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Machine Learning as a Tool to Forecast the Power Quality of wind Energy Power Plants: A Systemic Literature Review

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ABSTRACT

The growing inclusion of renewable energy utilities into the national energy system grid presents an ever-increasing need for a high level of quality in output power injected into the grid. The need for grid expansion to include wind energy renewables requires accurate forecasts of the power quality. The country's grid operator needs real-time accuracy to stabilize and monitor the grid capacity and load demands continuously. The industry currently uses tools to predict the wind energy production power curve. computational intelligence techniques are needed to evaluate the availability of this energy beforehand, due to the variable and unpredictable nature of the wind behaviour. The purpose of this work is to highlight the current research conducted and associated gaps in the field of renewable wind power production forecasting techniques using Machine Learning as a tool to predict the power quality on the national grid. The Preferred Reporting Items for Systemic Review and Meta-Analysis (PRISMA 2020) protocol guides the study. The study drew from several literature sources, most of which focused on forecasting wind power output. The keywords below and Boolean operators were used in our search criteria in Google Scholar, Web of Science, and IEEE Explore. Section II details the exclusion and inclusion criteria employed in this work. There is more research and study that needs to be conducted around machine learning and deep learning algorithms in the wind industry-particularly around forecasting techniques that aim to predict the quality of power generated by wind power plants. The results also show that there are available public datasets. The restriction of this study is the English language papers, forecasting, variable power generation, wind energy, and renewables power quality applications.

Keywords: Grid, Wind Energy, Forecasting, Variable Generation, Renewable Energy, Machine Learning (Ml), Deep Learning (Dl), Algorithms, Power Quality.

INTRODUCTION

The Global Wind Energy Council (GWEC) is forecasting that the worldwide wind-installed capacity is to be over 640 GW in the next five years (2023-27) [1]. This growing market will have a significant impact on power systems developers and maintainers. Institutions of higher learning and research centres are presented with the need to teach and understand this technology in more depth and various applications and connections [2]. The complexity of integrating these energy mixes onto a national grid, looking at the positive and negative effects, modern and cost-effective wind energy projects, and their reliability during their life cycle [2, 3].

Wind power and other distributed generation renewable energy sources like photovoltaic (PV) systems can be connected to the grid or remain unconnected to the grid (stand- alone systems) [4, 5,]. Wind power generation is one of the most attractive renewable power generation technologies [6]. To prevent power fluctuations of wind power due to their intermittent nature (weather conditions variations), some form of reliable additional energy or energy storage is generally needed [4, 5, 6, 7]. Battery bank systems for energy storage are typically used for this. This additional energy slightly increases the reliability and flexibility of generated power, to compensate for the wind power's intermittent nature.

The connection of a wind power plant to the grid needs to be in line with the national grid code of the country. The grid code specifies the power quality that is expected to be injected by the wind generators into the nation's system [6,8].

The South African grid code requires the Renewable Power Plants (RPP) to monitor and report on power quality using an IEC 61000-4-30 Class A power quality monitoring device. The parameters highlighted in line with power quality as stipulated in the code are flicker, harmonics, and unbalanced voltages. Voltage and current quality distortion levels emitted by the power plants must not exceed a set limit as determined by the Network Service Provider (NSP) [6,8]. The paper will review machine learning techniques and applications in the renewable industry. The scope of applications to be covered is limited to forecasting techniques employed in wind generation technology. The paper aims to identify research progress in the renewable energy field and highlight potential datasets that can be used for further research purposes.

Figure 1 below illustrates a typical power-wind speed curve of a wind turbine.

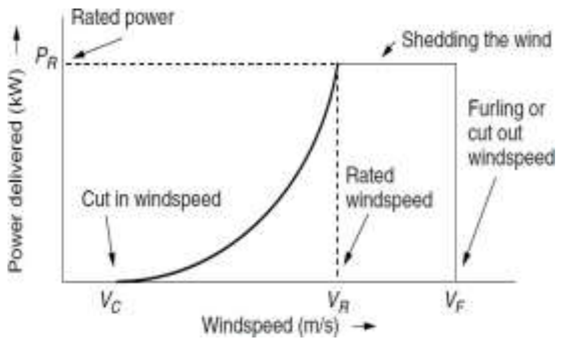

Figure 1. The idealized wind power curve (adapted from [4]).

METHODOLOGY

The PRISMA 2020 guidelines, checklist, and flowchart served as the base for us on how to conduct this systemic review. The following subtopics are covered in this section: eligibility criteria, information sources, search strategy, selection procedure, data collection procedure and data items, bias assessment and reporting, and synthesis method.

2.1 Eligibility Criteria

We initially conducted a random selection of studies from reputable scholarly databases. To ensure data integrity, we imported the Research Information Systems (RIS) files of these studies into Zotero, and VOSviewer where we diligently checked for any potential duplications. Additionally, Zotero played a pivotal role in amalgamating data files sourced from various databases. Any files identified as duplicates were systematically eliminated from our dataset.

Subsequently, we embarked on a rigorous process of identifying literature that harmonized with our research objectives. The initial step involved screening the abstracts of these identified studies. Our approach to screening was a collaborative effort involving two independent reviewers who meticulously assessed the literature. Any inconsistencies were subject to thorough discussion until a unanimous consensus was reached.

Our inclusion or exclusion criteria were based on the following key questions:

a) Does the study align with the specific objectives of our research?
b) Is the study presented in the English language?
c) Does the study primarily address ML algorithms in wind energy?
d) Does the study delve into topics related to forecasting techniques using ML, particularly on wind power plants?
e) How does the quality of the study measure up?

In our evaluation of the literature's quality, we posed the following critical questions:

a) Is the study's primary aim clearly articulated?
b) Does the presented evidence substantiate the study's findings adequately?
c) Do the study's outcomes align with its stated objectives?
d) How well-structured is the overall presentation of the research?

To ensure the relevance and timeliness of our findings, we specifically focused on reviewing published studies within the timeframe of 2004 to 2023. This approach not only enhanced the quality of our findings but also enabled us to gauge the advancements made within the subject matter. Studies failing to meet the criteria outlined above were excluded from our analysis, while those satisfying the criteria were thoughtfully incorporated into our study.

2.2 Information Sources

We analyze in the review, the documents published for electric power forecasting contained in SCOPUS, Web of Sciences, Science Direct, Multidisciplinary Digital Publishing Institute (MDPI), and the Institute of Electrical and Electronics Engineers (IEEE), according to the criteria shown in Figure 2 and following the steps of the PRISMA methodology [9].

We sourced our literature from reputable and credible sources, including Google Scholar, Web of Science, and IEEE Xplore. It's important to note that due to subscription constraints, we were only able to access abstracts from IEEE Xplore and Google Scholar. Despite this limitation, we successfully identified and collected several pertinent publications from these sites.

Figure 2. Search methodology for information sources [9].

Our data collection process concluded in November 2023, representing the latest available information from these databases.

2.3 Search Strategy

We systematically conducted literature searches by employing a specific pattern. To identify relevant studies, we utilized a set of keywords and Boolean operators, including **"Forecasting power," "Wind generation", "Deep Learning", "Machine Learning in Renewables," "Power Quality in Renewables," and "Grid code wind parameters."** These search terms were carefully chosen to encompass a wide spectrum of related literature.
Additionally, we applied an English language filter to ensure our focus on studies written in the English language, thus enhancing the relevance and accessibility of the literature.

2.4 Selection Process

Our literature search yielded 368 potential papers from the designated sources, with Google Scholar contributing the most (244) and MDPI the least (15). After removing duplicates (43) and screening abstracts (271), we retrieved 105 full-text articles for further assessment. Based on our defined eligibility criteria, we ultimately included 87 studies in our final dataset. Fig.3 below details the selection process and our specific inclusion/exclusion criteria.

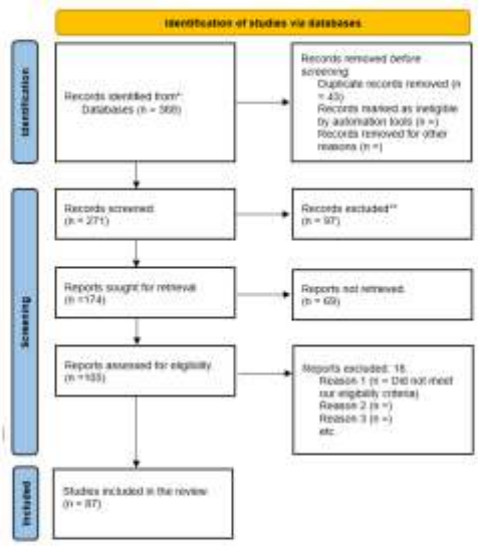

Figure 3. PRISMA 2020 inclusion and exclusion flow diagram (edited).

