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REVIEW ARTICLE

# A Comprehensive Review of Artificial Intelligence and Wind Energy

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**Abstract**

Support of artificial intelligence, renewable energy and sustainability is currently increasing through the main policies of developed countries, e.g., the White Paper of the European Union. Wind energy is one of the most important renewable sources, growing in both onshore and offshore types. This paper studies the most remarkable artificial intelligence techniques employed in wind turbines monitoring systems. The principal techniques are analysed individually and together: Artificial Neural Networks; Fuzzy Logic; Genetic Algorithms; Particle Swarm Optimization; Decision Making Techniques; and Statistical Methods. The main applications for wind turbines maintenance management are also analysed, e.g., economic, farm location, non-destructive testing, environmental conditions, schedules, operator decisions, power production, remaining useful life, etc. Finally, the paper discusses the main findings of the literature in the conclusions.

**Abbreviations**

| | |
|---|---|
| AI | Artificial intelligence |
| WT | Wind turbine |
| ANN | Artificial neural network |
| SCADA | Supervisory control and data acquisition |
| CNN | Convolutional neural network |
| PCA | Principal component analysis |
| GA | Genetic algorithm |
| PSO | Particle swarm optimization |
| O&M | Operation and maintenance |
| SVM | Support vector machine |
| FEM | Finite element modelling |
| NDT | Non-destructive testing |
| ANFIS | Adaptive neuro-fuzzy inference system |
| NPV | Net present value |
| EKF | Extended Kalman filter |
| AHP | Analytic hierarchy process |
| MILP | Mixed integer linear programming |
| CAD | Computer aided design |
| RCAM | Reliability-centred asset maintenance |
| NA | Not Available, unknown |

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## 1 Overview of Artificial Intelligence and Energy

Nowadays, the concept of Artificial Intelligence (AI) is not clearly stablished. For example, according to the European Commission, "*AI refers to systems that display intelligent behaviour by analysing their environment and taking actions—with some degree of autonomy—to achieve specific goals. AI-based systems can be purely software-based, acting in the virtual world or AI can be embedded in hardware devices*" and "*Systems that display intelligent behaviour by analysing their environment and taking actions—with some degree of autonomy—to achieve specific goals*" [1]. Similar definitions are given by the International Committee for Information Technology Standards (INCITS), defining AI as: "*data processing systems that perform functions normally associated with human intelligence*"; and "*The capability of a device to perform functions that are normally associated with human intelligence*" [2]; The International Organization for Standardization (ISO) [3]; and The Office of the President of the Russian Federation: "*Technological solutions that make it possible to simulate human cognitive functions*" [4]. Furthermore, the Institute for Information and Communications Policy (IICP) of the Ministry of Internal Affairs and Communications (MIC), that organized the Conference toward AI Network Society in Japan [5], refers to "AI software" as "*software that has functions to change its own outputs or programs in the process of the utilization, by learning data, information, or knowledge; or by other methods*", etc.

Tobin et al. [6] studied the research papers published in AI over the time. There have been approximately 60,000 papers published per year, with a growth of 12.9% over the past 5 years, being the growth of 2.3% in all research. This is explained due to the technical advances that enable the use of AI techniques in computing technologies, as well as the variety of applications for AI, such as problem solving and optimization, data analysis, image recognition and text processing.

According to Scopus, there have been 15,368 publications from 1970 to 2019 in AI applied to Energy production. Figure 1 shows that a significant number of publications began to appear from 2003, with constant rising up to date, where only in 2009 and 2018 the amount of publications decreased. It cannot be concluded that the research production decreased in 2009 and 2018, because the acceptation of any manuscript has a delay from when it is submitted to when it is accepted. The curve trend presents an exponential growth from 2000 to 2019.

Top of Fig. 2 shows the publication world map from 1970 to 2019 in AI and Energy by countries. Below the map, the countries that have published more publications are shown, led by USA (2350) and China (2247), followed by India (1366) and then UK (716), Spain (517), Germany (508), Italy (480), etc.

Data shown in Fig. 3 represents the publication world map according to the population of each country, in this case per million people. The results found differ from Fig. 2. The countries that present more publications per million people are Luxembourg (28,2), Singapore (28,0), Australia (27,4) and Cyprus (24,8), followed by Switzerland (19,2), Ireland (17,8), Portugal (17,4), etc., most of them from Europe. United States is 30th (7,2), China in 63rd (1,6) and India in 76th (1,0).

Figure 4 shows the main financial support systems for the publications abovementioned. China is leading it, followed by US and Europe.

Figure 5 shows the main energy topics covered by AI over 1970–2019 (source Scopus). Energy efficiency (1889) and energy utilization (1861) are the issues focusing more research, having more than 3 times research papers each that any other topic. Renewable energy, considering also solar energy and wind power, could be then grouped together with the previous topics (1556), but is only a gross approach because some papers could consider both topics together, e.g., renewable energy resources and solar energy. It could be concluded that energy efficiency and utilization, followed by renewable energy, are the main topics covered by the research community in the last decades.

Figure 6 shows the principal AI algorithms, approaches or methods applied to Energy over 1970–2019. The main algorithms are based on Learning Systems (2182), doubling the number of papers of Neural Networks (1274), Machine Learning (1091) and Decision Support Systems (1024). Learning algorithms could be considered together with learning systems, i.e., they sum 2910 papers.

The guideline to be a global innovation center, with the requirements of the CCP Central Committee and the State Council, set these main algorithms as [7]:

- *Big data intelligence*: Data- and knowledge-driven AI methods for data processing.
- Cross-media sensing and computing: Sensing that exceeds human abilities aimed at asynchronous orders and mart sensing and reasoning engines.
- *Hybrid and enhanced intelligence*: Combined use of human and artificial intelligence.
- *Swarm intelligence*: Information processing associated to the behaviour of groups of individuals.
- *Autonomous coordination and control*: Machine and system operation without human intervention.
- *Optimized decision-making; High-level machine learning*: Decision making based on the use of different machine learning structures considering uncertainties.

