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Review of current artificial intelligence methods and metaheuristic algorithms for wind power prediction

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ABSTRACT

Due to the insufficient fossil resources and the increasing environmental challenges, the world is heading for a more use-oriented to renewable energy sources, specifically to wind energy. A number of predictive techniques are available for the efficient use of wind energy. This article, which is a review of methods of artificial intelligence (AI) and meta-heuristic algorithms for wind energy prediction, fits into this context. There are two distinct categories: the first consists of traditional methods that are commonly used in this context, like different types of artificial neural networks (ANN), support vector machines (SVM) and fuzzy logic; the second is a combined approach which mixes the classic artificial intelligence methods and the meta-heuristic algorithms for the optimization of the forecast output. Then, a summary and comparison between the methodologies are established, and the advantages and limits of each technique are defined. The combination of the classic artificial intelligence and metaheuristic algorithms has a greater performance than the utilization of classic methods only. Nevertheless, using hybrid metaheuristic algorithms with classic artificial intelligence prediction methods can provide a higher precision.

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1. INTRODUCTION

With worldwide engagements to reduce warming, harmful gases emitted and the lack of the fossil resources, the electricity production from renewable energies has become a predominant solution [1]–[5]. Nowadays, Wind as a clean and sustainable energy is more economical than the other energies thanks to the accelerated progress of wind turbine technology [1]. New wind farms continue to increase due to the reduction of their costs due to falling costs and mass production of generators [4], [6]. Due to the continuous increase in the use of wind resource, forecasting power output of installed wind turbines becomes critical [7]. Responding to the market needs, several approaches are implemented to predict wind power. The main goal is providing an accurate prediction and improving it for different time horizons and for different hard wind farms emplacement [8].

The four classic and well-known categories are: physically based approaches, statistically based approaches, artificial intelligence-based (AI) approaches and combinational approaches. Several papers have used artificial intelligence methods for wind energy forecasting. Gomes and Castro [9], a comparison between artificial neural networks method (ANN), autoregressive moving average (ARIMA) and persistence method is done. Results confirm the good performance of the ANN and ARIMA in the prediction of the wind especially ARIMA. A wind energy production forecast at "Pawan Danawi" using as training algorithm Levenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization in [10]. The performance of all three tests is confirmed by the results, however the Levenberg-Marquardt training algorithm performs the best in terms of prediction.

The combination of AI methods and metaheuristic algorithms is largely applied to forecast wind energy. The use of metaheuristics has been identified as an appropriate tool to deal with many challenging problems in optimization [11], [12]. Sun *et al.* [13], long-term memory network (LSTM) and modified particle swarm optimization (PSO) algorithm are implemented as a mixture to make a forecast of the wind energy. Results show that the technique used is more accurate in comparison to the standard LSTM. Sun *et al.* [14], an advanced genetic algorithm is presented for optimizing the Elman neural network model used for predicting wind energy. The suggested approach is validated through the comparison of the obtained results to the real values.

This review article presents the current AI methods for wind energy forecasting on the basis of papers published in the last few years. For each paper, we try to extract the inputs used, the evaluation factors, and the advantages and limitations of each method used. This can give us a general idea of how AI methods work in the context of wind power prediction and then we can improve on the weaknesses of each method.

For having an overview of existing articles on the use of artificial intelligence methods for wind energy forecasting, bibliometric research was done using the Science Direct Platform. The query used for analysis is “Artificial intelligence methods applied for the forecasting of wind energy”. Figure 1 presents the number of articles about wind power prediction using the artificial intelligence techniques published from 2010 to 2021 and indexed by Springer. The rise in the number of papers confirms the importance and relevance of the topic.