The collected data for each application and the number of data items for each application are illustrated in Fig.4 below

2.5 Data Collection Process And Data Items

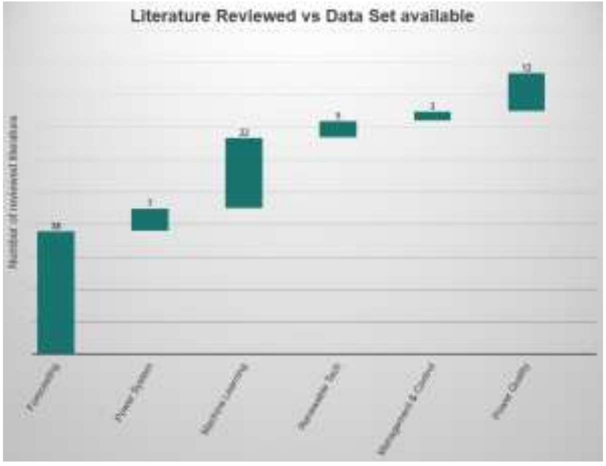

Figure 4. Number of reviewed papers for each application and the publicly available dataset.

To ensure methodological rigor, we employed a two- reviewer screening process with independent literature selection followed by consensus discussions to resolve any discrepancies. While we primarily relied on credible databases for literature mining, 9 abstracts were included despite limited access. We recognize that this inclusion may introduce potential bias and influence the generalizability of our findings. Therefore, we ultimately narrowed the review to 9 out of the initial 87 studies identified.

2.6 Synthesis Method

We leveraged histograms as a key tool in our qualitative examination of study objectives. By visually exploring the distribution of data from individual applications and publicly available datasets, we were able to identify patterns and trends that might have been obscured by traditional numerical analysis. This is illustrated below.

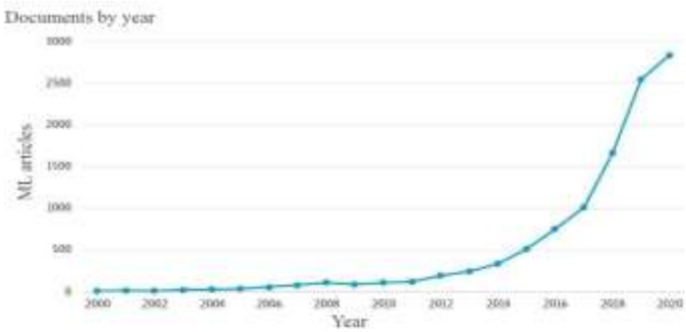

Figure 5. Frequency chart illustrating the number of articles on ML and deep DL within the energy systems domain (adapted from [9, 10]).

This trend, particularly pronounced since 2012, is fueled by the growing sophistication of DL techniques and their potential to tackle complex energy challenges with unprecedented accuracy and efficiency. As ML and DL continue to infiltrate the field, their impact on analysis, optimization, and ultimately, the future of energy systems, promises to be immense [10, 11].

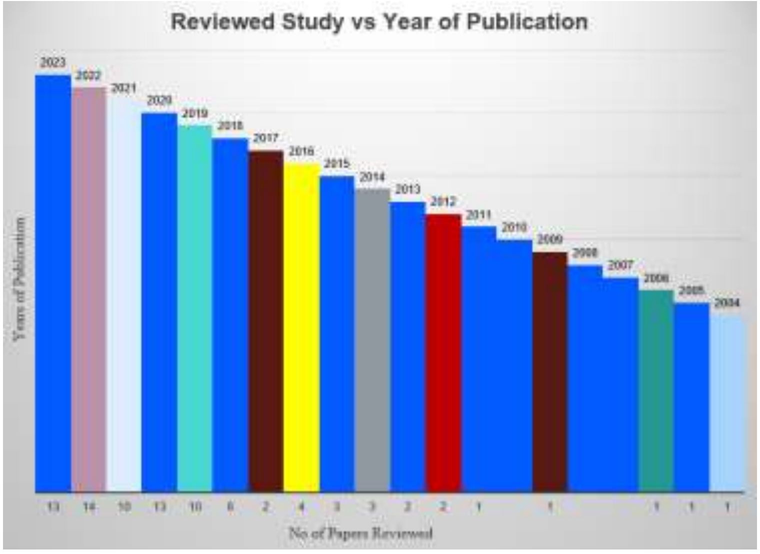

Figure 6. Number of reviewed papers and their respective year of publication.

LITERATURE REVIEW

3.1 An Overview of Studies Focusing on ML-Based Forecasting in Renewable Energy

The exponential growth of ML research in energy systems, showcased in Figure 5, speaks volumes about its rapidly escalating significance. Figure 7, generated using VOSviewer software, presents a visual representation of the interconnectedness of various subfields within energy systems through their association with ML and DL [10].

The diameter of each circle corresponds to the frequency of its associated keyword, with larger circles indicating greater occurrence in the analyzed articles. An interesting observation emerges within the realm of energy-related AI research, the terms "machine learning" and "deep learning" appear more frequently than "artificial intelligence" itself. This may be attributed to the software's focus on keyword prominence within published articles, leading to a smaller diameter for the broader term ("artificial intelligence") compared to its more specific subfields ("machine learning" and "deep learning") [10].

It is crucial to note that VOSviewer specializes in constructing and visualizing bibliometric networks, providing insights into the relationships between research areas based on textual analysis [10].

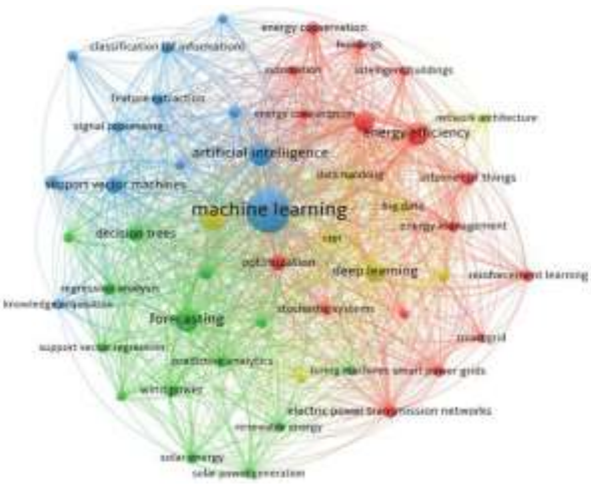

Figure 7. Diverse facets of ML and DL within the domain of energy systems (adapted from [10].)

A critical review of the extant literature in this field reveals that most applications typically rely on a confined subset of approximately 10 well-established ML algorithms [10, 12].
While these algorithms have demonstrably yielded effective results, a potential deficit in terms of creative exploration and algorithmic innovation is apparent. This observation suggests a promising avenue for future research: investigating the applicability of a more diverse repertoire of ML and DL algorithms, including techniques such as Convolutional Neural Networks (CNNs) and Long Short- Term Memory (LSTM) networks [10, 12].
Further research should not only focus on expanding the algorithmic toolbox but also delve into more imaginative applications of ML and DL within energy systems. This includes exploring areas with seemingly indirect yet potentially impactful applications [10].

Table 1 below provides a comprehensive overview of various ML and DL algorithms commonly utilized in power systems applications. It systematically contrasts their advantages and disadvantages across diverse scenarios, enabling informed selection of the most suitable technique for specific tasks within the power domain [13].

