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A Survey of Artificial Neural Network in Wind Energy Systems

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Abstract—Wind energy has become one of the most important forms of renewable energy. Wind energy conversion systems are more sophisticated and new approaches are required based on advance analytics. This paper presents an exhaustive review of artificial neural networks used in wind energy systems, identifying the methods most employed for different applications and demonstrating that Artificial Neural Networks can be an alternative to conventional methods in many cases. More than 85% of the 190 references employed in this paper have been published in the last 5 years. The methods are classified and analysed into four groups according to the application: forecasting and predictions; design optimization; fault detection and diagnosis; and optimal control. A statistical analysis of the current state and future trends in this field is carried out. An analysis of each application group about the strengths and weaknesses of each ANN structure is carried out. A quantitative analysis of the main references is carried out showing new statistical results of the current state and future trends of the topic. The paper describes the main challenges and technological gaps concerning the application of ANN to wind turbines, according to the literature review. An overall table is provided to summarize the most important references according to the application groups and case studies.

Index Terms— Artificial neural networks, wind turbines, wind energy conversion systems.

I. INTRODUCTION AND MOTIVATION

NOWADAYS, wind energy is one of the most important renewable energy sources. In 2016, wind energy systems (WES) provided more than 420 GW, and this is expected to rise to more than 1000 GW in the 2030s [1]. WES are undergoing a modernization process where the number of requirements has increased to ensure efficient energy production [2, 3]. There has been an increase in WES and their complexity, as well as the demand for new techniques and methods to improve reliability [4], maintenance [5] and investments [6], leading to greater competitiveness in the energy market.

The wind energy market, as one of the most exploitable and growing markets, requires both technical and economic advances. Regarding the technical aspects, efforts are oriented towards harnessing the wind to a maximum level. There are many issues addressed in the literature, such as the aerodynamic optimization of wind turbines (WT) [7], the optimization of blade shapes [8], the study of power curve under different circumstances [9], the optimization of WT position in a wind farm [10], etc. With respect to the economic issues, the main objective is to maximize profits obtained from the available resources. For this purpose, the literature covers topics such as wind speed modelling [11], strategies based on energy price forecasting [12], the study of the interactions between wind energy and the power market [13], wind turbine life cycle analysis [14], etc. This paper shows an exhaustive review of the current techniques and methods concerning these issues employing artificial neural networks (ANN)

WTs are equipped with a large number of devices to evaluate the humidity, temperature, vibration, etc. [15]. Data acquisition systems measure all the variables in order to determine the system condition [16]. Data processing requires robust algorithms [17] that enable as much information as possible to be gathered from the available data [18]. Machine learning algorithms are widely employed due to their ability to process a large amount of data, ANNs being one of the most employed methods [19].

ANNs are complex structures based on biological neurons. These structures provide a good solution to problems that cannot be analytically defined. An ANN consists of neurons which are simple processing units, and weighted connections between those neurons. A typical structure corresponds to the multilayer perceptron (MLP), shown in Fig.1 [20].

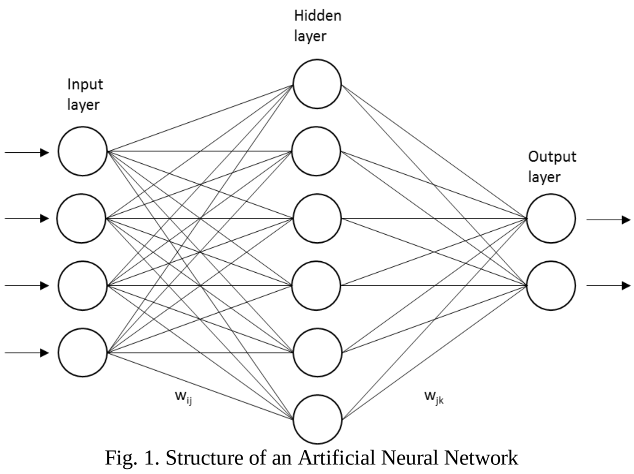

Fig. 1. Structure of an Artificial Neural Network

The ANN receives a dataset and starts a training process to adjust the weights of the interconnections between neurons. The training will be supervised if the output is known, otherwise it will be named unsupervised training [21].

There are four basic variables that characterize an ANN: the topology; the training method; the type of association between input and output data, and; the presentation of the information. More than 50 types of ANN can be distinguished, for example: MLP; radial basis function neural network (RBFNN); backpropagation networks (BPNN); Wavelet neural network (Wavelet NN); self-organized-map NN (SOM NN); Recurrent NN; time delay NN; Hopfield network; auto-associative NN; convolutional NN; learning vector quantization networks; adaptive resonance theory (ART) NN; neuro-fuzzy networks; dynamic NN.

ANNs are employed in fields due to their numerous advantages, e.g. medicine, chemistry, robotics, geospatial analysis, etc. ANNs can be used to generate functions to explain a certain phenomenon when the data does not allow such functions to be created by hand [22]. The main advantages are [23]:

- Adaptive learning: They can learn to perform tasks through a training process.
- Self-organization: ANNs can create their own structure to represent the information through a training process
- Fault tolerance: The ANN can still operate when its structure is damaged (tolerance to degradation), and distorted or incomplete when the data are noisy (tolerance to data).
- On-line operation: They can be implemented in parallel and work fast. Consequently, they are specially programmed to carry out on-line processes.
- Easy implementation into the systems: There are specialized chips that can facilitate the integration of ANNs into the systems.

The originality and contribution of this paper are summarized as:The main motivation of this paper is to generate an uploaded compilation of research works, models, methods and algorithms, where researchers and professionals in the wind energy field can find the current state (and ideas of the future trends) of the use of ANNs in WES. This paper can also be useful for finding novel research lines that can improve the operation of the existing methods. It shows the benefits of each type of ANN for different purposes.

II. ANN APPLICATIONS IN WIND ENERGY

This paper presents an exhaustive state-of-the-art ANN applied to the wind energy field. The objective of this section is to classify the ANN methods regarding the problem to be addressed. The NNs are useful for solving a wide range of problems from seven categories [24]:

- Pattern classification: The ANNs can detect patterns in a dataset through supervised learning.
- Clustering: The data similarities, or dissimilarities, are identified via unsupervised learning. The network will assign similar data to the same group (or cluster).
- Function approximation: ANNs can be applied to problems where a theoretical model cannot be applied. They can approximate the input data to a function with a certain degree of detail.
- Forecasting: A NN can be trained by time series to obtain a prediction of the future behavior.
- Optimization: A solution that maximizes, or minimizes, a function subject to different constraints can be found.
- Association: An associative network can be employed to reconstruct corrupted data by developing an associative pattern.
- Control: It is possible to determine the inputs that will cause a desired system behavior.

This research work considers the following classification, focusing on the study of the most influential and studied problems. It is shown in Table I.

The four major categories (forecasting and prediction, fault detection and diagnosis (FDD), design and control optimization) are related to the nature of the problem that will be addressed in this paper. The secondary categories represent the specific part of WES that will be considered for analysis. FDD will be studied in detail in this paper due to the large number of studies and methods that have been developed in recent years.

TABLE I. CLASSIFICATION STRUCTURE OF THE APPLICATIONS OF ANN IN WIND TURBINES

ARTIFICIAL NEURAL NETWORKS AND WIND ENERGY	**FORECASTING AND PREDICTIONS**	Wind speed
		Wind power
		Other parameters
	DESIGN OPTIMIZATION	Wind turbine
		Wind farm
	FAULT DETECTION AND DIAGNOSIS	Gearbox and bearings
		Generator, power electronics and electric
		Rotor, blades and hydraulic
		False-alarm rate reduction
	OPTIMAL CONTROL	Maximum power tracking
		Pitch angle
		Speed
		Reactive power
		Converter

III. FORECASTING AND PREDICTIONS

The prediction of the wind energy production is a complex task, but it is crucial to establish optimal planning by energy suppliers, wind energy market actors, wind farm owners and operators, maintenance teams, etc. For example, energy suppliers can avoid overproduction by considering energy storage systems or by coordinating the estimated wind energy production and the demand [25]; generators can adopt strategies for making offers into electricity markets [26, 27]; the maintenance tasks can be scheduled according to predictions [28, 29], etc.

