The potential of wind energy via an intelligent IoT-oriented assessment

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Abstract

In contemporary times, renewable energy reliability has been an important field of research that is combined with the Internet of Things (IoT) including the opportunities for improving and challenging the work. Wind energy harvesting in IoT (WHIoT)-based framework is investigated considering the associated potential in the historical city of Bam is proposed in this paper. Weibull distribution function, wind power, and energy density were computed for three heights of 40, 60, and 80 m. The results at 80 m show that the maximum monthly wind speed average of 8.48 m/s occurred in July while the minimum value was observed in December with a value of 3.92 m/s. It was demonstrated that during the summer season power density and energy density are at peak values. This is an advantageous observation for Bam city with higher demand for energy during hot summer. The performance of six different wind turbines was assessed in terms of energy production and capacity factor. Finally, an economic assessment was performed to investigate the suitability of Bam city for the installation of small-scale wind turbines.

Keywords "IoT" · "Wind energy" · "Weibull distribution" · "Economic Assessment" · "Wind speed"

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1 Introduction

Energy is the most important factor in society for sustainable development and economic growth. Today, fossil fuels are still the dominant source of energy regardless of their environmental concerns [1]. In the UN 2015 Conference for climate change, many countries chose to fight against climate change and took necessary measures. However, the withdrawal of some countries from this agreement, the U.S. for instance, has challenged the achievement of this agreement. Thus, the necessity for reducing dependency on fossil fuels is even more crucial than in the past. In this regard, many countries adopt new policies to prioritize renewable energy over fossil fuels. Therefore, the role of renewable energy in achieving sustainable development and environmental protection [2] has significantly increased. Such achievement also benefits from the reduction in cost, technology advancement, and improvement in wind farm efficiency. Currently, the technology of harvesting energy from wind is a distinguished industry in the field of green energy and as a result, wind power harvesting is competitive to the conventional sources of energy [3].

Iran is among the countries with the largest oil and gas reservoir and plays a significant role in energy organizations such as The Organization of the Petroleum Exporting Countries (OPEC). Iran heavily depends on natural gas and oil for its domestic energy demand. Such dependency is the motivation for exploring new sources of energy other than natural gas and oil. Also, fossil fuel resources are limited and the need for replacing them with renewable and sustainable energy sources is the major concern of many countries. Iran has enormous potential for harvesting wind and solar energy but pushes aside by its wealth of oil and gas. According to the Iranian Renewable Energy and Energy Efficiency Organization, solar and wind energy are the dominant utilized renewable energy in Iran with 43% and 41% market share, respectively. The total installed renewable energy power plants reach 700 MW in 2019. The geopolitical location of Iran assists the country to be also a major electricity exporter to its neighbors such as Iraq. On the other hand, energy demand in Iran grows significantly. Therefore, to meet the energy demand both for domestic use and export, it is necessary to seek other sources of energy. To assure potential investors to invest in any wind farm project, it is necessary to prepare a technical and economic feasibility study. Hence, the feasibility study provides the investors an outlook regarding the financial prospects of the project. The main contributions of the proposed framework can be summarized as follows:

- A novel assessment of the wind energy potential in historical cities has been investigated.
- A new evaluation method for the annual power density, energy density and capacity factor are proposed.
- We introduce the unit cost of energy (UCE) as the economic feasibility metric indicator in Internet of Things (IoT) oriented energy harvesting and provide insight into the best wind turbine option for implementation.
- We emphasize the importance of energy demand reduction in smart cities and shed the light on the future of wind energy planning.

2 Related works

Wind energy potential has been investigated by several researchers in order evaluate the possibility of utilizing such energy. For such investigation, it is required to predict the wind speed. There are several probability density functions such as Rayleigh function, gamma function, beta function, lognormal function, Weibull distribution function, and logistical function, which researcher previously utilized for frequency of wind speed curve [4]. Some of these functions are special cases of another distribution, for instance the chi-square and Weibull distributions are special cases of generalized gamma distribution [5].

