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Review

A Comprehensive Review of Machine Learning Models for Optimizing Wind Power Processes

Cosmina-Mihaela Rosca [1] and Adrian Stancu [2,*]

[1] Department of Automatic Control, Computers, and Electronics, Faculty of Mechanical and Electrical Engineering, Petroleum-Gas University of Ploiesti, 39 Bucharest Avenue, 100680 Ploiesti, Romania; cosmina.rosca@upg-ploiesti.ro

[2] Department of Business Administration, Faculty of Economic Sciences, Petroleum-Gas University of Ploiesti, 39 Bucharest Avenue, 100680 Ploiesti, Romania

* Correspondence: astancu@upg-ploiesti.ro

Abstract: Wind energy represents a solution for reducing environmental impact. For this reason, this research studies the elements that propose optimizing wind energy production through intelligent solutions. Although there are studies that address the optimization of turbine performance or other indirectly related factors in wind energy production, the optimization of wind energy production remains a topic insufficiently explored and synthesized in the literature. This research studies how machine learning (ML) techniques can be applied to optimize wind energy production. This research aims to study the systematic applications of ML to identify and analyze the key stages of optimized wind energy production. Through this research, case studies are highlighted by which ML methods are proposed that directly target the issue of optimizing the wind power process through wind turbines. From the total of 1049 articles obtained from the Web of Science database, the most studied ML models in the context of wind energy are the artificial neural networks, with 478 papers identified. Additionally, the literature identifies 224 articles that have studied random forest and 114 that have incorporated gradient boosting about wind power. Among these, 60 articles have specifically addressed the issue of optimizing wind energy production. This aspect allows for the identification of gaps in the literature. The research notes that previous studies have focused on wind forecasting, fault detection, or turbine efficiency. The existing literature addresses the indirect optimization of component performance. Thus, this paper identifies gaps in the current research, discusses ML algorithms in the context of optimizing wind energy production processes, and identifies future directions for increasing the efficiency of wind turbines through integrated predictive methods.

Keywords: wind energy; wind turbine performance; machine learning; optimization; artificial neural networks; predictive modeling; renewable energy

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Academic Editor: Rui Araújo

Received: 13 March 2025
Revised: 27 March 2025
Accepted: 27 March 2025
Published: 29 March 2025

Citation: Rosca, C.-M.; Stancu, A. A Comprehensive Review of Machine Learning Models for Optimizing Wind Power Processes. *Appl. Sci.* **2025**, *15*, 3758. https://doi.org/10.3390/app15073758

1. Introduction

Wind energy represents an alternative renewable energy source, with wind power as a central element. The principal objective of renewable resources derives from the necessity of environmental protection. To achieve this objective, it was necessary to find a solution that allows for the reduction in carbon emissions and the minimal use of fossil fuels. The efficiency of integrating wind energy into electrical grids is influenced by the natural variability in the wind, difficulties in production integration, challenges in production forecasting, and the necessity of periodic maintenance for wind turbines.

The motivation for this study lies in the increasing demand for integrating AI tools across all fields of activity. Many researchers adopt an interdisciplinary approach between a specific domain and AI. This research addresses this issue by identifying studies that optimize turbine performance and energy yield. ML techniques are studied in wind energy for forecasting, fault detection, and operational efficiency. Although a consistent number of articles address this topic, they are approached individually and do not provide a systematic analysis of the direct optimization of production. This article analyzes materials from the specialized literature and identifies gaps that need to be addressed in future research. The material is intended to serve as a reference point for generating ideas related to future studies on optimizing wind energy production in the context of ML.

This article is addressed to researchers, academics, and industry professionals. It highlights the limitations of traditional methods in optimizing wind energy production. Most articles study predictive strategies on individual components. The authors consider that articles addressing optimization strategies about ML algorithms using simultaneous predictive components are rare. Therefore, the authors will identify the literature gaps, analyze these ML algorithms in the context of wind energy, and propose future directions that researchers should explore in upcoming articles.

The present paper aims to address the problem of optimizing wind energy production by employing modern tools. The specialized literature explores machine learning (ML) models for various purposes, from optimizing turbine functionality to predicting energy production capacity. ML models analyze variations in production through their ability to process large volumes of data. Essentially, studying a large volume of meteorological and operational data can generate predictions aimed at estimating the performance of a wind energy system. In the specialized literature, ML applications operate in wind power forecasting, fault detection at the component level of the wind system, turbine control, or operational cost reduction.

Beyond these numerous analyses in the literature, several gaps require further investigation. Most research studies have addressed the implications of ML in the context of energy and wind systems for the forecasting problem. Still, they do not focus on production optimization, which includes forecasting problems as a subproblem of a more significant concept. This research aims to contribute to the wind power field by studying the implications of ML in the wind power optimization process.

The analysis of the literature materials identifies only 60 articles out of 1049 that address the importance of optimizing wind energy production through ML. This value demonstrates that this field is insufficiently explored. This research contributes by highlighting existing gaps and proposing future directions for improving the efficiency of wind energy through advanced ML techniques. This article reviews the existing AI approach in wind turbines as a sustainability measure. The scope of this study is limited to the performances of these systems and the optimization process, which has economic and environmental impacts. To the authors' knowledge, this review-type research is the first in the specialized literature exclusively focused on this issue.

This paper is structured into seven sections. Section 2 presents the basic concepts of wind power, turbines, and ML techniques in the wind power context. In addition, classic methods in the field of wind energy and the latest technological advancements in turbine design optimization are outlined. The research methodology, including the selection process of scientific articles, data sources, search strategies, inclusion/exclusion criteria, and data analysis techniques, are described in Section 3. Section 4 focuses on ML models applied to wind power and the evaluation metrics employed by the ML models for the optimized wind power process. The analysis of influencing parameters in wind energy with ML is depicted in Section 5. Section 6 presents the discussion by underlining the analysis of results, comparative analysis of ML models, evaluation of impact and contribution, research gaps identification, study limitations, the impact of discoveries on the improvement of wind energy and future solutions, and recommendations for future research. Finally, the conclusions are displayed in Section 7.

2. Basic Concepts of the Wind Power and Turbines

The wind power process converts the kinetic energy of the wind into mechanical energy. This is converted into electrical energy through a wind turbine. The central physical element of this process is the wind turbine. The conversion process depends on the dynamics of wind flow and the advanced technology involved in the conversion process [1]. For this reason, the turbine's location directly influences wind power generation. The technology generally refers to optimizing output power by integrating parameters such as air density and turbine blade's swept area [2]. Wind turbines generate power at a specific wind speed, called the cut-in speed. The maximum output rate is reached at another speed named the rated speed [3,4]. The study by Bu [5] mentions environmental and geographical factors as central elements for wind power scaling. Traditional power distribution faces challenges in the grid context. To overcome this, the measurements of ramp events need to be precise for forecasting and operational strategies adopted in the wind energy system [6,7]. Managing uncertainties in wind forecasting is debated in the literature, with the primary goal of achieving output stability. If the wind source energy penetration exceeds 30% of demand on an electric grid, the management should already be informed by the forecasting mechanism [8]. This management must timely identify meteorological disturbances such as storms or cold fronts [9]. These events directly affect the system's output [10,11].

2.1. Wind Power Turbines

Wind turbines located in a geographic area are known as wind farms. Turbines on land are called onshore, while those at sea are called offshore [12]. Bu [5] discussed how these turbines are arranged relative to one another in terms of array density, which determines production capacity. Consequently, production optimization refers to the physical distribution of turbines and operational parameters. Optimization must also account for minimizing the negative impact on grid stability and the environment [13].

Turbines are primarily categorized into horizontal axis wind turbines (HAWTs) and vertical axis wind turbines (VAWTs). HAWTs are commonly used for large-scale energy generation because they capture wind energy at higher altitudes. At the same time, VAWTs are utilized in smaller, localized settings where space or wind conditions are unfavorable to the former [14,15].

The performance parameters of wind turbines depend on various design features, including blade configuration and aerodynamics. For example, blade curvature and angle directly influence performance, as seen in studies comparing different blade designs, such as the Savonius and Darrieus turbines [15,16]. Modern HAWTs exhibit peak efficiencies through optimized blade designs that increase their ability to harness wind energy over a broader range of wind speeds [17]. Advanced materials and designs, such as blades with specific angles, can further influence the performance by reducing drag and maximizing thrust [18,19]. Utilizing available resources effectively aids in making informed decisions regarding the installation and operation of turbines [20,21].

Maintenance and fault detection influence wind turbine longevity and performance consistency. The literature analyzes various advanced techniques, including ML approaches for predictive maintenance and performance diagnostics [22,23]. Yan et al. [24] and Palasai et al. [25] present the integration of self-diagnosis systems to predict potential failures in turbine components, optimizing maintenance schedules and reducing operational costs. Regarding the control of wind turbines, they are studied to minimize structural damage. Zhang et al. [26] propose an innovative control system based on active rotary inertia driver (ARID) and type-3 fuzzy logic system (T3-FLS). The authors optimized the management of wind turbine failures through fractional stability theorems. These approaches complement the load degradation reduction strategies described in the paper [27].

Climate and environmental factors impact wind turbine design and productivity. Turbulent wind conditions and extreme weather substantially affect turbine operations. The research has continued to explore structural adaptations and operational strategies to mitigate these challenges, ensuring reliable energy production even under adverse conditions [17,28].

Achieving the optimization objective is intensely debated in the literature through the following desiderata [29,30]:

- Integrating wind power ramp control strategies with the ability to effectively manage fluctuations associated with changing wind conditions;
- Implementing advanced models and ML techniques for selecting wind turbine types based on specific site conditions and expected wind resource characteristics.

These methodologies are associated with investments in technology and infrastructure to maximize the farm's efficiency. Most countries are attempting to adopt these sustainable measures to use renewable energy [31,32]. Based on this plan, large-scale wind power generation requires plans and measures regulated by law at both the technological and environmental levels [33]. This is achievable through collaborations among academics, policymakers, the population, and the industry. This methodology will ensure long-term opportunities for innovation and environmental stewardship. Upholding economic and ecological standards will address the global demand for cleaner energy sources [34,35]. Technological advances contribute to reducing carbon emissions. As a result, it has created sustainable energy systems. The issue is addressed through sociopolitical frameworks that support renewable energy adoption [36] and industry practices [37,38].

2.2. Classic Methods in the Field of Wind Energy

Predictive maintenance is heavily debated in the wind energy industry because defect prevention reduces production costs. Classical methods are used to predict defects, but ML approaches offer undeniable advantages over traditional methods.

Classic predictive maintenance methods are based on techniques such as the following:

- Vibration analysis measures the vibration frequencies of mechanical components, such as bearings or wind turbine shafts [39]. Different elements are analyzed through vibrations. Zhang et al. [40] studied the vibrations of traction cables that affect the wind turbine blades' static tests. The study analyzed the influence of cable length and pulley position to provide recommendations to avoid resonance and reduce vibrations. If the amplitude of the vibrations exceeds a preset threshold, the system triggers an alert.
- Statistical process control uses historical data to identify deviations from normal parameters. For example, if the temperature of a motor rises above a specific value for more than several minutes, this indicates a problem. The analyzed studies emphasize the need for the statistical monitoring of wind energy. Numerical models are evaluated using statistical comparisons between simulated data and meteorological observations, emphasizing regional wind variability and underestimation or overestimation errors [41]. The article by Shambira et al. [42] used statistical distributions, such as Weibull, generalized extreme value (GEV), etc., to evaluate the wind energy potential. In the paper [43], the simulation of blade icing is optimized through statistical analyses

that correlate factors such as wind speed, temperature, and liquid water content. This approach highlights nonlinear relationships for prediction. Nonlinearity highlights the need to explore ML models that offer better results in these scenarios.

