Cleaner Engineering and Technology 17 (2023) 100691

Contents lists available at ScienceDirect

Cleaner Engineering and Technology

journal homepage: www.sciencedirect.com/journal/cleaner-engineering-and-technology

Onshore versus offshore wind power trends and recent study practices in modeling of wind turbines' life-cycle impact assessments

Belachew Desalegn[a,b,*], Desta Gebeyehu[c], Bimrew Tamrat[a], Tassew Tadiwose[a], Ababa Lata[d]

[a] Bahir Dar Energy Center, Bahir Dar Institute of Technology, Bahir Dar University, P. O. Box 26, Bahir Dar, Ethiopia
[b] Department of Physics, College of Natural and Computational Science, Wolaita Sodo University, P. O. Box 138, Wolaita Sodo, Ethiopia
[c] Department of Physics, Addis Ababa University, P. O. Box 1176, Addis Ababa, Ethiopia
[d] Department of Physics, College of Natural and Computational Science, Gambella University, P. O. Box 126, Gambella, Ethiopia

ARTICLE INFO

Keywords:
Onshore & offshore systems
Capacity factor
Levelized cost of energy
Life-cycle impact assessment modeling

ABSTRACT

Wind energy has gradually become one of the most efficient and reliable forms of sustainable energy, and it is being globally utilized to accelerate the expansion of green power production. However, recent projections of onshore & offshore wind energy systems indicate that further improvements are continuously required in terms of the deployments, capacity factors, costs, etc. to achieve an optimal wind power generation. According to these projections, the most critical current issue is the offshore systems' high levelized cost of energy, which demands the enhancements of the technologies to ensure the cost reduction in the future. Moreover, a number of reports are underscoring that offshore power systems can also leave a larger carbon footprints through their life-cycles compared to the onshore counterpart. On the other hand, the modelling methods of the power plants' life-cycle impact assessment (LCIA) have nowadays become among the most compelling research problems in the field of wind power systems engineering. In addition to comparatively assessing the characteristics of onshore & offshore energy systems based on some reports & studies, this work is therefore aimed at rigorously exploring the existing study practices in modelling the wind power plants' LCIA. A number of these practices were based on the implementation of various conventional modelling methods that may not help to make accurate assessments of the wind power plants' life-cycle impacts. Hence, one of the main contributions of this study is to summarize a novel LCIA modelling approach based on Internet of Things (IoT) and predictive digital twin technologies. Unlike the conventional methods, real-time data extraction from the power plants makes these technologies possible to conduct the most accurate assessments of the life-cycle impacts.

1. Introduction

The global electricity has recently seen an enormous increase in power generation from renewable energy sources, particularly wind resources. Meanwhile, this growth does not seem to be sufficient in helping to meet the global emissions targets as set by the United Nations Convention on Climate Change (UNCCC). For instance, 2020 was the year in the history of the global wind industry at which the installation of exceedingly larger new wind power capacity (more than 110 GW) was added in helping to achieve the cumulative capacity of more than 732 GW from where it was close to 622 GW at 2019 and 564 GW at 2018, according to reports by International Renewable Energy Agency (IRENA) (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). These historical figures of wind power installation indicate that there was around 90% year-on-year increase, but very rapid rates of year-on-year rises should be achieved in the subsequent years in order to realize the world reaches net zero emissions by 2050, where the wind power global cumulative capacity has been projected to reach 6044 GW after it would reach 2015 GW by 2030 (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). On the other hand, the most recent report by (*Global Wind Report, 2023 - Global Wind Energy Council*, n.d.) has unveiled that cumulative installations of wind energy technologies

* Corresponding author. Bahir Dar Energy Center, Bahir Dar Institute of Technology, Bahir Dar University, P. O. Box 26, Bahir Dar, Ethiopia.
E-mail addresses: belachewdesalegn76@gmail.com (B. Desalegn), dgebeyeh68@gmail.com (D. Gebeyehu), betselotbim@gmail.com (B. Tamrat), tasstad@gmail.com (T. Tadiwose), abelataguta001@gmail.com (A. Lata).

https://doi.org/10.1016/j.clet.2023.100691
Received 28 June 2023; Received in revised form 30 September 2023; Accepted 5 November 2023
Available online 8 November 2023

were being observed to grow with declining rates; yet the world needs to be generally maximizing renewable power production with a highly increasing rate over the next few decades in order to stay on a net-zero route and counteract the worst impacts of climate change (Salah et al., 2022).

With the advancements in wind energy conversion technologies, the global wind power market has virtually quadrupled in size over the past decade and wind energy is proved to be one of the most cost-effective and robust power sources across the world (Desalegn et al., 2023). Yet, as the green energy technologies with remarkable de-carbonization potential per MW, the wind energy reports indicate that the current rate of wind power installation will not be adequate enough to realize carbon neutrality by the end of half of this century (Global Wind Report, 2021, n.d.). Consequently, immediate and broad attention should be given by policymakers, researchers, and wind power technologies developers now in ensuring to increase wind power generation over the next years with the required pace (Siram et al., 2022). Indeed, wind power development holds broad economic and environmental benefits, and carries a huge potential for the future due to the substantial amount of wind energy that still remains unharnessed (Adeyeye et al., 2020). Even though wind energy recently contributes to only about 6% of global electricity production (Irfan et al., 2019), the energy that can be extracted from onshore and offshore wind resources is more than 35% as abundant as the demand of the entire world population (Tong, 2010). On the other hand, onshore wind power generation could be compromised by factors such as land use, visual impact of facilities on land, limitations on onshore power technologies, etc. (Konstantinidis and Botsaris, 2016); whereas regardless of its own conspicuous limitations, the offshore wind energy may be utilized by counteracting the disadvantages that could be encountered in developing onshore wind energy (Desalegn et al., 2022).

Wind velocity is higher and more dependable at offshore locations than onshore ones. More importantly, offshore wind energy is known to be characterized by higher power density, and superior capacity factor compared to onshore wind energy (Díaz-Motta et al., 2023). Meanwhile, offshore power installations have shown promising growths over the past few years; and more significant progresses in offshore wind technology are expected to be subsequently made with enhancements of research models and engineering designs (Shields et al., 2022). In operational characteristics, offshore wind power plant is also proven to show outstanding electricity producing capability in comparison to the onshore counterpart (Prieto-Araujo and Gomis-Bellmunt, 2016). On the other hand, one of the main challenging drawbacks that is associated with offshore wind power plants includes: its high levelized cost of energy (LCOE), which would primarily arise from the plants' configuration complexity (Shields et al., 2021). In this regard, future projections-based recent report by (IRENA-International Renewable Energy Agency, 2023), and further studies including (Ng and Ran, 2016) indicated that the LCOE for offshore systems may be reasonably falling as further future advancements could possibly take place in offshore wind-based research studies and technologies.

Furthermore, a number of research studies including (Kaldellis and Apostolou, 2017) generally demonstrated that offshore wind power systems have a relatively higher carbon footprint compared to onshore systems. Even though carbon footprints by wind power systems are generally considered to be insignificant compared with emissions by the conventional power systems, and even believed to be lower than the carbon footprints that could be left by solar power systems (Doerffer et al., 2021); it is still very important to pursue robust modeling techniques in making the most accurate and objective evaluations of their impacts (Tetteh et al., 2021), and the findings may eventually be utilized to enhance the operational characteristics of the wind power plants as required (Yuan et al., 2023).

On the other hand, numerous existing research practices commonly relied on some traditional modeling methods for studying the wind power plants' life-cycle assessments, which include the estimations of different emissions resulting from the power plants' carbon footprints. One of these methods would implement manual calculations depending on the process-based and life-cycle assessment baselines, which were provided by International Life Cycle Data (ILCD) handbook (European Commission. Joint Research Centre. Institute for Environment and Sustainability., 2010), Intergovernmental Panel on Climate Change (IPCC) guidelines (Navarro (mexico et al., 2014), and also which include historical data that could be collected from different sources. Another traditional method would rely on different software solutions that include Simapro (Goedkoop et al., 2013), Ecoinvent (Weidema B P et al., 2013), GaBi (Dr. Martin Baitz et al., 2012; CML 2001 in (Ling-Chin and Roskilly, 2016), IMPACT 2002+ (Jolliet et al., 2003), etc., and which were being built based on ILDC & IPCC databases with an objective of enhancing the assessments of life-cycle impacts through determining the levels of carbon emissions, energy consumptions, and the times required to remove emissions and compensate the consumed energy. However, these methodologies may not be efficient and effective in helping to produce more accurate and acceptable results of life-cycle impact assessments for wind power plants due to several factors. First, life-cycle assessment baselines (ILCD and IPCC) and supporting software tools were originally developed for a general purpose application in power systems of different operational dynamics (Wimbadi and Djalante, 2020); and therefore, employing these traditional methods for modeling and evaluation of wind power systems' life-cycle impacts may not be methodically sounding as the dynamics of wind power systems are entirely different from other power systems, such as the conventional power technologies (Z. Chen, 2013). Hence, as most of the existing modeling methods that are associated with wind turbines' life cycle impacts evaluations are based on average historical data that would be adopted from various industries and ILDC & IPCC manuals, the findings of the life cycle impacts assessments may not be fully credible by employing these methods (Adekanbi, 2021).

One of the objectives of this review paper is to identify the advanced life-cycle modelling techniques that consider the inclusion of real-time and dynamic data in order to achieve the robust life-cycle impacts assessments for wind power plants. Accordingly, the advantages of the advanced methods, such as Internet of Things (IoT), predictive digital twin and machine learning models, are discussed against the conventional methods by briefly overviewing the most recent developments as follows. First, the application of IoT technology (Alhmoud and Al-Zoubi, 2019) in the assessments of the wind power plants' life-cycle impacts can be seen in terms of automating the process of data collection in order that information from different sources be integrated and processed. Unlike the conventional methods, real-time data extraction from the power plants makes IoT possible to conduct accurate assessments of the life-cycle impacts by simultaneously taking into account multiple factors (Adekanbi, 2021). This technology can also be integrated with machine learning, and artificial intelligence technologies for ensuring more efficient, and reliable modeling of life-cycle assessments, this could ultimately result in generally smarter power systems with mitigated life-cycle impacts (Rebouças Filho et al., 2019). Moreover, predictive digital twin is another advanced technology that was introduced as an option to replace the conventional methods for ensuring robust assessments of the power plants' life-cycle impacts, it is the virtual representation of real-time data involved in the entire wind power plants' life-cycles (Haghshenas et al., 2023). Through real-time monitoring data, high performance simulation accuracy and robust simulation prediction, predictive digital twin can realize the digital description and smart application service of the power plants' whole life-cycle from concept, design, manufacturing, operation, maintenance to scrapping (Zhong et al., 2023).

