbuwir, B. V., Hermans, C., Spiessens, F., Suykens, J., & Deconinck, G. (2022). Transfer learning in demand response: A review of algorithms for data-efficient modelling and control. *Energy and AI*, 7. Available from <https://doi.org/10.1016/J.EGYAI.2021.100126>.

- Pospíchal, J., Kubovčík, M., & Dirgová Luptáková, I. (2022). Solar irradiance forecasting with transformer model. *Applied Sciences*, 12(17). Available from <https://doi.org/10.3390/AP12178852>, <https://www.mdpi.com/2076-3417/12/17/8852>.
- Pujari, K. N., Miriyala, S. S., Mittal, P., & Mitra, K. (2023). Better wind forecasting using evolutionary neural architecture search driven green deep learning. *Expert Systems with Applications*, 214. Available from <https://doi.org/10.1016/J.ESWA.2022.119063>.
- Rahman, S., Punt, L., Ardakanian, O., Ghiassi, Y., & Tan, X. (2022). On efficient operation of a V2G-enabled virtual power plant. In *9th ACM international conference on systems for energy-efficient buildings, cities, and transportation* (pp. 119–128). Association for Computing Machinery, Inc. <https://dl.acm.org/doi/10.1145/3563357.3564067>.
- Ramírez, L., & Vindel, J. M. (2017). *Forecasting and nowcasting of DNI for concentrating solar thermal systems. Advances in concentrating solar thermal research and technology*. Woodhead Publishing. Available from <https://doi.org/10.1016/B978-0-08-100516-3.00013-7>.
- Ramos, D., Faria, P., Gomes, L., & Vale, Z. (2022). A contextual reinforcement learning approach for electricity consumption forecasting in buildings. *IEEE Access*, 10. Available from <https://doi.org/10.1109/ACCESS.2022.3180754>.
- Rangelov, D., Boerger, M., Tcholtchev, N., Lämmel, P., & Hauswirth, M. (2023). Design and development of a short-term photovoltaic power output forecasting method based on random forest, deep neural network and LSTM using readily available weather features. *IEEE Access*, 11. Available from <https://doi.org/10.1109/ACCESS.2023.3270714>.
- Ribeiro, L. A., & da Silva, P. P. (2015). Qualitative Delphi approach of advanced algae bio-fuels. *Management of Environmental Quality: An International Journal*, 26(6). Available from <https://doi.org/10.1108/MEQ-03-2014-0046/FULL/PDF>.
- Sanusi, U., & Come, D. (2016). Feature selection for accurate short-term forecasting of local wind-speed. In *IEEE 8th international workshop on computational intelligence and applications, IWCIAPROCEEDINGS 2015* (pp. 121–126). <https://doi.org/10.1109/IWCIAP.2015.7449474>.
- Schreiber, J., Vogt, S., Sick, B., & Temporal, T.E. (2021). Convolution networks for transfer learning problems in renewable power time series forecast. In *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*. 12978 LNAI https://link.springer.com/chapter/10.1007/978-3-030-86514-6_8, https://doi.org/10.1007/978-3-030-86514-6_8/TABLES/4.
- Shaikh, P. H., Shaikh, A., Memon, Z. A., Lashari, A. A., & Leghari, Z. H. (2021). Microgrids: A review on optimal hybrid technologies, configurations, and applications. *International Journal of Energy Research*, 45(9). Available from <https://doi.org/10.1002/ER.6666>, <https://onlinelibrary.wiley.com/doi/10.1002/er.6666>.
- Sharma, M., Mittal, N., Mishra, A., & Gupta, A. (2023). Survey of electricity demand forecasting and demand side management techniques in different sectors to identify scope for improvement. *Smart Grids and Sustainable Energy*, 8(2). Available from <https://doi.org/10.1007/S40866-023-00168-Z/TABLES/7>, <https://link.springer.com/article/10.1007/s40866-023-00168-z>.
- Sharma, N., Sharma, P., Irwin, D., & Shenoy, P. (2011). Predicting solar generation from weather forecasts using machine learning. In *IEEE international conference on smart grid communications, SmartGridComm 2011* (pp. 528–533). <https://doi.org/10.1109/SMARTGRIDCOMM.2011.6102379>.
