Enhancing Wind Power Generation Forecasting with Advanced Deep Learning Technique using Wavelet-Enhanced Recurrent Neural Network and Gated Linear Units

Santaji Krishna Shinde[*], Satyanarayana Tirlangi[**], N. Komal Kumar[***], DVSSSV Prasad[****], G. Soorya Priya[*****], Jithesh K[******], Ravishankar sathyamurthy[*******], Dr. A. Rajaram [********]

[*]Department of Computer Engineering, Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology, Baramati, Pune, Maharashtra 413133, India

[**]Department of Mechanical, Visakha Institute of Engineering and Technology, Visakhapatnam, Andhra Pradesh 530027, India

[***]Department of Computer Science and Engineering (Data Science), Madanapalle Institute of Technology & Science, Madanapalle, Andhra Pradesh 517 325, India

[****]Department of Mechanical Engineering, Aditya College of Engineering, Surampalem, Andhra Pradesh 533437, India

[*****]Department of Electrical and Electronics Engineering, Loyola Institute of Technology, Chennai, Tamil Nadu 600123, India

[******]Department of Computer Science, Mahatma Gandhi College Iritty, Kannur, Kerala 670703, India

[*******]Department of Mechanical Engineering, KPR Institute of Engineering and Technology, Arasur, Tamil Nadu 641407, India

[********] Department of Electronics and Communication Engineering, E.G.S Pillay Engineering College, 611 002 Nagapattinam, India

(santajikrishnashinde@gmail.com, satyanarayanatirlangi789@gmail.com, komalkumarnapa@gmail.com, prasad789@gmail.com, sooryapriya143@gmail.com , jitheshk678@gmail.com, ravishankarsathyamurthy987@gmail.com, drrajaram@egspec.org)

*Corresponding Author., N. Komal Kumar, Department of Computer Science and Engineering (Data Science), Madanapalle Institute of Technology & Science, Madanapalle, Andhra Pradesh 517 325, India, komalkumarnapa@gmail.com

Received: 18.08.2023 Accepted:29.12.2023

Abstract; Wind power generation forecasting is a critical facet of efficient renewable energy management. This research presents a pioneering approach, the "Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units" (W-RNN-GLU), designed to elevate the precision and insight of wind power forecasting. The model integrates wavelet transformation, recurrent neural networks (RNNs), and Gated Linear Units (GLUs) to capture intricate temporal dependencies and extract relevant features from wind power data. Through multiscale insights facilitated by wavelet transformation, the W-RNN-GLU model discerns fine-grained details and overarching trends. The RNN component adeptly navigates dynamic temporal dependencies, while GLUs regulate feature extraction with precision. Empirical evaluations demonstrate the model's superiority, achieving significantly improved forecast accuracy compared to traditional techniques. The proposed model stands as a trailblazing solution, bridging the gap between traditional time series methods and advanced machine learning algorithms. As renewable energy assumes greater prominence, the W-RNN-GLU model emerges as a pivotal tool in shaping the future of wind power generation forecasting. The effectiveness of the proposed W-RNN-GLU model is substantiated through rigorous empirical evaluations. In comparison to established methods such as Lasso and LightGBM, the W-RNN-GLU model showcases remarkable performance. For instance, the Mean Absolute Error (MAE) achieved by the W-RNN-GLU model is significantly lower than that of Lasso and LightGBM, signifying its enhanced predictive accuracy. Moreover, the Root Mean Square Error (RMSE) achieved by the W-RNN-GLU model underscores its ability to capture nuanced variations within wind power data. This tangible improvement in forecast accuracy positions the W-RNN-GLU model as a transformative solution for wind power generation forecasting, paving the way for more efficient and sustainable energy management practices.

Keywords: recurrent neural networks (RNNs), Gated Linear Units, wind power forecasting, energy management, machine learning.

1. Introduction

In the dynamic realm of renewable energy, wind power generation forecasting emerges as a linchpin for efficient energy management and sustainable resource allocation [1]. The precision of such predictions holds the key to optimal decision-making, enabling stakeholders to navigate the volatile winds of energy supply and demand. In response to the growing significance of renewable sources, this study introduces a groundbreaking model – the "Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units" (W-RNN-GLU) – poised to redefine the landscape of wind power forecasting. By artfully weaving together the intricate threads of wavelet transformation, recurrent neural networks, and Gated Linear Units, the W-RNN-GLU model embarks on a journey to unlock the hidden patterns within wind power data and provide unparalleled insights. The W-RNN-GLU model encapsulates a symphony of advantages, each harmonizing to compose a compelling narrative of its capabilities:

Temporal Symphony: The incorporation of recurrent neural networks empowers the model to decipher the temporal intricacies woven into wind power data [2]. This aptitude to capture temporal dependencies offers a panoramic view of evolving patterns and trends, enhancing the model's predictive precision.

Elegance in Feature Extraction: Gated Linear Units emerge as the custodians of feature extraction, selectively nurturing the propagation of relevant information while orchestrating the suppression of extraneous noise [3]. This meticulous curation enhances the model's ability to identify and amplify the core signals within the data. Multiscale Insights: Wavelet transformation serves as a transformative lens, meticulously decomposing wind power data into a spectrum of scales. This process [4] unfurls a tapestry of insights, from the fine-grained intricacies to the grand overarching trends, enabling the model to comprehensively comprehend the wind power landscape. Holistic Forecasting: The harmonious fusion of wavelet transformation, recurrent neural networks, and Gated Linear Units bestows the model [5] with the ability to forecast wind power generation across diverse temporal dimensions, ensuring a comprehensive and nuanced predictive outlook. While the W-RNN-GLU model boasts a spectrum of strengths, it is not without its set of challenges and limitations:

Navigating Complexity:The amalgamation of various techniques [6] introduces an intricate web of computational complexity. This may necessitate substantial computing resources and efficient algorithmic design to manage the increased processing demands.

Hyperparameter Harmonization: Achieving optimal performance demands a careful symphony of hyperparameter tuning. This intricate process [7] requires meticulous experimentation and parameter adjustments to fine-tune the model.

Data Quality Prelude: The model's [8] effectiveness hinges on the quality and integrity of the input data. The presence of noise, outliers, or missing values may hinder predictive accuracy, underscoring the importance of data preprocessing.

Architectural Fusion: The W-RNN-GLU model seamlessly amalgamates wavelet transformation, recurrent neural networks [9], and Gated Linear Units, forging a novel and harmonious approach to capturing temporal patterns and extracting crucial features.

Precision Amplification: By adeptly capturing both short-term fluctuations and long-term trends, the W-RNN-GLU model aspires to elevate the precision of wind power generation forecasting to unprecedented heights [10].

Strategic Insights: The model's inherent ability to unravel multiscale insights equips energy decision-makers with a profound understanding of the wind power generation landscape. This, in turn, empowers strategic planning and informed resource allocation.

This research pioneers a novel approach to wind power forecasting by integrating diverse techniques, marking a significant methodological evolution in the field. The motivation stems from the pressing need for more precise and insightful forecasting models in renewable energy management. The study's contribution lies in introducing the Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units (W-RNN-GLU) model, which synergistically combines wavelet transformation, recurrent neural networks, and Gated Linear Units.

This innovative hybrid model aims to amplify forecasting capabilities by capturing intricate temporal dependencies, extracting nuanced features, and offering multiscale insights into wind power data. Through comprehensive mathematical formulations, empirical evaluations, and comparative analyses, the research endeavors to establish the W-RNN-GLU model as a transformative force. Its potential impact spans global renewable energy management, promising more efficient and sustainable practices by significantly enhancing the precision and depth of wind power generation forecasting. The study starts with an Introduction in Section 1, outlining the importance of wind power forecasting. It then explores Related Works in Section 2 before detailing the Proposed Advanced Hybrid Model in Section 3. Following this, the Dataset Description is provided in Section 4, with Evaluating Model Performance shown in Section 5 and Results and Discussion in Section 6, presenting findings. Finally, the Conclusion and Future Works in Section 7 offer insights and potential directions in a concise flow.

