IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 27, Issue 3, Ser. 3 (May. – June. 2025), PP 31-38
www.iosrjournals.org

An Extensive Review Of Metaheuristic Algorithms For Wind Power Prediction

Geetika Sharma*, Madal Lal, Kanwal Preet Singh Attwal
Department Of Computer Science And Engineering, Punjabi University, Patiala, Punjab, India

Abstract
Wind power is the leading renewable energy source, a naturally replenished, inexhaustible resource. Fossil fuels, one of the primary sources of carbon dioxide and other greenhouse gases, are being replaced by wind energy. Accurate wind power forecasting is essential for improved energy generation planning, grid scheduling, energy output generation and demand balance, trade, etc. Preprocessing the data, choosing a suitable prediction model, fine-tuning the model parameters, and assessing the forecast results are some of the procedures involved in achieving an accurate wind power prediction. Choosing an appropriate prediction model and a model optimization technique is critical. Enhancing the prediction accuracy requires optimizing the prediction model's primary parameters using metaheuristic techniques. Various metaheuristic algorithms have been proposed, and each has its own characteristics. This paper provides a thorough analysis and classification of metaheuristic optimization techniques. Furthermore, the benefits and drawbacks of these algorithms are also discussed.
Keywords: *metaheuristic algorithm, optimization, wind power prediction, data preprocessing*

Date of Submission: 23-05-2025 Date of Acceptance: 03-06-2025

I. Introduction

Many conventional energy sources, like coal, oil, and natural gas, are limited and significant producers of greenhouse gases that fuel climate change. On the other hand, renewable energy sources, such as hydroelectricity, biogas, wind, and solar, do not negatively impact the environment. Fossil fuels are being replaced in the power sector due to the rapid expansion of clean electricity driven by solar and wind [1]. Wind energy is a significant and swiftly expanding source of electricity worldwide. Wind generated more than 2494 TWh of electricity in 2024, accounting for 8.1% of total electricity. In 2023, wind power accounted for 7.8% of global electricity consumption, up from 7.3% the year before [2]. The top wind power generation countries by 2024 are shown in Fig. 1 [3].

Wind power is variable, and its uncertainty gives rise to various challenges in the operation of wind systems. Reliable wind energy forecasting is crucial for optimized maintenance activities, grid stability, supply-demand balancing, efficient market trading, reduced operating costs, etc. The wind power prediction can be improved through different methods, such as statistical approaches, machine learning algorithms, and deep learning techniques. [4]. The steps involved in wind power prediction include:

a) Collecting data on wind power, including weather-related factors like temperature, humidity, and wind speed as well as turbine-specific factors like gearbox temperature, blade pitch angle, and control box temperature.

b) Preprocessing the data, which includes various techniques such as data correction, handling missing values, data normalization, feature selection, data decomposition, correlation analysis, and data transformation.

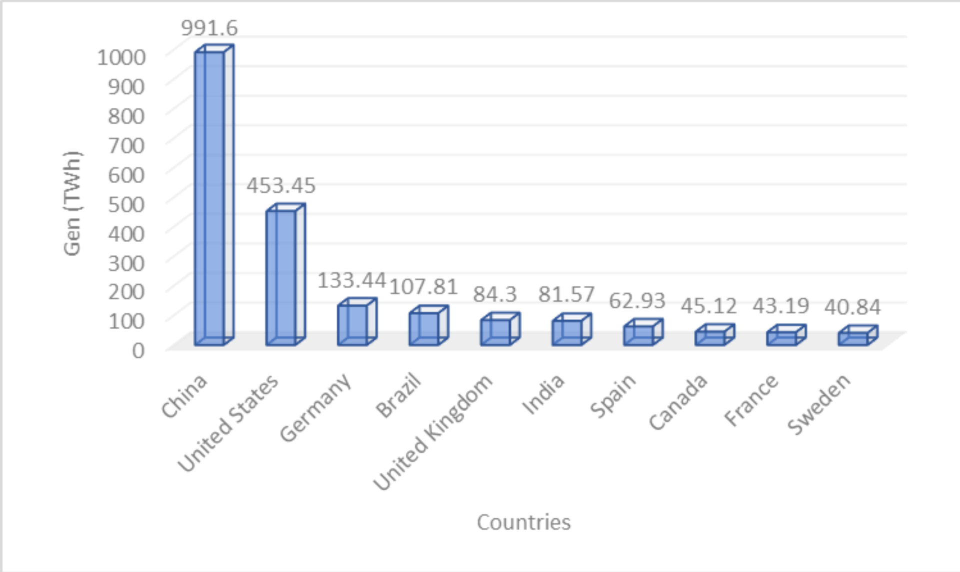

Fig. 1: Top ten wind power generation countries by 2024

c) The next crucial step is selecting an appropriate prediction model. After choosing the model, its parameters are fine-tuned to achieve optimized prediction results. The model is subsequently trained with the data that has been processed.
d) Ultimately, the anticipated results are contrasted and examined alongside the real output value to assess the model's effectiveness.

