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Review

New Tendencies in Wind Energy Operation and Maintenance

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Abstract: Both the reduction in operating and maintenance (O&M) costs and improved reliability have become top priorities in wind turbine maintenance strategies. O&M costs typically account for 20% to 25% of the total levelized cost of electricity (LCOE) of current wind power systems. This paper provides a general review of the state of the art of research conducted on wind farm maintenance in recent years. It shows the new methods and techniques, focusing on trends and future challenges. In addition to this, this work includes a review of the following items: (i) operation and maintenance, (ii) failure rate, (iii) reliability, (iv) condition monitoring, (v) maintenance strategies, (vi) maintenance and life cycle and (vii) maintenance optimization As for offshore wind turbines, it is crucial to limit the maximum faults, since the maintenance of these wind farms is more complex both technically and logistically. Research into wind farm maintenance increased by 87% between 2007 and 2019, with more than 38,000 papers (Scopus) including "wind energy" as the main topic and some keywords related to O&M costs. The LCOE in onshore wind projects has decreased by 45%, while in offshore projects it has decreased by 28%. The O&M costs of onshore wind projects fell 52%, while in the case of offshore projects, they have declined 45%. Thus, the results obtained in this paper suggest that there is a change in research on wind farm operation and maintenance, as in recent years, scientific interest in failure has been increasing, while interest in the various techniques of wind farm maintenance and operation has been decreasing.

Keywords: wind energy; new tendencies; review; maintenance; optimization

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1. Introduction

Renewable energies have become the greatest ally for the generation of electrical energy worldwide that is free of CO_2 emissions. In the first quarter (Q1) of 2020, renewable energies reached a worldwide share of electricity generation of nearly 28%, i.e., an increase of 2% compared to Q1 2019. Even with the outbreak of the COVID-19 pandemic, total global renewable electricity generation was estimated to increase by almost 5% in 2020 [1]. Taking into account that hydroelectric technology was developed throughout the 20th century, wind power is, among the current technologies for generating electrical energy from renewable sources, the most widely implemented renewable energy around the world. In 2018 (currently the last consolidated year, 31 December 2020), wind power had an installed capacity of more than 560 GW, assuming a worldwide production of more than 1.2 million GWh (Table 1).

On the other hand, a simple query in Scopus on the number of articles including "wind energy" in the title, abstract or keywords (Table 1) shows that there are more than 28,000 articles in the Scopus database going back to 2008 (data collected in November 2020). This result means an average annual scientific production related to wind energy of more than 2000 articles (Scopus).

The levelized cost of energy (LCOE) is the primary metric for describing and comparing the underlying economics of power projects (Figure 1). For wind power, the LCOE represents the sum of all costs of a fully operational wind power system over the lifetime of the project with financial flows discounted to a common year. The principal components of the LCOE of wind power systems include capital costs, operation and maintenance costs and the expected annual energy production [2]. Assessing the cost of a wind power system requires a careful evaluation of all of these components over the life of the project [3]. The capital costs, which account for 10–15% of the total project cost, include all expenses incurred in the purchase of land, buildings, construction and equipment. Equipment is worth between 70% and 80% of the total project cost, mainly due to the cost of the turbine. Construction is worth around 5% to 20% of the total project investment. The operation and maintenance (O&M) cost is the cost associated with the operation and maintenance of a wind farm.

Table 1. Wind energy data (data collected from [1] and Scopus database).

Measure	Year					
	2008	**2010**	**2012**	**2014**	**2016**	**2018**
Capacity (MW)	1.20×10^5	1.81×10^5	2.67×10^5	3.49×10^5	4.67×10^5	5.63×10^5
Production (GWh)	2.18×10^5	3.43×10^5	5.26×10^5	7.13×10^5	9.56×10^5	1.26×10^5
Number of Articles in Scopus	1014	1558	2255	2448	2597	3167

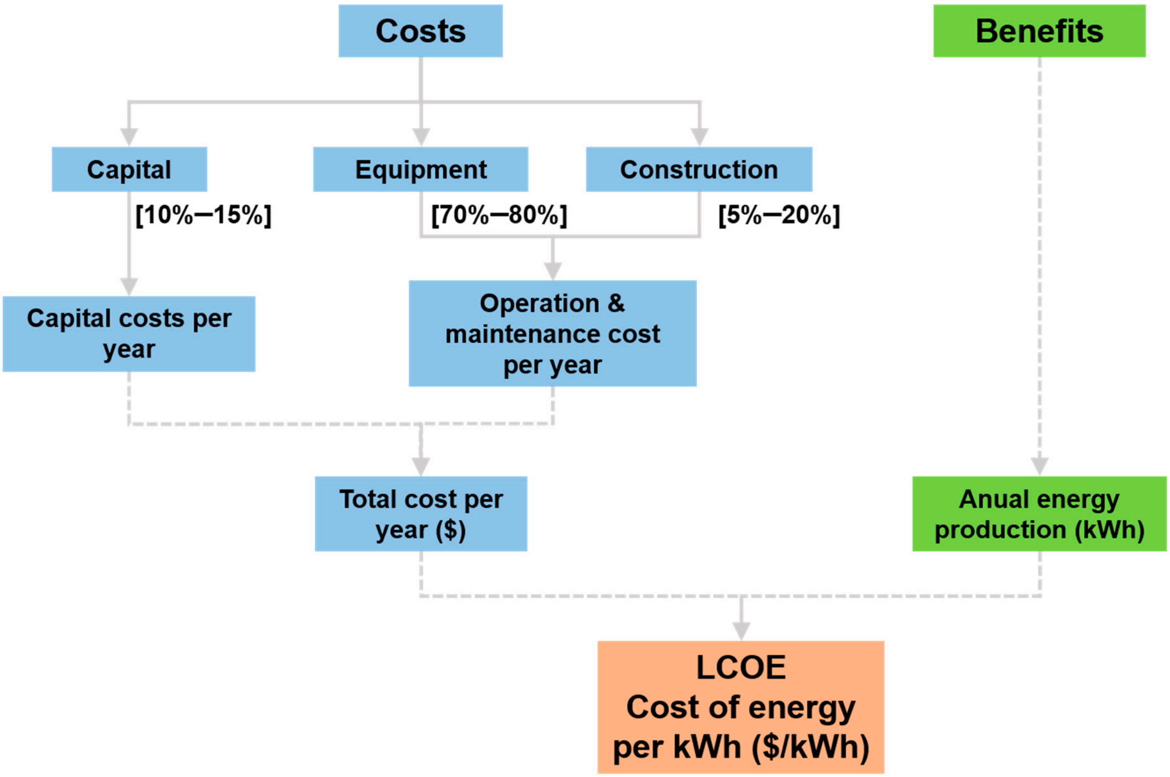

Figure 1. The economics of wind energy.

The fixed and variable O&M costs are a significant part of the overall LCOE of wind power. O&M costs can account for between 11% and 30% of onshore wind LCOE, and typically account for 20% to 25% of the total LCOE of current wind power systems [3–5]. When, years ago, wind farm promoters signed full O&M contracts with manufacturers of wind turbines, they trusted that technologists would provide the highest level of development in the maintenance of their installations. Time has shown that in most cases this has not happened and that gradually the owners of the installations have been losing responsiveness and knowledge of their own facilities, while perceiving that the interests of the technologist had more relevance than the park and its owners. For this reason, in recent times, the O&M of wind farms has resulted in different concepts, which sometimes were not the most appropriate depending on the casuistry and the owners of the installations [6]. Currently, there is no clear procedure showing researchers new research fields to which to devote their attention [7–10]. Accidents involving wind turbines increase year by year, which is why the cost of manufacturing, logistics, installation, grid control and maintenance of offshore wind turbines remains high [11]. For decades, much effort has been made in developing wind turbine condition-monitoring systems and inventing dedicated condition-monitoring technologies. However, the high cost and the various capability limitations of available achievements have delayed their extensive use [12]. A considerable percentage of the maintenance cost is caused by unexpected drive train failures [13]. Today, the availability of wind turbines usually approaches 98% [14].

