*Journal of Innovative Technology, Vol. 7, No. 2, pp. 23-35, September 2025*
*http://doi.org/10.29424/JIT.202509_7(2).0003*



# Machine Learning and Optimization Techniques for Wind Energy prediction: Challenges and their Solutions

Shehzada Taimur [1], Muhammad Asif Zahoor Raja [2*]

## ABSTRACT

Green energy is the need of the hour in the present era because the world is facing drastic climate change. With global warming at its peak and fossil fuel reserves depleting at an extremely fast rate, the need of the hour is switch to renewable sources of energy and identify ways to expand global reserves to meet the rising power demands. Wind power has become a popular source of generating clean renewable energy and reduces economic vulnerability caused by traditional fuel prices. The inclusion of wind power in the existing electric scheme helps accelerate the transition to sustainable energy. In this regard, Internet of things (IoT) has a key role in creating a effective path for integrating a wind power plant with power system. Since, one of the major challenges in adapting wind energy plants is their highly unpredictable output nature due to different weather conditions. Hence forecasting the output of a wind power plant for either a short or long span of time is highly important. Wind power prediction is necessary for a stable power system and the optimal operation of the wind farm itself. Accurate forecasting of wind power ensures the energy demand is appropriately met. This paper gives a wide-ranging analysis and addresses specifically the implementation of machine learning schemes for wind power prediction as well as the utilization of various optimization approaches in this field and their contribution to substantial development and valuable insights for improving performance and predictability of wind power plants. Further the advantages and drawbacks are discussed categorically to give better insight to the reader.

*Key words:* Wind power forecasting, Machine learning, Optimization, Modeling techniques.

## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| 1 | AD | Adaptative Dynamic |
| 2 | AO | Aquila Optimizer |
| 3 | ANN | Artificial Neural Network |
| 4 | ANFIS | Adaptive Neuro Fuzzy Inference System |
| 5 | ARIMA | Auto Regressive Integrated Moving Average |
| 6 | BLSTM | Bidirectional Long Short-Term Memory |
| 7 | BO | Bayesian Optimization |
| 8 | BPNN | Back Propagation Neural Network |
| 9 | CEEMDAN | Complete Ensemble Empirical Mode Decomposition with Adaptive Noise |
| 10 | CNN | Convolutional Neural Network |
| 11 | DA | Dual Attention |
| 12 | DACE | Design and Analysis of Computer Experiments |
| 13 | DFBER | Dynamic Fitness alBiruni Earth Radius |
| 14 | DNR | Dendritic Neural Model |
| 15 | DP | Dynamic Programming |
| 16 | DT | Decision Trees |
| 17 | IABC | Improved Artificial Bee Colony Algorithm |
| 18 | ELM | Extreme Learning Machine |
| 19 | EMD | Empirical Mode Decomposition |
| 20 | ETS | Exponential Time Smoothing |
| 21 | FA | Firefly Algorithm |
| 22 | FMDT | Fuzzy Decision-Making Tool |
| 23 | GA | Genetic Algorithm |
| 24 | GAN | Generative Adversarial Network |
| 25 | GLSTM | Genetic algorithm Long Short-Term Memory |
| 26 | GWO | Guided Whale Optimization |
| 27 | GrWO | Grey Wolf Optimization |
| 28 | HEO | Heuristic Exhaustive Optimization |
| 29 | HMG | Hybrid Micro Grid |
| 30 | ICSA | Improved Clonal Selection Algorithm |
| 31 | IFOA | Improved Fruit Fly Optimization |
| 32 | KOA | Kepler Optimizer Algorithm |

Manuscript received February 21, 2025; revised March 10, 2025; accepted March 11, 2025.

[1] Ph.D. Scholar, Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Taiwan.

[2*] Professor (corresponding author), Department of Data Science and AI Applications, Graduate School of Engineering Science and Technology, National Yunlin University of Science and Technology, Taiwan. (email: rajamaz@yuntech.edu.tw)

| | | |
|---|---|---|
| 33 | KRLS | Kernel Recursive Least Squares |
| 34 | LSTM | Long Short-Term Memory |
| 35 | LSSVM | Least Squares Support Vector Machine |
| 36 | MAPE | Mean Absolute Percentage Error |
| 37 | MKL | Multiple Kernel Learning |
| 38 | MLP | Multi-Layer Perceptron |
| 39 | NN | Neural Network |
| 40 | NWP | Numerical Weather Prediction |
| 41 | PCA | Principal Component Analysis |
| 42 | PDF | Pure Data selection Framework |
| 43 | PSO | Particle Swarm Optimization |
| 44 | RBF | Radial Basis Function |
| 45 | RF | Random Forests |
| 46 | RNN | Recurrent Neural Network |
| 47 | SARIMA | Seasonal ARIMA |
| 48 | SOA | Seagull Optimization Algorithm |
| 49 | TLBO | Teacher Learning Based Optimization |
| 50 | TSVR | Twin Support Vector Regressor |
| 51 | UC | Unit Commitment |
| 52 | WT | Wavelet Transform |
| 53 | XG | Extreme Gradient |
| 54 | 1D | One Dimension |

## 1. INTRODUCTION

Wind exists due to difference in temperature of earth surface from one area to another. It is the movement of air from a higher-pressure area to an area with a lower pressure. Wind energy is a form of renewable energy that is produced by exploiting the kinetic energy of wind. In ancient times, mariners used to sail by utilizing wind power. However, presently wind turbines wring electricity from air. This energy is collected by using windmills which change the movement of air into mechanical energy. The mechanical energy in the next step is converted into electrical energy through a generator. Wind power is viewed as a sustainable and clean source of energy as it does not produce toxic emissions and air or water pollution during operation, making it an environmentally friendly substitute for fossil fuels. Wind power plants can be a useful component of net-zero plan. It plays a significant role in reducing reliance on non-renewable sources and contributes to efforts aimed at combating climate change. Since the wind is available free of cost, the running costs of a windmill are negligible after a turbine is erected hence wind energy is one of the cheapest sources of energy. Wind power can be utilized on various scales, from small residential turbines to large wind forms that generate electricity for thousands of homes. The efficiency and output of wind power generation depend on many factors such as wind speed, turbine design and its location. Figure 1 below depicts a wind power plant having multiple wind turbines in series erected in open landscape. The power generated at the power plant is having low voltage I converted to high voltage power through transformers in the nearby substation. A high voltage transmission line helps with the transmission of power to load centers. A cleaner environment is self-explanatory.

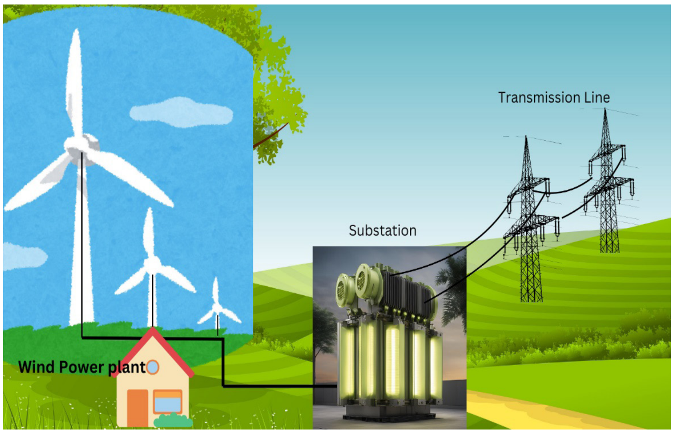


**Fig. 1 Wind power plant**

Wind power forecasting is the process of predicting the amount of electricity that will be generated by wind turbines over a specific period. Like other dependent factors, wind power output also depends on a set of features. Some features affect the output more e.g., velocity of the air, area of the blades etc., while others affect it less e.g., temperature, air density etc. The forecasting is essential for effective energy management and grid stability, as wind energy production can be highly variable due to changing weather conditions. The following are the crucial components necessary to be considered for wind power forecasting.