It has been demonstrated that ANNs are efficient when physical processes are not understood or are very complex [30]. The main parameters considered for predictions are wind speed and wind power.

A. Wind speed forecasting

Wind speed is an essential parameter for the WES operation. The most important models for wind speed forecasting are [31]: the physical methods, such as the numerical weather prediction (NWP); the statistical methods [32], where the most popular is the ARIMA model; the intelligent models, where the most popular are based on ANNs; and the hybrid forecasting models, that combine different types of algorithms. Physical methods are better for predicting wind speed in the long-term. Statistical methods and artificial intelligence models are efficient for short-term wind speed prediction.

To quantify potential uncertainties associated with forecasts, Quan et al. implemented a NN-based method for the construction of prediction intervals [33]. These uncertainties associated with forecasts were also quantified by Ak et al. using a MLP [34].

Table II shows a classification of the predictions according to the time-horizon.

TABLE II. WIND SPEED PREDICTION VS TIME HORIZON [35]

TIME HORIZON	RANGE
Very-short term	Seconds - 30 minutes
Short-term	30 minutes - 6 hours
Medium-term	6 hours - 1 day
Long-term	1 day-1 week ahead

Most of the research studies and methods for wind speed forecasting are focused on very-short-term or short-term forecasting.

Very short-term predictions are useful for turbine control applications in the range of seconds. Therefore, computational cost is an essential factor to the models to be used in online applications.

Safavieh et al. employed wavelet-based networks and particle swarm optimization, obtaining more accurate results compared with a MLP, but it requires high computational costs [36].

Kani and Ardehali suggested a combination of a MLP and Markov chains [37]. This method reduces the predicted errors and the uncertainties with a moderate computational cost. Therefore, the model is practical for use in online applications.

Gao et al. proposed an hybrid model based on chaos phase space reconstruction and NWP-General regression NN [38]. This method reduces the impact of inaccurate meteorological information. The abovementioned models concluded that the hybridization of ANNs provides better results than single ANN methods for very short-term wind speed predictions.

Regarding short-term forecasting, Li et al. employed three different ANNs (linear element network, BPNN and RBFNN) for 1 hour ahead predictions [39]. This study concludes that there is not a unique ANN that provides the best results in all the cases.

The BPNN developed by Palomares et al. can also be employed for 1 hour ahead predictions [40]. This method improved the results of the persistence model, and demonstrated that data obtained from traditional agricultural measurements can be useful in predicting wind speed with acceptable results.

Philippopoulos and Deligiorgi proposed a feed-forward ANN method for a coastal region with a very complex topography [41]. They demonstrated that this model is accurate due to the ability of the ANNs to incorporate the unstable characteristics of the wind due to the topography.

Salcedo-Sanz et al. developed a MLP-based method for predicting wind speed at different points of a wind farm [42]. They proved that this model in a real wind farm obtains small mean absolute error values.

Several research works on short-term wind speed forecasting consider different models, e.g. two-layers ANN [43], RBFNN [44], IRBFNN [45], ensemble of mixture density ANN [46], non-linear adaptive model [47], deep ANN [48], adaptive boosting (adaboosting) ANN [49], etc. All these studies demonstrate that most of the ANN based models are more accurate than methods without artificial intelligence. The best model for each case depends on the type of data and the criteria for the estimation.

The ANNs are also employed to develop algorithms for medium term wind speed forecasting. The increase in the time-horizon causes less accurate forecasting. Wang et al. combined an Elman recurrent ANN with machine learning techniques for a medium-term wind speed prediction [50]. The authors concluded that the hybrid methods provide more accuracy for this prediction horizon than other models.

Some authors have developed hybrid models: Zhang et al. employed ANNs in two different hybrid models that combine empirical model decomposition and support vector machine [51], obtaining better results than those provided by the traditional decomposition forecasting aggregation models.

Meng et al. showed a wind speed forecasting by a hybrid model that comprises wavelet decomposition and ANN [52]. This method improved the forecasting performance compared to empirical mode decomposition methods. An adaptive wavelet ANN is employed by Doucoure et al. for a multi-resolution analysis for predicting wind speed time series [53]. This model allows the complexity (order) of the prediction system to be optimized. Ak et al. trained a MLP trained with a multi-objective genetic algorithm [54], obtaining a reliable estimation of the prediction intervals.

Li and Shi made a comparison between adaptive linear element, BPNN and RBFNN [55]. They realized that factors such as the inputs of the model and the learning rates affect the accuracy of the estimation. Liu et al. proposed a novel multi-stage hybrid approach for high accuracy predictions based on the secondary decomposition algorithm and Elman NNs [31].

The literature for long-term wind speed predictions is not very extensive due to low accuracy. For example, Malik [56] proposed a BPNN trained with data from 22 cities. This paper optimizes the number of hidden neurons in order to reach a maximum accuracy.

Finamore et al. presented a method for the medium-long term prediction based on a MLP and the spatiotemporal evolution of weather [57]. The model gave interesting results, being able to reduce the effects of weather anomalies.

Moustris et al. proposed a 24-h ahead wind speed prediction with an ANN model that is analyzed together with the wind and air pressure historical data [58]. The results of this model provide an adequate forecast that can be useful in supporting maintenance tasks. A long-term prediction model was also developed by Azad et al., using a feed-forward BPNN for predicting the trend of the incoming year [59]. The proposed method provided the best results for monthly mean wind speed, 30 days ahead and 1 year ahead, compared with other ANN models (Time Delay, Nonlinear Autoregressive, Feed-Forward and Layer-Recurrent). Additional long-term wind speed forecasting models can be found in [60] and [61].

B. Wind power forecasting

Many forecasting studies for wind power in the short, medium and long term have been found in the literature.

Regarding the short-term forecasting, Zameer et al. [62] proposed an ANN-Genetic programming based model. It employs a combination of Feed-forward BPNN, RBFNN and Broyden Fletcher Goldfarb Shanno NN. The model was applied to several wind farms providing estimations results with a high level of accuracy.

Ma et al. proposed a hybrid method that involves a generalized dynamic fuzzy NN [63]. The accuracy of the method presents results that are 5.33% more accurate than results obtained with BPNN.

Dong et al. suggested a hybrid model combining an integrated processing strategy and a linear neuro-fuzzy function to forecast wind power [64]. Other hybrid models are based on neuro-fuzzy [65], GA-BP NN[66], wavelet ANN [67] or Adaptive Wavelet ANN [68]. Short-term wind power prediction methods are based on BPNN [69], Elman ANN [70], convolutional and recurrent ANNs [71], Boltzmann machine [72], artificial bee colony ANN [73], ANN combined with PSO [74] or with PSO-FCM [33], or recurrent ANN [75].

ANN methods are mainly employed for short-term wind power predictions because the accuracy decreases when the time horizon is long [76]. Wang et al. designed a network structure for long term predictions, based on the combination of matrix time series with Bernstein polynomial, with an accurate estimation up to 24 hours [77].

Bhaskar et al. employed a two-stage model, composed of a wavelet ANN and a feed-forward NN, to predict wind power up to 30 hours with acceptable accuracy [78]. The proposed model is compared with persistence, and new reference benchmark models individually confirm the effectiveness of the model.

Wan et al. generated prediction intervals of wind power through an hybrid ANN approach [79]. The results demonstrated that the proposed approach can be used in practical applications.

An estimation of the annual energy output of a WT was developed by Jafarian and Ranjbar, performing a RBFNN and generalized regression network model by three inputs: average of wind speed, standard deviation of wind speed and the air density [80].

Li et al. compared GNN, SGNN, RBFNN, and Extreme Learning Machine regarding the computational cost, time horizon and accuracy [81]. They concluded that the best method is different according to the time-horizon.

Models for both wind speed and wind power forecasting have also been developed. Olaofe employed a BPNN to predict wind speed and power up to 5 days ahead [30]. One drawback of this model is that the ANN requires many input samples to provide good confidence outputs. Barbourins and Theocharis employ locally recurrent multilayer networks for long-term wind speed and power forecasting [82]. Multilayer networks are also employed by Jung and Kwon to predict annual energy production of WT [83]. The work presented by Petković et al. consists of an adaptive neuro-fuzzy inference system to predict the wind power form, wind speed and speed direction [84].