Taking into account the relevance that wind energy has acquired throughout the 21st century in terms of scientific interest, as well as the influence that O&M costs have on the determination of the LCOE of the technology, the subject of this study is based on the maintenance of wind farms. The first objective of this paper is to offer an overview of the research from 2007 to 2020 on the maintenance of wind farms and equipment in wind farms, both onshore and offshore. Taking into account the scientific interest in this line of work, previous articles analyzed general wind energy research [15], as well as wind energy operation and maintenance [6], but only focused on the period until 2012. In addition, there are also articles that have analyzed the influence that new O&M techniques have on the reduction of LCOE in offshore wind farms [16]. The second objective is to analyze the influence of such research on the different costs of wind energy in recent years (2007–2020), as well as on the LCOE and O&M cost evolution.

2. Materials and Method

To achieve the review of the research carried out on the maintenance of wind farms from 2007 to 2020, it is necessary to identify the different fields of O&M cost that are going to be studied. The definition of each group of variables is included below.

1. Operation and maintenance of wind farms (O&M): The term "operation and maintenance" is studied as a variable in itself, since it appears as a generic keyword in the research conducted.
2. Failure rate and analysis (FAIL): Investigations involving issues related to equipment failures are included in this variable.
3. Reliability (RELI): Reliability, availability and maintainability are attributes of the design of systems that have a significant impact on the maintenance of a developed system.
4. Condition-monitoring system (C_M): This variable is the grouping of research that deals with condition monitoring. This tool searches the processes of monitoring a condition parameter in machinery, in order to identify a significant change that is indicative of a fault developing. It is an important component of predictive maintenance.
5. Maintenance strategies (M_STRA): A maintenance strategy defines the rules for the sequence of planned maintenance work; therefore, the different types of maintenance under investigation are grouped in this variable.
6. Maintenance and life cycle cost (M_COST): Research covering topics related to equipment costs are taken into account in this variable.
7. Maintenance optimization (M_OPT): A variable that meets the keywords "optimization and maintenance processes".

To facilitate the study of these fields of O&M cost (Figure 2), a group of keywords is defined for each field (Table 2). It should be noted that several experts, with more than 20 years of professional experience, helped the authors to identify the most important keywords and their grouping methodology. These experts are responsible for the maintenance of several wind farms in the region of Galicia (Spain), affiliated with private companies.

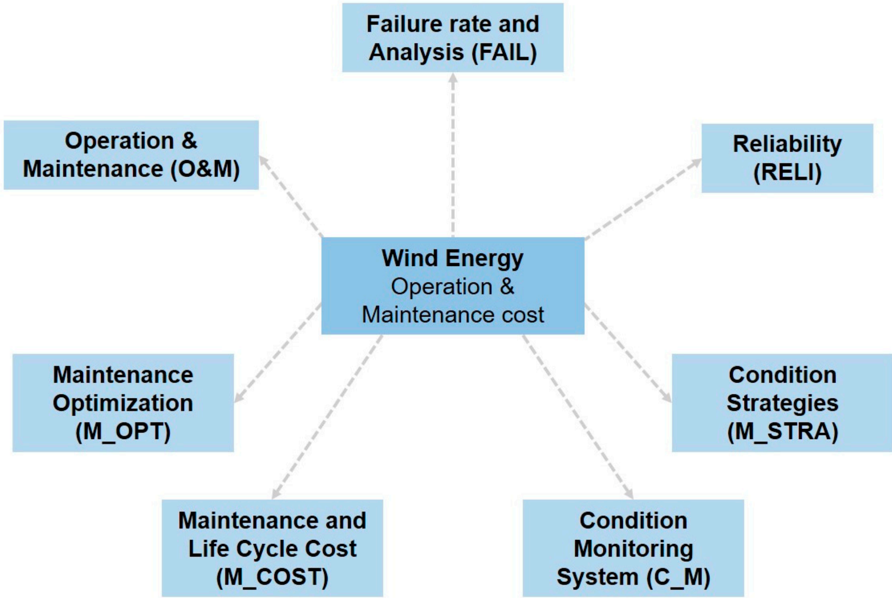

Figure 2. Outline of wind energy O&M cost fields.

Table 2. Keywords grouped in the grouping variables.

Group	Number of Keywords	Keywords
O&M	1	Operation and maintenance
FAIL	1	Failure rate
	2	Fault detection
	3	Failure of gearboxes
	4	Failure analysis
	5	Failure
	6	Failure (mechanical)
RELI	1	Reliability
	2	Availability
	3	Maintainability
	4	Profitability
	5	Reliability analysis
C_M	1	Condition monitoring
	2	Condition-monitoring systems
	3	Algorithms
	4	Condition-based maintenance
M_STRA	1	Maintenance strategies
	2	Low maintenance
	3	Turbine maintenance
	4	Maintenance planning
	5	Maintenance free
	6	Preventive maintenance
	7	Predictive maintenance
	8	Maintenance activity
	9	Maintenance action

Table 2. *Cont.*

Group	Number of Keywords	Keywords
M_COST	1	Maintenance cost
	2	Costs
	3	Investment
	4	Cost–benefit analysis
	5	Investment
	6	Life cycle costs
M_OPT	1	Optimization
	2	Maintenance optimization

Subsequently, a search is carried out for the different keywords in the Scopus database. The search in Scopus is done by searching for the topic "wind energy" and each keyword in the title, abstract or keywords. A statistical study of the grouped variables is then carried out. After this study, it will be possible to obtain conclusions on the most important keywords in this area.

3. Overview of Wind Farm O&M Research

3.1. Operation and Maintenance (O&M) of Wind Farms

The reliability of wind energy systems is a critical factor because decreased reliability directly affects the return string on account of increased costs of O&M, and it reduces the availability of energy due to disruption of the functioning due to the occurrence of faults.

Most approaches to reduce operating and maintenance costs for wind power projects are the same as those associated with any industrial plant, and any technique within the framework of maintenance can be applied to wind turbines.

The most important issues [6] in the operation and maintenance of wind energy concern the following aspects:

- site and seasonal asset disturbances
- stakeholder requirement trade-off
- reliability and asset deterioration challenges
- diagnostic, prognostic and information and communication technology applications
- maintenance optimization models

Wind farm maintenance directly determines its benefits, therefore, it is necessary to analyze the typical wind generator failures and build their health management files. Zhang et al. [7] investigated the location of the failure, development and trends, based on wavelet transform of fault diagnosis. When a wind turbine is shut down due to an error, profits are not obtained and, in addition, operational and maintenance costs are increased, with the objective to reduce these operation and maintenance costs. Solutions have been developed by condition monitoring [8] that detects and diagnoses anomalies of wind turbines. The development of advanced techniques to detect the occurrence of mechanical and electrical wind turbine failures at a sufficiently early stage [9] is very important for maintenance actions. The challenges being faced in wind farm operation and maintenance, with wind turbines dispersed and positioned in remote locations, have been very difficult in terms of quick access and they are expensive.

In wind farms, there is a large amount of information and, on these grounds, the methodology of decision making using failure prognosis developed in [10] can be used to identify the best strategies to increase the robustness of the wind farm operation and maintenance in order to maximize economic and environmental benefits simultaneously.

The number of offshore wind farms is increasing due to, among other reasons, their high capacity for power generation. However, the costs [11] of operation and maintenance are high. According to the Condition Monitoring of Offshore Wind Turbines report of the Energy Research Centre in the Netherlands, the operation and maintenance costs in future offshore wind farms that will be built from larger units are expected to be EUR 30 to 50/kW per year. The integration of the health monitoring information provides the initial steps for reducing operation and maintenance costs for an offshore wind farm while increasing turbine availability and overall profit. Detection strategies have been developed by Myrent et al. [17] for these fault mechanisms with the intent of integrating them into an operation and maintenance paradigm, and the integration of the health-monitoring information provides the initial steps for reducing operation and maintenance costs in an offshore wind farm while increasing turbine availability and overall profit.

The main studies are focused mainly on the operation and maintenance, but they also have to cover offshore logistics, energy production and the total project cost. A study [18] found 49 models that address parts of the life cycle or the entire life cycle of an offshore wind farm. Tracht et al. [13] described an approach to the planning of parts considering the constraints that exist in offshore maintenance, and this model proves to be the limiting factor influencing the costs of maintenance and operation using an analytical model scenario. The difficulties of access to offshore wind farms and a shortage of appropriate transport vessels and installations are challenging [12] the operation and maintenance of these farms in these remote places, and research is beginning to develop a methodology [19] for the reliability-centered maintenance of low-accessibility facilities.