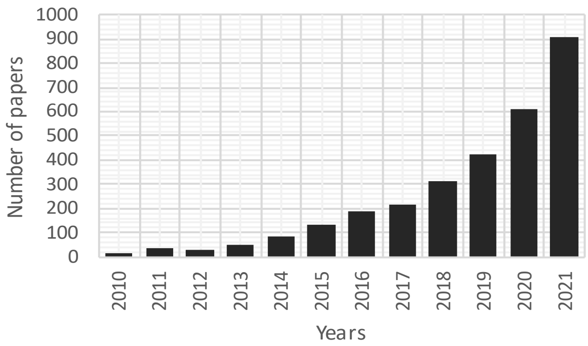

Figure 1. Number of articles in years

2. METHOD

In this article, we have tried to follow a systematic methodology based on several steps: research, reading, analysis and summary. A systematic review of the literature involves a targeted selection of data, including the types of information to be considered in the analysis. This can consist of journal papers, book chapters, and published works related to the area of research [15].

2.1. Research and reading

We have opted for Google Scholar to search articles from different databases using specific terms such as "wind power prediction" and "metaheuristic algorithms and artificial intelligence for wind power prediction. Specifying search terms helps us target recent papers in the desired context. In this step, we have tried to categorize the selected articles by reading the abstract and the introduction of each one. Then, we read the content of the papers and extracted the interesting and relevant information in order to make an analysis and come out with a comparison.

2.2. Analysis

After reading several papers on the subject of wind energy forecasting in general, it was clear that wind forecasting methods fall into two categories. We have attempted to analyze each category. The first category is classified by time scale according to the type of application. The second category is classified by methodology and each type of methodology has its own employment criteria.

2.2.1. According to time-scales

Forecasting systems are divided to four categories based on time horizons. The first one is very short and it is about a couple of seconds until half an hour in advance. The second one is short and it is from half an hour to number of hours in advance. The third one is medium and it is between several hours and one day in advance. The last one is long and it is from day to one week or few weeks in advance [11], [12]. Time-scale classification and their application as shown in Table 1.

Table 1. Time-scale classification and their application [16]

Time scale	Range	Application
Very Short	about a couple of seconds to half an hour in advance	- Clearing of the electricity market - Real-time grid exploitation
Short	from half an hour to several hours in advance	- Planning for economic load sharing - Operational Safety in the Electricity Sector
Medium	from several hours to a day in advance	- Decisions of unit commitments - On-line/Off-line generator rulings
Long	from day to one week or few weeks in advance	- Optimized cost of operation - Feasibility analysis for the conception of the wind farm

2.2.2. According to methodology

Forecasting system is categorized by methodology in four ways: physically based approaches, statistically based approaches, and AI and hybrid ones [17]. Physical methods are based on sophisticated computational models using forecast meteorological data (NWP). Physical models don't require a lot of historical data, and this is an advantage because they can be adapted to new wind farms. However, these models are complex [18] and require good knowledge of meteorology and site characteristics. In addition, The difficulty of obtaining NWP information from meteorological stations is a primary factor in the non-use of this type of technique by scientific researchers [19].

Statistical methods are more commonly used for very short or short time horizon of forecasting. They are based on one or more parameters and relate historical values of meteorological data to the predicted power of the wind turbine. Proven statistical parameters, including expected meteorological and expected powers, can be updated using recent weather data [20]. The most frequent types employed for predicting future wind energy values are autoregressive moving average (ARMA) models [21], Kalman filters [22] and grey theory [23].

Due to the potential data mining and feature extraction capabilities of AI methods [24], they offer more promising performance than physical and statistical methods [25]. ANNs, SVM and Fuzzy Logic are commonly used for dealing with nonlinear relationships between input and output by minimizing errors. Hybrid methods are combination of various approaches: physically and statistically based methodologies or short and medium time horizon models [26]. Over the past few years, metaheuristic algorithms have been welcomed by many researchers because they are efficient, robust, and flexible. The purpose of using meta-heuristics is to achieve the most efficient metric for a predictive model [19].

2.3. Summary

2.3.1. Standard methods

a) The artificial neural network (ANN)

ANN is represented as a popular approach for forecasting wind energy [2], [27]. ANN is composite elements that perform biological functions Take the basic neuron as an example [28]. The benefit of using ANN is the learning of the input-output relationship through non-statistical method. Also, there is no need to any predetermined mathematical models. ANNs provide results with minimal error the same or similar patterns exist [29].

