Offshore Wind Energy: Resource Assessment

Garlapati Nagababu and V. S. K. V. Harish

Contents

Abstract Recent advancements in technologies and increased attention towards renewable energy sources have made offshore wind energy systems as one of the largest and significant electrical power generators. In this chapter, fundamentals of offshore wind energy physics along with resource assessment methodology are described in detail. The process of resource assessment consists of the use of different data sets, different resource and energy estimation models. Wind, being an intermittent resource for power generation, mandates statistical methods to estimate the parameters with uncertainties. Researchers have employed several methodologies to assess offshore wind power density using resource estimation models and geographical information systems. Present chapter will be beneficial in getting familiar with the wind resource data analysis and different aspects of resource assessment.

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1 Introduction

Wind energy is implied type of solar energy generated due to the warming of the earth exterior and rotation of earth on its axis [1]. The air in the contact with surface absorbs the heat and moves upwards, whereas the denser and colder moves downwards; this generates vertical movement of the air. Moreover, the distribution of heat around the globe is different as the equatorial part gets more heat than the polar regions. Owing to achieve equilibrium, the denser air moves towards the less dense air which generates the lateral movement of air. These both vertical and lateral movements of air particles are termed as wind. Additionally, the rotation of earth on its axis generated Coriolis effect (CE) that causes winds to deviate towards right side (clockwise) of its direction in northern hemisphere and towards left side (counter-clockwise) of its direction in southern hemisphere (refer Figs. 1 and 2). CE is most significant near the polar regions and nominal near the equator.

The offshore wind energy means the wind energy available at the marine regions, i.e. water surfaces of seas and oceans. Offshore wind energy is an ample and untapped source of renewable energy available all over the globe in different intensities. The harvesting of offshore wind energy is an intricate engineering and scientific challenge [2]. This chapter is focused on the current status offshore energy, different aspects of wind resource assessment, energy estimation models and future trends in the field.

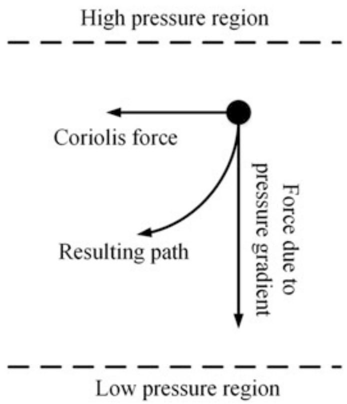

Fig. 1 Impact of Coriolis effect on the wind direction

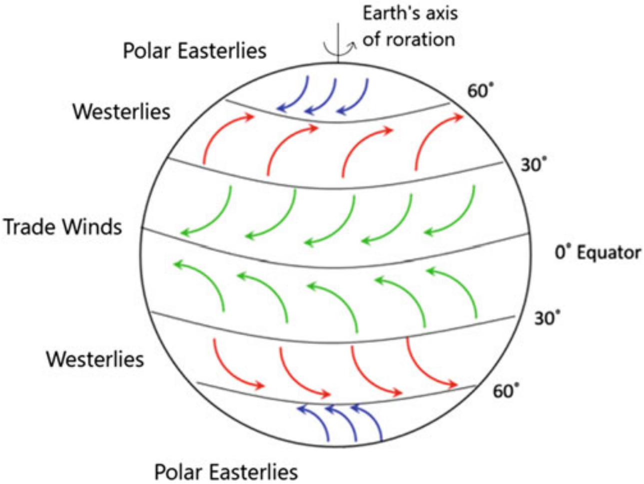

Fig. 2 Depiction of wind patterns with Coriolis effect

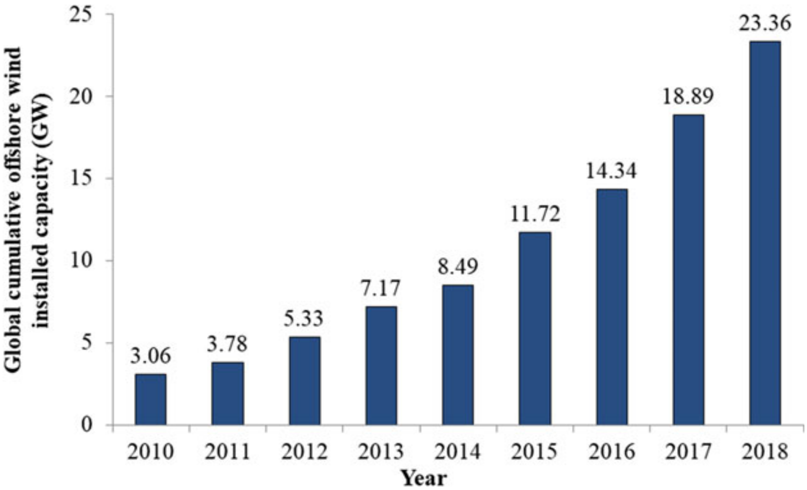

Fig. 3 Global aggregate offshore wind power installed capacity (2010–2018)

1.1 Background

The field of offshore wind energy is still in an infant phase and not older than two decades as shown in Fig. 3 [3]. There are incredible opportunities in offshore regions but numerous complications to be seized. While focusing on the offshore wind energy resources, the differences from onshore resources like environmental conditions, project infrastructure, project design, power evacuation facilities and safety measures have to be considered [1].