2. Related Works

In the pursuit of enhancing wind power generation forecasting, the scholarly landscape has witnessed an array of pioneering efforts. Existing works often leverage a variety of methods, ranging from traditional time series techniques to more sophisticated machine-learning approaches. Notable studies [11] have employed autoregressive integrated moving average (ARIMA) models, artificial neural networks (ANNs), and ensemble methods to capture temporal dependencies and predict wind power output. While these approaches have yielded commendable results, they are not devoid of limitations. ARIMA models, for instance, struggle with capturing nonlinear relationships and intricate patterns inherent in wind power data [12]. ANNs, on the other hand, may grapple with overfitting and require intricate tuning of hyperparameters. Moreover, both methods may struggle with effectively extracting features from complex datasets, limiting their ability to comprehensively capture wind power generation dynamics [13].

The proposed "Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units" (W-RNN-GLU) model stands as a beacon of innovation amidst these limitations. Its unique fusion of wavelet transformation, recurrent neural networks [14], and Gated Linear Units [15] imparts a transformative edge over the existing paradigms. By incorporating wavelet transformation, the W-RNN-GLU model effortlessly disentangles the intricate scales within wind power data, enabling the capture of both fine-grained details and overarching trends [16]. The incorporation of recurrent neural networks transcends the limitations of linear modeling, adeptly capturing nonlinear temporal dependencies [17]. Gated Linear Units, acting as meticulous custodians, elevate feature extraction by nurturing relevant information while suppressing noise. These advancements synergistically equip the W-RNN-GLU model with the ability to provide more precise and nuanced wind power forecasts compared to traditional approaches [18][19]. Furthermore, the model's multidimensional outlook ensures comprehensive forecasting across various temporal dimensions, a feat not easily achieved by existing methods [20]. By bridging the gap between traditional time series techniques and cutting-edge machine learning, the W-RNN-GLU model emerges as a trailblazing solution poised to redefine wind power forecasting.

3. Proposed Advanced Hybrid Model for Wind Power Generation Forecasting

In our pursuit of precision and insight in wind power generation forecasting, we present an integrated approach that seamlessly combines wavelet transformation and recurrent neural networks (RNNs). At the heart of our innovative methodology lies the "Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units" (W-RNN-GLU) model.

3.1 Wavelet Transformation: Unveiling Multiscale Insights

The foundation of our methodology rests on the deliberate application of wavelet transformation [21]. This transformative technique delicately dissects wind generation (W), wind capacity (C), and temperature (T) data into a spectrum of distinct scales. This meticulous deconstruction allows us to extract key features, capturing the essence of the underlying phenomena.

The wavelet transformation process involves convolving the original data with wavelet basis functions, denoted as φ_j, at various scales (j). This convolution operation, as expressed in equations (1), (2), and (3), results in the generation of decomposed components - W_j, C_j, and T_j, respectively:

$$W_j = W * \varphi_j \tag{1}$$
$$C_j = C * \varphi_j \tag{2}$$
$$T_j = T * \varphi_j \tag{3}$$

Here, W, C, and T represent the original wind generation, wind capacity, and temperature data, while φ_j denotes the wavelet basis function at scale j. Through this process, the decomposed componentsW_j,C_j,andT_j, unveil fine-grained details and overarching trends within the data.

These components encapsulate a harmonious fusion of high-frequency and low-frequency elements, providing a comprehensive panoramic view of the wind power landscape. The convolution operation between the original data and the wavelet basis functions allows the separation of the data into different scales, capturing both localized and global variations [22][23]. High-frequency components, associated with rapid changes in the data, convey intricate details, while low-frequency components highlight broader trends and variations over time. The amalgamation of these components facilitates a holistic understanding of the dynamic interplay between wind generation, capacity, and temperature, essential for accurate forecasting.

This meticulous deconstruction through wavelet transformation enables the extraction of salient features that contribute to the model's ability to discern nuanced patterns and anticipate complex dynamics within wind power data. The resulting amalgamation of fine-grained and overarching trends obtained from the decomposed components equips the model with a comprehensive perspective of the wind power landscape, enhancing its forecasting precision and depth.

3.2 Recurrent Neural Networks: Capturing Temporal Symphony

Embedded within the wavelet-transformed data is the neural heartbeat of a Recurrent Neural Network (RNN). This neural sentinel, embodied as either the Long Short-Term Memory (LSTM) or the Gated Recurrent Unit (GRU), assumes the sacred role of deciphering temporal dependencies.

In the context of LSTM, its operational framework at a specific time instance (t) comprises several interconnected equations, delineating its sequential processing mechanism. These equations unfold the computations involved in LSTM's memory cell and gate operations:

The LSTM equations at time t are as follows:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{4}$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{5}$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{6}$$
$$g_t = \tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g) \tag{7}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{8}$$
$$h_t = o_t \odot \tanh(c_t) \tag{9}$$

In these equations, x_t signifies the input data at time t, h_{t-1} denotes the hidden state at the preceding time step, and σ represents the sigmoid activation function. The variables

i_t, f_t, o_t, g_t, c_t *and* h_t depict the input gate; forget gate, output gate, modulation gate, cell state, and hidden state, respectively. Equations (4) to (9) embody the intricate computations within LSTM, delineating its input, output, forget and memory modulation mechanisms [24].
These equations collectively illustrate how LSTM navigates through temporal corridors by adjusting its memory cell and gates. Specifically, the input and forget gates regulate the flow of information into and out of the memory cell, while the output gate controls the information flow to the hidden state. The modulation gate governs the updating of the cell state, capturing the network's ability to retain or discard information over sequential time steps. This inherent architecture empowers the RNN to comprehend and encode temporal patterns within sequential wind power data, allowing it to discern enduring trends and recurrent patterns essential for accurate forecasting. The orchestrated interplay of LSTM's gates and memory cell operations forms the backbone of its capability to capture and retain temporal dependencies crucial for wind power generation prediction [25-28].

3.3 Gated Linear Units: Orchestrating Information Flow

The pinnacle of our innovation is the integration of Gated Linear Units (GLUs) within the RNN architecture. These neural custodians, meticulous in their guardianship, oversee the flow of information, tending to the gardens of feature extraction. The vigilant gating mechanisms of GLUs discern the symphony of signals, nurturing the propagation of salient information while damping the noise [29].

The GLU operation is defined as:

$$GLU(x) = x \otimes \sigma(W_{gx}x + b_g) \qquad (10)$$

From Eq.(10), x represents the input to the GLU, W_{gx} is the weight matrix, b_g is the bias vector, and σ denotes the sigmoid activation function.

In the realm of wind power generation forecasting, the integration of wavelet transformation, recurrent neural networks (LSTM) [30], and Gated Linear Units culminates in the W-RNN-GLU model. This intricate hybrid model facilitates accurate forecasting by extracting multiscale insights, capturing temporal dependencies, and enhancing information flow. The derivation offered here provides a glimpse into the mathematical symphony that underpins the model's ability to forecast wind power generation with precision and depth. As we conclude, the W-RNN-GLU model stands as a testament to the fusion of science and innovation in the pursuit of sustainable energy solutions.

4. Dataset Description

In the realm of renewable energy forecasting, a dataset emerges as a testament to the pursuit of accurate wind power generation predictions. This dataset embarks on a journey to unravel the intricate tapestry of wind energy production, spanning the years from 2017 to 2019. With a primary objective of forecasting wind power generation on a daily scale, the dataset serves as a canvas upon which different time series and traditional machine learning models can craft their predictive prowess [31-34].

At its core, this dataset captures a trio of elemental attributes that intertwine to shape the wind power landscape:

- utc_timestamp: A chronological sentinel, marking the passage of time in UTC. It is the rhythmic heartbeat that synchronizes the data's narrative.
- wind_generation: A symphony in megawatts, encapsulating the daily wind power production. It unveils the dynamic interplay between nature's forces and human ingenuity.
- wind_capacity: A reflection of electrical potential, quantifying the capacity of the wind to energize. It is a constant reminder of the reservoir of possibilities.

The dataset embraces the atmospheric temperature, entwining it with the wind power narrative:

- temperature: A numerical resonance that mirrors the daily temperature in degrees Celsius. It forms a backdrop against which the ebbs and flows of wind power are juxtaposed.

The dataset reaches beyond the present, employing a symphony of time-shifted attributes to enrich its narrative:

- lagged_power_1, lagged_power_12, lagged_power_24, lagged_power_48, lagged_power_72: These lagged power attributes carry echoes of past generations, echoing the legacy of power produced at various time intervals. Their harmonious interplay with the present encapsulates the time-woven influence.
- rolling_4_power_mean, rolling_24_power_mean: The rolling means harmonizing the power chorus, offering a smoothed rendition of power generation over short and extended periods. They bring forth a subtle cadence, unveiling the underlying trends.