A. Data collection

Although accurate forecasting is a challenging task due to inherent fluctuation and intermittency of wind energy, but the availability of high-resolution data from on-site power stations provides valuable intuition for the development of a novel data-driven forecasting model. Data collection is one of the principal factors, as accurate forecasting has a core dependence on the quality of the data. The performance of the model in terms of energy consumption, network life, fairness index and efficiency index depend upon appropriate data collection [1]. Some of the major attributes of data collection are timeliness, accuracy and completeness [2]. Historical data on wind direction, speed, temperature and other meteorological factors are collected from various sources, including weather stations and satellite observations such as SODAR and LiDAR. Data is collected in real time over spatial and temporal variations. Reliable forecasting bases over effective data collection. The quality and amount of data is the fundamental factor in developing a data driven model. The study [3] provides data collection methods in detail and its processing, highlighting the suitable processing of data in contributing to developing a more effective model. In general, there are two main types of data: real-time data set and simulated data (also known as synthetic data). A comprehensive review of methodologies and techniques used for data collection is presented in [4]. This study enables researchers to compare data collection methodologies by highlighting the key challenges to minimizing data biasedness. NREL is a major source of data and widely used dataset in this field [5] and it offers simulated wind data from over 126000 offshore and land based windy sites of USA.

B. Modeling techniques:

Most of the forecasting techniques depend on having an appropriate number of data samples to ensure correct predictions. Still, equipment erratic functions during data collection may lead to inadequate datasets, significantly decreasing forecasting accuracy. This issue is addressed by [6] presenting a double stage forecasting technique that enhances accurate prediction capability of the model by addressing data volatility and incompleteness. A Bi-LSTM based generative adversarial network positively reconstructs missing points while capturing complex correlations and temporal dynamics. Various statistical, physical and hybrid models are used to analyze the collected data and make predictions. The analysis may be a time series analysis to identify trends/patterns of a dataset. Choosing a suitable technique for forecasting purposes is critical step because the modelling technique transforms the raw data into applicable insights. The selection of models depends on factors like availability of data, forecast time horizon, and computational horizon. Data driven models have been well known in the field of big data science to infer nonlinearity between dependent and independent variables [7,8]. The model predicts values for unknown instances on the basis of available data. Figure 2 given below shows the model development process in this regard.

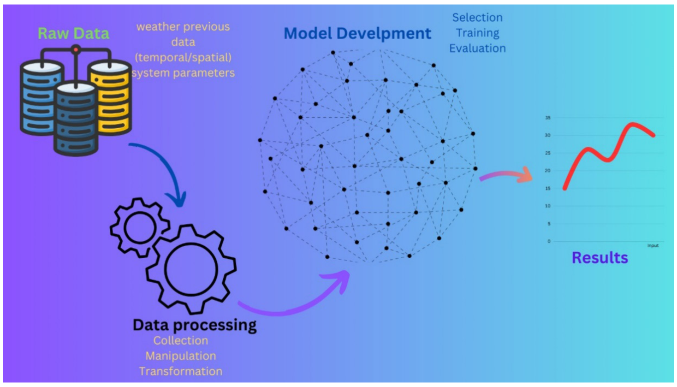


**Fig. 2 Data Driven Wind Energy forecasting model development process**

C. Time horizon:

Wind power forecasting may be broadly divided into four categories on the basis of time horizon, i.e., very short term, short term, medium term and long term. Short term and long-term forecasting have different applications. Predicting power generation for the subsequent few hours to a few days and predicting over months or years has different applications. However, it is worth noting that the level of accuracy of prediction reduces as much as length of time period increases as we are aware of the intermittent nature of the wind. This idea is discussed in detail in [9]. The authors explain that the model's accuracy diminishes as the prediction horizons goes longer. The forecast performance of the model appears to depend on the forecast period [10].

### 1.1 Research queries

This work is conducted in order to go through the literature on the application of intelligent ML algorithms and their efficacy to predict output of wind power plants. Furthermore, this study presents a clearer understanding of the tendencies in this field over the past five years. The following principal questions, we have tried though this study to answer.

Q1. Which variable of the weather has the most substantial effect on wind power plant output?

Q2. What kind of challenges may be faced in wind power forecasting?

Q3. What are the wind power generation forecasting models based on machine learning?

### 1.2 Literature review:

The output of a wind farm is given by following equation

$$P = 0.5 C_p \pi \rho R^2 v^3$$

Here Cp is the coefficient of performance, ρ is air density, R is length of the blade of the wind turbine and v is the speed of air (in meters per second). As per equation, the most significant variable affecting wind power plant output is wind speed. However, it is worth noting that a variation in air density, direction, turbulence, temperature and humidity also have consequent changes in the output of the plant. Wind power output is directly proportional to the cube of velocity of wind, striking the turbine blades. The relation shows that even a minute change in wind velocity can bring a huge change in the output. As far as considering air density, the mass of air per unit volume has a direct effect over the output of wind turbine. The denser the air, more is the output while light air brings low output energy from wind turbine. Sudden variation and heavy turbulence of wind has a damaging effect on the output. A smooth, steady and stable wind is idyllic for reliable wind power generation. Some other factors like atmospheric temperature and humidity level influence the air density and subsequently have an indirect impact on changing the output of a wind farm.

## 2. IMPORTANCE OF WIND POWER FORECASTING

Precise wind power forecasting is very vital for reliable and efficient operation of the power system having a high wind power penetration. Accurate forecasting is vital for grid stability, integration with grid, economic efficiency. Overall, wind power forecasting plays a crucial role in the transition to renewable energy sources, helping to ensure that wind energy can be effectively utilized in the energy grid. Wind power forecasting is conducted over different time horizons. These may be very short-term, short-term, medium-term and long-term. The following table 1 explains the purpose of various time horizons well.

**Table 1 Time horizon of wind power forecasting and its significance**

| | Horizon | Range | Application |
|---|---|---|---|
| 1 | Very short-term (in minutes) | Up to 30 minutes | - Instant grid operation<br>-Electricity market clearing<br>-Regulatory activities |
| 2 | Short-term (in hours) | 30 minutes to 6 hours ahead | -Load increment/decrement decisions<br>-Economic load dispatch planning |
| 3 | Medium-term (in days) | 6 hours to 1 day ahead | -Generator offline/online discission<br>-Resave requirement decisions |
| 4 | Long-term (in years) | In months | -Operation management<br>-Maintenance planning<br>-Optimum operating cost<br>-The feasibly study for design of new wind farm |

Each one of the above discussed time horizons have their own advantage and may utilized in a different and vast research field.

Wind power for casting is very crucial for several reasons, particularly as the reliance on renewable energy sources increases. Here are some of the key points in this regard.

A. Integration of Renewable Energy: Forecasting becomes more essential as more wind farms are integrated into the energy system. Wind power forecasting is necessary to accommodate intermittency and variability of wind energy. Correct power forecasting empowers grid operators to effectively integrate wind power sources into the system.

B. Grid stability and reliability: Accurate forecasting helps grid operators to maintain a balance between electricity supply and demand. Wind power forecasting helps in planning and managing rapidly fluctuating nature of wind energy to prevent blackouts, disruptions or grid failure. Accurate forecasting reduces the risk of grid instability caused by sudden changes in wind conditions. Efficient forecasting also supports smoother integration of wind power sources for a dependable and consistent power supply.

C. Economic efficiency: Accurate forecasting leads to cost saving by optimizing the operation of wind plants. It allows for better scheduling of backup of traditional energy plants and mitigating the need for expensive standby power sources during high demand periods. Similarly, precise wind power forecasting helps in cost effective energy business and enhances the economic feasibility of wind power plants.

D. Investment decisions: Reliable forecasting enhances the attractiveness of wind energy as a viable investment. Correct forecasting provides the stockholders with insights into the projected energy output and the subsequent revenue potency of a wind power project, helping to measure its economic feasibility.

E. Market participation: Wind power producers can participate effectively in energy markets when they can predict their output. This allows them to bid accurately in electricity markets, maximizing their revenue.

F. Environmental Benefits: Improving the predictability of wind energy generation can help minimize the dependance on fossil fuels, resulting in lower greenhouse gas production and a smaller carbon footprint of electricity generation. Consequently, contributing to combat against climate change. By exploiting natural wind flow, wind energy reduces water and air pollution resulting in saving the ecosystem and promoting sustainability. Wind energy acts as a major stakeholder of the concept of transition to a net-zero emission and plays a critical role in environment protection and supporting the endeavors for a cleaner planet.

G. Enhanced energy management and Operational planning: Wind power forecasting aids in the operational and maintenance scheduling. This ensures that wind farms operate efficiently and effectively leading to help in reducing energy costs for consumers.