Artificial neural networks and deep learning methods have been utilized for predicting wind power. One of the main challenges in machine learning is to improve these models [5]. The researchers' primary focus over the past few decades has been to optimize the model's parameters and structure. Many factors are considered when optimizing ANNs and deep learning models, including learning parameters, activation nodes, network structure, weights, and hyperparameters [6,7]. Gradient-based techniques for architectural training have been employed in numerous previous studies. However, because of these algorithms' shortcomings, an optimization method is required. Metaheuristic methods are used extensively in the structure and parameter optimization of deep learning models because training them is an NP-hard optimization issue. The learning process is enhanced when deep learning is trained using metaheuristic algorithms, which shortens the execution time and improves accuracy [8].

The remaining sections of the paper are organized in the following way: Section 2 discusses the fundamentals of wind power prediction. Section 3 reviews different metaheuristic algorithms, and finally, Section 4 presents the conclusions.

II. Wind Power Prediction

Predictive Factors for Wind Power

Predicting wind power is challenging since it is influenced mainly by wind speed, which is inconsistent and varies erratically over time. Wind speed further depends on various other meteorological factors and location [9]. The meteorological variables that directly or indirectly influence wind power are: wind speed, wind direction, air density, air temperature, humidity, air pressure, rainfall, and precipitation. Numerous turbine-specific factors significantly impact wind power generation. Numerous researchers have included these factors in their investigations to enhance the precision of predicting wind power [10]. The variables consist of motor speed, impeller speed, blade torque, and blade pitch angle, etc.

Time Horizons

There are various time scales into which the wind power forecast models can be categorized. Based on different requirements for operation, these time ranges can be classified into four groups [11], as illustrated in Fig. 2. The primary applications of very short-term prediction are real-time grid operation, turbine management, different regulatory actions, and clearing the power market. Short-term prediction helps in planning load dispatch and making informed load decisions. Energy trading, online and offline generating decisions, and operational security in the electricity market all rely on medium-term prediction. Long-term prediction is employed for reserve requirements, functional management, and maintenance scheduling [12].