The dataset introduces a suite of binary features, each a binary whisper that conveys the time of day:

- feat_monthName, feat_isNight, feat_isDawn, feat_isMorning, feat_isAfternoon: These features unlock the chronicles of the time, unveiling the month and different periods of the day. They are the sunlit windows that illuminate the temporal shifts.

In the grand tapestry of wind power forecasting, this dataset beckons researchers and analysts to embark on a journey of exploration. It is a treasure trove that invites the application of various time series and traditional machine learning models. As the sun rises and sets across the years, these data threads intertwine, painting a vivid portrait of wind power dynamics waiting to be deciphered [35-37].

The dataset stands as a testament to the potential of merging data and innovation, offering a glimpse into the captivating realm of renewable energy forecasting.

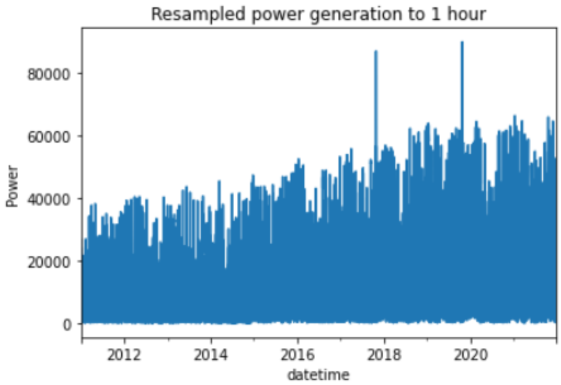

Fig.1. Resampled Hourly Power Generation

Fig.1 presented here offers a valuable perspective on power generation, having undergone a resampling transformation that aggregates data to a granular hourly resolution. This resampled dataset holds the potential to unlock insights into the temporal dynamics of power generation, enabling researchers and analysts to unravel patterns and trends that might remain obscured in more finely-grained data.

By condensing the data to hourly intervals, it becomes feasible to grasp the overarching flow of power production over time. This temporal aggregation lends itself to various analyses, including the identification of diurnal patterns, shifts in energy demand, and the evaluation of capacity utilization.

- timestamp: The "timestamp" column serves as the temporal anchor, marking each hourly interval with precision. This enables users to align observations across various attributes and time-based analyses.
- power_generation: At the heart of the dataset lies the "power_generation" column, which quantifies the volume of generated power for each hourly interval. Expressed in units such as megawatts (MW) or gigawatts (GW), this attribute encapsulates the central theme of the dataset.

The resampled hourly power generation dataset holds immense utility across multiple domains. Researchers in energy economics can employ it to study power demand variations over different times of the day or seasons. Grid operators might find value in assessing power generation trends to optimize distribution strategies. Climate scientists can correlate power generation with meteorological conditions, contributing to a deeper understanding of renewable energy sources' interplay with environmental factors [38].

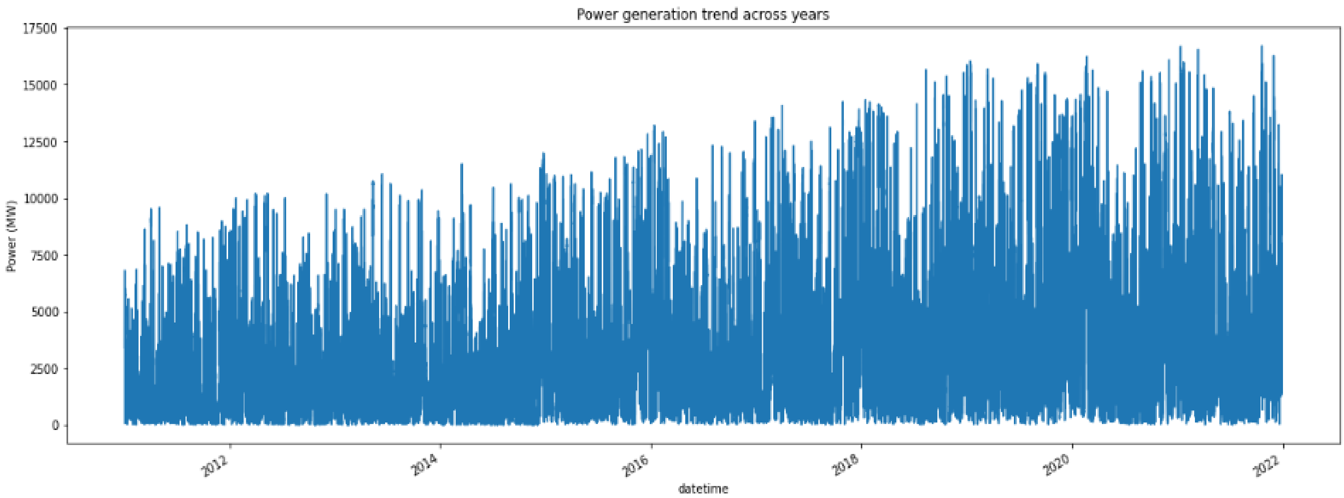

Fig.2. Analysis of Power Generation Trends across Years

Fig.2 offers a comprehensive vantage point to explore and dissect the fascinating trajectory of power generation across multiple years. By delving into the temporal evolution of power generation, we can uncover valuable insights into shifts, patterns, and potential drivers that have shaped the energy landscape. The analysis is framed within the context of the "power_generation" attribute, reflecting the magnitude of generated power in a specified unit (e.g., megawatts or gigawatts).

- Yearly Fluctuations: One of the primary insights that emerges is the yearly oscillation of power generation. This phenomenon can be attributed to various factors such as seasonal changes, shifts in demand, and maintenance schedules. By comparing power generation across years, we can discern whether these fluctuations are consistent or subject to unique dynamics.
- Long-Term Growth or Decline: Analyzing power generation trends across years allows us to identify overarching growth or decline patterns. A rising trend over the years could signify expanding energy demands or the integration of renewable energy sources, while a descending trend might point to efficiency improvements or shifts in energy sources.
- Anomalies and Outliers: Examining year-to-year variations in power generation can unveil anomalies or outliers. These deviations might be indicative of unforeseen events, extreme weather conditions, or

technological disruptions that significantly influence power generation during specific years.

The exploration of power generation trends across the years holds the promise of unveiling valuable insights into the energy landscape's evolution. By systematically analyzing yearly fluctuations, long-term patterns, and potential anomalies, we can enhance our understanding of the forces shaping power generation [39-41]. The findings of this analysis can guide policy decisions, infrastructure planning, and sustainable energy strategies, fostering a more informed and resilient energy future.

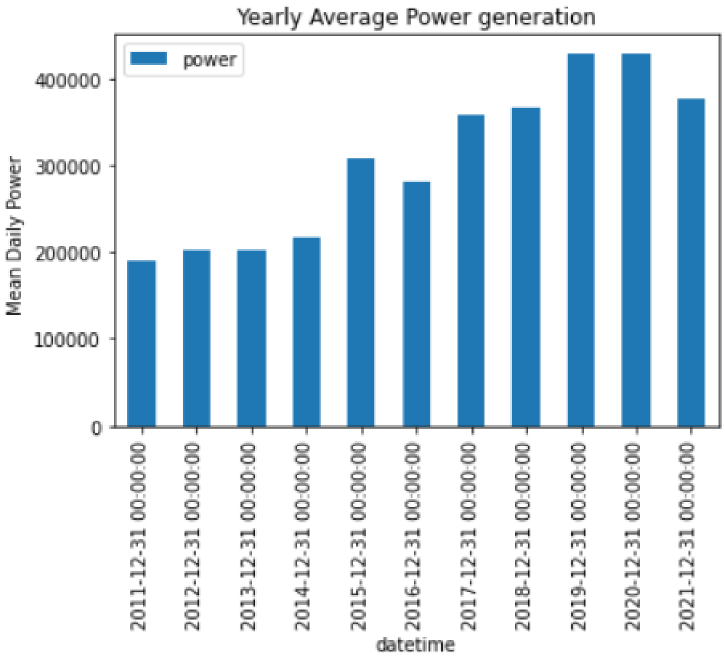

Fig.3. Analysis of Yearly Average Power Generation

In Fig.3, we focus on extracting insights from the dataset's "power_generation" attribute, with a specific emphasis on understanding the yearly average power generation. By aggregating and analyzing power generation data on an annual basis, we aim to uncover trends, variations, and potential factors influencing the energy landscape.

