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Optimization Models for Operations and Maintenance of Offshore Wind Turbines Based on Artificial Intelligence and Operations Research: A Systematic Literature Review

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Abstract

Maintenance of offshore wind turbines is critical for expanding wind energy production, yet it presents significant challenges due to harsh operational conditions. This issue, discussed extensively in Operations and Maintenance (O&M) periodicals, can hinder the economic viability of wind energy. With European and emerging markets planning large-scale wind energy production, optimizing installation and maintenance resources is crucial. Our research focuses on numerical techniques to inform maintenance strategies and decisions, addressing key discussion areas. Our methodology involves a systematic literature review of 122 scientific works, with descriptive and content analyses revealing insights into maintenance planning. Quantitative techniques, while studied separately, can enhance understanding of technical aspects in maintenance decision-making, provided their limitations are addressed. The research underscores the importance of considering various factors in offshore wind farm maintenance planning to align with planner objectives.

Keywords: offshore wind energy, O&M, optimization, artificial intelligence, operations research

1. Introduction

The production of renewable energy has expanded worldwide encouraged by decarbonization initiatives of major economies, the rearrangements of supply chains, caused by the COVID-19 pandemic as well as geopolitical conflicts, such as the Russia-Ukraine war. Wind energy, especially offshore, has stood out in this scenario due to its significant capacity factor (in some projects, equivalent to 40 ~ 50%) and the regulation of its environmental requirements for installation projects, which is aligned to the sustainable performance goals formulated by multilateral institutions such as the United Nations (UN) (Iea, 2019; Nerlinger & Utz, 2022; Serafini et.al, 2022).

The growth registered by the wind industry in the last two years is unprecedented: in 2021 there was a growth of 1.8% in installed capacity when compared to 2020, which totalled 94 GW. Onshore and offshore wind farms correspond, respectively, to 77% and 23% of this total. These results support the understanding of the energy sector's resilience in the face of the serious economic crises that affect countries in the second decade of the 21st century. In 2023, relevant political changes in emerging countries such as Brazil and interventions by international monetary authorities in the most industrialized nations to reduce inflationary trends will have repercussions as well as the enactment of policies that accelerate the expansion of renewable energies by 2030. (Mckenna et.al, 2015; Reis et.al, 2021; Gwec, 2022; Gwec, 2023).

This significant growth is a result of the new offshore wind farms, supported by European and emerging countries as a strategy to remain competitive in the production of durable consumer goods and commodities. However, there are considerable challenges to be overcome in this industry, such as the high dependence on an adequate port infrastructure, close to the energy producing parks; regional regulatory and technical aspects that can hinder the production and distribution of the energy; and the maintenance of wind turbines, a limitation which can severely impair continuous growth due to high industrial costs (Baagøe-engels & Stentoft, 2016; Akbari et.al, 2016; De castro, 2019; Nguyen et.al, 2022).

Studies on wind turbine maintenance present computational models that improve the accuracy of Maintenance Planning and Control initiatives by up to 94%, contributing to the optimization of the costs involved in this process. The offshore environment, unlike onshore, limits the accessibility to wind turbines and subjects them to faster degradation processes than on land, which makes operation and maintenance challenging and expensive (Boccard, 2009; Sinha & Stell, 2015; Poulsen & Hasager, 2016; Kang et.al, 2019; Falani et.al, 2020).

Some works have been addressing the main gaps identified in the studies on offshore wind turbine maintenance. For stance, a study carried out by Ilić et.al (2011) addresses the issue of preventive maintenance for wind turbines, including the identification of failures, maintenance techniques and maintenance schedule optimization. Moreover, another study carried out by Morales et.al (2018) proposes a model for scheduling the maintenance of offshore wind turbines using mathematical optimization techniques. Likewise, a study carried out by Skaare et.al (2016) analysed the impact of maintenance on the availability and lifetime of offshore wind turbines. Also, Costa et.al (2021) addresses the maintenance of offshore wind turbines, identifying gaps in terms of monitoring, inspection and fault diagnosis. The authors highlight the importance of new technologies and tools for the maintenance of offshore turbines, including drones, robots and remote sensors. Finally, Chen (2019) highlights the importance of preventive and corrective maintenance for offshore wind turbines, as well as the lack of accurate data on the performance and lifetime of these turbines. The authors highlight the importance of a systematic approach to the maintenance of offshore turbines, which takes into account factors such as reliability, safety and cost-effectiveness.

Accordingly, the current systematic review focuses on the discussion of numerical techniques commonly addressed to direct the most appropriate maintenance strategies, maintenance scheduling and health diagnosis of critical components within wind installations, especially those offshore, in order to ensure the maintainability of these assets, reducing operation and maintenance costs.

Thus, some of the key questions the current work seeks to address are: a) What are the main techniques used to optimise operations and maintenance of wind turbines, especially in the offshore scenario? b) What is the main data needed to analyse the predictability of failures of these assets? c) What are the advantages and disadvantages of the different methods presented in the studies? d) Which methods lack an in-depth conceptual discussion and therefore make room for new basic research? e) Although some of these methods are studied individually, what are the consequences of overcoming their distinctions for the planning of Operations and Maintenance of offshore wind turbines?

It is evident that the techniques of Artificial Intelligence and Operations Research, usually applied in optimising the aspects discussed so far, although acting axiomatically with distinct preference structures, can converge to a complete understanding of the technical aspects involved in the decision to perform preventive, predictive or corrective maintenance, mitigating the uncertain conditions under which the decision maker has to act (Roy, 1996; Hillier; Lieberman, 2013).

2. Method

According to the definition of the Oslo Manual (1997) of the Organization for Economic Cooperation and Development (OECD), scientific research is "original and planned investigation that aims to discover new knowledge and achieve advances in scientific understanding. Similarly, according to Kerlinger (1986), scientific research is the process of formulating problems, collecting data, analysing and interpreting them, in addition to disseminating results, with the aim of answering questions of knowledge. Also, Bunge (2003) argues that scientific research is a systematic, controlled, empirical and critical investigation of hypotheses about the relationship between phenomena.

A systematic review is a structured and methodologically rigorous approach to the identification, evaluation and synthesis of all relevant studies on a specific research question (Moher et.al, 2009); applying clearly defined methods to obtain relevant evidence from a specific research topic, with the aim of identifying gaps in knowledge and guiding future research (Grant & Booth, 2009; Higgins & Green, 2011; González & Toledo, 2012). The current study is a systematic literature review. Thus, it aims to generate structured knowledge on a topic whilst it is developed in stages, which are detailed in Figure 1.