These methods work well in simple scenarios where defects are addressed linearly, described by a small number of variables. However, they encounter difficulties when it comes to managing complex systems. Wind turbines involve many sensors in maintenance processes that monitor environmental parameters. Nonlinear interactions between components characterize this behavior.

This drawback is managed by the ability of ML models to analyze large amounts of data and learn from the system's behavior. The algorithms presented in this paper belong to the ML category. They simultaneously process multiple variables and identify hidden correlations that are impossible for humans to detect, as well as for applications that do not include AI components. This human incapacity is explained by the inability to perform complex calculations beyond those of a computing system. Additionally, processing a volume of data as large as that handled by an AI-equipped computing system is impossible. For these reasons, ML models are superior to traditional methods.

2.3. ML Techniques in the Wind Power Context

ML algorithms are categorized into the three main types of supervised learning, unsupervised learning, and reinforcement learning, with each suited for different kinds of tasks and data structures. Supervised learning is used for classification tasks [44,45]. In this case, the model learns from labeled training data to predict outcomes on unseen data. Common algorithms in this category include support vector machines (SVMs), K-nearest neighbors (KNNs), and various tree-based methods like decision trees and random forests [46–49]. In contrast, unsupervised learning seeks to find the hidden patterns or intrinsic structures in unlabeled data, making it useful for clustering tasks and anomaly detection [50–52]. The paper by Zheng et al. [53] proposed the AMBi-GAN model for detecting anomalies in industrial multidimensional time series. The proposed model utilized LSTM mechanisms. The model was applied to wind turbines to detect faults. Granados et al. [54] introduced a new algorithm called bagged trees that detects anomalies based on vibration analysis. The analysis was conducted to predict synthetic defects using ML techniques. The results provided an accuracy of 87%. Reinforcement learning focuses on learning optimal actions through trial and error within a given environment and has applications in dynamic decision-making situations [55].

The performance of ML algorithms is evaluated using metrics. These metrics are correlated with the implemented algorithm. The most popular metrics are accuracy, precision, recall, and F_1-Score [56–58]. Accuracy measures the proportion of true results among the cases examined. Precision and recall provide insights into the model's ability to identify instances accurately [5]. The F_1-Score balances these two metrics, making it particularly useful when dealing with imbalanced datasets, where one class may significantly outnumber the other [56,57].

Naive Bayes is used in text classification and various probabilistic applications. Its foundational principle revolves around Bayes' theorem, providing a straightforward yet powerful classification approach. Studies have demonstrated its performance in numerous contexts, often surpassing other algorithms, such as KNN, in accuracy [59].

Algorithms such as AdaBoost and gradient boosting increase the prediction accuracy by combining multiple weak classifiers to create an intense overall model. XGBoost has gained acclaim for its performance in competitive data science contexts [60].

Techniques like principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) are commonly employed for dimensionality reduction in handling large datasets. PCA seeks to reduce dimensionality while preserving as much variance as possible in the data. On the other hand, t-SNE is particularly effective for visualizing high-dimensional data in lower dimensions by capturing complex relationships between data points [61].

ML models are studied in the specialized literature to fulfill the following purposes with optimization implications [62]:

- To optimize processes to maximize energy production;
- The prediction of meteorological events correlated with the prediction of energy production vs. network energy consumption;
- Ensuring the prediction of maintenance needs in wind farms.

These objectives can be achieved using ML techniques that process large amounts of historical data, based on which predictions can be made [38]. In the past, the study of wind power optimization was limited to understanding mechanical and atmospheric phenomena [63] without implications of AI technologies. This modeling involved the analysis of nonlinear dynamics' processes. The adoption of these modern technologies simplifies the data analysis and modeling processes. A comparison between traditional modeling and ML-specific modeling is presented in the research [63,64]. The works address the problem through artificial neural networks (ANNs) to forecast short-term wind power. Implementing ML techniques in wind farm-specific processes has reduced the level of complexity of evaluations but increased the accuracy of the results obtained [65,66]. Numerous advantages have been gained by replacing the traditional approach with ML. The comprehensive review presented by Deng et al. [65] highlighted the superiority of extreme ML and deep learning (DL) architectures in wind energy prediction. Combining convolutional neural networks (CNNs) with long short-term memory (LSTM) networks has led to forecasting capabilities [67,68].

ML models have proven particularly valuable in predicting wind power because they can discern patterns in large datasets. In one comprehensive review, it was noted that various algorithms, including but not limited to, extreme ML and DL architectures, have been successfully employed for wind energy prediction [65]. Enhanced algorithms like the combination of CNN with LSTM networks have showcased remarkable improvements in forecasting capabilities [67]. The hybrid perspective approach allows for short-term analysis and predictions in reduced time complexity, favoring rapid decision-making [69]. The application of such models reflects the trend of ML being integrated with specific meteorological forecast data [70,71]. Yang et al. [72] offered principles indirectly applicable to wind energy, highlighting the importance of modeling renewable resources in climate uncertainty. In this way, the relationship between atmospheric conditions and wind energy production is clarified [73].

The literature also studies ML for the predictive maintenance of wind turbines. The objective of these predictions is to minimize turbine downtime. ML algorithms aim to detect failures early by analyzing specific data on turbine performance to achieve this objective. This proactive approach's direct consequence is minimized downtime, which reduces operational costs [74,75].

2.4. The Latest Technological Advancements in Turbine Design Optimization

Technological advancements in various fields have led to the concept of interdisciplinarity. The literature also offers multidisciplinary elements in other fields that are different from AI. Wind energy research encompasses a variety of interconnected domains, including material science innovations [76], economic modeling [77], policy development, social acceptance studies, material science innovations, etc. For example, the paper [78] presented interdisciplinary perspectives on the socio-economic and technological factors that influence wind energy development. The paper by Zhang et al. [79] addressed design directions regarding anchoring systems. Among all the expansion directions of multidisciplinary research on optimizing wind energy processes, the AI direction is the most popular due to the integration of intelligent components in all fields of activity. Thus, revolutionary concepts such as digital twin, dynamic airflow control, wind turbines with active blades and innovative materials, distributed control systems and smart microgrids, and wake steering have been introduced.

Figure 1 synthesizes the interdisciplinary approach to optimizing wind energy. This synthesis highlights the importance of integrating modern technologies across different fields. Centered on wind energy, the scheme highlights the connections between interdisciplinary fields (such as innovations in materials science, economic modeling, policy development, and social context) and advanced solutions like digital twin, Internet of Things (IoT) systems, dynamic air control, smart micrigrids, smart grids, and distributed control systems. These elements contribute to optimizing wind turbine performance through mechanisms such as active blade control (adaptive blade control) and wake steering (optimizing turbine positioning to reduce interference between them). The authors emphasize that ML is a key tool that integrates these components to identify predictions as close to reality as possible, early defect detection, and wind farm management strategies.

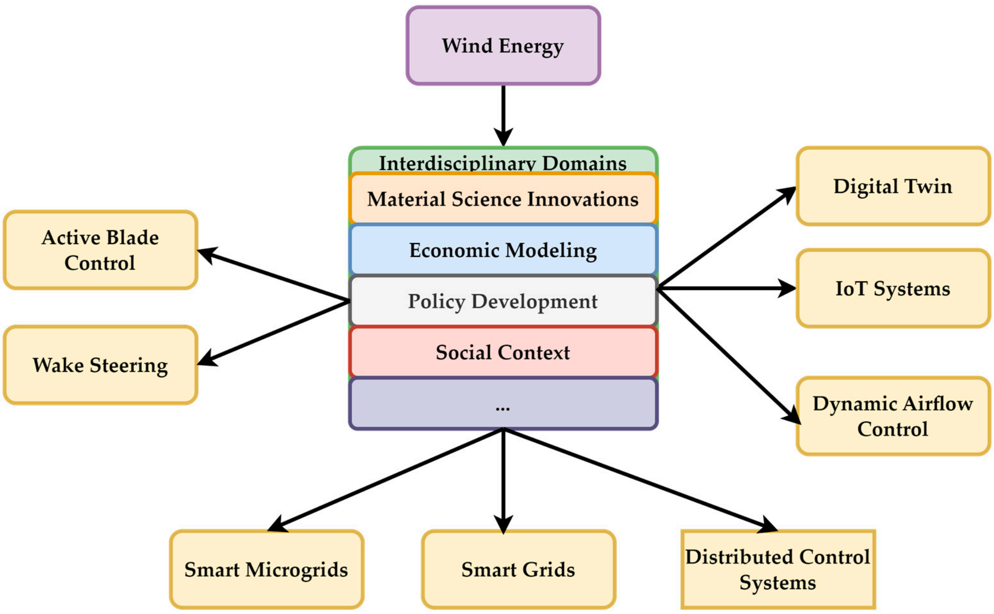

Figure 1. Smart technologies and interdisciplinary solutions for optimizing wind energy systems.

The digital twin concept creates a digital replica of wind turbines. This concept allows for the real-time simulation of operational scenarios to prevent defects. By integrating ML models, these systems can identify hidden patterns in the historical data. The patterns determine the adjustment of operating parameters, which reduces long-term wear [80–82].

Active blade control represents adaptable blades that can change their shape in real time to optimize energy capture. This concept is studied in the literature [83–85] to identify the materials that reduce weight and increase efficiency, such as carbon fiber composites or nanomaterials. The sensors integrated into the blades allow for real-time monitoring of stresses and vibrations, which generates a considerable volume of study material in the literature. However, searches for “Active Blade” and “Machine Learning” in Web of Science (WOS) yield no results, indicating that the field has not yet been explored.

Additionally, dynamic airflow control represents another important innovation. The turbines have advanced sensor and actuator systems that adjust the blades according to wind variations. These technologies optimize the angle of attack of the blades and the distribution of aerodynamic forces to maximize energy capture and reduce mechanical stresses. Dynamic airflow control is not explored in the specialized literature in combination with ML elements for the analysis of optimizing wind energy production.

Distributed control systems and smart microgrids aim to decentralize turbine control to optimize wind farm energy flow. These systems are integrated with various energy storage elements [86,87]. When combined with blockchain technology for decentralized energy management, these technologies can help manage transactions between producers and consumers.

Wake steering technology studies the optimal way of distributing the turbines within the park. This placement takes into account the topography and air currents. This technology aims to minimize losses caused by interference between turbines [88].

Another reference element for wind energy is smart grids. This concept allows for bidirectional communication between energy providers and consumers, which means that data about energy consumption is transmitted in real-time to network operators. The paper by Wang et al. [89] explored the market and auction mechanisms for managing distributed resources. Similarly, Li et al. [90] addressed issues relating to flexible resources through local problem decomposition methods in managing wind energy variability.

The IoT is another field that has been intensively explored across all areas of activity. This technology is used in parallel with AI technologies. Hu et al. [91] presented the energy harvesting and speed sensing (EHSS) system. This IoT system achieves a current density of 28.7 mA/m^2 and an energy efficiency of 96%.

3. Methodology

This section presents the research methodology, including the selection process of scientific articles, data sources, search strategies, inclusion/exclusion criteria, and data analysis techniques.