3.2. Failure Rate and Analysis (FAIL)

The technological development of wind energy has favored more complex processes, so the failure rate of systems is increasing and a strategy to model reliability and optimize the maintenance of wind power generation systems is needed. It is essential to determine and record the main underlying cause of failure events; data logging and statistical processing of information failures [20] could improve the reliability of the system components. For instance, the results of the failure statistics and evaluation of expert opinion [21] were focused on the most critical subsystems with respect to the failure frequency and its consequences: the gearbox, generator, electrical system and the hydraulic system.

Krishna [20] proposed a remote instrument monitoring system, which constitutes of a wireless sensor network-based supervisory control and data acquisition (SCADA) system, with multiple sets of sensors distributed widely across each turbine in the wind farm. This not only helps to monitor the health of the turbines but also helps to take preventive action before critical and catastrophic failures take place.

Kusiak and Li [8] explored the data failure provided by supervisory control and data acquisition and provided failure prediction at three levels: failure and no failure prediction, severity and prediction of a specific failure. For each level, emerging failures were expected between 5 and 60 min before they occurred and several data mining algorithms were applied to develop predictive models of failures.

Modern onshore wind turbines achieve a high availability of 95–99%. However, these values only give information from the time that wind turbines are in operation and the energy produced was not considered when compared to its theoretical production and the availability based on energy availability differs when it is based on time. To investigate this difference, Faulstich et al. [21] examined the effect of speed failure rates depending on wind energy production by the analysis of turbines subjected to different wind speeds to determine the the energy loss due to the downtime of the turbine. Furthermore, another study [22] determined that failures are classified into three classes according to downtime; the gearbox and the generator have the same amount of downtime, while the highest numbers of failures are in the pitch and the electrical system. In this paper, a discrete event model was developed to simulate the operation, the occurrence of failures and the maintenance of onshore wind farms. To reduce these downtimes of the gearbox, some works [23] performed a prognostic of its failures by utilizing robust multivariate statistical techniques with existing SCADA data on wind farms.

Li et al. [24] took a doubly fed generator and, based on the mathematical model of the Markov process and the theory of reliability, built a model of reliability for wind power generation. Haddad et al. [25] developed model maintenance options, developing a hybrid methodology based on Monte Carlo simulations and decision trees for a cost–benefit–

risk analysis of prognostics and health management. The methodologies in this paper address the fundamental objective of system maintenance with prognostics: to maximize the use of the remaining useful life while concurrently minimizing the risk of failure, showing the value of having a prognostics system for gearboxes and determining the value of waiting to perform maintenance.

Mechanical failures of wind turbines represent a significant cost in terms of both repairs and downtime. In this sense, Lu et al. [26] proposed a Hilbert–Huang transform (HHT)-based algorithm to effectively extract fault signatures from generator current signals for wind turbine fault diagnosis.

Hameed et al. [27] sought to open a new panorama of knowledge in understanding the actual behavior of offshore wind turbines in the marine environment and proposed the creation of a database to help with design to operation.

Finally, Amirat et al. [28] provided an assessment of the failure detection techniques based on the homopolar current component of the generator stator.

On the other hand, electrical systems are responsible for more failures [29] than mechanical or structural systems in offshore wind turbines, but they are comparatively easy to repair. However, it is important to reduce the failure rate and improve the maintainability of the electric systems. The downtime of an offshore wind turbine is very important in the event of a failure, and this results in losses in electricity generation and revenue, so different topologies are evaluated, including a comparison between AC and DC star networks. In this sense, star topologies are suggested by Ho and Ran [30] for a secure connection and to centralize power electronics, which have high failure rates, making them more accessible for maintenance and repair.

Finally, it also follows from the analysis of operation and maintenance that weather conditions [31] may affect failure rates of offshore wind turbines. For the analysis of maintenance and failure detection, different types of strategies can be applied, such as neural network training [9,32], prognostics and health management systems [11] and nonlinear state estimation techniques [33].

3.3. Reliability (RELI)

The reliability based on the characteristics of wind energy is the basic signature quality of the wind turbine, so it is necessary to apply a proposal [27] to meet the same objectives; technical reliabilities include design [34], manufacturing and maintenance. The most reliable and sustainable [35] systems have a lower environmental impact and high energy and exergy efficiency.

The enormous proliferation of wind farms around the world has emerged as an alternative to traditional power generation and as a result of economic issues that require control systems to [27] optimize the availability and benefits. Pinar et al. [36] classified the main designs, focusing on reliability, to collect and compare data within a selection of the most important studies of the literature. The results obtained by the application of several studies indicate the importance of the technical availability factor [37] in annual energy production.

Modern onshore wind turbines reach values of 95–99% availability. However, these values only give information from the time that wind turbines are operational and they do not treat the energy produced compared to its theoretical production. This availability, based on energy, differs from the availability based on time due to the fact that forced inactivity times tend to occur during periods of high production potential. The objective of the optimization model [38] is the combination of system maintenance costs and revenue loss of wind energy, which is mainly limited by the reliability of power generation and maximum load regulation adequacy. The proposed model is important to extend classical scheduling maintenance [39] to include the expected market prices and weather conditions. Faulstich et al. [21] examined the effect of failure rates depending on the wind speed on energy production. Tavner et al. [31] focused on the influence of weather and wind turbines based on the failure rate and downtime, to try to understand the causes and consequences of failure.

To assess the ability for system maintenance, system reliability is one of the key performance indicators, for instance, in the work [40], Vensim software was applied for the modeling of dynamic systems and software simulation with the objective of evaluating and controlling reliability.

Wind turbine reliability analysis is based on the systemic approach of the wind turbine subsystems, as their total reliability depends directly on the reliability of the subsystems. The model used in [14] was a method for identifying likely causes of system failure called fault tree analysis. Simplification of the energy generator units [41] keeps the manufacturing and maintenance costs down and increases reliability. Bala et al. [29] presented the approaches to achieve reliability at the component level and at the level of electrical components. A model of the optimizing maintenance interval for the wind turbine gearbox considering the profit maximization component per unit time is presented in [42]. Kostandyan and Sørensen [43] considered a failure mode with a corresponding limit state in relation to estimating the reliability, considering failures, for example, due to a fault in an electrical component or loss of grid. The potential benefits of simplifying multiple power converters in each turbine, implying a saving cost, reduced losses and maintenance and increased [44] reliability of the system, were analyzed, focusing on total energy extraction. Additionally, due to the regulation of the electricity market, the distribution network reliability becomes more and more important, and the test after installation or after repair of failures significantly reduces the failure rate during normal operation. Putter and al. [45] described the evolution of the very low frequency technology testing.

An intelligent alarm management system [46] for wind farms improves the wind turbine reliability and would reduce downtime, increase availability and lead to a well-organized maintenance program. A discrete event model was developed in [22] to simulate the operation, the failure occurrence and wind turbine maintenance, with the goal of determining the main factors influencing maintenance costs and the availability of the turbines in the wind farm.

Qiao et al. [47] integrated a control platform based on the wind farm SCADA system to assist the work of the farm as a predictable, controllable system and reliable, high-quality generation was designed.

To increase maintenance efficiency and increase availability, ref. [48] used an example of a failure in a gearbox after almost four years of operation and with nearly 7 weeks of lost availability. The paper identifies research questions that could produce a better maintenance regime for wind farms based on usage and remote condition monitoring. Early detection of failures via condition monitoring can help [49] to prevent major failures and significantly reduce associated costs. It also allows maintenance program optimization, reduced downtime, increased availability of assets and improved safety and operational reliability.

The technology of the vertical axis wind turbine scale arose as a solution to reduce the overall costs of the life cycle and improve profitability [50] and competitiveness with other commercial technologies. However, durability and availability have always been the weak points of this technology [51].

The concept of reliability-centered maintenance may constitute [21] the basis for the development of quantitative models for maintenance or selection and optimization strategy, but it can also provide an assessment to further improve turbine design. The amount of information from SCADA systems for wind farms is enormous, so the use of neural networks to cope with all the information and try to detect failures in some equipment at an early stage [52] is a promising method. The training of the neural network represents a major disadvantage, but if these problems are solved, the results are very interesting, and failures can be detected several months [9] in advance. In this sense, with neural networks [53], it was found that there were significant relationships between gearbox failures and changing climatic conditions. Haddad et al. [54] have provided an optimization model based on real options and stochastic dynamic programming to maximize the availability of an offshore wind farm with a capacity for prognosis. Real options theory provides promising ways to address the economic aspects of prognostics and health management (PHM) after prognostic indication, and evaluation of the costs necessary to meet the availability requirements.