1.2 Status of Offshore Wind Energy

In the European oceanic regions, majority of the wind power plants are situated in North Sea, Irish Sea and the Baltic Sea. In Europe, the United Kingdom, Germany, Denmark, the Netherlands, Sweden and Belgium have majority of the offshore wind power capacity [3, 4]. Except these European countries, only China has significant installed capacity. The United States is the only country having the wind power project in the American offshore region. Further, the country-wise current offshore wind power installed capacities is listed in Table 1.

2 Offshore Wind Energy Conversion System

One of the largest-scale renewable energy technologies, the offshore wind energy conversion system (O-WECS), possesses several advantages over onshore WECS. Typically, an O-WECS has higher wind speeds with lower wind shear and innate turbulence which enhances its ability to take advantage of larger wind turbine arrangements. Also, studies have proved that an O-WECS of same capacity has lower environmental impacts as compared to an onshore WECS [6]. Apart from large power generation capability, the O-WECS can also assist in increasing the reliability of supply for remote and rural areas [7]. Although, O-WECS possesses such attractive merits, large-scale deployment has witnessed critical engineering challenges such as large investment costs due to specialized equipment and machinery, expensive support structures, untrained manpower to work at offshore conditions, maintenance issues and specialized techniques and measures for combating corrosion. The International Electrotechnical Commission defines an offshore wind

Table 1 Country-wise offshore wind power capacity scenario in 2018 [5]

Region	Country	Cumulative offshore wind power installed capacity (MW)
Europe	United Kingdom	7,963
	Germany	6,380
	Belgium	1,186
	Denmark	1,329
	Netherlands	1,118
	Other European countries	302
Asia-Pacific	China	4,588
	South Korea	73
	Other Asian countries	171
North and South America	United States	30

turbine in its IEC 61400-3:2009 [8], which has been replaced by IEC 61400-3-1:2019) as “wind turbine with a support structure which is subject to hydrodynamic loading”. An offshore wind turbine can be fixed using supporting structures at the seabed or else they may *float*, as well.

Power calculations for an O-WECS involve similar techniques, laying foundation from the fundamentals of fluid mechanics. Temporal and spatial variations of the wind characteristics such as speed, orientation and turbulence over a specific period of time are recorded at particular time [9]. All these factors affect the power generation potential for an offshore wind turbine with turbulence dictating the design of the turbines. Statistical methods are used to model the wind characteristics with uncertainties. Monte Carlo simulations, Gaussian distributions, Gaussian mixture curves and Weibull functions have been majorly used to model the wind speed frequencies for a location under study. Shape and scale factors of the probability distribution functions, used for modelling the uncertainties in the wind characteristics, are fixed according to the long-term mean wind speed (based on sampled timely averages). Wind speed, direction, mass flow rate and density are used to calculate the power of the wind per unit square metres. External design conditions such as ocean waves and currents, characteristics of subsea soil, ice floats, and salinity in water are considered for wind turbine design which affects the wind power calculations indirectly through associative changes in wind shear.

Total area spanned by the wind turbine blades (blades are the primary components of a wind turbine rotor), swept area, solidity factor, tip-speed ratio, drag and roughness of the blade’s surface are significant factors which affect the rotor design for an O-WECS; refer to Fig. 4. Losses in the rotor blade, airfoil characteristics, materials used for manufacturing and the type of control used for wind turbine rotor are other factors.

Rotor of a WECS is responsible for converting the kinetic energy of the wind into rotational mechanical energy and the torque gained by the rotor is transmitted to the shaft, usually through a gearbox. Gearboxes are mechanical transformers which are employed to increase the speed of the shaft connecting the generator. Wound-rotor induction generators of an O-WECS convert rotational mechanical energy of the shaft into electrical power using electromagnetic induction principle. Rotation speed of the generators is dependent on the magnetic pole pairs and the frequency of the alternating current generated. Power electronic converters are used to connect the power generated by the generator to the electrical power grid. Converters are also employed with filters to cancel out the harmonics in the alternating current generated thereby enhancing the quality of power generated. This is very important if the O-WECS power needs to be evacuated to the main power grid and does also makes a true economic sense.