C. Other parameters forecasting

Additional important parameters can be predicted through ANN models. Ouyang et al. [85] proposes a comparison between four data-mining algorithms applied to control the yaw position of a WT. The algorithms are based on support vector machine (SVM), MLP, random forest algorithm (RFA) and gradient boosted regression trees (GRBT). The prediction of the wind direction is represented by its sine and cosine components. The results are compared with the real dataset. The mean absolute error (MAE), the root mean squared error (RMSE) and the correlation coefficient (CC) are shown in Table III. The MLP model is considered the best model for predicting the cosine direction of wind. It has been shown that these methods present better results than traditional approaches.

TABLE III. COMPARISON OF ERRORS OF DIFFERENT ALGORITHMS

	Sine predict error			Cosine predict error		
	MAE	RMSE	CC	MAE	RMSE	CC
SVM	0.1079	0.1632	0.9719	0.1268	0.1815	0.9650
MLP	0.0935	0.1603	0.9703	0.0803	0.1468	0.9766
RFA	0.0820	0.1468	0.9771	0.0869	0.1525	0.9749
GRBT	0.0993	0.1652	0.9704	0.1026	0.1672	0.9701

Sargolzaei and Kianifar proposed a RBFNN for predicting the torque and the power factor in a Savonious WT [86]. The predicted values by the model are compared with the measured parameters. This study demonstrated that the ANN techniques can be applied as an effective method for predicting and assessing the performance of WTs.

Shamshirband et al. predicted the noise annoyance caused by WTs [87]. This is an emerging problem due to the large increase in the number of WTs. A model to simulate the WT noise levels is proposed using an adaptive neuro-fuzzy inference system (ANFIS). The model can predict the noise level with higher accuracy and lower computational costs than conventional ANNs.

Statistical criteria are commonly employed to evaluate the prediction accuracy of the different models. The MAE and the mean absolute percentage error (MAPE) are commonly used, defined by:

$$MAE_j = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - f_{i,j}\right|$$

$$MAPE_j = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{y_t - f_{i,j}}{y_t}\right|$$

where T is the number of data used for comparison; y_t is the real value and $f_{i,j}$ the estimated values.

The accuracy of forecasting will vary according to the time horizon. Madhiarasan and Deepa compared the minimum square error (MSE) of an ensemble ANN for different time scale predictions [88]. Fig. 2 shows that the accuracy of the estimation has a strong dependence on the time horizon.

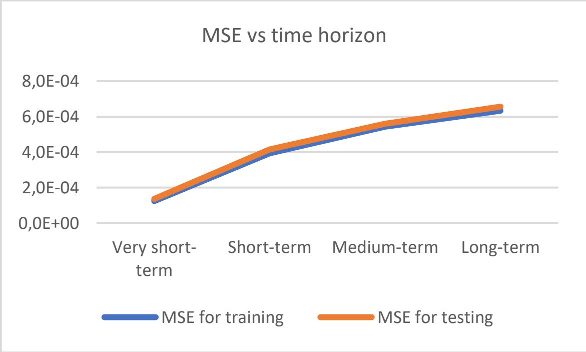

Fig. 2. Evolution of MSE versus time horizon

A comparison between the main models is presented in Table IV. The MAE and MAPE (if they are provided) of the mentioned models are indicated. This table also shows the type of ANN based model and the forecasting time horizon. The blank cells correspond to unknown values.

TABLE IV. WIND SPEED PREDICTION VS TIME HORIZON

REFERENCE	TYPE	MAPE	MAE	TIME HORIZON
WIND SPEED FORECASTING				
Safavieh	MLP	3.57		Seconds
Kani	ANN–MC	3.14		7.5s
Liu	WPD-FEEMD-Elman	8.68	1.05	30min
Li	BPNN		1.13	1h
C.Palomare	BPNN		0.18	1h
GongLi	RBF	18.90	1.11	1h
GongLi	BPNN	19.4	1.15	1h
GongLi	ADALINE	19.4	1.15	1h
Hu	SHL DNN		1.79	2h
Noorollahi	ANFIS	27.83	0.89	3h
Noorollahi	BPNN	28.22	0.89	3h
Noorollahi	RBF	30.68	0.95	3h
Meng	WPD–CSO-NN	54.08	0.36	5h
Boubacar	MRA-AWNN		12.4	5h
Wang	PMERNN	20.03	1.44	6h
Azad	BPNN		0.80	24h
Salcedo	MLP		1.45	48h
Chang	IRBFNN-EF	3.86		72h
Zhongxian	MDN		1.66	72h
Malik	FF	22.8	0.48	12 Months
WIND POWER FORECASTING				
Zameer	GPeANN		0.0643	1h
Wang	GA-BP with EEMD	6.82		1h
Aghajani	RBF + HNN + W T + ICA	1.84		1h
Wu	CNN + LSTM	5.62		1h
Peng	MRBM		0.123	1h

Liu	PNN	11.20	7.874	1h
Dong	DSNP-oLLNF		0.639	2h
Wang	PDSTA + BNN		3.21	24h
Kanna	MRA- AWNN		0.867	30h
Liu	BRSA	7.63	2.19	48h
Barbounis	OF-MLN		1.5	72h
Chitsaz	ICSA		9.7	1 week

In conclusion, ANNs are widely employed for forecasting wind speed and wind power. All the models and methods presented are more efficient when the time-horizon is short. This is the reason why most of the ANN models are employed for short-term predictions. ANN is employed for forecasting, e.g. RBFNN, neuro-fuzzy function, feed-forward, BPNN, conjugated gradient, recurrent ANN or Elman NNs. However, most of the approaches use hybrid methods, being more accurate, but they need a lot of input samples when the forecast horizon is long to provide a good result. The MAE and the MAPE present a dependence on the forecasting time horizon as indicated in Table IV. However, it is very difficult to determine whether the ANN based method provides the best results, since forecasting is usually constrained by the nature of the data, the time horizon and the computational cost.

IV. DESIGN OPTIMIZATION

The aerodynamic design of WTs is essential for achieving good efficiency and, consequently, for obtaining more efficient WES. ANNs are also applied with design purposes due to their ability to consider a high number of aerodynamic variables, e.g. lift coefficient, drag coefficient, Reynolds number, angle of attack, viscosity, etc. [89]. There are many studies where airfoils, wing sections and the wing tips are optimized through ANN. However, this paper is only focused on those studies that are specifically aimed at WT design. This section distinguishes between two different aspects, the design of WTs and the design of wind farms.

A. Wind turbine design

Regarding the design of WT, the main fields where the ANNs play an essential role is in the design of the airfoils and the selection of the tip speed ratio.

Chen and Agarwal proposed the optimization of flatback airfoils for WTs using a genetic algorithm with an ANN [90]. The computational efficiency of the genetic algorithm is improved significantly due to the ANN. It has been demonstrated that the method can find the global optimal flatback airfoils.

The design of the airfoil sections for the blades of a horizontal axis WT was carried out by Mortazavi et al. [91]. The ANN are trained using computational fluids dynamics to obtain a Pareto optimal set of solutions. The airfoil design was also considered by Ribiero et al., where the use of ANN results reduced the computational time around 50% [92].

A MLP was employed by Díaz et al. [93] to perform a correction of the lift coefficient for the design of the angles of attack of WT airfoils. This model allows accuracy solutions to be found without using complicated and costly non-linear models.

The design of tip speed ratio affects the power generated and, consequently, the efficiency of the energy conversion process. Ata and Kocyigit [94] proposed an ANFIS approach in order to predict the tip speed ratio and the power factor of a WT. The model demonstrated that ANFIS improves the performance of conventional methods with a maximum mean percent error of ±4.32%.

Yurdusev et al. indicated that selecting the tip speed ratio is the first step in a WT blade design [95]. The study investigates the optimal speed ratio of the WT profiles most used in practice. A three-layer feed forward network was considered. The results show that the ANN model is very fast and accurate. The algorithm can be easily adapted to other WT profiles due to the generalization and adaptability capabilities of ANNs.