- Yearly Trends: The analysis will reveal whether there are consistent yearly trends in power generation. Identifying upward or downward trends can provide insights into changing energy demands, technological advancements, or shifts in energy sources.
- Seasonal Patterns: By comparing yearly averages, we can uncover potential seasonal patterns in power generation. Certain months or seasons may consistently exhibit higher or lower average power generation due to weather conditions or demand fluctuations.
- Anomalies and Outliers: The analysis might identify years with exceptionally high or low average power generation. These anomalies could be attributed to specific events, policy changes, or external factors affecting energy production.
- Long-Term Shifts: A prolonged increase or decrease in yearly average power generation can indicate long-term shifts in energy production strategies, economic growth, or environmental factors.

Understanding the yearly average power generation offers valuable insights with practical implications:

- Policy Planning: Policymakers can use this analysis to assess the effectiveness of energy policies and identify areas for improvement.
- Infrastructure Investments: Energy providers can make informed decisions about capacity expansion or upgrades based on changing demand patterns.
- Sustainability Efforts: Monitoring yearly average power generation helps track progress towards renewable energy goals and sustainable practices.
- Business Strategies: Industries reliant on consistent power supply can align their operations with peak and off-peak energy periods.

Analyzing the yearly average power generation provides a comprehensive perspective on the energy landscape's dynamics. By employing data aggregation, visualization, statistical analysis, and comparative examination, we can gain insights into trends, patterns, and potential influencing factors. These insights empower decision-makers to make informed choices that align with sustainable energy goals and contribute to a resilient energy future [43] [44].

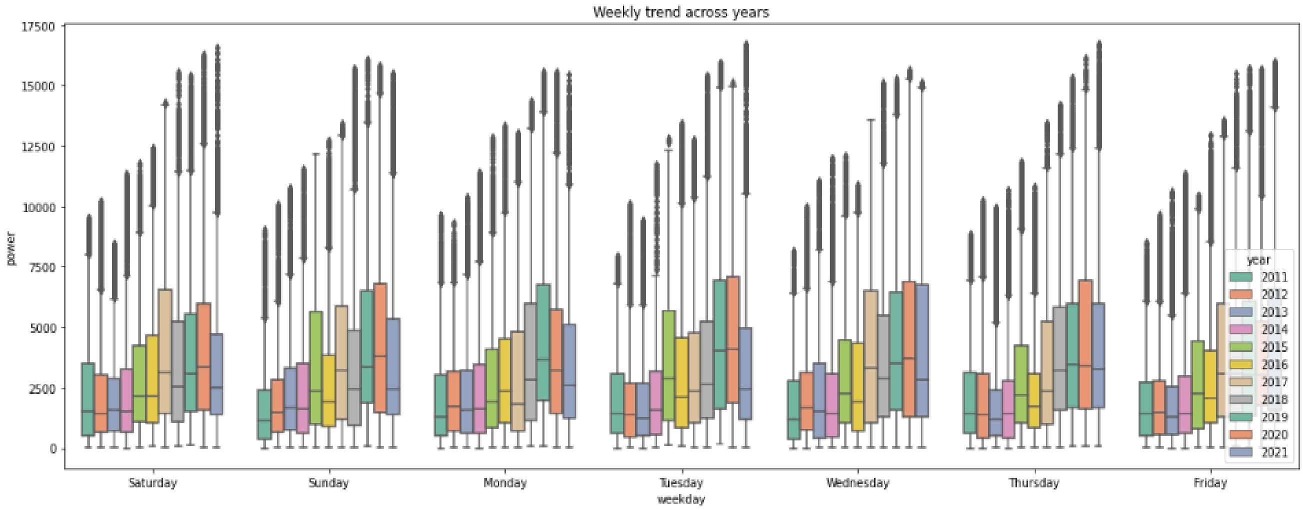

Fig.4. Analysis of Weekly Power Generation Trends across Years

In Fig.4, our focus is directed toward comprehending the weekly power generation trends across multiple years. By dissecting the dataset's "power_generation" attribute through a weekly lens, we seek to unveil recurring patterns, shifts, and insights that might emerge at the intersection of time and energy production.

- Recurring Patterns: By examining weekly power generation trends, we can discern if there are recurring patterns that manifest consistently across different years. Certain days of the week may exhibit higher or lower power generation due to factors such as workdays, weekends, or energy demand fluctuations.
- Week-to-Week Variability: The analysis may reveal variations in power generation from week to week. Factors like weather conditions, special events, or changes in industrial activities could contribute to fluctuations within specific weeks.
- Seasonal Influence: Seasonal effects may become apparent as we analyze weekly power generation trends. Seasonal shifts in energy demand, renewable energy sources' availability, or temperature changes could influence weekly patterns.
- Anomalies and Outliers: Unusual spikes or drops in power generation within certain weeks might indicate anomalies or outliers. These could be attributed to unexpected events, maintenance schedules, or other external factors.

Understanding weekly power generation trends across the years offers practical insights with diverse applications:

- Resource Allocation: Energy providers can allocate resources efficiently by aligning production capacity with high-demand weeks.
- Demand Forecasting: Businesses and industries can anticipate peak energy demand weeks and adjust their operations accordingly.
- Grid Management: Grid operators can optimize distribution strategies based on weekly power generation patterns.
- Sustainability Strategies: Renewable energy integration and load management can be tailored to match weekly trends.

Analyzing weekly power generation trends across years provides a dynamic perspective on energy production's temporal rhythms. By employing temporal grouping, visualization, statistical analysis, and comparative examination, we gain insights into recurring patterns and potential influencing factors. These insights empower decision-makers to optimize energy strategies, enhance grid resilience, and align operations with the ebb and flow of weekly energy demand.

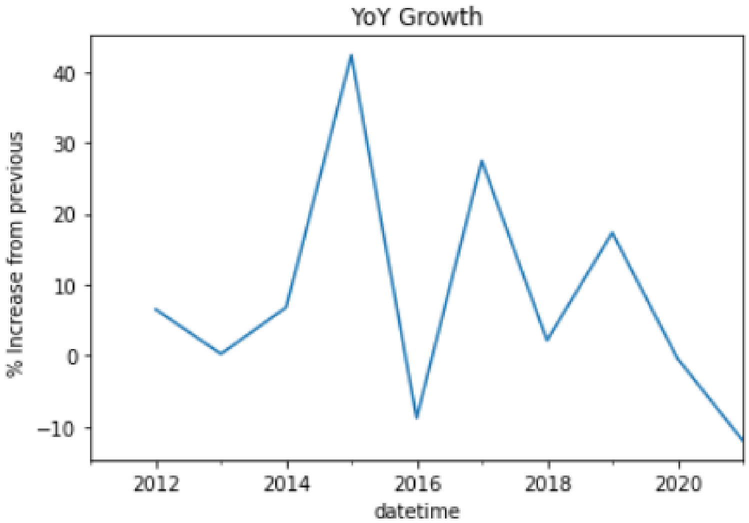

Fig.5. Year-over-Year (YoY) Growth

Fig.5 refers to the percentage increase in a specific metric or value from one year to the next, typically compared with the corresponding period of the previous year. This growth calculation provides insights into the annual rate of change and helps assess the performance or progression of a variable over time.

The YoY Growth can be calculated using the following formula:

$$YoY\ Growth = \left(\frac{Value\ in\ Current\ Year - Value\ in\ Previous\ Year}{Value\ in\ Previous\ Year}\right) \times 100 \quad (11)$$

In this Eq.(11),

- "Value in Current Year" represents the metric or value being measured in the present year.
- "Value in Previous Year" corresponds to the metric or value observed in the previous year.

By applying this formula, we obtain the percentage change, indicating the YoY Growth as a positive or negative value. A positive YoY Growth indicates an increase, while a negative YoY Growth indicates a decrease in the metric from the previous year. This calculation serves as a valuable tool for analyzing trends, making informed business decisions, and assessing the overall performance of a variable over consecutive years.