**Fig. 1** Publications on AI and Energy 1970–2019 ( *Source*: Scopus)

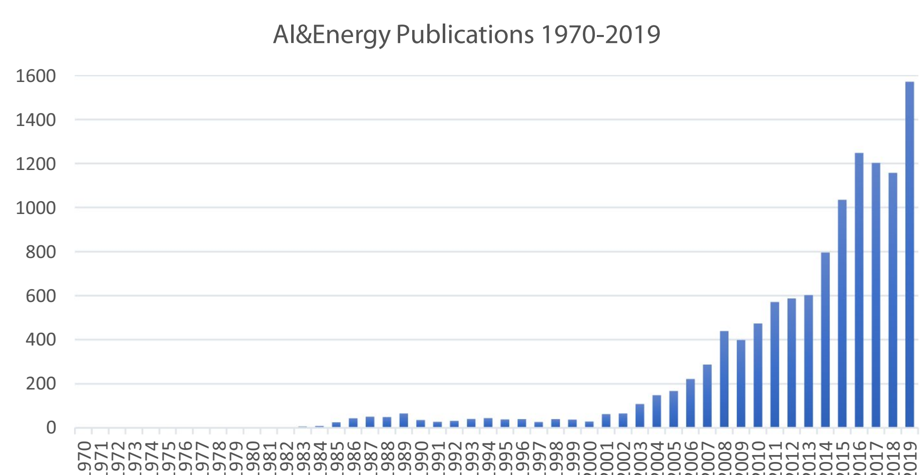
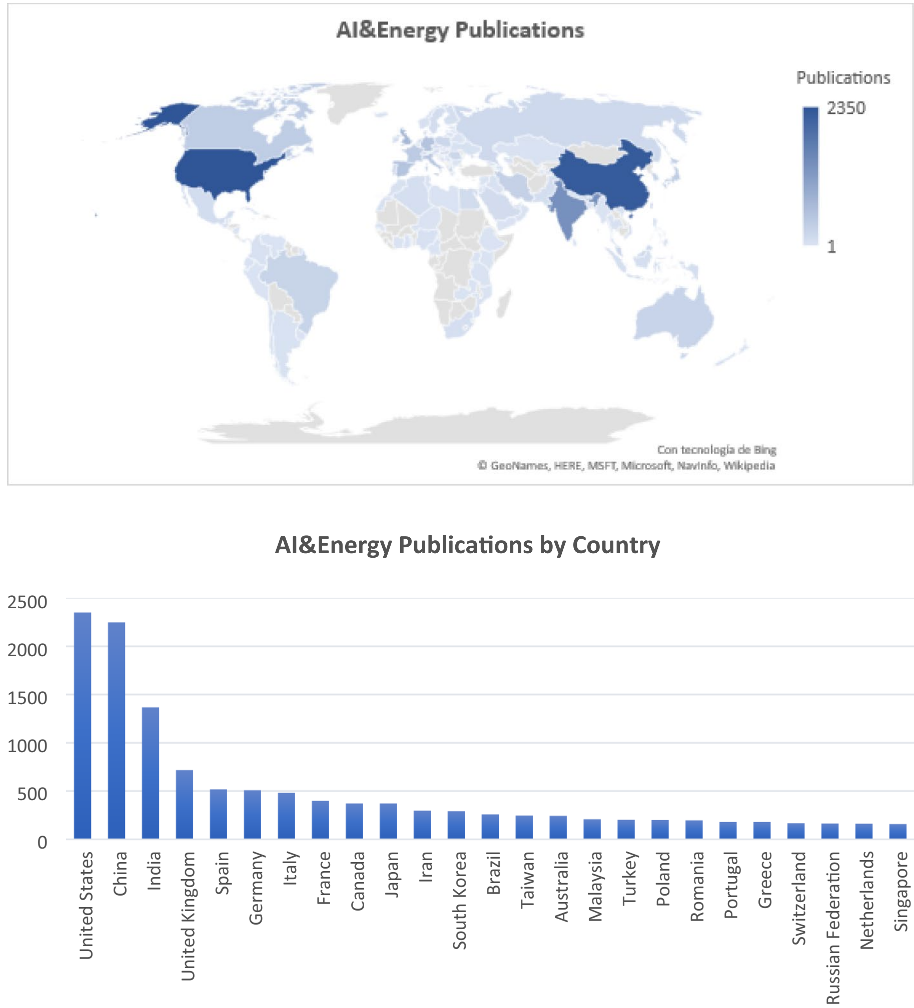


**Fig. 2** Publications on AI and Energy by Country ( *Source*: Scopus, 1970–2019)




- *Brain-inspired intelligence computing*: Research theories and methods on brain-inspired sensing and learning, among others.
- *Quantum intelligent computing*: Models and algorithms based on the use of quantum computing.

The decree of the president of the Russian Rederation on the AI developed in the Russian Federation classifies the main algorithms as [4]:

- The algorithmic simulation of biological decision-making systems, including distributed collective systems such as a bee swarm or an ant hill.
- Autonomous self-learning and the development of algorithm adaptability to new objectives.
- The autonomous decomposition of difficult tasks, as well as seeking and synthesizing solutions.

This paper analyses the most relevant publications found related to wind farm maintenance management. Research has been done by employing Scopus scientific database, and then evaluating how useful is each publication in terms of relationship to the topic, algorithms applied and novelty of research. Each Section presents the main applications of each AI technique and analyses qualitatively the publications found, with a table summarizing the information for each of them. Data found should only be considered as an approximation of the real values, providing statistical information of the current state of the art. Figure 7 left presents the publications until 2020 in the bars and the cumulative evolution in the line, whilst Fig. 7 right presents the proportion of publications until 2020.

There is a clear positive trend in general, showing a growing interest in the topic, despite the events from 2020 that caused a halt in the number of conferences. As presented in Fig. 7 right, most publications are either conference papers or articles, with few reviews and book chapters, showing the necessity to study current literature to deduce current topics of interest and knowledge gaps. To supply this need, the subsections presented below show the most common applications of AI techniques for wind turbine (WT) monitoring systems.