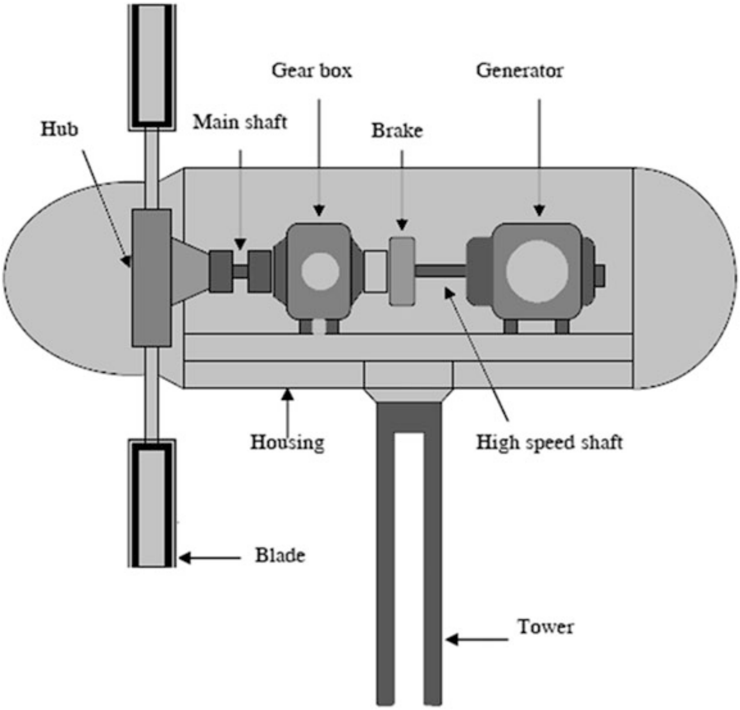

Fig. 4 Structure of typical horizontal axis wind turbine

3 Wind Resource Assessment

The wind resources exhibit very stochastic nature. Wind speed (WS) and direction may vary erratically with time at any location. Basically, wind resource assessment is the measurement of the wind energy available on some particular location or the target region. Measurement of wind resource comprises of recording and analysing the fluctuations in WS and changes in wind directions with reference to time at any particular point or multiple points or through a focused region [1]. Wind distribution is a crucial element in resource assessment along with the intensity of WS. Due to the disparities in WS fluctuations, two identical wind turbines positioned at different locations with equal average WS may harvest completely altered amount of energy [2]. Besides the daily and seasonal fluctuations, the wind distribution may vary year with years, even to the range of 10–30% [10]. Therefore, prior to the establishment of wind power project, long-term wind resource assessment is essential.

3.1 *Different Types of Data Sets*

Wind resource assessment is conducted using the data collected from different sources. Primarily there are three sources of wind data: on-site measurements, weather station networks, and numerical climate models [11]. Method of data collection varies for onshore and offshore regions; refer to Fig. 5. Onshore wind measurements are done using the anemometers mounted on wind mast at different heights and sensors placed on meteorological stations. The measurement of wind parameters in offshore region is more difficult as compared to the onshore regions due to apparent reasons of atmospheric uncertainties. It is done by means of the deployment of different types of buoys as per the conditions (distance from shore and depth of water). Generally, for near shore lower depth regions, the met buoys are used; whereas for higher water depth regions, moored buoys are employed. Moreover, some of the offshore meteorological stations, some other type of work stations (e.g. petrochemical units) and the moving ships are the source of limited wind data [12]. There are several methods of wind measurement that are applicable to both onshore and offshore regions, which are remote sensing recording, reanalysis data sets and other climate models. Remote sensing measurement involves the use of satellites, i.e. scatterometer [13, 14], SODAR (sonic detection and ranging) and LIDAR (light detection and ranging) instruments [11, 15]. Reanalysis data sets are an assimilation of long-term historical meteorological observational data, using a single consistent assimilation scheme. Depending on the focused region or location,

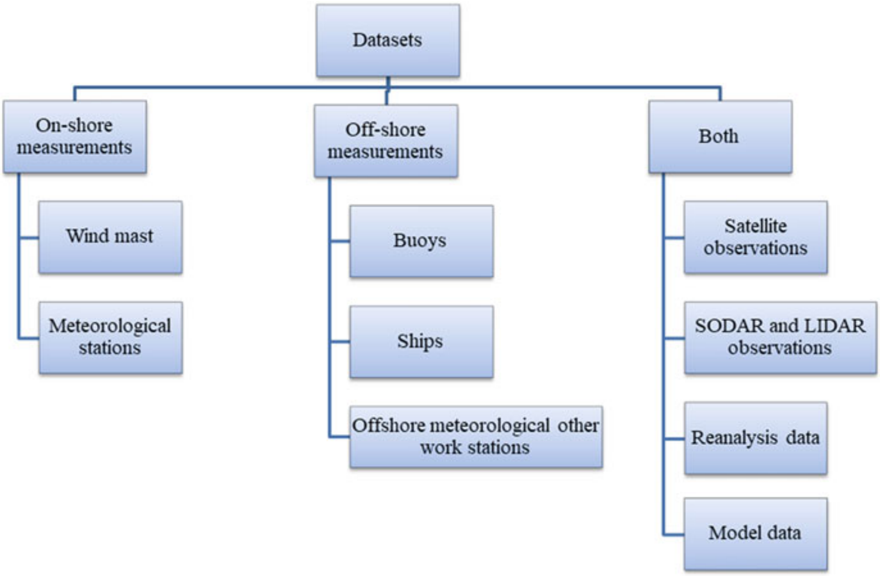

Fig. 5 Different types of data available from various sources for onshore and offshore regions

any one or multiple data sets are used for the resource assessment. Model data sets are generated through the mathematical models developed using atmospheric physics on the raw data available from different sources.

3.1.1 Satellite Data

Recently, satellite data has been employed comprehensively for the offshore wind resource assessment due to the advancement in marine resource measurement techniques. A laboratory based in Denmark (Risø National Laboratory), along with a number of associated institutes, steered SAT−WIND research programme and proved the feasibility of utilizing satellite observed data, together with surface wind recording data accumulated through scatterometers, altimeters, passive microwave remote sensors and synthetic aperture radars (SAR), during mid-years of last decade.

A global evaluative study on ocean wind power at multiple heights, usable speed ranges and siting depths utilized QuikSCAT satellite data and observed global mean wind power density (WPD) of 776 W/m^2 at 100 m height (1.6 times of the same at 10 m height) [16]. Among the available space-borne radar systems (e.g. scatterometers, passive microwave radiometers), SAR satellite imagery provides relatively higher resolution wind atlases [17]. A study focused on Baltic Sea found out SAR data to have higher accuracy with observed WPD of 300–800 W/m^2 [18]. Further, the same group of researchers utilized synergetic satellite data (Envisat ASAR, ASCAT and QuikSCAT) in order to increase the data samples and attain higher resource assessment accuracy with lower statistical uncertainty [19]. An evaluative wind energy resources assessment in the Ionian Sea of Western Greece found QuikSCAT satellite data to overestimate the wind resource by 8–13% with reference to buoy data [20]. Higher uncertainties of wind retrievals were observed at lower WSs (below 5 m/s). Further, it was detected that WS recoveries from QuikSCAT at nearshore stations (54 km) are not much accurate with reference to offshore regions owing to the ground contagion. Jiang et al. [21] performed a distributive study on offshore wind power with QuikSCAT Level 2 satellite recordings (9 years data with 0.5° horizontal resolution). The study concluded Fujian Province to have superior wind potential than the other offshore regions of China.