The composition of the ANN is illustrated in Figure 2:

- Input Layer: extract the network data.
- Hidden Layer: handle the raw information sent by the previous layer.
- Output Layer: receive the obtained value communicated by the cached layer, treats it, then gives the result.

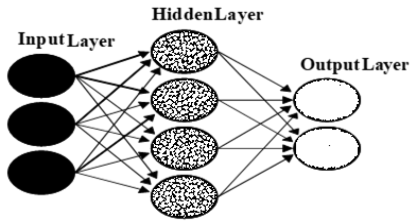

Figure 2. The three layers of ANN [30]

Ramaswamy [30], the back-propagation neural network technique for predicting daily wind energy on the NWP data set in Mongolia, China is adopted. Lu and Chang [31] proposed radial basis function neural network approach with a Taiwan Power Co environment for wind energy forecasting. Acikgoz *et al.* [32], predicting wind energy using extreme learning machine (ELM) for complex terrain" in Turkey according to the roughness index value (RIX). Zhang *et al.* [33] proposed "similar day clustering principle and ELMAN neural network" to forecast wind power with high performance compared to traditional ELMAN. The advantage of the previous methods is the simplicity of their implementation and thanks to that, they are commonly applied in wind energy prediction [19].

b) Support vector machines (SVM)

Supervisory learning introduces SVM. The target of using this technique consists in obtaining an hyper-plane inside an space of N dimension, in which N represents characteristics which can be used to categorize the data points [34]. The SVM maximizes the geometric separation among the class instances to be separated [35]. Moreover, SVM has a consistent precision whether the number of characteristics is low or high. In comparison to various algorithms, the errors generally vary according to the number of characteristics, but the SVM has the ability to maintain the stability of the performance [34]. Figure 3 shows the SVM graph: Class 1 is represented by the squares and Class 2 by the circles and the maximum margin from data points to the hyper-plane is shown [36].

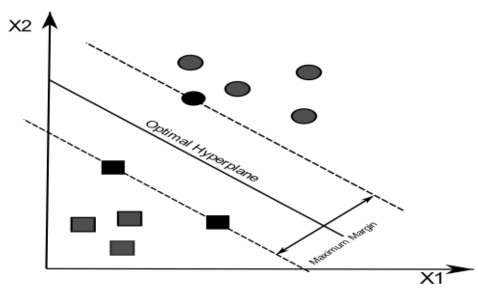

Figure 3. SVM chart [36]

Zeng and Qiao [37] has proposed a prediction process for wind energy through SVM for by employing the data supplied by the NREL. Predicting wind velocity, and then using the force-wind velocity characteristic of wind generator for predicting wind energy. SVM prediction almost tracks expected volatility of very short-term WPF. Zendehboudi *et al.* [38], the SVM mode approach has certain advantages, such as ease of use, significantly reduced computation timing and expense, encourages many researchers to employ it for solving various challenges. However, the disadvantage of SVM is that it requires relatively complex computation. Least squares support vector machines (LSSVM) help overcome this shortcoming [39].

c) Fuzzy logic

This approach is developed from multivalued theory. It is composed of a fuzzy ensemble and a fuzzy sub-ensemble [40]. It uses membership functions to distinguish fuzzy sets and deal with fuzzy relations [41]. Akhtar *et al.* [42] proposed a wind energy prediction case using fuzzy logic. Wind power predictions are based on data obtained from fuzzy-based systems for giving air pressure and for determining wind speed. Singh and Rizwan [43], comparing the forecast of wind energy by Fuzzy logic, ANN and ANFIS, and ANFIS model provides the best performance than the two other techniques as results. The building blocks of the fuzzy system consist of four blocks [44], as shown in Figure 4.