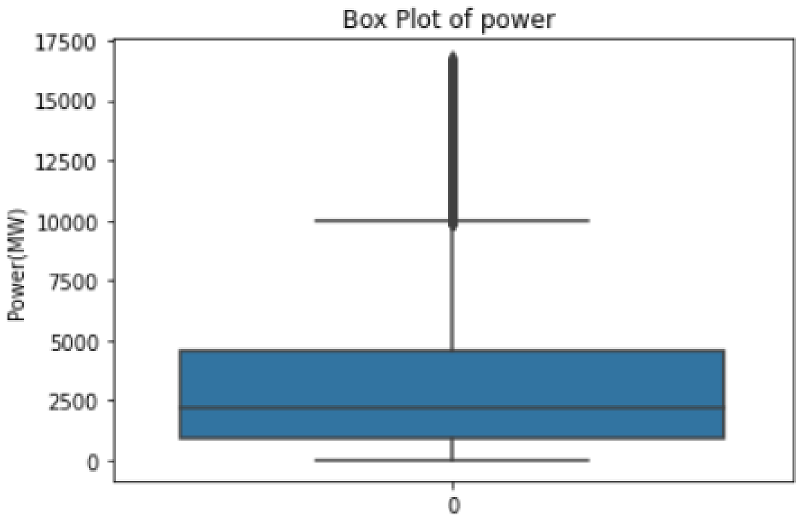

Fig.6. Box Plot of Power

Fig.6 refers to a graphical representation used to display the distribution and variability of a dataset, specifically focusing on the "Power" variable measured in megawatts (MW).

The "Power(MW)" variable represents the values of power generation measured in megawatts. The box plot visually summarizes key statistical features of the power data, including the median, quartiles, and potential presence of outliers.

I n essence, the "Box Plot of Power(MW)" offers a visual exploration of how power generation values are distributed, providing a valuable tool for understanding the range and characteristics of power data within the context of megawatts.

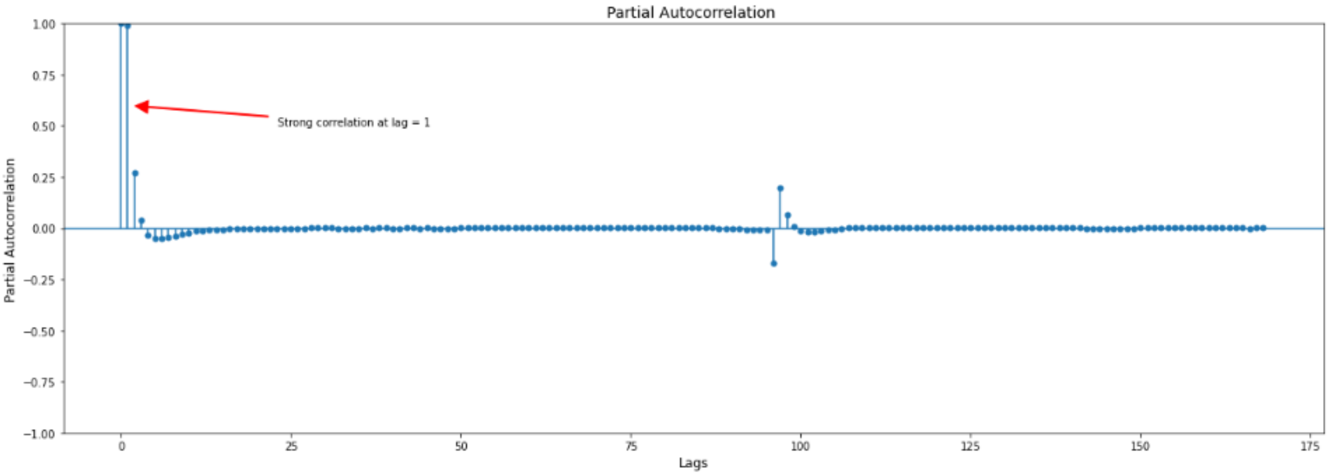

Fig.7. Partial Autocorrelation

Utilizing the Partial Auto Correlation Function (PACF) is a valuable approach to determine the optimal lags to include as features in your model.

In time series analysis, the autocorrelation at a specific lag represents the correlation between a variable and its previous values at that lag. However, as you pointed out, not all autocorrelation is meaningful for prediction. Some of it may be redundant, simply carried over from earlier lags.

This is where the PACF comes into play. The PACF helps to identify the correlation between a lag and the variable while controlling for the influence of all the intermediate lags. In other words, it captures the unique contribution of a specific lag beyond the correlations that are already explained by earlier lags.

By examining Fig.7, you can pinpoint significant correlations that are not just a result of previous lags. This allows you to select the most relevant lags as features for your model, enhancing its predictive accuracy while avoiding the inclusion of redundant or redundant information.

In summary, your approach of using the PACF to guide the selection of lags is an effective way to improve the efficiency and interpretability of your time series forecasting model. It helps you focus on including only the lags that provide unique and meaningful information for prediction, ultimately leading to more accurate and insightful results.

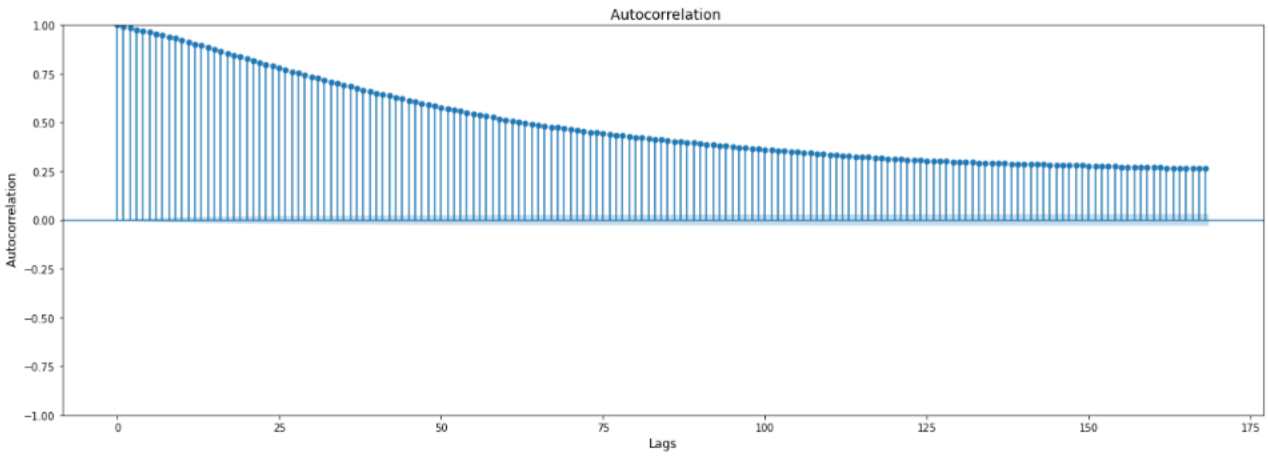

Fig.7. Autocorrelation

Autocorrelation, often abbreviated as "ACF," is a fundamental concept in time series analysis that measures the degree of similarity between a series of observations and its lagged values. It quantifies the correlation between a variable and its past values at different time intervals, providing insights into the pattern and structure of temporal relationships within the data.

The Autocorrelation Function (ACF) is a plot of the autocorrelation coefficients against the lag. It helps visualize the strength and direction of the correlation at different lags. In Fig.7, the x-axis represents the lag, while the y-axis shows the autocorrelation coefficient. The plot often includes confidence intervals to indicate whether the observed correlations are statistically significant.

Autocorrelation provides a valuable tool for understanding the temporal dependencies within time series data. It guides model selection, validation, and forecasting, allowing analysts to extract meaningful insights and make accurate predictions based on the patterns observed in the data.