Soukissian and Papadopoulos [22] have examined the impacts of alternative sources of wind data on wind resource analysis on four sites of Aegean Sea. The satellite data was found to be overestimating, while the model data were underestimating the WS with respect to buoy measurements. Available offshore WPD in any region must be evaluated very cautiously while utilizing the alternative data sets. Otherwise, it may mislead the results. Realistic linear relationships are established among the buoy observations and numerical weather prediction (NWP) simulation data and satellite recordings for homogenization and calibration of latter data sets.

The accuracy of satellite data for offshore regions evaluated by different researchers is summarized and presented in Table 2. For offshore studies, the statistical parameters such as R, standard deviation, bias and correlation coefficient

Table 2 Overview of the studies on the accuracy of satellite data for offshore regions

Authors	Data	Scope	Temporal		Spatial	Reference for correlation	Correlation		RMSE (m/s)	Standard deviation (m/s)	Bias (m/s)
			Duration	Resolution	Resolution (degree)		R^2	Pr			
Pimenta et al. [23]	QuikSCAT	South-Eastern Brazil	1999–2007	Daily	0.5 × 0.5	Oil platform, buoys	-	0.81	-	-	0.35
Jiang et al. [21]	QuikSCAT	China	2000–2008	Daily	0.5 × 0.5	Wind masts	0.71	-	-	1.3	-
Carvalho et al. [24, 25]	QuikSCAT	Peninsula coast	2000–2008	12 h	0.25 × 0.25	5 buoys	0.89	-	1.89	1.77	0.61
	CCMP		1987–2011	6 h	0.25 × 0.26		0.88	-	1.72	1.72	0.1
	NCDC−BSW		1987–2011	6 h	0.25 × 0.25		0.89	-	1.93	1.74	0.83
	IFREMER−BWF		1999–2009	6 h	0.25 × 0.26		0.9	-	1.75	1.69	0.39
Chang et al. [26]	ASCAT	South China Sea	2009–2013	12 h	12.5 × 12.5 km	7 coastal meteo-rological stations	-	0.8	-	1.83	−0.4
	ENVISAT SAR		2009		150 m		-	0.75	-	2.09	−0.3
Gadad and Deka [27]	OSCAT	Karnataka state, India	2011–2012	12 h	0.5 × 0.5	INCOIS real-time automated weather station data	-	0.6	1.9	-	-
Carvalho et al. [28]	ASCAT	Iberian Peninsula	2007–2015	12 h	0.25 × 0.25 0.125 × 0.125	Buoys	0.93	-	1.26	1.18	0.42
	OSCAT		2010–2014	12 h	0.125 × 0.125		0.83	-	2.21	1.98	0.87
	CCMP		1987–2011	6 h	0.25 × 0.25		0.84	-	1.17	1.72	0.34

(continued)

Table 2 (continued)

Authors	Data	Scope	Temporal		Spatial	Reference for correlation	Correlation		RMSE (m/s)	Standard deviation (m/s)	Bias (m/s)
			Duration	Resolution	Resolution (degree)		R^2	Pr			
	Blended Sea winds (NCDC-BSW)		1987–2015	6 h	0.25 × 0.25			-	2.83	2.57	1.06
Soukissian et al. [29]	Blended sea winds (NCDC-BSW)	Mediterranean Sea	1995–2014	6 h	0.25 × 0.25	Buoys	-	0.88	1.818	-	−0.191
Guo et al. [30]	QuikSCAT	Global ocean	1999–2009	12 h	0.25 × 0.25	NDBC buoys	0.78	-	0.39	-	0.23
	ASCAT-A		2007–2015		0.25 × 0.25		0.77	-	0.33	-	0.09
Remmers et al. [31]	ASCAT	Irish waters	2012–2017	12 h	0.125 × 0.125	Buoys	0.81	-	0.36	-	−0.07
Surisetty et al. [14]	QuikSCAT	India	1999–2009	12 h	0.125 × 0.125	Buoys	-	0.87	1.39	1.62	0.7
	OSCAT		2010–2014	12 h			-	0.84	1.56	1.49	0.49
	ASCAT-A		2010–2016	12 h			-	0.88	1.37	0.71	0.14
	ASCAT-B		2012–2016	12 h			-	0.87	1.43	0.83	0.2
Elsner [32]	Blended sea winds (NCDC-BSW)	Africa	1995–2005	6 h	0.25 × 0.25	Buoys	-	-	-	-	-
Zaman et al. [33]	Satellite altimetry data	Malaysia	1993–2011	Monthly	2 × 2	Buoy	-	0.835	1.385	-	0.55

- not found

(either Pearson's R or R2) are the very frequently utilized techniques. Different studies on satellite data for offshore (see Table 2) show correlation coefficient in the range of 0.6 to 0.81, standard deviation in the range of 1.3 to 2.09 m/s, root mean square error (RMSE) from 1.72 to 1.93 and bias −0.4 to 0.83 m/s. From literature, it can be observed that IFREMER−BWF satellite data is well correlated with buoy data in Peninsula coast with a correlation coefficient of 0.9.