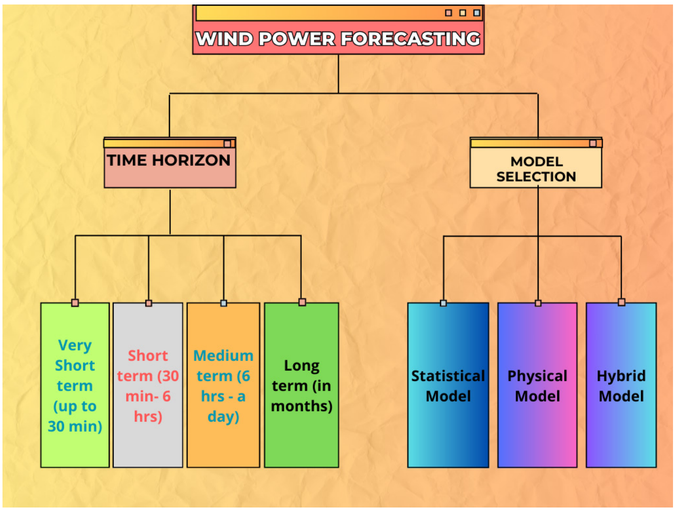


**Fig. 3 Wind Power forecasting**

## 3. WIND POWER FORECASTING MODELING

Model development involves different assumptions for the sake of mathematical manipulability and simplification of complex real-world problems. These assumptions are often not practically realistic and may lead to an inaccurate predictive result if not chosen appropriately. Some of the commonly considered assumptions include linearity, continuity, zero interference and noise and loss free environment etc. Wind power forecasting modelling may be generally characterized into three main approaches. Statistical models, Numerical or Physical models, and hybrid models. These models are discussed below.

A. Physical Models:

A physical model is a precise, concrete and weighted representation of a real-world complex process used for visualization, investigation and analysis. Such models are helpful in understanding complex phenomena by imitating their physical behavior and characteristics. Physical/Numerical models are based on physical principles of numerical weather prediction, Mesoscale model and computational fluid dynamics (CFD). Numerical weather prediction is a kind of mathematical equations to simulate atmospheric processes and make prediction on the basis of these equations. Mesoscale refers to high resolution model of a smaller geographical area and making predictions for a very large area and time on the basis of this model. CFD is also a physical model which simulates airflow and can provide insights about wind at a specific site. A short-term wind power prediction based on clustering CFD method is presented in [11]. Physical model does not need complex mathematical assumptions but they are expensive, time consuming, less flexible and have limited scalability. Pros and cons of such techniques are discussed in [12]. A semi-physical model is proposed in [13] based on the physical principles of the signal conversion process of a pneumatic valve.

B. Statistical Models:

Statistical models are mathematical or numerical representations used to analyze data, identify patterns and calculate predictions on the basis of available data. These models rely on past data to recognize patterns and relationships that can be utilized for forecasting. e.g., Time series analysis (ARIMA, STL etc.) are used to analyze historical wind speed data to make predictions. These models are broadly categorized according to their application like, regression, clustering (DT, Naïve Bayes classifier, RF), probabilistic modelling (Bayesian Networks, Hidden Markov Models) and time series analysis (ETS, ARIMA, SARIMA). Regression models can be employed to make predictions based on various input features and meteorological data. The statistical approach treats engineering model as a black box and hence statistically adjusted models lack physical interpretability [14]. Validation of a statistical model is done by using a subset of the same data used for modelling. The major problems in statistical model validation and calibration are categorically discussed in [15,16], offering valuable insights.

C. Hybrid Models:

The combination of two or more modeling approaches is known as hybrid modeling. A hybrid model is used to grab benefits and to avoid shortcomings of both of the above techniques to improve forecasting accuracy. For example, using wavelet transform with LSTM or combination of Random Forests and Neural Networks. The choice of forecasting techniques be subject to numerous factors including specific application, accessibility to data, required level of accuracy, and computational means. Although hybrid models enhance the predictive accuracy, robustness and efficiency across various fields but are computationally expensive and complex.

Figure 4 describes the distribution of research articles by countries on the topic of wind power prediction. The figure illustrates that mainly Asian countries working on this cheap source of energy specifically China is leading the world in this regard and USA following it. Some considerable contributions are also has been taken by Australian and EU countries.

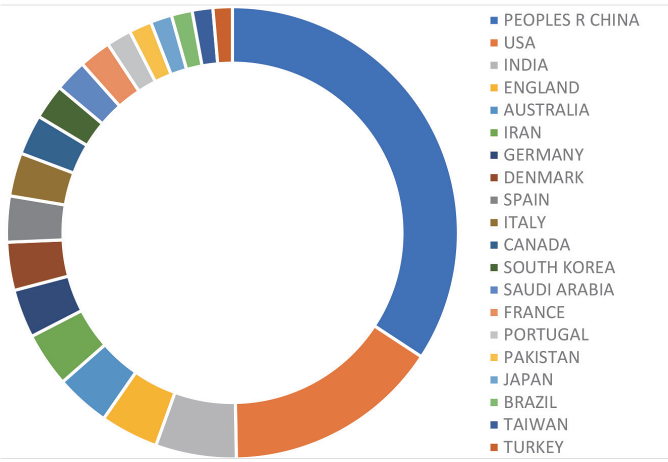


**Fig. 4 Wind power forecasting wrt region worldwide**

Challenges in wind power forecasting:

Some of the key challenges in this field may impact on the accuracy and reliability of predictions are as given below.

A. High uncertainty and variability:

Wind is inherently unprecedentedly unpredictable. Its speed and direction change very rapidly, which makes it difficult to provide an accurate forecast.

B. Complex atmospheric conditions:

Wind patterns are influenced by a number of outlying factors including atmospheric conditions and topography. Modelling these complex interactions may be highly challenging, especially in the area with diverse geographical features.

C. Data availability and its quality:

Accurate forecasting relies on real time quality data. Unavailability or insufficient data can affect forecasting.

E. Model Limitations: Different forecasting models as discussed above have their own strengths and weaknesses and prediction of each may differ from one another.

F. Seasonal variability:

Wind patterns can vary significantly by season making it difficult for model to forecast well round the year.

### 3.1 Data Collection and Methodology

Source of Data:

The web of science database selected for its interdisciplinary, versatile, advanced bibliographic pinpointing features and peer-reviewed literature. This platform includes renowned journals in the field of energy power and provides extensive access to a large number of papers. These favorable characteristics make the web of science comparatively one of the best choices for going through bibliography and literature.

Keyword and article selection procedure:

The procedure followed is pictorially presented in figure 5 and given in detail as below.

Step 1: "Wind Power Forecasting" selected as major Key term while "Machine Learning" and "Optimization" as added key term dated 20-12-2024.

Step 2 (Exclusion): Step 1 resulted in 212 documents, then in step 2, we excluded Review article, Early access, Open publisher-invited reviews, book chapters, documents with language other than English and refined our search to articles on the above key terms in English language only.

Step 3 (Inclusion): In this step, we filtered out selection by selecting the articles published in All open access with research area of Engineering in the year of 2020 onwards only. This refinement resulted in 88 papers finalized for discussion and technical analysis of advantages and drawbacks.

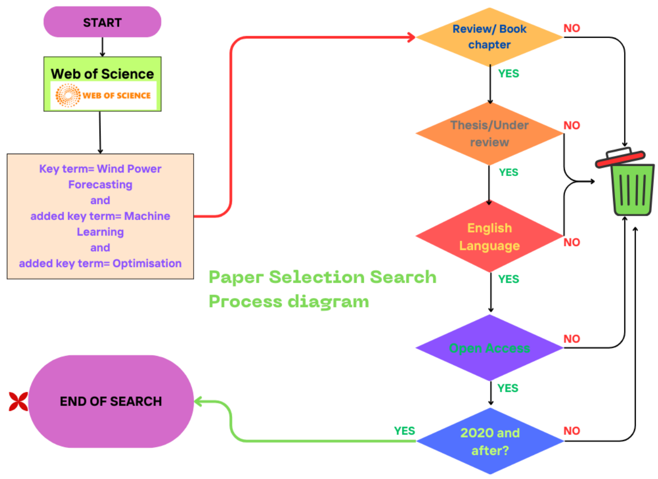


**Fig. 5 Procedure followed for paper selection**

A 2D pie chart as given below in figure 6 is a typical representation of the number of research articles authored by various researchers worldwide in field of wind power forecasting regardless of specifying of model. Amongst them, Wang JZ has the maximum number of contributions, having 124 articles, followed by Pinson P with 76 articles and Wang Y having 71 articles in this field with 46 of them.