3.1. Employed Methodology for ML Models Applied to Wind Power

This research was conducted using the WOS database, which was chosen for its extensive high-impact coverage. Other databases, such as Scopus and IEEE Xplore, were considered but excluded due to content overlap and accessibility constraints. The search queries used in WOS covered various topics related to wind power and ML. The primary search string was the following:

TS = ((“wind power” OR “wind energy”) AND “machine learning”) AND PY = (2020–2025)

Figure 2 summarizes the entire research process presented in Section 4. This figure presents the evaluated ML algorithms from an initial WOS search, which is subsequently refined by applying the constraint “optimization,” followed by “production,” and then the algorithms’ evaluation metrics. The flowchart diagram (Figure 2) illustrates the step-by-step methodology, outlining the search, selection, and analysis process. In Section 3.1, the bibliometric analysis included the following search:

TS = ((“wind power” OR “wind energy”) AND “ALGORITHM”) AND PY = (2020–2025)

The word ALGORITHM was replaced with various ML algorithms. The Supplementary Materials related to this research, ML_models.xlsx, presents in sheet 4.1 all the queries that enabled the analysis of the current state of the wind energy domain regarding ML for the interval 2020–2025. Subsequently, the search domain was narrowed by adding “optimization”. In this way, it was intended to identify in the literature all articles that address the issue of optimizing processes involved in wind energy production while maintaining the previously analyzed context. Additionally, all queries are available in the Supplementary Materials ML_models.xlsx in sheet 4.2. The search follows the format:

TS = ((“wind power” OR “wind energy”) AND “ALGORITHM”AND “optimization”) AND PY = (2020–2025)

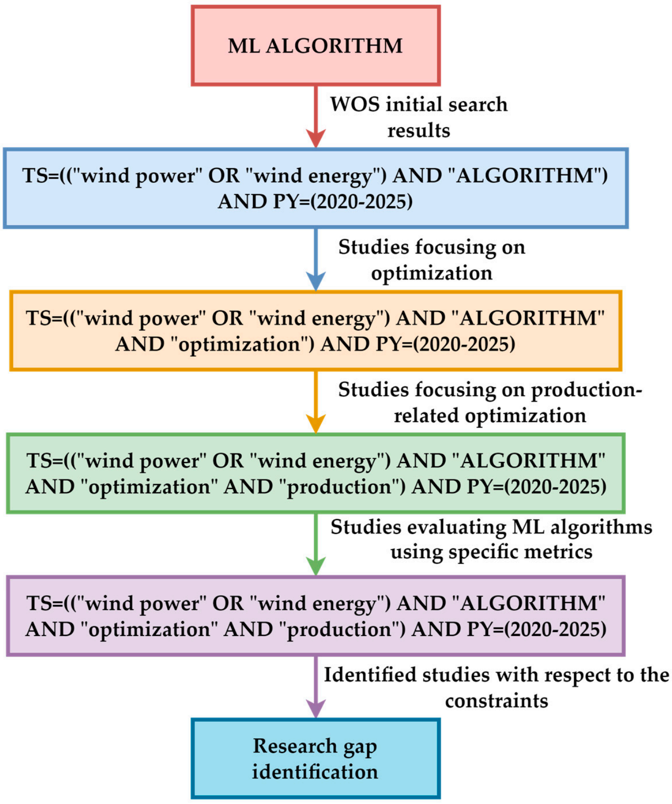

Figure 2. Step-by-step methodology of the ML models classification for wind power (Section 4 of the research).

In Section 4.3, the search was further narrowed by adding the word “production”. In this way, the research was intended to study materials that address the theoretical optimization of wind energy production processes in practice. The narrowing of the domain aims to limit the focus to the practical application of theoretical concepts. The results are available in the Supplementary Materials ML_models.xlsx in sheet 4.3 in the general format:

TS = ((“wind power” OR “wind energy”) AND “ALGORITHM” AND “optimization” AND “production”) AND PY = (2020–2025)

In Section 4.4, evaluation metrics for ML algorithms are introduced, and the queries are expanded to include all metrics associated with each algorithm individually. The general query is the following:

TS = ((“wind power” OR “wind energy”) AND “ALGORITHM” AND “optimization” AND “production” AND “METRIC”) AND PY = (2020–2025)

The METRIC word was replaced systematically with the corresponding value for each evaluated algorithm. The results are summarized in Section 4.3, and each value correlated with the WOS query is detailed in the Supplementary Materials ML_models.xlsx, sheet 4.4.

To refine the selection, the following inclusion criteria were applied:

- Peer-reviewed journal articles and conference proceedings;
- Studies explicitly discussing ML models applied to wind energy optimization;
- Research addressing performance evaluation metrics for ML models.

This analysis illustrates the current state of ML in wind energy optimization by refining search strategies, inclusion criteria, and bibliometric trends.

3.2. Employed Methodology for Analyzing Influencing Parameters

For Section 4, more specific queries were executed to refine the research focus on factors influencing the wind energy production process. The general WOS query is:

TS = ((“wind power” OR “wind energy”) AND “machine learning” AND “PARAMETER”)

The evaluated PARAMETER includes wind speed, wind direction, climatic conditions, meteorological forecasting, turbine design, grid connectivity, turbine height, and terrain topology. The WOS queries and their corresponding results are detailed in the Supplementary Materials ML_models.xlsx, sheet 4.5.

Section 4 discusses a separate refined search focused on optimization-related studies. This analysis was conducted by exporting the results generated with WOS. A custom C# script was developed to identify, from keywords, the frequency of unique keyword occurrences in research papers that contain optimization elements related to the wind energy production process. Additionally, the C# script was employed to analyze the annual trend of publications on wind energy production optimization (excluding 2025) and for articles by publishers in the context of wind energy optimization analysis.

The flowchart in Figure 3 illustrates the C# 7.3 program’s systematic approach to analyzing wind energy optimization research. By extracting keywords, calculating their frequency, and filtering data by year and publisher, the program helps to identify the trends and gaps in the literature.

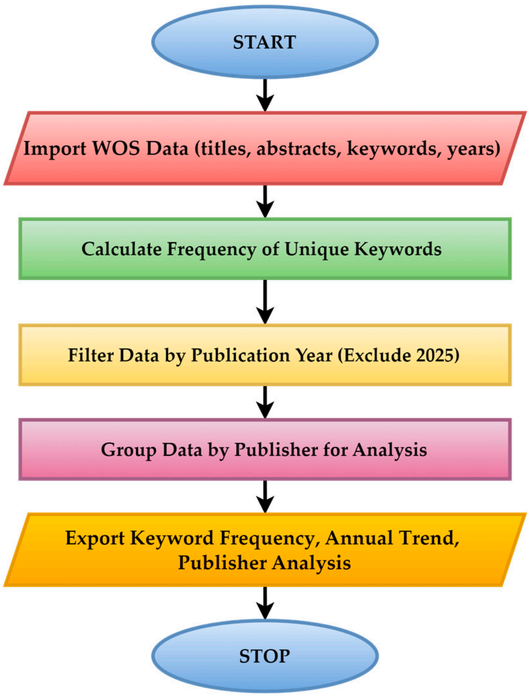

Figure 3. Flowchart of the C# program for identifying research gaps and trends in wind energy optimization studies.

This custom C# script helps uncover underexplored areas, such as specific parameters or optimization techniques, the research interests in particular areas, and guiding future research priorities. The annual trend analysis also highlights shifts in research focus over time.

4. ML Models Classification for Wind Power

The following analysis identifies the recent scientific materials published between 1 January 2020 and 1 March 2025 on developing ML models for wind energy. This context aims to serve as a reference in the literature to extract the most significant advances in the field of wind power.

By analyzing the existing research on the WOS platform and synthesizing it in Figure 4, 1049 articles are associated with the wind power domain addressed through ML techniques between 1 January 2020 and 1 March 2025. Figure 4 represents a co-occurrence map of terms created with VOSviewer 1.6.20 for the analysis of predictive maintenance of wind turbines using ML. Thus, the central keyword is ML. The most extensive cluster contains the six elements of decomposition, LSTM, models, prediction, speed, and wind power forecasting. The second cluster includes forecasting, ML, and wind energy. The third cluster has two associated elements: renewable energy and wind power. The temporal evolution of the research shows a transition from older studies (2021–2022, represented in blue colors) towards more recent research (2023, in yellow). Out of the 1049, 30 are specific to predictive maintenance, and 26 directly address the issue of wind turbines.

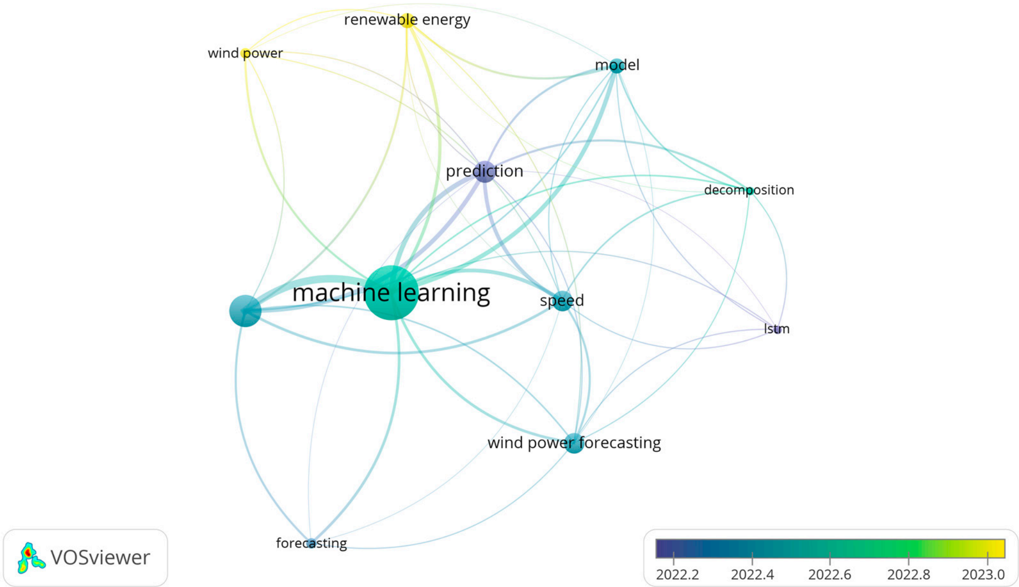

Figure 4. Co-occurrence map of terms for wind power approach using ML.

4.1. ML Models Applied to Wind Power

The specialized literature identifies many specific ML models. In what follows, ML models of wind power or wind energy are analyzed using the articles listed in WOS. The analysis covers the period between 1 January 2020 and 1 March 2025. The identified values are summarized in Figure 5.

One of the most studied models used in this context is linear regression, which has been utilized in 149 scientific articles. This model is used to understand the relationships between different variables employed when analyzing the influence of the factors presented in the previous section on the performance of wind turbines, such as weather conditions.

The use of logistic regression in only 42 articles suggests that its application is more limited and valuable in classification problems, such as fault detection in wind turbines.