3.1.2 Reanalysis Data

Reanalysis data is the assimilation of ground meteorological stations, deployed buoys, transit ships and satellite data sets into general circulation model and delivers long-term high spatial resolution data with higher reliability [34]. The National Centers for Environmental Prediction (NCEP)-Department of Energy (DOE) and the European Centre for Medium-Range Weather Forecasts (ECMWF) offer WS component with temporal resolution of 6 h, from the year 1979 [35]. Moreover, it eases the evaluation of seasonal and annual variability of wind climate over different regions due to its spatial and temporal homogeneity. Reanalysis data can be utilized for global [36] as well as certain target region or country like Europe [37, 38] and the United States [39, 40].

Carvalho et al. [24] compared different analyses (NCEP-GFS and NCEP-FNL), reanalyses (ERA-Interim, NCEP-R2, NCEP-CFSR and NASA-MERRA), satellite data (CCMP, NCDC, IFREMER and QuikSCAT) and WRF modelled offshore winds with buoy data along the Iberian Peninsula coast. They found WRF modelled data is best alternative to buoy data. Further, NCEP-GFS or NCEP-CFSR data showed better wind power flux, so that, these two datasets can be used as an alternative to WRF modelled data. A study using high spatial and temporal resolution NCEP-CFSR reanalysis data concluded that CFSR reanalysis data is consistent with observation data and provides reliable wind data for offshore regions of China [41]. On the contrary, the 30 years duration CFSR data have been observed to be less accurate at higher elevation in the United Kingdom, when compared to the synoptic weather stations (12 offshore and 264 onshore) [42]. ERA-Interim reanalysis data delivers the most reliable initial and boundary layer simulation of near-ground wind properties [24, 25].

Several researchers have evaluated distinct reanalysis and mesoscale models for assessing wind properties for different regions (refer for the summarized overview in Table 3). RMSE, bias and a correlation coefficient (either Pearson's R or R2) are the most commonly used parameters for the study or error matrix in offshore studies. Here, it can be observed that the RMSE and bias are comparatively lower in almost every case for the mesoscale data.

Table 3 Overview of the studies on the accuracy of reanalysis data for offshore regions

Author	Data	Temporal		Spatial		Reference for correlation	RMSE	Correlation		Bias (m/s)
		Duration	Resolution	Scope	Resolution (degrees)			Pr	R^2	
Hawkins et al. [43]	NCEP−FNL + WRF	10 years	6 h	UK	0.1	Buoys, lightships, platforms	1.33	-	0.9	−0.02
Menendez et al. [44]	ECMWF ERA-interim + WRF	20 years	Daily	Spain	15 km	Buoys	-	0.7–0.9	-	0–1
Staffell and Green, [45]	Downscaled MERRA	20 years	Hourly	UK	Site	Buoys	-	-	-	1.6
Carvalho et al. [24, 25]	NCAR(R2) + WRF	10 months	Hourly	Iberian Peninsula	0.083	5 Buoys	2.43	0.76	-	0.34
	ERA−interim + WRF						1.85	0.88	-	0.48
	CFSR + WRF						1.94	0.87	-	0.6
	MERRA + WRF						2.01	0.86	-	0.59
	NCEP−FNL + WRF						1.89	0.87	-	0.53
	NCEP−GFS + WRF						1.89	0.88	-	0.56
Carvalho et al. [24, 25]	NCEP−NCAR (R2)	1 year	6 h	Iberian Peninsula	2.5	5 Buoys	3.43	-	0.6	0.87
	ERA−Interim		6 h		0.75		2.45	-	0.8	0.58
	CFSR		Hourly		0.5		1.85	-	0.9	0.16
	MERRA		Hourly		0.6		1.93	-	0.9	0.52
	NCEP−FNL		6 h		1		2.3	-	0.9	0.98
	NCEP−GFS		6 h		0.5		1.89	-	0.9	0.22
Stopa and Cheung [46]	CFSR	1979–2009	Hourly	Peru	0.5	1 Buoy	1.37	0.81		6.14%
				Hawaii		4 Buoys	1.37	0.86	-	−3.90%
				Gulf of Mexico		5 Buoys	1.52	0.87	-	0.43%
				NW Atlantic		5 Buoys	1.73	0.89	-	4.23%
				Alaska		5 Buoys	1.7	0.91	-	3.90%
				NE Pacific		5 Buoys	1.5	0.91	-	2.38%

- not found

3.1.3 Wind Power Potential

Researchers have used different methodologies to assess offshore WPD by employing different resource estimation models and Geographical Information System (GIS) approach. There are various parameters that affect the installation of offshore wind farms. For evaluating WPD at particular location or region, there are some aspects (i.e. sea utilization authorization, technology, economics and environment) that have to be studied.

An evaluative study performed on offshore wind resources of Southeastern Brazil using QuikSCAT satellite data for mapping the wind energy properties over large oceanic extent found that the coastal area of Brazil has an overall potential of 102 GW electrical energy generation [23]. Using bathymetry and properties of current wind electric technology maps of WS, WPD and practical turbine output can be determined. Dvorak et al. [47] created an offshore wind resource assessment for California by combing multiyear mesoscale modelling results, validated using offshore buoys with high-resolution bathymetry. Similarly, a group of researchers investigated offshore wind climate along the coast of Kanto area by a mesoscale model considering economic and social criteria estimated by GIS [48]. The study identified overall annual wind resource along the coastline of Kanto, which is about 287 TWh without considering the socio-economic aspects. Mesoscale model is observed to be performing well while determining the offshore WPD. Capacity factor (CF) can be considered as an index for evaluation of the economic feasibility of wind farm. Onshore wind farms can be said to be economically feasible if CF is more than or equal to 20%.