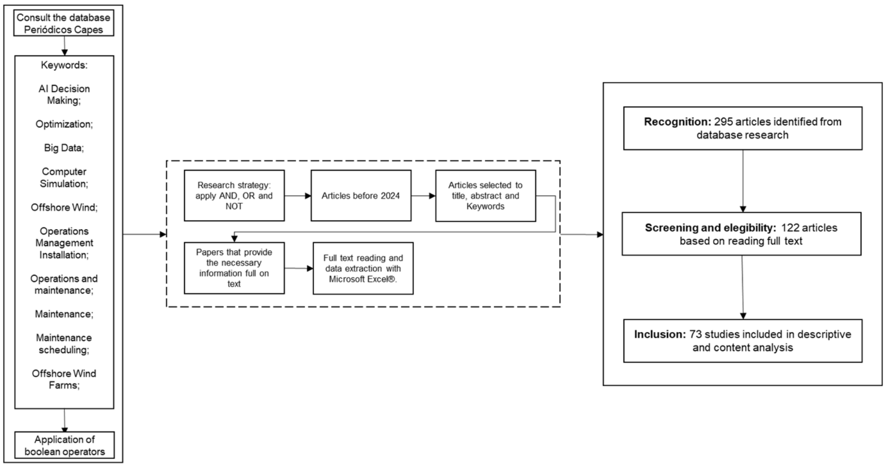

Figure 1. Research stages

In the first stage, the research sought to identify studies that addressed methods for optimising decision-making in Operations and Maintenance (O&M) in the Offshore Wind Energy based on research in the Periódicos Capes database (which brings together Scopus, Web of Science and Science Direct databases, amongst others, allowing access to a wide quantitative range of studies aligned with the research theme).

Subsequently, the second stage was initiated, which consisted of finding articles through a search on the platform Periódicos CAPES, using the following keywords: “AI decision making”, “Optimization”, “Big Data”, “Computer Simulation”, “Offshore Wind”; “Operations Management Installation”, “Operations and Maintenance”, “Maintenance Scheduling” and “Offshore Wind Farms”.

In the third stage, the relevant articles were selected and their abstracts analysed. Articles that were not related to the research objective were excluded. As a result, 122 articles were selected (73 as content articles and 49 as support articles for the analysis).

In the fourth stage of the research, the texts were read and extracted, as well as their classification in terms of structure and content, through the elaboration of an Excel® spreadsheet, observing the following elements: keywords, title, year, author, country where the research was conducted, origin of the authors, journal/congress proceedings, University/Research Center/Company, type of study, approach, objectives, research object, research focus, objective of the article, results found, employed quantitative/qualitative method, advantages and disadvantages of the catalogued methods. Finally, in the fifth stage, the results were prepared for subsequent publication.

3. Results and Discussions

3.1 Quantitative Methods and Decision Making

Decision-making can be conceived as the choice by a decision-making centre (an individual or a group of individuals) of “the best” amongst “the possible ones”; thus, decision is related to reasoning. One of the possible definitions of artificial intelligence (AI) refers to cognitive processes and, mainly, to reasoning. Before making any decision, people also reason, so it is expected to explore the links between AI and decision making (Rezamand et.al, 2020; Bouzekri et.al, 2017; Antoniadou et.al, 2015).

When focusing on areas in which the presence of judgement, decisions and human evaluations is significant, such as decision analysis, the decision-making process may be convoluted; thus, the application of formal modelling tools is highly complex, leading to difficulties in addressing the imprecision related to such areas and problems (Zadeh, 2015).

In order to account for the imprecision related to such situations, it is necessary the use of fuzzy sets: the variety with which they could be used would require a significant registration effort, a fact that makes a more specialised theoretical contribution necessary, which is not the objective of the current study. The current authors have attempted to exemplify its most common representation, which is the triangular shape, explained axiomatically in the following definitions purposes.

Definition 1: Consider X a space of objects generically represented by x. In that case, a fuzzy set Ã *in X is characterised by an association or compatibility function* $\mu_{\tilde{A}}(x)$ *that associates each object in* Ã *with a real number between 0 and 1* (Zadeh, 1965).

$$\tilde{A} = \left\{\left(x, \mu\tilde{A}\ (x)\right)\middle|x\ \epsilon\ X\right\} \tag{1}$$

Definition 2: The real fuzzy numbers are then defined as a convex and normalised fuzzy subset $\tilde{A}$ *of the real line* R *with the association function* $\mu_{\tilde{A}}(x)$ *that satisfies the following properties* (Dubois & Prade, 1980; Liao et.al, 2013; Castro, 2020):

a) $\mu_{\tilde{A}}(x)$ is a continuous mapping of R for the closed range [0,1].
b) $\mu_{\tilde{A}}(x) = 0$ for all objects $x\ \epsilon\ (-\infty,\ a)$.
c) $\mu_{\tilde{A}}(x)$ is strictly increasing on the interval [a, b].
d) $\mu_{\tilde{A}}(x) = 1$ for all objects $x\ \epsilon\ [b, c]$.
e) $\mu_{\tilde{A}}(x)$ is strictly decreasing on the interval [c, d].
f) $\mu_{\tilde{A}}(x) = 0$ for all objects $x\ \epsilon\ [d,+\infty]$.

Whence a, b, c and d are Real Numbers.

Assuming $x, l, m, u\ \epsilon\ R \rightarrow [0,1]$, so that $\{x\ \epsilon\ R\ |\ l < x < u\}$. A triangular fuzzy number $\widetilde{T}$ is defined as:

$$\mu_{\widetilde{T}}(x) = \{\frac{1}{m-l}x - \frac{l}{m-l},\quad x\ \epsilon\ [l,m]\ \ \frac{1}{m-u}x - \frac{u}{m-u},\quad x\ \epsilon\ [m,u]\ \ 0,\ \text{Otherwise} \tag{2}$$

Figure 2 illustrates the triangular fuzzy numbers' behaviour.

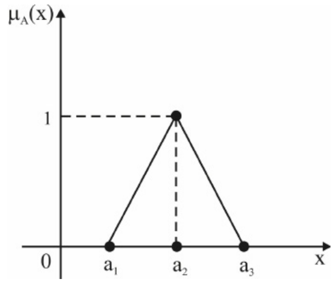

Figure 2. Triangular fuzzy number.

Source. Elizabeth and Sujatha (2015).

Definition 3: Assuming two triangular fuzzy numbers denoted as $\tilde{A} = (l, m, u)$ *and* $\tilde{Y}(y_1, y_2, y_3)$, *operations with fuzzy numbers are as follows* (Chen, 2000; Elizabeth; Sujatha, 2015; Castro, 2020)

a) Addition: $\widetilde{A}(+)\widetilde{Y} = (l + y_1, m + y_2, u + y_3)\quad l \geq 0, y_1 \geq 0$;
b) Subtraction: $\widetilde{A}(-)\widetilde{Y} = (l - y_1, m - y_2, u - y_3)\quad l \geq 0, y_1 \geq 0$;
c) Multiplication: $\widetilde{A}(\times)\widetilde{Y} = (l \times y_1, m \times y_2, u \times y_3)\quad l \geq 0, y_1 \geq 0$;
d) Division: $\widetilde{A}(\div)\widetilde{Y} = (l \div y_1, m \div y_2, u \div y_3)\ l \geq 0, y_1 \geq 0$.