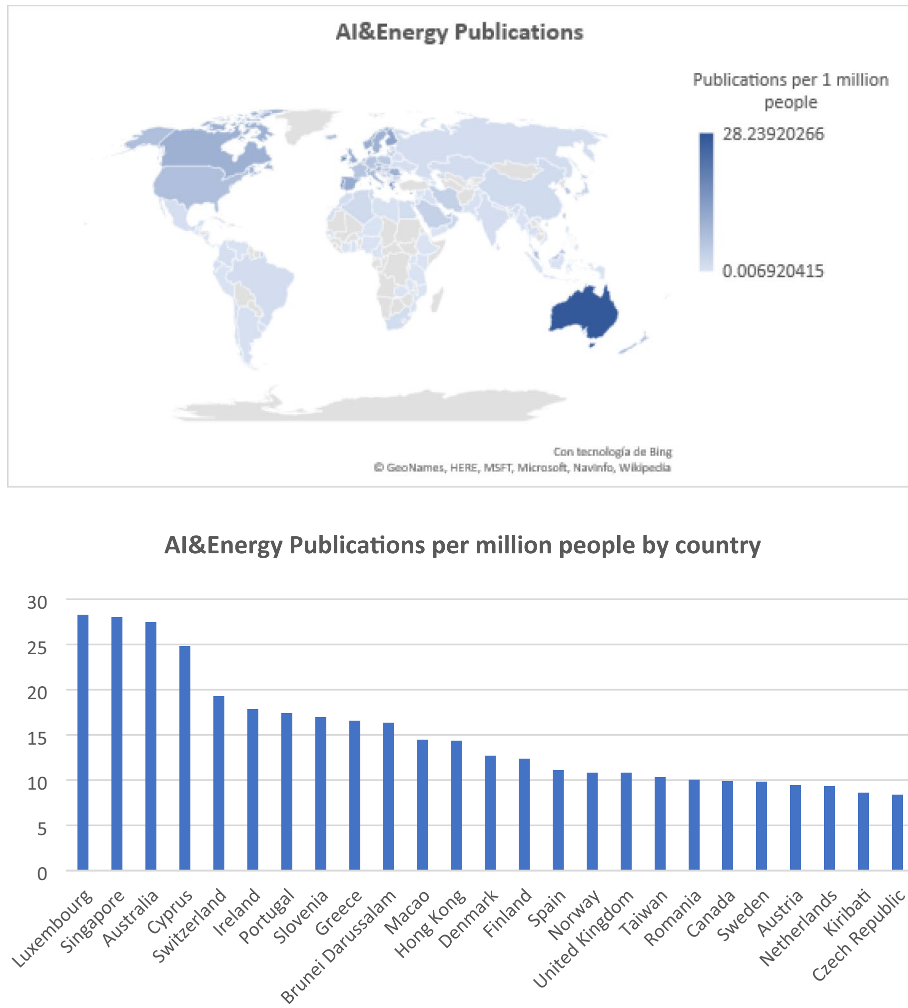



**Fig. 3** Publications on AI and Energy per 1 million of people by country ( *Source*: Scopus, 1970–2019)

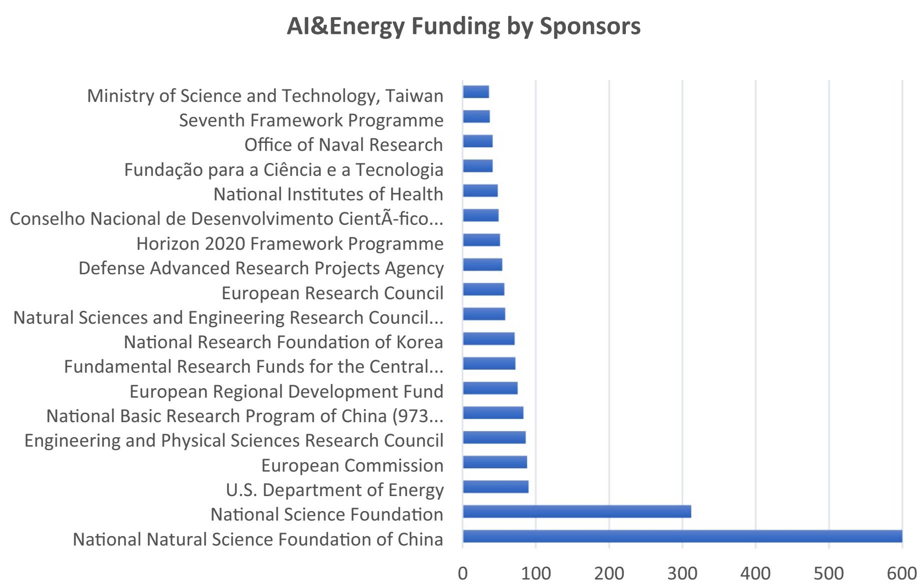



**Fig. 4** Publications on AI and Energy funded by sponsors ( *Source*: Scopus, 1970–2019)

The main novelties of this paper are summarized as:

- The paper presents a complete and update compilation of the main research studies in the AI and WT maintenance.

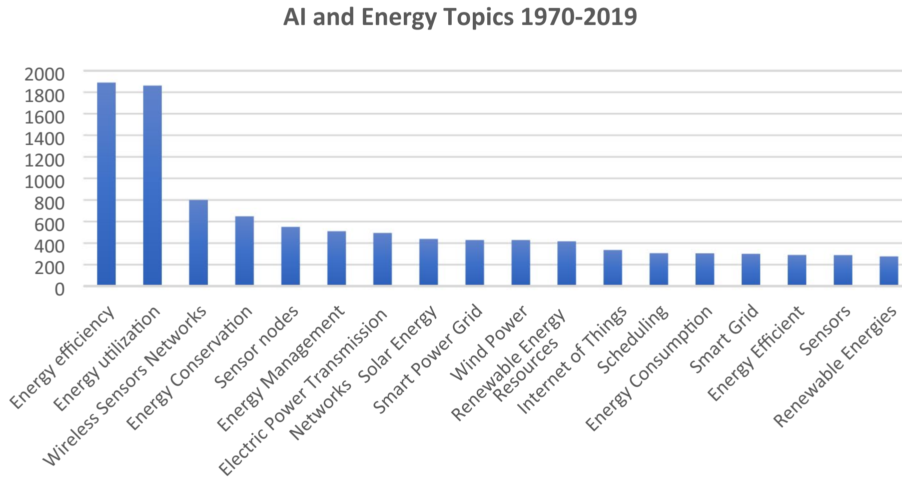



**Fig. 5** Main topics in Energy covered by AI ( *Source*: Scopus, 1970–2019)

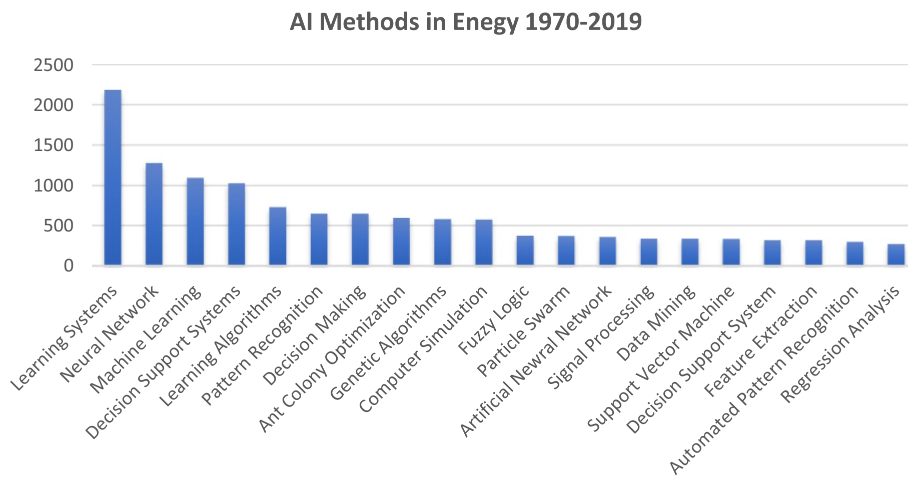



**Fig. 6** Main AI algorithms applied to Energy ( *Source*: Scopus, 1970–2019)

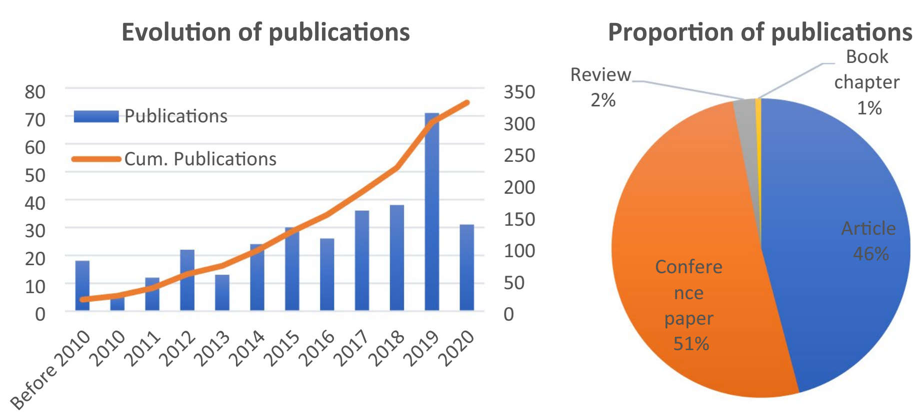



**Fig. 7** Evolution of publications until 2020 (left) and proportion of publications (right)

- The paper analyses individually and together the most important AI techniques, including approaches, methods, algorithms and models.
- The main applications for WT maintenance management are studied.

This paper is structured into the following sections: Sect. 2 shows the main research studies in Artificial Neural Network; Genetic Algorithms and Particle Swarm Optimization are analysed in Sects. 3, 4 discuses Fuzzy Logic; the statistical methods are considered in Sects. 5, 6 analysed the

Decision Making Techniques; and finally, Sect. 7 provides the main conclusions.

## 2 Artificial Neural Networks

Artificial Neural Networks (ANN) consist of a set of nodes (neurons) organized and connected in layers, in which each connection is a signal processed and transmitted to the following layer until an output response is provided [8, 9]. They are classified depending on the number of layers, the neurons per layer, and the connections between them, being common types the feedforward neural networks (FNN), recurrent neural networks (RNN), and convolutional neural networks (CNN) [10, 11].