Through a review of the recent developments, the most important contribution of this study is, therefore, to suggest a novel approach to the life-cycle impact assessment modeling based on the IoT and digital twin technologies, which can be utilized to effectively address the limitations resulting from applying the traditional modeling methods. In fact, IoT and digital twins work together in optimizing the wind power systems operation. IoT technology connects wind power plants' sensors to the internet and ultimately powers digital twins with real-time data of wind power systems operation. Moreover, some of the most significant advantages of IoT-enabled wind power systems include: enhanced power production efficiency, predictive maintenance, remote monitoring, improved safety and integration with grid systems. These allow wind power operators to attain optimal performance by maximizing power output, contribute to improved overall power operation by reducing maintenance costs and downtimes of the turbines' key components, save time and resources, alleviate possible system failures as a result of harsh weather conditions, etc. through continuous gathering and analysis of wind turbines' real-time data. More importantly, with maximization of power production and minimization of turbines operational downtimes, the application of IoT in wind power industry can significantly contribute to a greener power generation by mitigating emissions due to the turbines' carbon footprints, and ultimately minimizing dependence on conventional energy sources.

The remainder of this study comprehensively presents on various issues of onshore & offshore wind energy systems, and its structure is organized as follows. This includes section 2, under which comparative assessments are conducted based on the nature of the power systems' technological trends, sites' wind characteristics, power deployment statuses, power plants' capacity factors, and levelized costs of energy. Moreover, the discussions pertaining to the levels of the power plants' life-cycle greenhouse gas emissions; and the recent advances in modeling techniques of the power plants' life-cycle impacts assessments are respectively presented under section 3, and section 4. In the end, section 5 summarizes the study by indicating future prospects of transition to more enhanced wind power production.

2. Onshore versus offshore wind energy development

Based on the geographical locations, wind resources across the world can be generally classified into two categories: one that arises from an onshore part of the earth while another arises from an offshore location. Consequently, wind energy harvesting may rely on onshore and offshore wind farm industries. A greater deal of wind energy has been harvested with onshore wind farm industries for several decades, and it is a well-matured alternative for maximizing wind power generation. On the other hand, offshore wind energy harvesting is presently receiving increasing recognition due to its robust and reliable wind speeds, inappreciable harm to the surrounding environment, limited constraints on sizes of wind energy conversion systems, etc. In comparison to onshore wind energy conversion technologies, offshore wind energy conversion technologies should be built on the ground under the sea, which seriously necessitates an additionally robust bearing structure. Nonconventional cables are required for the transmission of electric power, and exceptional vessels and equipment are needed for installation and maintenance activities. These issues bring high costs to offshore wind power generation, which is considerable compared to the cost associated with onshore wind power deployment.

Offshore wind energy harvesting has a number of unique advantages as well. Offshore wind energy conversion systems are less noticeable than onshore systems because the actual size and noise of offshore systems can be diminished or eliminated by the outlying location of the sea. Moreover, the process of deploying of offshore wind energy conversion systems may be remarkably smooth compared to that of onshore wind energy technologies. Onshore wind energy harvesting may cause several challenges such as the unsuitability of transporting outsized systems components and public protests because of different issues associated with site selections, which include health impacts (noise and visual impacts) and conflict of interest over land resource use. Hence, these challenges can put restrictions on a number of potential areas for onshore wind energy development. Offshore wind energy development promotes advanced technologies to the wind energy industry in several aspects: with regard to the construction of the wind energy conversion systems and their network with the electricity grid, with regard to the logistics for transportation, installation, operation, and maintenance; and this brings about increasing interest in the advanced integration of research domains (Fernández-Guillamón et al., 2019). Furthermore, the pros and cons of onshore and offshore wind energies are illustrated and compared in Table 1.

2.1. Onshore and offshore wind characteristics, and wind energy potential assessment methods

Onshore and offshore wind resources are characterized by several variables that can positively or negatively affect the efficiency of the respective wind energy that is to be harnessed for the generation or maximization of electric power. For instance, the magnitude of average wind speed and wind power density at each hour of the day or at each day of the month or at each month of the year are directly associated with the ranges of wind energy distributions across the onshore or offshore areas. Wind speed is caused by the movement of air that is resulted from air pressure differences, which are a result of temperature variations in air molecules. Consequently, the wind speeds at onshore and offshore locations may largely differ as there can be substantial temperature differences across these two different points. In addition, wind speeds can be measured at different heights and the measurements vary from low heights to high heights. Likewise, wind power density is also an important quantity that can be measured to determine the quality of wind energy. The measurements of wind power densities can

Table 1
Utilization of onshore versus offshore wind energy: Technological opportunities and challenges (Adedipe et al., 2018; Gao et al., 2021; Hevia-Koch and Klinge Jacobsen, 2019; Manwell, 2012).

Classification	Opportunities	Challenges
Onshore wind energy	☑ Offering reduced installation costs. Investment compensation may be as rapid as two years. ☑ Energy harvested can be delivered to the grid system with minimum effort. ☑ Large professionals would specialize in onshore wind energy installation. ☑ Remarkable reduction in the maintenance cost, and reduced complexity of installation process compared to its offshore counterpart.	☒ Onshore wind power industries demand a more rigorous prediction of wind conditions and speeds compared to offshore wind energy industries in order to harvest power with maximum efficiency and stability. ☒ Limitations in using potential sites due to high land costs and possible urban expansions. ☒ Inhabitants' grievance due to visual and noise impacts produced by onshore wind energy industries in the vicinity of residential areas.
Offshore wind energy	☑ Accessibility of vast sites, opted for multi mega-scale wind power generation. ☑ Threats as the results of visual and noise impacts are no longer issues. ☑ Robust wind speeds, which usually become stronger as the gap between the water body and shore increases. ☑ Reduced turbulence, which ensures the wind energy conversion systems to capture the energy more reliably and minimizes the fatigue loads on the systems. ☑ Weak wind-shear, thus creating convenience to employ shorter towers.	☒ Exceeding cost of marine foundations. ☒ Addition of high cost to integrate into the grid systems due to increasing distances between offshore wind farms and onshore power loading centers. ☒ Substantial cost and time are needed during installation of wind farm infrastructures as the installation process may be interrupted due to the harsh offshore weather conditions. ☒ Restricted access for supervisions and maintenance during operation.

be taken at different heights across onshore and offshore areas to assess its qualities for installations of wind farms. Similar to wind speeds, the scales of wind power densities also rely on locations (onshore and offshore) where the measurements are taken, and show variations depending on altitudes at which measurements are set to be implemented. In the discussions to follow under this section, average wind speed and wind power density variations across onshore and offshore locations are analyzed based on the measured data acquired from the previous research work. Brief summaries on the modeling concepts and methods of wind energy potential assessments are also finally provided based on the most recent literatures.

The onshore and offshore monthly-based average wind speed measurements that are adopted here for the purpose of discussion correspond to the selected heights that include 10m, 40m, and 80m. In the practical application, the measured wind speeds can be extrapolated to estimate further ranges of wind speeds for numerous heights under the condition when the wind speed measurements are conducted by consideration of limited options of heights. In this sense, various techniques can be employed for extrapolation of average wind speed but power law was claimed to be suitable and efficient in (Gul et al., 2019). Moreover, Fig. 1 (Li et al., 2020) illustrates the variations of average wind speeds based on monthly measurements for varying heights across onshore and offshore locations. Just as it can be clearly visible, the measured values of average wind speeds generally get high as the heights go up across both onshore and offshore locations. However, the average wind speed across onshore location varies at a narrower range compared to that of offshore average wind speed, which shows variation

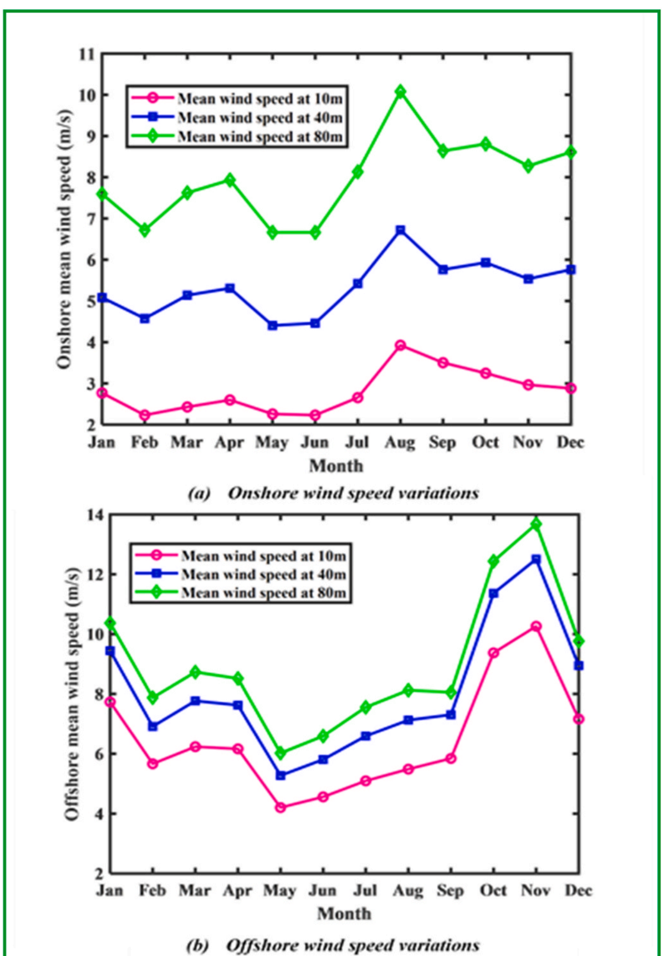

Fig. 1. Comparison of onshore and offshore mean wind speeds at 10m, 40m and 80m heights (Li et al., 2020).

at a substantially high scale. For example, from Fig. 1 (a) (Li et al., 2020), the measurement of onshore average wind speed on monthly basis shows increments from around 2.22 m/s to about 3.90 m/s across a height of 10 m, and then, shows variation from around 6.64 m/s to about 10.05 m/s across the height of 80 m.