Table 1. ML/DL Techniques Pros & Cons Overview Table (adapted from [13])

Technique	Pros	Cons	Applications
Recurrent Neural Network (RNN)	The system can process sequential data and time series data, and it can handle long-term dependencies.	Prone to overfitting, slow training, and may suffer from vanishing or exploding gradients.	Energy price forecasting (time series), speech recognition, and sentiment analysis
LSTM	The model can effectively manage long-term dependencies, making it particularly valuable for analyzing time series data.	Prone to overfitting and may require careful tuning.	Time series, speech recognition, natural language processing, load forecasting, and energy price forecasting (time series)
Autoencoders	Can reduce dimensionality and noise in data and it can be used for unsupervised learning	Large amounts of data are required, and interpretation can be challenging.	Anomaly detection, image, and speech recognition
Extreme Learning Machine (ELM)	Fast training; capable of handling large datasets.	Models with limited interpretability may not generalize well to new data.	Renewable energy forecasting, image and speech recognition, predictive analytics
General Regression Neural Network (GRNN)	Fast training and capable of handling noisy data.	It is limited to regression tasks and may not scale well with large datasets.	Renewable energy forecasting, time series prediction, and function approximation

Rotated Binary Neural Network (RBNN)	It is effective for non-linear regression and classification tasks	It requires careful tuning of network architecture and hyperparameters	Image and speech recognition, anomaly detection

Table 1 cont. ML/DL Techniques Pros & Cons Overview Table (adapted from [13])

Technique	Pros	Cons	Applications
Wavelet Neural Network (WNN)	Capable of handling multi-resolution and multi-scale data	Careful selection of wavelet basis functions is necessary, but this process can be computationally expensive.	Image and signal processing, time series prediction
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Capable of handling uncertainty and non-linearity in data	Careful selection and tuning of fuzzy rules and can be computationally expensive	Control systems, fault diagnosis
Deep Belief Network (DBN)	Able to learn hierarchical representations of data, which is effective for unsupervised learning	Large amounts of data are required and interpreting it can be challenging.	Image and speech recognition, natural language processing
Ensemble Learning	Able to improve performance and reduce overfitting by combining multiple models	Can be computationally expensive and may require careful tuning	Renewable energy forecasting, image and speech recognition, and natural language processing
Transfer Learning	Capable of leveraging pre-trained models to improve performance and require less data	The model may not perform well on new data and is limited to similar tasks.	Applications in Forecasting, Diagnostics, Recognition, and NLP
Linear Regression	Easy to implement, quick training	Limited to linear relationships	Predictive analytics
Logistic Regression	Easily understandable and performs effectively with small datasets.	Supposes linearity, It only applies for classification	Predict power outages, classify extreme weather events, market, and healthcare
Decision Trees	Understandable, can handle both categorical and continuous data	Prone to overfitting	Predictive maintenance, finance

Table 1 cont. ML/DL Techniques Pros & Cons Overview Table (adapted from [13])

Technique	Pros	Cons	Applications
Random Forest	High accuracy, less prone to overfitting	Computationally expensive compared to DT, difficult to interpret	Operation control strategy, image classification, and fraud detection
Support Vector Machines (SVM)	Capable of handling high-dimensional data, can handle non-linear relationships, robust to noise	This process is computationally intensive and requires careful parameter tuning.	Text classification, bioinformatics
K-means clustering	Simple and fast, useful for data exploration and segmentation	Requires a pre-determined number of clusters and can be sensitive to initial conditions	Market segmentation, image segmentation
Principal Component Analysis (PCA)	Able to reduce dimensionality and noise in data, useful for data exploration and visualization	The information may not cover everything and could be hard to understand.	Image and speech recognition, natural language processing
Reinforcement Learning	Can learn through trial and error, useful for decision-making in dynamic environments.	Requires a lot of data and can be prone to overfitting	Game playing, robotics
Artificial Neural Networks (ANN)	The system can understand intricate connections, process extensive datasets, and represent non-linear relationships.	Requires large amounts of data and can be difficult to interpret	Predict energy demand (stationary), energy resource forecasting, image recognition, and speech recognition
CNN	Highly effective for image analysis, it can learn features automatically	Needs a lot of data, is computationally expensive, not suitable for low spatial or temporal resolutions	Object detection, image classification, and predicting energy demand based on satellite images of areas

As the surge of renewable sources continues, precise predictions are becoming imperative for efficient energy management strategies. This review comprehensively surveys extant literature, encompassing both journal articles and conference proceedings, to provide an in-depth understanding of the present state of machine learning-based forecasting in renewable energy.

3.2 Wind Energy Forecasting:

Due to the inherent non-linearity and stochastic nature of wind energy, characterized by unpredictable fluctuations and uncontrollable behaviour, accurately predicting its output remains a significant challenge. This necessitates the development of efficient and robust forecasting models to ensure consistent power generation from wind sources [14, 15, 16, 17].

3.2.1 Categorization of Wind Power Forecasting

Research in wind power forecasting can be broadly categorized based on the predicted time horizon:

i. Short-term Wind Power Forecasting

This category focuses on predicting wind power for relatively short periods, typically ranging from one hour to several consecutive days [18]. These techniques are crucial for operational tasks in power grid management, such as scheduling energy resources and maintaining a stable electricity supply [19, 20].

ii. Long-term Wind Power Forecasting

This category extends the prediction scope to longer timescales, often ranging from a few days to a year [18, 19]. Such forecasts are vital for strategic planning in the energy sector, including capacity expansion, market participation, and investment decisions.

3.2.2 Methodological Approaches

Wind energy forecasting encompasses a diverse range of techniques and models, each catering to the specific challenges and requirements of their respective time horizons [21]. These methodologies can be classified into various categories, such as:

i. Statistical Models

These leverage historical wind data and relevant meteorological parameters to establish statistical relationships and predict future power output. Common examples include autoregressive models, time series analysis, and statistical learning algorithms [22, 18].

ii. Historical Data Analysis

This approach involves a comprehensive examination of extensive historical meteorological datasets, encompassing wind speed, direction, atmospheric pressure, and other relevant variables. The primary objective is to uncover patterns, trends, and seasonal variations within this data that can inform future wind predictions [23, 24].

- **Time Series Analysis**: This is a commonly employed statistical technique for analyzing historical data series. It involves decomposing the data into components like trend, seasonality, and random fluctuations to understand underlying patterns and forecast future values [25].
- **Regression Analysis:** This technique establishes relationships between wind speed and other meteorological variables, such as temperature, pressure, and humidity. By identifying these relationships, regression models can predict wind speed based on forecasted values of the associated variables [26, 27].
- **Anemometer Data Analysis:** Focuses on using real-time data collected from on-site anemometers, which measure wind speed and direction at the specific location of a wind farm. This high-resolution data enables short-term wind forecasting and plays a crucial role in operational decision-making [28-29].

Advanced statistical techniques to analyze anemometer data effectively, such as techniques like time series analysis, machine learning algorithms (MLA), and ANN are often employed.

These methods can extract complex patterns and relationships within the data to generate accurate short-term wind forecasts [20, 23, 30, 31, 32].

3.2.3 Physical Models

These rely on Numerical Weather Prediction (NWP) models to simulate atmospheric dynamics and generate forecasts of wind speed and direction. These forecasts are then translated into predicted power output using wind turbine power curves [30].

i. Wind Flow Models

These models apply mathematical and physical principles to simulate the behaviour of wind flow across a designated geographical area. Computational Fluid Dynamics (CFD) techniques are often central to this approach, offering high-steadiness simulations of the intricate interactions between wind, terrain features, and atmospheric conditions like turbulence and temperature gradients [13,33] The resulting wind resource maps assist in assessing potential wind farm locations, optimizing turbine layout, and minimizing environmental impacts [13].

ii. Wake Models

These models focus on the wake effect, where the upstream turbine's flow disruption impacts the wind speed and power output of downstream turbines. By incorporating wake models, wind farm developers can accurately estimate the power production reduction in downstream turbines, enabling optimal turbine placement and maximizing overall energy generation [13, 34].

3.2.4 Hybrid Models

While individual forecasting methods have their strengths and limitations, hybrid models offer a promising approach. These models combine elements from statistical and physical approaches, effectively leveraging the strengths of each while mitigating their weaknesses. This harmonious approach often results in more robust and accurate forecasts, particularly for longer lead times [12, 35, 36, 32]. Several hybrid techniques have emerged in recent years, each offering unique advantages:

i. Ensemble Forecasting

This technique involves running multiple simulations with slight variations in initial conditions. The resulting spread of outcomes provides a valuable quantification of forecast uncertainty, enhancing decision-making even amidst inherent complexities [25, 37-38].

ii. Machine Learning Approaches

MLAs hold significant promise for unlocking hidden patterns and relationships within wind data. Some prominent examples include:

ANNs: These algorithms, inspired by the human brain, excel at learning complex non-linear relationships between input features (meteorological variables) and wind power output. ANNs can effectively capture intricate dependencies and capture hidden patterns within data, leading to robust predictions [39, 40].