ANN are largely used for applications as false alarm detection [12–14], data analysis for fatigue estimation [8] and state classification [15], but their most common application is to detect faults in different components, being the most common the gearbox, the blades and the bearings [16–18]. Gearboxes are the most studied components due to their importance and likelihood to failure [9]; therefore, the use Artificial Neural Network (ANN) to detect and diagnose faults in this component is rising [9]. The most common source of information is supervisory control and data acquisition (SCADA) data [19–21] or vibration signals [22–24]. Combinations with other techniques are common to improve performance, such as with Decision Trees [25, 26], Particle Swarm Optimization [27, 28], Genetic Algorithms [29, 30], Mahalanobis distance [31, 32], Bayesian filters [33]; and variations of Machine Learning [34–36] and Big Data techniques [37, 38]. Faults in blades are commonly detected or predicted analysing signal from ultrasonic [39–41] and visual sensors [42], the latter mostly analysed by Convolutional Neural Networks (CNN) [10, 11]. Most common faults are structural damage [43, 44] and icing [45, 46]. Most used signals to monitor bearings are vibration [47, 48], temperature [49, 50] or other SCADA data [51–53]. Less frequently studied, but also mentioned, are the drive train using ANN alone [54, 55] or with other AI techniques [56, 57], the generator [58, 59] or the infrastructure [60, 61]. In general, SCADA data is applied to predict [62, 63] and detect faults [64–66] in wind farms. In summary, ANN are largely used for fault detection and prediction for all of the WT components, either by themselves or combined with other AI techniques.

Maintenance management using ANN commonly uses SCADA data to assess decision making [67, 68], maintenance optimization [69, 70] or cost optimization [71]; and models that integrate technical [72], economic [73, 74] and environmental data [75]. It is frequent to use ANN to minimize the number of useful variables [76, 77] and sensors to monitor WTs and farms [78]. Most useful variables are temperature [79, 80], power generation [81] and vibrations. Maintenance cost optimization and decision making often consider aspects such as remaining life time [82, 83], inspection time window [84] and costs [85, 86]. A less studied application of ANN is power forecasting [87]. Variables used for power prediction using ANN are generally wind speed [88, 89], power output [90, 91], temperature [92] and other weather data [93], and previous data stored in the system [94] for short-term predictions [95]. Regression and data reconstruction is also useful to forecast data [96, 97]. ANN are thus widely applied for maintenance management and optimization, either to optimize maintenance costs or to predict WT state.

It is frequent to combine ANNs with other techniques to improve their accuracy and performance. Common combinations with AI techniques are with big data techniques for fault detection [98–100] and monitoring [101], fuzzy logic for fault diagnosis [102], prediction [103] and monitoring [104], Principal Component Analysis (PCA) for fault detection [105] and monitoring [106, 107], Genetic Algorithms (GA) for fault prediction [108, 109], Particle Swarm Optimization (PSO) for power management [110], Markov chains [111], and K-means clustering [112]. Statistical methods such as Bayesian networks [113, 114] and $R^2$ adjustment [115, 116] are also applied, together with simulations [117–119], prototypes [120, 121] and online classification systems [122, 123]. It is not uncommon to compare different techniques to decide the best choice [124, 125]. Comparisons found on the literature are respect to data mining [126] Bayesian classification [127] and other mathematical models [128]. As expected, ANN efficiency increases when merging this AI technique with many others for any application.

To summarize, the most common application of ANN is fault detection and prediction on components as the gearbox or the blades. SCADA data is fundamental to do so, especially vibration, temperature and visual data. ANN are also applied to assess maintenance, optimize Operations and Maintenance (O&M) costs and power forecasting, mostly using economic and environmental variables. ANN are some of the most mature AI techniques, therefore, it is frequent to compare them to others to evaluate their performance, mostly big data, fuzzy logic and PCA. Table 1 summarizes the cited references in this section, classifying them by algorithms used, their applications and data considered.

## 3 Genetic Algorithms and Particle Swarm Optimization

Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) behave similarly, in the manner that both algorithms consider variables as groups of individuals interacting among themselves with a common objective. GA are

**Table 1** ANN applications, data considered and references

| Application | Algorithm | Data/variables | Refs. |
|---|---|---|---|
| Literature review | ANN | NA | [87] |
| Fault prediction | ANN | SCADA data | [22] |
| | | Noise to signal ratio, gearbox data | [23] |
| | | Data from manufacturer | [116] |
| | ANN, fuzzy logic | Time based data, temperature | [103] |
| | ANN, data mining | SCADA data, gearbox temperature | [19] |
| | | Vibration | [34] |
| | ANN, clustering algorithms | Icing, delay window in PCA algorithm, data fusion | [45] |
| | | SCADA data, condition data | [112] |
| | ANN, SVM | Vibration | [47, 48] |
| | ANN, GA | Vibration | [108] |
| Fault detection | ANN | SCADA data | [10, 20, 21, 40, 62, 66, 67, 98–100] |
| | | Fault data | [15, 58, 121, 122] |
| | | Power output | [8] |
| | | Visual data | [11] |
| | | Simulation, power output | [117] |
| | | NA | [115] |
| | ANN, fuzzy logic | Vibration, correlation components | [43] |
| | | Signal frequency analysis | [54] |
| | | System dynamics, noise | [102] |
| | ANN, data mining | Fault data | [13] |
| | | Bearing data | [52] |
| | | Structure state | [60] |
| | | SCADA data | [59] |
| | | Blade vibrations | [77] |
| | ANN, decision trees | Vibrations | [25, 26] |
| | | SCADA data | [69] |
| | | Fault data | [127] |
| | ANN, clustering algorithms | Fault data | [61] |
| | ANN, statistical methods | SCADA data, external condition, turbine loading, previous state | [32] |
| | ANN, PCA | Vibration | [105] |
| | ANN, AI model | Failure data | [120] |
| Fault diagnosis | ANN, data mining | Wind speed, pitch angle | [42] |
| | | Fault and alarms | [101] |
| | ANN, PSO | Wavelet analysis, time domain analysis | [27] |
| | ANN, Bayesian networks | Fault data | [33] |
| | ANN, clustering algorithms | Fault data, fault types | [57] |
| False alarm detection | ANN, fuzzy logic | Vibration monitoring | [12] |
| Condition monitoring | ANN | Vibration | [24] |
| | | SCADA data | [31, 49, 64, 65, 107] |
| | | Gearbox data | [68] |
| | | Simulation | [73] |
| | | Signal filtering | [76] |
| | | Rotor speed, temperature | [80] |
| | | Statistical data | [85] |
| | | Simulator, power | [118] |
| | | SCADA data, wind speed, power output | [119] |
| | ANN, fuzzy logic | SCADA data | [70, 104] |
| | ANN, GA | SCADA data | [29] |