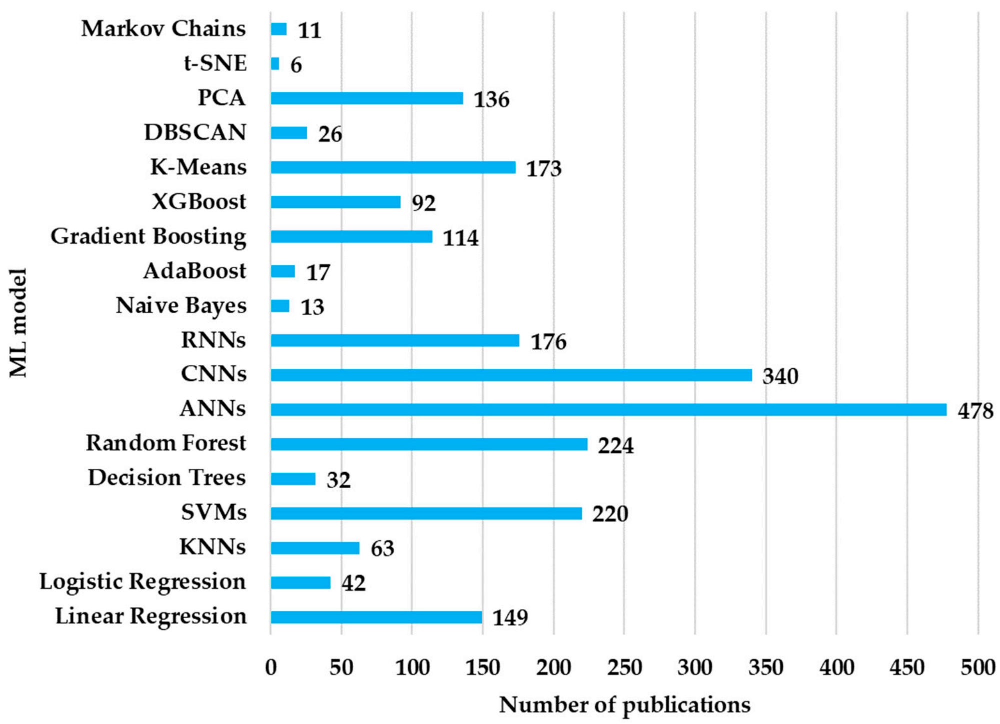

Figure 5. Overview of ML models used in wind power and wind energy research.

Models such as KNNs, used in 63 articles, and SVMs, with 220 articles, have broad applicability in classifying and analyzing data from turbine monitoring systems. KNN is appreciated for its ability to work with small or medium datasets. SVM is preferred for complex datasets, especially when there is a clear separation line between the analyzed data classes. Although used in only 32 articles, decision trees represent a technique for interpreting and explaining the decisions made by models. They can be used for the optimization and control of wind turbines.

On the other hand, with 224 articles, random forest represents an extension of decision trees and is often used in prediction and diagnostic applications due to its ability to handle large and complex datasets. ANNs and CNNs are ML models extensively studied in the specialized literature. With 478 articles for ANN and 340 for CNN, these models are extremely popular due to their ability to learn from complex data and identify hidden patterns in turbine operational data.

Recurrent neural network (RNN) models have been identified in the literature, and 176 articles have been written about them. DL models have provided 867 articles in the literature. AdaBoost and gradient boosting models, with 17 and 114 articles, respectively, are used in classification and regression applications.

Other techniques, such as K-Means (173 articles), density-based spatial clustering of applications with noise (DBSCAN) with 26 articles, PCA with 136 articles, and t-SNE (6 articles), are used in data analysis and dimensionality reduction. These are well suited for applications working with large wind turbine or wind farm datasets. Finally, Markov chains, with only 11 articles, are applied in modeling the probabilistic behavior of wind systems and can be used for forecasting wind variability and energy production.

These results show that ML models have been intensively studied in the last five years. This analysis highlights the superiority of the ANN model in addressing ML models for the concept of wind energy.

4.2. ML Models for Optimized Wind Power Concept

The previous research on wind energy and the application of ML algorithms has raised the question of how many of these address the optimization of wind energy production processes. After adding the word "optimization" to WOS searches, new perspectives were obtained on the applicability of each ML model to optimizing wind energy systems. These results are summarized in Figure 6.

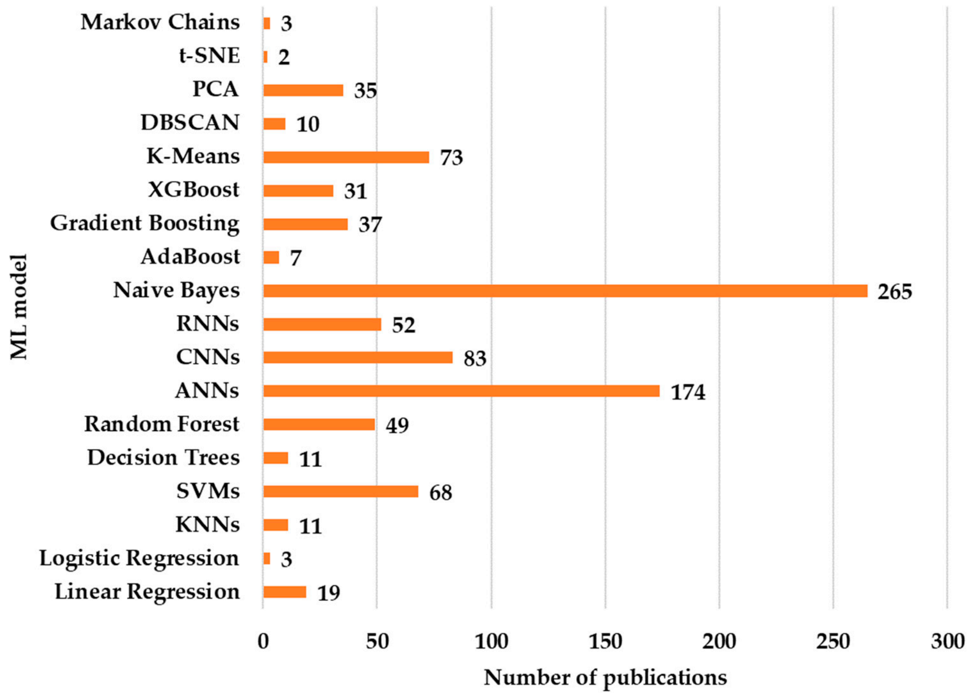

Figure 6. ML models for wind energy optimization.

Linear regression generated 19 articles, meaning it is less used for directly optimizing turbine performance. This result reflects that the linear regression model cannot capture the complexity of the phenomena behind the parameters influencing wind energy production and, therefore, its optimization. Logistic regression is identified with only three articles and is rarely applied in this context.

KNN and decision tree models, each with 11 articles, show that they are incompatible with optimization in wind energy production. However, SVM recorded 68 articles in the last 5 years. This value demonstrates the usefulness of these algorithms in optimizing turbine performance and energy production.

With 49 articles, random forest demonstrates the model's ability to handle large datasets. This model is suitable for optimizing wind turbine performance because it manages data complexity. Similarly, with 174 articles, ANN shows the ability to learn from complex data, being extensively studied in the problem of optimizing wind energy production. Likewise, with 83 articles, CNN demonstrates the model's suitability for analyzing wind turbine sensor signal data to improve optimization processes.

RNN was identified in the literature with 52 articles. These address short-term forecasts and modeling of the dynamics of wind turbines. Regarding boosting models, AdaBoost (7 articles) and gradient boosting (37 articles) are less debated in the literature but help improve performance by combining multiple classifiers. The XGBoost, with 31 articles, is considered an efficient model for optimizing ML processes, and it is being applied to improve wind energy predictions. Clustering models such as K-Means, with 73 articles, allow for the grouping of data based on common characteristics, and they are used for segmenting and analyzing turbine behavior. DBSCAN (10 articles) is used to identify densely clustered data groups, and PCA, with 35 articles, helps reduce data dimensionality.

Therefore, ANN, CNN, RNN, random forest, and SVM models are the most widely used in the field due to their ability to learn from complex data and optimize energy generation processes. This detailed analysis shows the superiority of the naive Bayes model in wind energy optimization, confirmed by the 265 articles identified in the WOS.

4.3. ML Models for Optimized Wind Power Process

The results from searching scientific articles on ML models applied in the wind energy production process highlight a notable interest in optimizing and improving this sector through various techniques. This discussion will analyze the results of the ML models used to address specific challenges of the wind energy production process. The results are graphically illustrated in Figure 7.

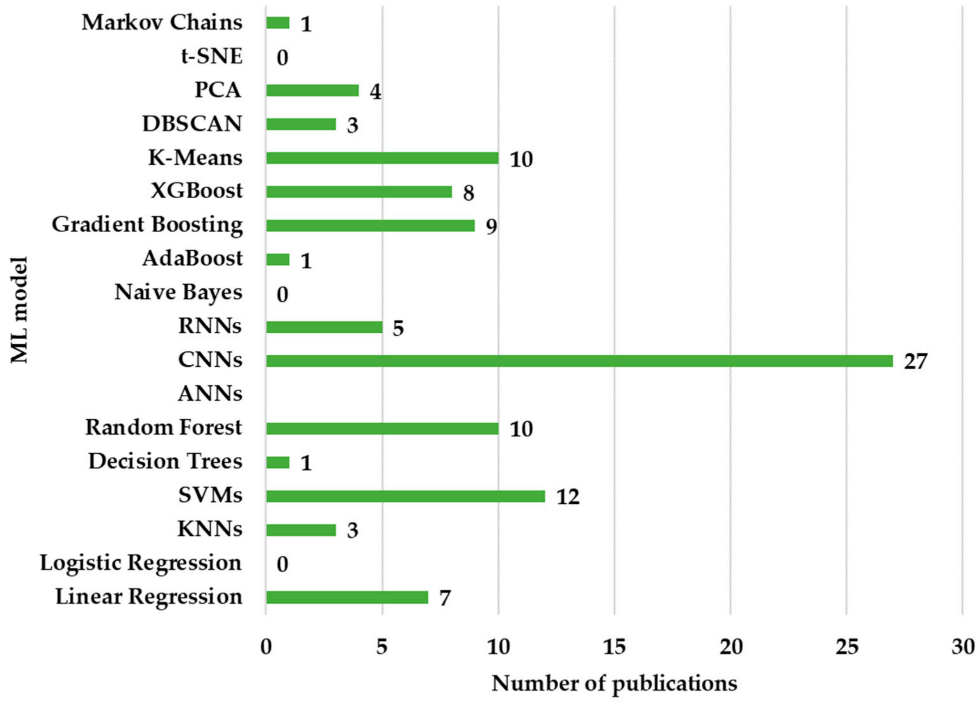

Figure 7. ML models for optimizing wind energy production processes.

The analysis of the application of various ML models in optimizing the wind energy production process suggests diversity in their usage. Each model has different applicability depending on the complexity of the process and the intended purpose.

Linear regression is identified in seven articles, indicating modest usage in optimizing wind energy production processes. Although frequently used in classification problems, logistic regression does not appear in the set of articles in the context of processes, suggesting that classification approaches are not as often used for optimizing wind energy production processes.

Only three articles mention KNN in the category of classification models, reflecting its relatively limited application in this field. Although potentially useful for data classification and identifying patterns or anomalies in wind turbine performance, this model is less efficient than more sophisticated techniques. Additionally, naive Bayes, which is usually employed for classification tasks, does not appear in the articles on wind energy process optimization, underscoring that more straightforward classification approaches are unsuitable for optimizing the wind energy production process.

The results regarding SVM and decision tree models suggest that SVM is used in 12 articles, indicating medium applicability. Decision trees are used less frequently, found in only one article, showing that this technique is less commonly used in this specific context.

Ensemble models, random forest (used in 10 articles) and gradient boosting (used in nine articles), are employed to understand better the variability and complexity of wind energy production processes. XGBoost, found in eight articles, is a popular method for enhancing models through advanced optimization techniques.

Regarding neural networks, CNNs are encountered in 27 articles, and RNNs in five. The values show that this type of network is used for sequential data processing, but their application in this field is more limited.