Assuming a scalar or constant $k \in R$ there will also be the following operations:

a) Multiplication: $\widetilde{A}(\times)k = (l \times k, m \times k, u \times k)\quad l \geq 0, k \geq 0$;
b) Division: $\widetilde{A}(\div)k = (l \div k, m \div k, u \div k)\quad l \geq 0, k \geq 0$.

Another important operation applied to fuzzy numbers is the distance between two numbers. The vertex method will be considered, however, there are several methods to calculate the distance:

$$d(\widetilde{A}, \widetilde{Y}) = \sqrt{\frac{1}{3}\ [(l - y_1)^2} + (m - y_2)^2 + (u - y_3)^2 \tag{3}$$

Definition 4: Linguistic variables are variables that have their values represented by linguistic terms (ZADEH, 1975). *These variables give support to approach complex or ill-defined decision-making situations that make it difficult to use quantitative expressions* (Chen, 2001; Zadeh, 1975).

Trapezoidal fuzzy numbers are an extension of triangular fuzzy numbers and are widely used in fuzzy control systems. They are defined by a trapezoidal membership function, which assigns a membership value to each possible value of the fuzzy variable. The trapezoidal membership function is defined by four parameters: a, b, c and d, wherein a ≤ b ≤ c ≤ d, according to the following equations (Wang et.al, 2007; Kumar et.al, 2013):

$$\mu(x) = \begin{cases} (x-a)/(b-a), a \le x \le b \\ (c-x)/(c-b), b \le x \le c \\ 0 \end{cases} \tag{4}$$

Figure 3 illustrates the behaviour of trapezoidal fuzzy numbers:

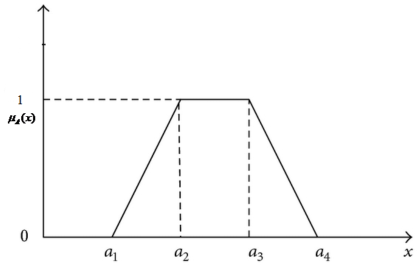

Figure 3. Trapezoidal fuzzy number

Source. Dinagar, Kamalanathan and Natarajan (2017).

Fuzzy logic is often used in control systems, as it allows dealing with situations in which accuracy is not critical, such as the maintenance of offshore wind turbines (Sierra-Garcia; Santos, 2021). Offshore wind turbine maintenance involves performing maintenance and repair tasks on such turbines. These tasks can be expensive and dangerous, and it's important to ensure they are only done when necessary. Fuzzy logic can be used to help determine when maintenance is required (Dao et.al, 2021).

A fuzzy logic system can be constructed using linguistic rules that define the conditions under which maintenance is required. For instance, a rule might be "If turbine vibration is high and wind speed is low, then maintenance is required". Fuzzy logic allows these rules to be expressed in terms like "high" and "low" rather than precise values (Qu et al., 2020). The system can then be fed with data from sensors such as wind speed and turbine vibration and produce output that indicates whether maintenance is required. The output can also be expressed in terms such as "highly recommended" or "cautiously recommended" (Suganthi et.al, 2015).

Artificial Neural Networks (ANN) are mathematical models that seek to reproduce the biological brain's behaviour pattern, including the ability to acquire, maintain and generalise knowledge. The most basic structure of an ANN is the artificial neuron (Aladag et.al, 2010; Van Belle et.al, 2014)

As in the biological structure, an artificial neuron has n inputs referring to external stimuli. These signals are weighted by synaptic weights and then linearly combined. The result of this combination undergoes the action of an activation function whose main characteristic is to be a differentiable function, as shown in Figure 4 (Guresen & Kayakutlu, 2011; Hajian & Styles, 2018):

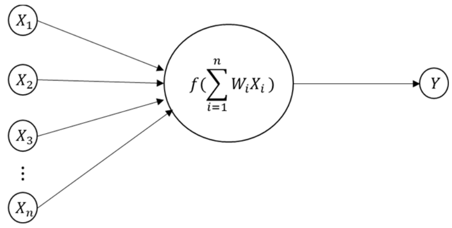

Figure 4. Schematic representation of an artificial neuron

The activation function controls the level at which the neuron is activated besides the signal strength at the neuron's output. In general, nonlinear activation functions are used, which translates into a rich ability to approximate functions. Two of the most common activation functions are the sigmoidal, or logistic, function and the hyperbolic tangent (TANH) function.

$$g(z) = \sigma(z) = \frac{1}{1+e^{-z}} \tag{5}$$

$$g(z) = \tanh \tanh\ (z) = \frac{(e^{z}-e^{-z})}{(e^{z}+e^{-z})} \tag{6}$$

In which:

$$y = w^{T} * x \tag{7}$$

Several studies address Neural Networks and Genetic Algorithms for decision-making processes that require satisfactory performance in a context of randomness (Morshed & Kaluarachchi,1998; Li et.al, 2021). These studies explore the advantages and disadvantages of these two techniques, aspects that will be explored in the current article.

In the discussion involving metaheuristics, heuristics, simulation models and mixed integer linear programming, classical techniques, such as the travelling salesman problem (TSP), are associated with models that propose the search for suboptimal solutions that adequately represent the described optimization problem. On the other hand, simulation models based on Marcovian data series legitimately seek alongside FIT functions to optimise scenarios that involve significant costs to achieve predictability. Whereas the simulation models build statistically reliable scenarios, it is evident that these models are far from being integrated with the sequencing algorithms, which could contribute to improve the simulation results, since they address the allocation of resources in restricted scenarios (Kleinrock,1975; Law, 2007; Hillier & Lieberman, 2006; Arenales, 2007).

Sequencing problems are understood as those that occur, mainly, in production facilities. Its basic formulation predicts that for each set of jobs n there is a number of machines m that are capable of executing them considering all the constraints to carry out the planned jobs set (Hoogeveen, 2005; Zhou, 2018).

3.2 Descriptive analysis

Bibliometric results show decreasing trends in the number of works on the subject. Thus, further research may be relevant to boost current discussions, pointing to future new paths to qualified scientific research. Figure 5 outlines this trend.

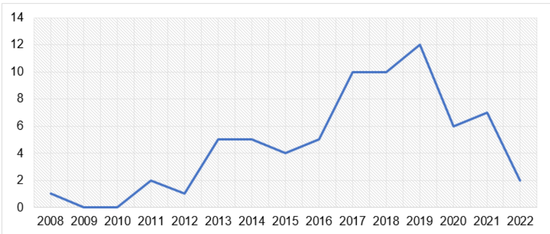

Figure 5. Trend in quantity of qualified publications per year

The analysed works are mostly of a quantitative approach (studies that explore the advantages and disadvantages of artificial intelligence techniques, combinatorial optimization and simulation to the planning and control of maintenance). There is, nonetheless, a significant percentage of qualitative research, utilising techniques that allow mapping decisions related to planning oriented to maintenance strategies. These listed points are illustrated in Figure 6.