**Table 1** (continued)

| Application | Algorithm | Data/variables | Refs. |
|---|---|---|---|
| | ANN, Bayesian networks | Fault data | [75] |
| | | Material, geometric features, FEM analysis, NDT data | [113] |
| | ANN, statistical methods | Temperature, operating parameters | [50] |
| | ANN, PCA | Equipment data | [106] |
| Maintenance | ANN, data mining | SCADA | [35] |
| | | Vibration | [37] |
| | | Power generation | [81] |
| | | Window length for patterns in big data series | [84] |
| | | Data from WTs | [125] |
| | ANN, GA | Damage degree | [41] |
| | | Wind speed | [97] |
| | ANN, PSO | Gearbox temperature, gearbox data | [28] |
| | ANN, clustering algorithms | NA | [124] |
| Maintenance planning | ANN, Bayesian networks | Fault data, statistical methods | [114] |
| | ANN, AI model | Bearing fault progression | [53] |
| Cost optimization, decision making | ANN | SCADA data | [51, 83] |
| | | Weather, costs | [72] |
| | | Costs | [74] |
| | | Concrete modelling, concrete strength | [79] |
| | | Reliability of components, operation conditions | [82] |
| | | Size and shape of deflectors | [86] |
| | | Vibration signals | [123] |
| | ANN, fuzzy logic | Economic, vibration signals | [55] |
| | | Temperature | [56] |
| Cost optimization | ANN, PSO | SCADA data | [71] |
| | | Costs | [110] |
| | ANN, AI model | SCADA data | [111] |
| Decision making | ANN, Kalman filter | Wind speed | [78] |
| | ANN, AI model | SCADA data | [128] |
| Weather forecasting | ANN | Power output, wind speed | [89] |
| | | Weather data, power output | [90] |
| | | Gust speed, average wind speed, failure modes | [92] |
| | | Wind speed states | [94] |
| | ANN, PSO | Wind speed data | [96] |
| Power forecasting | ANN | SCADA data | [91] |
| | | SCADA data, wind data | [93] |
| | ANN, AI model | Power output, Wind speed | [88] |
| Data forecasting | ANN, fuzzy logic | Wind speed and direction | [95] |
| | ANN, data mining | Sensor data, maintenance time data, data aggregation | [126] |
| Material testing | ANN | Ultrasonic tests, damage level | [39] |
| Power restoration | ANN, GA | Fault data, power output | [109] |

algorithms that are inspired by evolutionary features such as selection, mutation and hybridization, adapting to the environment imitating a model of the collective evolution process of the individuals [129, 130]. PSO considers the variables as a group of animals searching for food, either cooperating or competing, in which each member of the group changes its search pattern and position considering the position of itself and other members [131–133].

GA and PSO are mostly applied as optimization tools. In this regard, most research focuses on optimization of microgrid size and configuration; scheduling to assess decision making; and assessing with the design of different components or aspects of WTs and farms [129].

Design optimization prior to wind farm construction is commonly done using GA combined with other AI techniques [130]. Most studied components are the foundations [134], generators [135, 136] and blades [86, 137]; whilst the aspects to be optimized are wind farm size [108, 138], layout [109, 139], power dispatch [140–142] and location [143–145]. One of the most common tasks assigned is microgrid size and configuration optimization, generally combining or comparing GA with PSO or other AI techniques to improve and evaluate their performance. Regarding microgrid size optimization, most common configurations combine WTs with photovoltaic panels [146, 147] and fuel cells [148] or diesel generators [146, 149]. Variables considered are mostly economic [147, 150, 151], operational [152] and environmental [146, 153, 154]. GA are frequently combined with other algorithms to reduce computational burden and improve the overall system optimization. Most authors agree that the combination of GA and PSO is currently one of the most powerful algorithms [131–133]. Other combinations are with fuzzy logic [155] and Monte Carlo methods [156]. In summary, GA are often used for optimizing wind farm and microgrid configurations, often combining them with other AI techniques such as PSO.

Maintenance scheduling and optimization is largely done using GA, mostly considering optimization problems as cost-based functions [157, 158]. Other variables considered are system reliability and faults [159, 160], power production [161–163], or environmental conditions [164]. Concrete applications of GA in programming and maintenance may be divided into large-scale maintenance planning [165–167], daily O&M scheduling [168–170], team allocation [171] and feasibility analysis [172]. Combinations with other AI techniques are made to improve the general performance of the system. Common combinations are with ANN [173, 174], Fuzzy Logic [175], Monte Carlo simulations [176], Bayesian analysis [177] and nonlinear optimization related to maintenance scheduling is fault detection [178], mostly on the gearbox [30, 179, 180] using vibration signal [29]; or on the blades [41, 181], combining ANN and machine learning [97, 182]. In conclusion, GA applied for maintenance planning are often combined with other AI techniques to improve their capabilities.

PSO is frequently merged with other AI techniques, and aimed at optimizing different aspects of WT design and maintenance management, such as power dispatch [110, 132], maintenance planning [141, 183] and gearbox condition monitoring using temperature [28] or vibration signals [27]. Microgrid size optimization is another recurrent application of PSO, considering both economic [184, 185] and environmental aspects [131, 186]. Most authors agree that the combination of GA and PSO is currently one of the most powerful AI techniques [131–133]. Other combinations are with fuzzy logic [155] and Monte Carlo methods [156]. PSO is thus considered for the same range of applications as GA, and often combined with this technique to improve their results.

In summary, most common applications of GA and PSO are related to optimization, both design and maintenance. To do so, the system is converted to an optimization problem with an objective function to be maximized, in the case of availability and power dispatch, or minimized in the case of costs and losses. It is common to combine GA and PSO as they provide remarkably good results in relatively low time, though combinations with other AI techniques such as ANN are also common. Variables used for optimization are generally related to economic and environmental aspects. Table 2 summarizes the cited references in this section, separating them by algorithms used, their applications and data considered.

## 4 Fuzzy Logic

Fuzzy logic is a form of continuous-valued logic in which the output value of variables continuously ranges from 0 to 1, opposed to Boolean logic, in which the values are only 0 or 1 [155]. Fuzzy logic allows decision making based on the degree of agreement of a system with a given premise, compared to contextualized values related to said system.

Fuzzy logic is commonly combined with other techniques to improve their performance on different applications, being the most common cost and reliability optimization [155], decision making, risk mitigation and preventive maintenance. Regarding optimization and decision making, variables most frequently considered are costs, [176, 187] and failure modes [188, 189]. Risk mitigation aims to predict WT conditions [95] to minimize risks and power losses [175, 190]. Preventive maintenance using fuzzy logic focuses on early fault detection [43, 70] fault prediction [56] and false alarm detection [12, 14]. Fuzzy logic is frequently combined with ANN for fault detection and prediction [102, 103]; creating the so-called Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to improve detection accuracy [104, 191, 192], generally using SCADA data. In summary, Fuzzy logic is frequently combined with ANN to optimize costs and assess decision making. Table 3 shows the main research studies done in Fuzzy Logic applied to WT maintenance.

## 5 Statistical Methods

This section discusses the statistical methods applied for WT maintenance found in the literature. These methods are based on the use of considerable amounts of data to evaluate