K-Means, found in 10 articles, is a clustering model for grouping data to analyze wind turbine performance patterns. Additionally, dimensionality reduction techniques such as PCA and t-SNE are used in four and two articles, respectively, showing the possibility of applying them for data visualization purposes or identifying relevant features from large datasets.

This analysis notes that the CNN model is the most extensively analyzed in the specialized literature on optimizing wind energy production processes.

4.4. Evaluation Metrics Employed by the ML Models for Optimized Wind Power Process

ML models are evaluated by calculating performance metrics. In what follows, the number of articles for each model addressing specific aspects of performance metrics will be identified in the literature using WOS. Table 1 summarizes the results obtained from the searches provided by WOS. The queries to receive these results can be consulted in the Supplementary Materials ML_models.xlsx, sheet 4.4.

Table 1 shows the scientific activity regarding algorithms for optimizing wind energy production according to the applied search criteria. The few articles identified in the WOS over the 2020–2025 period indicate difficulties in approaching this topic in a manner that meets all search criteria.

Additionally, the scarcity of publications may reflect the emerging nature of this research field. Optimizing wind energy production through specific algorithms requires the development of complex models capable of integrating meteorological variables, historical data, and operational constraints. This entails significant investment in computational infrastructure and access to large databases.

Another factor that could explain the low results is the difficulty of integrating optimization methods based on metrics in the wind energy domain. Most studies on wind energy focus on turbine efficiency, environmental impact, and grid integration. The use of optimization algorithms is a relatively new topic. Traditional algorithms, such as SVM, random forest, and ANN, do not appear to have been extensively used for this purpose, according to the data analyzed in Table 1.

The results identified for other methods, such as ANN or gradient boosting, suggest the potential for using advanced ML techniques for wind energy optimization. However, these have not yet been widely explored. The lack of values for metrics such as accuracy, F_1-Score, or AUC-ROC indicates that the models developed and presented in the literature are not sufficiently performant to yield conclusive results.

Regarding unsupervised learning techniques, such as K-Means or DBSCAN, the zero values for evaluation metrics suggest that these methods have not been applied or have not succeeded in identifying patterns for optimizing wind energy production. This could be explained by the complexity of the wind energy production phenomenon, which depends on multiple variables that are difficult to capture through standard clustering methods.

Table 1. The number of articles in WOS addressing ML algorithms and performance metrics in wind energy optimization.

ML Model	Performance Metrics	Number of Publications
Linear Regression	R^2	1
	Mean Absolute Error	3
	Mean Squared Error	2
	Root Mean Squared Error	2
Logistic Regression	Accuracy	0
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
KNNs	Accuracy	1
	Precision	1
	Recall	1
	F_1-Score	1
	AUC-ROC	0
SVMs	Accuracy	2
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
Decision Trees	Accuracy	1
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
Random Forest	Accuracy	3
	Precision	2
	Recall	0
	F_1-Score	0
	AUC-ROC	0
ANNs	Accuracy	6
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
CNNs	Accuracy	1
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
RNNs	Accuracy	3
	Precision	0
	Recall	0
	F_1-Score	0
	AUC-ROC	0
Naive Bayes	Accuracy	0
	Precision	0
	Recall	0
	F_1-Score	0

Table 1. *Cont.*

ML Model	Performance Metrics	Number of Publications
AdaBoost	Accuracy Precision Recall F_1-Score	0 3 0 0
Gradient Boosting	Accuracy Precision Recall F_1-Score	3 3 1 1
XGBoos	Accuracy Precision Recall F_1-Score	1 1 0 0
K-Means	Silhouette Davies–Bouldin Index Inertia	0 0 0
DBSCAN	Silhouette Davies–Bouldin Index	0 0
PCA	Explained Variance Ratio Reconstruction Error	0 0
t-SNE	Perplexity Trustworthiness	0 0
Markov Chains	Transition Matrix Stationary Distribution	0 0

These results highlight the gap between the large volume of research on wind power and the limited number of studies addressing the optimization of wind energy production processes through ML models.

5. Analyzing Influencing Parameters in Wind Energy with ML

ML models have shown potential in the specialized literature for improving wind energy production processes by identifying and analyzing parameters that influence this process. The following analysis aims to review the ML models used in the specialized literature, focusing on the factors that affect the optimization of the efficiency and performance of wind turbines and, therefore, the overall wind energy production process.

The parameters identified as strong influencers in this process are wind speed, wind direction, climatic conditions, meteorological forecasting, turbine design, grid connectivity, turbine height, and terrain topology. These will be analyzed concerning wind energy production.

5.1. Statistical Literature Considerations

One parameter influencing the optimization of the wind energy production process is meteorological forecasting. The papers [92] and [93] published in 2024 and 2025 are identified in the specialized literature for analyzing meteorological forecasting within the context established by this analysis. Another parameter that influences wind energy production is wind speed itself. In this setup, 309 papers are identified in the specialized literature. Additionally, wind direction is another parameter that has generated 31 results in the specialized literature. Turbine design has produced a single paper in WOS search [94]. Climatic conditions are analyzed in the context of five papers. Grid connectivity has one associated paper in the literature [95]. Elements such as terrain topography or turbine height have not generated results in the literature. These values are synthesized in Figure 8, which presents the number of papers for each identified parameter.

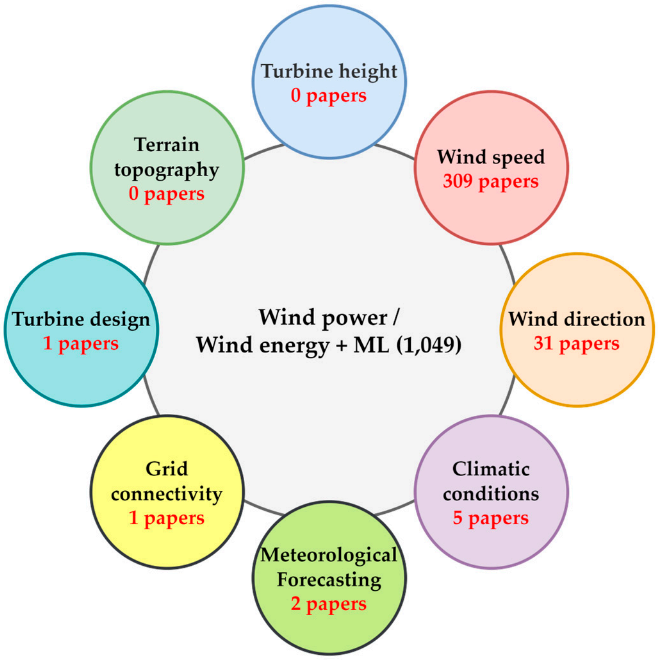

Figure 8. Distribution of research papers across key parameters in wind energy production.

The first identified parameter that influences wind energy production is wind speed itself. In this setup, 309 papers are identified in the specialized literature. Additionally, wind direction is another parameter that has generated 31 results in the specialized literature. Turbine design has produced a single paper in WOS search [94]. Climatic conditions are analyzed in the context of five papers. Grid connectivity has one associated paper in the literature [95]. Elements such as terrain topography or turbine height have not generated results. These values are synthesized in Figure 8, which presents the number of papers for each identified parameter.

Three hundred and two articles address wind turbines from an ML perspective. Of these, 60 contain optimization elements for the wind energy production process. In the 60 publications, 317 keywords were identified. The frequency distribution of keywords across the 60 publications is illustrated in Figure 9. In total, 194 distinct keywords were identified. Notably, the term “optimization” appeared in 17 of the 60 publications. The analysis in Figure 9 provides insights into research trends in wind energy and optimization through ML. The identification of 317 keywords underscores the diversity of approaches and topics explored. The fragmentation of research interests is evident, as 194 keywords were mentioned only once.

Out of these 60 articles, the two published in 2025 were excluded, as the analysis results would not have been relevant in this context. Subsequently, the number of articles published each year was counted. The graph in Figure 10 shows the growing interest in optimizing the wind energy process using ML techniques.

Of the 60 papers discussed above, 2 consider failure detection [96,97] as an optimization wind power objective.

The literature addresses optimizing wind energy production using ML in a single paper [98]. This paper studies ML for the energy prediction of wind turbines through linear regression algorithms, for which an R^2 of 61.99% was obtained, random forest regression with an R^2 value of 76.08%, and LASSO regression with 61.10%. The article was published at the end of 2024, and these results suggest the need for further improvements.

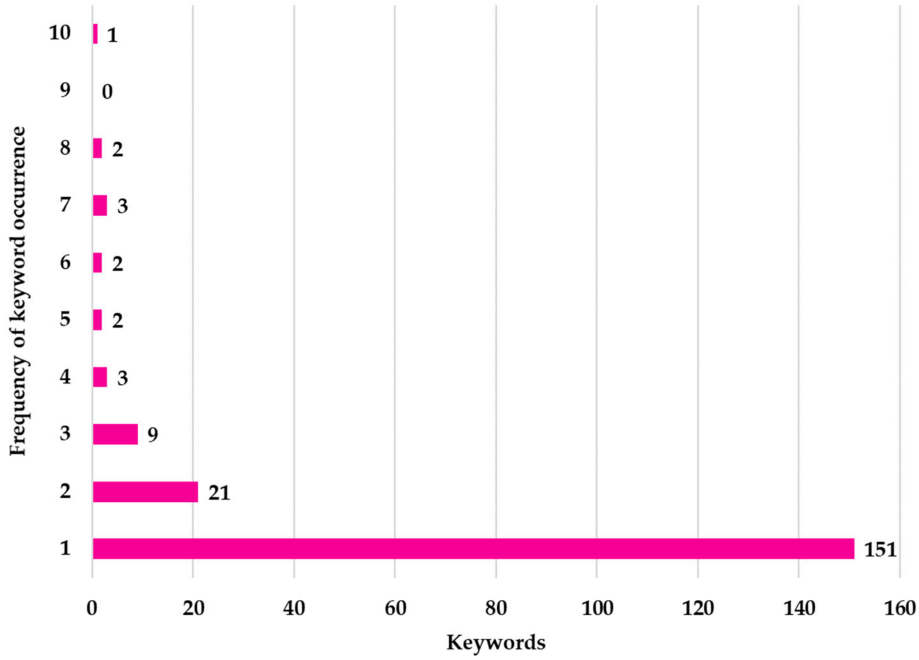

Figure 9. Frequency of unique keyword occurrence in research papers that contain optimization elements for the wind energy production process.

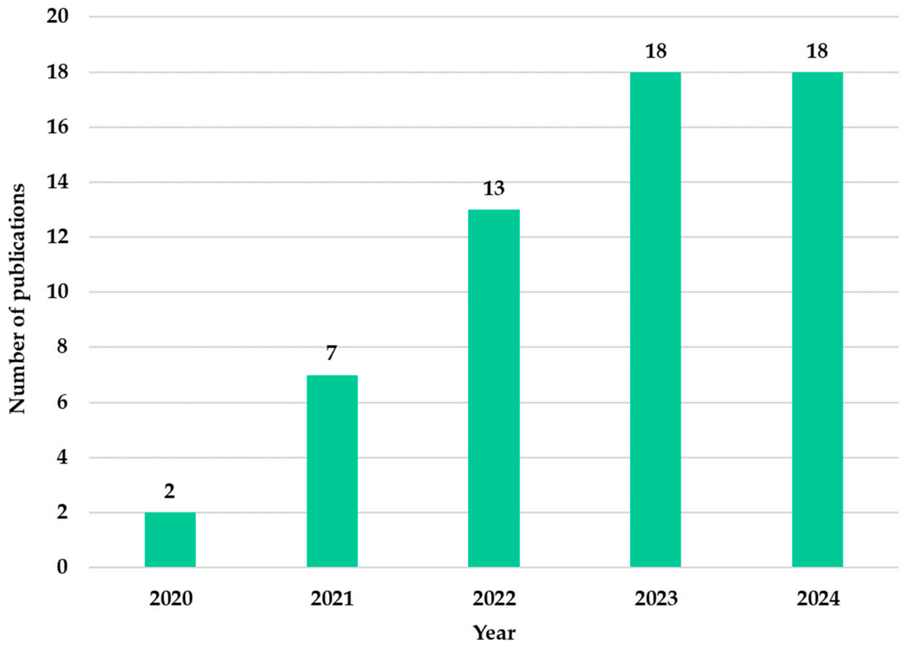

Figure 10. Annual trend of publications on wind energy production optimization (excluding 2025).