SVMs: leverage powerful algorithms to classify and predict wind speed or power production based on historical data. They are particularly adept at handling high-dimensional data and can deliver accurate forecasts, especially in situations with complex influencing factors [40].

Random Forests and Ensemble Methods: These techniques combine predictions from multiple decision trees, resulting in improved overall accuracy and robustness. This approach is particularly beneficial in the presence of uncertainties and complex data structures, further enhancing the reliability of wind energy forecasts [41,42].

3.2.5 Integration of Remote Sensing Technologies:

The incorporation of data from remote sensing technologies like Lidar (Light Detection and Ranging) and Sodar (Sonic Detection and Ranging) systems adds another layer of valuable information to wind forecasting models. These systems measure wind characteristics at various altitudes, providing an enhanced understanding of wind dynamics and improving the accuracy of predictions, especially for longer lead times [43, 44].

By embracing hybrid models and integrating diverse data sources, wind energy forecasting continues to evolve toward greater accuracy and reliability. This advancement contributes significantly to optimizing renewable energy integration, enhancing grid stability, and paving the way for a sustainable energy future [31, 45, 46].

3.2.6 Further Development

Forecasting wind energy remains a dynamic field of research, marked by sustained endeavours to enhance the accuracy, reliability, and lead time of prediction models. This ongoing research bears substantial implications for optimizing the integration of renewable energy, fortifying grid stability, and fostering a sustainable energy future. Wind energy forecasting often embraces a blended approach involving various methods, acknowledging that a multifaceted strategy can enhance the precision and reliability of predictions. The choice of a specific method depends on factors such as the forecasting scope, data availability, and the unique characteristics of the wind farm [13, 47].

3.3 Studies that Employ MLAs for a Distinct Set of Wind Energy Forecasts

ML and DL have significantly propelled the field of renewable energy forecasting, but challenges remain for further advancement. These challenges pertain to crucial factors influencing model accuracy, such as the choice of ML/DL algorithms, the selection of appropriate input data, and the effective handling of missing data [13].

Additionally, the development of robust and interpretable models is crucial for providing valuable insights into the intricate factors that impact renewable energy generation, ultimately fostering deeper understanding and improved forecasting capabilities.

ML techniques extend their capabilities beyond forecasting to optimizing the management of renewable energy systems. By predicting generation patterns, these techniques enable enhanced efficiency and effectiveness in these systems [13].

Recognizing the diverse strengths and weaknesses of different MLAs, researchers categorize them into three primary groups: supervised learning, unsupervised learning, and reinforcement learning [13, 45].

3.3.1 Supervised Machine Learning: Guiding Models with Labeled Data

Within the realm of ML, supervised learning stands as a fundamental approach that empowers algorithms to learn from meticulously labeled data. In this paradigm, the training dataset consists of carefully curated input-output pairs, where the input represents the data the model will learn from, and the output signifies the desired outcome or target value [13, 48].

This structured approach enables the model to discern patterns and relationships within the data, subsequently applying these insights to make predictions or classifications on new, unseen data. Supervised learning encompasses two primary subcategories, each with distinct purposes:

i. Regression

Algorithms within this category excel at predicting continuous numerical values. Examples include forecasting wind power generation levels, estimating energy consumption patterns, or predicting the degradation rate of solar panels [25,27].

ii. Classification

Algorithms in this domain focus on predicting discrete categories or classes. Applications in renewable energy might involve classifying the operational status of wind turbines (active or idle), identifying anomalies in energy consumption data, or detecting faults within solar panel systems [49, 50].

These subcategories are illustrated in the figure below.

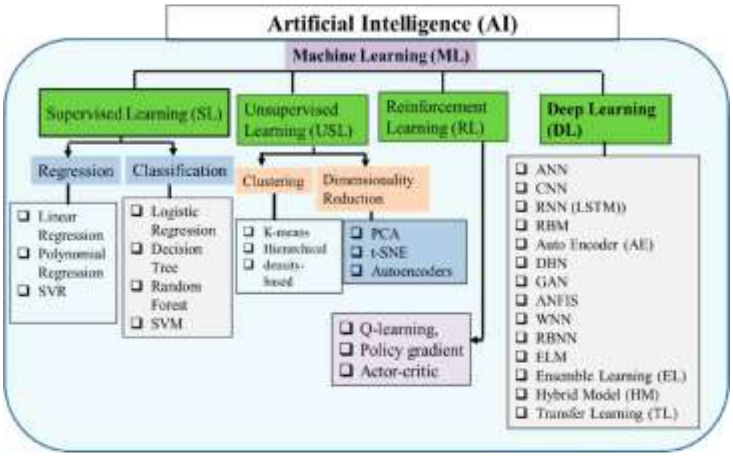

Figure 8. MLAs, their Categories, and Types (adapted from [13]).

iii. Forecasting Based on ANN and Least Squares (LS) -SVM:

- **SVM for Fault Identification in Power Transformers:** Effective Fault Classification: SVMs demonstrate significant potential for accurately identifying various faults in power transformers, including energy discharge, partial discharge, and thermal faults, based on Dissolved Gas Analysis (DGA) data [40,51].
- **Superior Performance**: SVMs have outperformed other classification techniques, such as Genetic Algorithms (GAs), Fuzzy Logic (FL), and Back Propagation (BP) algorithms, highlighting their efficacy in this domain [40].
- **Kernel Optimization**: Employing kernel function estimation and radial basis function computation enhances the classification accuracy of SVMs, contributing to their overall effectiveness [38, 40].
- **LS-SVM with Wavelet Decomposition (WD) for Wind Power Prediction**: Complex Terrain Performance: An example would be a comparative study evaluating the performance of LS-SVMs combined with WD for predicting power production in a wind farm located in complex terrain [52].
- **Time Horizon Analysis**: The study assessed the performance of LS-SVM with WD across different time horizons to gain insights into its accuracy and suitability for short-term, medium-term, and long-term predictions [40].
- **Comparison with ANN Methods**: The results of LS-SVM with WD were compared with hybrid ANN-based methods to determine the most effective approach for wind power prediction in challenging terrain scenarios [40].

iv. Wavelet-Based Forecasting for Improved Wind Power Prediction

- **Data Decomposition**: WD techniques effectively separate time series data (wind speed, temperature, pressure) into distinct frequency bands, unveiling daily, seasonal, and long-term patterns [40, 53].
- **Discrete Wavelet Transform (DWT) Algorithm**: This algorithm, developed by Mallat [40], employs decomposition and reconstruction techniques, along with low-pass and high-

pass filters, to extract approximations (low-frequency representations) and details (high-frequency components) from the original signal.

- **Model Performance Enhancement:** Incorporating WD into forecasting models often leads to improved accuracy and captures nuanced patterns within complex time series data [40, 51].

v. k-Nearest Neighbors (kNN) Algorithm

kNN): A Popular Supervised Learning Tool for Power Systems. In the realm of machine learning for power systems, kNN algorithm reigns as a widely utilized supervised learning technique. It excels at data classification by leveraging distance computations to identify the k closest data points to a new, unlabeled observation.

This nearest neighbour concept forms the basis for assigning the new data point to the most prevalent class among its k closest neighbours [54]. The strength of kNN is in the simplicity of its implementation. kNN frequently delivers robust and reliable classification performance, particularly for well-defined data spaces with clear class distinctions.

Limitations of kNN are computational burden with large datasets. The versatility of kNN extends to multiple facets of power system analysis and management: This algorithm often forms an integral part of fault recognition systems for power transformers. By analyzing sensor data and comparing it to known faulty states represented by k-nearest neighbours, the algorithm can effectively identify potential equipment malfunctions. kNN plays a crucial role in understanding the operational behaviour of power transformers. It achieves this by classifying historical data under various operating conditions. Crucial understandings can be gathered into performance trends and potential optimization strategies. Within the domain of asset management for power systems, kNN frequently finds itself compared to other prominent ML models such as SVMs, ensemble methods, and decision trees [55, 56]

vi. Convolutional Neural Networks

CNNS are widely used in wind power forecasting for their capacity to capture complex relationships within data. They are capable of regressing intricate non-linear relationships with commendable accuracy [18].

vii. Restricted Boltzmann Machines (RBMs)

RBMs are supervised neural networks that learn complex probability distributions over input data. They consist of two layers with binary nodes, offering feature extraction capabilities. Largely used as a pre-processing step to enhance forecasting models like neural networks [13].