Among these statistical models, Weibull distribution has been extensively employed for wind speed in studies [6–8]. Weibull function has demonstrated satisfactory result and accurately fit the wind speed frequency. Weibull distribution function can be employed as two-parameter or three-parameter distribution function. While two-parameter Weibull distribution function has convenience and flexibility relative to other statistical distributions, three-parameter Weibull distribution was suggested for representation of low wind speed [9]. Tuller and Brett [10] investigated the goodness of fit of the Weibull and Rayleigh distributions to the distributions of observed wind speeds in a topographically diverse area and concluded three-parameter has a better fit over two-parameter Weibull distributions and Rayleigh distribution for their study. On the other hand, Bowden [11] reported that three-parameter distribution offers no significant improvement over two-parameter Weibull distribution. Several researchers have investigated wind energy potential in Iran. These technical and economical investigations cover the different provinces of Iran where the climate changes significantly [12–16]. These studies investigate the wind energy in Iran while employing two-parameter Weibull distribution and demonstrated the suitability of the method for Iran.

Alhmoud and Al-Zoubi [17] suggested an IoT system to convert the data retrieved from the wind energy into actionable information to improve the performance of the wind turbine, driving the wind energy cost down and reducing the risk. The authors proved that the suggested system can be used to increase the reliability of measurement strategies, accuracy monitoring, and assurance of quality.

The demand for Artificial Intelligence (AI) and Internet of Things (IoT) have been also increased in recent years in the field of alternative energy resources [18–20]. For instance, the authors in [21, 22] suggested hybrid approaches of clustering-based probabilistic decision tree and deep learning to forecast wind power on large scales. Khan et. al. suggested a hybrid approach of clustering-based probabilistic decision tree to forecast the wind power efficiently. The authors used wind data to extract playing level fields for each feature after applying normalization and standard deviation. K-means clustering algorithm is applied to classify the samples into several groups that contain historical wind data. Various comprehensive comparisons are discussed showing the accuracy results of their research [21].

Khan et. al [22] proposed a new hybrid approach of principal component analysis (PCA) and deep learning-based research to uncover the hidden patterns

using wind data and forecast the power of the wind. The authors applied PCA to wind data to extract the hidden wind data features and to achieve meaningful information. A TensorFlow framework is used to forecast wind power considering features and followed by the tuning of deep learning parameters to reach the optimal results to predict the wind signals and their approach has been applied to datasets from the National Renewable Energy Laboratory (NREL). The results of their research showed that they can accurately predict wind power using a span ranging from hours to years.

Batcha and Geetha [23] prepared a survey paper and they mentioned that AI can be used when the calculations are decoding gigantic knowledge arrangements to the Personal Computers, they can function without the need of specific programming and be utilized in Probabilistic Energy Forecasting. The authors examined the study of the IoT for a significant duty in solar-powered vitality, and the approach of AI is discussed and utilized in solar-oriented vitality.

Almonacid-Olleros et al. [24] suggested a new IoT architecture with machine learning paradigms in photovoltaic systems to forecast output energy. The authors evaluated several machine learning algorithms such as Linear regression, k-Nearest Neighbors, Support Vector Machines and Random Forest, to follow the behavior and energy production of a photovoltaic system in conjunction with the ambient data which retrieved by IoT environmental devices. The authors improved the results, considering the machine learning algorithms and compared their results with the state of art analytical model, and achieved significant differences in learning time as well as the performance.

Another research has been made by Yeh et al. [25] in long cycle maintenance prediction of wind turbines using machine learning models. The authors built a hybrid network to train the predictive model based on convolutional neural networks and support vector machines. The results showed that the prediction of their proposed method achieves high accuracy, and it is used to drive up the efficiency of wind turbine maintenance.

Akyuz and Demircan [26] proposed a research work based on IoT with Cloud Computing to monitor the wind turbine. The authors measured the parameters that are crucial for the performance evaluation of small power wind turbine and the measured data are used to evaluate the performance of the suggested system to avoid errors. The authors used the parameters such as wind speed, air temperature, battery voltage, current and recorded the data on a data logger. Microsoft Azure cloud computing has been used to record the data.