Other aspects of the WT design are considered by Supeni et al., creating a model for predicting the number of wires needed to recover the deflection of a smart WT blade [96]. The ANN is trained using multiple BPNN and NARX methods. This work concludes that, although NNs usually provide a certain degree of inaccuracy, the computational cost is low. Rubio proposed a hybrid method for modelling the dynamic behavior of a WT [97]. This method is based on the combination of the analytical and a BPNN models. It is an improvement on the analytical model because it provides a reduced root mean square error.

Romanski et al. presented a multi-layer feed-forward ANN based model for demonstrating the capability of ANNs to correlate the operation parameters of a counter-rotation WT. They correlated the generated power with the average velocity of the air stream, wedge angles of the rotor blades and the distance between rotors. They confirmed that the solution was valuable in the design and construction decision-making processes [98].

Jae-Chul et al. proposed a BPNN to reduce the time for performing analysis, minimizing the prediction errors [99]. The objective of this study is to solve a multi-objective optimization process by giving the adequate shape and the best geometry to the system.

B. Wind farm design

The design of a wind farm is a very complex process since it is necessary to consider a great number of variables. This section studies the application of ANN based models for optimizing some of these variables.

Ekonomou et al. developed an ANN model in order to calculate the optimal number of WTs in a wind farm, considering several factors such as the terrain morphology, the wind speed and main direction, the type of WT, costs, etc. [100].

Shamshirband et al. established an ANFIS model as an alternative to analytical approaches for studying the WT wakes and their interactions [101]. This effect is important in the design of wind farms, and for maximizing the energy output and the lifetime of the WTs. The approach presents the following advantages: no required knowledge of the internal system parameters; multi-variable problem solution, and; fast calculation.

Petkovic et al. [102] developed a process for selecting the most influential parameters of a wind farm project investment. This model employs an ANFIS method to calculate the net present value, which is the most important criteria for investment estimating. The model considers multiple variables, e.g. price of electricity, interest rate, costs, number of turbines, etc... This paper conclude that Fuzzy variables can facilitate the prediction of those variables. This author also employed ANFIS based method to identify the most influential factors on the wake effect of WTs [103].

The design optimization is a crucial stage for ensuring the efficiency of the WTs and the wind farms. ANNs are commonly employed in this stage to determine the value of parameters that must be fixed before the implementation of the systems. Some of these parameters are the airfoils, the tip speed ratio, characteristics of blades, the behavior of a WT, the geometry of components, number of WTs, interaction between WTs, etc. In this field, ANNs are very useful because they can interrelate a multitude of variables to simulate scenarios close to reality. For design purposes, the computational time is not a determinant factor because the main objective is to obtain accurate results. The most employed ANNs based methods for design purposes are ANFIS and BPNN. The backpropagation training has the advantages of accuracy and versatility, although it is usually time-consuming and complex. ANFIS presents a very high learning ability, i.e. for a similar network complexity, ANFIS presents a smaller convergence error than a simple MLP [104]. In addition, ANFIS requires fewer parameters to be adjusted than conventional ANNs.

V. FAULT DETECTION AND DIAGNOSIS

There are many methods for detecting failures in WTs based on condition monitoring (CM) techniques, **called FDD when it is also diagnosed**. Several reviews that focused on these techniques can be found in the literature, e.g. FDD through CMS [105], FDD for maintenance management[106] or pattern recognition for FDD [107]. This section shows an exhaustive study of the FDD based on ANN. The main advantage of ANNs is their capability to represent complex nonlinear relationships through pattern recognition [108]. Most of the methods employ ANNs to identify patterns of SCADA signals that could indicate the occurrence of a fault [109].

There are models to evaluate the whole system and detect anomalies [110]. However, most of the algorithms and models are created to evaluate specific components. The following categories have been set according to the main WT components: gearbox and bearings; generator, power electronics and electric controls; rotor blades and hydraulic controls; and false-alarm rate reduction.

A. Gearbox and bearing

Gearboxes generate a high failure rate in WTs [5]. The bearing failures are usually caused by cracks. The bearing and gearboxes are critical components because their failures cause long downtimes. In this section, the ANNs are used as a tool to detect, prevent and/or predict some failures of gearboxes and bearings.

Schlechtingen and Santos made a comparison between the regression model, autoregressive ANN and full signal reconstruction ANN, to identify two types of bearing damage [111]. The feed-forward network type was chosen in all models. This work concludes that the methods can identify the damage before the bearing fails. Table V shows a comparison of the results indicating the anticipation of each method to the alarm limit violation (ALV).

TABLE V. COMPARISON BETWEEN THE MODELS [111]

	First ALV (days)	Second ALV /trend (days)
Regression	25	18
Full sig. reconst. NN	30	25
Autoregressive NN	50	25

The regression model is simpler than ANN, but the ANN models provide better results since they can predict the ALV.

Kusiak and Verma employ high-frequency SCADA data from 24 WTs to analyze bearing faults [112]. The dataset is employed to feed five ANN algorithms to detect bearing faults from over-temperature events. Table VI shows the network configurations.

TABLE VI. CONFIGURATIONS OF THE ANN MODELS [112]

Net. Nam	Network structure	Training algorithm	Hidden activation	Output activation
NN1	MLP 18-16-1	BFGS 380	Tanh	Identity
NN2	MLP 18-17-1	BFGS 622	Logistic	Identity
NN3	MLP 18-5-1	BFGS 214	Logistic	Exponential
NN4	MLP 18-15-1	BFGS 370	Logistic	Logistic
NN5	MLP 18-16-1	BFGS 377	Logistic	Exponential

The best ANN configuration was the NN2 in that it could predict faults with an accuracy of more than 97%. This model predicted the faults 1.5 hours before their occurrence.

Zhang and Wang describe a ANN technique for early FDD [113]. The technique is applied to the main shaft rear bearing using a standard BPNN. This work concludes that the ANN can be applied to other WTs with the main advantage that it can deal with a large amount of SCADA data without omitting information.

Bangalore and Tjernberg indicated that ANNs are a good method for CM applications based on SCADA [114]. An ANN is trained with historical SCADA data of bearings. This model was able to detect the deterioration in a bearing a week before the CM system genetated an alarm. Bangalore et al. also proposed a condition monitoring approach, where the data are filtered and inputted into ANN models that represent the normal operation of the WT [115]. The method is applied to case studies with failures in gearboxes.

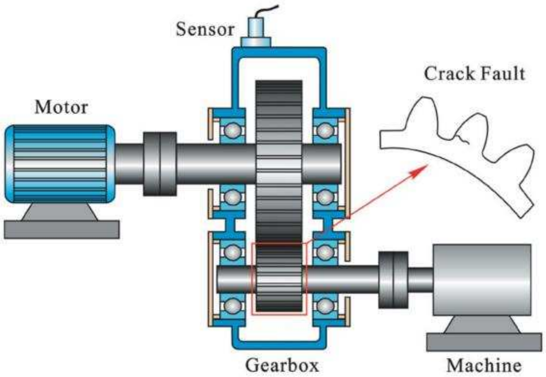

Fig. 3. Scheme of the crack fault in the experiment gearbox [116]

Li et al. proposes a new approach for crack detection in a gearbox (see Fig.3) based on discrete wavelet transform and an ART ANN [116]. The ANN recognizes the changing trend from the normal state to detect the cracks.

Strączkiewicz and Barszcz explained that the CM systems are usually designed to provide diagnostics based on wideband features, e.g. RMS or Peak to Peak [117]. The problem is that the parameters strongly fluctuate and miscorrelate to operation parameters. A BPNN model is created and applied to detect a ring gear fault in a planetary gearbox. The method detected an early stage of damage several months before the gearbox was replaced. ANNs have been very useful for handling highly varying operation parameters because of their ability to model nonlinear dependences.

Ali et al. showed an application for automatic bearing degradation assessment without human intervention [118]. A feature extraction is done from the vibration signals of the bearing. A multilayer ANN is fed with these feature parameters. The results demonstrate that the method is suitable for online bearing diagnosis with a reduced computational cost. It is also used as a method based on Weibull distribution and ANNs for predicting the remaining useful life of the bearings. It has been shown that this method is effective for decision-making in predictive maintenance activities [119].

Biswal et al. focused on the fault size estimation of gear root crack using vibration signals. For this purpose, some features are extracted from the signals [120]. The features are used to input a feed forward back propagating ANN. This study demonstrated that this procedure is very efficient in predicting the size of these types of faults.