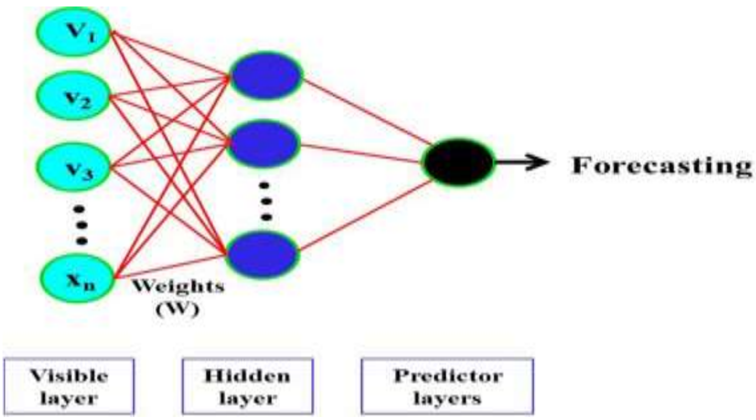

Figure 9. RBM forecasting architecture (adapted from [13]).

3.3.2 Unsupervised Learning for Wind Power Forecasting:

i. Auto Encoder for Renewable Energy Forecasting:

While supervised learning algorithms dominate wind power forecasting, unsupervised learning techniques like autoencoders offer valuable insights by extracting hidden patterns and features from vast datasets.

Built on deep neural networks, autoencoders excel at feature extraction and dimensionality reduction, making them ideal for preparing data for subsequent forecasting models [13, 57].

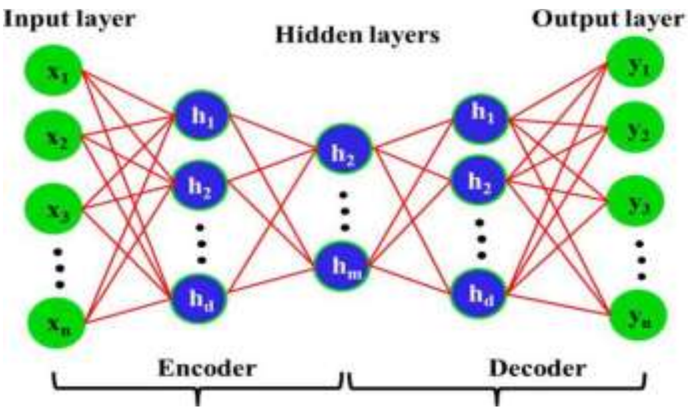

Figure 10. The autoencoder's basic design (adapted from [13]).

In the context of wind power forecasting, autoencoders can be employed in several ways:

- **Feature Extraction from Diverse Data:** Autoencoders can process a variety of data relevant to wind power generation, including weather data (wind speed, direction, temperature), historical energy production records, and geographical information. By analyzing these diverse inputs, the autoencoder learns to identify hidden patterns and relationships, extracting meaningful features that capture the underlying dynamics of wind energy production [13, 58].
- **Enhanced Supervised Learning Models**: The extracted features generated by the autoencoder can then be used to train supervised learning models, such as SVMs or ANNs. These enriched feature sets provide the forecasting models with a more exact understanding of the influencing factors, leading to improved prediction accuracy and reduced error rates [59].
- **Dimensionality Reduction for Efficiency**: Autoencoders excel at reducing the dimensionality of complex datasets, which is particularly advantageous in wind power forecasting due to the abundance of high-dimensional data. This dimensionality reduction can significantly improve computational efficiency while still preserving the essential information needed for accurate forecasting [10, 13].
- **Conclusion:** Autoencoders offer a promising avenue for unsupervised learning in wind power forecasting. Their ability to extract meaningful features, reduce data complexity, and enhance supervised models makes them valuable tools for improving forecasting accuracy and efficiency. As research in this area continues, we can expect even more advanced applications of autoencoders to emerge, further optimizing the management and integration of renewable energy sources into the grid.

ii. K-means Clustering

This algorithm identifies groups (clusters) of similar data points within wind power datasets, revealing underlying patterns and enabling the development of specialized forecasting models for each cluster [13].

- **PCA:** By projecting high-dimensional wind power data onto a lower-dimensional space, PCA identifies the most relevant features while reducing computational complexity. This allows for improved interpretability and model efficiency [13].

- **Gaussian Mixture Models (GMMs):** GMM models the probability distribution of wind speed, enabling probabilistic forecasting. This provides not just a single prediction but a range of possible outcomes with their respective probabilities, catering to the inherent variability of wind power [13, 60].
- **Self-Organizing Maps (SOMs):** SOMs visualize wind power data on a grid, automatically clustering similar data points. This visual representation aids in identifying anomalies and hidden patterns, facilitating proactive maintenance and enhanced system reliability [56, 60].

3.3.3 Deep Reinforcement Learning for Asset Management

Deep reinforcement learning (DRL) offers promising avenues for improving asset management in renewable energy systems. Key aspects of DRL in this context include:

i. **Contextual Information Analysis:** Extracting meaningful insights from data under noisy conditions, such as fluctuating energy production.
ii. **Price-Action Estimation:** Learning optimal pricing strategies and scheduling decisions based on real-time market dynamics.
iii. **Time-Dependent Data Analysis**: Adapting to changing environmental and market conditions through dynamic decision-making.

Several studies demonstrate the potential of DRL for asset management:

- DRL for power quality control in electric grids, highlighting reduced design complexity and enhanced decision-making [61].
- Hybrid DRL-ANN model for optimal electricity trading, solving linear cost function problems in power flow optimization [62].
- Reference [63]. Adaptive DRL for improved power storage efficiency in hybrid systems, utilizing generation, storage, load, and controllable asset indicators.
- DRL-ANN integration for power grid maintenance, enhancing system reliability [64].
- Machine learning solutions for smart grid challenges, focusing on asset maintenance, power generation, load management, and safety data analysis [65].

3.3.4 DBNs for Forecasting

DBNs are deep neural networks composed of stacked RBMs. Like RBMs, DBNs are unsupervised learning models trained to extract features and representations from input data, particularly relevant for renewable energy forecasting. DBNs employ a layer-wise unsupervised learning approach, where each layer independently extracts features from data, leading to a rich and informative representation suitable for forecasting tasks [10,13].

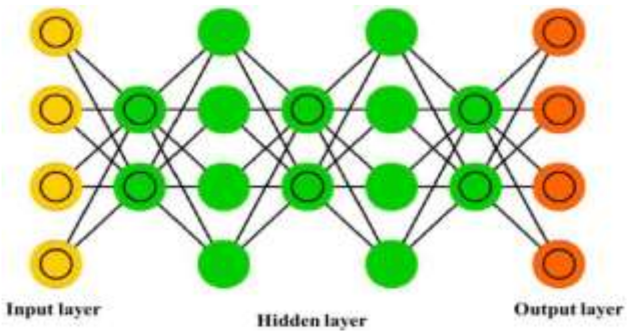

Figure 11. The basic architecture of DBN (adapted from [84]).

DBNs are powerful tools for renewable energy forecasting due to their ability to extract complex features. DBNs can learn from unlabeled data, which is abundant in renewable energy applications [13].

i. **ANFIS:** This hybrid model combines the strengths of ANNs for learning from data and fuzzy logic for handling uncertainty. With the Capability of modelling complex relationships between inputs and outputs, making it suitable for forecasting tasks [13, 66]. Its structure consists of five interconnected layers:

- **Input Layer:** Accepts input data.
- **Fuzzification Layer**: Converts crisp input values into fuzzy membership degrees.
- **Rule Layer**: Specifies fuzzy rules that relate inputs to outputs.
- **Normalization Layer**: Normalizes rule firing strengths.
- **Output Layer**: Defuzzifies output values and generates a final crisp output.

Widely used in renewable energy forecasting due to its ability to capture both linear and nonlinear patterns in data. ANFIS demonstrated superior performance with trapezoidal membership functions for wind speed and temperature prediction, achieving a mean square error of 7.2989 m/s for wind speed and 3.8364 °C for temperature [23, 66].