Ahmadi et. al [42] developed three models used to investigate the impact of input data on forecasting accuracy. The first model was trained with the average and standard deviation of wind speed values measured at a height of 40 m with a 10-min sampling time. To evaluate the impact of sampling time on model performance, a second model was trained with wind speed values measured at a height of 40 m with 1-h, 12-h, and 24-h sampling times.

3 Site description

Kerman province attracts researchers due to its historical and agricultural importance. Therefore, locations such as Kerman city [14] and Shahrbabak [27] have been investigated in terms of wind energy potential. This study investigates the feasibility of harvesting wind energy in Bam city. Kerman Province is the largest province of Iran located in the southeast of the country. The province covers 11% of the land area of Iran with an area of 183,285 km^2 and a population of 3 million. The climate of the province varies from north to south. The North and central region of this province have a dry and moderate climate. On the other hand, the weather is warm and relatively humid in the southern part of the province. Most of the province is largely steppe or sandy desert, although there are some oases where dates, oranges, and pistachios are cultivated which the province is famous for. Bam is one of the biggest cities in Kerman province, houses "Arg-e Bam" the largest adobe building in the world, which is listed by UNESCO as part of the World Heritage Site. Despite the long history and the World's renowned Pistachios, the region still suffers from the devastating earthquake in 2003 which destroyed the city of Bam and the Citadel and its environs [28].

4 Wind data

The wind monitoring mast of Bam is located at 28º88′N 58º59′E and installed by The Renewable Energy Organization of Iran (SUNA) to measure the meteorological properties of the region. The mast height is 80 m and different sensors were mounted on three different heights of 40, 60, and 80 m. Data have been acquired by sensors such as wind anemometer, wind vane, temperature, radiation, and humidity sensors. The wind data were captured using a cup generator anemometer and acquired at 10 min time intervals from sensors mounted at three different heights. Several parameters have been acquired including wind speed, wind direction, temperature, humidity, and global radiation for the region. Data logger device reports maximum, minimum, average, and standard deviation values of wind speed together with average and standard deviation values of wind direction for each time interval of 10 min. Other properties such as air temperature, relative humidity, and global radiation are also available. In this study, the meteorological data acquired for one year from 1/01/2015 to 21/12/2015. This location has been chosen for investigation due to proximity to residential area and agricultural area. Thus, such a location provides the opportunity for electricity generation for both irrigation and residential use.
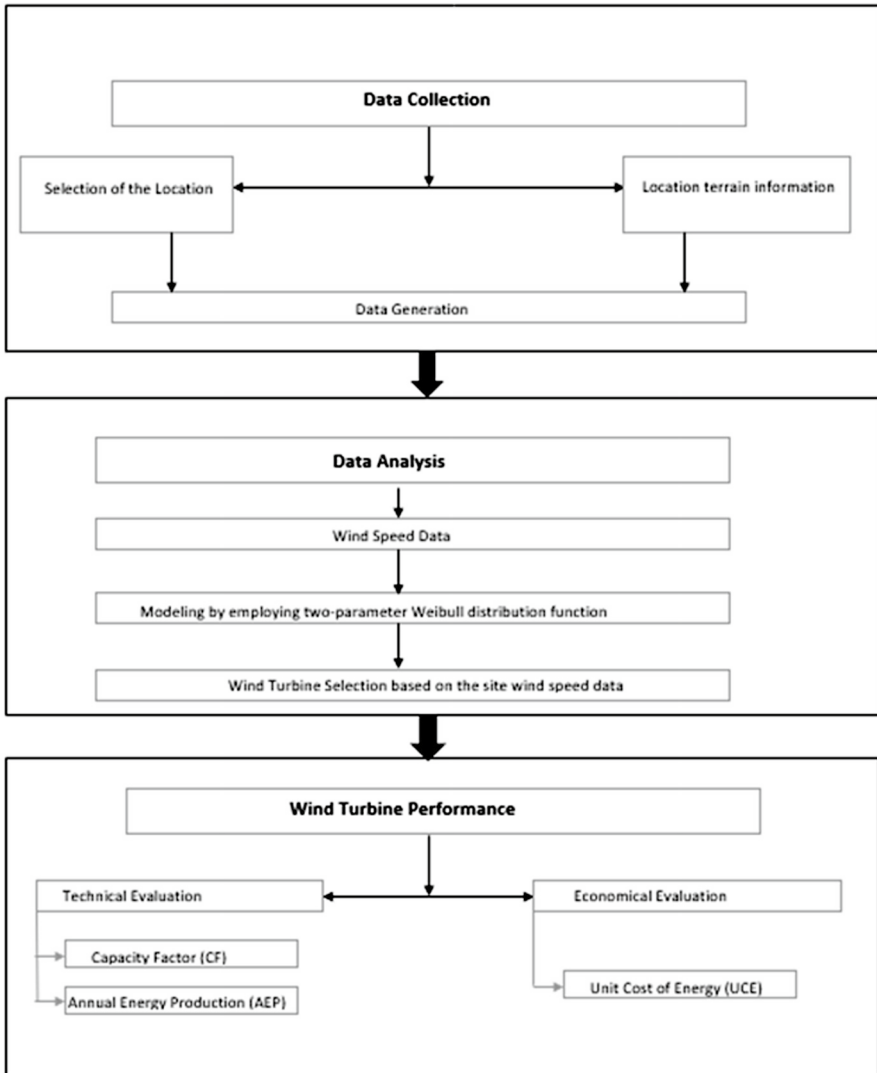
Fig. 1 Flowchart of the process of the present study