Figure 11 presents the number of articles disseminated in each publication. It shows how many articles were identified between 1 January 2020 and 1 March 2025 and provides a clear picture of the distribution in wind energy production optimization. The analysis of these data highlights the contribution of each publisher to the advancement of research, with MDPI being the undisputed leader. This demonstrates the publishers' support for technological and scientific development in this field.

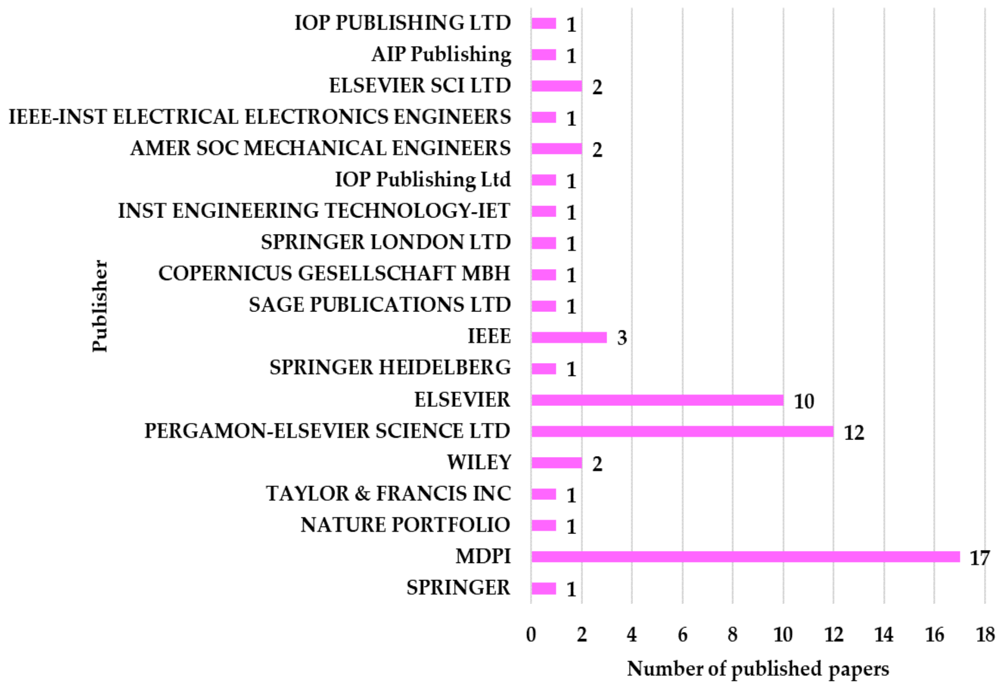

Figure 11. Articles by publishers in wind energy optimization.

The total number of times cited in WOS Core for the 60 publications was 1026, and the total number of times cited in all databases was 1057. These values suggest an increased interest in these articles, with citations representing discussions of the subject in another article that cites them.

5.2. Detailed Literature Content Review of ML Applied in Wind Energy Optimization Process

The 60 papers are organized into five categories as follows:

- Twenty papers address wind energy and wind speed forecasting. These are divided as mentioned next (Figure 12):
    - Two papers conduct review-type analyses, noting that ML models are studied to optimize wind farm power generation and minimize downtime. Farrar et al. [88] explored ML applications in wind turbine control, covering wind speed and power prediction, mechanical fault detection, and electrical fault prevention. A novel physics-inspired neural network model [99] also integrated wake effects into wind power forecasting. Guo et al. [99] increased prediction accuracy by over 20% compared to traditional models. This approach highlights the importance of considering wake effects in short-term forecasting;
    - Five papers are specific forecasting studies. The study by Yelgeç and Bingöl [100] used LSTM, XGBoost, and Bayesian-optimized for weather forecasting. A comparative ML analysis in [101] optimizes LightGBM, reducing RMSE to 190.34 kW. Javaid et al. [102] evaluated hydrogen production from suburban wind, showing that LSTM provides the best estimates. In Mongolia, the models improved wind forecasting accuracy, reducing errors by up to 36.19% [103]. Xin et al. [104] presented a hybrid DL model for Baltic Sea wind speed forecasting in the context of wind energy.
    - Eight papers tackled wind energy production optimization from an ML perspective. Sireesha and Thotakura [105] analyzed the optimization of wind energy in Andhra Pradesh, India, using an optimized neural network model that achieved 97.1% accuracy. Another ML model was presented by Li et al. in the paper

at [106] that enhances wind speed prediction through AI and proposes a new performance metric called AECP. According to Ashwin Renganathan et al. [107], ML- and LiDAR-based models optimize wind farm design. The ANN-Jensen model [108] improves the prediction of wake-induced power losses. In the paper by Luo et al. [109], DWFE used combined ML models for dynamic wake estimation. The HHO-XGBoost model proposed by Dong et al. [110] predicts offshore turbine vibrations. Song et al. [111] enhanced rotor speed prediction using LiDAR. The research by Mayer et al. [112] presented a data-driven method for predicting offshore turbine structural vibration accelerations using extreme gradient boosting;

  - Four papers adopted hybrid approaches, combining technologies. Safari et al. [113] introduced the DeepVELOX model for wind energy forecasting, achieving a MAPE of 0.0002 and an R^2 of 1. In South Africa, a hybrid model demonstrated the feasibility of distributed wind generation for agriculture. Short-term offshore wind speed forecasting using seasonal econometrics, autoregressive integrated moving average as a comparison with AI models is presented in the paper [114]. Kirchner-Bossi et al. [115] developed a hybrid physics–data-driven model, improving short-term wind energy forecasting by 16% through optimized predictor selection. A novel 48 h forecast model for small turbines used hybrid methods and neural networks, reducing errors by integrating seasonal and historical variables [116].

- Fifteen papers address wind turbine optimization and control via ML methods. These are categorized as stated below:
  - Two are review-type papers and focus on grid-connected wind farms. These discuss maximizing energy production and downtime. ML algorithms are analyzed for wind turbine control, wind speed forecasting, and fault detection [88,117];
  - Five papers are case studies conducting applied analyses on specific data. Advanced wind turbine optimization techniques include indirect control for tracking the maximum power point of doubly fed induction generators [118], ML-based modeling, and periodic pitch angle adjustment to improve energy production [119]. Also, in the paper by Dorosti et al. [120], the optimization of VAWT was proposed using an ML and optimized torque control based on wind speed estimation [121]. Optimization methods such as neural networks and genetic algorithms reduce computational costs and enhance the performance of diffuser-augmented turbines [122];
  - Eight papers present innovative studies, which include new methods and advanced techniques. These studies have proposed solutions, such as integrating an ANN-based framework for power and turbine lifespan prediction. This was made possible through a two-stage control system that extends the lifespan of wind farms with minimal power reduction [123]. Additionally, location-specific wake steering techniques and ML models were introduced to improve energy production and reduce fatigue loads [124]. Flow control in wind farms using reinforcement learning (RL) has demonstrated improvements in energy production and a reduction in computational costs [125,126]. Using computational fluid dynamics (CFD) and ML, aerodynamic optimization and noise reduction for vertical Savonius rotors bring notable performance improvements [127].
- Twelve papers address the issue of fault detection and maintenance from the perspective of ML and optimization of wind power production processes. These are divided according to the previously used categories as indicated next:

- ○ A case study by Santiago et al. [97] synthesized materials from the literature on fault detection and diagnosis in wind turbines so that the condition of components can be predicted and significant failures can be prevented before they affect performance. The article [97] analyzed various predictive maintenance approaches that use data collected from sensors and supervisory control and data acquisition (SCADA) systems to predict issues before they materialize and to determine the necessary corrective actions;
- ○ Seven articles present case studies discussing the application of ML IoT technologies for improving the performance and maintenance of wind turbines [128]. The studies explore the use of ML for analyzing turbine manufacturing operations [129], energy prediction [98], fault diagnosis [130,131], and anomaly detection based on power curves and ensemble learning [132]. Additionally, methods are investigated for classifying imbalanced data for generator fault detection [133] and drivetrain fault diagnosis in turbines through advanced DL techniques combined with signal processing [134];
- ○ Four papers are positioned as innovative content articles. These present how ML and advanced technologies are applied to improve the efficiency of wind turbines and fault detection. The studies examine the use of ML for intelligent fault detection and turbine placement optimization [96] and for optimizing sensor node placement for anomaly detection [135]. Additionally, methods for automatically quantifying turbine blade edge erosion based on field images [136], fuzzy reliability assessment, and fault prediction using ML [137] are investigated. ML models address the issue of wind turbine placement by analyzing meteorological data (wind speed and direction, turbulence frequency), topography (terrain height, natural or artificial obstacles), and the interaction between turbines through the "wake" effect (the wind shadow area) created by neighboring turbines. Based on this data, ML techniques identify optimal turbine configurations. The goal is to maximize energy production. The results are obtained through simulations and adjustments based on continuous feedback from experimental data. From these considerations, the necessity of a large volume of data that can be analyzed arises.

- Seven papers investigate wake effects and airflow control, being divided as listed below:
    - ○ Three articles are review-type. The study by Dörterler et al. [138] explores ML applications in wind energy, Chatterjee et al. [139] detail recent advances in ML applications for variable renewable energies, and Masoumi [140] focuses on ML applications for offshore wind farms;
    - ○ A case study by Park et al. [141] proposes an ML-based forecasting system to improve prediction accuracy in the wind energy sector, considering the wake effect on wind turbines. This paper uses SCADA data to predict wind speed and power generation, evaluating errors through various regression metrics;
    - ○ Three articles present applications in the field of this category. Gajendran et al. [142] propose an ML model based on symbolic regression for forecasting wind turbine wakes under rotation conditions. This paper accurately predicted wind deflection and velocity deficit. Kaseb and Montazeri [143] study the use of metamodels for aerodynamic optimization of a ducted aperture in a tall building to maximize the wind speed when a wind turbine captures. This recorded remarkable results in increasing available power. The third paper analyzes the application of ML in the wind energy field from design to energy-water interaction, highlighting the importance of metamodels [144].
- Six papers address the optimization of hybrid systems and energy storage. These are divided as detailed next:

- Three case study-type articles. Firstly, the research conducted by Zhou et al. [145] discusses advances in ML related to multi-energy communities by analyzing their mechanisms and applications. Secondly, Bedakhanian et al. [146] also present a thermo-economic and environmental assessment of compressed air energy storage (CAES) integrated with a wind farm in Denmark. Thirdly, Neshat et al. [104] explore a DL model for short-term wind forecasting at the Lillgrund offshore wind farm;
- Three articles present new methods and advanced technologies for optimizing these systems. Veers et al. [147] describe significant challenges in future wind turbines' design, manufacturing, and operation. Additionally, using ML techniques, Behzadi et al. [148] present an efficient solution for hybridizing renewable energy with hydrogen-based storage to reduce peak demand. Moreover, Ding et al. [149] propose an innovative methodology for optimizing a renewable energy system, power to gas, and solid oxide fuel cells.