Again, as it can be seen from Fig. 1 (a), the onshore average wind speed measurement additionally indicates that all peak values (at heights of 10 m, 40 m, and 80 m) correspond to August. On the other hand, across the offshore location (based on (Li et al., 2020) study platform), the variation of offshore average wind speed on monthly basis is measured to represent broad ranges from a height of 10 m to a height of 80 m. For example, from Fig. 1 (b) (Li et al., 2020), the low and peak measurements for monthly-based average wind speed are about 4.15 m/s, 10.28 m/s across the height of 10 m and about 6.03 m/s, 13.66 m/s across the height of 80 m. As it can be evident from Fig. 1 (b) again, offshore location sees the highest average wind speed at the month of November.

The study of wind power density helps to estimate the capacity of wind power to be generated at certain locations and facilitate the development of ideal wind energy harvesting technologies. Hence, wind power density provides firsthand information about the quality of available energy across onshore and offshore locations, which can be harnessed to generate electricity with the applications of enhanced wind energy harvesting technologies. Two methods can be used to estimate wind power density. One of the most accurate method is based on the measurement of average/mean wind speed data. Another optional method is to use a suitable distribution function for computing wind power density. Among others, Weibull distribution function in (Aslam, 2021) was reported to have outperforming qualities, such as simplicity, flexibility, adaptability, and high capability in analyzing wind data. As a quantitative information, Fig. 2 (Li et al., 2020) depicts wind energy distributions across onshore and offshore locations. As it can be seen from [Fig. 2] (a) and (b), power densities for both onshore and offshore locations are illustrated at heights of 40 m, 50 m, and 70 m across the months, but the offshore location is identified to be covered with stronger wind speed distribution compared to onshore location. In Fig. 1 (a) (Li et al., 2020), power density across onshore location rises from 77.29 W/m^2 (in June) to 355.60 W/m^2 (in August) at the height of 40 m, whereas in Fig. 1 (b) (Li et al., 2020), power density across offshore location at the same height (40 m) rises from 197.22 W/m^2 (in May) to 1370.11 W/m^2 (in November). Similarly, at the heights of 50 m and 70 m, offshore wind power density is appeared to be more robust compared with onshore wind power density, which increases from 116.29 W/m^2 to 524.29 W/m^2 at a height of 50 m and 209.13 W/m^2 to 917.53 W/m^2 at height of 70 m across onshore location; and 219.67 W/m^2 to 1521.55 W/m^2 at height of 50 m and 221.39 W/m^2 to 1564.90 W/m^2 across the offshore location.

In general, wind energy potential can be affected by multiple environmental factors including the location of wind resource measurement, wind speed (m/s) at height of wind turbine hub, turbulence intensity (the ratio of standard deviation of fluctuating wind velocity to mean wind speed), air power density (kg/m^3) where the turbine system is located, wind direction $(0^0 - 360^0)$, and wind sheer (m/s) or changes in wind direction and speed under wind turbine hub (Pang et al., 2021). Compared to onshore energy, offshore wind energy potential is less affected by these factors as pointed out in (Lins et al., 2023). On the other hand, numerous existing studies proposed various modelling methods that mainly be based on the wind speed and its direction in order to assess the wind energy potential at different sites. Even an insignificant increase in wind speed results in a significant wind energy yield as wind energy is directly proportional to the cube of wind speed, and hence, wind speed is the most important factor that largely affect wind power. But wind speed frequently fluctuates with the air temperature variation over a time period in different onshore-offshore locations and seasonal conditions. In this instance, wind speed can be taken as a

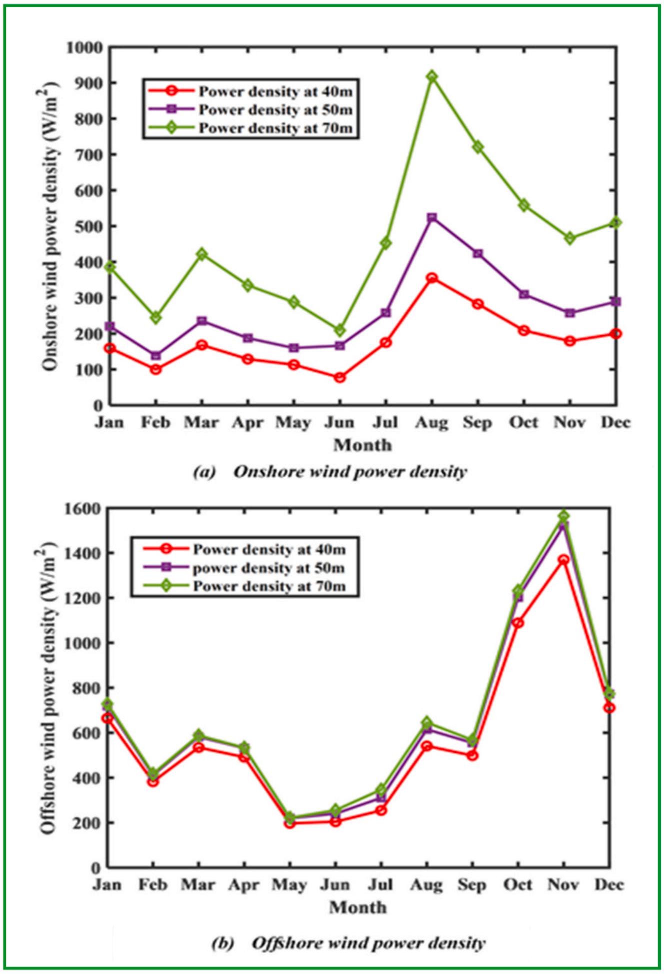

Fig. 2. Comparison of onshore and offshore wind power densities at height of 40m, 50m and 70m (Li et al., 2020).

random parameter and a probability density function can be used to describe it. Consequently, the wind speed's probability density function can serve as a fundamental basis in order to evaluate the potential of wind energy and stochastic characteristics of wind (Z. Wang and Liu, 2021). If the wind speed's frequency distribution is comprehensively illustrated by an estimation of probability density function, the evaluations of the wind power density and wind turbines' wind power output can be eventually made, which can be used for making a rational decision regarding a feasibility of installing a wind farm in a selected location, and it can also help to minimize the wind power output estimation related uncertainties and errors (H. Chen et al., 2021). In addition, the accurate estimation of probability density function can also help for a selection an ideal wind energy conversion system and an evaluation of a generation system reliability. Hence, the wind energy potential prediction and an ideal power system selection can be favorably made through accurate evaluation of wind speed's probability density function (Hu et al., 2016).

Wind characteristics can be described by various groups of parametric and nonparametric models, where single and mixture distribution models are taken to be the types of parametric models. Gamma, Raleigh, Inverse Gaussian distribution, lognormal and Weibull distribution models (Aries et al., 2018; Pishgar-Komleh et al., 2015) represent among the most widely used single distribution models at present. Among these models, the two parameter Weibull distribution model is largely considered to be a robust and as a result of its simplicity this model is taken to be the best candidate for application in the field of wind industry for wind energy potential estimation. However, in particular cases where the probability of null wind speed or the wind speed lower than 2 m/s is remarkable, the performance of the two parameter Weibull distribution is compromised for a high frequency of null wind speed. When the percentage of null wind speed is higher, the three parameter Weibull distribution produces a favorable result of energy estimation (Wais, 2017). Electricity generation by a wind turbine system can only be realized under a condition when wind speed dwarfs the cut-in speed. Researchers in (Deep et al., 2020) underscored that a three parameter Weibull distribution should be employed in modeling wind speed data between the cut-in and cut-out speeds, and the location parameter is able to be coincident with the cut-in wind speed.

Wind energy potential is also mainly affected by wind direction when assessing the characteristics of wind at a particular location. A study in (Gugliani et al., 2018) insisted that it is pointless to assess wind energy potential at a certain area without including wind direction analysis in an assessment. A further discussion presented in (Han and Chu, 2021) also underlined that wind resource availability changes with the direction of wind, particularly in the sites of low-speed and complex landscape. For modeling wind direction data, the mixture model of von Mises distribution was extensively suggested (Masseran et al., 2013). In addition to the von Mises distribution, the circular statistical distributions that include the uniform distribution, wrapped-normal distribution and so forth are additionally preferable for modeling of wind direction analysis. A mixture of von Mises distributions offered an adaptable model for wind direction studies that have a number of modes as indicated by research findings in (Carta et al., 2008). However, wind direction statistical modeling is more difficult and complex in comparison to modeling of wind speed. Yet, both wind speed and wind direction are dependent random variables, wind speed is characterized by a direction and information about wind speed in wind energy potential analysis can be complemented by wind direction (Zou et al., 2020). Accordingly, several bivariate distribution models-based joint distribution models of wind speed and direction have been introduced by many researchers including (Huang et al., 2023) in their efforts to describe wind speed and direction simultaneously.

2.2. Recent trends of onshore and offshore wind power generation

As it can be seen from Table 2, both onshore and offshore wind power installation trends generally represent explosive growths with varying rates. The growth figures of offshore installation indicate promising improvements in consecutive years with fast increasing rates, and its share in electricity generation is apparently getting noticeable across the years. However, at the current moment, onshore wind energy occupies a dominant cumulative share (about 95%) in contributing to globally installed electricity. Yet again, in years of the approaching future (2030–2050), offshore wind energy is projected to be developed with the addition of significant power capacities to attain a cumulative capacity of 228 GW by 2030 and 1000 GW by 2050 from the recent cumulative capacity of 55.678 GW according to report by IRENA2019 (*IRENA (2019), Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). In other words, these projections will generally serve in contributing to the broader green future in an indispensable way if it could be achieved. Similarly, the projections of onshore wind energy developments indicating a cumulative capacity of 1787 GW by 2030 and 5044 GW by 2050 represent remarkable steps towards a full electric power transition, IRENA2019 (*IRENA (2019), Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.).

According to IRENA2021 reports (*IRENA (2021), Renewable Energy Statistics, 2021 The International Renewable Energy Agency, Abu Dhabi.*, n. d.), cumulative wind power (onshore + offshore) installation was increased with rate of about 90.5% in 2020 compared to the progress

Table 2
Global cumulative installed and projected capacities of onshore and offshore wind power (2011–2050).