5 A Framework for wind energy harvesting in IoT (WHIoT)

The employed methodology for the wind energy harvesting in IoT (WHIoT) has been demonstrated in Figs. 1 and 2. Figure 1, represents the flowchart of the process.

The importance of the suggested framework is that the system can be followed by using the wind energy measuring equipment and the by the system administrators considering the input data from the acquisition devices. The equipment
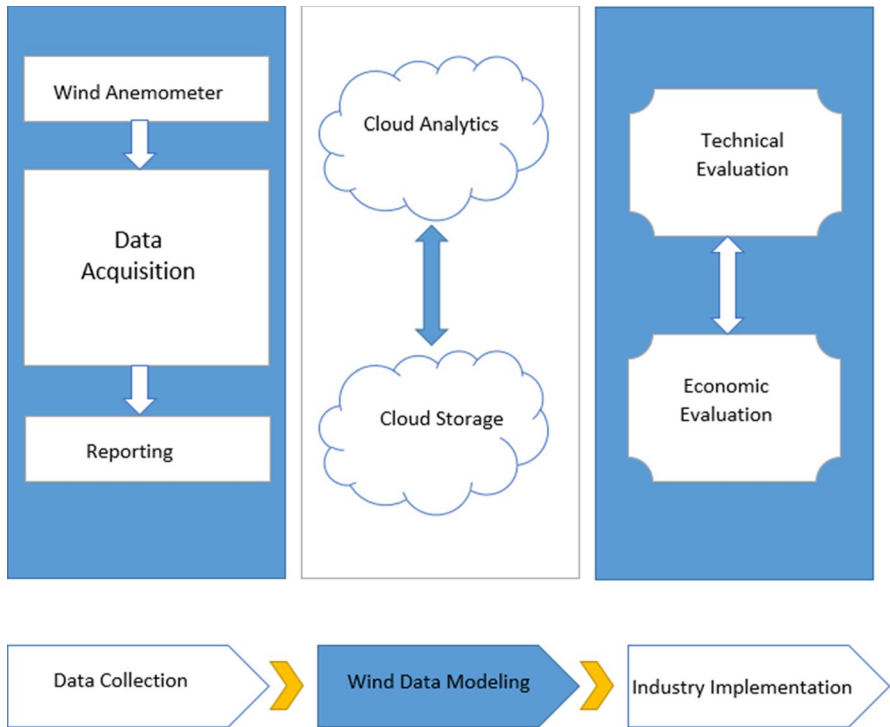
Fig. 2 Architecture diagram of main components and implementation of IoT

and sensors can be used for measuring the wind speed, where the system is followed by an AI model using the various input parameters and the specifications of machine specifications.