- The fuzzifier: the input block for this system. In this block sharp values are converted to fuzzy values.
- The rule base: It is an essential step in fuzzy logic. Mainly used to control the output variable.
- The inference Engine: It basically concatenates the "IF-THEN" statement with the data of the fuzzy input and maps the output using the fuzzy principle.
- The de-fuzzifier: The final sharpening value of the fuzzy output according to the membership function of the variable output [44].

The tree types of common artificial intelligence methods to forecast the wind power are summed up in the Table 2. This table summarizes the papers that used classical artificial intelligence methods. The focus is on the inputs used, which are generally the velocity and direction of the wind, the time period and the evaluation criteria chosen. The most important details of each paper are also cited such as the limitations found, the comparisons made between several methods and the results obtained.

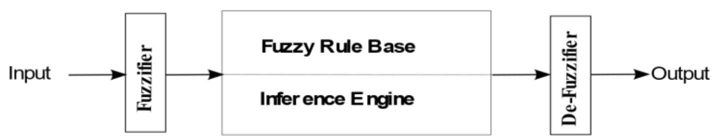

Figure 4. The building blocks of the fuzzy system [44]

Table 2. Summary of the tree types of AI prediction methods [31]–[33], [37], [42], [43], [45]

	Methods	Input variables	Term	Metrics	Details
[45]	BPNN	- Wind velocity - Wind direction - Pressure - Temperature - Relative humidity	Short	MAE RMSE	- The accuracy of the input data affects the prediction effect, so it must be checked before being input into the predictive model for testing - The prediction results of the back-propagation neural network (BPNN) method meet the appropriate requirements in this paper, but the classical BP algorithm converges with slow speed and it has an ease falling in a local minimum - Rapid changes in wind velocity can affect prediction precision of the BPNN
[31]	RBFNN	- Wind speed - Ambient temperature - Wind power data sets	Short	MAPE RMSE	- To achieve the minimum functional error, GSDM can be employed to fit the heavy weight values of the network connection of the Gaussian metrics of the prediction method - Compare the results with the traditional BPNN, BPNN, Levenberg-Marquardt and traditional RBFNN, the proposed one performs better
[32]	ELM	- Wind velocity - Wind direction - Wind energy information	Very short	NRMSE Coef. R	- The utilization of ELM model provides a good prediction of the studied giant wind turbines situated in a difficult location of Turkey - The activation function represents an important part in the precision of the ELM performance. The function is determined as the sigmoid tangent "tansig" - The results compared to the BPNN confirm the better performance and accuracy of the ELM, especially in summer than in winter
[33]	ELMAN	- Wind speed	Short	MAE	- After three days of comparison, the Elman method outperforms the BPNN and the traditional ELMAN - Inconsistent meteorological factors in some cases due to lack of training data
[37]	SVM	- Wind speed	Very Short Short	MAE MAPE	- The applied technique first predicts wind velocity, then uses the force-wind velocity characteristics for predicting wind energy - The comparison of SVM with persistence method and RBFNN method confirms the high performance of SVM in very short and short term - The error increases when the wind speed changes sharply and the horizon increases. So, additional meteorological variables such as temperature and pressure should be provided or combined with NWP to improve forecast accuracy
[42]	Fuzzy logic	- Wind speed - Air density	Short	RMSE MAD MSE	- The proposed fuzzy logic system-based method is used to forecast wind energy in five different geographical and climatic conditions in India - Fuzzy logic performs more precisely than SVM and BPNN
[43]	Fuzzy logic, ANN and ANFIS	- Wind speed - Air density	Short	ARE SSE MAPE SDE	- The paper compares three prediction methods at different points - The results confirm that ANFIS has a good performance over the last ANN and fuzzy logic

2.3.2. Combined methods: AI methods and metaheuristic algorithms

a) Particle swarm optimization and AI methods

This algorithm represents a populational-based approach in which every possible decision is described by a swarm in a population of particles [46]. The particles change their positions in a multispace search until either the optimum condition is achieved or the calculation limits are surpassed [47]. PSO belongs Swarm-based algorithms. This approach is applied for optimizing the settings of prediction methods, such as artificial intelligence methods, by initializing them as particle swarms and using iterative search to provide prediction performance.

