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ARTICLE REVIEW

MAPPING OF ARTIFICIAL INTELLIGENCE AND ROBOTICS TECHNOLOGIES APPLIED TO OFFSHORE WIND ENERGY

MAPEAMENTO DAS TECNOLOGIAS DE INTELIGÊNCIA ARTIFICIAL E ROBÓTICA APLICADAS À ENERGIA EÓLICA OFFSHORE

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ABSTRACT

Objective: this paper aims to map the main artificial intelligence and robotics technologies that are being applied in offshore wind farms around the world, as well as highlight the possible classification of these technologies in Brazil.

Methodology/approach: the methodology of the work consists of carrying out a bibliometric study based on a Scopus database where a series of quantitative and qualitative analyses were made and, finally, the main papers were grouped into 8 central clusters found.

Originality/Relevance: The relevance of the work consists of presenting to researchers the main fields that have been studied in the applications of AI and robotics in the context of offshore wind farms and, therefore, allows new research to occur in these fields found from the clusters. In addition, the work summarizes in which stages throughout the development of offshore projects each of the clusters can be applied, thus allowing a significant advance for possible projects to be carried out in Brazil in the future.

Main conclusions: as a result of the research, eight main clusters of research carried out in the field were identified, as well as their possible classification in the Brazilian scenario in the future.

Theoretical/methodological contributions: the scientific contributions that the paper presents to researchers are diverse, among which we can list: the mapping of the main journals that have publications on the theme of AI and robotics applications in the field of offshore wind energy, the main trends in AI and robotics technologies applied to offshore wind energy around the world and, finally, the mapping of the most relevant paper on AI and robotics applications in the context of offshore wind energy, as well as their evidence in the Brazilian context.

Keywords: Artificial Intelligence, Robotics, Offshore Wind Farm, Systematic literature review

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RESUMO

Objetivo: este artigo busca mapear as principais tecnologias de inteligência artificial e robótica que estão sendo aplicadas nos parques eólicos offshore ao redor do mundo, bem como evidenciar o possível enquadramento dessas tecnologias no Brasil.
Metodologia/abordagem: a metodologia do trabalho consiste na realização de um estudo bibliométrico a partir de uma base de dados da Scopus onde foram feitas uma série de análises quantitativas e qualitativas e, por fim, os principais artigos foram agrupados em 8 clusters centrais encontrados.
Originalidade/Relevância: a relevância do trabalho consiste em apresentar aos pesquisadores os principais campos que vem sendo estudadas as aplicações de I.A e robótica no contexto das eólicas offshore e, portanto, permite com que ocorram novas pesquisas nesses campos encontrados a partir dos clusters. Além disso, o trabalho sintetiza em quais etapas ao longo do desenvolvimento dos projetos offshore cada um dos clusters pode ser aplicado permitindo desse modo um avanço significativo para possíveis projetos a serem realizados no Brasil no futuro.
Principais conclusões: como resultado da pesquisa, constatou-se oito principais clusters de pesquisas realizadas no campo, bem o possível enquadramento no cenário brasileiro no futuro.
Contribuições teóricas/metodológicas: as contribuições científicas que o artigo apresenta para os pesquisadores são diversas, dentre as quais pode-se elencar: o mapeamento das principais revistas que existem publicações sobre a temática de aplicações de I.A. e robótica no campo da energia eólica offshore, as principais tendências de tecnologias de I.A. e robótica aplicadas à energia eólica offshore ao redor do mundo e, por fim, o mapeamento dos artigos mais relevantes sobre as aplicações de I.A. e robótica no contexto das eólicas offshore além de sua evidência no contexto brasileiro.

Palavras-chave: Inteligência Artificial, Robótica, Parque Eólico Offshore

1. INTRODUCTION

Over the last decade, various renewable energy technologies have risen to great heights given the energy transition that the world's countries have experienced (Mitchel et al, 2022). In this context, offshore wind energy has been an ally in leveraging the decarbonization processes of sectors and mediating the advancement of artificial intelligence and robotics technologies in the energy sector (Rinaldi, Thies, & Johanning, 2021).

Offshore wind energy has grown exponentially over time. By 2023, the world had reached 75 GW of installed offshore wind power, but new installations are still needed to take advantage of the energy potential available on the planet, leveraging new opportunities to combat climate change (GWEC, 2024).

It is common knowledge that AI and robotics technologies have made great strides in recent years in different sectors, including the energy sector (Mitchell, 2022). In the latter, it is worth mentioning that climate change and global warming have been central to the agenda of various governments and organizations striving to reduce environmental impacts on society (Noronha et al., 2023). Therefore, for these agendas to be met, the alliance between technology and sustainable business models sees the potential of offshore wind energy as an alternative for harnessing the natural resource of wind and generating electricity on the high seas (Bailey; Brookes; Thompson, 2014).

Based on the context presented, the research question is: "What are the applications of Artificial Intelligence and Robotics for the offshore wind industry?". The work has two objectives, divided into the main objective and the secondary objective. These objectives are: (i) to map the main Artificial Intelligence and Robotics technologies that are being applied in Offshore Wind Farms around the world; and (ii) to consolidate the existing practical applications presented in the market and the literature, highlighting their framework for the national context.

The research gap that this work aims to fill is based on the work of Rinaldi, Thies and Johanning (2021) and Mitchell et al. (2022), who demonstrate that Artificial Intelligence and Robotics applications for offshore wind need to be studied in depth in different market contexts, taking into account the need to ensure cost reduction and process optimization for their implementation. In addition, the authors Rinaldi, Thies and Johanning (2021) and Noronha et al. (2023) add that it is necessary to investigate AI and robotics solutions applied to the innovation ecosystem and Industry 4.0 to ensure the scalability and development of the technology in developing markets.

The scientific contribution of the research consists of raising a series of artificial intelligence and robotic applications for offshore wind farms, identifying eight clusters that are represented in the theoretical framework of the work. These applications ratify that A.I. and Robotics can assist the development of offshore wind turbines, accelerating their development process in the short and medium term, reducing costs and serving as support for the technology to become increasingly competitive.

The practical and managerial contribution, on the other hand, is represented by the kaleidoscope "Applications of artificial intelligence throughout the development phases of an offshore wind project" (Figure 4), where the framework of the various A.I. applications that can be used from initial wind studies to the park decommissioning stage is evident.

2. THEORETICAL REFERENCE

The fundamentals here presented were taken from the scientific areas of Engineering, Information Technology and Robotics, in order to illustrate the main guiding references for meeting the research objective (Winston, 1984).

2.1 Artificial Intelligence and Robotics

Artificial Intelligence is presented as a field of study in the areas of computer science and information technology (Winston, 1984), and is conceptually the extension of human intelligence through the use of systems and computers for learning, adaptation and self-correction. According to seminal research (Vinuesa et al., 2020; Vijayalakshmi et al., 2023), AI can help combat climate change by providing resources that generate greater efficiency in the process, avoid gas emissions into the atmosphere, create a less polluting production chain and even produce renewable energy.

From the same perspective, robotics is the technological segment that encompasses the use of mechanics, electronics and computing (Campos, 2019). The interaction of machines and humans are fundamental factor for the field of study of robotics, considering issues of automatic mechanics, controlled or automated by integrated circuits. Robotic solutions and AI support the automation and technological industrialization of sectoral segments of the economy (e.g. Infrastructure, Energy, Sanitation and Transport), accelerating the ability to scale solutions to maximize the productivity and efficiency of processes and projects.

2.1.1 Wind Predictability

For offshore wind farms to be more scalable, one of the topics involving Artificial Intelligence (AI) that are used around the world is *Wind predictability* (Paula et al., 2020 and Sacie et. Al., 2022). AI technologies in this environment bring greater security for the operation of the electricity system, for possible maintenance of the offshore production chain, and energy marketing, as well as providing an increase in efficiency throughout the wind farm's energy generation (Paula et al., 2023).