**Table 2** GA and PSO applications, data considered and references

| Applications | Algorithms | Data/variables | Refs. |
|---|---|---|---|
| Fault prevention | GA | Voltage and electronic parameters of capacitor | [136] |
| Fault prediction | GA, ANN | Vibration | [30, 108] |
| Fault detection | GA | Fault data, environmental data | [153] |
| | | NA | [180] |
| | GA, PSO | Power output, wind farm data, simulation data | [138] |
| Fault diagnosis | PSO, ANN | Vibration | [27] |
| Maintenance | GA | Fatigue aspects, mechanical loads | [134] |
| | | Different scenarios | [135] |
| | | Costs | [181] |
| | GA, ANN | SCADA data | [29] |
| | | Wind speed | [97] |
| | GA, PSO | Energy demand | [133] |
| | PSO, ANN | Gearbox temperature, gearbox data | [28] |
| Decision making | GA | Terrain topology, Costs | [145] |
| | | Costs | [166] |
| | | Costs, technical aspects | [167] |
| | | Costs, scheduling | [169] |
| Reliability analysis | GA | Wind speed, light intensity, costs | [149] |
| Feasibility analysis | GA | Solar radiation, wind speed, Costs | [172] |
| Maintenance optimization | GA | WT data | [152] |
| | | Economic data | [157] |
| | | Reliability | [159] |
| | | Fatigue coefficient, wind characteristics | [160] |
| | | Power generation, costs | [161, 163] |
| | | NA | [165, 168] |
| | | Costs | [162] |
| | | Weather conditions | [164] |
| | | Component condition | [179] |
| | GA, Bayesian analysis | Probabilities of damage, deterioration models | [177] |
| Design optimization | GA | Design process, Finite Element Modelling | [137] |
| | | Economic and ecologic | [139, 154, 178] |
| | | Power production, power fluctuation | [140] |
| | | Costs | [147, 151] |
| | | Environmental aspects | [146] |
| | | Reliability, costs, reliability benefits | [170] |
| | GA, ANN | Fault data, power output | [109] |
| | | Costs | [173] |
| Cost optimization | GA | Costs | [158] |
| | PSO, ANN | Costs | [110] |
| | GA, fuzzy logic | Maintenance costs, energy interaction costs, cost of pollutant treatment | [155] |
| | | Costs, reliability | [175] |
| | GA, fuzzy logic, Monte Carlo methods | Costs | [176] |
| | GA, ANN | Size and shape of deflectors | [86] |
| | | Damage degree | [41] |
| | GA, Monte Carlo methods | Costs | [156] |
| Layout planning | GA | 1 year of wind measurement data | [143] |
| | | Solar radiation, wind speed, costs | [144] |
| | | Loss of Power Supply Probability, annual cost sensitivity | [148] |

**Table 2** (continued)

| Applications | Algorithms | Data/variables | Refs. |
|---|---|---|---|
| | | Location, topography, economic | [171] |
| | GA, ANN | Location, economic | [174] |
| Optimization | GA, PSO | Economic | [131, 150] |
| Maintenance, cost optimization | GA, PSO | Algorithms compared | [141] |
| | | NA | [132] |
| Microgrid design optimization | PSO | Costs | [184, 185] |
| | PSO | Costs, environmental data | [186] |
| Power tracking | PSO | Simulation, power output | [183] |

**Table 3** Fuzzy logic applications, data considered and references

| Applications | Algorithms | Data/Variables | Refs. |
|---|---|---|---|
| Fault prediction | Fuzzy logic, ANN | Temperature | [103] |
| Fault detection | Fuzzy logic, ANN | Vibration, correlation components | [43] |
| Fault diagnosis | Fuzzy logic, ANN | System dynamics, noise | [102] |
| False alarm detection | Fuzzy logic, ANN | Vibration data | [12] |
| Condition monitoring | Fuzzy logic, ANN | SCADA data | [70] |
| | ANFIS | SCADA data | [104, 191, 192] |
| Risk mitigation | Fuzzy Logic, Fuzzy analytic network process | Qualitative variables | [190] |
| Decision making, cost optimization | Fuzzy logic, ANN | Temperature | [56] |
| | Fuzzy logic, GA | Costs | [155] |
| | | Costs, reliability | [175] |
| Decision making, optimization | Fuzzy Logic, sorting algorithms | Statistical data | [187] |
| | | Fatigue data | [188] |
| | | Pollutant emissions, economic | [189] |
| Modelling, cost optimization | Fuzzy Logic, Monte Carlo methods | Economic | [176] |
| Data forecasting | Fuzzy logic, ANN | Wind speed and direction | [95] |

their statistical characteristics and application to the problem studied. Most common methods are based on three techniques: Bayesian analysis, where probability represents knowledge of the system instead of possibility of an event occurring [114, 193, 194]; Markov processes, in which the probability of an event happening depends on the previous state of the system [195, 196]; and Monte Carlo simulations, based on random sampling to obtain results and solve problems [197–199]. The latter two are also found, but less used.

Bayesian analysis is most applied for decision making and WT condition monitoring. Condition monitoring focuses on applying Bayesian analysis to predict or detect faults using monitoring data [114, 193, 194]. Bayesian networks are frequently combined to improve their performance with ANN [114] or Machine Learning [33, 113] on components such as the gearbox or the blades [200, 201]; or to detect faults on WT state transitions [75, 202, 203]. Decision making using Bayesian analysis focuses on applying maintenance strategies that minimize O&M [204] and life-cycle costs [177, 205]; assessing risk analysis considering failure modes [206], environmental variables [207] and inspection and repair costs [208]; and estimating information validity [209, 210].

Markov processes are mostly focused on cost optimization and maintenance assessment. Variables considered to do so are uncertainty and costs [195, 196], weather conditions [211], and failure modes [212]. Combinations with other AI techniques found in the literature are also focused on maintenance evaluation, using clustering algorithms [213] and ANN [111]. Monte Carlo simulations are generally aimed at optimizing costs and assess decision making considering economic aspects [197–199], weather uncertainties [214] and failure modes [156]. PCA is also found in the literature [215], but focused on blade fault detection [216].

In conclusion, most common applications of statistical methods are decision making considering both economic and environmental aspects; and risk analysis considering economic aspects and failure modes. There are comparatively less publications than for other AI techniques; this may occur because statistical methods cannot be considered

**Table 4** Statistical methods applications, data considered and references

| Applications | Algorithms | Data/variables | Refs. |
|---|---|---|---|
| Fault prediction | Bayesian analysis | Study on model residuals | [202] |
| Fault detection | Bayesian analysis | Fault data | [205] |
| | | NA | [206] |
| | PCA | SCADA data | [216] |
| Fault diagnosis | Bayesian analysis, ANN | Fault features | [33] |
| Maintenance assessment | Markov processes, clustering algorithm | SCADA data, anomaly indexes | [213] |
| Maintenance optimization | Bayesian analysis, ANN | Fault data | [114] |
| Maintenance planning | Monte Carlo simulation | Economic, weather | [214] |
| Scheduling optimization | Bayesian analysis, ANN | Probabilities of damage, deterioration models | [177] |
| Risk assessment | Bayesian analysis | Weather, heating capacity, probability of being killed | [207] |
| | | Costs | [208] |
| | Monte Carlo simulation | Economic, WT components | [197] |
| Decision making | Bayesian analysis | Costs | [204] |
| | | Activity data, project data | [209] |
| | | Information provided by the SHM system | [210] |
| | Markov processes | Fault data | [212] |
| | Monte Carlo simulation | Economic, NPV curve | [198] |
| Condition monitoring | Bayesian analysis, ANN | Material, geometric features, FEM analysis, NDT data | [113] |
| | | Fault data | [75] |
| Cost analysis | Markov processes | Economic, simulated data | [195] |
| Cost optimization | Markov processes | Mechanical loads | [196] |
| | | Economic, weather | [211] |
| | Markov processes, ANN | SCADA data | [111] |
| | Monte Carlo methods, GA | Economic | [156] |

fully AI techniques, therefore, the filtering applied is likely to eliminate publications that apply these methods. Table 4 presents the main research studies based on statistical methods for AI maintenance.

## 6 Decision Making Techniques

Decision making is oriented in two directions: planning (both short and long term) and variable assessment. Among planning tasks are to decide the best suited components [217, 218], short or long term planning [159, 187], power prediction [219, 220], route optimization [221, 222], state definition [223, 224], WT manufacturing [225], and risk assessment [226–228] and mitigation [229, 230]. Variable assessment is aimed at defining the best suited variables to perform O&M tasks [231–233] and to reduce computational costs [211, 234], as well as to predict fault apparition considering signal uncertainties [235–237] or failure probability [238, 239]. Hur et al. [78] provided a feasibility study to estimate the useful variables for WTs and farms monitoring using ANNs and EKF, and proposed that only one WT of each cluster should be equipped with measurement data and the remaining ones with estimators. Multi-Criteria Decision Analysis was applied by Richmond et al. [240] to define the criteria to be applied for offshore wind energy, presenting an industry survey to analyse these criteria. Sobral et al. [241] analysed the influence of three factors (reliability, maintainability and logistics) on offshore wind farms availability and determined their relative importance using Analytical Hierarchy Process.