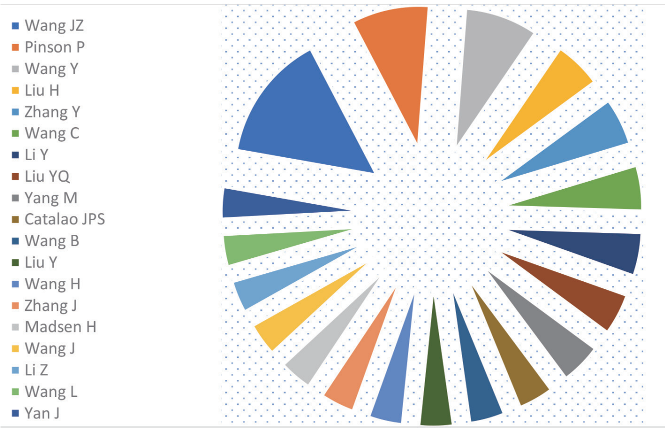


**Fig. 6 Wind power forecasting with respect to authors worldwide**

Further details in this regard are as in Figure 7 as given below illustrating the amount of research work produced by various institutes worldwide. Egyptian Knowledge bank and the National Institute of Technology leading the rest of the institutions with 18 articles each, US Department of Energy with 12 articles. Zhejieng University with 10 articles and several other institutes having 6-9 articles on average. This data highlights contributions of different organizations across the globe.

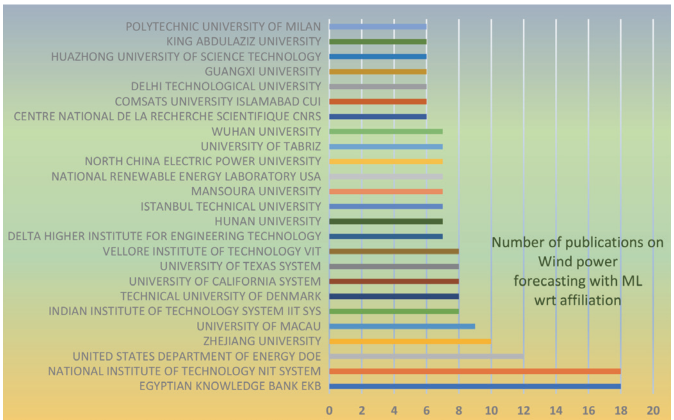


**Fig. 7 Wind PF publications with respect to ML by affiliation**

The Table 2 given below describes different machine learning techniques and corresponding optimization strategies adopted in various research. It may be observed that LSTM dominates by being used as algorithm most of the time.

**Table 2 Various techniques applied**

| Serial Number | Reference | Technique applied |
|---|---|---|
| 1 | [11] | ANN |
| 2 | [18] | CNN, LSTM |
| 3 | [19] | WD-LSTM |
| 4 | [20] | ARMA, PSO SVM |
| 5 | [23] | CNN-LSTM |
| 6 | [34] | BiLSTM-CNN-WGAN-GP |
| 7 | [46] | LSTM-K-means, SCO |
| 8 | [42] | GA, CEEMD, LSTM |
| 9 | [50] | LSTM-K-means |
| 10 | [43] | SVM, RF |

## 4. MACHINE LEARNING AND OPTIMIZATION IN WIND POWER FORECASTING

As discussed above in research methodologies section, we have considered papers that has been published in 2020 or after. Figure 8 demonstrates the number of research papers published per year, displaying a significant change in research activity after 2020. Before 2020 the numbers were relatively very low, with only up to 4 papers per year. However, there was a notable jump in 2020 to 17 papers, marking it as a key point. The research in this regard accelerated in 2023 with 46 papers in a single year. High publication ratio continued in 2024 representing sustained interest in renewable energy resources exploitation.