Wind predictability is an area that aims to measure the stochastic variable of wind over various horizons to obtain the best way of dealing with the intermittency of the wind source, as well as ensuring the best control of the asset (Soman et al., 2010). Wind predictability techniques are used to ensure safer power dispatch and adequate support for the Operation and Maintenance activities of offshore wind farms (Sacie et al., 2022).

In this sense, there are several works and methodologies in the literature that use so-called Machine Learning models ("*Machine Learning*[1]") and Deep Learning ("*Deep Learning*[2]") to carry out wind predictability over different time horizons (Lawam et al., 2014). These models usually use various meteorological variables, such as air temperature, relative humidity, and wind direction, among others, to predict the wind and, consequently, the energy generation of the offshore wind farm (Paula et al., 2023). Another possibility is to use only the wind variable to predict over a short time horizon (30 minutes to 6 hours), as discussed in (Soman et al., 2010).

Several papers in the literature have stated that there is no ideal model for wind forecasting (Paula et al., 2020; Neshat et al., 2021; Balluff et al., 2015). Therefore, the use of these technologies will depend on their applicability, the location of the offshore wind farm, the behavior of the wind stochastic variable and other variables that may influence the predictability.

[1] *Machine Learning*: is a field of A.I. that focus to develop statistical algorithms that can learn from data and perform tasks without a specific goal. A more in-depth look at Machine Learning is also described in section 2.2.8.

[2] *Deep Learning*: is a subset of *Machine Learning* that uses methods based on artificial neural networks for simulations.

2.1.2 Preventive maintenance

Another field that has come to the fore when it comes to AI and Robotics technologies applied to the offshore wind sector is the various techniques for Preventive Maintenance of developments, aimed at reducing Operation and Maintenance (O&M) costs and maximizing the potential use of the energy resource of the farms (Ren et al., 2021).

Preventive Maintenance is the activity of continuous monitoring to identify in advance the need for possible repairs and maintenance of parks (Santos et al., 2015). This type of maintenance usually uses a variety of data, such as temperature, system vibration, pressure and electric current, and allows corporations to act in advance to avoid possible losses (Rinaldi et al., 2021).

The combination of AI and robotics for the preventive maintenance of offshore wind farms has been used to ensure that the technologies help the longevity of the projects, using drones, telecommunication systems and operation centers that provide real-time data to increase their efficiency in offshore energy production (Pencelli et al., 2024; Leonard et al., 2016; Yang et al., 2022). Mitchell et al. (2022) present some of these preventive maintenance technologies that can be used throughout the operation of offshore wind farms. These include: *Crawlers*, which are drones with technology for tracking, inspecting and monitoring large infrastructure works (Yang et al., 2022); *Autonomous Underwater Vehicle* (UAV) which are autonomous underwater vehicles designed to inspect and monitor the ocean conditions of offshore wind farms (Leonard et al., 2016) and the *Quadruped,* which is a four-legged robot used to carry out real-time inspections of offshore wind farms (Pencelli et al., 2024).

2.1.3 Offshore wind turbine configuration

Turbine Configuration is understood as an area that focuses on to improve the performance of wind farms with the best arrangement of turbines to make effective use of the energy resource of a given region. Among the various fronts on which AI can act in this environment, the following stand out: real-time blade orientation and design modelling (Ding et al., 2024), project layout optimization (Silva et al., 2010) and control of the asset in operation to identify patterns throughout the commercial operation of the farms (Song et al., 2024).

Blade design and orientation is an area that aims to develop the blades of offshore wind turbines to obtain the best use of the energy resource and the useful life of the equipment. The use of AI in blade design aims to achieve the best degree of structural and aerodynamic efficiency for wind turbines. Thus, the best design selected by the AI system minimizes the weight of the blades on the tower structures and allows the real-time performance of offshore wind turbines to be increased (Ding et al., 2024).

Another means applied in this field is project layout optimization via AI systems. In this context, AI systems are used to assist in mathematical modelling to simulate the performance of offshore wind farms, taking into account various variables, including fluid dynamics (wind) and annual/temporal energy production (Silva et. al., 2010).

The concept of asset control is based on monitoring the conglomerate or unit of offshore wind turbines. This control takes the form of data collection, helping to dispatch energy production (Song et al., 2024).

2.1.4 Environmental monitoring

AI systems have helped in initiatives to better conserve marine life, birds and ocean conditions. In the case of marine life, remote sensing systems are used to monitor environmental conditions (Ditria et al., 2022). Linked to these systems, there is a large storage of data in the cloud for the subsequent use of AI and sampling techniques for better environmental control of the site (Schneider et al., 2023). In this sense, advanced AI techniques such as *IForest* are being used to detect anomalies and non-compliant behavior common in the oceans, enabling the entrepreneur to take early action (Ingram et al., 2024).

As far as bird monitoring is concerned, various AI systems have been widely used to detect birds using different monitoring systems (Salkanovic et al., 2020). In Niemi et al. (2020), for example, a deep learning technique (*Deep Learning*) is applied in which a radar provides the coordinates of the birds and a *convolutional neural network* is trained to detect the species of the bird, as well as its movement.

All of these systems allow for better control of environmental life in offshore wind farms. However, several authors in the literature have found that there is no single technique that can be applied to all wind farms (Kou et al., 2022; Chan et al., 2013). For this reason, it is necessary to carry out an in-depth study, taking into account the location where the plants will be installed to preserve environmental aspects.

2.1.5 Smart grids

Various AI techniques have been used for smart grids to make it possible to: (i) predict the consumption needed by the population; (ii) predict the power dispatch of offshore wind farms on the electricity grid; and (iii) enable more accurate mathematical modelling for better optimization of smart grids. Concerning consumption prediction, the work of Cicek et al. (2015) addresses aspects (e.g. uncertainty of renewable generation, energy use, production schedule) that need to be managed for a more efficient demand response program by smart grids.

About power predictability, various AI techniques can be used to provide better control of the operation of offshore wind farms. In this way, various machine learning algorithms can be used for better power predictability over different time horizons to provide better planning by smart grids (Archer et al., 2017).

From the point of view of the mathematical modelling of smart grids, the initial development of a model based on the IEC 61400-25[3] standard standards for the communication of smart grids with offshore wind farms (Nguyen et al., 2012). The researcher ALI et al. 2021, demonstrate through a comparative study how mathematical solutions and AI help to achieve better control of the voltage and frequency stability of power grids integrated with offshore plants.

2.1.6 Offshore Remote sensing of offshore areas

The use of sensors makes it possible to obtain various data from wind turbine components, such as the temperature and vibrations of the entire framework of offshore wind farms as a whole (Zhou et al., 2022). The authors Ahuir-Torres et al. (2019), present a real-time remote sensing technology that allows detailed information to be obtained on the corrosion process of offshore wind turbine structures.

About the life cycle of equipment, different IoT technologies have been used. The literature shows how IoT systems are used to evaluate components in the offshore wind industry in real-time using a platform developed to evaluate the life cycle of various elements that make up offshore wind farms. Some research has used the classification methodology known as k-means[4] to create groups with information on the structural health of various turbines and verify the possibility of extending the useful life of offshore wind farm structures (Yeter et al., 2022).

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[3] IEC 61400-25: it is a standard that deals with the necessary information that entrepreneurs need to submit for the real-time monitoring and control of wind farms.

[4] *K-means*: it is a method that aims to partition a number "n" of observations into "k" clusters, which observation belongs to a cluster with the closest mean.