During data collection as the first stage, wind speed data have been acquired and also location terrain including latitude, longitude, and the elevation of the sites have been taken into consideration. The wind speed data have been formatted to correspond to a typical meteorological year. Then, the data have been modeled by employing a well-known method of Weibull distribution function. The next step is to select the number of commercially available wind turbines to assess their technical performance and economic feasibility to propose suitable wind turbines for wind energy development in the site. The suggested system is made up of three phases. The data collection phase includes data acquisition from the wind anemometers. In the wind data modeling, the wind speed data are considered and modeled by employing a two-parameter Weibull distribution function, as well as wind turbine selection based on the site wind speed data. All the data are stored in cloud storage to be used for the performance evaluation of the wind turbine where technical and economical evaluation is considered as two parts for implementation in industry. Figure 2 demonstrates architecture diagram of main components and implementation of IoT.

Wind energy potential can be estimated by employing statistical analysis. Therefore, statistical distribution parameters can be employed to compute wind energy characteristics such as mean speed, standard deviation, wind energy, and power density. The accuracy of the parameter estimation has a significant role in the selection of a suitable wind turbine for the investigated site to maximize wind farm electrical energy output and minimize the cost of energy generation. In this process, the number of acquired data, the time interval between data acquisition, the goodness of the fit test for the distribution of the parameters, and evaluation criteria of statistical data are key parameters affecting the performance of the distribution parameter estimation methods. Various probability density functions such as Weibull, Beta, Rayleigh, Gamma, Gaussian, and lognormal distribution can be employed to describe wind speed frequency. Weibull distribution is one of the common methods due to its simplicity, which can describe wind speed distribution with appropriate accuracy. The Weibull probability density function is defined as [29, 30]:

$$f_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left(-\left(\frac{v}{c}\right)^k\right), \tag{1}$$

where $f_w(v)$ is the wind speed probability for wind speed v. Also, k and c are shape parameter (dimensionless) and scale parameter (m/s), respectively, and can be evaluated as follow [31, 32]:

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086} \tag{2}$$

$$c = \frac{\bar{v}}{\Gamma(1 + 1/k)}, \tag{3}$$

where $\bar{v}$ is mean of wind speed for a specified period and σ is the standard deviation of wind speed and can be evaluated as follow:

$$\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i \tag{4}$$

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(v_i - \bar{v})^2\right]^{0.5} \tag{5}$$

These parameters also can be evaluated as follows [33]:

$$\bar{v} = \int_0^{\infty} vf_w(v)dv = c\Gamma\left(1 + \frac{1}{k}\right) \tag{6}$$

$$\sigma = \sqrt{c^2\left[\Gamma(1 + 2/k) - [\Gamma(1 + 1/k)]^2\right]} \tag{7}$$

where $\Gamma(x)$ is the gamma function and can be computed as follows [31]:

$$\Gamma(x) = \int_{0}^{\infty} exp(-u)u^{x-1}dx \tag{8}$$

Wind power per unit area can be evaluated as follow:

$$\frac{P}{A} = \frac{1}{2}\rho v^3 \left(W/m^2\right), \tag{9}$$

where A is the perpendicular area, ρ is the density and v is the wind speed.

In addition, the Weibull probability density function can be employed to evaluate wind power density as follow [34]:

$$\frac{P}{A} = \frac{1}{2}\rho \int_{0}^{\infty} v^3 f(v)dv = \frac{1}{2}\rho c^3 \Gamma\left(1 + \frac{3}{k}\right) \tag{10}$$

Hence, the wind energy density over a specific period, T, and Capacity factor, C_f, can be evaluated as [35, 36]:

$$E = PT \tag{11}$$

$$C_f = \frac{E_{out}}{E_r} \tag{12}$$

Capacity factor C_f is a very significant parameter of the productivity of wind turbines. The parameter represents the fraction of the total energy delivered over a period, E_{out}, divided by the maximum energy that could have been delivered if the turbine was operating at maximum capacity over the entire period, $E_r = (365days) \times (24hr/day) \times P_r$.