Xu and Mao [48], the Elman technique was employed for forecasting wind energy and PSO is implemented to achieve the optimization of the forecasting process. Forecasting results show that the utilization of PSO algorithm can enhance the behavior of Elman model and obtain a better precision. Lu *et al.* [49] proposed an application of the SVM method using the PSO algorithm in forecasting wind power. The real computation example demonstrates how the forecast method adopted by this paper possesses an excellent convergence and accurate prediction. Pousinho *et al.* [47], a mixture of PSO and ANFIS method is proposed. PSO algorithm is applied for improving the efficiency of the predictive model by regulating the members features required to obtain smaller errors. The comparison between the PSO-ANFIS method and several methods as persistence, NN and WNF confirms the robustness and good accuracy of the proposed method.

b) Genetic algorithm and AI methods

The genetic algorithm is a soft computational approach designed to generate a model that mimics nature. The GA is included in the evolutionary algorithm. It is one of the frequently used algorithms for optimizing wind farms thanks to its precision and reduction calculating time [50], [51]. The basic components of a genetic algorithm are: 1. Problem coding 2. Suitability evaluation 3. Reproduction operator 4. Selection criteria 5. Termination criteria [52]. In A combination of BPNN and GA is applied for predicting wind energy output. The technique will be tested against the real dataset of a wind installation of 2.5 MW in Beijing. Zhang *et al.* [53], wind energy forecasting using SVM method and GA has been proposed. The GA is applied to increase the prediction efficiency of the predictive method and to decrease the forecasting uncertainty.

c) Gravitational search algorithm and AI methods

Gravity search algorithms are one of the most popular types of physics-based algorithms. The gravitational search algorithm (GSA) algorithm involves a specific search process method that takes into account the separation between adjacent particles to update their positions. This algorithm for optimizing is a population dependent one, which is composed of several particles known as agents, that are handled like items with their corresponding weights [52]. GSA is chosen for predicting shortly time wind power in [39]. GSA is utilized for obtaining the optimum metrics for LSSVM. The performance of the applied approach is confirmed after a comparison between the results of the BPNN model and the SVM method. GSA is more likely to be used with the LSSVM wind prediction method than the other methods in the research articles.

Using a good combination of forecasting methods will improve the results. The tree types of combination of common meta-heuristic algorithms and artificial intelligence methods are summed up in the Table 3. This table resumes the papers that have dealt with the combination between classical artificial intelligence methods and metaheuristic algorithms. The velocity and direction of wind and the historical wind energy represent the most utilized inputs, as well as the short term is the common thing between the papers. We have tried to list in brief the limitations found, the comparisons made between different methods and the results achieved of each paper.

Table 3. Summary of the tree types of combined AI prediction methods [23], [39], [47], [48], [53], [54]