2.1.7 Autonomous robotics systems

The automation of systems employing robotics is defined in the literature as the use of robots and other relevant automated technologies to perform tasks that in the ordinary environment are carried out by human beings (Parsons et al., 1982). In this sense, autonomous robotic systems are considered complex aggregations (robots) that are subject to changes in behavior, based on events and situations during their operating process.

In the offshore wind sector, these systems have been listed in various studies in the literature that demonstrate the importance and applicability of autonomous robotics for wind farm control and maintenance activities (Khalid et al., 2022). Among the various technologies that have emerged within the offshore wind scenario, the following stand out: *Autonomous Surface Vehicle* (ASV), *Autonomous Underwater Vehicle* (AUV), *Quadruped Robot, Unmanned Aerial Vehicle* (UAV) and *Climbing Robot* (Michell et al., 2022). The *Autonomous Surface Vehicle* (ASV) are autonomous robots that have the ability to monitor on the high seas possible suspicious vessels that could invade and damage the structures of offshore parks (GU et al., 2024). The *Autonomous Underwater Vehicle* (AUV) are autonomous robots used to carry out marine inspections and measurements to ensure safety for offshore wind farms (Michell et al., 2022).

The *Quadrupet Robot* are autonomous four-legged robots that can be used for various purposes in the context of offshore wind farms (Michell et al., 2022). The *Unmanned Aerial Vehicle* (UAV) are drones that are remotely piloted in the regions of offshore wind farms and can collect relevant information for detecting possible faults and defects in wind turbines. Finally, *the Climbing Robot* are robot used to climb offshore wind turbines and inspect the blades using advanced X-ray tomography.

2.1.8 Identifying standards for the layout of offshore wind farms

The main objective of creating project layouts in the offshore wind sector is to discover the best position for the wind turbines so that the energy resources available in coastal regions can be used to maximum effect (Hou et al., 2019). According to the National Electric Energy Agency (ANEEL), the layout[5] of a wind farm is defined as the polygon that encompasses all the wind turbines of the generating plant.

From this perspective, A.I. applications can be used to optimize the layout of projects and support the final choice of the arrangement to be built. Among the various methodologies that can be applied are: (a) gradient-based heuristic algorithms (Kokash et al., 2005); (b) discrete genetic algorithms (Pillai et al., 2016); and (c) various Machine Learning techniques (Fischetti et al., 2019).

A heuristic algorithm is an approach that attempts to find several solutions to the same problem to find the best optimization for a given problem. Gradient-based heuristic algorithms has mathematically modelled to find the best locations for allocating wind turbines to avoid the wake effect. This methodology allows for the discovery of the best locations for the inclusion of new wind turbines during the commercial operation of the offshore wind farm and therefore maximizes the use of the available energy resource (Kokash et al., 2005).

Discrete genetic algorithms are solutions designed to solve problems based on discrete values, i.e. values that are not continuous. The mathematical approach used aims to discover the positions the turbines can occupy and optimize them to maximize performance. It also aims the best positioning for the electricity grid that will interconnect the offshore wind farm's generating units (Pillai et al., 2016).

[5] Available at:
https://sigel.aneel.gov.br/portal/home/group.html?id=6e891539d9604d3486314ee4dd9300ae#overview

Machine Learning (ML) is a sub-field of A.I. that use data to leverage the potential for more innovative, efficient and sustainable solutions. ML techniques can be combined with discrete algorithms to find the best layout for offshore wind farms. When evaluating offshore wind farm layouts, ML approaches complement discrete algorithms so that the data can be analyzed in greater depth and the best set can be chosen from among those found by applying genetic algorithms (Fischetti et al., 2019).

3. METHOD

The work's methodology consists of a bibliometric study and mapping of papers on the subject within the field of artificial intelligence and robotics applied to Offshore Wind Energy. This method is a systematic way of collecting, critically evaluating, integrating, and presenting findings from multiple research studies on a research question or topic of interest, providing a way to assess the level of quality and magnitude of existing evidence on an issue or topic of interest (Pati and Lorusso, 2018). A systematic review is a review planned to answer a specific question, using data from the literature on a given topic as a source and with methodological rigor (Rother, 2007).

To do this, a Scopus database was used with the criteria presented in 2.3.2 to identify various scientific papers on the subject studied, and Python and Excel were then used to generate graphs and explore the main results achieved. Finally, the main papers were grouped into the eight main clusters identified. The work pipeline is shown in Figure 1.

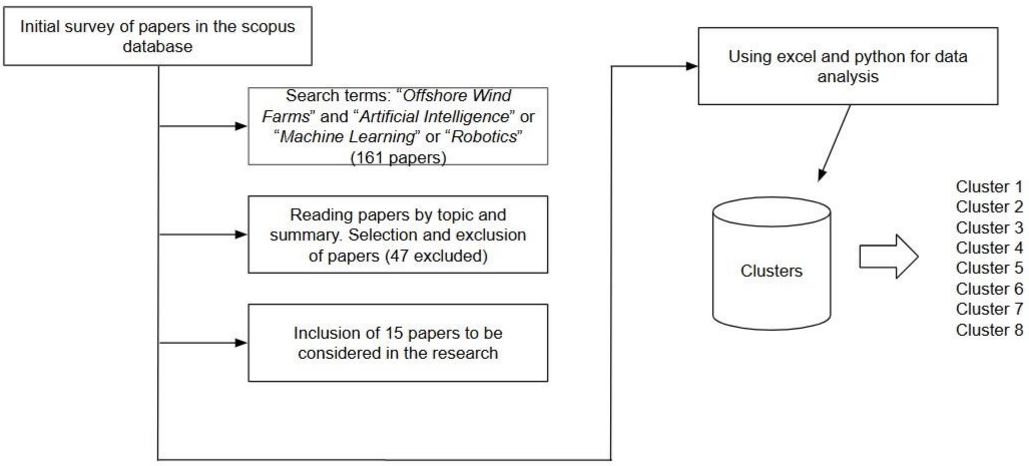


Figure 1. Work Pipeline
Source: Authors

3.1 Data Collection, Extraction and Processing

The methodology of the paper consists of a systematic review of the literature from a Scopus database, in which the following filters were used for collection: "*Offshore Wind Farms*" and "*Artificial Intelligence*" or "*Machine Learning*" or "*Robotics*".

The database of 161 papers was extracted in Excel format and papers from 2009 to 2024 were identified. Next, two criteria were used to exclude some papers from the database: (i) papers that were not related to the subject under study; and (ii) papers that were not published in scientific journals (e.g. book chapters, congresses and conferences).

Thus, 47 papers meeting these criteria were excluded from the original database. At this point, it is worth noting that many of the papers did not deal with the filters carried out simultaneously according to the logical constraints imposed and, for this reason, this exclusion stage was necessary.

Subsequently, 15 papers were included, which were highly relevant to the subject under the study, where the Scopus database ended up not filtering out these materials. The criteria for including the papers took into account that the research carried out aims to consolidate A.I. and Robotics technologies within the context of Offshore Wind Energy, which is the general objective of the research. Therefore, the following criteria were used for inclusion: (i) papers dealing exclusively with the application of A.I. and Robotics technologies within the context of Offshore Wind Energy.