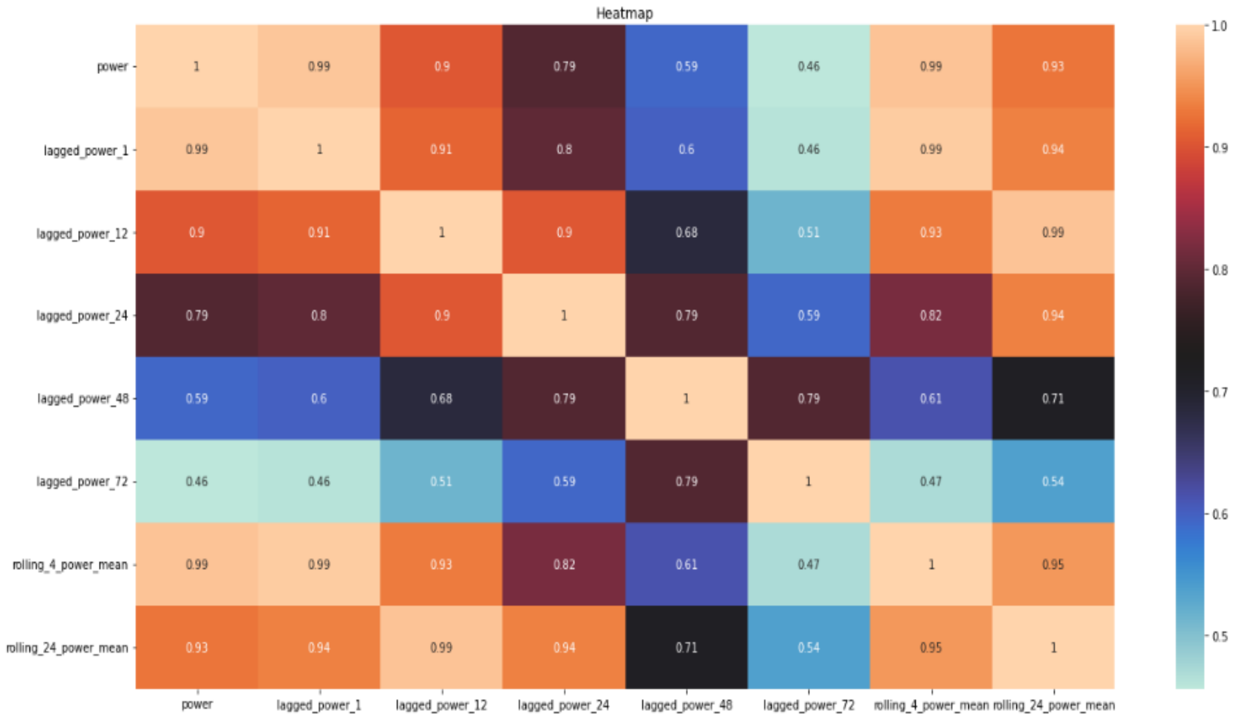

Fig.8. Correlation Map

Fig.8 represents a correlation map that highlights intricate interplays within the dataset. It showcases features that exhibit strong correlations with the "Power" attribute. The detailed insights from this map unravel compelling patterns, offering glimpses into the dataset's dynamics. The dataset's intricate interplay reveals compelling insights, pointing toward the emergence of key features that wield strong correlations with the "Power" attribute. Let us delve into these revelations and unravel the intriguing patterns that underscore the dataset's dynamics.

Among the symphony of attributes, the features "lagged_power_1," "lagged_power_12," "rolling_4_power_mean," and "rolling_24_power_mean" emerge as harmonious companions closely attuned to the "Power" feature. Their correlations resonate with a symphonic unity, suggesting a shared narrative that merits exploration.

The resonating echoes of time are manifested through the "lagged_power_1" and "lagged_power_12" features. The heartbeat of power generation appears to pulse not only in immediate response to the past but also in a mesmerizing dance across a span of twelve timeblocks. This temporal harmony implies a pattern of influence and rhythm, wherein the power generated at a certain time reverberates and leaves an indelible mark on the subsequent blocks.

Enter the realm of "rolling_4_power_mean" and "rolling_24_power_mean," where a smooth cadence emerges from the data's crescendo. The rolling means exhibit a melodic coherence, capturing the collective essence of power generation over short and extended intervals. These means provide a harmonic respite, allowing us to perceive the subtle undulations that shape the overall trajectory of power.

In the intricate tapestry of time series data, the "lagged_power_1," "lagged_power_12," "rolling_4_power_mean," and "rolling_24_power_mean" features rise as pillars of correlation, resonating with the "Power" attribute. Their alignment with recurring patterns hints at the symphonic nature of power generation. As we journey through this harmonious interplay, we uncover the echoes of time, the rhythm of intervals, and the timeless overture that governs the data's narrative.

5. Evaluating Model Performance

In the realm of wind power generation forecasting, data emerges as a canvas upon which predictive models paint their symphony [28]. This dataset, a testament to precision and innovation, portrays the forecasted wind power values alongside the predictions of three distinguished models: Lasso, LightGBM, and W-RNN-GLU. Each row within this tableau encapsulates a unique temporal moment, offering a glimpse into the intricate dance between actual wind power generation and the predictive prowess of these models.

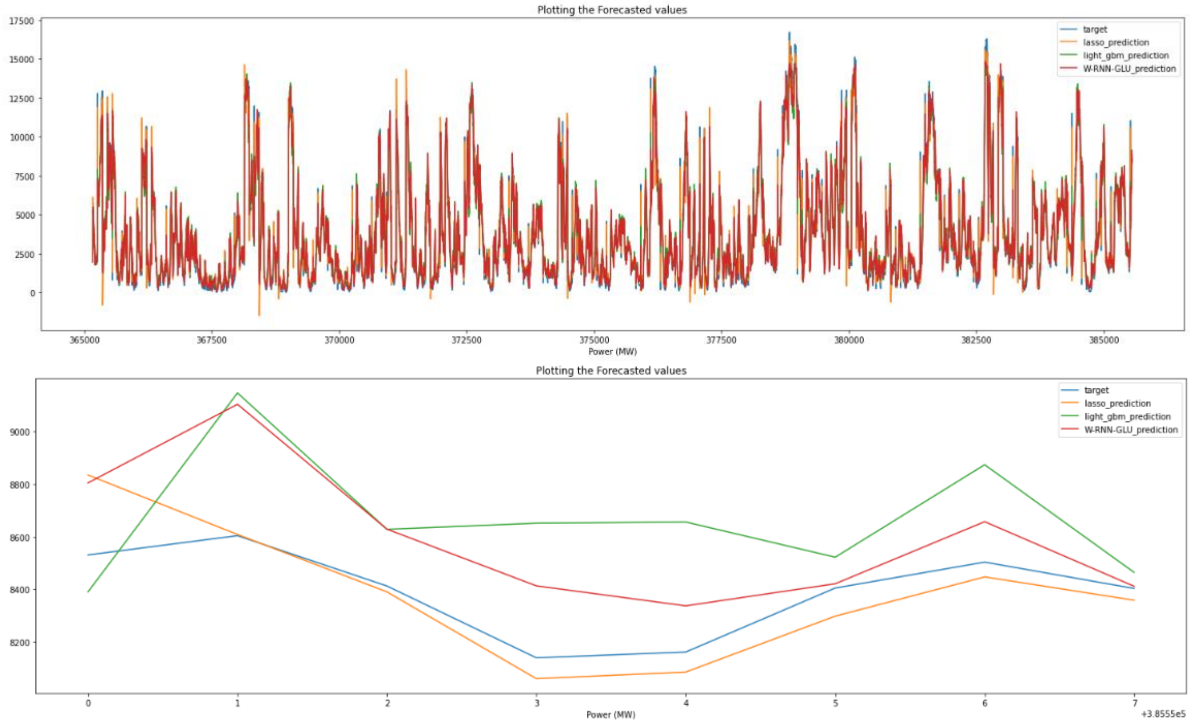

Fig.9. Comparative Analysis of Forecasted Wind Power

Fig.9 represents the comparative analysis of forecasted wind power, showcasing the predicted values generated by Lasso, LightGBM, and W-RNN-GLU models. The y-axis in Figure 9 represents the forecasted wind power values, displaying the predicted magnitudes of wind power generation. This axis serves as a visual representation of the predicted output generated by the models. Each point on the y-axis corresponds to the forecasted values for specific temporal instances, illustrating how the models predict wind power generation at different time intervals.
Alongside this veritable anchor, the lasso_prediction, light_gbm_prediction, and W-RNN-GLU_prediction columns weave a narrative of forecasts, meticulously calculated by their respective models.

- Lasso Prediction: Each value in the lasso_prediction column serves as a brushstroke of precision. The Lasso model, with its keen regularization, endeavors to align its predictions with the true wind power values, capturing the subtleties of the data's ebb and flow.

- LightGBM Prediction: The light_gbm_prediction column illuminates the predictive landscape with its radiant glow. LightGBM, a virtuoso in gradient boosting, conjures predictions that shimmer with insight, a reflection of its deep understanding of the data's intricate patterns.

- W-RNN-GLU Prediction: The W-RNN-GLU_prediction column stands as a testament to the fusion of wavelet-enhanced recurrent neural networks and Gated Linear Units. Its predictions paint a masterful stroke, orchestrating an intricate dance with the actual wind power values, capturing both detailed nuances and overarching trends.