Microscale wind flow model and the coupled numerical mesoscale atmospheric model with long-term global reanalysis climate data set were employed by Waewsak et al. [49], in order to generate high-resolution wind resource maps of the Gulf of Thailand at varying heights above sea level. The study further pointed that, using a multi-criteria decision- making method, the possible regions for grid-attached wind power generation can be identified. Estimated technical power potential for the Gulf of Thailand is about 7,000 MW with annual generating capacity of 15 TWh. Kim et al. [50] have presented and additional strategies for site-selection process for feasible offshore wind farm sites in the coastline regions of Jeju Island, South Korea. The site-selection criteria can be categorized in four divisions: (a) energy resources and economics, (b) preservation zones and topography safeguard, (c) human actions and (d) aquatic environment and oceanic ecosystem. The spatial methods of GIS can be used for investigating the resources available in the particular country or region. However, among prescribed four categories, the energy resource availability and economics are also integral part of the process.

In addition to the mesoscale models, the wind power potential can also be derived by means of satellite data. Gadad and Deka [27] assessed the offshore wind resources of Karnataka, India, by adopting Oceansat-2 scatterometer (OSCAT) data and GIS approach. Prior to utilization, the OSCAT satellite data is validated by real-time meteorological station data, collected from Indian National Centre for

Ocean Information Services (INCOIS) for India. The estimation of wind power generation calculated for RE power 5 MW wind turbine (based on class of water-depth) for the considered region is 9.091 GW for monopole foundation (0–35 m), 11.709 GW in jacket-type foundation (35–50 m), 23.689 GW in advanced jacket-type foundation (50–100 m) and 117.681 GW for floating foundations (100–1,000 m).

Different researchers evaluated the offshore wind power potential using different methodologies for different countries are summarized and presented in Table 4. It can be observed that majority of researchers used log law for extrapolating wind speed to required height.

3.2 Significant Parameters Involved in Resource Assessment

The most concerned parameters in resource assessment are WS and wind direction. The values of wind power density and power potential are calculated for specific location or region at particular hub height with the help of WS data for given time period. Wind power potential (*P*) is the quantitative amount of power that can be generated by means of wind energy. Wind power density (WPD) is the wind power potential available per unit area of the plane at right angles to the wind direction.

$$P = \frac{1}{2}\rho A U^3 \tag{1}$$

$$WPD = \frac{P}{A} = \frac{1}{2}\rho U^3 \tag{2}$$

where, U is wind speed (m/s) and A is the area of the plane (m^2).

Further, the characteristics of atmospheric boundary layer are integral part of resource assessment process due to its impact on the intensity of WS. The atmospheric boundary layer, which is also termed as planetary boundary layer, is the lowest part of the atmosphere in contact with earth surface. The physical characteristics of air in atmospheric boundary layer like relative humidity, temperature, velocity and density vary quickly with space and time [3].

Variation in WS in vertical direction is defined by wind shear, as a function of height from the surface [11]. There are two methods of wind shear calculation: (1) power law and (2) log law. Power law is a popular method for presenting the relation between WS and height. The expression for the WSs v_1 and v_2 at height h_1 and h_2, respectively, can be presented as follows:

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1}\right)^{\gamma} \tag{3}$$

Table 4 Summary of studies reported for evaluation of offshore wind power potential

Source	Scope	Model	Wind data with spatial resolution	Vertical profile	Wind turbine model (capacity in kW)	CF (%)	Exclusionary factor	Available potential (GW)	AEP (TWh)
[23]	Brazil	GIS	QuikSCAT (0.5°)	Log law	GE 3.6 s (3,600)	52	10 to 46%	102	-
					Repower 5 M (5,000)	44			
[47]	California	Mesoscale model version 5 (MM5) weather model, GIS		Log law	RE power 5 M (5,000)	Variable	33%	75.5	661
[51]	China EEZ	GIS	QuikSCAT (1 km)	Log law	RE power 5 M (5,000)	37.5	Shipping lanes, bird path, submarine cables, coast buffer	-	1,566
[20]	Ionia Sea		QuikSCAT (0.25°) and buoy wind data	Log law	Vestas V112 (3,000)	35–52	-	-	20
					Siemens SWT–3.6 –107 (3,600)				
					General Electric GE 3.6 sl (3,600)				
					Multibrid (5,000)				
					RE power 5 M (5,000)				

(continued)

Table 4 (continued)

Source	Scope	Model	Wind data with spatial resolution	Vertical profile	Wind turbine model (capacity in kW)	CF (%)	Exclusionary factor	Available potential (GW)	AEP (TWh)
[52]	Inner Mongolia, China		Surface observational data	Power law	CONE−450 (450)	45	-	-	-
					NM600/43 (600)	-			
					YT/850 (850)	64			
					NODEX−N70/ 1,500 (1,500)	-			
					GAMMA−60 (1,500)	-			
					SL 3,000/90 (3,000)	-			
[48]	Coast of Kanto, Japan	Mesoscale meteorological model RAMS, GIS	ECMWF (2.5°)		MWT − 92/2.4 (2,400)	>25, 30, 35	Excluding areas with fishing rights, natural park regulations and harbour operations and 10 km offset distance from the coastline	-	287
[49]	Gulf of Thailand	Mesoscale compressible community (MC2) model, GIS	NCEP/NCAR R1 global reanalysis data (2.5°)	Log law	-	25	-	7	15

- not found

where γ is wind shear exponent which depend on the type of surface. For, open shear regions, wind shear is taken as 0.08 [11].