Guo et al. proposed a recurrent ANN health indicator in order to predict the remaining useful life of bearings [121]. Recurrent ANNs are useful because they introduce a notion of time to the ANN model. The health indicator is constructed after a feature extraction process. The results showed that the proposed method performed better than the commonly used SOM-based health indicator.

Additional models for gearbox and bearing fault diagnosis are created through wavelet transform and ANN [122]; convolutional ANN models [123, 124]; local mean decomposition and ANN [125]; RNFC filter and ANN [126]; BP ANN [127] and improved BP ANN [128]; ANN trained by particle swarm optimization algorithm [129].

B. Generator, power electronics and electric controls

A doubly fed induction generator (DFIG) is the most used generator in large variable speed WTs [130]. This configuration requires two converters to generate electricity, see Fig.4. The strong nonlinearities of the converter circuits mean that ANN models are a useful tool for analyzing them. The ANN can be trained to learn the mapping relation between the fault information and type [131].

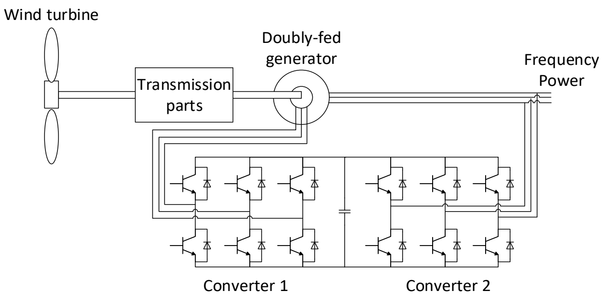

Fig. 4. Circuit of a DFIG wind turbine [131].

You and Zhang proposed a SOM ANN to develop a fault diagnosis system for converters of WTs. Some experiments are presented to allocate the fault position within the windfarm and to ensure the fault type [132]. A study of SOM networks applied to converters was also carried out by Zhang and Zhang [133]. They demonstrated that an intelligent fault diagnosis system must be able to distinguish types of converter, fault diagnosis and locations. They consider that the SOM network presents a low computational time.

Ko et al. presented a fault detection method for switch devices of three-parallel power converters [134]. This method employs the measure of three-phase currents to achieve pattern recognition through an

ANN. Several experiments are carried out to prove the reliability of the method.

The dynamic recurrent ANN models proposed by Teleby et al. can detect faults in the generator's angular velocity sensor by using dynamic NN [135] and recurrent NN [136]. These fault diagnosis systems employ two ANN models to simulate normal system behavior. The networks were placed in parallel with the system. The results showed that the proposed models operated fast, precisely and accurately, obtaining a very low rate of false or missed alarms.

Islanding is an undesired phenomenon that occurs when a part of the electrical system contains both loads and distributed generation, being electrically isolated from the rest of the system. Islanding needs to be prevented due to safety reasons, and to keep a high-quality power supply to customers. Ghadimi employs a hybrid intelligent ANFIS network to detect this phenomenon [137]. Islanding is also detected in reference [138] by feeding a two-layer feed-forward network with the symmetrical components of the second harmonic of voltage and current signals. This method can detect islanding operation very fast for a certain interval of load values.

C. Rotors, blades and hydraulic controls

Blades are the WT components with the highest failure rate and downtime [3]. The main fault is associated with structural failure, e.g. crack, fatigue, wear, corrosion, deflection, etc. [5]. The rotor hub can suffer clearance loosening at the blade root, unbalance, etc. [5].

Ibrahim et al. employed data from a CM system together with an ANN model for fault feature and diagnosis [139]. This work aims to make the diagnosis of rotor unbalance through current signals. The method proposes different networks for ranges of rotational speed. The study demonstrates that the rotor unbalance and transient and permanent faults can be detected with high accuracy. Malik and Mishra use probabilistic NNs for imbalance fault identification [140]. The study shows four probabilistic ANN models using different input variables. A simulation is carried out under six different conditions: aerodynamic asymmetry; rotor furl imbalance; tail furl imbalance; blade imbalance; nacelle-yaw. The simulated results show that the probabilistic NNs provide results with more accurate, less training/testing time than other ANN methods and better diagnosis than conventional methods.

Fu et al. studied the blade tip deflection measurement. Fig.5 shows a scheme of the blade tip deflection [141]. This deformation can cause the collision of the WT blades with the tower during the operation. A three-layer feed-forward ANN is created and inputted with 3-dimensional gyroscope data. The results show that the gyroscope sensors, together with the ANN analysis, is an accurate approach for monitoring the tip deflection in real time. Vera-Tudela and Kühn created models with two-layer feed-forward ANN for blades fatigue loads estimation [142]. A total of 48 ANNs are evaluated to predict two fatigue loads indicators in six wind farms. The results show high accuracy under specific conditions. For example, the estimations are better in an edgewise direction than in a flap wise direction, but decrease under wake conditions.

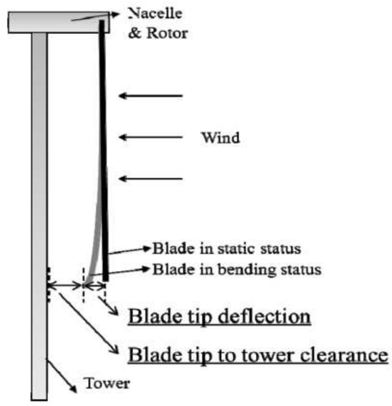

Fig. 5. Blade tip deflection scheme [141]

Gantasala et al. proposed a model for detecting ice accretion on the blades [143]. The technique employs wireless sensors to measure blade vibrations during operation. The natural frequencies are achieved with a few ice masses on the blade. These frequencies are used to train the ANN model. Certain experiments are carried out using random scenarios. This work concludes that the model can estimate ice masses. It works better when the ice mass increases.

Chen et al. developed a method to detect automatically significant blade pitch faults [144]. It employs an a-priori knowledge-based ANFIS with the ability to interpret unseen conditions. The method can be employed with high accuracy and precision for obtaining a prognostic warning before the pitch alarm is raised.

Kusiak and Verma use an approach for diagnosis blade pitch faults, blade angle asymmetry and implausibility [145]. This study employs the following machine learning approaches: bagging; ANN; pruning rule-based classification tree; K-nearest neighbor, and; genetic programming algorithms. The best solution was found by the genetic programming algorithms, the ANN-based method being the second most accurate method.

Dervilis et al. proposes two models for structural health monitoring of WT blades [146]. Sensors are installed to collect acoustic signals that will be interpreted by MLP and RBFNN. According to the results, the MLP has the advantage of limiting the number of sensors that are required to cover the entire blade. The model can detect a change before the crack becomes visible. Dervilis et al. [147] employed Auto-associative ANN and RBFNN models for failure detection of blades. They employ experimental measurements obtained through vibration analysis of the 9m CX-100 blade type under fatigue loads.

D. False-alarm rate reduction

Nowadays, the complexity of the modern WTs and their control systems cause an increasing number of false alarms. They are one of the major concerns of the WT operators, because they can generate important costs and downtimes, e.g. from a simple review of the supposed damaged system to an emergency shutdown of the WT. Maintenance tasks are affected by this problem.

Reference [114] shows a method to reduce the false alarm rate. It evaluates the average of the Mahanalobis distance over a period of three days. This procedure reduces the possibility of erroneous signals from the SCADA, or shortcomings of the ANN model, see also reference [148].

Schlechtingen and Santos aimed to reduce the fluctuations in the prediction error [149]. It means that the system triggers fewer false alarms. An ANFIS model is proposed to evaluate the dataset from the SCADA. The model can perform an accurate pattern recognition analysis.

Adouni et al. proposed a fault detection and identification procedure to support decisions when a severe grid fault occurs [150]. The model includes six ANNs that describe the three phases of the grid (amplitude and phase). Fig.6 shows the configuration of the model. This method is immune to unknown inputs and noise and, therefore, it is very sensitive to false alarms.