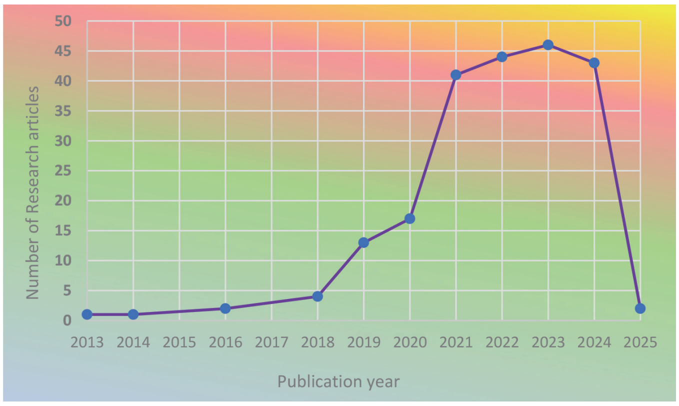


**Fig. 8 Wind power forecasting with ML and optimization wrt publication year**

The paper [27] introduces a demand response (DR)-based technique for optimization of prosumer micro grids and load demand forecasting by utilizing a hybrid ML approach. The proposed method combines MLP-ANN, ANFIS and RBF-ANN models to recognize the most accurate predictive patterns, leading to improvised forecasting of key value variables such as wind speed, effective area and load demand. Results depict that the proposed hybrid methodology surpasses traditional machine learning techniques, achieving noticeable saving in operational costs and enhancements in forecasting accuracy. These results underscore the potentiality of combining hybrid machine learning approaches with DR-based methods to enhance sustainability, optimize PMG operations and minimize costs. [28] presents a Genetic Long Short-Term Memory (GLSTM) framework that effectively combines the sequential data learning capability to enhance short-term power prediction. By optimizing critical LSTM variables such as the number of neurons and window size, the GLSTM demonstrates superior predictive validity and robustness. The outcomes reveal notable upgradation performance metrics and errors (MSE, RMSE, MAE). Comparison of GLSTM with some of standard techniques such as SVM, baseline regressors, deep NN and traditional LSTM achieved an average implement of 6-35% in prediction accuracy, 30% in performance in RMSE over multiple wind farms dataset. The Wilcoxon signed-ranked test further proves the statistical importance of integrating GA with LSTM, ensuring the novelty and efficacy of this approach. The property of GLSTM to combine high accurate output with less computational complexity makes it highly applicable and may be applied to many other time series prediction problems. A novel hybrid neural network-based technique for single day forecasting is presented by [29] thoroughly evaluating five modern techniques: wavelet neural network trained by PSO, Radial Basis function neural network, ELM based NN and MLP Neural Network. This analysis describes that this method provides sufficient accuracy while single feature forecasting but no enhancement in accuracy for multi feature analysis. Among all evaluated models, WNN trained by ICSA aches the highest accuracy, while ELM based NN minimizes computational time, enabling users to select models based on application specific requirements. The stated scheme not only establishes an effective framework for wind speed forecasting but also lays a foundation for reliable and economically efficient operation of wind power systems. This study discusses the practical application in Saskatchewan. The authors [30] emphasize the critical role of accurate short term wind power forecasting in a hybrid battery- wind plants. The method proposed in this study is machine learning based penalty cost minimization strategy that integrates wind power with battery energy storage management. Among the tested methods, Wavelet twin support vector regressor (TSVR), Random forest-TSVR and gradient boost methods. Wavelet-TSVR model proved its accuracy 92.33%. Unit Commitment (UC) is a complex integration optimization methodology used in power systems. The complexities of UC are discussed by the author in [31]. UC is a hybrid Dynamic Programming and Genetic Algorithm (DP-GA), critical optimization method aimed at determining the optimal start and shutdown cycles of generation units, plays a pivotal role in balancing load demand, minimizing costs and ensuring smooth system operation. The increased integration of RES due to depletion of reserves and rise in costs of traditional fuels, highlights the necessity of reliable UC techniques that has the ability to accommodate various characteristics of RES. The under-discussion UC method was applied to an IEEE-30 bus hybrid power plant system. The outcomes validate the effectiveness of this method. The authors suggested an Enhanced Crow Search Algorithm Optimization Extreme Machine Learning (ENCSA-ELM) in [32] model for short term wind power prediction. This ELM proved by outcomes to have high prediction accuracy, enhanced performance and valuable impact over the system. The system under study have improved efficiency, lower operating costs and economic grid operation due to efficacy of the proposed scheme. A shortcoming of this scheme is the requirement of certain test functions. Wind speed is one of the most crucial factors, affecting wind power output. Accurate wind speed forecasting is critical for ensuring stability and safety of the power systems with increased wind plants integration. The study [33] proposes an Adaptive Dynamic Particle Swarm Optimization (AD-PSO) technique combined with Guided Whale Optimization algo to optimize the optimization variables of LSTM network for prediction of wind speed. The said strategy is analyzed by using one-way ANOVA and Wilcoxon's rank -sum test, proved its robustness. in similar way, the ensemble optimization method outperformed other traditional techniques including Random Forestes (RF), K-NN and Neural Network. This study underscores the capability of hybrid optimization algorithms in enhancing the efficiency of deep learning models for further complex forecasting systems. Another hybrid technique based on combination of BLSTM and 1D CNN deep learning model presented by [34], effectively attains high space-time feature for a short-term wind speed prediction. The proposed method has a real-world application in Saudi Arabia. From the performance indices such as MSE, MAE, MAPE and RMSE validate the model's performance. The said methodology may be applicable to additional features like ambient temperature and atmospheric pressure to increase the prediction correctness. XGBoost optimization combined with Bayesian optimization is proposed by authors in [35]. The proposed combination enhances the prediction accuracy as compared to other methods such as SVM, XGBoost, ELM and LSTM as demonstrated by the results in terms of performance, robustness and reliability. The analysis of evaluation metrics including MAE, RMSE and R-squared confirms this comparison. Wind speed is one of the most crucial aspects of the wind power plant output. Wind speed forecasting on short term basis is important for an optimum operation of a given plant. The scheme proposed for wind speed prediction introduced in [36], is a hybrid scheme, combining Multiple Kernel Learning and Empirical Mode Decomposition (EMD). The proposed scheme is a deep learning model, especially effective in areas where wind speed signals are of nonstationary and nonlinear nature. The EMD component decomposes differentiates complex signals into a manageable substitute for an improved feature extraction. At the same instant, MKL adaptively specifies weights to various functions, resulting in an optimized forecasting process. The validity of this method is checked by using data from New Zealand wind plants, proving the performance of the subject model to be superior. This model also has the properties of strong generalization and low prediction errors. In [37], the authors consider the inherent variability of wind as well as the photo voltaic energy and its effect over efficient energy management. The authors introduce a Kernel Recursive Least-Squares (KRLS) machine learning algorithm for forecasting wind and PV power production and side by side a Link Scheduling algorithm for efficient data transfer in wireless sensor networks. The forecasting model exhibits enhanced performance, attaining an impressive R2 score of 88.17% for wind and 99.7% for PV energy. At similar instance, the Link Scheduling algo improves the performance by decreasing latency 22% and increasing resource utilization by 38%. Resultantly, the KRLS model's robustness and accuracy proves it to be helpful for supporting sustainable and reliable power systems. Wind direction is also an important aspect in this context. The research article [38] presents a novel practical strategy for forecasting wind direction by adapting weighted ensemble of ML models, optimized through an ensemble of PSO and Guided Whale Optimization (WOA). The said ensemble is then compared with four regressor models namely, Random Forests, Support Vector Regressor, Decision Tree and Multi-Layer Neural Network for verification of efficiency of proposed ensemble model. The data set has been taken from Kaggle. Statistical analysis tools including Wilcoxon's rank-sum test and ANOVA further confirmed the model's accuracy. The key features are the ability to balance exploitation and exploration, effective optimization and high accuracy. A twofold technique in wind power forecasting presented by [39]. This study provides a scheme to develop a wind power forecasting model by implementing an improved fruit fly optimization algorithm (IFOA) reinforced by Back Propagation NN. The proposed scheme is implemented by using a WSN for collecting real-time meteorological data and uniting it with meteorological forecast datasets. The experimental results prove the performance of the model comparatively better than many other approaches, achieving MAE and RMSE values of 0.11 and 0.16 respectively. The article [40] highlights the vital role of accurate wind power prediction for effective management of renewable energy generation. Hence suggesting a reliable forecasting model to address this need. This study introduces Dendritic Neural Regression model integrated with SOAAO, an ensemble of meta metaheuristic optimization techniques namely seagull optimization algorithm and Aquilla optimizer. The SOAAO technique enhances the search ability of traditional SOA by combining AO as a local search mechanism. This method is used to train and select optimum weights of DNR model variables which makes a time-series forecasting model. The said model was tested using four different datasets of real wind turbines for demonstrating their accurate and robust response. The DNR-SOAAO method scores High R2 value of up to 0.96. The authors in [41] introduces an intelligent and innovative statistical technique for wind power prediction. This technique utilizes clustering analyses, statistical analysis and ideas of the Wind Resource Typical Year (WRTY) to enhance applicability and accuracy. This technique provides numerous advantages such as wide range applicability and accurate forecasting as proven by low MAPE values. Despite the stated strengths, this method also has some limitations including low spatial resolution, dependence on initial clustering conditions and complexity with multi-parameter probabilistic distribution functions. A short-term wind power forecasting technique presented by [42] is a novel integrated forecasting model that uses secondary decomposition techniques and parameter optimization by utilizing Grey Wolf Optimizer (GWO). The suggested model describes superior forecasting performance. This method combines wavelet transform and CEEMDAN for secondary decomposition of wind power data, decreasing forecasting complexity and enhancing feature abstraction. A novel integrated wind speed forecasting model presented in [43] is a combination of IABC-LSSVM and CEEMDAN, appropriately address challenges faced in a dynamic and non-linear wind. The proposed method utilizes the property of CEEMDAN of decomposition to minimize randomness and maximize predictability, simultaneously, the IABC algorithm optimizes the implementation of the LSSVM model. The significant accurate performance of this hybrid model is proven by case studies. Hence this study highlights the potentiality of CEEMDAN-IABC-LSSVM not only in the context of wind power forecasting but also for other complex fields. A short-term wind power forecasting hybrid deep learning model based on PCA-CNN-BLSTM is proposed by authors in [44]. This approach is a practical and comprehensive method effectively used for control and energy management of microgrids. The proposed scheme utilizes teacher learning based optimization (TLBO) for economic load dispatch and the aforementioned forecasting technique to address the major challenges in operation of microgrids, such as complexity, non-linearity and accurate forecasting. The effectiveness of the proposed methodology was evaluated using IEEE 33-bus system and data of a real wind farm in Australian Wool north site. The results prove significant operational cost minimization and underscore the importance of accurate wind power prediction, keeping grid efficiency in view. The research article [45] introduces a Recurrent Neural Network wind power forecasting model reinforced by a novel Dynamic Fitness AlBiruni Earth Radius algorithm for forecasting wind power patterns. The efficacy of the proposed model is compared with its alternatives such as BER, FHO, JAYA, GWO, PSO and WOA in terms of evaluation metrics including RRMSE, MAE, NAE, MBE, WI, r, R2. The results depict a strong correlation between predicted and observed values of model as proven by low RMSE and high statistical reliability evidenced through Wilcoxon signed-rank test and ANOVA. The author suggests that RNN-DFBER model is a reliable and powerful scheme for wind power prediction. The shortcomings of numerical weather prediction (NWP) are addressed by the authors in [46] by introducing Pure Data-selection Framework (PDF). PDF improves the forecasting accuracy by selecting optimal subsets of NWP, using K-means and support vector classification.  In order to handle computational challenges, this model integrates a DACE-based metamodeling algorithm and a heuristic-exhaustive optimization (HEO) algorithm. Analysis of weekly data experimental results provide superior accuracy as compared to monthly or further long run data sets. The under-discussion method may also be applied in forecasting other variables such as load, wind speed and solar power. Deep-VELOX framework presented by [47] is a novel development in wind energy technology, combining ML techniques with turbine designs. By integrating Grey wolf optimization and Gradient Boosting Regressor algorithm within the IN-VELOX wind turbine model, Deep-VELOX gain remarkable level of wind power forecasting accuracy. The Key Performance Indicators such as MAPE of 0.0002, MSE of 0.0352 and an RMSPE of 0.0974 highlights its best predictive precision. This method has also to ensure consistent energy generation and minimize forecasting disparities. Deep-VELOX can optimize turbine performance at low wind speeds. Short -term wind power forecasting has a critical role in integration of wind energy into electricity grids. The authors [48] present an ANN-based short term forecasting approach optimized with combined with Firefly optimization algorithm. The research demonstrates the excellent performance of FA in attending the challenges of wind power forecasting model. The results verify that ANN-FA model is an effective tool for energy management and efficient exploitation of wind energy sources. It provides an improved, accurate and reliable. While discussing specifically the application of machine learning techniques in forecasting wind energy, figure 9 describes deliberately that many of the authors in this field has a quite similar level of contribution in this regard. Leading contributors with six papers each include Ahmed T, El-Kenawy, Song YH, Vaccaro A, Wan C and Zhang J. Authors Deb, Khafaga DS, Kumar N, Wang L, Wang Y and Wood DA have written five papers each. This data depicts the set of names of researchers actively participating in and emphasizing global attention in utilizing ML methods for forecasting purposes.