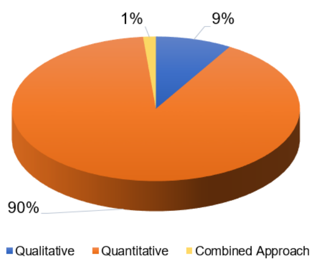

Figure 6. Approach to systematised studies

Most of the research analysed are classified as modelling and simulation followed by case studies. Thus, it is possible to infer that research developers on the subject are interested in evaluating scenarios in applied contexts to test the sensitivity of variables that are of interest to decision models, despite the need to investigate randomness of the maintenance cost variable as well as its relationship with the reliability of the assets that are under scrutiny of the operations planning. Figure 7 shows the categorization of studies regarding its methods.

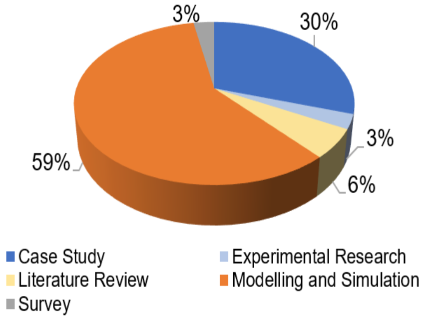

Figure 7. Catalogued search methods

Based on the presented data, the authors found the need to observe in what sense the key words of these studies were aggregated and what likely subjects may influence the current literature review. The result showed that the maintenance of wind turbines in the offshore scenario; the understanding of its logistical aspects (such as the modals that should assist in the transport of the teams that performed these maintenances); and the monitoring and evaluation of failures to ensure reliability in the aggravating scenario of energy production at sea, since faster degradation of wind turbine components is expected, seems to be the main scope on which the current research will focus. Figure 8 displays the keyword analysis.

Figure 8. Keywords analysis

Source. Wordle (2023).

The highest impact publications come from Europe, the United States and China, following a global trend of qualified knowledge concentration; as seen in Figure 9.

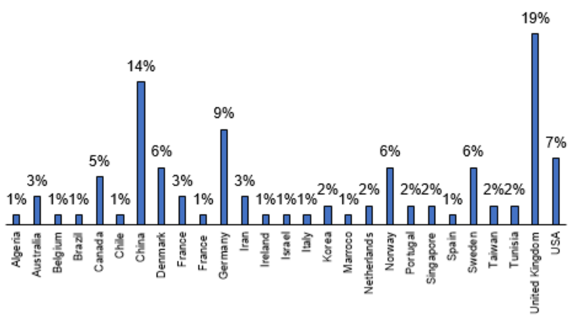

Figure 9. Percentage of publication by countries

The main universities and research institutes that publish relevant research on the topic are mostly concentrated in the United Kingdom, China and Germany. Figure 10 represents the total number of studies published by the 10 main technology centres in those countries.

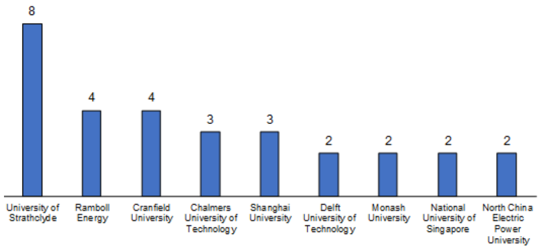

Figure 10. Studies published in the ten main research centres

The top ten qualified journals observed in this literature review are shown in Figure 11. These journals are presented according to the number of citations presented in the study, as well as their respective Journal Citation Report (JCR): qualifying metric for high-impact scientific productions.

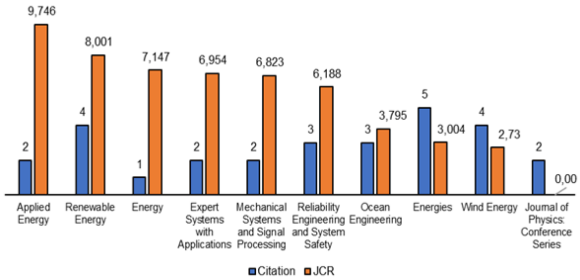

Figure 11. Top journals, citations and JCR

The main quantitative methods observed for wind turbine maintenance optimization are shown in Figure 12. It is possible to observe the design of the four main groups of quantitative techniques that will be explored in the current research: neural networks, fuzzy sets, simulation and scheduling models.

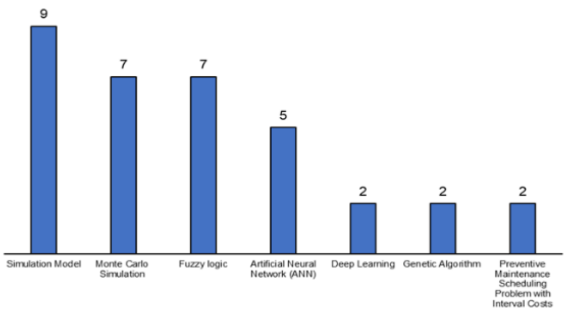

Figure 12. Main quantitative techniques observed

These methods are the subject of the current content analysis discussion. The main advantages and disadvantages of the systematic group will be presented alongside their use limitations; furthermore, it will be presented the gaps found in the scientific discussion.

3.3 Content Analysis

The maintenance of offshore wind turbines is a critical area of research to ensure the reliability and performance of these systems. Efficient preventive maintenance strategies, based on continuous monitoring data, can minimise downtime and maximise energy production (Zhang et.al, 2018). Predictive maintenance plays a key role in the efficient management of offshore wind turbine maintenance. The use of advanced sensors and data analysis techniques, such as machine learning, allows early detection of failures and proper scheduling of maintenance activities, reducing costs and improving operational availability (Li et.al, 2019).

The maintenance of offshore wind turbines presents unique challenges due to the harsh environment in which these systems operate. Corrosion, vibrations and adverse weather conditions can significantly impair the service life of components. It is essential to develop maintenance strategies based on risk analysis and consideration of life cycle costs to ensure the reliable operation of such equipment (Schröder et al., 2019).

The use of remote access technologies and robotics has shown to be promising for the performance of maintenance tasks on offshore wind turbines. Autonomous inspection and repair systems can reduce the need for human intervention in hazardous and difficult-to-access environments, improving safety and reducing maintenance costs (Artigao et.al, 2021).

Optimising maintenance logistics is key to reducing operating costs in offshore wind farms. Efficient scheduling of maintenance activities, spare parts inventory management and careful planning of human resources are crucial aspects for successful maintenance of offshore wind turbines (Ding et.al, 2018).