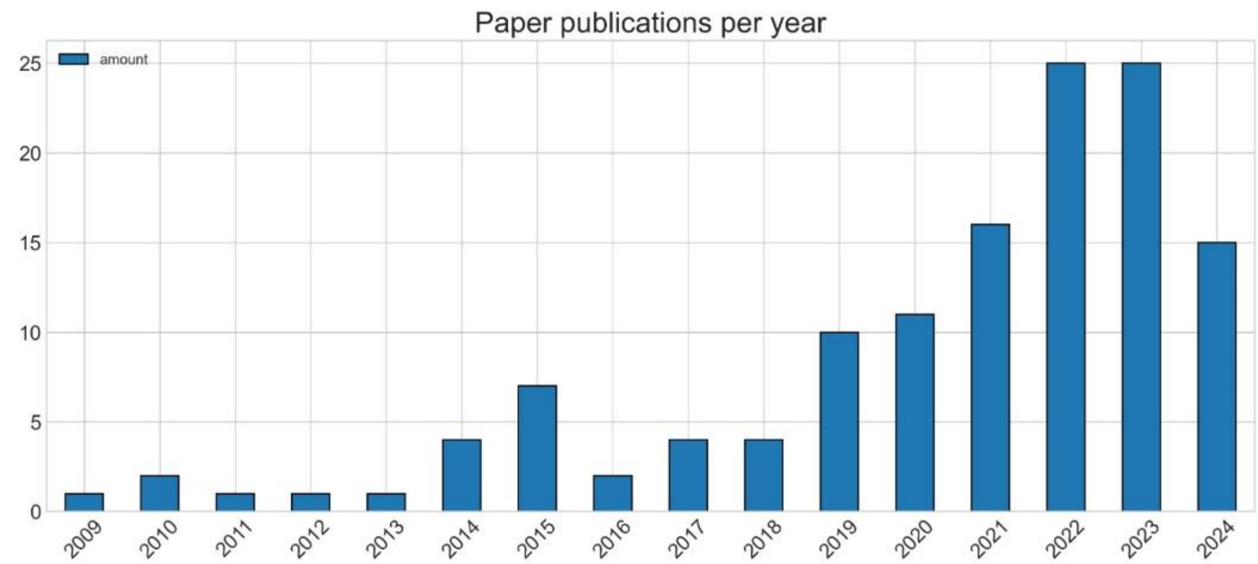
Finally, a data analysis stage was carried out so that we can have an overview of the entire mapping of published works, with the following analyses carried out: (i) analysis of citations and number of publications per year; (ii) ranking of the 5 most cited papers; (iii) ranking of the 5 journals with the most publications and respective citations; (iv) ranking of the 5 most cited authors; (v) word cloud with the subjects most addressed in the paper titles; and (vi) clusters with the main papers identified and their respective technology;

4. RESULTS AND DISCUSSIONS

This section presents the results and discussions obtained from the data analysis stage of the research. This statistical study of publications is relevant because it allows researchers to see which fields are most interesting for research and what could be studied in the future.

4.1 Data Analysis

Firstly, an analysis was made of citations and the number of publications in recent years. Figure 2 shows the two graphs obtained using the *Searborn* library of *Python* to generate the images. In figure 2, it is clear that publications of work related to A.I. and robotics applied to Offshore Wind Energy have been increasing, especially in recent years (2019 to 2023).



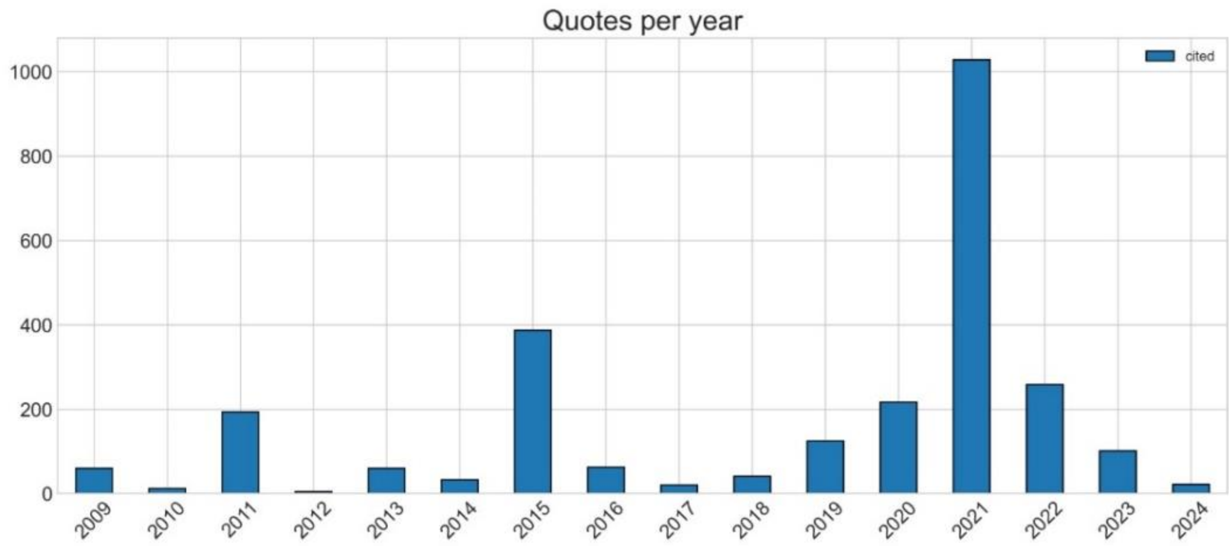


Figure 2. Papers publications per year and citations per year

Source: Authors

In this sense, it is also important to note a significant increase in 2015, when seven papers were published. These seven papers specifically sought to carry out research related to the optimization of offshore wind farm turbines, as well as related to the predictability of energy and power that the farms could generate in the future. It is believed that this research may have been the "trigger" for the generation of other works in subsequent years and for the growth of offshore wind capacity around the world. In terms of the number of citations per year, it is clear that the papers published in 2021 were highly relevant, with 39.2% of the citations in the database. In that year, research reviews were carried out, as well as various studies related to the fields covered in the theoretical framework (section 2.1) of the paper.

It is also worth noting the number of relevant citations in 2011 and 2015. In 2011, the work of (Gonzalez-Longatt et al., 2011) was extremely important in the development of a solution for the better integration of offshore wind farms into electricity grids and, consequently, ended up being widely cited by related research in subsequent years. In 2015, the massive number of citations was also due to the development of solutions that served as the basis for related research carried out in recent years on: wind predictability, turbine optimization and preventive maintenance of offshore wind farms.

The second analysis was of the 5 most cited papers in the database. Table 1 shows the results obtained.

Author (year)	Papers title	Number of citations	Theoretical Reference
Ren et al., 2021	*Offshore wind turbine operations and maintenance: A state-of-the-art review*	393	Preventive maintenance (section 2.2.2)
Gonzalez-Longatt et al., 2011	*Optimal electric network design for a large offshore wind farm based on a modified genetic algorithm approach*	193	Smart grids (section 2.2.5)
Hou et al., 2015	*Optimized placement of wind turbines in large-scale offshore wind farm using particle swarm optimization algorithm*	183	Offshore wind turbine configuration (section 2.2.3) and Identifying standards for the layout of offshore wind farms (section 2.2.8)
Neshat et al., 2021	*A deep learning-based evolutionary model for short-term wind speed forecasting: A case study of the Lillgrund offshore wind farm*	145	Wind Predictability (section 2.2.1)
Shafiee et al., 2021	*Unmanned aerial drones for inspection of offshore wind turbines: A mission-critical failure analysis*	95	Environmental Monitoring (section 2.2.4), Remote sensing of offshore areas (section 2.2.5) e Autonomous robotics systems (section 2.2.7)

Table 1 - Ranking of the 5 most cited papers.
Source: Authors

The 5 most cited papers correspond to 38.5% of database citations and were therefore highly relevant given the total number of 129 a papers in the database. It can be seen that in this ranking of five papers, three of them are from the year 2021, which was the year in which there were the most publications, see Figure 3.