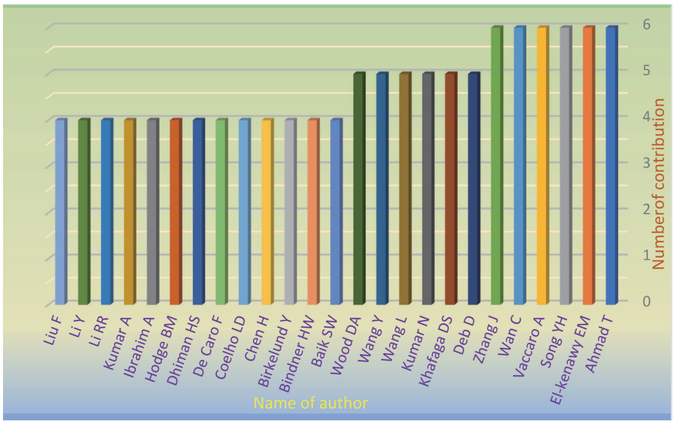


**Fig. 9 Authors of ML based wind power forecasting**

The research article [49] proposes a 10-minute (very short-term) forecasting MLO mode and examines its comparison with five operational models, such as EC 0.1, EC0.125. JMA, GFS, CMA. The efficiency of the proposed scheme is improved by 39% as compared to JMA, the most effective in terms of MAE and RMSE. It may be concluded from reading the results that proposed method is more effective due to combination of statistical and statistical model with ML methods. A BiLSTM-based approach is introduced by [50] for prediction of wind speed, using the novel GADTO algorithm, which integrates genetic algorithm and dipper throated optimization (DTO). This GADTO combination enhances the performance of the model by optimizing BiLSTM variables and selecting important features, resultantly achieving superior accuracy as compared with other methods. Assessment on Kaggle dataset verify that the proposed scheme is robust, having an RMSE score of 0.00046 and powerful validation through Wilcoxon and ANOVA tests. The stated results demonstrate the method's effectiveness, presenting a promising tool for wind speed forecasting and energy planning. The research article [51] also presents a hybrid short-term wind power forecasting (3hours-24hours) model that combines data driven and physics-based approaches, achieving noticeable improvements as compared to traditional methods. By expanding the forecasting space to include a broad range of meteorological variables within large geographical domain, integrated with ANN for evaluation and an adhoc GA for parameter value selection, the model result in a superior performance having RMSE of 11% and 11.6% for 12h and 24h respectively. The suggested method is effective for wind farms specifically in complex terrains by using variables like vertical wind shear and turbulent kinetic energy for improvement in prediction accuracy. Future enhancements may further improve the results with significant error reduction.

**Table 3 Pros and cons of various ML techniques**

| S.No | Reference | Technique | Pros | Cons |
|---|---|---|---|---|
| 1 | 27 | ANN-ANFIS-RBF | Enhanced forecasting accuracy, cost efficiency, improved resource utilization, flexibility | implementation complexity, data quality dependent, uncertainty, risk of overfitting |
| 2 | 28 | GLSTM | Improved prediction accuracy, optimized parameters, robust and versatile, statistical validation via Wilcoxon signed-ranked test. | Complexity, time consuming, sensitivity to GA parameters, generalization challenge |
| 3 | 29 | WNN-ICSA | innovative approach, real world application, efficient in single feature efficacy, economical | Limited geographic data (Saskatchewan, Canada), model complexity, more computational time for multi features and no improvement in accuracy, limited to wind speed |
| 4 | 30 | NN-ELM | comprehensive evaluation, reliable, Fast | ignores other major external factors like turbine efficiency |
| 5 | 31 | Wavelet-TSVR | Highly accurate, fast, scalable and adaptable, implementation on a hybrid plant | complexity in implementation, |
| 6 | 32 | UC (DP-GA) | Improved accuracy, effective optimization performance, ability to adjust with RES. Robust, | complex, scalability issues for large system, |
| 7 | 33 | AD-PSO, GWO | accuracy, efficient feature selection, comparatively superior, validity checked by statistical tools, scalable | complex, risk of overfitting, limited validation data (Kaggle) |
| 8 | 34 | BiLSTM-1D CNN | Accurate, robust temporal modelling, versatile | complex, applied in Saudi Arabia only |
| 9 | 35 | XGBoost-BO | accurate, practical, scalable | dependance on Bayesian optimization, lack of other meteorological variables, low performance in case of extreme turbulent weather |
| 10 | 36 | MKL-EMD | enhanced accuracy, manageability, adaptive weight allocation, robustness to complex signals, generalization capability, | Computationally complex, need expert for model training, low interpretability |
| 11 | 37 | KRLS | High accuracy, Dynamic adaptability, real time data application, simplicity, applicable on commercial level | Scalability of WSN, Lack of integration with storage systems, |
| 12 | 39 | IFOA-BPNN | reduced errors, Real-time data integration, combination of data sets, practical | Interference challenges, limited evaluation metrics, data transmission constraints, complex, scalability issues |
| 13 | 40 | DNR-SOA-AO | High forecasting accuracy, Improved algorithm, robust metaheuristic approach, less local optima issues | limited focus on noise and interference, MAPE and computational time evaluation are not considered, complex |
| 14 | 42 | WT-CEEMDAN-GrWO | Improved accuracy, Robustness, Broad applicability, improved parameter tuning, | dependence on initial conditions, limited interpretability, scalability |
| 15 | 44 | PCA-CNN-BLSTM & TLBO | comprehensive framework, Robust, accurate forecasting, cost effective grid operation, real world validation, integrates optimization technique with ML models for better outcomes | Complexity, potential of overfitting, expert requirement |

| | | | | |
|---|---|---|---|---|
| 16 | 45 | RNN-DFBER | Dynamic optimization, Improved forecasting, comprehensive validation, versatile, comparison with diverse models | Complexity, sensitivity to optimization variables |
| 17 | 46 | DACE-HEO | improved accurate forecasting, well performance in similarity-based techniques, scalability, optimized computation | complexity in data subset selection, large computation time, limited real-time application |
| 18 | 48 | ANN-FA | improved accuracy, robust, computationally efficient | large scale data and rapid dynamic environment handling issues |
| 19 | 51 | ANN- GA | low error, broad prediction space, custom feature selection, adaptability to complex terrain, improved performance in turbulent environment | large data required, reliance on basic ANN, limited geographic applicability |
| 20 | 54 | Conv-DA-LSTM | accuracy, robust, seasonal adaptability, efficient | complex, interpretability issues |
| 21 | 57 | KOA-FMDT | multi objective optimization, robust | complex, depend on forecast data, lack of practical implementation |