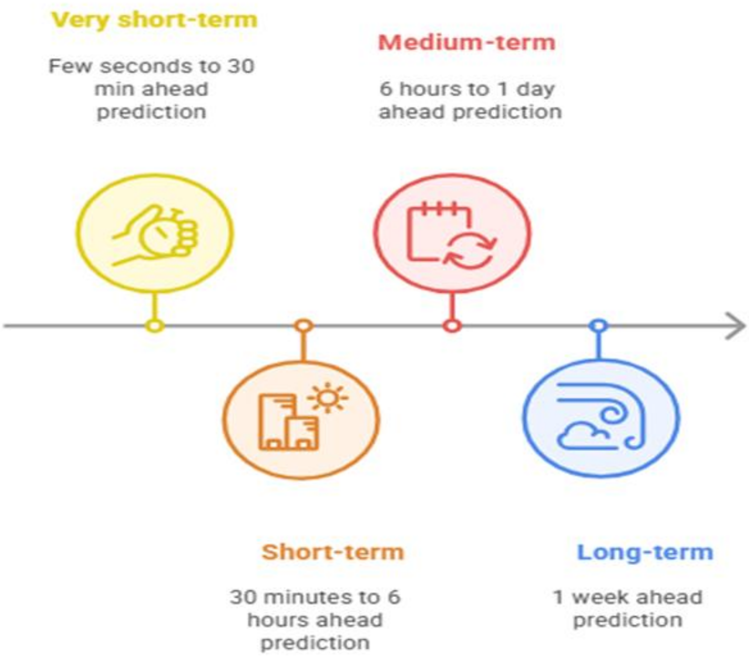

Fig. 2: Time Horizons for Wind Power Prediction

Wind Power Prediction Models

As shown in Fig. 3, wind power forecasting models can be generally categorized into four types: physical models, statistical models, machine learning models, and hybrid models [13]. Physical models use the numerical weather forecast system's relatively approximate forecast value to make predictions based on weather, temperature, and physical data surrounding the wind farm. To determine linear and non-linear connections between meteorological factors and power generation, statistical models such as Markov chains, regression analysis, Kalman filtering, and auto-regressive moving average (ARMA) models necessitate substantial historical data on wind power or wind speed. Future power predictions are made using these relationships. Machine learning and deep learning are gaining popularity as prediction methods due to their exceptional capacity to handle challenging nonlinear issues. Comparing these models to traditional statistical models, they perform better. Machine learning models encompass various types such as artificial neural networks (ANNs), support vector machine (SVM), multilayer perceptron (MLP), and extreme learning machine (ELM). Deep learning models consist of architectures like long short-term memory (LSTM), recurrent neural networks (RNN), and convolutional neural networks (CNN). Hybrid prediction models involve integrating multiple predictive models, such as CNN paired with GRU [14], CNN combined with LightGBM [15], or LSTM alongside CNN [16]. By incorporating the benefits of each distinct model, these models aim to increase the aggregate prediction's accuracy.

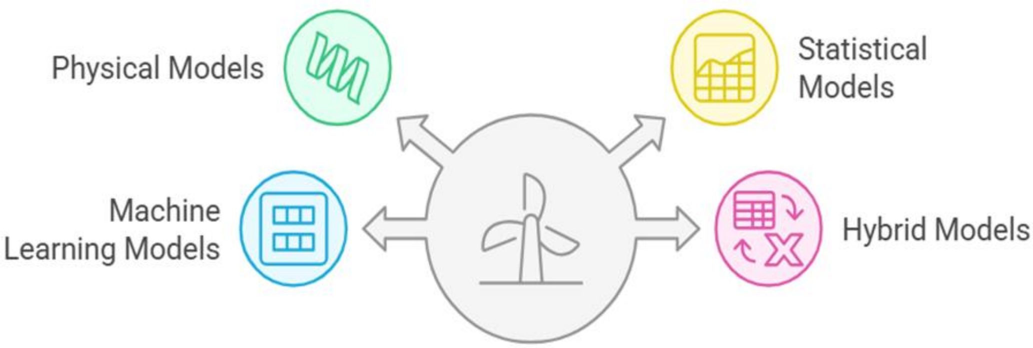

Fig. 3: Wind Power Prediction Models

III. Metaheuristic Algorithms

Overview

Metaheuristic algorithms represent advanced algorithmic structures that direct the search for effective solutions in intricate optimization challenges. They are made to effectively explore the solution space, frequently imitating human decision-making or natural occurrences. These algorithms search the solution space iteratively to identify optimal solutions [17]. Instead of ensuring the discovery of a global optimum, they seek to search the space and arrive at a good solution effectively. These algorithms adjust the solutions across iterations to increase fitness and include heuristic principles to direct the search. Meta implies upper level or beyond, whereas heuristic means to guide an investigation. A heuristic is a set of rules based on experience used to solve problems [18]. Metaheuristics, approximation techniques incorporating fundamental heuristic concepts, produce a more effective investigation and utilization of research space. The search space refers to the realm encompassing all possible solutions, limited by the constraints of the physical system.

Artificial neural networks and deep learning algorithms have become increasingly popular in recent years. Numerous applications, including data mining, classification issues, forecasting, pattern recognition, text and speech recognition, time series processing, and many more, use these techniques [19]. A significant focus of ongoing research has been the necessity to improve these methods. Any model's structure and parameters have a substantial impact on its accuracy. Therefore, one of the researchers' primary goals has been to optimize these factors. Many previous studies have optimized the model's parameters using the gradient descent method. Nevertheless, it has some drawbacks, including that these algorithms are derivative-based, meaning that the cost function needs to be continuous, that it could become trapped at a local minimum, and that the execution time is relatively high. These restrictions have made the employment of optimization algorithms necessary [8]. Because metaheuristic algorithms randomly explore the solution space, they are less likely to become stuck in local optima. They are frequently more effective at locating global optima than the gradient descent method, which makes their use for optimizing the model's structure seem very promising. In addition to facilitating quicker training, metaheuristic algorithms yield more accurate outcomes.