Year	I. Historical Data (GW)			
	(IRENA (2021), *Renewable Energy Statistics, 2021 The International Renewable Energy Agency, Abu Dhabi.*, n.d.; IRENA-International Renewable Energy Agency, 2023; Renewable Energy AgencyI, 2022)		(*Global Wind Report 2021*, n.d.; Global Wind Report, 2023 - *Global Wind Energy Council*, n.d.; GWEC-GLOBAL-WIND-REPORT-2022, n.d.)	
	Onshore	Offshore	Onshore	Offshore
2011	216.344	3.776	234	4
2012	261.579	5.334	283	5
2013	292.705	7.171	312	7
2014	340.816	8.492	362	8
2015	404.458	11.717	421	12
2016	452.515	14.342	473	14
2017	495.381	18.837	522	19
2018	539.888	23.626	568	23
2019	593.291	28.355	621	29
2020	698.043	34.367	707	36
2021	769.196	55.678	780	57
2022	836	63	842	64
	II. Projections (GW)			
	(*IRENA (2019), Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.)		(*GWEC.NET Associate Sponsors Supporting Sponsor Leading Sponsor*, n.d.)	
	Onshore	Offshore	Offshore	
2030	1787	228	380	
2050	5044	1000	2000	

made in 2019. Yet, another report by Global Wind Energy Council (GWEC 2021) (*Global Wind Report 2021*, n.d.) estimated it to be around 56 %. Some differences between the two reports were observed particularly in terms of onshore historical installation data (2011–2022), and this could be as the result that the reports might be independently conducted at different seasons in years. On the other hand, quite recently, IRENA and GWEC (GWEC.NET *Associate* Sponsors Supporting Sponsor *Leading* Sponsor, n.d.) jointly predicted under different scenario that 380 GW and 2000 GW of cumulative offshore capacity would be achieved by 2030 and 2050 respectively. This latest development may indicate that more potential for offshore wind power installation lies ahead.

In addition, trends of onshore and offshore wind energy harvesting are demonstrated in Fig. 3 with reference to operational data that was based on the monthly average performances of particular onshore and offshore wind farms, which is adopted from (*Andrew ZP Smith, ORCID: 0000-0003-3289-2237; "Capacity Factors at Danish Offshore Wind Farms". Retrieved from https://Energynumbers.Info/Capacity-Factors-at-Danish-Offshore-Wind-Farms on 2021-11-02 19*:21 GMT, n.d.). Under section 2.1, mean wind speed and wind power density have been characterized as important indicators in determining wind resources potential at onshore and offshore locations. Moreover, the levels of measured wind speed and wind power density have been analyzed across onshore and offshore locations at different heights, and comparison has been made between onshore and offshore locations based on

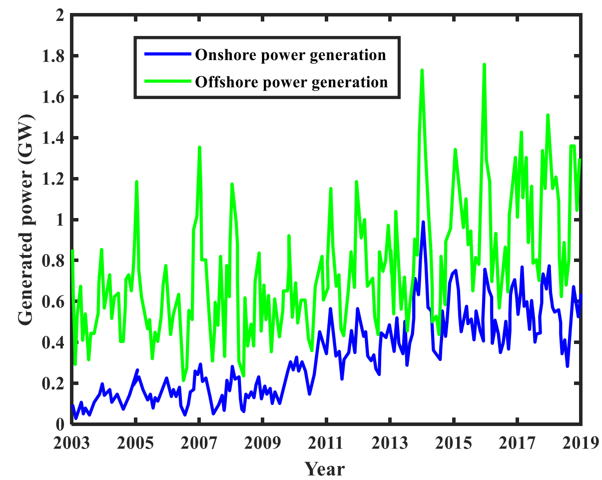

Fig. 3. *Monthly average onshore and offshore wind power generation from 2003-2019 (*Andrew ZP Smith, ORCID: 0000-0003-3289-2237; "Capacity Factors at Danish Offshore Wind Farms". Retrieved from https://Energynumbers.Info/Capacity-Factors-at-Danish-Offshore-Wind-Farms on 2021-11-02 19:21 GMT*, n.d.).*

these measured data. Accordingly, offshore location has appeared to be more favorable in terms of wind resource distribution based on measured data of mean wind speed and estimated wind power density. Under this section, the discussion and analysis generated under section 2.1 can be practically interpreted and validated based on the operational data of onshore and offshore wind power generation from a real-world wind farm, which is demonstrated by Fig. 3. As it can be observed from this figure, the onshore and offshore wind farms of equal capacity (2 GW) yield different amount of power simultaneously, and offshore wind farm relatively shows better performance. This is due to the underlying reason that offshore location is regularly the windiest compared to its onshore counterpart.

Next, under subsections 2.2.1 & 2.2.2, the parameters that further determine the characteristics of the onshore and offshore wind farm operations, which are capacity factor, and Levelized cost of energy (LCOE) for onshore and offshore wind power plants are assessed based on a recent report by International Renewable Energy Agency (IRENA (2019)).

2.2.1. Power capacity factor of onshore and offshore wind energy systems

The capacity factor can be understood as the ratio of average wind power generated by wind power plants to peak power capacity specified with wind power plants. Onshore wind power plants are most probably characterized by their lower capacity factors due to their installation locations compared to offshore wind power plants. The qualities of wind speeds and wind power densities across onshore locations can be affected by multiple environmental factors such as natural landscapes including forests and hills, and structures built by man including buildings and towers. These factors may seriously obstruct the incoming wind speeds or cause to create intermittent wind characteristics that are not qualified for the desired operation of onshore wind power plants. This in turn degrades the output power qualities of onshore wind power plants. On the other hand, there would be no such obstacles that can potentially affect offshore wind power plants. Because ocean water does not experience obstacles over its surface that could cause fluctuations of wind flows. Wind resources across oceans are therefore regularly stronger and can be harnessed to generate larger scales of power with significant capacities for an individual wind turbine.

According to the recent report by (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.), the global estimated average capacity factor for new onshore wind power plants has grown from 27% in 2010 to 34% in 2018 and will be expected to grow significantly in the next nearly 30 years. Onshore wind power plants are projected to have a maximum capacity factor of 55%, a minimum capacity factor of 30%, and an average capacity factor of 42.5% by 2030. Moreover, the projection has revealed that onshore wind power plants would attain a maximum capacity factor of 58%, minimum capacity factor of 32%, and an average capacity factor of 45% by 2050 as illustrated in Fig. 4 (with green colored line) (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). In the case of offshore wind power plants, the global weighted average capacity factor has grown from 38% in 2010 to 43% in 2018 and will be projected to show explosive growth in the next nearly three decades. Offshore wind power plants are expected to have maximum, minimum, and average capacity factors of 58%, 36%, and 47% respectively by the year 2030. In addition, offshore wind power plants would continue to show further improvement by attaining a maximum capacity factor of 60%, minimum capacity factor of 43%, and an average capacity factor of 51.5% by 2050 as illustrated in Fig. 4 (with blue colored line) (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.).

As it can be generalized from the facts discussed above, capacity factors are mainly influenced by wind resources and design of wind turbine system. The design of the wind turbine system influences the system's capacity to harness energy from incoming wind. Low wind speeds and turbulent wind are generally the two most challenging aspects that affect the operation of the turbine systems. Hence, advanced turbine systems that can efficiently harness lower wind speeds result in improvement of their capacity factors, and wind turbine systems that can operate by withstanding turbulent wind also have increasing capacity factors (Lau et al., 2023).

2.2.2. Levelised cost of onshore and offshore wind energy systems

Cost is the prime factor in determining the feasibility of onshore and offshore wind power generation. Due to its benefit of cost-effectiveness, wind power generation has experienced explosive growth over the last several decades when compared to power generation from other renewable energy alternatives. As a means to standardize the cost for various energy systems, levelized cost of energy (LCOE) is normally used as an indicator. LCOE indicates the cost that is incurred in the production of electricity from the energy sources (including wind resources) over the given lifetime of power plants. Moreover, LCOE incorporates the main energy price factors that include research and development expenses, start-up investment, capital expenditure, expenditures associated with the operation and maintenance of power generation systems. Mathematically, LCOE is computed as follows (Stehly2020. *2019 Cost of Wind Energy Review. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5000-78471.* https://Www.Nrel.Gov/Docs/Fy21osti/78471.Pdf., n.d.):

$$LCOE = \frac{C_{Dev} + C_{Cap} + C_{O\&M}}{E_A} \tag{1}$$

Such that: C_{Dev} stands for annual start-up development cost, C_{Cap} represents annual capital cost, $C_{O\&M}$ stands for annual operation and maintenance cost, E_A represents annual average energy generation. As it can be clear from equation (1), in order to lower the energy costs, minimizing the system development cost, reducing capital, and operation and maintenance costs are required. Another efficient method involves enlarging the cumulative power generation and maximizing the power generation systems' lifespans. Moreover, compared to onshore wind power plants, the main aspects that affect the LCOE of offshore wind power plants are distance from shore, load factor and availability; and these require higher costs for installations of mooring systems and long power transmission cables (Myhr et al., 2014).

Fig. 5 illustrates an average LCOE associated with onshore wind (blue colored line) and offshore wind (red colored line) power generation based on historical data and future projections. The global estimated average LCOE related to wind power generation was roughly 0.06 USD/kWh for onshore and 0.165 USD/kWh for offshore in 2014, owing to the swift progressions of technologies and engineering research studies (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). Recently, the LCOE for onshore wind power generation is reported to be attractive in comparison to every conventional power generation sources and expected to be entirely efficient in years to come. The LCOE for offshore wind power systems should also attain a significant reduction as there is more reasonable space to do so. According to a

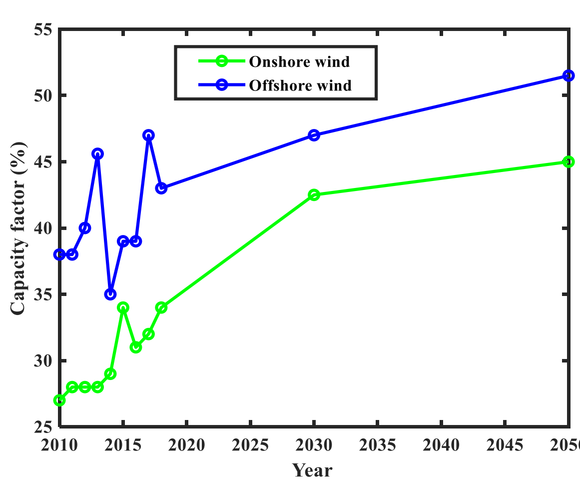

Fig. 4. *Global capacity factors of onshore and offshore wind farms based on historical data and future predictions (*IRENA (2019), Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.).*

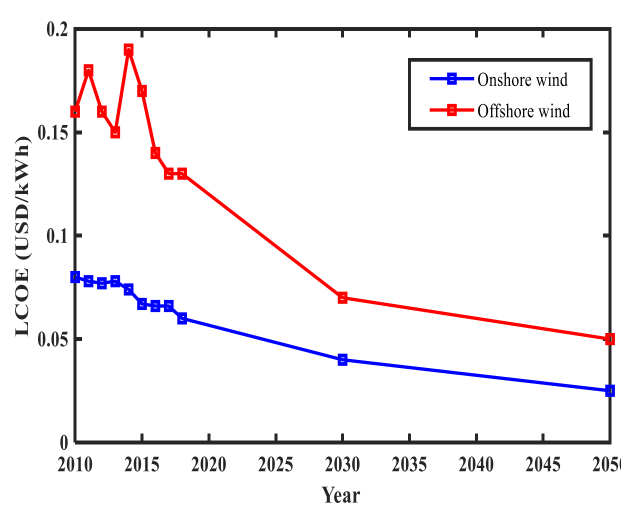

Fig. 5. *Global Levelized Cost of Energy (LCOE) for onshore and offshore wind power industries: historical data and future projections (*IRENA (2019), Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.).*

recent report by researchers in (Wiser et al., 2021), wind power cost reduction of 37%–49% could be generally achieved by 2050.