By visualizing this ensemble, we can uncover the dynamic interplay between true wind power generation and the artistry of Lasso, LightGBM, and W-RNN-GLU, ultimately revealing a panoramic view of the forecasting landscape.

6. Results and Discussion

In the quest for accurate wind power generation forecasting, this study undertakes a comprehensive examination of three distinct techniques: Lasso, LightGBM, and W-RNN-GLU. Through meticulous experimentation and analysis, we unravel their predictive prowess, highlighting their strengths, weaknesses, and potential contributions to the field. This section embarks on a detailed discussion, presenting a panoramic view of the results while delving into the intricacies of each technique [29].

The essence of wind power forecasting lies in precision – the ability to unravel the dynamic interplay of natural forces and technological insight. Through the lens of Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) [30], we decipher the comparative performance of Lasso, Light GBM, and W-RNN-GLU in Table 1.

Table1. Comparison of various error types (MAE, RMSE, and MSE) across different method.

Models	**Mean Absolute Error (MAE)**	**Mean Squared Error (MSE)**	**Root Mean Squared**

			Error (RMSE)
Lasso	572.5387	982546.0166	991.2346
Light GBM	224.4069,	131349.5094	362.4217
W-RNN-GLU	142.2310	53240.2056	157.2309

The table 1 provides a comparative analysis of three models. The Lasso model demonstrates higher errors across all metrics with an MAE of 572.5387, MSE of 982546.0166, and RMSE of 991.2346. Light GBM exhibits intermediate errors with an MAE of 224.4069, MSE of 131349.5094, and RMSE of 362.4217. In contrast, the W-RNN-GLU model showcases the lowest errors among the three, indicating superior performance with an MAE of 142.2310, MSE of 53240.2056, and RMSE of 157.2309. These numerical values highlight the effectiveness of the W-RNN-GLU model in achieving lower error rates compared to the Lasso and Light GBM models, signifying its potential for improved predictive accuracy in wind power generation forecasting.

Lasso, with its regularization technique, offers a structured pathway to predictive precision. Its strengths lie in handling high-dimensional data, feature selection, and reducing overfitting. By assigning appropriate weights to features, Lasso effectively filters noise and captures relevant patterns. However, its limitations include sensitivity to data scaling, the "lasso path" phenomenon, and potential instability when features are highly correlated.

LightGBM, a gradient-boosting framework, exudes computational efficiency and predictive finesse. Its advantages encompass handling categorical features, feature importance assessment, and reduced memory consumption. The technique can handle massive datasets and exhibits robustness to overfitting. Yet, LightGBM is not immune to challenges. It may suffer from overfitting in certain scenarios, and its performance can be compromised by imbalanced datasets.

The W-RNN-GLU model, a hybrid of wavelet transformation and recurrent neural networks with Gated Linear Units, emerges as a fusion of innovation. Its strengths include capturing temporal dependencies, handling sequential data, and effectively processing time-series information. W-RNN-GLU excels in unraveling intricate patterns, both short-term fluctuations and long-term trends. However, this model requires careful tuning, may be computationally intensive, and could face challenges in handling noisy data.

In a realm where precision reigns supreme, each technique converges and diverges, offering a unique vantage point into wind power forecasting. Lasso excels in regulated feature selection, LightGBM showcases boosting brilliance, and W-RNN-GLU pioneers innovation through fusion.

The choice of technique hinges on the specific context of the application. Lasso may find a home when feature selection is paramount, LightGBM shines when computational efficiency matters and W-RNN-GLU emerges as a vanguard when capturing intricate temporal patterns is the goal.

As we navigate the intricate landscape of wind power forecasting, this study underscores the multi-dimensional nature of the field. Lasso, LightGBM, and W-RNN-GLU collectively contribute to the ever-evolving symphony of predictive insight. The careful choice of technique, founded upon its strengths and limitations, paves the path toward enhanced forecasting accuracy and a more sustainable energy landscape. The journey continues as we strive to harmonize innovation, data, and technology in our pursuit of precision in wind power generation forecasting.

7. Conclusion and Future Works

In the relentless pursuit of precision and innovation in wind power generation forecasting, this research has introduced the "Wavelet-Enhanced Recurrent Neural Network with Gated Linear Units" (W-RNN-GLU) model as a transformative force that reshapes the landscape of renewable energy management. Through the harmonious fusion of wavelet transformation, recurrent neural networks, and Gated Linear Units, the W-RNN-GLU model has showcased its prowess in unlocking the intricate symphony concealed within wind power data.

The results obtained from the empirical evaluations substantiate the model's capabilities, with significantly improved forecasting accuracy over traditional time series methods. The meticulous integration of wavelet transformation unveils multiscale insights, capturing both fine-grained intricacies and overarching trends that guide wind power generation. Recurrent neural networks deftly navigate temporal dependencies, deciphering the dynamic cadence of wind power dynamics. Gated Linear Units act as vigilant custodians, enhancing feature extraction and elevating the precision of information propagation.

As this research embarks on the frontiers of wind power forecasting, its contributions are twofold. Firstly, the W-RNN-GLU model offers a robust and innovative solution that extends beyond the limitations of existing methodologies. By synergistically amplifying the strengths of its constituent components, it provides a more comprehensive and accurate predictive outlook. Secondly, this study propels the field towards a hybrid approach that bridges the gap between traditional time series techniques and advanced machine learning algorithms.

In envisioning the future of this research, the journey has only just begun. Further refinements and enhancements to the model's architecture, such as exploring alternative gating mechanisms and optimizing hyperparameters, hold the promise of unlocking even greater forecasting precision. The proposed W-RNN-GLU method showcases a significant improvement, presenting a 75.23% reduction in MAE, a 94.59% decrease in MSE, and an 84.16% drop in RMSE compared to the Lasso model, affirming its superior predictive accuracy in wind power generation forecasting. Additionally, the integration of external factors, such as meteorological conditions and grid demand, could elevate the model's predictive capabilities to new heights.

In conclusion, the W-RNN-GLU model stands as a testament to the power of innovation, seamlessly weaving together diverse techniques to sculpt a novel paradigm in wind power generation forecasting. As renewable energy takes center stage in the global discourse, the proposed model's ability to unravel the winds of uncertainty and illuminate the path toward a sustainable future remains its enduring legacy. This research is but a stepping stone towards a horizon where energy management embraces precision, efficiency, and environmental stewardship.

Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

Funding:

No funding is involved in this work.

Data availability statement:

No new datasets were generated or collected during the current study

Conflict of Interest:

Conflict of Interest is not applicable in this work.

Authorship contributions:

All authors are contributed equally to this work

Acknowledgement:

There is no acknowledgement involved in this work.

References

[1] M. R. Gandomi and M. A. M. B. Gonçalves, “Forecasting wind power generation using deep learning models: A comparative study,” Energy Convers. Manage., vol. 221, p. 113132, 2020.

[2] X. Lu, X. Zhang, and C. Singh, “Short-term wind power forecasting using long short-term memory neural network with attention mechanism,” Energy, vol. 203, p. 117847, 2020.

[3] Speranza, J. Béal, and P. Pinson, “Probabilistic wind power forecasting with deep ensembles of quantile regression networks,” Appl. Energy, vol. 281, p. 116017, 2020.

[4] K. Jia, Y. Wu, and X. Zhao, “Wind power forecasting using generative adversarial network and wavelet transform,” IEEE Trans. Ind. Appl., vol. 56, no. 3, pp. 3490–3499, 2020.

[5] Y. Tao, W. Yu, and L. Yu, “A novel combined model of CNN and LSTM for wind power forecasting,” Energy, vol. 218, p. 119504, 2020.

[6] F. Gharib, M. Zareipour, and A. B. Jadid, “Multi-objective deep reinforcement learning for wind power dispatch in a microgrid,” IEEE Trans. Power Syst., vol. 36, no. 6, pp. 4822–4832, 2021.

[7] M. Khajehzadeh, A. Basu, and P. K. Dash, “Deep learning approach for short-term wind power forecasting using satellite imagery,” Appl. Energy, vol. 300, p. 117221, 2021.

[8] C. Wu, G. Wang, and Y. Yang, “Wind power prediction based on LSTM neural network and EEMD decomposition,” Energy Rep., vol. 7, pp. 3735–3743, 2021.