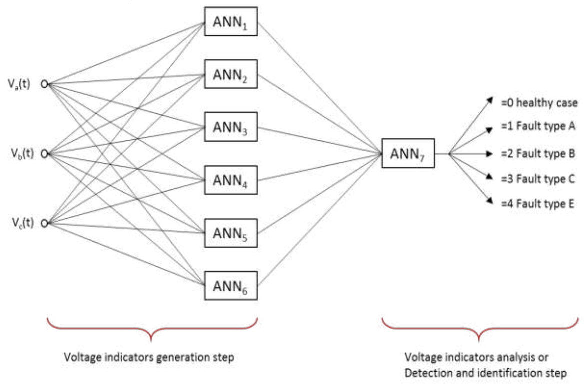

Fig. 6. Configuration of the six ANN-based model [150]

The advantages of ANN are employed to detect faults and perform diagnostics of WTs are shown as follows. Most of the ANN based methods are created to detect failures in gearbox and bearings. The fault detection does not require a fast computation process and therefore, the main factor is the accuracy of the method. Consequently, BPNNs are commonly employed in this field because they usually provide accurate results although the computational cost is high. Recurrent ANNs are also employed because they allow recent failures to be incorporated to the structure through feedback processes. In this case, the feedback leads to an increase in the adaptation of the ANN to the different symptoms of failure. ANNs in unsupervised learning are also employed, such as SOM and ART networks, because they can detect anomalies without using historical failure data. This is an important advantage since, on many occasions, the historical data does not show the status of the WT for all the possible failures.

VI. Optimal control

It has been demonstrated that ANNs are very robust in control tasks. For this reason, they are widely employed in a multitude of systems. For instance, ANN controllers have been designed for flight control, robot manipulators, maritime dynamic positioning system, induction motors, product storage, etc. In this section, several studies are discussed in which the benefits of ANN are employed to control diverse parameters of WTs.

A. Maximum power point tracking

Maximum Power Point Tracking (MPPT) is an essential requirement for maximizing the energy extraction from natural wind energy and, consequently, for increasing the efficiency and rentability of the WES.

Ganjefar et al. propose a quantum ANN as a controller to improve the efficiency of the MPPT methods [151]. These networks are equipped in adaptive control structures of tip-speed ratio and optimum torque MPPT methods. The technique was efficient in both methods, better than conventional ANN and PID (proportional integral derivative) controllers. A similar study was carried out by Karakaya and Karakaş, who made a comparison between ANN, lookup-table (LUT) and curve-fitting (CF) controllers [152]. The ANN controller was based on a two-hidden layer configuration. The results of this study are shown in Table VII.

TABLE VII. Comparison between MPPT controllers [152]

Controllers	Percentage error according to 10 test data	Percentage error according to 20 test data
ANN	0.35	0.17
LUT	2.81	1.4
CF	8.34	6.2

ANN controllers produce better results than the other ones, e.g. 274.05 better than CF and 244.27% better than LUT (see Table V).

Medjber et al. proposed a new control strategy based on ANN and fuzzy logic controllers to regulate the power transfer between the WT and the grid [153]. The objective was to ensure the MPPT for a DFIG. This study compares active and reactive power, currents and voltages, using both a single layer hidden ANN and a fuzzy logic controller. The response time obtained by the first controller was considerably reduced.

Hong et al. introduced a feed-forward general regression ANN controller to drive the turbine speed extracting the maximum power [154]. The approach combines the ANN with ant colony optimization. The controller allows the system stability to be maintained and the desired performance to be reached even under uncertainties.

Petković proposes a method based on ANFIS to estimate the power coefficient [155]. This parameter can be used to find the optimal operating points and design a controller to optimize the power generated. The study concludes that ANFIS is efficient at estimating Weibull parameters for WES.

Mehta et al. modelled an ANN based predictive controller to maximize the power capture of a mid-sized hydrostatic WT [156]. The fluid power transmission is technology with a high research interest. It employs a pressurized fluid flow to transmit the torque of the rotor blades. The ANN controller is more effective than a conventional PI controller.

Brekken et al. focused on the control and coordination of energy storage systems [157]. These systems are essential for mitigating the output uncertainty of a large wind farm. This work demonstrated that ANN control strategies prove effective for this purpose.

Other methods for MPPT control have been developed employing BPNN [158], RBFNN [159, 160], neuro-fuzzy [161], hybrid particle swarm optimization-ANN [162], growing neural gas network [163] or Elman NN [164].

B. Pitch angle control

The pitch control is performed to reduce the mechanical stresses and the variations of the generator torque. The conventional control strategy is the proportional and integral (PI) controller. Some advanced control strategies include fuzzy based controllers, multivariable control strategies or ANN based strategies.

The control systems allow the WTs to operate in different scenarios because they can adapt the operation mode to specific conditions. Bagheri and Sun propose an adaptive RBFNN to design controllers for variable-speed and variable-pitch WTs [165]. It means that the power using a nonlinear control can be maximized.

Other studies aim to maximize the power generation by controlling the pitch angle [166]. It has been demonstrated that these control tools are efficient, providing good robustness and low computational costs. Perng et al. suggested a RBFNN in order to build a proportional-integral-derivate controller for the pitch system [167].

Jafarnejadsani et al. [168] developed a RBFNN based strategy in order to control the pitch angle of the blades, and to modify the speed of the rotor. This paper demonstrated that the ANN control is very robust to uncertainty.

Ahmet and Özer [169] proposed an ANN based pitch angle controller, where MLP and RBFNN are employed. This model enables the power output to be successfully regulated and overloading during high wind speeds to be avoided.

Mjabber et al. [170] investigated an RBFNN based controller for pitch angle of variable speed WT. The controller indicated better results than the PI controller, demonstrating more stable energy extraction from wind power.

Han et al. [171] developed an individual pitch controller based on a LIDAR+ RBFNN model for optimizing the pitch angle and the electromagnetic torque. Some simulations demonstrated that this controller can improve wind energy efficiency and reduce fatigue loads. Another individual pitch controller was developed by Liu et al. [172]. They used a RBFNN with online training to mitigate the loads of blades, hub and yaw bearings.

C. Speed and torque control

The control of the speed and torque of the WT rotor is one of the most common aspects for ensuring the proper behavior of the WTs at variable and unstable wind speeds. This control allows maximum power to be extracted without risking the integrity of the WT.

Hong created a sliding mode speed controller by a feed forward ANN torque compensation, providing robustness to the wind driven induction generator system [173].

Assareh et al. [174] presented a hybrid method for controlling the torque in WTs. A RBFNN, trained with a gravitational search algorithm, is employed to tune gains of a proportional and integral controller. A good performance of the method is demonstrated by a simulation in a 5 MW WT.

Jaramillo-Lopez et al. [175] showed a ANN based identifier designed in order to approximate the mechanical torque of the WTS. A RBFNN is employed for this purpose. The proposed scheme provides high robustness according to the simulations carried out.

Petković et al. proposed a system where an ANFIS regulator adjusts the speed of a variable-speed generator [176]. The method can extract more power when the turbine is operating at variable-speed mode. The work concludes that the ANFIS scheme is easily adaptable with optimization techniques with low computational costs.

Wang et al. [177] focused on the torque control for offshore WT on Spar floating platform. They developed an advanced RBFNN for operating at speeds lower than rated wind speeds. The proposed controller results are robust against complex wind and wave disturbances and very adaptive to unstable system parameters.

Mjabber et al. [178] presented a RBFNN based controller for approximating the nonlinear dynamics of the WT that ensures the optimal tip-speed ratio at different wind speeds. This controller improved the efficiency by 2% in comparison with NDSFCK (Nonlinear Dynamic State Feed-Back Control with Kalman estimation) controller.

D. Reactive power control

Tang et al. used a ANN based controller for the reactive power control of DFIG [179], where a reactive power controller based on adaptive dynamic programming (ADP) is developed. The ADP control comprises both an action and a critic network. Two three-layer NNs have been used to implement both parts. The results show that the sag and overshot of the active power can be reduced, and the stability and damping characteristics can be improved. These authors also developed a goal representation heuristic dynamic programming to investigate the reactive power control of a wind farm. In this model, an ANN is employed to adjust the parameters [180] .

Wei Qiao et al. [181] proposed a novel interface neurocontroller designed with a RBFNN. This model is employed for steady-state and transient reactive power compensation. It is demonstrated that the controller improves the postfault power oscillation damping of the system.