The content of these five papers deals with preventive maintenance of offshore wind farms (section 2.2.2), smart grids (section 2.2.5), identification of standards for the layout of offshore wind farms and configuration of offshore wind turbines (sections 2.2.8 and 2.2.3), wind predictability (section 2.2.1) and environmental monitoring, autonomous robotic systems and remote sensing of offshore areas (sections 2.2.4, 2.2.7 and 2.2.6). In other words, all the topics covered in the theoretical framework have a direct correlation with the five most cited papers in the database studied.

Another relevant analysis is the five journals with the most publications between 2009 and 2024. See Table 2. The journals in which most papers have been published account for 12.9% of the number of citations in the database. This means that publishing papers in these journals does not necessarily guarantee more citations. However, it is important to take into account the fact that the largest number of publications in these journals have been carried out in recent years (from 2021 to 2024), so perhaps this is why they do not have as many citations when compared to the overall number of citations in the database.

Magazine	Quantity	Number of citations
Ocean Engineering	5	23
Renewable Energy	5	110
Wind Energy	4	48
Energy	4	112
Applied Sciences (Switzerland)	3	44

Table 2 - Ranking of the five journals with the most publications and number of citations.
Source: Authors

Another important approach is to look at the authors who have the most citations, i.e. the individuals who have the most relevant work in the field base de dados. Table 3 lists the five authors with the highest number of citations.

Autor (ano)	Número de citações	Número de artigos
REN et al., 2021	393	1
GONZALEZ-LONGATT et al., 2011	193	1
HOU et al., 2015	183	1
NESHAT et al., 2021	145	1
SHAFIEE et al., 2021	95	1

Table 3 - Ranking of the five most cited authors
Source: Authors

The most cited authors account for 38.5% of the citations in the database. Coincidentally, each of the most cited authors has only published one paper on the subject within the database evaluated and, for this reason, this analysis shows the synergy between the number of citations in Table 3 and Table 1.

In addition, a word cloud was created using Python's *WordCloud* library to identify the main themes covered by the paper. In this sense, it is important to note that words that are of little relevance to this analysis were excluded, namely: papers, prepositions, conjunctions, pronouns and auxiliary verbs. Figure 3 shows the result obtained.

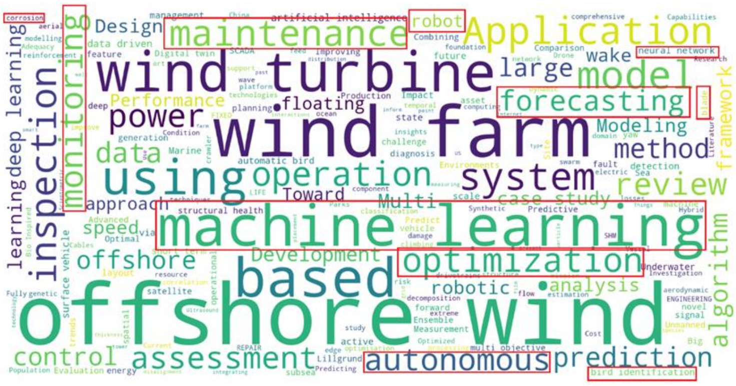


Figure 3 - Word cloud with papers titles.
Source: Authors

Figure 3 shows that most of the papers have words that directly correlate with the approaches explained in section 2.1 of the paper. The terms circled in red validate that the database presented all the applications of A.I. and robotics within the offshore wind study area.Table 4 shows the circled term and in which section covered in the theoretical framework the framed term applies.

Terms circled in red	Papers section	Cluster
Corrosion	Section 2.2.2	Preventive maintenance of offshore wind farms
Monitoring	Section 2.2.3	Offshore wind turbine configuration
Maintenence	Section 2.2.2	Preventive maintenance of offshore wind farms
Robot	Section 2.2.7	Autonomous robotic systems
Neural Network	Seção 2.2.1, 2.2.4, 2.2.5	Wind Forecasting; Environmental Monitoring and Smart Grids
Forecasting	Seção 2.2.1	Wind forecasting
Blade	Seção 2.2.3	Offshore wind turbine configuration
Machine Learning	Seção 2.2.1, 2.2.5, 2.2.8	Wind forecasting; Smart grids and Identifying standards for the layout of offshore wind farms
Optimization	Seção 2.2.5	Smart grids
Autonomous	Seção 2.2.2 e 2.2.7	Preventive maintenance of offshore wind farms and autonomous robotic systems
Bird Identification	Seção 2.2.4 e 2.2.6	Environmental monitoring and remote sensing of offshore areas

Table 4 – Word Cloud Terms and Applicability
Source: Authors

As can be seen, each term circled in the word cloud fits into some category of the clusters made in section 2.1 of the paper and therefore validates the subdivision made in the theoretical framework stage of the paper. In addition, to answer the general research question: "What are the Artificial Intelligence and Robotics applications for the offshore wind industry?", Table 5 was created, which portrays the most relevant papers in the database, the main technology of each field, the author (year) and the due justification for the cluster. The clusters refer to the group of topics that are related during the analysis of all the papers contained in the collected database.

Cluster	Main Technology	Authors (Year)	Application Justification
Wind forecasting	Deep Artificial Neural Networks ("*Deep Learning Models*")	Neshat et al., 2021 Balluff et al., 2015 Lawam et al., 2014 Sacie et al., 2022	The use of deep learning solutions is important for power dispatch control
Preventive maintenance of offshore wind farms	Autonomous robots	Ren et al., 2021 Santos et al., 2015 Rinaldi et al., 2021 Yang et al., 2022	Use of robots for better control of Operation and Maintenance (O&M) activities at offshore wind farms
Offshore wind turbine configuration	Optimization algorithm based on the collective of swarms *("Particle swarm optimization algorithm")*	Hou et al., 2015 Ding et al., 2024 Song et al., 2024 Silva et. al., 2010	Algorithm that uses wind direction variation to check the best configuration for wind turbines
Environmental monitoring	Convolutional Neural Networks ("*Convolutional Neural Networks*")	Niemi et al., 2018 Schneider et al., 2023 Salkanovic et al., 2020 Ingram et al., 2024	Algorithm used to identify the route of birds and their species
Smart grids	Modified genetic algorithm	Gonzalez-Longatt et al., 2011 Archer et al., 2017 Nguyen et al., 2012	Algorithm created to discover the best electrical grid configuration for offshore wind farms
Remote sensing of offshore areas	Unmanned aerial vehicles *()*	Shafiee et al., 2021 Zhou et al., 2022 Yeter et al., 2022	Use of unmanned aerial vehicles to collect data for remote sensing of offshore areas
Autonomous robotics systems	Autonomous surface vehicles (*Autonomous Surface Vehicle*)	Campos D.F. et al., 2021 Parsons et al., 1982 Khalid et al., 2022 Michell et al., 2022	Use of autonomous surface vehicles to control the maritime environment of offshore wind farm areas
Identifying patterns for the layout of offshore wind farms	Machine learning models ("*Machine Learning Models*")	Yang K. et al., 2023 Fischetti et al., 2019 Kokash et al., 2005	Using machine learning algorithms to optimize the layout of offshore wind farms

Hou et al., 2019

Table 5 – Mapping of the main papers in the database, their respective technology and application

Source: Authors

The selection of clusters is based on the theoretical framework (section 2.1) and is based exclusively on the applications observed throughout the papers in the database and also on the main terms observed in the word cloud. The clusters are divided into: (a) *Wind forecasting*; (b) *Preventive maintenance of offshore wind farms*; (c) *Configuration of offshore wind turbines*; (d) *Environmental monitoring*; (e) *Smart power grids*; (f) *Remote sensing of offshore areas*; (g) *Systems. autonomous robotics; and* (h) *Identification of standards for the layout of offshore wind farms.*

Finally, the figure 4 was drawn up, which represents the stages in the development of offshore wind farms around the world, as well as the applications of A.I. and robotics that can be applied to the national scenario. The stages are subdivided into Project (initial stages of the study to set up the offshore wind farm); Installation and Commissioning; Operation and Maintenance; and Decommissioning.