Log law is an optional substitute to power law for the evaluation of wind-speed variation with height, which is based on the logarithmic boundary layer profile and uses surface roughness length (z_O) as an important parameter. The expression for log law can be given as follows:

$$\frac{v_2}{v_1} = \frac{\ln (h_2/z_o)}{\ln (h_1/z_o)} \tag{4}$$

The value of surface roughness length depends on the type of surface. The smoother the surface, the lower the roughness length. The value of roughness length for water areas (offshore regions) is taken in the range of 0.1–0.3 mm, which represents roughness class 0 [53].

The air moving near the surface experiences unexpected variations in wind velocity and direction due to turbulence created by obstacles and surface roughness. Presence of turbulence reduces the wind power potential and also generates fatigue forces on wind turbine components. The turbulence intensity gets influenced by shape and size of obstacles. The turbulence zone might be spread over up to 2 times the height of obstruction in upwind direction and about 10–20 times in downwind direction. The impact of turbulence in vertical direction reached around 2–3 times the height of the obstacle. Mathematically the intensity (*TI*) of the turbulence can be represented in terms of mean WS ($\overline{U}$) and standard deviation (σ) as follows:

$$TI = \frac{\sigma}{\overline{U}} \tag{5}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \left(U_i - \overline{U}\right)^2}{N - 1}} \tag{6}$$

where N is the number of observation of WS.

3.3 Resource Estimation Models

According to a review presented by Landberg et al. [54], various wind resource estimation methods are folklore, only measurements, measure-correlate-predict (MCP), global data sets, wind atlas approach, models based on in situ data, mesoscale models and combined mesoscale-microscale models. Further, depending on the different sources of data, various resource estimation models are classified in three categories, namely, mesoscale models, computational fluid dynamics (CFD) models and microscale models [11]. The objective of resource estimation models is to take the wind data available from different sources for locations and generated the wind data for desired location. The generated data consist of WS at multiple heights (or WS at particular height with wind shear) and wind directions.

Mesoscale models provide weather projections with spatial resolution of 20–20,000 km and temporal resolution from hours to days. Mesoscale takes reanalysis data, altitude data and surface roughness data to provide model's external forcing by means of boundary conditions. Mesoscale Compressible Community (MC2) model, Karlsruhe Atmospheric Mesoscale Model (KAMM) and Mesoscale Model5 (MM5) are the widely utilized mesoscale models. CFD models consist of turbulence models having Reynolds-averaged Navier-Stokes (RANS) equations with and used for finer spatial resolution applications [11]. CFD models are applied while modelling the airflow across a complex terrain and thermal effects. CFD models take digital terrain models, roughness maps and wind data as the inputs. The products of the model are steady-state time-independent results of WSs and directional distributions.

Microscale models resolve small-scale contours and roughness geographies. The models are applied to the scales in the order of 100 km and are utilized for large wind farm regions spread over hundreds of kilometres. Wind Atlas Analysis and Application Program (WAsP) is the most commonly used microscale model and was initiated in the late 1980s [55]. Few other famous wind assessment software tools like windPRO and WindFarmer employ WAsP engine [11]. Mesoscale models can be combined with the microscale models as per requirement [54]. KAMM and WAsP is the most widely used combination of mesoscale and microscale models.

3.4 Wind Energy Estimation Models

Wind energy estimation models are the methods to be used for the resource assessment by means of collected data. The data might be obtained from any single or multiple sources as elaborated in Sect. 3.1. There are multiple methods available for the estimation of wind energy as listed below and elaborated in the following subsections:

- Wind turbine-based resource estimation
- Direct or non-statistical method
- Statistical method
- Extreme wind-based estimation

3.4.1 Wind Turbine-Based Energy Estimation

This approach is implemented to assess the productivity of wind turbine in terms of maximum power potential and power generated through wind turbine by means of time series wind data (averaged WS values). Now, the power available in the wind with velocity, U, is given by Eq. (1) [3]. However, the actual amount of power generation (P_w) relies upon power curve of given wind turbine. In stall-regulation wind turbine, the power generation reduces on further increment in WS from the rated value. However, in pitch-regulation-based wind turbine, the power generation remains the same as the rated power between rated and cut-out WSs. The power curves are generated using the test data of wind turbines as per the guidelines of International Electrotechnical Commission (IEC), Geneva [56].

3.4.2 Direct or Non-statistical Energy Estimation

While having the large number of data values, the averaging approach is utilized. For N number of WS observations U_i, the data is averaged over the time interval of Δt. The expressions for the parameters evaluated in this resource estimation approach are as given below.

The mean WS, ($\overline{U}$), over long-term WS data is given as Eq. (7):

$$\overline{U} = \frac{1}{N}\sum_{i=1}^{N} U_i \tag{7}$$

The standard deviation of WS (m/s) is given as Eq. (8):

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(U_i - \overline{U}\right)^2} \tag{8}$$

The mean WPD (W/m^2) is Eq. (9):

$$\frac{\overline{P}}{A} = \frac{1}{2}\rho\frac{1}{N}\sum_{i=1}^{N} U_i^3 \tag{9}$$

Average power generated by wind turbine (W)

$$\overline{P}_w = \sum_{i=1}^{N} P_w(U_i) \tag{10}$$

where $P_w(U_i)$ is power computed from power curve as elaborated in Sect. 3.4.1.