The study [52] emphasizes the importance of accurate wind power prediction in integration of wind power into power system. This study compares three states of the art optimization techniques namely, Optuna, Scikit opt and Hyperopt that enhance the performance of LSTM and CNN models. The finding describes that Optuna gives the highest output for both models, while Hyperopt attains best accuracy for LSTM based forecasting models. The research article [53] highlights the critical potential of machine learning specifically Support Vector Regressor (SVR), aiming at the challenges in energy management and generation forecasting within RES integrated grids. By utilizing previous data of weather patterns, energy production and grid statuses, the SVR model forecast more accurately as compared to traditional techniques. The accurate response facilitated major operational improvements, such as 8.4% reduction in operating expenses, 10% enhancement in demand-supply balance, 15% reduction in peak demand and 12% increment in renewable energy utilization. The article highlights the role of advanced forecasting algorithms in fostering sustainability, enhancing grid stability and minimizing renewable energy variability. These indicators highlight the role of ML based intelligent techniques in shaping environmentally friendly, cost effective and resilient energy management. [54] introduces an optimized hybrid deep learning technique for short-term wind power forecasting in desert locations based on past meteorological dataset and modern frameworks like Conv-DA-LSTM. The proposed model specifically happens with parameters optimization, achieving highest accuracy (0.93) and lowest error rates (RMSE: 71.866). At similar instant, consistent performance across high wind speeds and across seasonal conditions was observed. This method improves wind power predictability and energy management. Another short-term (1h-6h) wind speed forecasting novel technique, actually utilized for ensuring integration of PV power into main power system suggested in [55]. This study also highlights the value of modern forecasting models for accuracy enhancement and provides a comparison of different forecasting models including physical models, statistical regression, ensemble techniques and machine learning. The suggested model uses GEKKO as parametric linear model combined with Kalman filter for post-processing and optimization algorithms, testify in achieving high accuracy in both probabilistic and deterministic forecasts. The results demonstrate the capability of the suggested ML model to adapt to variability in RES. [56] describes the application of a multi-objective fuzzy framework for optimization of hybrid microgrid consisting of wind energy, PV and battery energy storage in case of a 33-bus distribution system. The key contributions of this study include minimizing voltage deviations, energy losses and power costs while utilizing forecasted data with modern optimization techniques. The study achieves significant improvements in hybrid microgrid optimization by using multi-objectives improved Kepler optimization algo, enhanced by Kepler's law and FMDT. The results depict reasonable results in terms of reducing power costs, voltage deviations and annual power losses. The study [57] discusses the limitations of deterministic techniques in managing the operational uncertainty occurring due to the introduction of solar and wind energy sources into power networks. The authors present an alternative probabilistic framework for minimizing risks and optimizing system operations. Validity of the proposed technique is checked through German power system. More insights are presented in this regard by [58]. A two-stage model proposed by [59] uses wavelet packet transform (WPT) in the first stage to decompose historical wind power signals and Deep CNN in the second stage to make predictions on the basis of available data.

## 5. CONCLUSION

In this article, we have presented a thorough review about renewable energy specifically wind energy and a structured analysis of scientific works related to wind power forecasting. The main purpose of this work is to prepare and share an organized view of the different models, methodologies and their features utilized for wind power forecasting and the current trends of inclusion of Machine Learning techniques in the said field. The database used for this study is Web of Science with major key word "Wind power forecasting" and added key terms "Machine Learning" and "Optimization". In addition to identifying the most used models, we have also explored the influence of data preprocessing techniques and feature selection on prediction accuracy. The study helps in selecting an appropriate model for research on wind energy prediction, additionally highlighting the pros and cons of the under-study techniques to analyze the different intelligent wind power forecasting methods, including machine learning models, traditional statistical approaches and utilization of optimization techniques.

## REFERENCES

[1] Wen, W., Zhao, S., Shang, C. and Chang, C.Y., 2017. "EAPC: Energy-aware path construction for data collection using mobile

sink in wireless sensor networks." *IEEE Sensors Journal,* **18**(2), pp.890-901.

[2] Morris, C. and Peterson, S.M., 2020. "A component analysis of an electronic data collection package." *Journal of Organizational Behavior Management,* **40**(3-4), pp.210-232.

[3] Chen, Y. and Xu, J., 2022. "Solar and wind power data from the Chinese state grid renewable energy generation forecasting competition." *Scientific Data,* **9**(1), p.577.

[4] Mauša, G., Galinac-Grbac, T. and Dalbelo-Bašić, B., 2016. "A systematic data collection procedure for software defect prediction." *Computer Science and Information Systems,* **13**(1), pp.173-197.

[5] Draxl, C., Clifton, A., Hodge, B.M. and McCaa, J., 2015. "The wind integration national dataset (wind) toolkit." *Applied Energy,* **151**, pp.355-366.

[6] Goh, H.H., Ding, C., Dai, W., Xie, D., Wen, F., Li, K. and Xia, W., 2024. "A Hybrid Short-Term Wind Power Forecasting Model Considering Significant Data Loss." *IEEJ Transactions on Electrical and Electronic Engineering,* **19**(3), pp.349-361.

[7] Aslam, S., Herodotou, H., Mohsin, S.M., Javaid, N., Ashraf, N. and Aslam, S., 2021. "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids." *Renewable and Sustainable Energy Reviews,* **144**, p.110992.

[8] Suárez-Cetrulo, A.L., Burnham-King, L., Haughton, D. and Carbajo, R.S., 2022. "Wind power forecasting using ensemble learning for day-ahead energy trading." *Renewable Energy,* **191**, pp.685-698.

[9] Obiora, C.N., Hasan, A.N. and Ali, A., 2023. "Predicting Solar Irradiance at Several Time Horizons Using Machine Learning Algorithms." *Sustainability,* **15**(11), p.8927.

[10] Kang, I.B., 2003. "Multi-period forecasting using different models for different horizons: an application to US economic time series data." *International Journal of Forecasting,* **19**(3), pp.387-400.

[11] Wang, Y., Liu, Y., Li, L., Infield, D. and Han, S., 2018. "Short-term wind power forecasting based on clustering pre-calculated CFD method." *Energies,* **11**(4), p.854.

[12] Viswanathan, V.K. and Linsey, J.S., 2012. "Physical models and design thinking: a study of functionality, novelty and variety of ideas.

[13] Miller, B., Vahid, F., Givargis, T. and Brisk, P., 2014. "Graph-based approaches to placement of processing element networks on FPGAs for physical model simulation." *ACM Transactions on Reconfigurable Technology and Systems (TRETS),* **7**(4), pp.1-22.

[14] Joseph, V.R. and Yan, H., 2015. "Engineering-driven statistical adjustment and calibration." *Technometrics,* **57**(2), pp.257-267.

[15] Lee, G., Kim, W., Oh, H., Youn, B.D. and Kim, N.H., 2019. "Review of statistical model calibration and validation—from the perspective of uncertainty structures." *Structural and Multidisciplinary Optimization,* **60**, pp.1619-1644.

[16] Rivers, D.L. and Boone, E.L., 2017. "Dynamic approach to linear statistical calibration with an application in microwave radiometry." *Journal of Statistical Computation and Simulation,* **87**(1), pp.17-28.

[17] Li, L., Li, Y., Zhou, B., Wu, Q., Shen, X., Liu, H. and Gong, Z., 2020. "An adaptive time-resolution method for ultra-short-term wind power prediction." *International Journal of Electrical Power & Energy Systems,* **118**, p.105814.

[18] Ren, J., Yu, Z., Gao, G., Yu, G. and Yu, J., 2022. "A CNN-LSTM-LightGBM based short-term wind power prediction method based on attention mechanism." *Energy Reports,* **8**,pp.437-443.

[19] Liu, B., Zhao, S., Yu, X., Zhang, L. and Wang, Q., 2020. "A novel deep learning approach for wind power forecasting based on WD-LSTM model." *Energies,* **13**(18), p.4964.

[20] Wang, Y., Wang, D. and Tang, Y., 2020. "Clustered hybrid wind power prediction model based on ARMA, PSO-SVM, and clustering methods." *IEEE access,* **8**, pp.17071-17079.

[21] Liu, Z., Hara, R. and Kita, H., 2021. "Hybrid forecasting system based on data area division and deep learning neural network for short-term wind speed forecasting." *Energy Conversion and Management,* **238**, p.114136.

[22] Huang, L., Li, L., Wei, X. and Zhang, D., 2022. "Short-term prediction of wind power based on BiLSTM–CNN–WGAN-GP." *Soft Computing,* **26**(20), pp.10607-10621.

[23] Kuang, H., Guo, Q., Li, S. and Zhong, H., 2021, "March. Short-term wind power forecasting model based on multi-feature extraction and CNN-LSTM." *In IOP Conference Series: Earth and Environmental Science* (Vol. 702, No. 1, p. 012019). IOP Publishing.

[24] Zhou, B., Ma, X., Luo, Y. and Yang, D., 2019. "Wind power prediction based on LSTM networks and nonparametric kernel density estimation." *Ieee Access,* **7**, pp.165279-165292.

[25] Neshat, M., Nezhad, M.M., Abbasnejad, E., Mirjalili, S., Groppi, D., Heydari, A., Tjernberg, L.B., Garcia, D.A., Alexander, B., Shi, Q. and Wagner, M., 2021. "Wind turbine power output prediction using a new hybrid neuro-evolutionary method." *Energy,* **229**, p.120617.