When competitive pressures force asset managers to prioritize their maintenance, the risk-based methodology presented by Bharadwaj et al. [55] is a rational, efficient and somewhat flexible method for the integral management of assets. In this sense, Ref. [56] presents the methodology of how Bayesian networks can be used to learn this model when past data are available.

3.4. Condition-Monitoring System (CM)

As discussed in the previous sections, the technical availability of wind turbines is high; however, this is due to fast and frequent maintenance, and not a good reliability level and maintenance management. Failures in larger turbines are greater so the condition-monitoring system will need to be improved [36] in order to improve the reliability of the farms.

Usually, wind turbines are acquired through after-sales service contracts lasting between 2 and 5 years, which include guarantees and preventive and corrective maintenance that could be adopted after the expiry of the contract period. However, severe unexpected failures can appear between scheduled maintenance intervals, resulting in the loss of money, time and energy production. Moreover, maintenance due to the occurrence of failures can lead to the catastrophic failure of critical components, producing severe consequences for safety, health and the environment.

The increase in the technical availability of wind turbines has to go hand in hand with a greater need for optimal maintenance. A condition-monitoring system could meet the needs of the wind industry for better maintenance management and increased reliability.

The CM is considered as one of the best solutions for maintenance problems [57]. It presents a great economic benefit [58] compared to other maintenance strategies and depending on the status of the CM. The CM is a widely used tool for failure detection [59], which minimizes downtime by increasing the reliability of the equipment. This allow us to observe the present state [60] of the wind turbine and send alarm signals. Alarm data require little storage [46] but provide rich information to the CM. With early failure detection, major failures can be prevented [49] and associated costs reduced.

The condition-based maintenance enables the generation of more energy by reducing failure rates [61] of the turbines, increasing availability. Different approaches to condition-based maintenance [62] focus on induction machines and drive trains in offshore applications. With the use of control algorithms [63], generating units can be simplified in order to reduce maintenance costs. Khattara et al. [64] developed a mathematical approach and a program of a Pareto genetic algorithm to calculate the cost of installation and minimal maintenance of a wind farm with minimal power loss during a fault.

The wealth of information and data that are in use during the operation of wind farms in SCADA can be treated with a promising technique [52] based on the use of neural networks, and can detect failures in equipment at an early stage. The treatment development of SCADA data, research on the correlation of data coming from SCADA and quantitatively assessing the state of wind turbines [12] are important for improving the condition-monitoring systems. Data management and how these data [65] can help make decisions, given the information they provide, are very important and very profitable for maintenance.

Furthermore, a SCADA data clustering model was trained and evaluated for accuracy through simulations, with the results showing that the proposed model [66] is able to accurately detect the deterioration condition of a turbine. Tools that can be used in the CM may be the data mining algorithms that are used to build models for predicting failures of wind turbines [67], improving the performance of statistical tools based on Kalman filter models [57] and algorithms with manageable solutions [68] of dynamic decision making.

The gearboxes are the most expensive subsystem and are responsible for the most inactivity, followed by drive trains [69], which are the biggest challenges for the CM and offer greater opportunities for research. New research in gearboxes is being developed, like in [33], and this is based on a new method of analysis using a CM temperature trend. Another method of improving the CM is the use of several sensors [70] to analyze different oil characteristics. Another method of oil condition monitoring is [71] based on a linear variable filter (LVF) as a dispersive element in an infrared configuration. With the use of singular spectrum analysis (SSA) [72], certain fluctuations in pressure in the hydraulic brake circuit were found, which were correlated with failures in the gearbox, showing that it is a new useful technique as an indicator of failure for maintenance.

Two components, the gearbox and the blades, are taken as study objects in [73] to make a model of condition-based maintenance optimization, and a model is established which is based on the semi-Markov decision process. The current CM is limited to detecting deterioration in the coating of the blades in offshore parks, and another challenge is the effective maintenance [74] of these protective coatings for blades in these wind turbines. The gearbox and generator, by means of automated warnings based on continuous CM with the analysis of vibration and acoustic emissions, were studied in a review [75]. A predictive maintenance strategy can be achieved with continuous CM noise in real time, as found in research [76]. The implementation of the diagnostic center for CM systems and diagnosis systems [77] is an innovative automation vibration analysis concept in wind farms.

To assist the CM in failure detection in turbine equipment, research has been conducted on neural networks [9] since failures can be detected months in advance. A tool for informing decision-making forecasts [10] of failure in the operation and maintenance of wind farms can be compared to maintenance strategies based on the condition. Prognostic strategies and health management provide early detection of failure modes, reducing the operation and maintenance costs for gearboxes [78]. This system was also used, by implementing it as part of a model of Condition Based Maintenance (CBM) with intelligent charging management research [17] of the effects of rotor imbalance and shear in a wind turbine. Other research has developed the business model of O&M [79].

3.5. Maintenance Strategies (M_STRA)

The enormous proliferation of wind farms worldwide has emerged as an alternative to traditional power generation and as a result of economic issues that require control systems in order [32] to optimize the availability and benefits. Some research focuses on finding the best maintenance strategy that minimizes the total cost and maximizes annual energy produced by wind turbines [80]. Based on information inputs of wind farms, developed decision making [10] can be used to identify the best strategies for maintenance and operation. For wind farms, it is essential to implement automatic control and intelligent routines to integrate them into power grid management. For instance, ref. [47] designed an integrated monitoring and maintenance control platform.

It is important to have a description of the common failure modes, monitoring techniques, diagnosis methods and an overview of the maintenance [62]. Once the parameters are neglected [58], most of the available literature is about system performance condition monitoring itself. As an example, in [49], online condition monitoring based on the voltages and currents of a wind turbine system is investigated, and in [81], there is a focus on strategies to follow in the maintenance cables of wind farms.

Improvements to maintenance strategies are being made, such as the proposal of a model that extends the classical programming maintenance [39] to include the expected market prices and weather conditions. Another paper [82] focuses on improving reliability-centered maintenance, since it presents challenges that are considered to achieve the optimal maintenance of turbines, reaching conclusions such as the need for improvements to staff training, the use of quantitative methods for decision support in maintenance and an economic model of the organization of maintenance support.

As for predictive maintenance strategies, they can focus on the use of this type of maintenance to optimize the operation of wind farms, illustrating [76] how this can be achieved through real-time noise monitoring. Another optimization method for this type of maintenance is the use of singular spectral analysis, with [72] showing that this new technique is useful as a failure indicator in the predictive maintenance of wind farms. Another effective predictive maintenance strategy is based on an approach to risk analysis and code coating [74] for the protection of marine turbine blades, which significantly reduces maintenance costs for this type of park. The blades suffer various faults and replacement will normally result in a long downtime. This downtime and these costs can be reduced, and the maintenance strategy that achieves these goals is called proactive maintenance. Nguyen et al. [83] presented an approach to optimize the proactive maintenance of offshore wind turbine blades.

On the other hand, Douard et al. [84] presented a probabilistic approach to introduce risk measurement indicators, and improved the ECUME tool to provide these indicators. In this sense, an event model (based on Monte Carlo simulation) and the hidden Markov model are introduced to model the evolution of meteorological and marine parameters and assess the risk of inaccessibility. In other works, discrete event systems [61,85] are used to develop a simulation model that mimics the maintenance operation of the wind farm market size. Each turbine is treated as a separate module for a cost-effective maintenance strategy and the design of a better quality [11] prognostic and health management system was applied.

Another improvement is based on the mathematical model of the Markov process and reliability theory [24] between reliability models for wind power generation is developed. Data mining is an innovative technique used to identify faults in various elements of wind turbines, as in [86], where it predicts failures within 1.5 h beforehand. Another promising technique is neural networks to [52] try to detect failures in some equipment and improve maintenance strategies. Moreover, the number of failure predictions is useful for planning reserves of the key components [87] for multiple devices running simultaneously and optimizing the support strategy of rational maintenance.

Besnard et al. [88] presented a stochastic optimization model for opportunistic maintenance services of offshore wind farms; optimization is performed on a daily basis to update maintenance planning based on current production and weather. Lin et al. [89] developed a methodology to develop reduced-order models to support the operation and maintenance of offshore wind turbines.

In [90], an opportunist policy is proposed, which is defined by three decision parameters to coordinate the various maintenance activities and minimize the maintenance cost rate, through a comparative study with the policy of corrective maintenance, and it shows the advantage of the method of opportunistic maintenance work to significantly reduce maintenance costs.