Metaheuristic algorithms have been a promising approach to deep learning and machine learning model training. Researchers have utilized these techniques to determine the optimal model architecture and hyperparameters. Table 1 compiles some studies that have employed metaheuristic algorithms for wind power prediction. Every study includes a list of the author's name, the year it was published, the prediction model, the components that were optimized, and the kind of metaheuristic algorithm employed.

Table 1: Summary of Metaheuristic Algorithms for ML/DL models

Reference	Year of Publication	ML/DL Model	Metaheuristic Algorithm used	Optimized Components
[20]	2021	CNN	Genetic Algorithm and Particle Swarm Optimization	Weights and hyperparameters
[21]	2017	RNN	Dragonfly algorithm	Parameter
[22]	2020	LSTM	Cuckoo Search Optimization	Weights
[23]	2023	CNN-LSTM	Coati Optimization Algorithm	Hyperparameter
[24]	2014	BPNN	Particle Swarm Optimization	Weights
[25]	2018	FFNN	Particle Swarm Optimization and Genetic Algorithm	Weights
[26]	2018	LSTM	Extremal Optimization Algorithm	Hyperparameter
[27]	2021	LSTM	Grey Wolf Optimizer	Weights
[28]	2022	DAR	Grasshopper Optimization Algorithm	Hyperparameter
[29]	2022	CNN	Grey Wolf Optimizer	Hyperparameter
[30]	2022	LSTM	Heap-based Optimizer	Hyperparameter
[31]	2020	TDCNN	Accidental Floater-Particle Swarm Optimization	Weights
[32]	2019	CNN	Genetic Algorithm	Weights

Categorization of Metaheuristic Algorithms

Metaheuristic algorithms can be divided into the following categories:

a) Evolutionary Algorithms:

These are optimization methods inspired by biological evolution. These are the rapidly developing optimization algorithms in the field of machine learning. These algorithms employ processes of selection, reproduction, and mutation to progressively enhance a population of possible solutions for addressing intricate issues [33]. The evolutionary algorithms are comprised of a population of individuals, where each individual signifies a viable solution. Each undergoes various steps and evolves from one generation to the next. The population is initially generated randomly, and then goes through steps like selection, recombination, and mutation over multiple generations. The fitness levels of all individuals in the population are assessed, and those with higher fitness values are selected as new individuals with a higher possibility of improving fitness. After several generations, the algorithm converges, and the individuals with the highest fitness values signify the optimum solution. Popular evolutionary algorithms include Genetic Algorithms, Differential Evolution, Genetic Programming, and Evolutionary Programming.

b) Swarm-based Algorithms:

These algorithms are developed in response to the behavior exhibited by social creatures. These algorithms can effectively solve the non-convex and nonlinear problems. The population of agents (insects, birds, etc.) navigate a search space using their prior knowledge and the optimal locations discovered by other swarm agents [34]. This group movement aids in finding a good, optimized solution for a problem. The operation of swarm-based algorithms adheres to specific procedures. To begin, the search space's agents or particles population is generated at random. The problem's objective function is specified, and subsequently, the fitness of each particle is assessed for this objective function. The particles navigate through the search space guided by the best position that is known to both the individual particle and the swarm, and their velocity that dictates their movement. The procedure of assessing and shifting the particles is repeated in cycles. Once the method has converged, the best solution obtained during the iteration is deemed the solution to the problem. Swarm-based algorithms include Particle Swarm Optimization, Artificial Bee Colony, Dragonfly Algorithm, etc.

c) Human-inspired Algorithms:

These optimized algorithms stimulate human actions and different learning strategies to solve problems. They mimic human learning, adaptation, and decision-making in various contexts [35]. Human-inspired algorithms take cues from different elements of human behavior, such as classroom learning and economic activities. These algorithms convert observed human behavior into mathematical frameworks to assist in identifying optimal solutions. They begin with a collection of potential solutions and enhance them progressively through methods inspired by human behavior. The algorithm iteratively improves the candidate solution multiple times, progressively fine-tuning it until an acceptable solution is achieved. These algorithms aim to identify the global optimum for a specified optimization problem. Some examples of algorithms inspired by human behavior are the Teaching and Learning Algorithm and the Human Evolutionary Optimization Algorithm.

d) Physics-based Algorithms:

The laws and concepts of physical occurrences inspire these algorithms. They aim to imitate the behavior of a physical system to find the best solution for a complicated issue [36, 37]. Natural concepts such as quantum mechanics, gravity, and electromagnetism are utilized to identify the most effective solutions to the complex problems. Natural mechanisms are employed to steer the quest for an ideal solution. For instance, the gravitational search algorithm (GSA) leverages gravitational interactions among potential solutions to draw them closer to the optimal regions of the search space. At the same time, electromagnetic field optimization (EFO) mimics the actions of charged particles and magnetic fields to direct the search. Every potential solution is regarded as an entity within the search space, possessing attributes such as mass or energy. The algorithm progressively modifies the position of these entities by applying simulated physical forces through multiple iterations. The simulated physical forces are employed to direct the search towards more promising areas in the search space, similar to GSA, where the gravitational force pulls candidate solutions toward regions with greater mass, signifying better solutions. These methods explore new areas within the search space while enhancing current solutions. The algorithm keeps adjusting the locations of the potential solutions until a stable outcome or a specified condition is achieved. Some physics-based algorithms include Simulated Annealing, Gravitational Search Algorithm, and Sine Cosine Algorithms.

e) Hybrid Algorithms:

A hybrid optimization algorithm integrates two or more optimization techniques, capitalizing on their advantages to solve a particular problem. The combination of algorithms can enhance the model's efficiency and accuracy. Some hybrid optimization algorithms used in past studies include Genetic Algorithm and Particle Swarm Optimization, Whale Optimization and Simulated Annealing, and Particle Swarm Optimization and Ant Colony Optimization. Liu et al. [20] proposed a hybrid optimization method using a genetic algorithm and particle swarm optimization to optimize a convolutional neural network's weights and other hyperparameters for wind power prediction. Semero et al. [25] optimized the weights of the feed-forward neural network by using a genetic algorithm and particle swarm optimization. In [38], Xia et al. successfully applied particle swarm optimization and the firefly algorithm to various complex applications.

Figure 4 presents the various categories of metaheuristic algorithms and examples of each category.

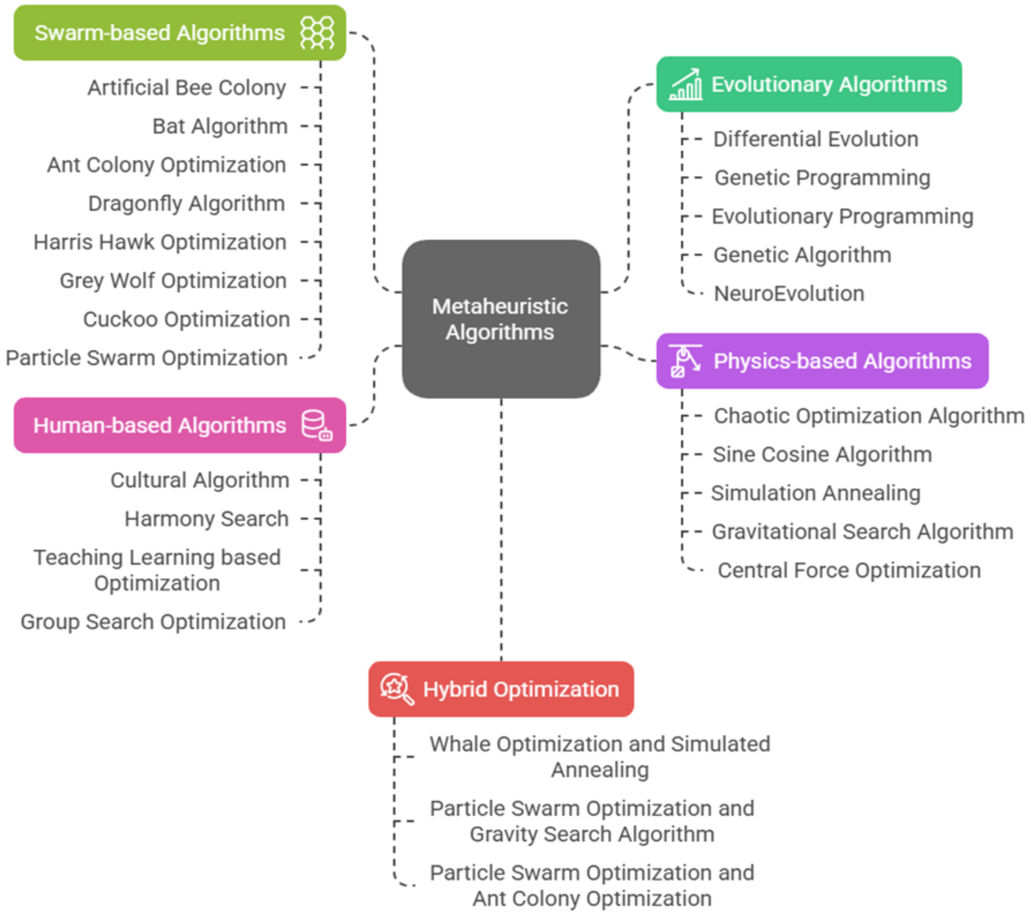

Fig. 4: Metaheuristic Algorithms: Categories and Example

Advantages and Disadvantages of Metaheuristic Algorithms
Table 2 outlines the advantages and disadvantages of several popular metaheuristic algorithms.