Additional Insights:

- **Parameter Optimization**: ANFIS employs hybrid learning algorithms to refine both premise and consequent parameters, enhancing model accuracy.
- **Interpretability**: The fuzzy rules within ANFIS can provide insights into the model's reasoning process, making it more understandable than purely black-box models.
- **Adaptability**: ANFIS can adapt to changing conditions and learn new patterns over time, making it suitable for dynamic environments like renewable energy systems [13].

ii. **RBNNs:** Possess a distinct structure and activation functions for specialized tasks. It excels at capturing nonlinear relationships and temporal dependencies in data. Its structure consists of three layers:

- **Input Layer**: Accepts input data.
- **Hidden Layer**: Contains radial basis function neurons that compute distances between input vectors and their centers.
- **Output Layer**: Produces the network's output based on weighted combinations of hidden layer activations.

Frequently used in renewable energy forecasting due to their ability to model complex patterns in wind speed, temperature, and energy generation data [13, 67].

iii. **GRNNs***:* Excel at predicting continuous quantities, making them invaluable for forecasting tasks in renewable energy. Their architecture comprises four distinct layers [13, 68]:

- **Input Layer**: This layer accepts the input data, which may be a single vector or a collection of vectors.
- **Pattern Layer**: Here, the network meticulously compares the input data to a set of stored prototypes, calculating the similarity between them. These prototypes act as reference points for prediction.
- **Summation Layer**: This layer aggregates the weighted outputs from the pattern layer, using the similarity values determined in the previous step.
- **Output Layer**: The final layer generates a continuous prediction based on the processed information.

GRNNs are trained through a process known as radial basis function (RBF) learning, effectively handling nonlinear relationships and noisy data. Capabilities: GRNNs can effectively model complex nonlinear relationships, which are often inherent in wind speed, solar irradiance, and energy demand patterns [13, 50].

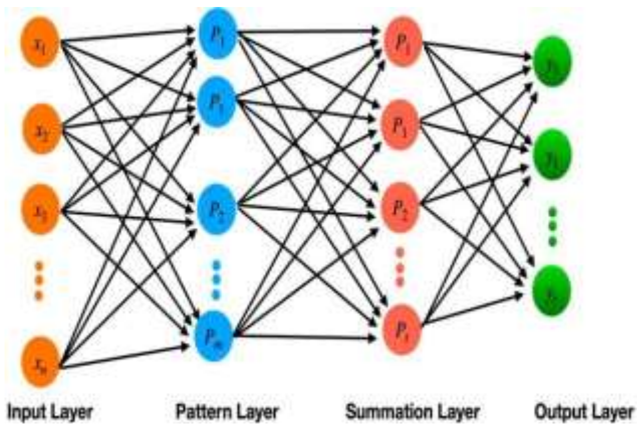

Figure 12. The schematic representation of GRNN (adapted from [13]).

Conclusion: Generalized regression neural networks provide a valuable tool for renewable energy forecasting, particularly when dealing with uncertain and complex data. Their robustness to noise, nonlinear modelling capabilities, and fast training make them well-suited for various forecasting tasks in this domain. However, it's essential to consider prototype selection and interpretability challenges when employing GRNNs [13].

iv. ELMs

Their structure and training models consist of:

- Single hidden layer of neurons
- Input and output layer connections are determined analytically using matrix inversion.
- Eliminates iterative gradient-based training, leading to computational efficiency.

Applications in Renewable Energy include Wind power prediction and Solar power forecasting [13,69].

Conclusion: ELMs offer a promising approach to renewable energy forecasting due to their computational efficiency, ease of implementation, and good generalization performance. Their fast training makes them particularly suitable for real-time forecasting applications. However, researchers and practitioners should carefully consider hyperparameter tuning and the choice of the number of hidden neurons to achieve optimal performance [13, 50].

v. Ensemble Learning (EL): Leverages the combined strengths of multiple individual machine-learning models to generate more accurate and robust predictions than any single model could achieve [13, 70]. This strategy is particularly beneficial when dealing with complex, noisy, or highly variable data, like those encountered in renewable energy forecasting.

The benefits are improved accuracy and reduced variance. EL mitigates the impact of individual model bias and variance, yielding more stable and reliable predictions [13].

Conclusion: EL offers a powerful and versatile approach to tackling the challenges of renewable energy forecasting. Its ability to leverage the strengths of multiple models, improve accuracy and robustness, and provide valuable insights makes it a valuable tool for ensuring efficient and reliable renewable energy integration into the power grid.

vi. Transfer Learning (TL): Leverages pre-trained models from related tasks to enhance forecasting accuracy and efficiency. Addresses challenges of data scarcity and computational resources. Applied in wind power prediction: The models are trained on weather patterns or other wind farms. With solar power forecasting, the models are pre-trained on cloud cover images or solar irradiance data. In energy demand forecasting, the models are pre-trained on historical consumption patterns [13,71].

Conclusion: TL holds significant promise for addressing challenges and enhancing renewable energy forecasting accuracy and efficiency. By effectively harnessing knowledge from pre-trained models, it can contribute to more reliable and cost-effective integration of renewable energy sources into power grids.

vii. **Hybrid Models (HMs):** Combine multiple machine-learning techniques within a single framework to enhance the accuracy and robustness of renewable energy forecasts. This approach leverages the strengths of individual models while compensating for their limitations, leading to superior performance compared to single-model approaches.

Applications in renewable energy forecasting include short- term forecasting: In this area, HMs have proven effective in forecasting renewable energy sources like solar power and wind speed within short timeframes (e.g., one day) [13,72].
Conclusion: HMs offer a powerful and versatile approach to tackle the challenges of renewable energy forecasting. By combining the strengths of multiple MLTs, they can significantly improve prediction accuracy, robustness, and flexibility. Careful consideration of model selection, integration, and interpretability is crucial for unlocking the full potential of HMs in advancing the field of renewable energy forecasting and its integration into efficient and reliable power grids.

3.4 MLTs to Forecast Specific Power Quality Parameters in Wind Energy

Predicting specific power quality parameters in wind energy plays a crucial role in maintaining grid stability, minimizing downtime, and optimizing wind farm operations [73]. Traditional fault analysis methods can be time-consuming and require significant expertise. ML offers promising alternatives for faster and more efficient prediction of power quality parameters, leading to improved wind farm performance and reliability [74].
Wind turbine systems consist of both mechanical and electrical components, making fault diagnosis complex. Additionally, wind power generation is highly variable due to fluctuating wind speeds and environmental conditions. These factors pose challenges for ML models in accurately predicting power quality parameters [75].

3.4.1 Several ML Techniques that Have Shown Potential for Power Quality Parameter Forecasting in Wind Energy:

i. **SVMs:** SVMs are effective in identifying non-linear relationships between wind farm data and power quality parameters [40].
ii. **ANNs:** Anns can learn complex patterns from large datasets, enabling robust prediction of various parameters [40].
iii. **DL:** DL employs techniques like CNNs and RNNs that excel at handling temporal and spatial dependencies in wind turbine data [25,76].
iv. **Random Forests:** These are ensemble models that combine multiple decision trees, offering high accuracy and robustness against noise [77].
v. **Application Examples:**

- **Voltage sag and swell prediction**: Utilizing SVM or ANN models to anticipate voltage deviations caused by grid disturbances or sudden changes in wind speed.
- **Harmonic distortion forecasting**: Employing CNNs or RNNs to predict the occurrence and severity of harmonic distortions generated by wind turbine converters.
- **Mechanical fault detection**: Leveraging random forests or anomaly detection algorithms to analyze sensor data and identify potential mechanical issues in wind turbine components [10].

3.4.2 Here are some specific ML techniques that can be used to forecast power quality parameters in wind energy:

i. Time Series Forecasting

- **Autoregressive Integrated Moving Average (ARIMA):** This classic time series model can capture temporal dependencies in power quality data, making it suitable for predicting short-term fluctuations in parameters like voltage, current, and harmonics [16, 78-79].
- **LSTM networks:** These powerful recurrent neural networks excel at capturing long-term dependencies and complex nonlinearities in time series data, making them well-suited for predicting wind power output, voltage sags, and other dynamic parameters [16, 78-79].
- **Prophet**: This open-source forecasting library from Facebook combines multiple statistical and machine learning techniques, including ARIMA and LSTMs, to offer flexible and accurate forecasting for various power quality parameters [16, 78-79].

ii. Anomaly Detection*:*

- **One-Class Support Vector Machines (OCSVMs):** These models can learn the normal operating range of power quality parameters and identify any deviations as potential anomalies, indicating potential faults [10,12].
- **Isolation Forests**: These tree-based models isolate anomalies by randomly partitioning the data, making them efficient for identifying outliers and abnormal behaviour in power quality data [16, 78-79].
- **Autoencoders:** These neural networks can learn compressed representations of normal data and flag deviations as anomalies, offering flexibility for handling diverse types of power quality parameters [40].

iii. Regression Models:

- **Support Vector Regression (SVR):** This robust regression technique can model the relationships between operating conditions and power quality parameters, allowing for the prediction of specific values based on sensor data [26- 27].
- **Random Forest Regression**: This ensemble method combines multiple decision trees to predict continuous power quality parameters, offering good generalizability and robustness to outliers [23].
- **Neural Regression Networks**: Multilayer perceptron and other neural network architectures can be trained to directly map sensor data to specific power quality parameters, providing flexible modelling capabilities [24,41].