The development of advanced techniques to detect [9] the appearance of mechanical and electrical failures of wind turbines at a sufficiently early stage is very important for maintenance actions. Future maintenance strategies [21] provide the most relevant functional failures and reveal their causes, to identify corrective measures to avoid breakdowns as much as possible.

At the same time, future strategies for diagnosing faults are identified by a qualitative fault tree analysis in [59]. Another maintenance strategy to consider is that which takes into account research in which life cycle inventories of a conceptual offshore wind farm are developed and assessed using a hybrid life cycle assessment methodology [91]. Besnard et al. [92] have presented an analysis of the transport strategy, a queuing model of maintenance activities and an economic model of the maintenance support organization.

It is also important to analyze the degradation cycle costs, maintenance and life for various coating systems [93,94] for offshore wind farms, and the maintenance of the blade as a whole [95]. The planning and scheduling of maintenance operations are decisive for wind farm availability and a key component of the operational costs. A challenging real-world application of integrated planning and scheduling is shown in [96], which formulates this problem as a Planning Domain Definition Language (PDDL).

At present, the maintenance scheduling focuses on the field of optimization of a single object, and [97] proposes a model of multi-objective optimization for maintenance scheduling of a transmission network, with the aim to reduce maintenance costs and the minimum expected energy that is not supplied, and the research developed a method of interactive multi-objective decision making. Another improvement proposal [98] for the maintenance schedule is a model that takes into account the peak regulation pressure balance for a power system and to have a fair value, the proposed model is solved by a genetic algorithm.

Gallo et al. [39] proposed a model that extends classical maintenance scheduling to include forecasted market prices and weather conditions, and this proposed maintenance schedule optimization occurs at a discounted cumulative profit of a wind generation portfolio in a fixed-time horizon.

For generator maintenance scheduling of large-scale wind power [38] integration, considering peak shaving and based on Benders decomposition, a model is divided into two parts: the main problem and three sub-problems of decentralized coordination, and this method is applied to the maintenance schedule for all generators in the test system.

Studies have proposed programming formulations for the problem of the optimization of maintenance schedules, and the scheduling problem [99,100] is modeled and solved as a mixed-integer linear program. Proposals for a generic wind power forecasting framework without regional or temporal restriction also take into account [101] the effect of energy lost in downtime imposed by scheduled maintenance and external disturbances.

3.6. Maintenance and Life Cycle Cost (M_COST)

The investment and maintenance costs are relatively insignificant [57,102] with respect to the variables of excessive cost, fixed cost and capital cost of the conventional generation system. However, according to [103], cost reduction remains necessary for wind energy systems so that renewable energy systems can be competitive. According to the Condition Monitoring of Offshore Wind Turbines report, the investment costs [11] for future offshore wind farms built from larger units, costs are expected to be EUR 1.4 to 2.0 k/kW. The analysis of the maintenance costs of wind farms shows that up to 40% of the investment is related [49] to unexpected component failures leading to unscheduled costly modifications. The operation, maintenance and unscheduled interruption costs make great targets for wind energy production [78] but are very risky.

The operation and maintenance have [36] an impact on the failure rates of wind turbines. Many research works focus on finding the best maintenance strategy that minimizes the total cost and maximizes annual energy produced by a turbine, and [80] takes into account the frequency of maintenance as a variable decision, keeping in mind that downtime of a turbine is very important in an eventual failure, and results in a loss [30] of production and income.

Since the maintenance is limited to appropriate time windows, there is a need for decision support tools to ensure that maintenance is carried out in a timely manner, with minimal cost and minimal downtime. Butler et al. [104] have, to this end, a methodology for the estimation of the remaining useful life of the main bearing of a wind turbine.

Offshore wind energy is identified as an emerging future energy growth technology, so the operation and maintenance require major access methods. The economic viability of offshore wind farms are subject to favorable wind conditions [105] compared to onshore farms, offsetting the additional installation and maintenance costs to a greater extent. The most effective way to reduce costs would be to continuously control [106] the state of the systems. This allows early detection of the health degeneration of the wind turbine. Due to the large amount of information that this requires, the use of neural networks [52] to deal with all the information and try to detect failures in some equipment at an early stage is a promising technique for cost reduction.

Wind turbine condition monitoring can significantly reduce [33] the wind farm maintenance cost, especially offshore. However, the high cost and various capacity constraints [12] of available developments have delayed its extensive use. The stochastic simulation model constructed in [58] quantifies the added economic value of implementing a system for condition monitoring of a gearbox.

There are proposals for programming models that extend classical maintenance [39] to include the expected market prices and weather conditions. Other research studies show [107] the benefits of opportunistic maintenance to significantly reduce maintenance costs. The method of calculating the life cycle cost is used to study various technologies and to select cost-effective concepts, such as in [50], which evaluates and compares two types of vertical axis wind turbines. Carvalho et al. [108] estimated the total maintenance cost of control device pitch, which is responsible for controlling the turbine blades. Nielsen and Sørensen [109] carried out a generic case study, where the wind turbine costs included in the model were assessed costs due to inspections, repairs and production loss, and the costs were compared with two maintenance strategies, with and without the inclusion of periodic inspections.

Su and Zhou [73] analyzed the inspection interval and maintenance cost under periodic and no periodic inspections and they described optimal maintenance policies. The risk-based methodology [55] presents a cost-effective manner to minimize life cycle costs in asset management. The degradation, maintenance and life cycle costs for various offshore coating systems [93] are important to analyze. A coating system with low maintenance [94] is usually requires lower life cycle costs, despite higher costs for a new construction phase. Research works were also carried out to reduce costs by developing predictive maintenance strategies for protective coatings [74] of wind turbine blades. The optimization model based on real options [54] provides promising ways to address the economic aspects of prognostics and health management. Another model is based on artificial neural networks that dynamically calculate the impact of operational conditions of the failures of wind turbines [110].

A new approach that can be taken by industry is rethinking the design of the turbines, and the way in which the wind turbine units could be simplified in order to reduce maintenance costs and increase the reliability of the system is described in [41,111]. Simplifying multiple power converters in each turbine would be [44] a possible benefit, including cost savings, loss and maintenance reduction and increased system reliability, however, Shafiee et al. [112] proposed an effective way to improve the reliability and availability of the converter system by adding at least one independent redundant converter in offshore wind farms, which ensures that the system will work in case of a converter failure. It can save a great deal of maintenance of offshore turbines with optimal [113] generator designs, and the fixed-pitch fixed-speed induction generator-based wind turbine presents low [114] maintenance costs in [115], and the results confirmed that the controllability of the wind farm is increased using a rotor impedance control technique. As the generators increase their power, their size and mass also grow, therefore, in offshore wind farms, greater reliability is required in order to minimize maintenance costs, so that electrical generators for a direct drive can be a reliable solution [116], since the gearbox is omitted. Transformers, due to their large size and weight, are very expensive elements [117] and complex in terms of maintenance.

3.7. Maintenance Optimization (M_OPT)

There are many types of analysis of maintenance optimization, but many of the research works found are based on optimizing the maintenance of the equipment found inside a wind turbine with different techniques, for example, the analysis of the inspection interval and cost maintenance in gearboxes [73] to obtain optimal maintenance policies, and another optimization method for gearbox maintenance is the given profit maximization [42] of each component per unit time. Studies are also carried out on power generation efficiency analysis [44] connected to a single large power converter operated with variable frequencies, considering wake effects. It is also important for maintenance optimization to have a good detection [118] of nacelle anemometer faults in a wind farm, minimizing the uncertainty. Another optimization is to braking system through the optimization of condition monitoring, as proposed by Entezami et al. [49].

Maintenance optimization programs [99] are carried out using Matlab simulation based on a deterministic optimization model [119] to define a maintenance strategy. The research work results could provide opportunities for maintenance strategy optimization, as proposed in [120], by using an artificial neural network.

Li et al. [24] proposed an optimization strategy based on the mathematical model of the Markov process and the reliability theory of a reliability model set of wind power generation. The research work [121] aims to introduce the idea of a complete tool, using software with condition monitoring data of wind turbines to anticipate component failure and it proposes maintenance time and implementation strategies. The research work [10] uses failure prognosis for the optimization of a decision-making methodology to identify the best strategies and have a robust operation and maintenance of a wind turbine.