As illustrated in Fig. 5, in looking towards a zero-emission future, the global averagely estimated LCOE for onshore wind power plants is projected to be significantly falling by attaining the maximum reduction in the history of wind power generation. By 2030, onshore wind power is expected to be entirely cost-effective by falling below the minimum range of fossil fuel (0.05 USD/kWh), and be at the range of 0.03 USD/kWh to 0.05 USD/kWh or averagely around 0.04 USD/kWh. It will further be expected to decline by 2050, and attaining a lower range of 0.02 USD/kWh and a higher range of 0.03 USD/kWh or averagely securing 0.025 USD/kWh. On the other hand, the global averagely estimated LCOE of offshore wind power systems in 2018 was 0.127 USD/kWh, showing more than a 20% decline with respect to cost in 2010 (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.). In stepping towards the full transition, the global averagely estimated LCOE for offshore generation of wind power would further decline, and securing a lower range of 0.05 USD/kWh and a higher range of 0.09 USD/kWh by 2030. In addition, by 2050, it is projected to decline and reach a lower range of 0.03 USD/kWh and a higher range of 0.07 USD/kWh. With the attainment of these projections, offshore wind could become a uniquely attractive candidate due to the fact that at these costs it would be directly competitive with fossil fuel-fired electricity with no need for important financial incentives (IRENA (2019), *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper), International Renewable Energy Agency, Abu Dhabi.*, n.d.).

In conclusion, various wind power technology systems can be employed for applications of onshore and offshore power generation. Since the last few decades, the advancements of these technologies have played a significant role in the improvement of onshore and offshore wind energy capacity factors and levelized costs. Accordingly, the projections that particularly associated with low-cost (LCOE) might be possibly achieved with highly enhanced research studies and technologies.

3. Life-cycle greenhouse gas emissions, carbon and energy payback periods by onshore and offshore wind power plants

The construction and installation of wind power plants require multiple tons of materials, which include: steel, concrete, fiberglass, copper, and exceptionally exotic chemicals such as neodymium and dysprosium utilized in permanent magnets-based technologies; and all of these materials are characterized as having carbon footprint. For instance, metallurgical coal is required to be combusted in blast furnaces in order to manufacture steel. This process is known to be energy-intensive. The process of concrete manufacturing also emits a great deal of carbon dioxide. Nevertheless, these emissions are not lasting throughout the power generation process, and the overall environmental impact by wind farms is therefore can be very negligible compared with fossil fuel-fired electric systems that emit carbon dioxide continuously due to the reason that combustion of coal and natural gas is the part of the power generation process.

As widely presented in several wind energy reports (NREL (Lantz et al., 2019), Vestas (Wind Systems, 2020) et al.), steel tower contributes to about 30% of the total carbon footprint left during the manufacturing of wind turbines, while the concrete foundation and the carbon fiber plus fiberglass blades making up 17% and 12% of carbon impacts, respectively. According to these reports, the carbon cost can generally be amortized by extending the lifespan of the wind power system, and its carbon footprint is 99% lower compared with coal-fired power plants, 98% lower compared with natural gas, and 75% lower compared with solar power. Moreover, wind turbines (including both onshore and offshore configuration) produce about an average of 11 g of CO_2 equivalent per kilowatt-hour (11 g CO_2-eq/kWh) of electric power generated, while for solar power with 44 g CO_2-eq/kWh, for natural gas with 450 g CO_2-eq/kWh, and for coal with 1000 g CO_2-eq/kWh (Carrara et al., 2020). These figures are not static, particularly in the case of wind power as a result of advancing technology. For instance, the carbon footprint of the monstrous offshore wind power plant is expected to fall to 6 g CO_2-eq/kWh in the future. In general, the greenhouse gas emissions by onshore and offshore wind power plants can vary depending on the capacity factor, component materials' recovery rate at the end of the life cycle, and wind turbine mass (Bhandari et al., 2020).

Table 3 presents the recent research findings associated with carbon footprints of onshore and offshore wind power generation for wind power plants with different capacities based on various life cycle impact modeling methods. The results vary depending on the region where the studies were conducted, rated capacities of wind power plants or turbines, and configurations of wind power plants: onshore versus offshore. To put into the context, wind turbines of similar capacity and configuration (both onshore) were reported to have varying carbon footprints (4.9 g CO_2-eq/kWh (Alsaleh and Sattler, 2019) and 0.082 kg CO_2-eq/MJ (S. Wang et al., 2019)) by researchers from different regions of the world; and the reason for this is due to the differences in the capacity factors and lifecycles of the two turbines. Moreover, the wind power plant (group of turbines) or individual turbine with higher rated power capacity, capacity factor, and longer lifespan has usually lower lifecycle emission. In this sense, according to (Bonou et al., 2016), the lifecycle CO_2 emissions for 3.2 MW and 2.3 MW power rated onshore turbines were claimed to be 5 g CO_2-eq/kWh and 6 g CO_2-eq/kWh, respectively; and whereas for offshore wind turbines with power capacities of 6 MW and 4 MW, their lifecycle emissions were reported to be 7.8 g CO_2-eq/kWh and 10.9 g CO_2-eq/kWh, respectively. On the other hand, offshore wind power generation is appeared to be characterized by slightly higher lifecycle greenhouse gases emissions than onshore wind power generation.

According to a report by (S. Wang et al., 2019), 2 MW of offshore wind turbine produced 0.13 kg CO_2-eq/MJ amount of emission, while its onshore counterpart with the same rated power (2 MW) produced 0.082 kg CO_2-eq/MJ amount of emission. On the other hand, offshore power plant with capacity of 100*3 MW generated 5.98 g CO_2-eq/kWh amount of emission, whereas its onshore counterpart with similar power capacity (100*3 MW) generated 4.97 g CO_2-eq/kWh amount of emission as reported (Y. Wang and Sun, 2012). Most important of all, the assessments provided in Table 3 relied on different methods and software tools. It is clear that the accuracy of a life-cycle impact assessment is generally affected by a proposed methodology, and a detail of this is pointed out in section 4. The most advanced methodologies for more accurate assessments of wind turbines' life-cycle impacts are also introduced under section 4.

On the other hand, it is also possible to estimate emissions payback periods for onshore and offshore wind power plants. Payback periods are the time spans required for wind power plants to generate adequate pollution-free electricity to compensate for the pollution by carbon that could be produced during the construction of wind power plants. Researchers in (Bonou et al., 2016) estimated the average carbon payback period for two onshore wind turbines having capacities of 2.3 MW and 3.2 MW, and two offshore wind turbines having capacities of 4 MW and 6 MW at around seven months. These turbines were reported to have a lifecycle of 20–25 years, and therefore, a period of seven months for carbon payback can be considered feasible enough. In addition, a comparative life-cycle analysis based on energy payback period was conducted by researchers in (Stavridou et al., 2020) for two onshore wind turbines of similar capacity (2 MW) and different tower designs, and 5–6 months for tabular steel tower-based design, and 4 months for the lattice self-rising steel tower-based design were estimated. This indicates that system dynamics could affect the energy payback performance.

Furthermore, researchers in (Chipindula et al., 2018) conducted life

Table 3
Life-cycle CO_2 emissions by onshore- and offshore-based wind power plant configurations.

Configuration	Power capacity	Modeling platform	Emission	Ref.
Onshore	200 wind turbines with 2 MW capacity each	ILCD (ISO 14040) and SimaPro 8	4.9 g CO_2-eq/kWh	Alsaleh and Sattler (2019)
Onshore	2 MW	ILCD (ISO 14044)	0.082 kg CO_2-eq/MJ	(S. Wang et al., 2019)
Offshore	2 MW		0.13 kg CO_2-eq/MJ	
Offshore	27 wind turbines with 3.6 MW capacity each + 1 wind turbine with 5 MW capacity	ILCD (ISO 14044)	25.5 g CO_2-eq/kWh	(J. Yang et al., 2018)
Onshore	18 wind turbines with 1.5 MW capacity each + 30 wind turbines with 0.75 MW capacity each	SimaPro 8/ ecoinvent 2.2 and GaBi/CML 2001	8.6 g CO_2-eq/kWh	Xu et al. (2018)
Onshore	1 MW	SimaPro8/ ecoinvent 3 (based on ISO 14040) and GaBi/IMPACT 2002+	7.35 g CO_2-eq/kWh	Chipindula et al. (2018)
Onshore	1.5 MW	ILCD (ISO 14040) and GaBi/CML 2001	11.8 g CO_2-eq/kWh	Ozoemena et al. (2017)
Onshore	2.3 MW	IPCC guideline, SimaPro 8/ ecoinvent 2 (based on ILCD Handbook) and ReCiPe	6 g CO_2-eq/kWh	(Bonou et al., 2016)
Onshore	3.2 MW		5 g CO_2-eq/kWh	
Offshore	4 MW		10.9 g CO_2-eq/kWh	
Offshore	6 MW		7.8 g CO_2-eq/kWh	
Onshore	2 MW	ILCD method	20.7 g CO_2-eq/kWh	(D. Yang et al., 2015)
Offshore	6 different turbine designs with 5 MW capacity each	ILCD (ISO 14044)	18–31.4 g CO_2-eq/kWh	Raadal et al. (2014)
Onshore	100 wind turbines with 3 MW capacity each	IPCC guideline (manual-based assessment)	4.97 g CO_2-eq/kWh	(Y. Wang and Sun, 2012)
Offshore	100 wind turbines with 3 MW capacity each		5.98 g CO_2-eq/kWh	
Onshore	186 wind turbines with 1.65 MW capacity each		8.21 g CO_2-eq/kWh	

cycle assessments for various configurations of onshore and offshore wind turbines by considering their environmental impacts, carbon, and energy payback periods while estimating their emissions. The proposed configurations include: (1) three onshore turbines with a total rated capacity of 5.3 MW, (2) two shallow water-based offshore turbines with total rated capacity of 4.4 MW, and (3) two deep water-based offshore turbines with total rated capacity of 7.3 MW. Accordingly, 6–14 months were reported to be required to pay back energy consumptions and carbon emissions by turbines at the onshore location; whereas 6–17 months were estimated for turbines commissioned at an offshore location. As per this study, energy consumption and carbon emission during life cycles can be compensated in shorter periods with onshore wind turbines than with offshore ones.