	Methods	Input variables	Term	Metrics	Details
[47]	PSO-ANFIS	- Historical wind power data	Short	MAPE SDE SSE	- The PSO is being used for improving efficiency of ANFIS by adjusting the desired membership of the function to minimize the errors - Historical wind power data is the most important input variable - The comparison between PSO-ANFIS and another five methods significantly validates the performance of the selected method in three seasons (winter, spring and summer).
[48]	PSO-ELMAN	- Wind velocity - Temperature - Wind direction - Humidity - Air pressure	Short	RMSE EAV	- The PSO is used to provide optimization of the Elman model, which increases the efficiency of the predictive process - The simulation was performed on a single generator wit of 15 KW - Comparing the suggested technique to the ELMAN method shows the good performance and lower error of PSO-ELMAN.
[23]	PSO-SVM	- Historical wind power data	Short	MAPE	- SVM is used as a wind energy prediction method with an improved PSO algorithm whose role is to achieve optimal SVM settings - Validing the efficiency of the used strategy by comparing the proposed method to the standard SVM method and the RBFNN method.
[54]	GA-BPNN	- Historical wind speed data. - Historical wind energy data	short	MSE MAE MAPE	- Developing a predictive technique by combining an ANN technique with GA and training by BPNN model for a wind installation of 2.5 MW in the Goldwind microgrid - The wind power forecasting results for the three selected days demonstrate that the combined model outperforms the classic BPNN model and the persistence method - Results indicate that the suggested application is able to achieve better prediction with low uncertainties.
[53]	GA-SVM	- Wind speed - Historical wind power data	Short	MSE RMSE RE	- In the SVM prediction model, the incorrect setting of parameters causes "underlearning" or "overlearning" behaviour, and it directly influences the precision of the forecast - After the use of the GA for optimization of the kernel function settings, the RE, MSE, and RMSE are all decreased, and the precision of the forecasting is increased.
[39]	GSA-LSSVM	- Wind speed - Wind direction	Short	RMSE MAE CC SSE SDE	- The LSSVM kernel and related settings function significantly impact the forecasting model output - The role of GSA is to adjust the parameters of LSSVM to achieve significant accuracy - To check the precision of the employed approach, comparisons are made with BPNN, SVM, SVM-GSA, LSSVM, and the results reveal the high accuracy of the LSSVM-GSA approach.

3. RESULTS AND DISCUSSION

The two categories of artificial intelligence are summed up and compared by citing the benefits and the limitations of each method. In addition, based on research bibliometric, the utilization frequency is defined as presented in the Table 4. After searching and reading the articles that dealt with the topic of wind power forecasting using traditional AI methods and the mixture between these methods and metaheuristic algorithms, we tried to distinguish the benefits and limitations of each method.

It is quite obvious that the combination of AI methods and metaheuristic algorithms has more advantages than AI methods alone, since metaheuristic algorithms try to optimize the inputs of AI methods. Comparing the frequency of use, and talking about AI methods, we find that ANNs are frequently used. On the other hand, we find that the PSO algorithm is the most used in combination with AI methods.

Table 1. Synthesis of AI prediction methods [7], [8], [11], [13], [14], [18], [20], [25]–[31], [55]

		Methods	Benefits	Limitations	Use frequency
Standard methods	[7], [8], [55]	ANNs	- Understand the relationship between input and output through non-statistical methods - Ease of use as no predefined mathematical models are required.	- ANNs often suffer from local minima and overfitting - ANN requires a lot of training resources.	****
	[11], [13]	SVM	- SVM has stable precision in both function-less and function-many situations - SVM keeps performance stable.	- The disadvantage of SVM is that it requires relatively complex calculations - If the parameters are not set well, the accuracy of SVM will be poor.	***
	[18], [20]	Fuzzy Logic	- Fuzzy based systems are easy to implement - Fuzzy logic is suitable for difficult systems.	- The main limitation is lack of study - ANFIS method is more commonly used than fuzzy logic.	**
Metaheuristic algorithms +standard methods	[26]–[28]	PSO+AI	- PSO is widely used because of its easy understanding and good convergence - It has good optimization ability for complex methods.	- It depends on the initial parameters - Poor local search ability.	****
	[29]–[31]	GA+AI	- GA is simple and easy to use - It does not depend on initial parameters.	- The convergence rate of GA is slow - Requires a lot of computing time.	***
	[14], [25]	GSA+AI	- GSA does not depend on initial parameters - Simply and uncomplicated to work with.	- Weak local search capability - It doesn't used very frequently.	*

4. CONCLUSION

The increase of the wind technologies utilization encourages the researchers to focus on the diverse methodologies used for forecast wind energy. In this paper, a review of the common artificial intelligence methods used for wind energy prediction. Each method has advantages and disadvantages as Suffering from overfitting, weak of learning and computational complexity. The combined methods present a good solution for more accuracy by benefiting of the advantages of each model and having a performant forecasting. Multi-combined methods which combine different type of meta-heuristic algorithms and AI prediction methods can provide a high precision and open up avenues for scientific research.

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