Barani and Abdi [182] employed a NARX NN that can be used for controlling the stator reactive power level. This paper compares a conventional PI controller with the ANN based controller. The proposed method provided better results than the conventional one.

E. Converter control

The modern WTs with DFIG configurations are equipped with back to back power converters for controlling the speed and torque of generator. A failure of the power converter will affect the WT operation and cause disturbance to the grid. This section discusses some ANN based models that control the operation of the converters.

Wai et al. designed a model including an adaptive control scheme and a fuzzy ANN for controlling a single-stage boost inverter [183]. The proposed fuzzy ANN control system was verified by experimental results. The controller provided significant improvements compared to the conventional double-loop PI control.

Li et al [184] investigated how to mitigate some limitations of the control mechanisms of conventional grid-connected rectifier/inverters. They implemented a BPNN that showed strong ability in tracing changing reference commands and satisfying control requirements.

Fu et al. [185] trained recurrent ANNs for optimal control of grid-connected converter obtaining a reduction of the computing time.

Kanellos et al. [186] proposed a novel neuro-control scheme for the generator side converter. This scheme contains two multilayer ANNs. The back-propagation method is employed for training both ANNs. The proposed scheme is applied to a simulated process presenting operational characteristics, as indicated by the reported simulations.

This section shows the application of ANN based methods for controllers. These methods are aimed at controlling different parameters that are intended to extract the maximum energy from the wind. These controllers are sometimes employed for ensuring the safety and the integrity of the WTs when they are under extreme environmental conditions. In this case, the controllers require low computational costs because immediate responses to sudden changes in the system's condition are needed. For this purpose, ANFIS and RBFNN are the most employed methods. ANFIS controllers are demonstrated to be the best controllers compared with the conventional PID controllers. RBFNN based controllers are demonstrated to have very strong tolerance of input noise and online learning ability. In addition, RBFNN controllers are very efficient in the transient stability performance of power systems. These abilities are very attractive for controllers.

VII. Discussion of NNs applied in Wind energy systems and some trends

A general analysis of ANN in wind energy conversion systems has been carried out considering the exhaustive state of the art presented in this paper. This paper classifies the ANN in WT into four categories: forecasting; fault diagnosis; design, and control. The selection of the most adequate ANN depends on factors that can be classified as:

- Endogenous factors of the problem: These factors are related to the nature of the problem, i.e. those characteristics that are imposed by the problem.
- Exogenous factors of the problem: those parameters that are selected for the person who addresses the problem. For example, the time-horizon of predictions, the robustness of the method, the accuracy of the analysis or the computational cost.
- Limitations: there are several characteristics that limit the accuracy of ANNs. The main drawbacks are the amount of inputs required, overtraining of the networks, the extrapolation errors and the difficulties of optimizing the network [187].

Considering the mentioned factors, an analysis of the literature identifies some challenges and technological gaps related to ANN application with respect to the tools and methodologies for WTs. They can be summarized as follows:

- The ANNs have been demonstrated to be effective for forecasting and predicting wind speed and wind power. The results shown in section III determine that ANNs usually generate results with more accuracy than other conventional methods, e.g. physical or statistical methods. However, the accuracy of the ANN based methods decreases significantly for long term predictions. In addition, the number of historical data required by ANN for long term prediction is high. A challenge in this field is to develop flexible ANN based methods adapted to the input data and the desired time horizon.

- In section IV, it is demonstrated that ANNs are employed for design optimization of WT components because they can simulate realistic scenarios through the interrelation of a large number of variables. The use of ANN in design optimization is limited to the aerodynamic parts of the WTs, e.g. airfoil sections of the blades. However, the capacity of these tools allows to other components to be optimized in the design stage. The optimization of thermal, hydraulic, electric or mechanical components is a current challenge where ANNs can be essential.
- ANNs can manage and analyse different dataset, being useful for the simulation of the behaviour of wind farms. Section IV. B shows that most of the simulation models based on ANNs enable several engineering aspects of the wind farm to be optimized, e.g. the location of the wind farm, the interaction between the different WTs. Future ANN based simulation models should be able to combine engineering, economic, environmental, and social aspects.
- Section V shows that ANNs are robust in that they can analyse data collected from monitoring systems, allowing faults detections and diagnostics. There is a multitude of analysis methods to detect faults in gearboxes, generators, rotors, blades, hydraulics. Most of these methods employ different ANN structures, depending on the requirements. However, the diagnostics can be wrong and then false alarms occur. The detection of false alarms is an important technological challenge, where ANN based methods could be applied to tackle it.
- Section VI demonstrates that ANNs are employed in control tasks due to their robustness. The ANN based controllers are usually adaptive to uncertainties and instabilities of systems. They have been demonstrated to be more efficient than PID or NDSFCK controllers. The study of optimization of ANN controllers are good at achieving faster responses to sudden changes of the WT condition without compromising accuracy and robustness.

Table VIII organizes the references considered in this paper according to the most employed ANN types and the specific application in WTs. It is important to note that the categories are not mutually exclusive, i.e. a model can belong to the ANN type according to its configuration, training algorithm, etc.

According to Table VIII:

- The ANN based methods in WES are mainly employed for forecasting, fault detection, control and design applications. Regarding the references of this paper, Figure 7 shows the frequency of use of the ANN based method in each application.

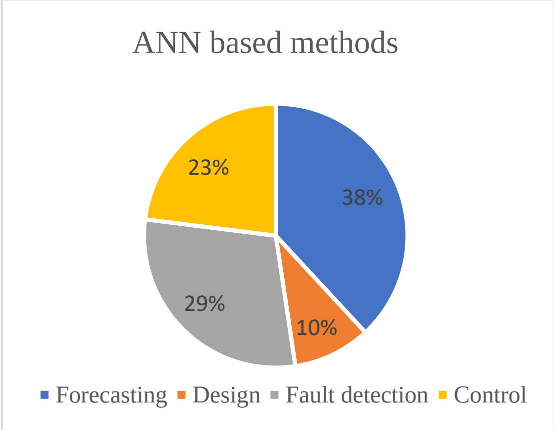

Fig. 7. Distribution of the applications of ANNs in WTs

- The forecasting and prediction applications employ a great variety of ANN types. However, the fault detection and the control are mainly performed by BPNN, ANFIS and RBFNN.
- In general, the BPNN is the most employed ANN type. However, it is mainly employed in applications that do not require a rapid response, such as fault detection, design optimization and not very short-term forecasting. This is because it provides very accurate results, but it also involves high complexity and high computational cost.
- RBFNN is the second most employed configuration. This configuration has a very good generalization ability, tolerance to input noise and fast online learning. These properties are very appropriate for addressing problems that require rapid response such as speed and torque control, pitch angle control and short time forecasting problems.
- The ANFIS is the third most employed ANN based method. This configuration is the most versatile and it is used for almost all the applications. **It is detachable the use of ANFIS controllers** because they are demonstrated to be more efficient than conventional PID controllers.
- Other configurations are used in more specific approaches. It is important to note that the requirements and constraints of the problem and the available data are crucial factors for determining the more adequate ANN based method.

Besides the qualitative analysis of the literature, some quantitative conclusions are extracted to describe the current state and the future trends in this field. For this purpose, Fig.8 and Fig. 9 show the evolution of the most employed ANNs configurations over the last ten years. They have been created using "Google-Scholar". The results obtained do not represent the exact number of models developed, but they can give an approximate idea of the trends and the evolution of each ANN type in WTs.

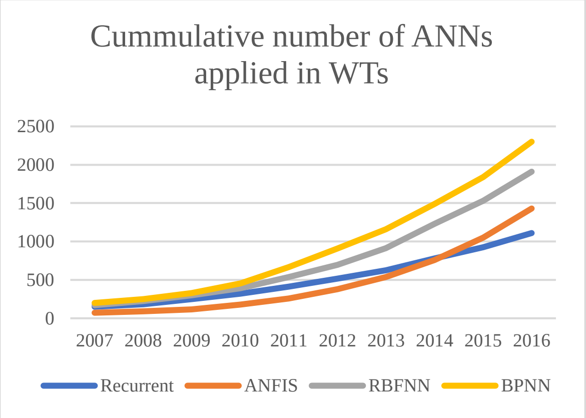

Fig. 8. Cummulative number of research studies

Over the last ten years, the most employed models are the BPNN and RBFNN based models; however, the ANFIS system presents the highest growth rate in the last years. One of the reasons that the ANFIS use is rising exponentially is because the volume of available data is increasing. These systems have the self-adjusting ability, which allows massive data to be processed, global errors to be minimized and computational costs to be reduced.