4. Recent challenges and advances in life-cycle impact assessment modeling

As outlined in Table 3, the life-cycle emissions by onshore and offshore wind turbines were shown to be estimated in two ways. One way was through manual calculation depending on the process-based and life-cycle assessment baselines, which were provided by International Life Cycle Data (ILCD) handbook and Intergovernmental Panel on Climate Change (IPCC) guideline; and historical data collected from different sources. Whereas, the second way relied on different software solutions that were being built based on ILDC and IPCC databases to facilitate the more accurate assessments of wind turbines' life-cycles impacts in determining the levels of carbon emissions, energy consumptions, and the times required to remove emissions and compensate consumed energy. However, these methodologies may not be efficient and effective in helping to produce more accurate and acceptable results of life-cycle assessments for wind turbines due to several factors. Life-cycle assessment baselines (ILCD and IPCC) and supporting software tools were originally developed for different fields and applications, and therefore, employing them for modeling and evaluation of wind turbines' life-cycle impacts may not be methodically sounding as the wind turbine systems dynamics are entirely different from other power systems, such as the conventional power technologies.

In general, most of the existing methods that are associated with the modelling of wind turbines' life-cycle impact assessments were based on the aforementioned traditional guidelines in addition to employing various software tools and average historical data that were manually collected from different plants. However, the findings of the life-cycle assessments may not be fully credible without the inclusion of real-time and dynamic data in model developments, particularly for complex systems like wind power plants. Hence, in order to ensure effective decision making that can ultimately result in realizing reliable operational efficiency of wind power plants, advanced methods that should implement real-time data in modeling of life-cycle assessments are required to be introduced.

In response to the limitations of the conventional life-cycle impact modeling methods, the machine learning-assisted technologies, namely Internet of things (IoT) (Alhmoud and Al-Zoubi, 2019) and predictive digital twin (Haghshenas et al., 2023) were presently reported to be the most powerful methods as they would take into account the system dynamics of wind power plants. These methods generally facilitate the acquisition of real-time data in modeling the wind turbines' life-cycle impacts in order to achieve more accurate assessments, which could eventually be implemented for turbine systems optimizations. The ultimate goal of the optimization by employing IoT and predictive digital twin technologies is to reduce or remove the degree of life-cycle impacts (emissions, etc.), and hence enhance the operational reliability of the power plants be based on the reported assessments (Adekanbi, 2021). Unlike the conventional methods, real-time data extraction from the power plants makes IoT possible to conduct accurate assessments of the life-cycle impacts by simultaneously taking into account multiple factors. This technology can also be integrated with machine learning, and artificial intelligence technologies for ensuring more efficient, and reliable modeling of life-cycle assessments, this could ultimately result in generally smarter power systems with mitigated life-cycle impacts (Rebouças Filho et al., 2019). Furthermore, predictive digital twin is another advanced technology that was introduced as an option to replace the conventional methods for ensuring robust assessments of the power plants' life-cycle impacts. This technology is the virtual representation of real-time data involved in the entire wind power plants' life-cycles. Through real-time monitoring data, high performance simulation accuracy and robust simulation prediction, predictive digital twin can realize the digital description and smart application service of the power plants' whole life-cycle from concept, design, manufacturing, operation, maintenance to scrapping (Zhong et al., 2023).

A further study presented in (An et al., 2021) also proposed an advanced life-cycle assessment modeling method that was based on a real-time application of Internet of Things (IoT) for enhancing wind turbines' operational efficiency. This technology was implemented for achieving the real-time, and reliable gathering of data that were associated with energy consumption, and environmental impacts throughout the wind turbines' lifecycles. More importantly, the nature of databases built through IoT technology would mimic the operational dynamics of wind turbines, and this would help to produce assessment results with an excellent degree of accuracy and objectivity. The life-cycle assessment model was developed by integrating the database that was built by the application of IOT into IMPACT 2002+, which would enable to design and implement a combined methods involving midpoint and endpoint. Accordingly, the complexity and uncertainty that could most likely be resulted by employing conventional methods were reported to be eliminated by IOT plus IMPACT 2002+ model.

A research work presented in (He et al., 2023), on the other hand, introduced a novel digital twin modeling method that was integrated with carbon footprint analysis by using the pile-leg lifting system as a prototype for offshore wind power installation platform. According to this work, rich product twin data can be generated by employing the data acquisition function module of the digital twin system, and this can facilitate an effective carbon footprint analysis of the prototype. Based on a closed-loop digital twin system consisting of a physical system's control service subsystem, carbon footprint analysis model, physical system, twin data, and virtual system, the result of the carbon footprint analysis was considered as the optimization target for the physical system. This work proposed a novel digital twin framework for the physical system's control service subsystem by implementing the master-slave design pattern and event state machine. Moreover, this work employed LabVIEW software to realize real-time data acquisition function, data storage function, and control instructions distribution function of the physical system's control service subsystem, and to establish a human-computer interface. A simple and effective model of carbon footprint analysis that gives consideration to cost factors and information uncertainty was also introduced by this work for electromechanical subsystems. The validity of the proposed digital twin model was finally demonstrated by implementing it in the prototype. In general, this technology offers an advanced approach to optimization of physical wind power plants by addressing the challenges imposed by the traditional carbon footprint assessment models.

In addition, studies in (Ghoroghi et al., 2022; Portolani et al., 2022) demonstrated the advancements and effectiveness of machine learning-based methods of modelling wind power plants' life-cycle impact assessments against the conventional methods, such as that listed in Table 3. Machine learning-based life-cycle assessment methods can contribute greatly in helping to reducing the impacts stemming from the dynamics of power plants. According to (Ghoroghi et al., 2022), wind power plants' Life-cycle impact assessment modelling that is underpinned by machine learning methods and informed by power plants' dynamic data paves the way to more accurate assessment while supporting life-cycle decision making. The application of machine learning models can be more quantified based on additional studies. For instance, a machine learning model that relies on a fusion of the feed-forward neural network (NN) and Electricity Technological Mix Forecasting (ETMF) algorithms was proposed in (Portolani et al., 2022) to forecast life-cycle assessment impact indicators for the consumption of electricity, and the superior accuracy of the proposed model was finally demonstrated against the conventional method.

The discussion under this section generally indicates that the conventional life-cycle impact assessment methods are not effective and efficient for optimization of wind power plants' operation. Hence, this paper has introduced the most robust modelling methods that particularly rely on IoT, predictive digital twin, and machine learning algorithms. These methods could help to conduct more reliable life-cycle impact assessments that could ultimately be used as inputs in decision-making for the wind power systems' management.

5. Conclusion

Onshore and offshore wind power generation have generally achieved varying levels of growths over the last few decades, and also expected to sustain more rapid and significant changes in the years to come. Global renewable (wind) energy research and technology institutions, such as IRENA and GWEC recently unveiled both independent and joint reports on the onshore and offshore wind power development trends based on the recent installations and future projections. Even though some differences have been observed with regard to historical achievements of onshore and offshore wind power installations, both (IRENA and GWEC) have indicated further improvements would be achieved with onshore and offshore technologies in terms of energy costs, power production, impacts of wind farms etc. in the upcoming future. However, these projections could not be smoothly achieved without the enhanced research studies, technologies, power deployments, policy considerations, etc. that are associated with these systems. Most vitally, relatively high offshore LCOE, and offshore wind power plants' life cycle impacts are the potential areas that demand further considerations in order to meet the desired standards that are required from the future wind farm industries. In particular, offshore wind power has become to receive a significant attention since the last few years and still has remained to be at the forefront of technological and research projects.

The accurate modeling and assessment of wind turbine systems' life cycle impacts is the critical research issues to date to provide the proper recommendations on the outcomes of the related studies, which could ultimately be implemented in optimizing the turbines' physical components. In this regard, many of the existing works relied on the traditional modeling methods that do not entirely define the characteristics and dynamics of wind turbines, and that would not lead to the objective evaluation of turbines' life cycle impacts. Recently, only few number of works have been published by employing modelling methods that fully represent the turbine systems dynamics and implement real-time data collection in making the assessments more objective and credible. Hence, more extended studies would be expected in this area to help further lowering of the impacts, particularly the emissions due to the power plants' carbon footprints by employing the most effective technologies, such as IoT and predictive digital twin. Unlike the conventional methods, real-time data extraction from the power plants makes these technologies possible to conduct the most accurate assessments of the life-cycle impacts. This study generally recommends the application of these technologies for the most reliable life-cycle assessments of wind power plants. Moreover, the findings of the assessments that would implement IoT and predictive digital twin methods could ultimately be used as inputs in decision-making for the wind power systems' management.

Author contribution statement

All authors listed above are significantly contributed to the development and writing of this paper.

Funding statement

This work was supported by Bahir Dar University Institute of Technology, Bahir Dar Energy Center; and Wolaita Sodo University.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Adedipe, O., Abolarin, M.S., Mamman, R.O., 2018. A review of onshore and offshore wind energy potential in Nigeria. IOP Conf. Ser. Mater. Sci. Eng. 413 (1) https://doi.org/10.1088/1757-899X/413/1/012039.

Adekanbi, M.L., 2021. Optimization and digitization of wind farms using internet of things: a review. Int. J. Energy Res. 45 (11), 15832–15838. https://doi.org/10.1002/ER.6942.