Table 2: Summary of Metaheuristic Algorithms

Category	Metaheuristic Algorithm	Advantages	Disadvantages
Evolutionary Algorithms	Genetic Algorithm (GA)	Do not rely on information on how the objective function varies in relation to its inputs.	Highly computationally expensive.
	Genetic Programming (GP)	Generating computer programs automatically; easy to use.	The evolved programs can be challenging to comprehend and analyze; the search space size tends to grow over time.
	Evolutionary Programming (EP)	No prior assumptions about the problem space are required; it has minimal cost for implementation.	Computationally expensive; does not ensure the optimal solution.
	Differential Evolution (DE)	Converges faster; simple and easy to use.	Susceptible to becoming stuck in local optima.
Swarm-based Algorithms	Particle Swarm Optimization (PSO)	Derivative-free; needs fewer parameters; easy to implement.	May be stuck in local optima; slow convergence; tuning parameter can be difficult.
	Ant Colony Optimization (ACO)	Identify effective solutions for intricate problems.	Can get trapped in local optima; parameter selection is challenging.
	Grey Wolf Optimization (GWO)	Simple and easy to implement; find optimal solutions for complex problems.	Gets trapped in local optima.
	Whale Optimization Algorithm (WOA)	It requires fewer control parameters and is easy to implement.	The global optimum may not always be reached by the algorithm.
	Cuckoo Search (CS)	Requires fewer parameters; strong search capability.	Slow convergence; gets stuck in local optima.

Human-based Algorithms	Teaching Learning Based Optimization (TLBO)	No need to tune particular algorithm parameters; resilience in different optimization problems.	Likely to get trapped in local optima and has weak global search capability.
	Harmony Search (HS)	Fewer parameters are to be tuned; implementation is simplified.	Finding a global optimum is challenging; significant computational expense.
	Group Search Optimization (GSO)	Converges quickly to optimal solution; has the capacity to identify global solutions; is easy to implement.	Fine-tuning of parameters is required.
Physics-based Algorithms	Simulated Annealing (SA)	Works well for complex problems.	Computationally expensive; finding an ultimate global solution is not assured.
	Gravitational Search Algorithm (GSA)	Robust; find global optimum solutions.	Slow convergence; appropriate adjustments of parameters are required.
	Chaotic Optimization Algorithm (COA)	Seek a global optimum solution; computationally less expensive.	Careful parameter selection is required; uninformed repetition searching.

IV. Conclusion

Reliable forecasting of wind power is crucial for balancing supply with demand, facilitating efficient trading, overseeing grid operations, and additional functions. As a result, several approaches have previously been put out to improve the prediction models' accuracy. One approach is to optimize the model with metaheuristic techniques to enhance its performance. This paper overviews various metaheuristic algorithms applied in wind power prediction. The benefits and drawbacks of the well-known optimization algorithms in each metaheuristic category are also included. The paper summarizes optimization algorithms from previous studies to improve wind power prediction model performance. Every optimization algorithm comes with its unique advantages and disadvantages. As a result, finding a suitable metaheuristic algorithm for a specific problem is challenging. To address the challenge, many algorithms must be tested based on their characteristics. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are the most widely utilized metaheuristic algorithms for optimizing the parameters and structure of wind power prediction models. Lately, several researchers have employed hybrid algorithms to enhance the optimization process's performance. The shortcomings of a particular algorithm can be offset by the functioning of other algorithms. In addition to strengthening algorithm performance, hybrid metaheuristic algorithms can also solve challenging optimization issues.

References

[1] Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J. (2019). A Review Of Deep Learning For Renewable Energy Forecasting. Energy Conversion And Management, 198, 111799.

[2] "Global Electricity Review 2025" Https://Ember-Energy.Org/Latest-Insights/Global-Electricity-Review-2025/ Accessed 23 May 2025.