- Shirzadi, N., Nasiri, F., Menon, R. P., Monsalvete, P., Kaifel, A., & Eicker, U. (2023). Smart urban wind power forecasting: Integrating weibull distribution, recurrent neural networks, and numerical weather prediction. *Energies*, 16(17). Available from <https://doi.org/10.3390/EN16176208>, <https://www.mdpi.com/1996-1073/16/17/6208>.

- Song, S., Kang, S., Lee, S., & Kim, C. K. (2023). Korean renewables management system: Copulas model-based adaptive droop control strategy for energy storage systems. *IEEE Access*, 11. Available from <https://doi.org/10.1109/ACCESS.2023.3337373>.
- Suh, J., & Choi, Y. (2017). Methods for converting monthly total irradiance data into hourly data to estimate electric power production from photovoltaic systems: A comparative study. *Sustainability*, 9(7). Available from <https://doi.org/10.3390/SU9071234>, <https://www.mdpi.com/2071-1050/9/7/1234>.
- Sweeney, C., Bessa, R. J., Browell, J., & Pinson, P. (2020). The future of forecasting for renewable energy. *Wiley Interdisciplinary Reviews: Energy and Environment*, 9(2), e365. Available from <https://doi.org/10.1002/WENE.365>, <https://wires.onlinelibrary.wiley.com/doi/10.1002/wene.365>.
- Torres, J. M., Aguilar, R. M., & Zuñiga-Meneses, K. V. (2018). Deep learning to predict the generation of a wind farm. *Journal of Renewable and Sustainable Energy*, 10(1). Available from <https://doi.org/10.1063/1.4995334/285796>, <http://aip/jrse/article/10/1/013305/285796/Deep-learning-to-predict-the-generation-of-a-wind>.
- Tulkinov, S. (2023). Grey forecast of electricity production from coal and renewable sources in the USA, Japan and China. *Grey Systems*, 13(3). Available from <https://doi.org/10.1108/GS-10-2022-0107/FULL/PDF>.
- Wahbah, M., Feng, S., El-Fouly, T. H. M., & Zahawi, B. (2020). Root-transformed local linear regression for solar irradiance probability density estimation. *IEEE Transactions on Power Systems*, 35(1). Available from <https://doi.org/10.1109/TPWRS.2019.2930699>.
- Wen, S., Wang, Y., Tang, Y., Xu, Y., & Li, P. (2019). Proactive frequency control based on ultra-short-term power fluctuation forecasting for high renewables penetrated power systems. *IET Renewable Power Generation*, 13(12). Available from <https://doi.org/10.1049/IET-RPG.2019.0234>, <https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-rpg.2019.0234>.
- Widén, J., Carpmann, N., Castellucci, V., Lingfors, D., Olauson, J., Remouit, F., Bergkvist, M., Grabbe, M., & Waters, R. (2015). Variability assessment and forecasting of renewables: A review for solar, wind, wave and tidal resources. *Renewable and Sustainable Energy Reviews*, 44. Available from <https://doi.org/10.1016/J.RSER.2014.12.019>.
- Wu, H., Xu, Z., & Wang, M. (2023). Unrolled spatiotemporal graph convolutional network for distribution system state estimation and forecasting. *IEEE Transactions on Sustainable Energy*, 14(1). Available from <https://doi.org/10.1109/TSTE.2022.3211706>.
- Zhang, W., Kleiber, W., Hodge, B. M., & Mather, B. (2022). A nonstationary and non-Gaussian moving average model for solar irradiance. *Environmetrics (London, Ont.)*, 33(3), e2712. Available from <https://doi.org/10.1002/ENV.2712>, <https://onlinelibrary.wiley.com/doi/10.1002/env.2712>.
- Zhu, J., Dong, H., Zheng, W., Li, S., Huang, Y., & Xi, L. (2022). Review and prospect of data-driven techniques for load forecasting in integrated energy systems. *Applied Energy*, 321. Available from <https://doi.org/10.1016/J.APENERGY.2022.119269>.