The energy generation E_w (in J or Wh)

$$E_w = \sum_{i=1}^{N} P_w(U_i)(\Delta t) \tag{11}$$

3.4.3 Statistical Method for Energy Estimation

Statistical analysis is utilized to estimate the amount of energy that can be generated at particular location if the wind turbine is installed, with the help of WS data at desired height. The statistical approach consists of probability distribution of WSs. Probability distribution (PD) presents the likelihood of the occurrence of particular WS. It is described using probability density function (PDF) and cumulative distribution function (CDF). PDF represents the probability of the existence of a particular WS ($\rho(U)$) during the observed time period at particular location and height, whereas the CDF presents the probability of observing WS value less or equal to a particular value ($F(U)$). Rayleigh and Weibull distributions are the most widely employed probability distributions. PD is further utilized for the calculation of estimated power generation as discussed in Sect. 3.4.4.

Rayleigh distribution is the easiest method of PD as it requires only single input variable, which is average WS. Expressions for PDF and CDF are given as Eq. (12) and (13):

$$p(U) = \frac{\pi}{2}\left(\frac{U}{\overline{U}^2}\right)\exp\left[-\frac{\pi}{4}\left(\frac{U}{\overline{U}^2}\right)^2\right] \tag{12}$$

$$F(U) = 1 - \exp\left[-\frac{\pi}{4}\left(\frac{U}{\overline{U}^2}\right)^2\right] \tag{13}$$

Weibull distribution uses a couple of parameters: shape and scale parameter, for the distribution of the available data. Due to the utilization of two input parameters, Weibull distribution presents the wind regime better than the Rayleigh distribution which is based on only one parameter (mean WS). Expressions for PDF and CDF are given as Eq. (14) and (15), respectively:

$$p(U) = \left(\frac{k}{A}\right)\left(\frac{U}{A}\right)^{k-1}\exp\left[\left(\frac{U}{A}\right)^k\right] \tag{14}$$

$$F(U) = 1 - \exp\left[-\left(\frac{U}{A}\right)^k\right] \tag{15}$$

where k is shape parameter and A is scale parameter (in m/s).

3.4.4 Wind Turbine Power Estimation

The average power generated through wind turbine can be computed using Eq. (16).

$$\overline{P}_w = \int_0^\infty P_w(U)p(U)dU \tag{16}$$

where $P_w(U)$ is power curve of selected wind turbine. Further, the average wind turbine power can be used to derive the performance of the turbine in terms of capacity factor (CF). CF is described as the ratio of actual power generated through wind turbine for given WS to the power generated by wind turbine at rated WS (rated power, P_R), over a given time duration, Eq. (17).

$$CF = \frac{\overline{P}_w}{P_R} \tag{17}$$

The expression of wind turbine power curve $P_w(U)$, in terms of WS, U, is given as Eq. (18):

$$P_w(U) = \frac{1}{2}\rho A C_p \eta U^3 \tag{18}$$

where η is the drive efficiency of wind turbine (given as Eq. (19)), A is the cross-sectional area of turbine rotor, ρ is the air density and C_p is rotor power coefficient (given as Eq. (20)):

$$\eta = \frac{\text{GeneratorPower}}{\text{RotorPower}} \tag{19}$$

$$C_P = \frac{\text{RotorPower}}{\text{PowerinWind}} = \frac{P_{\text{rotor}}}{\frac{1}{2}\rho A U^3} \tag{20}$$

3.4.5 Extreme Wind Speeds

Generally, the wind energy estimation models are based on WS values. However, extreme wind is also an important parameter to be considered while designing the wind turbine, since the turbine is to be subjected to those extreme wind events. Extreme wind stands for the highest value of WS occurring over longer time period. Extreme winds are generally expressed as reoccurrence (or repetition) period. The extreme wind is highest WS averaged for given time span, with yearly probability of occurrence of $1/N$ years.

3.5 Key Issues in Resource Assessment

Major issue in wind resource assessment across the world is the lack of consistent and dependable data [57]. As discussed earlier, there are limited source of offshore wind data. Moreover, the experimental methods of data collection face environmental problems and hence cannot record long-term continuous data. Therefore, the long-term wind resource assessment has to be conducted based on reanalysis data or model data, which are less preferable than the measured data and has to be validated [15].

4 Summary

Offshore wind harvesting for energy generation is picking up interests in many parts of the world. The concept of offshore wind energy conversion system was introduced, and significant parameters involved in modelling such a system were outlined. Primary focus was to outline different methods of wind resource assessment to assess and analyse the wind data in terms of speed, orientation and other characteristics. While focusing on the offshore wind energy resources, the differences from onshore resources like environmental conditions, project infrastructure, project design, power evacuation facilities and safety measures have to be considered. Also, the wind resource data used for the resource assessment can be obtained either from any single source or through multiple sources. Different types of data are available from various sources for onshore and offshore regions. Multiple methods involved in collection and analysis of wind speed data have been categorized as wind turbine-based resource estimation, direct or non-statistical method, statistical method and extreme wind-based estimation method. The global amount of wind resource availability has been estimated to be of 10^{15} kWh/year, which is significantly higher than the global electricity consumption of 55×10^{12} kWh/year. Hence, there is a long way to go in terms of wind power deployment.

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