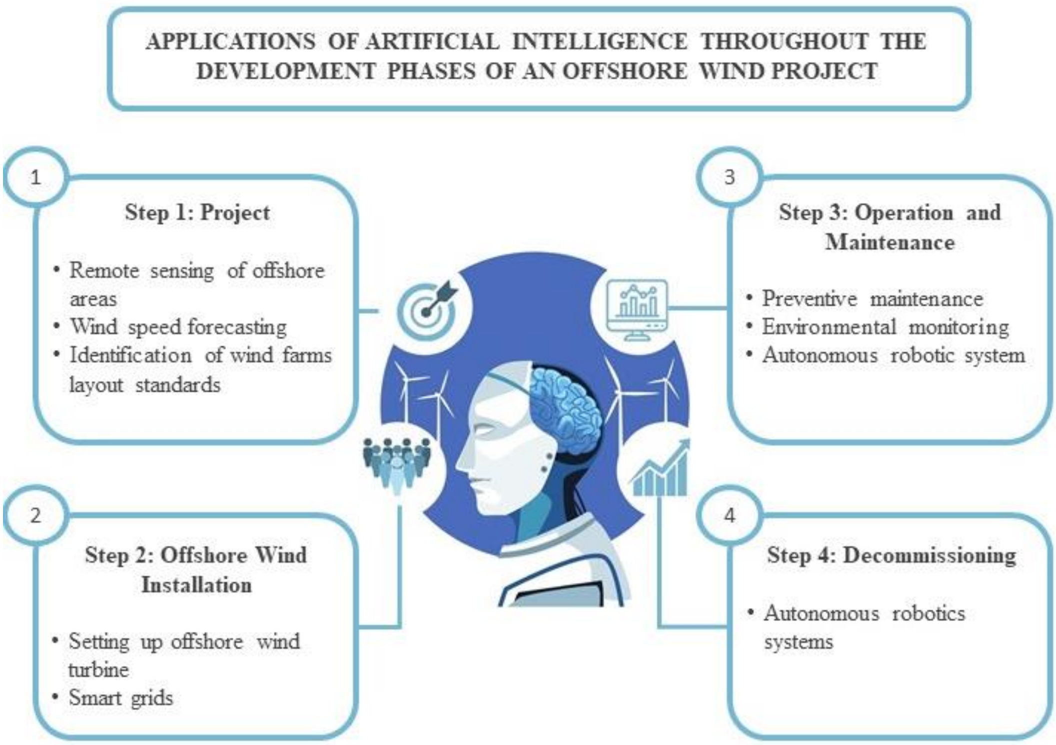


Figure 4 - Stages in the development of offshore wind farms

Source: Authors

As can be seen in Figure 4, it is possible to observe that all the clusters obtained in Table 5 have a framework throughout the development stages of offshore wind farms. Therefore, when the first offshore wind farms begin to be implemented in Brazil, it will be fully possible to use the technologies portrayed in the work to boost the production chain and growth of the source in the country for subsequent years, as discussed by (Noronha et al., 2021).

5. FINAL CONSIDERATIONS

In the papers presented, a systematic analysis of the literature was carried out using a Scopus database containing 161 papers on applications of A.I. and robotics in the offshore wind sector. According to the results presented after cleaning and processing the data (see section 2.4.1), it can be seen that the topic is growing, especially from 2021 to the current year, with a tendency to continue to be researched more and more in the coming years.

The general objective of this work was to map the main A.I. and robotics technology being applied in the context of offshore wind farms. This objective was met through Figure 3 and Tables 4 and 5, where the main terms contained in the titles of the papers were observed, as well as separating the main clusters found according to the applications observed throughout the database and in synergy with the paper's theoretical framework (section 2.1). The specific objective was met based on Figure 4 shows the clusters found at each stage of the construction of offshore wind farms. In other words, in future applications in Brazil, it will be possible to use the A.I. and robotics technologies mapped in each of the stages presented.

Relating the main research question "*What are the applications of Artificial Intelligence and Robotics for the offshore wind industry*", the justifications for the applications have been expressly answered in Table 5 by summarizing the most relevant papers contained in the database according to the criteria presented in section 2.4.1.

The paper's scientific contributions to researchers are diverse, including: mapping the main journals that have published on the subject of A.I. and robotics applications in the field of offshore wind energy; the main trends in A.I. and robotics technologies applied to offshore wind energy around the world; and mapping the most relevant papers on A.I. and robotics applications in the context of offshore wind energy;

From the point of view of the energy market, it was possible to objectively summarize the main A.I. and robotics technologies that can be applied in each of the stages throughout the development of offshore wind projects, as shown in Figure 4. Finally, future suggestions for work include updating the database with new papers published in the coming years, and carrying out a systematic analysis of specific literature on each of the main technologies identified in Table 5.

5.1 Future Studies and Limitations

Additionally, it is recommended that future researches could explore the applications for different contexts like other emerging markets or even technologies that go beyond offshore wind, because some of the applications reviewed in this work can be used for other ocean technologies (e.g. hydrogen). Furthermore, it is important to highlight the researchers stress out the future studies suggestions of the main cited papers in the literature and presented in this work. These suggestions are summarized on Appendix 1.

#nº	Author (year)	Research Gaps
1	Ren et al. (2021)	• **Key Research Gaps in Offshore Wind Turbine O&M**: Several areas need improvement to optimize O&M in offshore wind settings. • **Algorithmic Limitations:** Existing algorithms face constraints such as lack of online updates, challenges with vessel reliability, limited vessel interaction and cooperation, issues with extreme weather, and other operational constraints, limiting flexibility and efficiency. • **Data Accessibility and Quality:** There is limited access to high-quality, real-time data, which is essential for developing predictive maintenance strategies and AI integration. • **Cost and Resource Allocation:** There is a need for more effective strategies to manage the high costs and logistical challenges of offshore maintenance, especially in remote locations.
2	Gonzalez-Longatt et al. (2011)	▪ **Incorporation of Full Cost Factors**: The optimization model should include comprehensive cost factors for transformer substations, high-voltage (HV) integration systems, and transmission systems, covering equipment, installation, operation, and maintenance. ▪ **Enhanced Cost Modeling**: Improving cost models is essential for achieving more precise optimization in large offshore wind farms.
3	Hou et al. (2015)	▪ **Incorporating Reserve Dispatch**: Address the reserve dispatch requirements for wind farms operating in power regulation mode rather than relying solely on the Maximum Power Point Tracking (MPPT) control strategy.
4	Neshat et al. (2021)	▪ **Advancing Metaheuristic Algorithms**: Conduct further research to develop more effective metaheuristic algorithms and advanced methods to enhance wind speed forecasting model performance.
5	Shafiee et al. (2021)	▪ **Enhancing RAM Analysis for Drones**: Further research is needed to improve the Reliability, Availability, and Maintainability (RAM) analysis of unmanned aerial drones, addressing limitations like restricted access to failure data, the impact of uncertainty in Failure Mode and Effects Analysis (FMEA) assessments (potentially using fuzzy set theory), and the need to weigh the relative importance of Occurrence, Severity, and Detection criteria. Additionally, the risk prioritization method used in this study could be extended to other autonomous inspection systems, such as Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs).
6	Chatterjee et al. (2021)	▪ Explore **predictive and autonomous O&M scheduling techniques** in the wind industry, with an emphasis on interpretability and transparency in AI models. ▪ Investigate methods to overcome challenges in obtaining **SCADA data** from wind turbines, particularly for enhancing failure prediction in Condition-Based Maintenance (CBM).
7	Ali et al.(2021)	▪ Conduct studies to assess the **impact of improved planning processes, advanced forecasting methods, and investments** in both existing and emerging technologies.
8	Antoniadou et al. (2015)	• Develop more efficient monitoring approaches to enhance early detection of structural failures in offshore wind turbines, considering the extreme marine environment and the need to reduce operational costs.
9	Papatheou et al.(2015)	• Integrate **additional features beyond the power curve** to enhance performance and condition monitoring of wind turbines. • Conduct a comprehensive **analysis of recorded error statuses** to improve fault detection and classification in turbines.
10	Yu et al. (2020)	• Incorporate environmental data such as temperature, humidity, and pressure to refine the network structure and enhance input data quality for **improved offshore wind power prediction.** Additionally, explore the potential of **Superposition Graph Neural Network (SGNN)** for other irregular point cloud predictions. • Develop an efficient **graph construction method to boost neural network efficiency** in spatial information extraction, aiming for a viable approach without relying heavily on advanced machine learning or computer graphics theories.