Maintenance optimization is essential to improve the behaviour of WT systems. In this regard, there are three main variables to optimize: power dispatch, time and O&M costs. Power optimization refers to maximizing usage without surpassing security limits [242] or decide the best-suited power supply considering economical and ecological aspects [243]. Time optimization generally refers to minimize inspections that may lead to downtimes. Inspection optimization is based on strategy decision [244] and team allocation [245, 246]; commonly environmental [212, 247, 248] and operational conditions [249–251]. Cost optimization not only refers to minimizing costs, but also to defining different variables in economic terms to operate in the same units [252, 253]. Variables commonly considered are maintenance costs [166, 210, 254], availability [255], power dispatch

[155] and environmental and geographical data [256, 257]. In conclusion, converting variables to economical units is common to assess maintenance and decision making. In summary, cost and time optimization are necessary to ensure functioning of WTs, considering variables as weather, WT availability and power output.

Scheduling refers to daily or weekly planning of inspections and weather forecasting for the near future. Wind farm planning generally considers economic and environmental aspects [258, 259], SCADA data [69], failure modes [260–262], availability [263] and WT information [264, 265], in aspects such as weather forecasting [266] and route optimization [267]. On the other hand, long term scheduling or planning refers to planning strategic decisions aimed at optimizing wind farm life-cycle maintenance [126, 205, 268]. Some of these strategic decisions are maintenance policy [269, 270], energy production policy [271], risk and investment assessment [272, 273], and WT end of life strategies [274]. Wind farm location is also included in long term planning, as it heavily influences power output and maintenance strategies to be carried out for each WT. Variables considered in this regard are geographic location [174, 275], environmental and social aspects [276, 277] and WT life cycle [278, 279]. Both short and long terms planning are essential for wind farm operation and maintenance, thus strategies as the presented above are extremely useful to improve it and save costs.

In summary, decision making aimed at wind farm maintenance is focused on optimization and assessment, where its most relevant applications are component selection based on determined aspects; and maintenance strategy selection, either for the short or long term. There is a wide variety of approaches to do so, hence the variety of algorithms considered for it. Problem statement and definition is essential to achieve an optimal response, so adequate variable definition is necessary. Both maintenance and scheduling optimization are needed, often converting variables to economic terms in order to have uniform units and thus facilitate problem solving. Table 5 summarises the main applications of decision making techniques.

## 7 Discussion of Findings

The previous sections discussed the most remarkable AI techniques applied for WT monitoring management. This section presents both a qualitative and quantitative analysis of the publications founds in the research. Figures 8 and 9 show, respectively, the distribution of AI techniques and applications for WT maintenance management.

The most common technique is ANN, being mentioned in 36% of the publications, followed by GA and fuzzy logic, that appear in 15% and 8% of publications, respectively. Remaining relevant AI techniques are data mining (5%) and PSO (4%), and all sorts of models applied for monitoring and maintenance (10%). The prevalence of ANN can be attributed to its maturity and variety of configurations. GA and PSO are also commonly applied and often combined for better efficiency of the algorithms. The rest of AI techniques provide worse results or are less developed, hence the lower proportion of research dedicated to them.

Regarding applications, not considering the AI technique applied, 25% of research focuses on optimization of any sort (costs, maintenance, routing, etc.); whilst fault detection and decision making are the main topics for 16% of research each. There are thus two main lines of thought followed: the first one is coordination and organization i.e., using AI to improve the maintenance and planning strategies for different components or for the whole farm; and the second one is signal analysis to prevent and detect component failures, mostly using ANN and big data.

The main findings of this review are summarized as follows:

- ANN is the most commonly applied AI technique, as it is already mature and showed a wide variety of applications. ANN are mostly applied for fault detection, optimization and general condition monitoring, showing their benefits as predictor and modeller. ANN are frequently combined with other AI techniques to enhance their capabilities. Most common combinations are with big data, PCA, and statistical methods.
- Half the research of GA focuses on optimization and, together with decision making and planning, it sums up to 74% of publications, highlighting its value for problem solving and decision assessment. Similar to this, PSO is shown to be used mostly for optimization, maintenance and forecasting. GA and PSO are frequently combined to improve problem solving and optimization.
- Fuzzy logic is mostly used for optimization and decision making, with 60% of research focusing on these two topics. It is mostly combined with ANN to assess decision making. There are also applications for fault detection, although they are not as common.
- Since big data and data mining methods extract information from large databases and datasets, it is expected that its two most common applications are fault detection and monitoring. Research on fault prediction and diagnosis is also considered applying these methods.
- Statistical methods (such as Monte Carlo simulations) are mostly used for optimization, condition monitoring, maintenance and forecasting, depending on the exact model considered. Similar to them, models are applied almost equally for planning, decision making and optimization, depending on the model considered.

**Table 5** Decision making techniques applications, data considered and references

| Applications | Algorithms | Data/ variables | Refs. |
|---|---|---|---|
| Scheduling | AHP methodology | NA | [217] |
| | Shannon entropy weight method | Energy generation | [218] |
| | Polynomial regression | WT operating status | [223] |
| | Multi criteria decision analysis | Behaviour data | [240] |
| | Modelling | Economic | [254] |
| | AI, decision support systems | Economic, geographical data | [256] |
| Long-term decision making | Bayesian decision theory | Fault data | [205] |
| | MILP planning model | Power generation, environmental aspects, costs | [268] |
| | Machine learning, data mining, neural networks | Sensor data, maintenance time data, data aggregation | [126] |
| | Analytic network process | Economic | [269] |
| | Deterministic and stochastic models | Economic | [270] |
| | Mathematical cost model | Economic, weather | [271] |
| | AI, geographic information system, | Location, type of turbine, maintenance costs | [272] |
| | NA | Economic | [273] |
| | Technological readiness level, commercial readiness index | Literature and reports | [274] |
| Decision making, cost optimization | Decision support model | Costs, reliability, energy production, availability | [255] |
| | GA, fuzzy logic | Maintenance costs, energy interaction costs, cost of pollutant treatment | [155] |
| Decision making, maintenance planning | Decision trees | NA | [238] |
| | | Failure probability | [239] |
| | Analytical hierarchy process | Location, water depth, accessibility, weather, spare parts | [241] |
| Maintenance planning | Grey fuzzy and internal value, ordered weighted averaging | Statistical data | [187] |
| | GA | Costs | [159] |
| | CAD, decision making tool | Damage, economic | [235–237] |
| | Web-GIS technique | NA | [258] |
| | Economic analysis | Power performance, economic parameters | [259] |
| | Trees, statistical techniques, Neural networks | SCADA | [69] |
| | Interface | Economic | [260] |
| | Binary decision diagrams, fault tree analyses | Literature data, weather | [261] |
| | AI | NA | [263] |
| | RCAM analysis | Statistical data | [264] |
| | Big data | SCADA | [265] |
| | Ensemble weather forecasts | Weather, economic | [266] |
| | Real options analysis | Power production, remaining useful life | [267] |
| Maintenance optimization | Stackelberg game | Operator decisions | [244] |
| | Decision support systems; agglomerative nesting analysis | Wind speed and wind gust data | [245] |
| | Artificial intelligence, heuristic approaches | Schedules, generator location | [246] |
| | Dynamic programming, | Failures detected | [247] |
| | Dynamic reliability thresholds | Maintenance and weather data | [248] |
| | Markov decision process | Fault data | [212] |
| | Data analysis methods | Environmental aspects | [249] |
| | Cloud based platforms, | Economic | [250] |