[26] Abualigah, L., Zitar, R.A., Almotairi, K.H., Hussein, A.M., Abd Elaziz, M., Nikoo, M.R. and Gandomi, A.H., 2022. "Wind, solar, and photovoltaic renewable energy systems with and without energy storage optimization: A survey of advanced machine learning and deep learning techniques." *Energies,* **15**(2), p.578.

[27] Faraji, J., Ketabi, A., Hashemi-Dezaki, H., Shafie-Khah, M. and Catalao, J.P., 2020. "Optimal day-ahead self-scheduling and operation of prosumer microgrids using hybrid machine learning-based weather and load forecasting." *IEEE Access,* **8**, pp.157284-157305.

[28] Shahid, F., Zameer, A. and Muneeb, M., 2021. "A novel genetic LSTM model for wind power forecast." *Energy,* **223**, p.120069.

[29] Abbasipour, M., Igder, M.A. and Liang, X., 2021. "A novel hybrid neural network-based day-ahead wind speed forecasting technique." *IEEE Access*, **9**, pp.151142-151154.

[30] Dhiman, H.S., Deb, D., Muyeen, S.M. and Abraham, A., 2021. "Machine intelligent forecasting based penalty cost minimiza-

tion in hybrid wind-battery farms." *International Transactions on Electrical Energy Systems,* **31**(9), p.e13010.

[31] Salman, D. and Kusaf, M., 2021. "Short-term unit commitment by using machine learning to cover the uncertainty of wind power forecasting." *Sustainability,* **13**(24), p.13609.

[32] Li, L.L., Liu, Z.F., Tseng, M.L., Jantarakolica, K. and Lim, M.K., 2021. "Using enhanced crow search algorithm optimization-extreme learning machine model to forecast short-term wind power." *Expert Systems with Applications,* **184**, p.115579.

[33] Ibrahim, A., Mirjalili, S., El-Said, M., Ghoneim, S.S., Al-Harthi, M.M., Ibrahim, T.F. and El-Kenawy, E.S.M., 2021. "Wind speed ensemble forecasting based on deep learning using adaptive dynamic optimization algorithm." *IEEE Access,* **9**, pp.125787-125804.

[34] Lawal, A., Rehman, S., Alhems, L.M. and Alam, M.M., 2021. "Wind speed prediction using hybrid 1D CNN and BLSTM network." *IEEE Access,* **9**, pp.156672-156679.

[35] Xiong, X., Guo, X., Zeng, P., Zou, R. and Wang, X., 2022. "A short-term wind power forecast method via xgboost hyper-parameters optimization." *Frontiers in energy research,* **10**, p.905155.

[36] Xu, Y. and Yang, G., 2020. "A Short-Term Wind Speed Forecasting Hybrid Model Based on Empirical Mode Decomposition and Multiple Kernel Learning." *Complexity,* **2020**(1), p.8811407.

[37] Nengroo, S.H., Jin, H. and Lee, S., 2022. "Management of distributed renewable energy resources with the help of a wireless sensor network." *Applied Sciences,* **12**(14), p.6908.

[38] Khafaga, D., 2022. "Optimization ensemble weights model for wind forecasting system." *Computers, Materials and Continua,* **73**(2), pp.2619-2635.

[39] Tian, W., Bao, Y. and Liu, W., 2022. "Wind power forecasting by the BP neural network with the support of machine learning. " *Mathematical Problems in Engineering,* **2022**(1), p.7952860.

[40] Al-qaness, M.A., Ewees, A.A., Elaziz, M.A. and Samak, A.H., 2022. "Wind power forecasting using optimized dendritic neural model based on seagull optimization algorithm and aquila optimizer." *Energies,* **15**(24), p.9261.

[41] Borunda, M., Ramírez, A., Garduno, R., García-Beltrán, C. and Mijarez, R., 2023. "Enhancing long-term wind power forecasting by using an intelligent statistical treatment for wind resource data." *Energies,* **16**(23), p.7915.

[42] Su, Z., Zheng, B. and Lu, H., 2023. "A combined model based on secondary decomposition technique and grey wolf optimizer for short-term wind power forecasting." *Frontiers in Energy Research,* **11**, p.1078751.

[43] Wang, H., Li, Y., Xiong, M. and Chen, H., 2023. "A combined wind speed prediction model based on data processing, multi-objective optimization and machine learning." *Energy Reports,* **9**, pp.413-421.

[44] Mohammadi, H., Jokar, S., Mohammadi, M., Kavousi Fard, A., Dabbaghjamanesh, M. and Karimi, M., 2023. "A Deep Learning-to learning Based Control system for renewable microgrids." *IET Renewable Power Generation.*

[45 Karim, F.K., Khafaga, D.S., Eid, M.M., Towfek, S.K. and Alkahtani, H.K., 2023. "A novel bio-inspired optimization algorithm design for wind power engineering applications time-series forecasting." *Biomimetics,* **8**(3), p.321.

[46] Chen, Y., Zhao, J., Qin, J., Li, H. and Zhang, Z., 2023. "A novel pure data-selection framework for day-ahead wind power forecasting." *Fundamental Research,* **3**(3), pp.392-402.

[47] Safari, A., Kheirandish Gharehbagh, H. and Nazari Heris, M., 2023. "DeepVELOX: INVELOX wind turbine intelligent power forecasting using hybrid GWO–GBR algorithm." *Energies,* **16**(19), p.6889.

[48] Ateş, K.T., 2023. "Estimation of short-term power of wind turbines using artificial neural network (ANN) and swarm intelligence." *Sustainability,* **15**(18), p.13572.

[49] Lei, T., Min, J., Han, C., Qi, C., Jin, C. and Li, S., 2023. "Multi-model ensemble forecasting of 10-m wind speed over eastern China based on machine learning optimization." *Atmospheric and Oceanic Science Letters,* **16**(5), p.100402.

[50] Alhussan, A.A., M. El-Kenawy, E.S., Abdelhamid, A.A., Ibrahim, A., Eid, M.M. and Khafaga, D.S., 2023. "Wind speed forecasting using optimized bidirectional LSTM based on dipper throated and genetic optimization algorithms." *Frontiers in Energy Research*, **11**, p.1172176.

[51] Kirchner-Bossi, N., Kathari, G. and Porté-Agel, F., 2024. "A hybrid physics-based and data-driven model for intra-day and day-ahead wind power forecasting considering a drastically expanded predictor search space." *Applied Energy,* **367**, p.123375.

[52] Hanifi, S., Cammarono, A. and Zare-Behtash, H., 2024. "Advanced hyperparameter optimization of deep learning models for wind power prediction." *Renewable Energy,* **221**, p.119700.

[53] R. Singh, A., Kumar, R.S., Bajaj, M., Khadse, C.B. and Zaitsev, I., 2024. "Machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources." *Scientific Reports,* **14**(1), p.19207.

[54] Belletreche, M., Bailek, N., Abotaleb, M., Bouchouicha, K., Zerouali, B., Guermoui, M., Kuriqi, A., Alharbi, A.H., Khafaga, D.S., El-Shimy, M. and El-Kenawy, E.S.M., 2024. "Hybrid attention-based deep neural networks for short-term wind power forecasting using meteorological data in desert regions." *Scientific Reports,* **14**(1), p.21842.

[55] Thaker, J. and Höller, R., 2024. "Hybrid model for intra-day probabilistic PV power forecast." *Renewable Energy,* **232**, p.121057.

[56] Duan, F., Eslami, M., Khajehzadeh, M., Basem, A., Jasim, D.J. and Palani, S., 2024. "Optimization of a photovoltaic/wind/battery energy-based microgrid in distribution network using machine learning and fuzzy multi-objective improved Kepler optimizer algorithms." *Scientific Reports,* **14**(1), p.13354.

[57] Draz, M., Pagel, F. and Albayrak, S., 2024. "Probabilistic risk assessment in power systems with high wind energy penetration." *IEEE Access.*

[58] Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids." *Renewable and Sustainable Energy Reviews,* **144**,

110992.

[59] Mujeeb, S., Alghamdi, T.A., Ullah, S., Fatima, A., Javaid, N. and Saba, T., 2019. "Exploiting deep learning for wind power forecasting based on big data analytics." *Applied Sciences,* **9**(20), p.4417.