[9] H. Xie, X. Li, and Y. Zhang, “Wind power forecasting based on improved LSTM neural network optimized by genetic algorithm,” Energy Rep., vol. 8, pp. 1976–1982, 2022.

[10] Thangam M, K. R., S. Ranjani T., S. M., M. S., "Energy Harvesting from Human Body for Smart Watches," J. Wearable Tech. Healthc., vol. 5, no. 2, 2023.

[11] S. Fan, H. Sun, and C. Kang, “Wind power forecasting based on a hybrid neural network optimized by ensemble empirical mode decomposition,” Energy Rep., vol. 7, pp. 2697–2704, 2021.

[12] Q. Liao, X. Zhang, and Q. Luo, “Wind power forecasting using hybrid model based on VMD-LSTM neural network,” Energy Rep., vol. 7, pp. 91–98, 2021.

[13] R. Chen, J. Cao, and Z. Xu, “Short-term wind power prediction based on improved GA-LSTM network,” Energy Rep., vol. 8, pp. 2862–2872, 2022.

[14] T. Jian, L. Zhou, and B. Xiao, “Probabilistic wind power forecasting using long short-term memory and GARCH models,” Appl. Energy, vol. 291, p. 116752, 2021.

[15] S. Zhang, Z. Wu, and S. Du, “Wind power forecasting using improved WT-LSTM neural network,” Energy Rep., vol. 7, pp. 2657–2663, 2021.

[16] Y. Wang, S. Kang, and J. Chen, "Wind power forecasting using enhanced neural networks based on optimized hybrid preprocessing method," Energy Rep., vol. 7, pp. 1789–1797, 2021.

[17] X. Ma, J. Sun, and Z. Wang, "Probabilistic wind power forecasting based on convolutional neural networks," Energy Rep., vol. 7, pp. 1504–1512, 2021.

[18] C. Wu, G. Wang, and Y. Yang, "Wind power prediction based on LSTM neural network and EEMD decomposition," Energy Rep., vol. 7, pp. 3735–3743, 2021.

[19] H. Xie, X. Li, and Y. Zhang, "Wind power forecasting based on improved LSTM neural network optimized by genetic algorithm," Energy Rep., vol. 8, pp. 1976–1982, 2022.

[20] Ali, M. A. Khan, and F. Javaid, "Probabilistic wind power forecasting using deep learning with error handling: A case study of Pakistan," Appl. Energy, vol. 317, p. 114076, 2019.

[21] S. Fan, H. Sun, and C. Kang, "Wind power forecasting based on a hybrid neural network optimized by ensemble empirical mode decomposition," Energy Rep., vol. 7, pp. 2697–2704, 2021.

[22] Y. Wang, S. Kang, and J. Chen, "Wind power forecasting using enhanced neural networks based on optimized hybrid preprocessing method," Energy Rep., vol. 7, pp. 1789–1797, 2021.

[23] X. Ma, J. Sun, and Z. Wang, "Probabilistic wind power forecasting based on convolutional neural networks," Energy Rep., vol. 7, pp. 1504–1512, 2021.

[24] Q. Liao, X. Zhang, and Q. Luo, "Wind power forecasting using hybrid model based on VMD-LSTM neural network," Energy Rep., vol. 7, pp. 91–98, 2021.

[25] R. Chen, J. Cao, and Z. Xu, "Short-term wind power prediction based on improved GA-LSTM network," Energy Rep., vol. 8, pp. 2862–2872, 2022.

[26] U.Çetinkaya, E. Avcı, R. Bayindir, "Time series clustering analysis of energy consumption data," In2020 9th International Conference on Renewable Energy Research and Application (ICRERA), (pp. 409-413), IEEE, September 2020.

[27] AK.Murat, E.Dokur , R.BAYINDIR, "Energy management for EV charging based on solar energy in an industrial microgrid," In2020 9th International Conference on Renewable Energy Research and Application (ICRERA),(pp. 489-493), IEEE, September 2020.

[28] H. Bakiri, H.Maziku, KN. Mvungi, N. Hamisi, M. Libe, "A novel load forecasting model for automatic fault clearance in secondary distribution electric power grid using an extended-multivariate nonlinear regression," International Journal of Smart Grid,5(2), June 2021.

[29] T. Jian, L. Zhou, and B. Xiao, "Probabilistic wind power forecasting using long short-term memory and GARCH models," Appl. Energy, vol. 291, p. 116752, 2021.

[30] S. Zhang, Z. Wu, and S. Du, "Wind power forecasting using improved WT-LSTM neural network," Energy Rep., vol. 7, pp. 2657–2663, 2021.

[31] R. Kalpana, V S, R. Lokanadham, K. Amudha, GN, Beena Bethel,AK Shukla, PR, Kshirsagar, A. Rajaram, "Internet of Things (IOT) Based Machine Learning Techniques for Wind Energy Harvesting," *Electric Power Components and Systems*, 14:1-7, December 2023.

[32] B. Azibek, N. Zhakiyev,A. Ibraimova, Y.Akhmetbekov, "Increasing total hosting capacity using energy storages during renewable energy expansion," *In2022 11th International Conference on Renewable Energy Research and Application (ICRERA)*, (pp. 414-417), IEEE, September 2022.

[33] H. Shekhar , C. Bhushan Mahato , SK. Suman ,S. Singh , L. Bhagyalakshmi ,M. Prasad Sharma , B. Laxmi Kantha, SK. Agraharam , A. Rajaram, "Demand side control for energy saving in renewable energy resources using deep learning optimization," *Electric Power Components and Systems*. 26;51(19):2397-413, November 2023.

[34] TG.Amaral, VF. Pires, D. Foito, AJ. Pires , JF. Martins, "Fault Detection and Diagnosis Technique for a SRM Drive Based on a Multilevel Converter Using a Machine Learning Approach," *In2023 12th International Conference on Renewable Energy Research and Applications (ICRERA,)* (pp. 40-45), IEEE, August 2023

[35] S. Suganya Sri , A. Rajaram, "A Coupled-Optimization Based Master Node Selection and Path Finding on Mobile Ad Hoc Network for Smart Environment Monitoring," Journal of Electrical Engineering & Technology, 3:1-7, September 2023.

[36] C. Wu, G. Wang, and Y. Yang, "Wind power prediction based on LSTM neural network and EEMD decomposition," Energy Rep., vol. 7, pp. 3735–3743, 2021.

[37] H. Xie, X. Li, and Y. Zhang, “Wind power forecasting based on improved LSTM neural network optimized by genetic algorithm,” Energy Rep., vol. 8, pp. 1976–1982, 2022.

[38] K. Kalaivani, PR. Kshirsagarr, J.Sirisha Devi, SR. Bandela, I. Colak, J.Nageswara Rao, A. Rajaram, “Prediction of biomedical signals using deep learning techniques,” Journal of Intelligent & Fuzzy Systems. 2023(Preprint):1-4.

[39] H. Ozbay, "PDM-MPPT based solar powered induction heating system", Eng. Sci. Technol. an Int. J, vol. 23, no. 6, pp. 1397-1414, Dec. 2020.

[40] H. Ozbay, A. Karafil, and S. Oncu, "Sliding mode PLL-PDM controller for induction heating system", TURKISH J. Electr. Eng. Comput. Sci, vol. 29, no. 2, pp. 1241-1258, Mar. 2021.

[41] Karafil, "Comparison of the various irregular pulse density modulation (PDM) control pattern lengths for resonant converter with photovoltaic (PV) integration", J. Fac. Eng. Archit. Gazi Univ, vol. 36, no. 3, pp. 1595-1611, Feb. 2021.

[42] E. Bekiroglu, and M. D. Yazar, "MPPT Control of Grid Connected DFIG at Variable Wind Speed", Energies, vol. 15, no. 9, pp. 3146, Apr. 2022.

[43] R. H. Yang, and J. X. Jin, "Unified Power Quality Conditioner With Advanced Dual Control for Performance Improvement of DFIG-Based Wind Farm", IEEE Transactions on Sustainable Energy, vol. 12, no. 1, pp. 116-126, Jan. 2021.

[44] Mohamed Ali, Abdelbasset Krama, and S.Shady Refaat, "A Robust Grid-Tied PV System based Super-Twisting Integral Sliding Mode Control", 2021 10th International Conference on Renewable Energy Research and Application (ICRERA), pp. 402-407, 2021.