[3] “Yearly Electricity Data” Https://Ember-Energy.Org/Data/Yearly-Electricity-Data/ Accessed 23 May 2025.

[4] Sharma, G., Lal, M., & Singh Attwal, K. P. (2022). A Comprehensive Review On Deep Learning Algorithms For Wind Power Prediction. International Journal Of Next-Generation Computing, 13(4).

[5] Han, F., Jiang, J., Ling, Q. H., & Su, B. Y. (2019). A Survey On Metaheuristic Optimization For Random Single-Hidden Layer Feedforward Neural Network. Neurocomputing, 335, 261-273.

[6] Ojha, V. K., Abraham, A., & Snášel, V. (2017). Metaheuristic Design Of Feedforward Neural Networks: A Review Of Two Decades Of Research. Engineering Applications Of Artificial Intelligence, 60, 97-116.

[7] Darwish, A., Hassanien, A. E., & Das, S. (2020). A Survey Of Swarm And Evolutionary Computing Approaches For Deep Learning. Artificial Intelligence Review, 53(3), 1767-1812.

[8] Kaveh, M., & Mesgari, M. S. (2023). Application Of Meta-Heuristic Algorithms For Training Neural Networks And Deep Learning Architectures: A Comprehensive Review. Neural Processing Letters, 55(4), 4519-4622.

[9] Van Der Merwe, W. S., Du Plessis, A. A., & Rix, J. A. (2023). WIND POWER FORECASTING: A REVIEW.

[10] Zhu, J., Su, L., & Li, Y. (2022). Wind Power Forecasting Based On New Hybrid Model With TCN Residual Modification. Energy And AI, 10, 100199.

[11] Wang, Y., Zou, R., Liu, F., Zhang, L., & Liu, Q. (2021). A Review Of Wind Speed And Wind Power Forecasting With Deep Neural Networks. Applied Energy, 304, 117766.

[12] Hanifi, S., Liu, X., Lin, Z., & Lotfian, S. (2020). A Critical Review Of Wind Power Forecasting Methods—Past, Present And Future. Energies, 13(15), 3764.

[13] Lydia, M., & Kumar, S. S. (2010, October). A Comprehensive Overview On Wind Power Forecasting. In 2010 Conference Proceedings IPEC (Pp. 268-273). IEEE.

[14] Gao, J., Ye, X., Lei, X., Huang, B., Wang, X., & Wang, L. (2023). A Multichannel-Based Cnn And Gru Method For Short-Term Wind Power Prediction. Electronics, 12(21), 4479.

[15] Ju, Y., Sun, G., Chen, Q., Zhang, M., Zhu, H., & Rehman, M. U. (2019). A Model Combining Convolutional Neural Network And Lightgbm Algorithm For Ultra-Short-Term Wind Power Forecasting. Ieee Access, 7, 28309-28318.

[16] Wu, W., Chen, K., Qiao, Y., & Lu, Z. (2016, October). Probabilistic Short-Term Wind Power Forecasting Based On Deep Neural Networks. In 2016 International Conference On Probabilistic Methods Applied To Power Systems (PMAPS) (Pp. 1-8). IEEE.