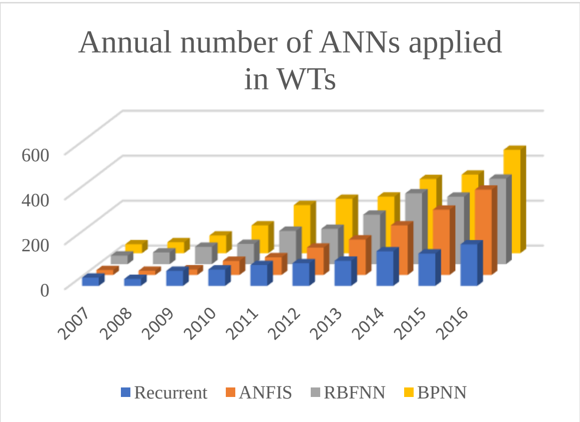

Fig.9. Annual number of research studies

Fig. 9 shows that, over the last ten years, the number of recurrent ANNs based models is increasing slowly, with some negative growth rates, e.g. 2008 and 2015. The number of RBFNN based models is increasing faster than recurrent models, but there are also some negative rates, e.g. 2015. The number of BPNN and ANFIS systems has increased without negative growth rates. The ANFIS models present an exponential growth over the last ten years.

VIII. Conclusions

The paper presents state-of-the-art artificial neural networks (ANN) applied to wind energy systems. The complexity of these systems is rising, and the methods and algorithms to ensure their efficiency are becoming more robust due to the volume of data and diversity of variables. The main ANN based models applied in wind energy systems and their characteristics have been explained in this paper. An extensive compilation of methods, algorithms and models has been developed. These methods have been grouped into four major categories. Some conclusions have been extracted concerning each category:

- Forecasting and predictions: Besides the list of the main references, a comparison of the errors in different forecasting models has been carried out. Neural networks are proved to be more efficient for short-term wind speed prediction, and the hybrid ANN based method provides better results for short term predictions than other conventional techniques.
- Design optimization: ANN based models for design optimization have been discussed. These models not only focus on wind turbines, but also on wind farms characteristics. In this field, the most employed methods are adaptive neuro-fuzzy inference systems and Back-propagation neural networks, since high accuracy is required and the computational time is not a determinant factor.
- Fault detection and diagnosis: The main ANN based techniques to detect faults and perform diagnostics of wind turbines have been discussed in this paper. Most of the ANN based methods are created to detect failures in gearbox and bearings. The fault detection does not require a fast computation process and, therefore, the main factor is the accuracy of the method. In this field, Back-propagation neural networks are commonly employed in this field because they usually provide accurate results. Recurrent ANNs are employed because they allow recent failures to be incorporated into the structure through feedback processes. ANNs in unsupervised learning (self-organized-map and adaptive resonance theory) are also employed because they can detect anomalies without using historical failure data.
- Control optimization: The most important and recent ANN based methods for controllers have been discussed in this paper. The controllers require low computational costs because immediate responses to sudden changes of the system condition are needed. For this purpose, neuro-fuzzy inference systems and radial basis function neural networks are the most employed methods.

This paper also provides an illustrative statistical analysis of the literature. These results describe the evolution over the last 10 years, the current state and the future trends of the ANN applications in wind turbines. A set of challenges and technological gaps regarding these applications has also been discussed. Finally, an overall table to summarize and to classify the main methods is provided.

The results of this paper can be used by researchers to discover the opportunities of new research lines by detecting those fields where improvements are required. Some of them are suggested in the set of challenges. These results allow developers and wind turbine components designers to select the most adequate structure for each case according to the response of different ANN type to certain requirements. ANN have been demonstrated to be useful for different applications and they can be combined with other tools to maximize their contribution through hybrid systems. In general, this paper can be used as reference guide for those who want to learn about the use of advanced techniques in the growing sector of wind energy.

TABLE VIII. SUMMARY OF MAIN METHODS

ANN TYPE	FORECASTING AND PREDICTION			DESIGN OPTIMIZATION		FAULT DETECTION AND DIAGNOSIS				OPTIMAL CONTROL				
	Wind Speed	Wind power	Others	WT design	Wind farm design	Gearbox and bearings	Generator, electronics	Rotor, Blades, hydraulics	False alarms	MPPT	Pitch	Speed Torque	React. power	Conv erter
Neuro-Fuzzy	[44]	[63], [64] [65], [84]	[87]	[94]	[101], [102], [103]	[119]	[137]	[144]	[149]	[152] [153] [155] [176] [161]			[157]	[183]
RBFNN	[39], [55]	[62], [45] [74],[80]	[86]					[146] [147]		[159] [160]	[165], [167] [168], [169] [170] ,[171, 172]	[174], [175] [177], [178]	[181]	
MLP	[37],[43], [47], [54], [57], [58]	[76], [83]	[85]	[91], [95], [93]	[100],	[111], [112] [115], [118]	[138]	[140] [141] [142] [145]	[148] [150]		[166], [169]	[173]	[179]	
BPNN	[39], [40], [44] [47] [55], [59]	[62],[66], [69]		[99], [97], [96]		[113], [114] [117], [120] [126], [127] [129]		[139] [143]	[114]	[158, 188]				[184] , [186]
Recurrent	[50]	[71],[75], [82]				[121]	[135, 136].							[185]
Wavelet	[36],[53]	[67, 68, 189] [78]				[122, 128];								
Elman	[50], [31]	[70]								[164]				
Feed-Forward	[41], [56], [59]	[62], [76], [78]		[95], [98]							[171]	[173]		
SOM NN							[132], [133]							
ART	[55]					[116], [119]								
Convolutional NN		[71]					[123, 124]							

IX. ABBREVIATIONS

ADALINE	Adaptive Linear Element
ADP	Adaptive Dynamic Programming
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
AWNN	Adaptive Wavelet Neural Network
BNN	Bernstein Neural Network
BPNN	Back-Propagation Neural Network
BRSA	Hybrid model combining based on Pearson correlation coefficient
CC	Correlation Coefficient
CNN	Convolutional Neural Network
CSO	Crisscross Optimization
DFIG	Double Fed Induction Generator
DNN	Deep Neural Network
DSNP-oLLNF	Hybrid model combining Discrete Wavelet Transform/ Singular Spectrum Analysis/ No Negative Constraint Combination Theory/Phase Space Reconstruction
EF	Error Feedback Scheme
FEEMD	Fast Ensemble Empirical Mode Decomposition
FDD	Fault Detection and Diagnosis
FF	Feed-Forward
GA	Genetic Algorithm
GNN	Gradient Neural Network
GPeANN	Genetic Programming based ensemble of Artificial Neural Networks
GRBT	gradient boosted regression trees
SGNN	Steepest Gradient Neural Network
HNN	Hybrid Neural Network
ICA	Imperialist Competitive Algorithm
ICSA	Improved Clonal Selection Algorithm
IRBFNN	Improved Radial Basis Function Neural Network
LF-MLN	Local Feedback Multilayer Networks
LUT	Lookup-Table
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MC	Markov Chain
MDN	Mixture Density Network
MLP	Multilayer Perceptron
MPPT	Maximum Power Point Tracking
MRA	Multi-Resolution Analysis
MRBM	Multilayer Restricted Boltzmann Machine
MSE	Minimum Square Error
NN	Neural Network
NWP	Numerical weather prediction
PDSTA	Primal Dual State Transition Algorithm
PMERNN	Hybrid method using Elman recurrent neural network
PNN	Probabilistic neural network
PSO	Particle Swarm Optimization
PSO-FCM	Particle Swarm Optimization based Fuzzy C Means
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RFA	Random Forest Algorithm
SCADA	Supervisory Control and Data Acquisition
SHL	Shared-hidden-layer
SOM	Self-organized-map
SVM	Support Vector Machine
WES	Wind Energy System
WPD	Wavelet Packet Decomposition

WT	Wind Turbine

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