Appendix 1 – Future studies suggestions
Source: Authors

The limitations of this paper are based on two main points: (a) methodology; and (b) context. First, the methodology criteria adopted during the process of selecting papers can consider more than one base of articles like Web Of Science, applying filters that can collaborate of the entire scientific overview, including texts related to books or book chapters. This could enhance the potential to understand new different applications or technologies. Second, regarding to the context, the future research could focus on the specific contexts, as mentioned before, trying to understand how this applications will affect or not the speed level of the markets in different context, as an example emerging economies or markets that are discussing the regulatory frameworks.

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7. REFERENCES

Ahuir-Torres, J. I., Souto, R. M., Lozano, R., de la Fuente, I. M., & González-García, Y. (2019). Benchmarking parameters for remote electrochemical corrosion detection and monitoring of offshore wind turbine structures. *Wind Energy, 22*(6), 857-876. https://doi.org/10.1002/we.2362

Antoniadou, I., Dervilis, N., Papatheou, E., Maguire, A. E., & Worden, K. (2015). Aspects of structural health and condition monitoring of offshore wind turbines. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*. https://doi.org/10.1098/rsta.2014.0075

Ali, S. W., Wang, L., Wu, X., Rehman, M. H., & Rashid, M. (2021). Offshore wind farm-grid integration: A review on infrastructure, challenges, and grid solutions. *IEEE Access*, *9*, 102811-102827. https://doi.org/10.1109/ACCESS.2021.3099302

Archer, C. L., Delle Monache, L., Rife, D. L., & Lundquist, J. K. (2017). The challenge of integrating offshore wind power in the US electric grid. Part I: Wind forecast error. *Renewable Energy, 103*, 346-360. https://doi.org/10.1016/j.renene.2016.11.047

Balluff, S., Bendfeld, J., & Krauter, S. (2015). Short term wind and energy prediction for offshore wind farms using neural networks. In *2015 International Conference on Renewable Energy Research and Applications (ICRERA)* (pp. 379–382). IEEE. https://doi.org/10.1109/ICRERA.2015.7418472

Chan, H.-C., Chen, C.-S., & Hsieh, C.-Y. (2013). Preliminary plan of underwater environmental monitoring in the offshore wind farm in the western sea of Taiwan. In *2013 MTS/IEEE OCEANS-Bergen* (pp. 1-4). IEEE. https://doi.org/10.1109/OCEANS-Bergen.2013.6608132

Campos, F. R. (2019). A robótica para uso educacional. BOD GmbH DE.

Chatterjee, J., & Dethlefs, N. (2021). Scientometric review of artificial intelligence for operations & maintenance of wind turbines: The past, present and future. Renewable and Sustainable Energy Reviews,v.373. https://doi.org/10.1098/rsta.2014.0075

Ding, X., Li, Y., Zhang, W., & Zhao, H. (2024). Artificial intelligence based abnormal detection system and method for wind power equipment. *International Journal of Thermofluids*, *21*, 100569. https://doi.org/10.1016/j.ijft.2023.100569

Ditria, E. M., Lopez-Marcano, S., Sievers, M., Jinks, E. L., Brown, C. J., & Connolly, R. M. (2022). Artificial intelligence and automated monitoring for assisting conservation of marine ecosystems: A perspective. *Frontiers in Marine Science*, *9*, 918104. https://doi.org/10.3389/fmars.2022.918104

International Renewable Energy Agency. (2023). Enabling frameworks for offshore wind scale up: Innovations in permitting. [S. l.]. Available at: https://www.irena.org/Publications/2023/Sep/Enabling-frameworks-for-offshore-wind-scale-up. Accessed on: August 10, 2024.

Fischetti, M., & Fraccaro, M. (2019). Machine learning meets mathematical optimization to predict the optimal production of offshore wind parks. *Computers & Operations Research*, *106*, 289-297. https://doi.org/10.1016/j.cor.2018.11.006

Gehring, C., Schreiber, M., & Fuchs, H. (2021). ANYmal in the field: Solving industrial inspection of an offshore HVDC platform with a quadrupedal robot. In *Field and Service Robotics: Results of the 12th International Conference* (pp. 247-260). Springer Singapore. https://doi.org/10.1007/978-981-16-0247-3_19

Gonzalez-Longatt, F. M., Wall, P., Regulski, P., & Terzija, V. (2011). Optimal electric network design for a large offshore wind farm based on a modified genetic algorithm approach. IEEE Systems Journal, 5(2), 268–276. https://doi.org/10.1109/JSYST.2011.2163027

Gu, Y., Zhang, L., Li, Y., & Liu, X. (2024). Vessel intrusion interception utilizing unmanned surface vehicles for offshore wind farm asset protection. *Ocean Engineering*, *299*, 117395. https://doi.org/10.1016/j.oceaneng.2024.117395

Hou, P., Liu, X., & Zhang, Z. (2019). A review of offshore wind farm layout optimization and electrical system design methods. *Journal of Modern Power Systems and Clean Energy*, *7*(5), 975-986. https://doi.org/10.35833/MPCE.2018.000718

Hou, P., et al. (2019). A review of offshore wind farm layout optimization and electrical system design methods. *Journal of Modern Power Systems and Clean Energy*, *7*(5), 975–986. https://10.1007/s40565-019-0550-5

Ingram, E. C., & Butler, L. (2024). Artificial intelligence and species distribution ensemble models inform resource interactions with offshore wind development. *bioRxiv*. https://10.1101/2024.06.10.598232

Khalid, O., Ali, M., Qureshi, A., & Saeed, K. (2022). Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends. *Wind Energy*, *25*(11), 1880-1899. https://doi.org/10.1002/we.2663

Kokash, N. (2005). An introduction to heuristic algorithms. Department of Informatics and Telecommunications, 1-8.

Kou, L., Zhang, W., & Li, H. (2022). Review on monitoring, operation and maintenance of smart offshore wind farms. *Sensors*, *22*(8), 2822. https://doi.org/10.3390/s22082822

Lawan, S. M., Ibrahim, A., & Alkali, A. (2014). Different models of wind speed prediction; a comprehensive review. International Journal of Scientific & Engineering Research, 5(1), 1760-1768.