Studies have shown that ML models applied to wind energy fault detection can achieve a 20% reduction in false alarms, while also providing valuable data for identifying the root cause of faults within 50% less time [40].

Early detection of faults in wind turbines is crucial for minimizing downtime and maximizing energy production. ML models are proving adept at this task, with some studies showing the ability to identify potential problems up to 24 hours before they occur [10].

3.5 ML Applications for a Particular Power Quality Prediction

3.5.1 Power Quality Disturbances and their Impact: Power quality disturbances (PQDs) disrupt the typical voltage, current, and frequency levels in the power system. These sudden deviations are often caused by:

- **Non-linear loads:** Devices like switching machines, rectifiers, and inverters draw uneven power, causing fluctuations.
- **Renewable energy sources (RES):** Integration of wind and solar can introduce new types of disturbances.

Reference [37, 80] explain, that frequent PQDs pose risk to equipment at all stages of the power system:

- **Generation:** Machinery at power plants can malfunction or suffer reduced lifespan.
- **Transmission**: Instability in the grid can lead to transmission losses and outages.
- **Consumption**: Appliances and electronics may experience errors, shorten their lifespan, or even fail.

Different disturbances manifest in various ways:

- **Voltage sag:** Sudden voltage drop, affecting equipment performance.
- **Harmonic distortion**: Unwanted frequencies superimposed on the main signal, causing overheating and malfunction.
- **Notch**: Brief spike or dip in voltage or current.
- **Flicker:** Variation in voltage at a rapid rate impacts lighting and sensitive equipment.
- **Spikes**: Short, sharp increase in voltage or current, damaging electronics.

Table 2 below presents a snapshot of recent studies employing MLTs for PQD event detection and classification. The table details the feature extraction methods, optimization/feature selection techniques, and specific ML algorithms utilized by each author. Examining Table 2 reveals the substantial success of MLT approaches in PQD analysis. Notably, SVMs have emerged as the most frequently adopted tool due to their high accuracy and computational efficiency. Furthermore, the table suggests that integrating optimization techniques can demonstrably enhance classification performance [81].

Table 2. Recent MLT in PQD Classification Review (adapted from [80]).

Feature extraction technique	**ML Algorithm**	**Selection Technique**	**Accuracy achieved**	**Summary of working methodology**
variational Mode Decomposition (VMD) + Spatial Transcription (ST)	SVM	SBS/SFS/ GSO	99.66%	Large feature vector involving 9 classes of events. Three decomposition modes were used, with few tuning parameters for VMD and ST. SBS yielded the best accuracy. The algorithm is robust and provides good results in noisy environments.
DWT + Multiresolution Analysis (MRA)	SVM	-	94%	Used a small dataset and applied a Gaussian kernel support vector machine (SVM) for feature mapping and classification. Used the DB4 wavelet at an 8-level decomposition and extracted features such as energy, entropy, and standard deviation. The feature set consisted of 27 dimensions. It's important

				to note that the algorithm was not tested on a large-scale dataset, and it may not produce accurate results when applied to large data.

Table 2 cont. Recent MLT in PQD Classification Review (adapted from [80]).

Feature extraction technique	ML Algorithm	Selection Technique	Accuracy achieved	Summary of working methodology
WT	SVM	PSO	95.83%	Using the DB4 wavelet as the mother wavelet, 8 feature vectors as the classifier input, PSO is used to optimize the SVM classifier parameter. The RBF kernel is used to classify the wavelet energy difference. The RBF kernel function performed better compared to a single kernel function.
WT	PNN	ABC	99.875%	Used ABC for optimization because it converges rapidly and has good memory. PNN was used to select dominant features and spread constants, and the selected features were evaluated using RBF and MLPNN. One limitation is that some aspects of PQD, such as inter-harmonic disturbances, were not considered in the study.
Continuous Testing (CT)	CNN	SSA	99.52%	The wrapping method was used for extraction. The lag-covariance matrix of the PQD waveform was constructed using the trajectory matrix algorithm. CT and MSSA were utilized for waveform decomposition into six different levels. Six frequency bands were used as features. The dropout technique was used to avoid overfitting, and ReLU was used for CNN activation. The robust algorithm produced excellent results even in noisy conditions.

Table 2 cont. Recent MLT in PQD Classification Review (adapted from [80]).

Feature extraction technique	ML Algorithm	Selection Technique	Accuracy achieved	Summary of working methodology
WT	ELM	PSO	97.60%	Extraction is performed using the wrapping method based on PSO with the wavelet energy criterion. DB4 is utilized, and the sampled signals are decomposed with a 13-level MRA.
WT	ECOC - SVM	SFS	98.69%	Generated data from voltage disturbances was used. Wavelet transform was used to decompose at 6 levels, and 8 statistical methods were used to extract features. A total of 200 instances were used for training and testing the SVM-ECOC classifier. The algorithm is robust in both noisy and noiseless conditions.
Wavelet Packet Transform (WPT)	SVM	GA	98.33%	WPT used to decompose at 4 levels. GA and SA were used to select dominant features out of 128 features for the RBF kernel SVM. 10-Fold validation was used during evaluation.
Wavelet Multiresolution Analysis (WMRA)	SVM	-	99.71%	ATP/EMTP was used to generate PQ events, while WMRA was utilized to extract features of a 3-phase voltage waveform using DB4. Data preprocessing involving normalization was applied, and 1-fold cross-validation of SVM for kernel and penalty parameter was performed during classification.

Table 2 cont. Recent MLT in PQD Classification Review (adapted from [80]).

Feature extraction technique	ML Algorithm	Selection Technique	Accuracy achieved	Summary of working methodology
Hilbert-Huang Transform (HHT)	RBFNN	-	94%	Feature extraction using HT and statistical methods separated data into real and imaginary parts. K-Means clustered features for training, excelling in noise-free settings.
Empirical Mode Decomposition (EMD) + Hilbert Transform (HT)	BNT	-	97.90%	EMD separated signal patterns into TMFs and sifted them. HT extracted features from IMF for amplitude and frequency, while SD and entropy were used for BNT classification.
WT	RBFNN	PSO	97.85%	20 types of PQD events were analyzed using D84 and symlet. A 4-level decomposition was used, and classification was done using a Gaussian function. The classification results were compared with FFML, LVQ, GRNN, and PNN.
EMD + HT	RBFNN	PSO	97.85%	EMD was utilized to separate features into IMF. HT was applied to the first 3 IMFs to obtain amplitude and phase for constructing the feature vector. PNN was used for mapping and classification.
WT	RBFNN	PSO	97.85%	D84 and symlet analyzed 20 PQD types, applying 4-level decomposition and Gaussian classification, with results benchmarked against FFML, LVQ, GRNN, and PNN.
EMD + HT	RBFNN	PSO	97.85%	EMD was used to decompose features into IMF. HT was applied to the first 3 IMF to obtain the amplitude and phase used for constructing the feature vector. PNN was employed for mapping and classification.

Understanding the impact and types of PQDs is crucial for implementing effective mitigation strategies. This could involve:

i. **Filtering technologies:** Removing unwanted harmonics from the system.
ii. **Power conditioning equipment**: Stabilizing voltage and current levels.
iii. **Grid-level management**: Optimizing power flow and addressing the integration of RES.

Existing PQ monitoring in power grids and wind farms suffers from data latency and limited real-time effectiveness [80]. Table 3 below displays how the PQ analysis approach has been mainly focused on historical data or immediate response measures, leaving a gap in real-time prediction and proactive decision support.

Table 3. PQ decision support base (adapted from [80]).