Based on the specialised literature, some works propose useful models for predicting failures and optimising maintenance planning for offshore wind turbines. For instance, Hou et.al (2019) proposes an optimization model based on genetic algorithms to determine the best maintenance schedule for offshore wind turbines, considering multiple objectives, such as minimising maintenance costs and maximising the availability of wind.

More recently, Jagtap et.al (2020) presents an optimization model based on a particle swarm optimization algorithm to determine the optimal maintenance plan for offshore wind farms. Their study considers factors such as maintenance costs, component reliability and operational constraints.

Furthermore, Li et.al (2017) propose the application of Markov decision processes to optimise the preventive maintenance of offshore wind turbines. The model takes into account the age of the equipment, maintenance costs and operational performance.

Finally, Lin et.al (2018) presents a comprehensive framework to optimise the operation and maintenance of offshore wind farms, incorporating multi-objective optimization techniques to maximise the availability of wind turbines, and minimise maintenance costs whilst considering the conditions of the marine environment.

3.4 Framework

To schematise the diversity of quantitative methods used to optimise the planning of maintenance operations for offshore wind turbines involves the understanding of the peculiarities common to these methods, their similarities and their objectives, which makes any attempt to represent them in a simple diagram rather challenging. However, the theoretical framework and their respective methods are shown in Figure 13.

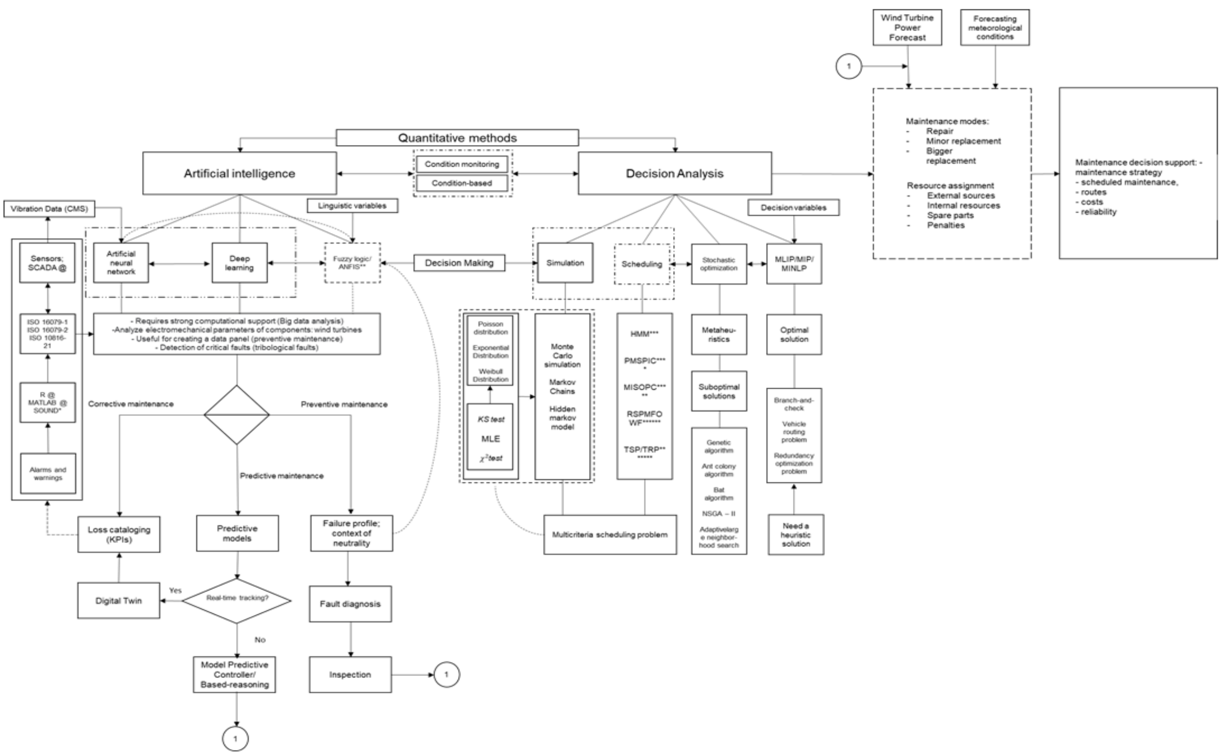

Figure 13. Theoretical framework

The systematic group ‘Artificial Intelligence’ aims to highlight situations that guide the investigation of components failure mainly from the monitoring of vibration and temperature data of the wind turbines, signalling the need for preventive, predictive and corrective maintenance. The defects monitored through these models are predicted by ISO series regulations and contribute to energy production planning, since they indicate the most opportune moment to carry out repairs when integrated with key performance indicators of energy production losses by maintenance needs (Jiang, 2021; Mills et.al, 2018).

Software such as SCADA and sensors arranged on wind towers are useful for handling vibration data from critical components such as nacelles and blades. The significant volume of data requires Big Data storage and the application of database techniques. Furthermore, statistical treatments in an unsupervised learning environment to convert vibration data into digital signals are useful for data analysis and management evaluations. Thus, SOM networks (Self Organizing Maps*) with regions indicating which type of fault may occur when the data shows a given trend are useful representations for decision guidance (Blanco-M et.al, 2018; Lin; Liu, 2020).

These techniques do require significant computational support, as they present an investigation of the decision maker's preferences, observing in which situations the decision maker feels comfortable to deliberate in a controlled condition of risk and uncertainty. Albeit essentially theoretical, models based on fuzzy logic can contribute to this purpose for maintenance planning, as they model the results observed from sensors and are able to delineate a probable range of decision acceptance that is intelligible (Khan et.al, 2022; Aryanfar et.al, 2022).

The presence of subjectivity in the decision-making process implies the emergence of techniques that seek to highlight biases and observe patterns that may be useful for the decision makers. For maintenance planning, such techniques may guide the structuring of strategies that trace the directions that should be adopted depending on the type of maintenance and the parameters investigated (ArzaghI et.al, 2017; Pinciroli et.al, 2023).

In operational research, so long as it is intended to observe the behaviour of specific variables, scenarios are opportune to model the decision through techniques such as Simulation. It proposes to investigate situations in which the arrival of entities in a system presents known continuous or discrete probability distributions based on hypothesis tests such as the χ^2 and the Kolmogorov-Smirnov, for instance, in which the fit of the distribution for the data series is observed. Because it is safe and practical, its usability stands out and is relevant for reliability estimates of the assets in the present study (Law, 2007).