A state-based degradation model for opportunity-based maintenance in offshore wind farms, using a gamma model [122] for the representation of the continuous degradation of components, features the chances of failure to be used in optimization.

Control optimization for the distribution of the fatigue of wind turbines in an offshore wind farm on the basis of an intelligent [123] agent theory is a viable way to optimize the distribution of fatigue in the farms, which will reduce the frequency of maintenance and extend their life.

Transport optimization for offshore wind farms can be analyzed under transport strategies [92], maintenance management and maintenance organization models. Rauer et al. [124] present a forecasting model for parts of an offshore wind farm, and this strategy is used to improve the availability and maintenance. Lost turbine availability is related to the failure of a component, but also depends largely on access to the turbine, and in [125], a computational approach based on probability calculations is developed, allowing estimates to be made on very fast offshore access probabilities and expected delays. Furthermore, Dinwoodie et al. [126] performed research on the modeling and prediction of wave height, which is one of the key criteria for access to offshore wind farms, and this was done through data mining.

The paper [127] presents an analysis of the windows of access to offshore wind farms for performing maintenance on the coasts of Ireland and Portugal, concluding that the implications of these low levels of access suggest that maintenance of power converter waves on the west coast may not be feasible and devices must be brought ashore for activities of O&M.

There are proposals to improve the maintenance of wind farms, such as opportunistic maintenance policies [107], with which optimization of these tasks is intended. The research work [80] aims to optimize maintenance by using the stochastic model, since wind turbines have a more complex process of degradation than equipment working under stationary conditions. In [88] is presented a model of stochastic optimization for opportunistic maintenance services based on a rolling horizon, that is, the optimization is performed on a daily basis to update maintenance planning based on the production date and weather forecasts. The paper [54] provides an optimization model based on real options and stochastic dynamic programming for maximizing the availability of an offshore wind farm.

The different types of tasks can be grouped, such as inspection, preventive maintenance and travel costs from one wind turbine to another. To perform these tasks, a hybrid [128] approach to the use of block replacement policy and a condition-based model has been adopted to leverage the strengths of each approach.

4. Discussion

The aim of this section is to analyze the research evolution in both the different O&M costs and the evolution of the LCOE of wind energy.

4.1. Maintenance Optimization (M_OPT)

As mentioned at the beginning of this article, more than 27,000 papers in the Scopus database (around 43% of all papers in Table 1) include wind energy as the main topic (data collected in November 2020). However, if the different fields of O&M costs are analyzed, more than 38,000 papers exist that deal with wind energy and some of the keywords of each group of variables (Table 2), as reflected in Figure 3. It should be noted at this point that the same article can be counted in different groups, as it contains different keywords. Taking into account the different groups (Figure 3), M_COST is the group achieving the highest number of results, with more than 12,000 papers (approximately 30%). C_M and M_OPT are positioned in second place, with more than 8000 results (approximately 20%) each. On the contrary, M_STRA and O&M are the groups with the lowest number of results in the database, not reaching 600 results each (approximately 1.5%).

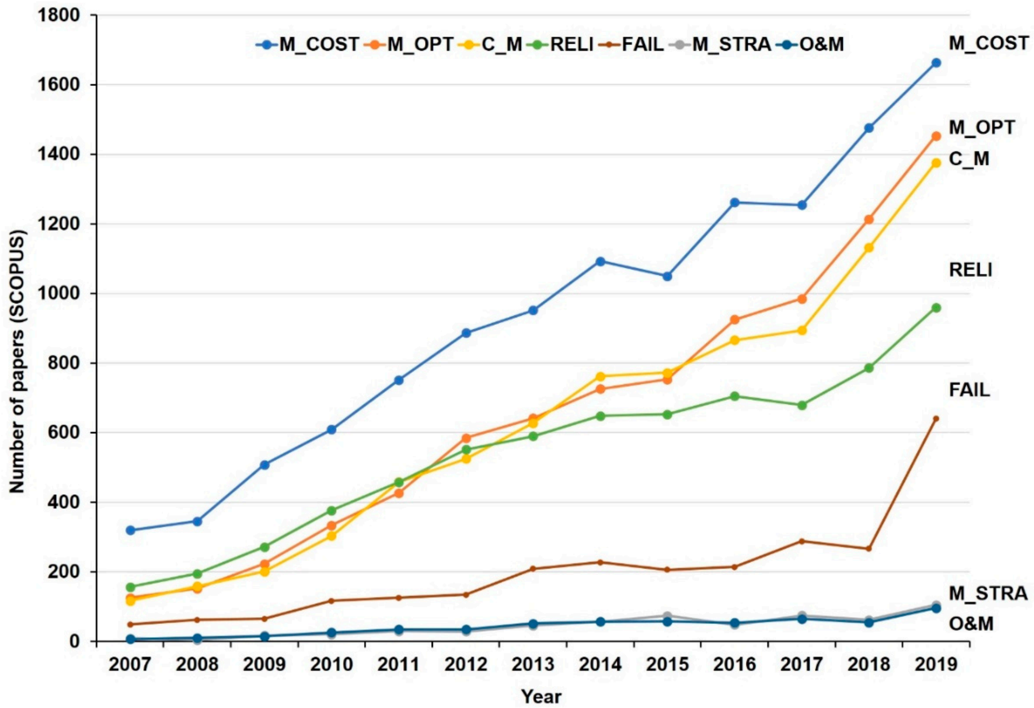

Figure 3. Wind energy O&M cost fields: number of papers in Scopus.

Looking at each of the keyword groups (Table 2), in the O&M group (Figure 4a), the most widely used keyword is "operation and maintenance", which was included in over 90 papers in 2019. In the FAIL group (Figure 4b), the most widely used keyword is "failure", with over 500 results by 2019.