[17] Rezk, H., Olabi, A. G., Wilberforce, T., & Sayed, E. T. (2023). A Comprehensive Review And Application Of Metaheuristics In Solving The Optimal Parameter Identification Problems. Sustainability, 15(7), 5732.
[18] Nassef, A. M., Abdelkareem, M. A., Maghrabie, H. M., & Baroutaji, A. (2023). Review Of Metaheuristic Optimization Algorithms For Power Systems Problems. Sustainability, 15(12), 9434.
[19] Liu, Z., Guo, H., Zhang, Y., & Zuo, Z. (2025). A Comprehensive Review Of Wind Power Prediction Based On Machine Learning: Models, Applications, And Challenges. Energies, 18(2), 350.
[20] Liu, J., Shi, Q., Han, R., & Yang, J. (2021). A Hybrid GA–PSO–CNN Model For Ultra-Short-Term Wind Power Forecasting. Energies, 14(20), 6500.
[21] Shi, Z., Liang, H., & Dinavahi, V. (2017). Direct Interval Forecast Of Uncertain Wind Power Based On Recurrent Neural Networks. IEEE Transactions On Sustainable Energy, 9(3), 1177-1187.
[22] Devi, A. S., Maragatham, G., Boopathi, K., & Rangaraj, A. G. (2020). RETRACTED ARTICLE: Hourly Day-Ahead Wind Power Forecasting With The EEMD-CSO-LSTM-EFG Deep Learning Technique. Soft Computing, 24(16), 12391-12411.
[23] Abou Houran, M., Bukhari, S. M. S., Zafar, M. H., Mansoor, M., & Chen, W. (2023). COA-CNN-LSTM: Coati Optimization Algorithm-Based Hybrid Deep Learning Model For PV/Wind Power Forecasting In Smart Grid Applications. Applied Energy, 349, 121638.
[24] Ren, C., An, N., Wang, J., Li, L., Hu, B., & Shang, D. (2014). Optimal Parameters Selection For BP Neural Network Based On Particle Swarm Optimization: A Case Study Of Wind Speed Forecasting. Knowledge-Based Systems, 56, 226-239.
[25] Semero, Y. K., Zhang, J., Zheng, D., & Wei, D. (2018). A GA-PSO Hybrid Algorithm Based Neural Network Modeling Technique For Short-Term Wind Power Forecasting. Distributed Generation & Alternative Energy Journal, 33(4), 26-43.
[26] Chen, J., Zeng, G. Q., Zhou, W., Du, W., & Lu, K. D. (2018). Wind Speed Forecasting Using Nonlinear-Learning Ensemble Of Deep Learning Time Series Prediction And Extremal Optimization. Energy Conversion And Management, 165, 681-695.
[27] Altan, A., Karasu, S., & Zio, E. (2021). A New Hybrid Model For Wind Speed Forecasting Combining Long Short-Term Memory Neural Network, Decomposition Methods And Grey Wolf Optimizer. Applied Soft Computing, 100, 106996.
[28] Arora, P., Jalali, S. M. J., Ahmadian, S., Panigrahi, B. K., Suganthan, P. N., & Khosravi, A. (2022). Probabilistic Wind Power Forecasting Using Optimized Deep Auto-Regressive Recurrent Neural Networks. IEEE Transactions On Industrial Informatics, 19(3), 2814-2825.
[29] Jalali, S. M. J., Ahmadian, S., Khodayar, M., Khosravi, A., Shafie-Khah, M., Nahavandi, S., & Catalao, J. P. (2022). An Advanced Short-Term Wind Power Forecasting Framework Based On The Optimized Deep Neural Network Models. International Journal Of Electrical Power & Energy Systems, 141, 108143.
[30] Ewees, A. A., Al-Qaness, M. A., Abualigah, L., & Abd Elaziz, M. (2022). HBO-LSTM: Optimized Long Short Term Memory With Heap-Based Optimizer For Wind Power Forecasting. Energy Conversion And Management, 268, 116022.
[31] Abedinia, O., Bagheri, M., Naderi, M. S., & Ghadimi, N. (2020). A New Combinatory Approach For Wind Power Forecasting. IEEE Systems Journal, 14(3), 4614-4625.
[32] Chen, G., Shan, J., Li, D. Y., Wang, C., Li, C., Zhou, Z., ... & Hao, J. J. (2019). Research On Wind Power Prediction Method Based On Convolutional Neural Network And Genetic Algorithm. 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), 3573-3578.
[33] Vikhar, P. A. (2016, December). Evolutionary Algorithms: A Critical Review And Its Future Prospects. In 2016 International Conference On Global Trends In Signal Processing, Information Computing And Communication (ICGTSPICC) (Pp. 261-265). IEEE.
[34] Ab Wahab, M. N., Nefti-Meziani, S., & Atyabi, A. (2015). A Comprehensive Review Of Swarm Optimization Algorithms. Plos One, 10(5), E0122827.
[35] Črepinšek, M., Liu, S. H., & Mernik, L. (2012). A Note On Teaching–Learning-Based Optimization Algorithm. Information Sciences, 212, 79-93.
[36] Can, Ü., & Alataş, B. (2015). Physics Based Metaheuristic Algorithms For Global Optimization.
[37] Chattopadhyay, S., Marik, A., & Pramanik, R. (2022). A Brief Overview Of Physics-Inspired Metaheuristic Optimization Techniques. Arxiv Preprint Arxiv:2201.12810.
[38] Xia, X., Gui, L., He, G., Xie, C., Wei, B., Xing, Y., ... & Tang, Y. (2018). A Hybrid Optimizer Based On Firefly Algorithm And Particle Swarm Optimization Algorithm. Journal Of Computational Science, 26, 488-500.