Although theoretically different from Scheduling problems, which seek to allocate restricted resources into carrying out work taking into account significant levels of efficiency; simulation can, along with these problems, have benefits in terms of the quality of the solutions presented, for instance, in industrial operations modelling, it can display the effects that a reprogramming or maintenance of machines has for the reduction of the total time of the routine operations (the makespan), which is applicable to the planning of energy production (Mohan et.al, 2019; Carreno et.al, 2019; Ahmadian et.al, 2021).

Other studies have presented the problem of Multicriteria Scheduling: a technique that aims to drive the decision maker into choosing the technical factors that should be the object of scrutiny by him or the group of decision makers, and from mathematical programming and data from reliable measurement systems to investigate the feasibility of solutions, proposing, if necessary, relaxations. The construction of scenarios together with the idea of sequencing operations and contributing to the optimization of systems taking into account the subjectivity of the decision maker seems to be the main advantage of this technique, which has not found significant growth in discussion in recent years although it is robust and structured (T’kindt & Billaut, 2003; Hoogeven, 2005; Lara et al., 2021).

The techniques presented in Figure 13 are detailed in terms of their advantages and disadvantages in Tables 1 and 2. The authors sought to detail the understanding of these models and problems, suggesting, when necessary, situations applicable to them.

Table 1. Advantages and disadvantages of AI techniques for optimising maintenance of offshore wind turbines

Methods - References	Advantages	Disadvantages
Artificial neural network (ANN) - Bangalore & Tjernberg (2013); Adouni et.al (2016); Bangalore et.al (2017); Gantasala, Lunend & Aidanpää (2017); Hossain et.al (2017); Ali et.al (2018).	I) Adaptive Learning: ANNs can learn to perform tasks through a training process. II) Self-organization: ANNs can create their own structure to represent information. III) Fault tolerance: The ANN can still operate when its structure is damaged (degradation tolerance), and distorted or incomplete when the data is noisy (data tolerance). IV) Online operation: It is implemented alongside other systems, working seamlessly, as It is specially programmed to carry out online processes. V) Practical implementation: There are specialized chips that can facilitate the integration of ANNs into different systems.	I) ANNs need considerable size samples to generate information, making a significant number of observations necessary, which may be inconvenient. II) Another disadvantage is that the optimization of the hidden layer of the ANN is time consuming, adding further complications into the computational process.
Deep learning (DL) - LeCun, Begio and Hinton (2015); Voulodimos et.al (2017); Bach-andersen, Rømer-odgaard & Winther (2018); Chen et.al (2019).	I) Learning distributed representations allows generalization to new combinations of learned resource values further to those observed during training; II) another significant advantage would be the composition of representation layers in a deep network	I) It can become ineffective if there are errors in the first layers, such errors can cause the network to learn to reconstruct the average of the training data. II) It requires a very large amount of data to obtain superior performance over other techniques.
*Fuzzy logic (FL)*** - Rezamand et.al (2021); Zhong et.al (2019); Nguyen et.al (2022); Amina et.al (2016); Azadegan et.al (2011); Bernardes et.al (2019); Choi & Kim (2017); Pezeshk & Mazinani (2019).	I) A simple and intelligent process. II) Easy to understand and implement. III) Allows for a more user-friendly and efficient implementation	I) The development of a fuzzy system model is rather challenging. II) Difficult to find suitable membership values for fuzzy systems. III) A fuzzy system cannot be applied to solve a problem that is not available in the form of if-then rules.
Extreme learning machine (ELM) - Bakri et.al (2019); Wang et.al (2021).	I) Showed greater accuracy and lower training cost than any other neural network structure, including Random Neural Network. II) it is possible to develop new neural network structures using extreme machine learning	I) Albeit extreme machine learning´s hidden layer input weights and threshold values are randomly generated; inappropriate parameters will lead to unsatisfactory regression results. II) When the sample imbalance is relatively large or training samples are relatively small, extreme machine learning generalization performance is not optimal.
Model-based reasoning (MBR) in AI - Echavarria et.al (2008); Khandelwal & Sharma (2013).	I) The ability to use functional/structural domain knowledge in problem solving, enhancing the DM´s ability to deal with a variety of problems, including those that the system designers have not anticipated. II) model-based decision makers tend to be very robust, complete and flexible problem solvers. III) Some knowledge is transferable between tasks, for model-based decision-makers are often developed using scientific and theoretical methods, since science strives for general application theories, this generality often extends to decision makers-based models. IV) Often, model-based decision makers can provide explanations; these can convey a deeper understanding of the failure to human users.	I) Lack of experiential (descriptive) knowledge of the domain - the heuristic methods used by rule-based approaches reflect a valuable class of expertise. II) Model-based reasoning usually operates at a level of detail that leads to high complexity; this is one of the main reasons experts developed heuristics in the first place. III) Unusual circumstances, for instance, bridge failures or the interaction of various failures in electronic components can change the functionality of a system in ways that are difficult to predict using an a priori model.
Model predictive controller (MPC) - Huang et.al (2017); Kazda et.al (2018); Schwenzer et.al (2021).	I) Strong modelling, learning and forecasting capabilities. II) the MPC determines the control law automatically through a model-based optimization.	I) If the drive cycle undergoes dramatic changes, the forecast will become unreliable; II) the disadvantage of MPC lies in the complexity of its algorithm, which requires more time than other controllers.
Digital Twin - Adamenko et.al (2020); Lopéz et.al (2022); Menon	I) Significant increase in transparency: the various models, which have updated information,	I) Difficulty in predicting the exact cost of the product in the initial phase of the life

et.al (2023)	facilitate the supervision of the product or system. The information is displayed in such a way that the user can see the current status directly and clearly. II) The digital twin reduces the time needed to take a product to market: simulations can be used in advance of how the product or system will behave before it is even completed, mitigating its weaknesses and improving its strengths.	cycle due to less data availability; II) It requires efficient machine learning and data analysis algorithms to manage and interpret the enormous amounts of data produced by digital twins.

The models based on artificial intelligence emphasise the investigation and analysis of vibrations caused by the weathering actions to which offshore wind turbines are subjected (mainly winds and tides). These data are captured, mostly, by sensors installed in these towers and evaluated by specialists who present these numbers through data visualisation tools in order to guide and support the decision to carry out maintenance, preventive and predictive. formulation of performance indicators related to interference (stops caused by failures or reduction of energy generation capacity that impacts production targets) and its implications for the economic viability of the wind farm.