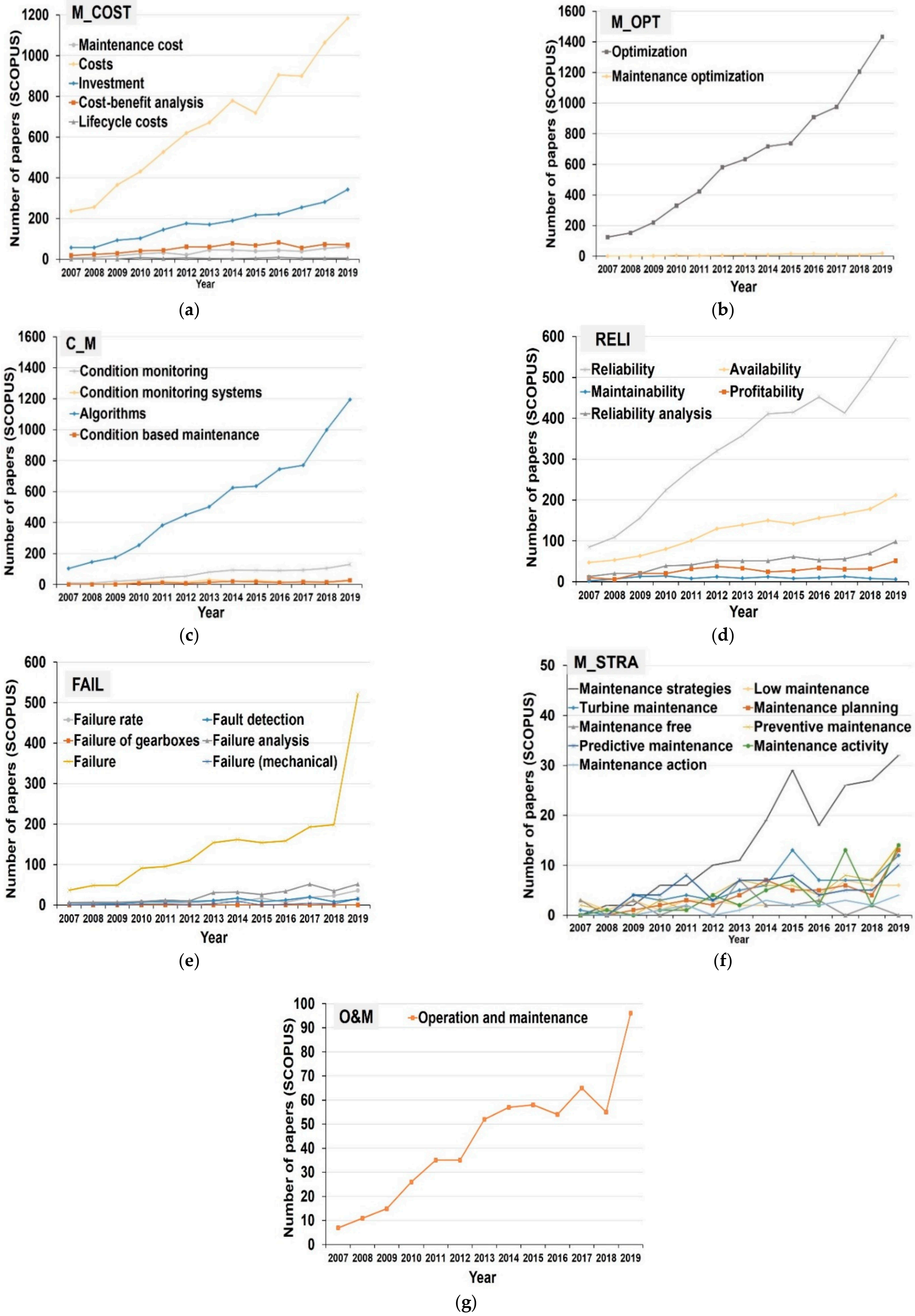

Figure 4. Wind energy O&M variables and number of papers in Scopus: (**a**) M_COST; (**b**) M_OPT; (**c**) C_M; **(d)** RELI; (**e**) FAIL; (**f**) M_STRA; (**g**) O&M.

In the RELI group (Figure 4c), the most found keyword is "reliability", with almost 600 results in 2019. In the group C_M (Figure 4d), the main keyword is "algorithms", which goes from approximately 100 results in the year 2007 to almost 1200 results in the year 2019. The group M_STRA (Figure 4e) does not obtain remarkable results over this period of time. The most outstanding keyword in this group is "maintenance strategies", exceeding 30 results in 2019. With regard to the group M_STRA (Figure 4f), the progression of the keyword "costs" stands out, which grows throughout this period, exceeding 1100 results in 2019, while the rest of the keywords in this group have not exceeded 400 results per year. Finally, in regard to the group M_OPT (Figure 4g), the keyword "optimization" drastically exceeds the keyword "maintenance optimization". In 2019, "optimization" exceeded 1400 results. Thus, it can be seen that the most significant keywords in the O&M of wind energy research are: "costs", "optimization", "algorithms" and "reliability".

Overall, the most widely used keywords over the period of time from 2007 to 2019 are: "costs" (M_COST group, Figure 4a) and "optimization" (M_OPT group, Figure 4b), with more than 8000 results each (appearing in 21% of the papers). More of the most found words are "algorithms" (C_M group, Figure 4c), with almost 7000 results (appears in 17% of the papers), and "reliability" (RELI group, Figure 4d), which appears in 10% of the papers. In contrast, the least found words in the database are: "failure of gearboxes" (FAIL group, Figure 4e), which appears in 0.01% of the papers; "maintenance action" and "maintenance free" (M_STRA group, Figure 4f), which appears in 0.05% of the papers.

Among the research articles indexed in Scopus related to the operation and maintenance costs of wind energy from 2007 to 2019, only 12 keywords considered in this article (Table 2) appear in more than 1% of the results obtained. Only four keywords ("costs", "optimization", "algorithms" and "reliability") mentioned above appear in more than 10% of the articles in Scopus. The rest of the keywords searched for (20 keywords) do not appear in even 1% of the results obtained.

In the case of the most widely used keywords between 2007 and 2019, it is worth noting the high level of interest recently (2017–2019) in the following words: "costs" (M_COST group, Figure 4a), "optimization" (M_OPT group, Figure 4b), "algorithms" (C_M group, Figure 4c) and "reliability" (RELI group, Figure 4d), increasing the results obtained by more than 200 and all of them reaching more than 500 results in the last consolidated year, 2019. Special mention should be made of the keyword "failure" (FAIL group, Figure 4e), which reached 200 results in 2018 and exceeded 500 results in 2019.

These data show a clear upward trend in failure research, while interest in different wind farm maintenance and operation techniques is declining. These trends may be due to the fact that wind technology has reached technical maturity and, hence, research on its operation and maintenance has lost interest. Meanwhile, as a result of this technical maturity, research now focuses on the study of the different cases and models of failure of the various equipment used in wind farms.

4.2. LCOE Wind Energy vs. Research on Wind Farm Maintenance

The O&M costs are a significant part of the LCOE of wind energy. O&M costs can represent between 11% and 30% of the LCOE of a wind project [3,4]. To be able to compare these LCOE and O&M cost values with the evolution of research in the maintenance of wind farms, it is necessary to perform a multiple linear regression model. In such a model, the regression function that relates the dependent variable (research articles, Y) to the different independent variables (M_COST, M_OPT, C_M, RELI, FAIL, M_STRA and O&M) obeys the following equation:

$$Y = \beta_0 M_{COST} + \beta_1 M_{OPT} + \beta_2 C_M + \beta_3 RELI + \beta_4 FAIL + \beta_5 M_{STRA} + \beta_6 O\&M \quad (1)$$

where $\beta_1, \beta_2, \ldots \beta_6$ represent the weight of each independent variable in the global value of the dependent variable Y.

As the evolution of all independent variables is known, it is possible to use IBM SPSS Statistics 25® software for information processing and the development of the multiple regression model. By knowing the evolution of all the variables, the multiple regression model obtains a determination coefficient (R^2)—which allows for knowing if the goodness of the model's fit is perfect, i.e., equal to 1. The equation for the evolution of maintenance research on wind farms is as follows:

$$Y = 0.256M_{COST} + 0.251M_{OPT} + 0.235C_M + 0.145RELI + 0.094FAIL + 0.018M_{STRA} + 0.015O\&M \quad (2)$$

According to the multiple linear regression model (Equation (2)) and as can already be seen in Figure 3, the highest weight (β) is obtained by the keyword groups M_OPT and M_COST, which shows that these are the groups that contribute the most research on the maintenance of wind farms. In contrast, the groups of variables with the least influence on research into wind farm maintenance are M_STRA and O&M. Despite the fact that, in general, FAIL has usually been one of the less important keywords in research work related to wind energy, it seems that the trend has been changing in recent years. In this sense, in the case of the keyword "failure" (FAIL group, Figure 4e), the results obtained have grown considerably, going from 200 results in 2018 to over 500 in 2019, which is more than double the results obtained in one year. Taking 2007 as a reference year, the results obtained for the keyword "failure" (FAIL group, Figure 4e) have increased more than ten-fold with respect to 2019.

Three different periods can be observed in the evolution of wind farm maintenance research between 2007 and 2019 (Figure 5):

- 1st Stage (growth): In 2007, the results obtained were less than 1000. Up to 2014, research in the field grows year by year from 785 results in 2007 to more than 3500 papers in 2013. This stage of growth in research into O&M costs in wind farms is taking place in parallel with the increase in wind projects around the world. At this stage, the scientific and technical interest in the technology was at its highest.
- 2nd Stage (stagnation): After years of constant growth, research into the maintenance of wind farms stagnates between 2014 and 2016. This period of stagnation in research into O&M costs in wind farms was influenced by the global economic crisis which began in 2007.
- 3rd Stage (growth): From 2016 onwards, research in the field increases again year by year, from more than 4000 papers in 2016 to almost 6300 results in 2019. This new phase of growth in O&M cost research is related to the growth of a social conscience in favor of the sustainability of the planet and increasing concern about the consequences of climate change.

With all these data, it is possible to reflect on the evolution of the LCOE and O&M and compare them with the evolution of research on wind maintenance farms. As can be seen in Figure 6, in the period 2007–2019, research into wind farm maintenance increased by 87%, while the LCOE of wind projects decreased by 55%. Between 2007 and 2019, the LCOE of wind projects declined from USD 0.082/kWh to USD 0.053/kWh [129]. In 2010, the LOCE was USD 0.075/kWh. For the O&M costs (Figure 6), between 2007 and 2019, the O&M costs of wind projects fell 30%, from USD 57/kW year to USD 44/kW year. In reference countries for wind energy, such as Germany, Ireland, Sweden and the United States, in 2008, the O&M costs of onshore wind projects ranged from USD 40/kW year (in the case of Ireland) to USD 78/kW year (in the case of Sweden). In 2018, O&M costs of onshore wind projects were around USD 40/kW year. In the case of offshore projects, between 2015 and 2018, the O&M costs declined from USD 118/kW year to USD 67/kW year [129,130].