**Table 5** (continued)

| Applications | Algorithms | Data/ variables | Refs. |
|---|---|---|---|
| | Machine learning, decision trees | Ultrasounds | [251] |
| Layout planning | Genetic algorithm | Location, economic | [174] |
| | NA | Geographic aspects, economic | [275] |
| | Model | Economic, farm location | [276] |
| | NA | Economic and environmental aspects | [277] |
| | NA | Data from a wind farm | [278] |
| | Stochastic systems | Stochastic data | [279] |
| Cost optimization | Mixed integer optimization | Economic | [252] |
| | NA | Economic | [253] |
| | Bayesian decision analysis framework | Information provided by the SHM system | [210] |
| Cost optimization, decision making | Genetic algorithm | Economic | [166] |
| Power prediction | Non-parametric statistics | Power output, environmental data | [219] |
| | Big data | NA | [220] |
| Power optimization | Mixed integer, non linear and non convex optimization problem | Economic | [242] |
| | HOMER software | Economic | [243] |
| Route optimization | M-planning | Uncertainties, maintenance data | [221] |
| | AI, multi agent systems, data mining | Weather, economic | [222] |
| Risk assessment | NA | Weather, snow accumulation | [226] |
| | Risk based decision making methodology | Risks, costs | [227] |
| | Decision making models | Turbine failure information | [228] |
| Risk mitigation | Decision making tool | Costs, failures | [229] |
| | Analytic network process, | Qualitative variables | [230] |
| Optimization | Simulation | Weather conditions, dynamic behaviour | [231] |
| | k-nearest neighbour, support vector machine | O&M data, SCADA data | [232] |
| | NA | Economic, simulation | [233] |
| | Markov decision processes | Economic, weather | [211] |
| | Cyber physical systems, | Connection, Conversion, Cyber, Cognition and Configuration level | [234] |
| | Neural networks, Kalman filter | Wind speed | [78] |

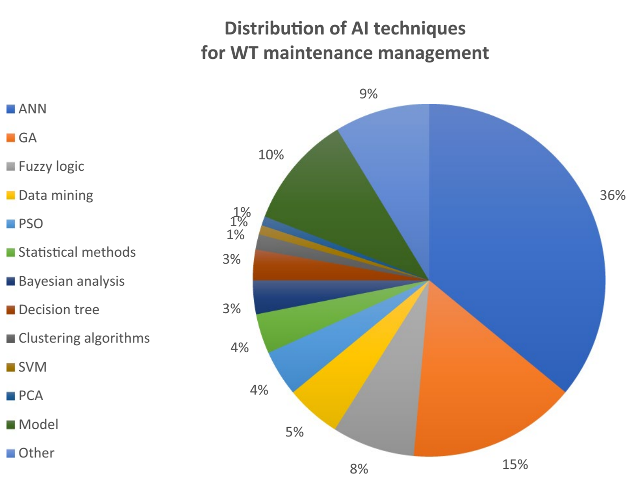



**Fig. 8** Distribution of AI techniques for WT maintenance management

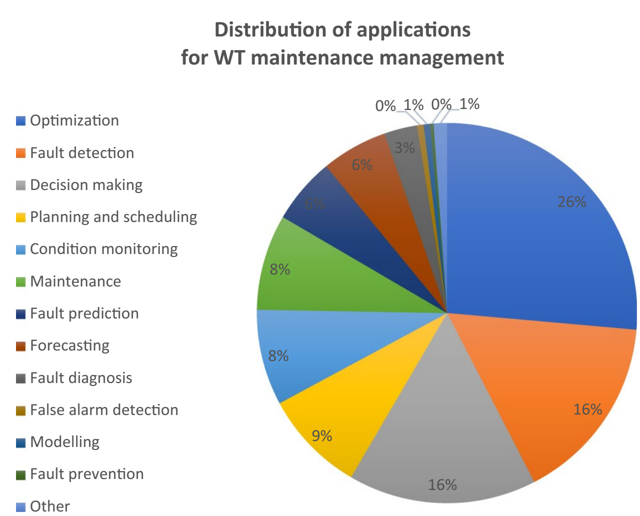



**Fig. 9** Distribution of applications for WT maintenance management

**Table 6** Summary of applications of AI techniques

| | ANN | GA | PSO | Fuzzy logic | Data mining | Statistical methods | Model | Bayesian analysis |
|---|---|---|---|---|---|---|---|---|
| Optimization | X | X | X | X | | X | X | |
| Fault detection | X | | | | X | | X | |
| Decision making | X | X | X | X | | | X | X |
| Planning and scheduling | X | X | X | X | | | X | |
| Condition monitoring | X | | | | X | X | X | X |
| Maintenance | X | | | X | | X | X | X |
| Fault prediction | X | | | | X | X | X | |
| Forecasting | X | | | | | X | X | |
| Fault diagnosis | X | | | | X | | X | |
| False alarm detection | X | | | | X | | X | |
| Modelling | | X | X | X | | | X | |
| Fault prevention | | | | | X | | X | |

- Optimization is the most common application for most AI techniques, often converting variables to economic terms to homogenise units and at the same point, inferring the costs derived from maintenance activities. Decision making and scheduling are generally derived from optimization, considering the problem solution as the best possible outcome.
- Fault detection is one of the main topics, usually related to signal analysis and pattern recognition. Opposed to this, fault prediction, and any kind of forecasting, is not a common research topic, hence the knowledge gap on it and the need to research more into this subject.

It is not surprising to observe that not all AI techniques serve for all applications, as most of them are designed with one purpose (e. g., GA and PSO are aimed at problem optimization). Thus, it is necessary to know the best suited algorithm for each application. Table 6 summarizes the most common applications of the most common AI techniques discussed in this piece of research.

## 8 Conclusions

This publication summarized and explained the current trends on AI applied for wind energy maintenance and monitoring, including the evolution of research and publications, and explaining the most relevant AI techniques. Generally, support for renewable energies is increasing, with governments aiming to obtain a sustainable energy production system. Wind energy is among the most relevant and mature, hence the amount of investment and research for both onshore and offshore types. Besides, the use of AI has been increasing thanks to the technological and computational advances, that allow complex calculations to be performed quickly and efficiently. Thus, the use of AI for wind turbine and farm maintenance is beneficial for all parts involved, as costs are reduced, and efficiency increased.

The most common AI techniques applied for WT maintenance are ANN, GA and PSO, fuzzy logic, statistical methods, and decision making techniques. ANN and its variations are the most versatile of them, as they can be used for monitoring, optimization, data forecasting and decision making, among others. GA and PSO are mostly applied for optimization and decision making, as these algorithms are designed for system optimization considering many different variables. Fuzzy logic is mostly applied for decision making and risk mitigation, mostly considering factors such as costs and component reliability. Statistical methods are mostly applied for maintenance and fault predictions, using considerable amounts of data for their estimations. Other AI techniques applied, though not as common are data mining, Bayesian analysis, decision trees or different models. Combinations of different AI techniques are common to improve their performance or neutralize weaknesses of single techniques.

Future results to be expected are an even larger increase of the amount of investment and thus publications, a rise on the variety and efficiency of AI techniques, and research on more combinations and comparisons between different AI techniques, in order to find the most optimal for each task.

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