Table 2. Advantages and disadvantages of decision analysis for maintenance optimization of offshore wind turbines

Problem -Methods - References	Advantages	Disadvantages
Simulation -Monte Carlo Simulation -Loizou & French (2012); Barthelemy (2019); Koukoura et.al (2021); Welte (2017); Faulstich et.al (2016); Scheu et.al (2017); Lei & Sandborn (2018); Pérez (2022).	I) Allows greater scope, clarity, rigor and understanding to the developer, leading to more consistent and rational decisions. II) By dehumanizing, to a certain extent, the decision-making process, it permits risk rationalization, increases consistency and exposes the multiplicity and extent of the risks involved. III) Provides insight not only into potential changes to the project to increase its profitability, but more importantly, it allows the sources of risk to be classified.	I) It is necessary to know probability distributions for each choice outcome. II) historical information is not always reliable or appropriate. III) subjective estimates. IV) continuous distribution of inputs gives rise to an infinite number of results which is unrealistic. V) it is easier to predict the capital cost item than the effective demand, therefore, more appropriate to cost-benefit issues rather than project profitability (NPV); VI) there is a correlation between the variables (economic, organizational, technical) so that when the independent variables are aggregated for risk assessment purposes, the effect of varying one may be offset by varying the other in an opposite direction. VII) the result of continuous probability can render the data inadequate, hiding causal relationships. VIII) It may direct attention to radical policies and design alternatives. IX) Demands more staff time for data collection and analysis.
Simulation -Markov Chains -Possan & Andrade (2014); Dawid et.al (2016); Boumi & Vela (2020).	I) In some cases, the use of this technique can be advantageous to explain the variability in the main parameters that have a significant influence on the degradation process (depreciation); II) The Markov Chain is a special case of a stochastic process chain with discrete parameters whose development can be carried out through a series of transitions between the scenarios of a system.	I) Significant computational costs associated with calculating the State Transition Matrix are widely reported. II) The accuracy of estimates using Markov chains is quite sensitive to data availability, making it unreliable in contexts small data sample sizes,
Simulation -Hidden Markov Model -Lau et.al (2012); Ramaki, Razoolzadegan & Jafari (2017); Zhao (2022).	I) By modelling several processes simultaneously, it allows the estimation of population-level effects, as well as more	I) It is reported that the application of the Hidden Markov Model implies infinite scenarios which makes the data integration

	efficient estimates of parameters that are common to all processes. II) These models are relatively easy to interpret. III) Allows greater flexibility in the modelling correlation structure because they relax the assumption that observations are independent given hidden scenarios	processes involved in the modelling very challenging. II) Complexity and high time consumption for training this model is also reported.
*Scheduling -Heuristic Multi-Objective Multicriteria Decision Making (HMM)**** -Hajibandeh et.al (2018); Gutjahr & Pichler (2016).	I) This model, when integrated with different components of electrical systems involved in the production of wind energy, leads to the understanding of scenarios that demand balance in the load profile.	I) The decision maker is forced to define the particular form of aggregation. II) this stochastic method takes into account the dependence between the stochastic objectives, but it has the obvious disadvantage that the aggregation function u, which should represent the decision maker's utility function to make the optimization model meaningful, must be known before computational analysis can be initiated.
*Scheduling -Preventive Maintenance Scheduling Problem with Interval Costs (PMSPIC)***** -Bangalore & Patriksson (2018); Yu et.al (2021); Figueredo et.al (2020).	I) Case studies demonstrated that the model is capable of providing optimal hybrid maintenance plans, which consider both condition and failure rates based on component age.	I) The approach performs poorly when the level of unmodeled randomness is significant.
*Scheduling -Mixed-Integer Second-Order Cone Programming (MISOPC)****** -Benson & Sağlam (2013); Ge et.al (2020).	I) Several of the examples of this model arise as reformulations or even relaxations of mixed-integer nonlinear programming problems (MINLPs), because MISOCPs can sometimes have advantages over MINLPs.	I) Convex MINLP solvers are not applicable for MISOPC, if they use linear gradient-based external approximations, since the second order cone constraints are not continuously differentiable.
Scheduling -Travelling salesman problem/Travelling Repairman Problem (TSP/TRP) ******* - Fischetti et.al (1993); Feng et.al (2021); Ouaarab et.al (2013).	I) The travelling salesman problem belongs to an important class of scheduling problems; it is easily stated and is one of the most studied problems in the literature due to its applicability to a large number of real cases. II) Minimizes the average time of departures considering the location of multiple customers	I) Heuristic methods (such as TSP) present difficulties in solving problems involving multiple nodes (cities, for instance). II) There is no efficient algorithm for the TSP and all its variants or relevant problems of the same class. The need to quickly find good (not necessarily optimal) solutions to these problems led to the development of various approximation algorithms, such as metaheuristics.
*Scheduling -Routing and Scheduling Problem of a Maintenance Fleet for Offshore Wind Farms (RSPMFOWF)******* -Dai et.al (2014).	I) Its objective, essentially, is to achieve the cheapest maintenance operation in the defined period, which involves service vessel costs and lost production.	I) It is useful for a limited period, for instance, one or several weeks in summer, when maintenance tasks can be carried out continuously. II) It does not take into account the cost of technicians on service vessels.
Stochastic optimization (Metaheuristics) -Genetic algorithm -Cabrera, Simon & Prado (2002); Zhou et.al (2020).	I) Good convergence. II) Easy and multi-objective optimization. III) Define an initial population improved by objective function approximations, making use of natural selection mechanisms and the laws of natural genetics. IV) Low computational cost.	I) It is not easy to fall into the optimum location. II) Low practicality. III) Limited to simulation
Stochastic optimization (Metaheuristics) -Ant colony algorithm -Liu et.al (2014); Zuo et.al (2015); Ren et.al (2020); Kefayat et.al (2015); Meng et.al (2012).	I) The algorithm is characterized by a high rate of convergence when preceded by the generation of "pheromones" through other techniques such as the Genetic Algorithm. II) All traces of pheromones are eventually reduced by an evaporation rate, which avoids stalling at a local minimum. III) Solves the multi-objective optimizations scheduling	I) Slow convergence, which requires strategies for the generation of pheromones. II) Precocity.