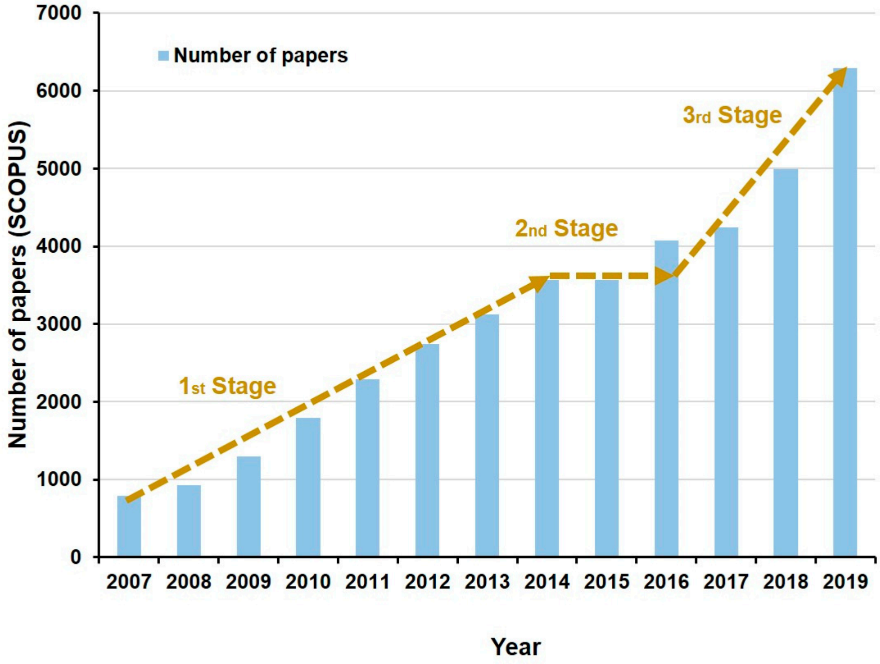

Figure 5. Wind energy O&M research evolution.

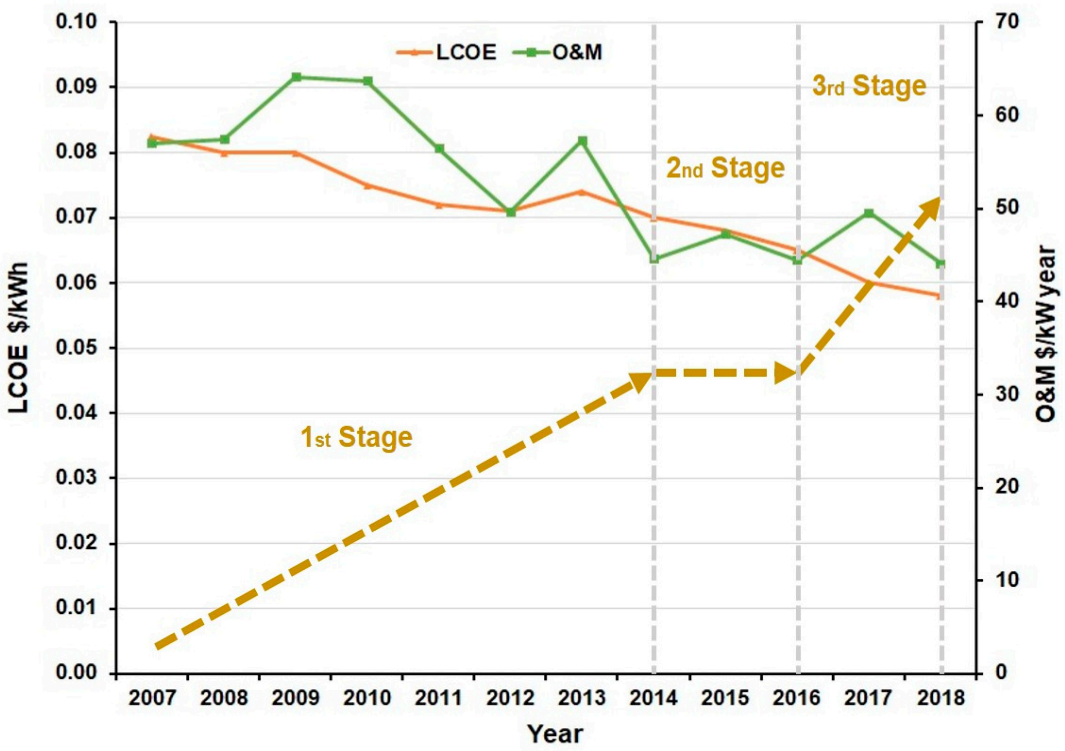

Figure 6. LCOE and O&M wind projects vs. maintenance of wind farm research.

Comparing the evolution of the LCOE and O&M with the evolution of research into the maintenance of wind farms, it can be seen that over the period 2007 to 2019, the LCOE maintained a downward trend. This downward trend is due, as mentioned above, to the fact that both annual production and total annual costs influence the determination of the LCOE. Thus, annual production has increased year by year since 2008 (Table 1).

In the case of O&M costs, the evaluation is different depending on the stage considered. For example, in the first stage (growth) of research into the maintenance of wind farms (2007–2014) there has been a clear decrease. In the second stage (stagnation) of the investigation, during the period 2014 to 2016, a stagnation of O&M costs is observed, while due to the influence of the technology's capacity to generate (Table 1), the LCOE continues to decrease. Finally, in the third stage (growth), from 2016 to the present, there is an increase in scientific production and stagnation in the decrease in O&M costs.

Bearing in mind that it is likely that the results obtained in the latest research have not been reflected in the reality of the operation and maintenance of wind farms, it is possible to predict that, in the coming years, there will be a decrease in both the LCOE, which is also influenced by the progressive increase in the annual production of the technology (Table 1), and the O&M costs, in a similar way to the trends observed in the first stage (growth).

In conclusion, the evolution of the investigation of the maintenance of wind farms has influenced, in an inversely proportional way, the O&M cost. In other words, in the periods in which scientific research in this field has increased, it has led to a reduction in this very important factor in the LCOE. However, the increase in electricity production from the technology (Table 1) has led to a constant decrease in the LCOE between 2007 and 2019, without taking into account the evolution of research into wind farm maintenance.

Therefore, it is possible to predict that the increase in electricity production capacity of wind technology over the next few years will lead to a progressive decrease in the LCOE, regardless of the evolution of research on this technology. However, this positive evolution in the research on the maintenance of this renewable technology will continue to influence the decrease in the O&M cost.

5. Conclusions

Research into wind farm maintenance increased by 87% between 2007 and 2019, so the Scopus database contains over 38,000 articles including wind energy as the main topic and some of the keywords related to O&M costs. The trend in research into gearboxes and transmission parts is towards increased reliability of both design conditions (reduction in multiplication stages, advanced architectures) and the reliability level of each component. Moreover, in terms of maintenance, research works focus on improving the reliability of developing different techniques' predictive maintenance, and the condition-monitoring component is one of the most important techniques for achieving this objective.

In addition to the development of a condition-monitoring system at a reasonable cost, research works should focus on improving the operability under fault conditions. This could be achieved with redundant systems or other solutions prior to the design of wind turbines.

There is a trend towards a change in research on the operation and maintenance of wind farms, as in recent years, scientific interest is increasing towards failure analysis, while interest in the different techniques for the maintenance and operation of wind farms is decreasing. Wind power technology may have reached technical maturity and, as a result, research is now focusing on studying the different cases and models of failure of the various equipment used in wind farms. In the period 2007–2018, the LCOE of onshore wind projects decreased with an annual rate of around 3.6%, while in offshore projects, it decreased with an annual rate close to 3.4%. In the case of O&M costs, in the period 2007–2018, the O&M costs of onshore wind projects decreased with an annual rate of 2.3%, while in the case of offshore projects, it decreased by 2.9%.

For the future, it is important to continue working on increasing the reliability of onshore wind turbines and optimizing maintenance costs. As for offshore wind turbines, it is crucial to limit the maximum faults, since the maintenance of these wind farms is more complex both technically and logistically, especially if it is large-scale corrective maintenance. Another important issue in terms of reducing maintenance costs and faults in the wind turbines is the development of more advanced algorithms for predicting wind conditions. Despite the estimated decline in research work in these fields, there is no doubt that these issues continue to be a great challenge for the optimization of such installations with a great impact on the environmental sustainability of the planet.

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