Adeyeye, K., Ijumba, N., Colton, J., 2020. Exploring the Environmental and Economic Impacts of Wind Energy: a Cost-Benefit Perspective, pp. 718–731. https://doi.org/10.1080/13504509.2020.1768171. Https://Doi.Org/10.1080/13504509.2020.1768171, 27(8).

Alhmoud, L., Al-Zoubi, H., 2019. IoT applications in wind energy conversion systems. Open Eng. 9 (1), 490–499. https://doi.org/10.1515/ENG-2019-0061/MACHINEREADABLECITATION/RIS.

Alsaleh, A., Sattler, M., 2019. Comprehensive life cycle assessment of large wind turbines in the US. Clean Technol. Environ. Policy 21 (4), 887–903. https://doi.org/10.1007/S10098-019-01678-0, 2019 21:4.

An, J., Zou, Z., Chen, G., Sun, Y., Liu, R., Zheng, L., 2021. An IoT-based life cycle assessment platform of wind turbines. Sensors 21 (4), 1–21. https://doi.org/10.3390/s21041233.

Aries, N., Boudia, S.M., Ounis, H., 2018. Deep assessment of wind speed distribution models: a case study of four sites in Algeria. Energy Convers. Manag. 155, 78–90. https://doi.org/10.1016/J.ENCONMAN.2017.10.082.

Aslam, M., 2021. Testing average wind speed using sampling plan for Weibull distribution under indeterminacy. Sci. Rep. 11 (1), 1–9. https://doi.org/10.1038/s41598-021-87136-8, 2021 11:1.

Bhandari, R., Kumar, B., Mayer, F., 2020. Life cycle greenhouse gas emission from wind farms in reference to turbine sizes and capacity factors. J. Clean. Prod. 277, 123385 https://doi.org/10.1016/J.JCLEPRO.2020.123385.

Bonou, A., Laurent, A., Olsen, S.I., 2016. Life cycle assessment of onshore and offshore wind energy-from theory to application. Appl. Energy 180, 327–337. https://doi.org/10.1016/j.apenergy.2016.07.058.

Carrara, T., Dias, A., Eur, C., Nd Pr Dy Tb, E., 2020. Ag Ga Ge Si Cd in Se Raw Materials Demand for Wind and Solar PV Technologies in the Transition towards a Decarbonised Energy System. https://doi.org/10.2760/160859.

Carta, J.A., Bueno, C., Ramírez, P., 2008. Statistical modelling of directional wind speeds using mixtures of von Mises distributions: case study. Energy Convers. Manag. 49 (5), 897–907. https://doi.org/10.1016/J.ENCONMAN.2007.10.017.

Chen, Z., 2013. Wind power in modern power systems. J. Modern Power Syst. Clean Energy 1 (1), 2–13. https://doi.org/10.1007/S40565-013-0012-4/FIGURES/9.

Chen, H., Birkelund, Y., Anfinsen, S.N., Staupe-Delgado, R., Yuan, F., 2021. Assessing probabilistic modelling for wind speed from numerical weather prediction model and observation in the Arctic. Sci. Rep. 11 (1), 1–11. https://doi.org/10.1038/s41598-021-87299-4, 2021 11:1.

Chipindula, J., Botlaguduru, V.S.V., Du, H., Kommalapati, R.R., Huque, Z., 2018. Life cycle environmental impact of onshore and offshore wind farms in Texas. Sustainability 10 (6). https://doi.org/10.3390/su10062022.

Deep, S., Sarkar, A., Ghawat, M., Rajak, M.K., 2020. Estimation of the wind energy potential for coastal locations in India using the Weibull model. Renew. Energy 161, 319–339. https://doi.org/10.1016/J.RENENE.2020.07.054.

Desalegn, B., Gebeyehu, D., Tamirat, B., 2022. Wind Energy Conversion Technologies and Engineering Approaches to Enhancing Wind Power Generation: A Review. Heliyon. https://doi.org/10.1016/j.heliyon.2022.e11263.

Desalegn, B., Gebeyehu, D., Tamrat, B., Tadiwose, T., 2023. Wind energy-harvesting technologies and recent research progresses in wind farm control models. Front. Energy Res. 11, 81. https://doi.org/10.3389/FENRG.2023.1124203/BIBTEX.

Díaz-Motta, A., Díaz-González, F., Villa-Arrieta, M., 2023. Energy sustainability assessment of offshore wind-powered ammonia. J. Clean. Prod. 420, 138419 https://doi.org/10.1016/J.JCLEPRO.2023.138419.

Doerffer, K., Bałdowska-Witos, P., Pysz, M., Doerffer, P., Tomporowski, A., 2021. Manufacturing and recycling impact on environmental life cycle assessment of innovative wind power plant part 1/2. Materials 14 (1), 1–21. https://doi.org/10.3390/ma14010220.

European Commission. Joint Research Centre, 2010. International Reference Life Cycle Data System (ILCD) Handbook General Guide for Life Cycle Assessment: Detailed Guidance. Publications Office. Institute for Environment and Sustainability.

Fernández-Guillamón, A., Das, K., Cutululis, N.A., Molina-García, Á., 2019. Offshore wind power integration into future power systems: overview and trends. J. Mar. Sci. Eng. 7 (11), 399. https://doi.org/10.3390/JMSE7110399, 2019, Vol. 7, Page 399.

Gao, A.M.-Z., Huang, C.-H., Lin, J.-C., Su, W.-N., 2021. Review of recent offshore wind power strategy in Taiwan: onshore wind power comparison. Energy Strategy Rev. 38, 100747 https://doi.org/10.1016/J.ESR.2021.100747.

Ghoroghi, A., Rezgui, Y., Petri, I., Beach, T., 2022. Advances in application of machine learning to life cycle assessment: a literature review. Int. J. Life Cycle Assess. 27 (3), 433–456. https://doi.org/10.1007/S11367-022-02030-3/TABLES/3 global wind report 2021. (n.d.).

Global Wind Report, 2023. Global Wind Energy Council (n.d.). Retrieved August 20, 2023, from. https://gwec.net/globalwindreport2023/.

Goedkoop, M., Oele, M., Leijting, J., Ponsioen, T., Meijer, E., 2013. Introduction to LCA with SimaPro Title: Introduction to LCA with SimaPro. www.pre-sustainability.com.

Gugliani, G.K., Sarkar, A., Ley, C., Mandal, S., 2018. New methods to assess wind resources in terms of wind speed, load, power and direction. Renew. Energy 129, 168–182. https://doi.org/10.1016/J.RENENE.2018.05.088.

Gul, M., Tai, N., Huang, W., Nadeem, M.H., Yu, M., 2019. Assessment of wind power potential and economic analysis at Hyderabad in Pakistan: powering to local communities using wind power. Sustainability 11 (5). https://doi.org/10.3390/su11051391.

GWEC-GLOBAL-WIND-REPORT-2022. (n.d.).

GWEC.NET. Associate Sponsors supporting sponsor leading sponsor (n.d.). www.gwec.net.

Haghshenas, A., Hasan, A., Osen, O., Mikalsen, E.T., 2023. Predictive digital twin for offshore wind farms. Energy Informat. 6 (1), 1–26. https://doi.org/10.1186/S42162-023-00257-4/FIGURES/19.

Han, Q., Chu, F., 2021. Directional wind energy assessment of China based on nonparametric copula models. Renew. Energy 164, 1334–1349. https://doi.org/10.1016/J.RENENE.2020.10.149.

He, B., Mao, H., Li, T., Xiao, J., 2023. A closed-loop digital twin modeling method integrated with carbon footprint analysis. Comput. Ind. Eng. 182, 109389 https://doi.org/10.1016/J.CIE.2023.109389.

Hevia-Koch, P., Klinge Jacobsen, H., 2019. Comparing offshore and onshore wind development considering acceptance costs. Energy Pol. 125, 9–19. https://doi.org/10.1016/J.ENPOL.2018.10.019.

Hu, Q., Wang, Y., Xie, Z., Zhu, P., Yu, D., 2016. On estimating uncertainty of wind energy with mixture of distributions. Energy 112, 935–962. https://doi.org/10.1016/J.ENERGY.2016.06.112.

Huang, S., Li, Q., Shu, Z., Chan, P.W., 2023. Copula-based joint distribution analysis of wind speed and wind direction: wind energy development for Hong Kong. Wind Energy 26 (9), 900–922. https://doi.org/10.1002/WE.2847.

IRENA, 2019. Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation Paper). International Renewable Energy Agency, Abu Dhabi (n.d.).

IRENA, 2021. Renewable Energy Statistics 2021. The International Renewable Energy Agency, Abu Dhabi (n.d.).

IRENA-International Renewable Energy Agency, 2023. World energy transitions outlook: 1.5°C pathway. World Energy Transit. 1–176 irena.org/Digital-Report/World-Energy-Transitions-Outlook-2022%0A. https://irena.org/publications/2021/March/World-Energy-Transitions-Outlook.

Irfan, M., Zhao, Z.Y., Ahmad, M., Mukeshimana, M.C., 2019. Critical factors influencing wind power industry: a diamond model based study of India. Energy Rep. 5, 1222–1235. https://doi.org/10.1016/J.EGYR.2019.08.068.

Jolliet, O., Margni, M., Charles, R., Humbert, S., Payet, J., Rebitzer, G., Rosenbaum, R., 2003. IMPACT 2002+: a new life cycle impact assessment methodology. Int. J. Life Cycle Assess. 8 (Issue 6), 324–330. https://doi.org/10.1007/BF02978505. Springer Verlag.

Kaldellis, J.K., Apostolou, D., 2017. Life cycle energy and carbon footprint of offshore wind energy. Comparison with onshore counterpart. Renew. Energy 108, 72–84. https://doi.org/10.1016/J.RENENE.2017.02.039.

Konstantinidis, E.I., Botsaris, P.N., 2016. Wind turbines: current status, obstacles, trends and technologies. IOP Conf. Ser. Mater. Sci. Eng. 161 (1) https://doi.org/10.1088/1757-899X/161/1/012079.

Lantz, E., Roberts, O., Nunemaker, J., Demeo, E., Dykes, K., Scott, G., 2019. Increasing Wind Turbine Tower Heights: Opportunities and Challenges. www.nrel.gov/publications.

Lau, K.K., Gleason, K.K., Mulder, R., Melese, Y., Lopes Cardozo, N., Xu, J., Zou, J., Ziegler, A.D., Wu, J., Zeng, Z., 2023. What drives the change of capacity factor of wind turbine in the United States? Environ. Res. Lett. 18 (6), 064009 https://doi.org/10.1088/1748-9326/ACCE4F.