	problem.	
Stochastic optimization (Metaheuristics) -Bat algorithm - Wu & Lin (2019); Fister et.al (2014)	I) Uses simple concepts and structures. II) Presents good exploration skills. III) Possibility to be applied as a global optimizer as well as a local optimizer. IV) Deals with multimodal problems efficiently; having a very fast rate of convergence due to the ability to focus on a region of promising solutions	I) Needs an improved control strategy to switch between refinement and variation at the right time. II) Requires techniques that accelerate the convergence so that an adequate performance can be observed.
Stochastic optimization (Metaheuristics) -Adaptive large neighborhood search (ALNS) -Lazakis & Khan (2021); Sacramento et.al (2019); Bach et.al (2019); Kuhn et.al (2020).	I) Optimizes vessel routes for the distribution of technicians amongst different wind farms in various periods. II) Neighborhoods are defined by destruction and repair operators, the former removes multiple requests from the current solution, whilst the latter reinserts removed requests to arrange a new solution. A diverse set of destroy and repair operators is important to ALNS performance.	I) A strong local search can block the ALNS acceptance mechanism to overcome local optima. II) Presents limitations in terms of coordination between order picking and routing decisions, which can be difficult to manage when planning offshore wind turbine maintenance operations.
Stochastic optimization (Metaheuristics) -Non-dominated Sorting Genetic Algorithm II (NSGA - II) -Konak et.al (2006); Zhong et.al (2018).	I) Single parameter (N). II) It has been exhaustively tested. III) Efficient	I) The agglomeration distance works only in objective space.
Mixed Linear Integer *Programming/Mixed Integer Programming(MLIP/MIP) -Branch-and-check (B&C)* -Thorsteinsson (2001); Froger (2017);	I) B&C shows a clear benefit, especially with a larger number of features. II) Cuts can be calculated by solving a continuous linear model. III) It can rule out more solutions for RMPs (restricted master problem) contributing to model accuracy.	I) For situations in which the subproblem arising from the master problem is difficult, B&C can result in significantly longer execution times.
Mixed Linear Integer Programming/Mixed Integer Programming(MLIP/MIP) -Vehicle routing problem (VRP) -Goetschalckx & Jacob-Blecha (1989); Applegate et.al (2002); Liu et.al (2019); Bao et.al (2021).	I) The importance of the vehicle routing problem and all its variations and extensions are based on the significant cost of physical distribution. II) Indicates optimized routes that involve sets of customers that need to be served by vehicles located in a common depot. III) Assuming that travel time is proportional to distance travelled, and that an insignificant amount of time is spent at the customer's location, the above objective is achieved by minimizing the length of the longest route, starting from the common depot, taken by a vehicle, contrasting with the typical objective centered on minimizing the total distance travelled by the fleet.	I) Studies show computational cost disadvantages in large-scale or complex problems optimized from VRP due to combinatorial explosion. II) Heuristic methods (such as the VRP) present difficulty in solving problems involving multiple constraints.
Mixed Nonlinear Integer Programming (MILNP) -Redundancy optimization problem (ROP) -Nourelfath & Dutuit (2004); Kim & Yun (1993); Shafiee et.al (2011).	I) The design objective is achieved by choices made from elements available on the market. II) For a problem with monotonically non-decreasing constraints (which is generally true for the redundancy optimization problem), the Kohda and Inoue algorithm performs a series of selection and exchange operations within the region (i.e., a selected solution by a certain criterion is examined by subtracting a redundancy from one subsystem and adding a redundancy to another to see if this trade-off produces an improved viable solution)	I) Studies that apply it assume unlimited repair resources to solve it. II) The redundancy optimization problem is usually formulated as a nonlinear integer problem that is difficult to solve due to the considerable amount of computational effort required to find an exact optimal solution.

The current analysis of the quantitative techniques leads to the belief that some methods still lack a detailed conceptual development so that they can be consolidated as applicable and useful models. The case of Scheduling techniques shows that heuristic models, although easy to implement, constitute suboptimal modelling, indicating the most likely path to reach an interesting solution to the problem, albeit neither a definitive nor a best set of solutions.

Some techniques, albeit relevant for theoretical research, are not characterised as pertaining to the systematic groups considered in the current theoretical review, this is due to several factors, such as: i) a qualitative approach; ii) investigation focused on cyclicality in energy generation as well as its effects on the predictability of energy losses; iii) mapping of the main stakeholders; iv) development of surveys that seek to map the various decisions necessary for the elaboration of maintenance strategies; and v) associations with some complementary technique (Devriendt et.al, 2014; Shafiee, 2014;Optehostert et al., 2017; Ahsan & Pedersen, 2018; Dao et.al, 2021; Rezamand et al., 2021).

Thereby, it is relevant to elucidate some concepts that are useful in the real situations of maintenance planning and the integration of the groups of methods considered so far: i) The concept of base condition for maintenance takes into account the real situation of an asset in order to decide which maintenance should be done, presenting indicators catalogued continuously; ii) Condition-based monitoring in maintenance is focused on preventing asset failures, downtime and unnecessary practices, monitoring the health of assets to determine what maintenance needs to be completed and when (Scarf, 2007; Srinivasan & Parlikad, 2013; Ali & Abdelhadi, 2022); and iii) Maintenance health diagnostics which are used to readily identify the health status of the equipment, besides distinguishing and determining fault locations and the requirements for effective maintenance of a given device.

It presents the application of Artificial Intelligence to situations involving preventive maintenance and health diagnosis based on qualitative information (e.g., service reports) and quantitative (e. g., vibrations and sensor data). They attest to the need for inspection and issuance of work orders, as well as managerial decisions to carry out the repairs, in a situation in which it is minimally required to understand and predict the weather conditions in loco as well as predictability of the wind turbine power. Thus, it is possible to determine material and human resources that should be committed to this maintenance.

4. Conclusions

The current work describes the main quantitative techniques, their advantages, disadvantages and overall application within offshore wind energy production. However, some questions remain open due to the extensive theoretical material available about the theme, showing potential for future research on many areas; for instance, the dimensioning of the variables involved in the base condition problems and maintenance monitoring of offshore wind turbines.

Another key point for future investigations is related to the scope of the study focused on the offshore scenario; some of the considerations presented are also applicable on the onshore reality, as long as they are duly substantiated. Countries such as Brazil (in which the research was based), for instance, have extensive areas that can be used for onshore wind energy generation and, therefore, there is a substantial demand for theoretical discussion to support the decision-making process of this emerging renewable energy industry.

As for quantitative techniques, the study revealed that it is necessary to integrate methods to overcome their advantages and disadvantages in a real context. Some of these models are studied separately and their advantages and disadvantages are not properly explored, at least in theory, which limits further understanding.

During the current research, it was identified that studies on maintenance optimization of offshore wind turbines, regardless of the techniques addressed, consider the reliability curve to predict possibilities of failure in the maintenance function. From the mathematical and conceptual point of view of maintenance management, this technical direction is acceptable; although, from the point of view of comfort in the decision, there are potential limitations. The decision maker may not understand the real meaning of reliability (categorised by very clear indicators such as MTBR, MTTF and other interferences). In this sense, it is suggested that future works may consider the risk function as a frontier (and not reliability) for decision-making regarding the maintenance of offshore assets, particularly wind farms and their wind turbines; Given that it is understood that the risk function (odds) better translates the subjectivity of the decision-maker and allows for a decision-making process that is more sensitive to losses due to unscheduled stops, penalties arising from the need to man crews for maintenance at sea, and, consequently, the costs arising from these maritime operations.

As for the research limitations, it is necessary to point out, firstly, the possibility of the likelihood of bias in the review, given the subjective aspects of the analysis, even after the consultation of the extensive theoretical framework presented. Secondly, the systematisation of the models presented was also complex due to the peculiarities of each algorithm under discussion, which required a specific theoretical study to detail their particularities, which constitutes a recommendation by the authors so that future applications of these techniques are carefully carried out under the supervision of data scientists and specialists in computational mathematics.

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