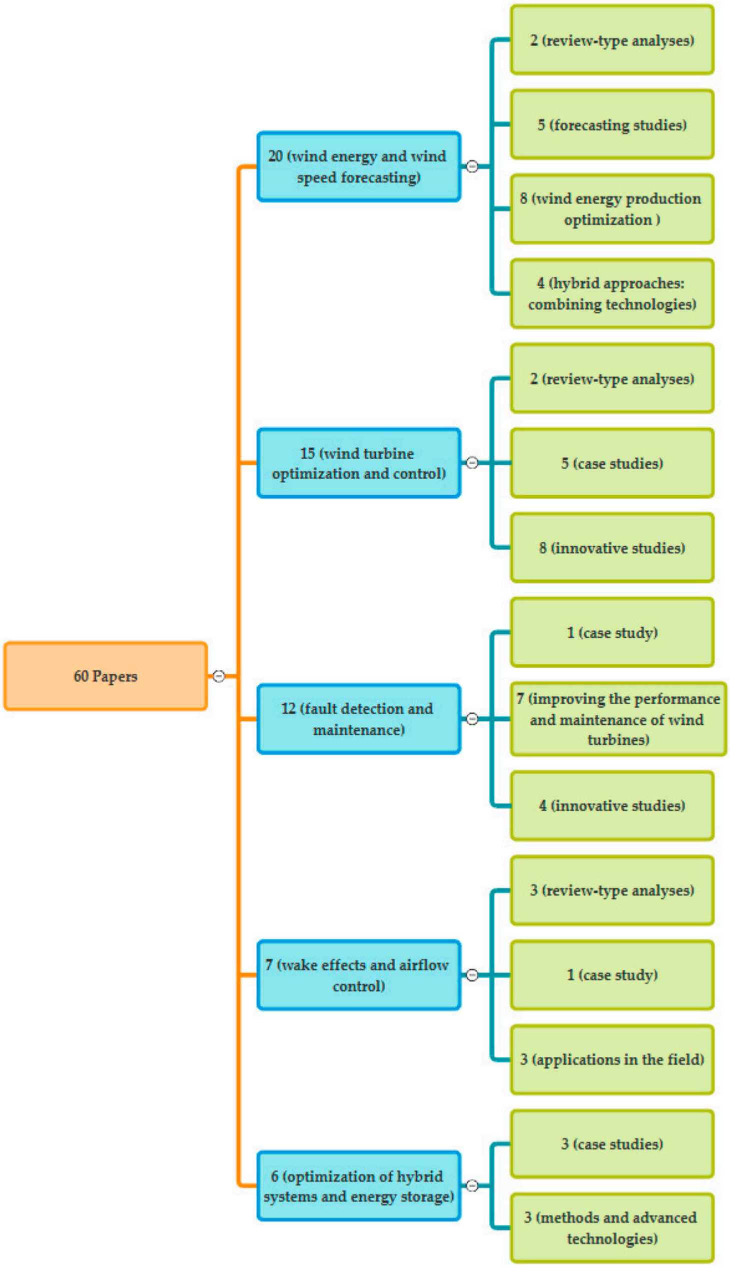

Figure 12. Categories and subcategories of the 60 papers.

All these papers approach ML by optimizing specific processes in renewable wind energy production.

6. Discussion

In this study, all specific scenarios of the wind energy production process were analyzed using ML techniques. Initially, the basic concepts specific to wind energy were presented, highlighting that wind turbines are the central element of the process. Additionally, parameters influencing process optimization were identified, including meteorological forecasting, wind speed and direction, turbine design, turbine height, terrain topology, climatic conditions, and grid connectivity. Subsequently, ML elements were introduced in the context of wind energy, with 17 models identified.

6.1. Detailed Analysis of Results

In this paper, a bibliometric analysis was conducted to evaluate the application of ML models in wind energy optimization. The study selection was based on a search in the WOS database. The primary search queries used in WOS included general ML models in wind energy. Next, optimization-specific studies were extracted, and production-related studies refined the result. Lastly, performance evaluation metrics related to ML, production, and optimization were analyzed. The search covered studies published between 1 January 2020 and 1 March 2025, to ensure that only the recent research was included. Among the analyzed models, ANN provided the most articles (478), followed by random forest (224) and gradient boosting (114). These results reflect the ability of these models to handle large volumes of data and model complex relationships between wind energy production parameters.

Scientific papers addressing wind energy production optimization without ML techniques were identified in the following analysis scenario to enable a comparative analysis with ML-based results. The results indicated naive Bayes had the highest number of articles (265), followed by ANN (174) and CNN (83).

In the third scenario, ML models were introduced alongside optimization problems, with 27 articles identified for CNN, 12 for SVN, and 10 for random forest and K-means. These results are explained by CNNs used for short-term wind energy production forecasting, K-Means for energy output prediction, and the other models for meteorological predictions.

The research has continued by investigating ML model performance evaluation metrics using standard tools such as accuracy, precision, recall, etc. All 17 identified models were quantified through these metrics. The most consistent results were obtained for linear regression, evaluated via R^2 in one article, mean absolute error in three articles, and mean squared error and root mean squared error in two articles.

These results demonstrate that models are not consistently evaluated in the literature when addressing wind energy production optimization using ML. Future research should address this gap.

After analyzing the four scenarios, factors influencing the optimization process were examined. The literature identified 1049 articles addressing ML perspectives, with narrowed searches yielding 309 for wind speed, 31 for wind direction, 5 for climatic conditions, 2 for meteorological forecasting, 1 for grid connectivity, and 1 for turbine design.

Subsequently, wind turbines were analyzed as the central element of optimization, with 302 articles identified. Of these, 60 included elements specific to the wind energy production process. For the 60 publications, 317 keywords were identified, 194 of which were unique (not shared between articles). Among these, 17 publications included the term "optimization". These findings highlight the fragmented approach to optimization in this field, suggesting the need for unified frameworks in future studies.

To assess researchers' interest in optimizing wind energy production using ML, a statistical analysis revealed growth from two articles in 2020 to eighteen in 2024. The year 2025 was excluded due to incomplete monthly data.

Regarding publications disseminating the most research on ML-based optimization, MDPI led with 17 articles, followed by PERGAMON-Elsevier (12) and Elsevier (10). This analysis aimed to highlight outlets with heightened interest in the topic.

Finally, the 60 reference articles were categorized by influencing parameters and subcategorized into review, research, or comparative analysis articles. Only 11 review articles were identified across five relevant categories.

6.2. Comparative Analysis of ML Models

As specialists in the field of ML, the authors carried out the comparative analysis of the models by analyzing previous specialized literature. To conduct the comparative study, they classified ML models and assigned scores based on performance criteria.

The previous presentation analyzed various ML models for wind energy applications. Table 2 summarizes key aspects of the most commonly used ML models, including their strengths, limitations, and typical applications in wind energy optimization, to provide a structured comparison of their effectiveness in different scenarios.

Table 2. Comparative analysis of the identified ML models in the literature.

ML Model	Strengths	Limitations	Applications in Wind Energy
Linear Regression	Simple, interpretable, fast to train	Limited accuracy for nonlinear relationships	Baseline forecasting, power curve modeling
Logistic Regression	Effective for classification tasks	Not suitable for continuous output prediction	Fault detection, failure classification
KNNs	Works well with small datasets, non-parametric	Computationally expensive for large datasets	Wind pattern recognition, anomaly detection
SVMs	High accuracy for classification problems	Slow training on large datasets requires feature scaling	Wind speed and power prediction
Decision Trees	Easy to interpret, handles nonlinear data	Prone to overfitting without pruning	Wind turbine performance assessment
Random Forest	Robust, reduces overfitting	Computationally expensive	Energy output prediction, predictive maintenance
Gradient Boosting	High accuracy, handles complex patterns	Prone to overfitting with small datasets	Wind speed forecasting, turbine fault prediction
XGBoost	Optimized for speed and performance	Requires careful hyperparameter tuning	Wind farm energy production modeling
ANNs	Handles complex nonlinear relationships	Computationally intensive, requires large datasets	Power output optimization, predictive maintenance
CNNs	Excels in pattern recognition from spatial data	Requires large, labeled datasets	Wind turbine image-based fault detection
RNNs	Effective for sequential and time-series data	Prone to vanishing gradient problem	Wind speed and power time-series forecasting
DL	High accuracy, learns complex patterns	Requires high computational power	Multi-variable wind energy forecasting

Table 2 highlights the diversity of ML models applied in wind energy research. While ANN, random forest, and gradient boosting techniques consistently demonstrate high performance, simpler models like linear regression and decision trees are often used as benchmarks.

Table 3 shows the comparison of ML models based on precision, efficiency, and weaknesses in optimizing wind energy production. The highest-precision models, such as ANNs, CNNs, RNNs, and gradient boosting models, provide the best forecasting and predictive maintenance precision. The scoring is performed on a scale from 1 to 5. For each criterion, the models received a score between 1 and 5, according to the following scheme:

- 1 point: Impossible to use in practice and not used in optimizing wind energy production;
- 2 points: Low performance associated with simple models, with modest results in the field;
- 3 point: Average performance for which ML models are intensively analyzed in the literature but which have been identified with a series of limitations;
- 4 points: Good performance in the field of wind energy production optimization;
- 5 points: Excellent performance determined by complex models capable of efficiently optimizing energy production.

Table 3. Comparative analysis of the identified ML models in the literature based on the wind energy optimization process.

ML Model	Precision (Score)	Efficiency (Score)	Weakness
Linear Regression	2	4	Cannot model complex nonlinear relationships
Logistic Regression	2	3	Poor performance for multi-class and complex problems
KNNs	3	2	Computationally expensive for large datasets
SVMs	4	3	Slow training for large datasets
Decision Trees	3	3	Overfits easily without pruning
Random Forest	4	4	Hard to interpret, computationally expensive
Gradient Boosting, XGBoost, AdaBoost	5	4	Requires hyperparameter tuning, high computational cost
ANNs	5	4	Black-box nature requires large datasets
CNNs	5	3	The high computational power required
RNNs, LSTM	4	3	Long training times, vanishing gradient issue
DL–Hybrid models	5	4	It needs big data, computationally expensive
K-Means Clustering	3	3	Poor performance on noisy data

The scores were determined through a comparative analysis of the reviewed studies. The values were determined by correlating the number of publications that use each model, and their performances mentioned in the literature.

Table 3 structurally explains which ML models work best for different wind energy optimization tasks. This approach will help researchers and industry professionals make future investigations. This study aims to identify academic and scientific interest in optimizing wind energy prediction using ML. The results show growing interest, though the number of articles remains small, likely due to limited access to extensive historical data. This data scarcity represents a key limitation.