PQ Type	Quality Analysis
Voltage deviation	Thyristor Voltage Regulator (TVR)
Harmonic	Power Filter/ Active Power Filter (APF)
Flicker	Thyristor Controlled Reactor (TCR)
Unbalance	Static Capacitor
Sag	Dynamic Voltage Restorer (DVR)

By recognizing the challenges and employing suitable solutions, we can ensure a stable and reliable power supply for both generators and consumers [15-16, 80].
Various ML models can effectively forecast power quality parameters. Model selection and performance depend on specific Power Quality Parameters (PQP) and data characteristics. Decision trees have demonstrated promising results in PQP forecasting [56].

i. **Simulating PQDs for Research:** Generating realistic data: Researchers use software like MATLAB to simulate PQDs based on IEEE standards. This creates large datasets with single or multiple classes of features, enabling the study of PQDs in controlled environments [82].
ii. **Extracting PQD Features***:* Signal processing techniques: Various methods are used to extract the most important characteristics of PQD waveforms, crucial for machine learning-based analysis:

- **Time domain techniques:** EMD effectively decomposes complex signals into simpler components, aiding feature extraction.
- **Frequency domain techniques**: Fourier Transform (FT) analyzes signals in the frequency domain, revealing frequency-related features essential for PQD characterization.

Key takeaway: Signal processing techniques, both in time and frequency domains, play a vital role in extracting meaningful features from PQD waveforms, enabling effective machine learning-based studies for comprehensive PQD analysis and classification [73,80].

iii. **ML Models:** The following figure illustrates the application of machine learning models for (PQD management in renewable energy systems.

The Model Structure (Figure 13) Inputs:

- Solar irradiance (SI)
- Wind speed (WS)
- Air pressure (PR)
- Air temperature (TEM)
- Power load (PL) Outputs:
- Frequency
- Voltage
- Total harmonic distortion of voltage (THDu)
- Total harmonic distortion of current (THDi) [73].

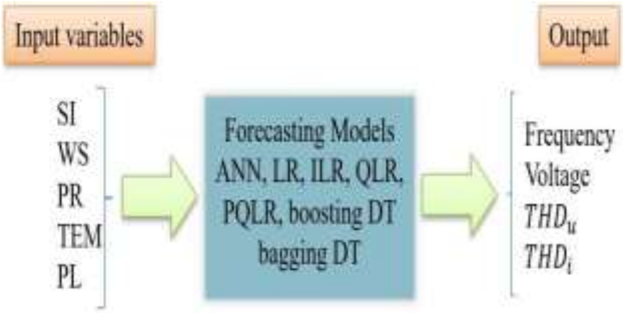

Figure 13. Typical ML model for Power Quality Parameter Disturbances (adapted from [73]).

ML Models Evaluated:

- ANN
- Linear regression (LR)
- Interaction linear regression (ILR)
- Quadratic linear regression (QLR)
- Pure quadratic linear regression (PQLR)
- Bagging decision tree (DT)
- Boosting decision tree (DT) Power Quality Parameters (PQPs) Studied:
- Power voltage
- Power frequency
- Total harmonic distortion of voltage
- Total harmonic distortion of current Additional Studies:

Decision tree for forecasting five PQPs: power frequency, power voltage, voltage and current total harmonic distortion, and short-term flicker severity [56,73,81].

3.5.2 Voltage Fluctuations and ML Solutions

Voltage fluctuations, including dips and flicker, can negatively impact wind power quality and equipment lifetime. The IEC 61000-3-7 standard sets guidelines for controlling emissions from variable loads in power systems [4, 6, 83, 84].

Existing approaches like fuzzy logic with particle swarm optimization face challenges with conventional monitoring reach areas. Research in [46,56,80] proposes two methods:

i. **Fuzzy logic with particle swarm optimization**: Improves bus monitoring capability and achieves optimal voltage sag allocation.
ii. **Voltage sag state estimation with genetic algorithm:** Offers comprehensive observation of voltage sags across the network.
iii. **Machine Learning for Voltage Dip Analysis:** ANNs, SVMs, LRs, and PCA show promise in characterizing and classifying voltage dips [46,56,80]. Deep learning techniques may outperform conventional methods for handling large datasets related to voltage fluctuations [56].

Key Takeaways: Voltage fluctuations in wind power systems require effective monitoring and analysis to ensure grid stability and equipment longevity. Machine learning techniques offer promising solutions for voltage dip characterization, classification, and potentially, real-time monitoring. Further research is needed to optimize and validate these techniques for different operating conditions and data sets [46, 56].

3.5.3 Harmonics and ML Solutions

Wind turbines can contribute to power quality issues like harmonics, affecting grid stability and equipment [46, 56, 80]. Research in [36, 85, 86, 87] explores intelligent ANN approaches for harmonic detection and mitigation. The proposed ANN in [64,86] employs a three-layer structure with backpropagation learning to identify harmonics according to IEC and IEEE standards. This method demonstrates promise with a low harmonic distortion index of 0.0757. Another study [64] utilizes AI within a parallel APF to address harmonics in two-wire power distribution systems. A novel Adaptive Notch Filtering (ANF) technique presented in [10] tackles several power quality issues, including harmonics, voltage regulation, and frequency deviations, using a reference voltage signal (according to IEC standards).

Key Takeaways: AI and ML show potential in identifying and mitigating harmonics caused by wind energy integration. Different techniques, like ANNs, APFs, and ANFs, offer diverse solutions for specific harmonics-related challenges. Further research and validation are needed to optimize these methods and enhance their effectiveness in various scenarios [46].

RESULTS AND DISCUSSION

4.1 Results

This systematic literature review delves into the application of machine ML for forecasting PQ in the growing wind energy sector. Analyzing a collection of 87 research articles published between 2004 and 2023, the review offers a comprehensive overview of the global development of ML-based forecasting models for electric power over the past 19 years. This wider perspective serves two key purposes:

4.1.1 Comprehensive Understanding*:* By examining a broad range of studies across various subfields, encompassing 38 articles on forecasting, 22 on machine learning, 5 on renewable technology, 7 on power systems, and 3 on management and control, the review provides a holistic understanding of the current landscape of ML applications for PQ forecasting in wind energy. This comprehensive analysis allows us to draw valuable insights and identify best practices applicable to the National grid connection/ interconnection context.

4.1.2 Contextualizing South African Specificities*:* Within the broader scope of global research, the review also focuses on a subset of 12 studies specifically addressing PQ forecasting using ML in the domain of renewable energy. This targeted analysis helps us identify MLTs that resonate with the unique challenges and opportunities of South Africa's wind energy sector, characterized by its recent grid integration and evolving regulatory landscape.

It is important to note that this review deliberately refrains from a comparative evaluation of individual ML model performance. Instead, it focuses on identifying and categorizing the diverse array of 12 ML tools, techniques, and applications employed for PQ forecasting in wind energy globally. By doing so, the review establishes the feasibility and potential of various ML approaches for ensuring PQ compliance in South African wind farms, as stipulated by the National Service Provider's requirements within the national grid code.

Furthermore, the review reveals a notable increase in research activity on ML-based PQ forecasting in recent years, with at least 46 articles published between 2020 and 2023 compared to 22 in the preceding four years (2016-2019). This trend underscores the growing recognition of ML's potential for enhancing grid stability and efficiency in the context of renewable energy integration.

4.2 Discussion and Summary

It is observed that the capabilities of ML and DL models hold immense promise for PQ forecasting in renewable energy sources like wind. Their ability to process vast amounts of data and uncover complex patterns, often undetectable by humans, translates to:

i. **Enhanced prediction accuracy**: Compared to traditional methods, ML and DL models offer more accurate PQ predictions, leading to improved grid stability and decision-making.

ii. **Real-time adaptability**: These models can dynamically adapt to changing weather conditions through real-time forecasting, further bolstering grid stability.

iii. **Optimized renewable energy operations**: Accurate PQ predictions contribute to maintaining the quality of supply within the national grid, minimizing instability, and boosting overall grid performance.

However, careful consideration must be given to data quality, model complexity, and validation to fully unlock the potential of ML and DL models for optimizing renewable energy operations and grid stability.

Hybrid Models and Challenges: Hybrid models, combining traditional time-series analysis with ML and DL algorithms, have also emerged as promising tools for renewable energy forecasting challenges.

Despite progress in applying ML and DL models for PQ forecasting, several challenges such as data scarcity, and transparency remain still.

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