Li, Y., Huang, X., Tee, K.F., Li, Q., Wu, X.P., 2020. Comparative study of onshore and offshore wind characteristics and wind energy potentials: a case study for southeast coastal region of China. Sustain. Energy Technol. Assessments 39. https://doi.org/10.1016/j.seta.2020.100711.

Ling-Chin, J., Roskilly, A.P., 2016. A comparative life cycle assessment of marine power systems. Energy Convers. Manag. 127, 477–493. https://doi.org/10.1016/J.ENCONMAN.2016.09.012.

Lins, D.R., Guedes, K.S., Pitombeira-Neto, A.R., Rocha, P.A.C., de Andrade, C.F., 2023. Comparison of the performance of different wind speed distribution models applied to onshore and offshore wind speed data in the Northeast Brazil. Energy 278, 127787. https://doi.org/10.1016/J.ENERGY.2023.127787.

Manwell, J.F., 2012. Offshore wind energy technology trends, challenges, and risks. Encyclopedia of Sustain. Sci. Tech. 7393–7425. https://doi.org/10.1007/978-1-4419-0851-3_697.

Martin Baitz, Dr, et al., 2012. GaBi Database & Modelling Principles.

Masseran, N., Razali, A.M., Ibrahim, K., Latif, M.T., 2013. Fitting a mixture of von Mises distributions in order to model data on wind direction in Peninsular Malaysia. Energy Convers. Manag. 72, 94–102. https://doi.org/10.1016/J.ENCONMAN.2012.11.025.

Myhr, A., Bjerkseter, C., Ågotnes, A., Nygaard, T.A., 2014. Levelised cost of energy for offshore floating wind turbines in a life cycle perspective. Renew. Energy 66, 714–728. https://doi.org/10.1016/J.RENENE.2014.01.017.

Navarro (mexico), Edmonds, J.Usa, Faaij, A., 2014. Edgar Hertwich (Austria/Norway), Damon Honnery (Australia), David Infield (UK). Mitigation of Climate Change.

Ng, C., Ran, L., 2016. Introduction to offshore wind energy. Offshore Wind Farms: Tech., Design Operation 3–8. https://doi.org/10.1016/B978-0-08-100779-2.00001-5.

Ozoemena, M., Cheung, W.M., Hasan, R., 2017. Comparative LCA of technology improvement opportunities for a 1.5-MW wind turbine in the context of an onshore wind farm. Clean Technol. Environ. Policy 20 (1), 173–190. https://doi.org/10.1007/S10098-017-1466-2, 2017 20:1.

Pang, C., Yu, J., Liu, Y., 2021. Correlation analysis of factors affecting wind power based on machine learning and Shapley value. IET Energy Syst. Integrat. 3 (3), 227–237. https://doi.org/10.1049/ESI2.12022.

Pishgar-Komleh, S.H., Keyhani, A., Sefeedpari, P., 2015. Wind speed and power density analysis based on Weibull and Rayleigh distributions (a case study: Firouzkooh county of Iran). Renew. Sustain. Energy Rev. 42, 313–322. https://doi.org/10.1016/J.RSER.2014.10.028.

Portolani, P., Vitali, A., Cornago, S., Rovelli, D., Brondi, C., Low, J.S.C., Ramakrishna, S., Ballarino, A., 2022. Machine learning to forecast electricity hourly LCA impacts due to a dynamic electricity technology mix. Front. Sustain. 3, 137. https://doi.org/10.3389/FRSUS.2022.1037497.

Prieto-Araujo, E., Gomis-Bellmunt, O., 2016. Wind Turbine Technologies. HVDC Grids for Transmission of Electrical Energy: Offshore Grids and a Future Supergrid, pp. 97–108. https://doi.org/10.1002/9781119115243.CH5.

Raadal, H.L., Vold, B.I., Myhr, A., Nygaard, T.A., 2014. GHG emissions and energy performance of offshore wind power. Renew. Energy 66, 314–324. https://doi.org/10.1016/j.renene.2013.11.075.

Rebouças Filho, P.P., Gomes, S.L., e Nascimento, N.M.M., Medeiros, C.M.S., Outay, F., de Albuquerque, V.H.C., 2019. Energy production predication via Internet of Thing based machine learning system. Future Generat. Comput. Syst. 97, 180–193. https://doi.org/10.1016/J.FUTURE.2019.01.020.

Renewable Energy Agency, I, 2022. RENEWABLE CAPACITY STATISTICS 2022 STATISTIQUES DE CAPACITÉ RENOUVELABLE 2022 ESTADÍSTICAS DE CAPACIDAD RENOVABLE 2022. www.irena.org.

Salah, S.I., Eltaweel, M., Abeykoon, C., 2022. Towards a sustainable energy future for Egypt: a systematic review of renewable energy sources, technologies, challenges, and recommendations. Clean. Eng. Tech. 8, 100497 https://doi.org/10.1016/J.CLET.2022.100497.

Shields, M., Beiter, P., Nunemaker, J., Cooperman, A., Duffy, P., 2021. Impacts of turbine and plant upsizing on the levelized cost of energy for offshore wind. Appl. Energy 298. https://doi.org/10.1016/J.APENERGY.2021.117189.

Shields, M., Beiter, P., Nunemaker, J., 2022. A Systematic Framework for Projecting the Future Cost of Offshore Wind Energy. https://doi.org/10.2172/1902302.

Siram, O., Sahoo, N., Saha, U.K., 2022. Changing landscape of India's renewable energy and the contribution of wind energy. Clean. Eng. Tech. 8, 100506 https://doi.org/10.1016/J.CLET.2022.100506.

Smith, Andrew ZP.. ORCID: 0000-0003-3289-2237; "Capacity factors at Danish offshore wind farms". Retrieved from. https://energynumbers.info/capacity-factors-at-danish-offshore-wind-farms *on 2021-11-02 19:21 GMT* (n.d.).

Stavridou, N., Koltsakis, E., Baniotopoulos, C.C., 2020. A comparative life-cycle analysis of tall onshore steel wind-turbine towers. Clean Energy 4 (1), 48–57. https://doi.org/10.1093/ce/zkz028.

Stehly, Tyler, Beiter, Philipp, Duffy, Patrick, 2020. 2019 Cost of Wind Energy Review. National Renewable Energy Laboratory, Golden, CO. NREL/TP-5000-78471. https://www.nrel.gov/docs/fy21osti/78471.pdf (n.d.).

Tetteh, E.K., Amankwa, M.O., Yeboah, C., Amankwa, M.O., 2021. Emerging carbon abatement technologies to mitigate energy-carbon footprint- a review. Cleaner Materials 2, 100020. https://doi.org/10.1016/J.CLEMA.2021.100020.

Tong, W., 2010. CHAPTER 1 Fundamentals of wind energy. WIT Transact. State Art Sci. Eng. 44, 1755–8336. https://doi.org/10.2495/978-1-84564-/205-1.

Wais, P., 2017. Two and three-parameter Weibull distribution in available wind power analysis. Renew. Energy 103, 15–29. https://doi.org/10.1016/J.RENENE.2016.10.041.

Wang, Z., Liu, W., 2021. Wind energy potential assessment based on wind speed, its direction and power data. Sci. Rep. 11 (1), 1–15. https://doi.org/10.1038/s41598-021-96376-7, 2021 11:1.

Wang, Y., Sun, T., 2012. Life cycle assessment of CO 2 emissions from wind power plants: methodology and case studies. Renew. Energy 43, 30–36. https://doi.org/10.1016/j.renene.2011.12.017.

Wang, S., Wang, S., Liu, J., 2019. Life-cycle green-house gas emissions of onshore and offshore wind turbines. J. Clean. Prod. 210, 804–810. https://doi.org/10.1016/j.jclepro.2018.11.031.

Weidema, B.P., et al., 2013. Overview and Methodology. Data Quality Guideline for the Ecoinvent Database Version 3. Ecoinvent Report 1(v3). The ecoinvent Centre, St. Gallen.

Wimbadi, R.W., Djalante, R., 2020. From decarbonization to low carbon development and transition: a systematic literature review of the conceptualization of moving toward net-zero carbon dioxide emission (1995–2019). In: Journal of Cleaner Production, vol. 256. Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2020.120307.

Wind Systems, V.A., 2020. The Vestas Sustainability Report 2020 How Do We Support the UN Sustainable Development Goals (SDGs)?.

Wiser, R., Rand, J., Seel, J., Beiter, P., Baker, E., Lantz, E., Gilman, P., 2021. Expert elicitation survey predicts 37% to 49% declines in wind energy costs by 2050. Nat. Energy 6 (5), 555–565. https://doi.org/10.1038/s41560-021-00810-z.

Xu, L., Pang, M., Zhang, L., Poganietz, W.R., Marathe, S.D., 2018. Life cycle assessment of onshore wind power systems in China. Resour. Conserv. Recycl. 132, 361–368. https://doi.org/10.1016/j.resconrec.2017.06.014.

Yang, D., Liu, J., Yang, J., Ding, N., 2015. Carbon footprint of wind turbine by life cycle assessment. Huanjing Kexue Xuebao/Acta Scientiae Circumstantiae 35 (3), 927–934. https://doi.org/10.13671/J.HJKXXB.2014.0906.

Yang, J., Chang, Y., Zhang, L., Hao, Y., Yan, Q., Wang, C., 2018. The life-cycle energy and environmental emissions of a typical offshore wind farm in China. J. Clean. Prod. 180, 316–324. https://doi.org/10.1016/j.jclepro.2018.01.082.

Yuan, W., Feng, J.-C., Zhang, S., Sun, L., Cai, Y., Yang, Z., Sheng, S., 2023. Floating wind power in deep-sea area: life cycle assessment of environmental impacts. Advan. Appl. Energy 9, 100122. https://doi.org/10.1016/J.ADAPEN.2023.100122.

Zhong, D., Xia, Z., Zhu, Y., Duan, J., 2023. Overview of predictive maintenance based on digital twin technology. Heliyon 9 (4), e14534. https://doi.org/10.1016/J.HELIYON.2023.E14534.

Zou, M., Fang, D., Djokic, S.Z., Di Giorgio, V., Langella, R., Testa, A., 2020. Evaluation of wind turbine power outputs with and without uncertainties in input wind speed and wind direction data. IET Renew. Power Gener. 14 (15), 2801–2809. https://doi.org/10.1049/IET-RPG.2020.0113.