6.3. Research Gaps Identification and Study Limitations

By analyzing the previous work, the following gaps in the research on ML for wind energy optimization have been identified:

- No studies specifically address the influence of geographic topology or turbine height on wind energy optimization. These factors help to understand the localized wind patterns and should be addressed in the literature as future research;
- The literature lacks standardized evaluation metrics for comparing ML models in wind energy optimization. This inconsistency complicates the assessment of model reproducibility of results;
- Clustering methods like K-Means and DBSCAN are underexplored in wind energy optimization. These techniques should be explored to identify patterns in wind turbine behavior;
- Most studies focus narrowly on forecasting wind speed or power output rather than addressing comprehensive production optimization. This fragmentation limits the development of unified optimization frameworks;
- Techniques like PCA and t-SNE are rarely used for dimensionality reduction in wind energy datasets. These methods could simplify complex data pattern recognition;
- Climatic conditions, terrain topology, and grid connectivity are underrepresented in the literature. These factors influence wind energy production and require deeper investigation;
- Many studies consistently fail to report key performance metrics (e.g., accuracy, F_1-Score, AUC-ROC). This gap hinders the ability to compare and validate ML models effectively;
- Most studies focus on short-term forecasting and optimization, leaving long-term strategies underexplored;
- Hybrid approaches that combine physics-based models with ML techniques are rare. These models could better capture the complex dynamics of wind energy systems;
- The fragmented nature of the current research highlights the need for unified frameworks that integrate meteorological variables, historical data, and operational constraints for comprehensive optimization.

The identified gaps highlight the need for standardized and interdisciplinary research in wind energy optimization using ML. Addressing these gaps could lead to advances in optimizing wind energy production.

6.4. The Impact of Discoveries on the Improvement of Wind Energy and Future Solutions

The analysis of the specialized literature on the use of ML for optimizing wind energy has highlighted a series of aspects that can contribute to improving the performance of wind turbines and their integration into global energy systems.

One primary aspect concerns optimizing energy production forecasts. DL and ANN models have demonstrated an improved ability to predict energy production based on meteorological and operational data. CNN and LSTM algorithms provide short-term predictions. This feature reduces uncertainty in energy planning.

Using random forest, gradient boosting, and XGBoost to analyze turbine power curves allows for assessing future production. This allows for efficient energy production management in decisions regarding storing surplus energy.

ML models can help increase operational efficiency through predictive maintenance. This allows for the early detection of turbine failures, directly reducing downtime and maintenance costs. Integrating IoT elements and SCADA data analysis allows for real-time turbine performance monitoring. This allows for the adjustment of parameters to optimize the process. Classification and anomaly recognition algorithms help optimize preventive maintenance strategies. Thus, the lifespan of the turbines is extended.

Relevant application solutions target hybrid technologies previously identified in the literature. For example, hybrid ML modeling with CFD can be used to estimate turbine efficiency based on atmospheric conditions. Implementing digital twins technology to test turbine optimization scenarios without interfering with the physical infrastructure is also recommended. The authors also recommend exploring the possibility of using synthetic data in evaluating wind energy efficiency. Another hybrid approach could be integrating cloud technologies to transmit and process data from the turbines. Multi-criteria planning allows for optimizing energy resources by introducing a two-phase model and a GSR/RGSG heuristic algorithm for managing resource conflicts [150,151]. This proposal is applied to the planning of hybrid wind systems characterized by the uncertainty of global resources. At the same time, Wang et al. [27] explore the optimization of maintenance costs for wind–photovoltaic hybrid systems. The simulations presented by Zhao et al. [152] conducted in MATLAB/Simulink demonstrate the ability to maintain stable frequency-voltage support for hybrid wind farms under variable conditions.

Developing new strategies for integrating wind energy into grids can be associated with intelligent storage systems (batteries, power-to-gas, green hydrogen) to compensate for wind intermittency [153]. Li et al. [154] explored the potential of gravitational storage. These technologies offer eco-friendly and cost-effective solutions for storing excess wind energy. Additionally, the paper by Yi et al. [155] discussed the role of the complete hydrogen-based energy chain in decarbonization. These approaches highlight the importance of integrating multi-energy systems to streamline the energy storage process.

In identifying the current limitations, it is explicitly mentioned that an interdisciplinary approach facilitates the energy transition toward a higher level of technological optimization. The convergence of AI, energy engineering, meteorology, and economic sciences can provide hybrid solutions for:

- Intelligent management of renewable resources through production optimization;
- The implementation of digital twin technology in energy networks;
- Enhancing wind turbine efficiency through predictive maintenance;
- Optimizing wind energy production through adaptive control;
- Integrating renewable sources into smart grids using advanced forecasting models;
- Improving energy storage efficiency with ML-based technologies that analyze demand and supply in real-time.

ML technologies can explore optimizing the hybrid cooperation between wind energy and other renewable sources (wind, solar, and hydro hybridization) to achieve an energy mix. Another strategic direction considers the development of AI algorithms for micro-grids. This allows local production management and intelligent energy distribution to the population or storage elements.

6.5. Recommendations for Future Research

Future research should focus on expanding datasets, exploring geographic and turbine height impacts, and developing standardized evaluation metrics for ML models in wind energy optimization.

To increase the number of research studies on optimizing wind energy production processes, the datasets should contain meteorological data from wind farms that include the following features:

- Wind speed and direction at different altitudes;
- Temperature and atmospheric humidity;
- Atmospheric pressure;
- Turbulence and extreme phenomena (storms, gusts of wind);
- Short-term and long-term forecasts for climate variations.

Currently, these datasets are either incomplete, do not belong exclusively to a specific park, or do not contain a sufficiently large volume of data to provide templates that ML models can identify. Information about the terrain's topography is extracted from features such as the following:

- The altitude and geographical structure of the area;
- Natural or artificial obstacles that can influence airflow;
- The distribution of turbines in wind farms;
- The impact of the wake effect;
- Operational data regarding network integration.

A few specialists cannot collect such datasets because they involve multidisciplinary collaboration. These data can only be collected from the wind farm, which is unavailable in the public version. The difficulty in accessing such a dataset hinders research in the field. Regarding the technical parameters of the turbines, they are characterized by the following:

- The power produced depends on the weather conditions;
- The efficiency of turbines at different wind speeds;
- Data regarding component wear;
- The degree of necessity of maintenance;
- Malfunctions detected;
- The operating duration of the turbines.

If there were possibilities to recombine the set in the case of datasets associated with meteorological data or terrain topology, the work would be complicated in the case of technical parameters. A data operator cannot recombine such a dataset, as it can only be extracted from the actual process.

Future work and prospects in wind energy optimization using ML should consider expanding the field by simultaneously addressing the factors influencing wind power production. Exploring hybrid models should combine multiple ML techniques and extend the research to models that have not yet been sufficiently studied in wind energy. The authors recommend studying the fluid dynamics of wind turbines.

Another recommendation from the authors is to publicly distribute data from wind farms so that researchers can study the data. It is well-known that ML models require large volumes of data to identify patterns. Additionally, a series of studies could be explored using synthetic data at the digital twin level. This combination could be a virtual replica of wind turbines that simulate real-world conditions.

Another idea could be to improve ML models by training them on quantum systems. This study could identify accuracies that have not been achieved in previous training. Additionally, the training could be repeated periodically by adding new data and incorporating the effects of recent decisions.

Wind energy optimization should be studied concurrently with other renewable energies, such as wind–solar systems. Another interdisciplinary direction through which optimization studies can be conducted involves IoT technology. This technology consists of installing sensors on wind turbines. They report the monitored values in real time through a Cloud infrastructure. The integration of ML models allows for decision-making to optimize production performance dynamics. The energy storage method can be implicitly identified from the category of these decisions.

Therefore, future research should focus on interdisciplinary collaboration. The next generation of hybrid AI models should enable real-time optimization. The evolution of wind energy production optimization is closely correlated with technological advancements in AI and electrical engineering.

7. Conclusions

This research studied 17 ML models for optimizing wind energy production. The analysis of the papers that identify the influencing parameters in the process is presented for detailed discussion. Among the main findings are the following:

- Frequent use of advanced ML models, such as ANNs, random forest, and gradient boosting, due to their ability to analyze complex data;
- Traditional models, such as linear and logistic regression, are used less frequently, as they cannot capture the complexity of phenomena influencing wind energy production;
- Unsupervised models, such as K-means and DBSCAN, are not significantly utilized, suggesting that cluster analysis is not yet widely exploited in this field;
- Growing interest in hybrid methods, which combine traditional and advanced approaches to improve predictions;
- Current limitations include difficulty accessing relevant data and the lack of standardized methodologies for evaluating model performance specific to wind energy production.

This research demonstrated that using ML models for optimizing wind energy production is not only feasible but also necessary to increase the efficiency of this sector. The literature analysis confirmed the hypothesis that ML models can improve the performance of wind turbines through production forecasting and optimization of influencing factors. The results emphasize that advanced ML methods enable better modeling of wind energy variability, leading to more efficient production planning and reduced operational costs.

By analyzing the data and models studied, the following general conclusions can be drawn:

- Neural network-based models are the most efficient for forecasting wind energy production due to their ability to analyze complex patterns in historical data;
- Random forest and gradient boosting models help identify and optimize factors influencing turbine performance;
- Hybrid models, which combine ML techniques, demonstrate the potential of integrating multiple methods into a unified approach;
- Integrating ML into wind farm management reduces uncertainty related to wind variability and improves resource utilization.

This study identified correlations between various variables involved in wind energy production. The most significant highlighted relationships including the following:

- Wind speed and energy production;
- Turbine layout;
- Predictive maintenance and turbine durability.

The relevance and impact of the research on the wind energy field have implications for both the scientific community and the energy industry. The main contributions are the following:

- Improving wind energy forecasting strategies;
- Increasing the operational efficiency of wind turbines;
- Reducing costs and environmental impact;
- Opening new research directions.

Based on the results and identified limitations, the following directions are recommended for future research:

- Developing more extensive and accurate datasets;
- Exploring more advanced ML methods;
- Optimizing hybrid architectures;

- Developing standardized methodologies for evaluating the performance of models explored for optimizing wind energy production processes.

This research demonstrates that using ML models represents a strategy for optimizing wind energy production. Advanced models provide enhanced data analysis capabilities and can improve the operational efficiency of wind turbines. However, the application of these technologies is still limited by data access, methodology standardization, and hybrid model integration challenges. Therefore, the future research should focus on overcoming these obstacles to maximize the positive impact of ML on the renewable energy industry.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app15073758/s1, ML_models.xlsx (includes sheets 4.1, 4.2, 4.3, 4.4 and 4.5).

Author Contributions: Conceptualization, C.-M.R.; methodology, C.-M.R. and A.S.; software, C.-M.R. and A.S.; validation, C.-M.R. and A.S.; formal analysis, C.-M.R. and A.S.; investigation, C.-M.R. and A.S.; resources, C.-M.R. and A.S.; data curation, C.-M.R. and A.S.; writing—original draft preparation, C.-M.R. and A.S.; writing—review and editing, C.-M.R. and A.S.; visualization, C.-M.R. and A.S.; supervision, C.-M.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Petroleum-Gas University of Ploiesti, Romania.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial neural network
ARID	Active Rotary Inertia Driver
CAES	Compressed air energy storage
CFD	Computational Fluid Dynamics
CNN	Convolutional neural network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DL	Deep learning
EHSS	Energy Harvesting and Speed Sensing
GEV	Generalized extreme value
HAWT	Horizontal Axis Wind Turbines
IoT	Internet of Things
KNN	K-Nearest Neighbor
LSTM	Long short-term memory
ML	Machine learning
PCA	Principal Component Analysis
RL	Reinforcement learning
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition
SVMs	Support Vector Machines
T3-FLS	Type-3 fuzzy logic system
t-SNE	t-Distributed Stochastic Neighbor Embedding
VAWT	Vertical Axis Wind Turbines
WOS	Web of Science

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