Leonard, J. J., & Bahr, A. (2016). Autonomous underwater vehicle navigation. In *Springer handbook of ocean engineering* (pp. 341-358). Springer. https://doi.org/10.1007/978-3-319-24115-4_21

Lozano-Minguez, E., Kolios, A. J., & Brennan, F. P. (2011). Multi-criteria assessment of offshore wind turbine support structures. *Renewable Energy, 36*(11), 2831-2837. https://doi.org/10.1016/j.renene.2011.04.010

Mitchell, D., Blanche, J., Harper, S., Lim, T., Gupta, R., Zaki, O., & Flynn, D. (2022). A review: Challenges and opportunities for artificial intelligence and robotics in the offshore wind sector. *Energy and AI, 8*, 100146. https://doi.org/10.1016/j.egyai.2022.100146

Neshat, M., Zhang, L., & Moosavi, R. (2021). A deep learning-based evolutionary model for short-term wind speed forecasting: A case study of the Lillgrund offshore wind farm. *Energy Conversion and Management, 236*, 114002. https://doi.org/10.1016/j.enconman.2021.114002

Niemi, J., & Tanttu, J. T. (2020). Deep learning–based automatic bird identification system for offshore wind farms. *Wind Energy, 23*(6), 1394-1407. https://doi.org/10.1002/we.2578

Noronha, M., Pimentel, R. F., & Pinho, M. R. (2021). The role of the innovation ecosystem and the structuring of a regulatory framework for the offshore wind energy market in Brazil. *International Journal of Business and Marketing, 6*(2), 32-51. https://doi.org/10.1002/bm.10001

Papatheou, E., Dervilis, N., Maguire, A. E., Antoniadou, I., & Worden, K. (2015). A performance monitoring approach for the novel Lillgrund offshore wind farm. *IEEE Transactions on Industrial Electronics, 62*(10), 6636–6644. https://doi.org/10.1109/TIE.2015.2442212

Parsons, H. McIlvaine, & Kearsley, G. P. (1982). Robotics and human factors: Current status and future prospects. Human Factors, 24(5), 535-552. https://doi.org/10.1177/1937586717747384

Pati, D., & Lorusso, L. N. (2018). How to write a systematic review of the literature. HERD: Health Environments Research & Design Journal, 11(1), 15-30.

Paula, M., dos Santos, A. R., & da Silva, J. (2023). Predicting energy generation in large wind farms: A data-driven study with open data and machine learning. *Inventions, 8*(5), 126. https://doi.org/10.3390/inventions8050126

Paula, M., dos Santos, A. R., & Guedes Soares, C. (2020). Predicting long-term wind speed in wind farms of northeast Brazil: A comparative analysis through machine learning models. *IEEE Latin America Transactions, 18*(11), 2011-2018. https://doi.org/10.1109/TLA.2020.9348816

Pencelli, M., Mendez, C., & Gálvez, E. (2024). Testing the robustness of quadruped robots for unmanned inspection activities in the energy industry. In *International Petroleum Technology Conference* (p. D021S083R008). IPTC.

Pillai, A. C., Venkatesan, S., & Kumar, S. (2016). Optimisation of offshore wind farms using a genetic algorithm. *International Journal of Offshore and Polar Engineering, 26*(03), 225-234. https://doi.org/10.1773/ijope.v26i3.225

Rinaldi, G., Thies, P. R., & Johanning, L. (2021). Current status and future trends in the operation and maintenance of offshore wind turbines: A review. *Energies, 14*(9), 2484. https://doi.org/10.3390/en14092484

Ren, Z., Verma, A. S., Li, Y., Teuwen, J. J., & Jiang, Z. (2021). Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renewable and Sustainable Energy Reviews, v.144*. https://doi.org/10.1016/j.rser.2021.110886

Rother, E. T. (2007). Systematic literature review X narrative review. Acta paulista de enfermagem, 20, v-vi.

Sacie, M., Sousa, D. F., & Oliveira, F. (2022). Use of state-of-art machine learning technologies for forecasting offshore wind speed, wave and misalignment to improve wind turbine performance. *Journal of Marine Science and Engineering, 10*(7), 938. https://doi.org/10.3390/jmse10070938

Shafiee, M., Zhou, Z., Mei, L., Dinmohammadi, F., Karama, J., & Flynn, D. (2021). Unmanned aerial drones for inspection of offshore wind turbines: A mission-critical failure analysis. *Robotics, v.10*. https://doi.org/10.3390/robotics10010026

Salkanović, E., Enevoldsen, P., & Xydis, G. (2020). Applying AI-Based solutions to avoid bird collisions at wind parks. In *Complementary Resources for Tomorrow: Proceedings of Energy & Resources for Tomorrow 2019* (pp. 111-124). Springer International Publishing. https://doi.org/10.1007/978-3-030-59254-8_10

Sattar, T. P., Leon Rodriguez, H., & Bridge, B. (2009). Climbing ring robot for inspection of offshore wind turbines. Industrial Robot: An International Journal, 36(4), 326–330. https://doi.org/10.1108/01439910910957075

Salvador, S., Gimeno, L., & Larruga, F. J. S. (2018). The influence of regulatory framework on environmental impact assessment in the development of offshore wind farms in Spain: Issues, challenges and solutions. *Ocean & Coastal Management, 161*, 165-176. https://doi.org/10.1016/j.ocecoaman.2018.04.016

Santos, F. P., Teixeira, A. P., & Guedes Soares, C. (2015). An age-based preventive maintenance for offshore wind turbines. In *Safety and Reliability: Methodology and Applications* (pp. 1147-1155).

Sattar, T. P., Leon Rodriguez, H., & Bridge, B. (2009). Climbing ring robot for inspection of offshore wind turbines. *Industrial Robot: An International Journal, 36*(4), 326-330. https://doi.org/10.1108/01439910910965289

Schneider, J., Klüner, A., & Zielinski, O. (2023). Towards digital twins of the oceans: The potential of machine learning for monitoring the impacts of offshore wind farms on marine environments. *Sensors, 23*(10), 4581. https://doi.org/10.3390/s23104581

Silva, A. J. S. F. da, de Sousa, A. J. S., & Reis, M. (2010). Técnicas de inteligência artificial e controlo adaptativo aplicadas à gestão de parques eólicos.

Soman, S. S., Dhingra, S., & Shinde, A. (2010). A review of wind power and wind speed forecasting methods with different time horizons. In *North American Power Symposium 2010* (pp. 1-8). IEEE.

Song, D., Wang, L., & Chen, Y. (2024). Review on the application of artificial intelligence methods in the control and design of offshore wind power systems. *Journal of Marine Science and Engineering*, *12*(3), 424. https://doi.org/10.3390/jmse12030424

Vijayalakshmi, S., V, A., & Rahman, M. (2023). The role of artificial intelligence in renewable energy. In *AI-Powered IoT in the Energy Industry: Digital Technology and Sustainable Energy Systems* (pp. 253-269). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-90556-3_15

Vinuesa, R., Aziz, W., & Hossain, M. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, *11*(1), 1-10. https://doi.org/10.1038/s41467-020-17528-8

Winston, P. H. (1984). *Artificial intelligence*. Addison-Wesley Longman Publishing Co., Inc.

Yang, P., Li, M., & Zheng, J. (2022). Design and control of a crawler-type wall-climbing robot system for measuring the paint film thickness of offshore wind turbine tower. *Journal of Intelligent & Robotic Systems, 106*(2), 50. https://doi.org/10.1007/s10846-021-01482-3

Yeter, B., Garbatov, Y., & Guedes Soares, C. (2022). Life-extension classification of offshore wind assets using unsupervised machine learning. *Reliability Engineering & System

Yu, M., Zhang, Z., Li, X., Yu, J., Gao, J., Liu, Z., You, B., Zheng, X., & Yu, R. (2020). Superposition graph neural network for offshore wind power prediction. *Future Generation Computer Systems, 113*, 68–77. https://doi.org/10.1016/j.future.2020.06.024

Zhou, F., Tu, X., & Wang, Q. (2022). Research on offshore wind power system based on Internet of Things technology. *International Journal of Low-Carbon Technologies*, *17*, 645-650. https://doi.org/10.1093/ijlct/ctab027