To investigate the suitability of the fitted Weibull distribution, the coefficient of determination (R^2) is computed. The coefficient also called the square of the Pearson correlation coefficient, shows the goodness of fit of probability density functions by evaluating the square of the empirical correlation between predicted wind speed and observations values. The coefficient ranges between the value of 0 to 1 to measure the estimation ratio of the distribution model. As the coefficient approaches 1, It demonstrates the best estimate [37, 38].

$$R^2 = \frac{\sum_{i=1}^{N}\left(y_i - z_i\right)^2 - \sum_{i=1}^{N}\left(y_i - x_i\right)^2}{\sum_{i=1}^{N}\left(y_i - z_i\right)^2}, \tag{13}$$

where z_i is the mean actual wind frequency percentages in time step i.

Economic feasibility is an important factor for potential investors. The economic feasibility measures the economic value of the project to determine the most feasible option. In this study, the feasibility of wind harvesting has been

investigated by evaluating the unit cost of electricity. Operation and maintenance cost can express as a percentage of initial investment as [29, 39]:

$$C_{OM} = mC_I \tag{14}$$

, where C_{OM} is operation and maintenance cost and C_I is the initial investment. Then the unit cost of energy can be expressed as:

$$UCE = \frac{C_I(CRF + m)}{E_r}, \tag{15}$$

where capital recovery factor (CRF) can be computed as follows:

$$CRF = \frac{d(1 + d)^t}{(1 + d)^t - 1}, \tag{16}$$

where t is useful life cycle of the turbines and d is discount rate.

6 Results and discussions

In this section, we assess the proposed WHIoT approach via extensive scenarios. For wind energy harvest planning, it is essential to analyze wind speed data. Therefore, to demonstrate the wind energy potential average monthly and seasonal wind speed will be investigated and the wind data modeled by employing the Weibull distribution function. Further investigation was conducted on diurnal mean wind speed for energy demand analysis and wind rose diagram for site planning. The section concluded with remarks regarding the feasibility of harvesting wind energy from the investigated site by evaluating technical and economic feasibility metric indicators.

Table 1 Monthly mean wind speed for three heights of 40, 60, and 80 m

Season	80 m	60 m	40 m
Jan	4.45	4.31	4.16
Feb	5.83	5.50	5.20
Mar	4.85	4.63	4.46
Apr	5.58	5.28	5.00
May	6.05	5.66	5.29
Jun	7.31	6.79	6.37
Jul	8.48	7.78	7.30
Aug	8.20	7.52	6.98
Sep	7.37	6.71	6.22
Oct	5.01	4.75	4.43
Nov	4.02	3.78	3.63
Dec	3.92	3.73	3.61
Annual	5.92	5.54	5.22

Table 2 Seasonal mean wind speed variation measured at three heights

Season	80 m	60 m	40 m
Spring	5.49	5.18	4.91
Summer	7.99	7.36	6.88
Autumn	5.47	5.07	4.75
Winter	4.73	4.51	4.32

Table 3 Monthly mean wind speed and Weibull parameters for different heights

	80 m	60 m $U_{ave}(m/s)$	40 m	80 m		60 m		40 m	
				k	$c(m/s)$	k	$c(m/s)$	k	$c(m/s)$
Jan	4.45	4.31	4.16	1.43	4.91	1.48	4.77	1.52	4.62
Feb	5.83	5.50	5.20	1.32	6.33	1.30	5.96	1.29	5.62
Mar	4.85	4.63	4.46	1.39	5.32	1.43	5.09	1.43	4.91
Apr	5.58	5.28	5.00	1.72	6.26	1.77	5.93	1.76	5.62
May	6.05	5.66	5.29	2.06	6.83	2.08	6.39	2.05	5.97
Jun	7.31	6.79	6.37	2.32	8.25	2.33	7.67	2.23	7.20
Jul	8.48	7.78	7.30	2.77	9.54	2.71	8.75	2.51	8.23
Aug	8.20	7.52	6.98	2.69	9.23	2.66	8.46	2.48	7.87
Sep	7.37	6.71	6.22	2.55	8.31	2.58	7.55	2.41	7.01
Oct	5.01	4.75	4.43	1.81	5.64	1.92	5.35	1.94	4.99
Nov	4.02	3.78	3.63	1.53	4.46	1.60	4.22	1.64	4.06
Dec	3.92	3.73	3.61	1.39	4.29	1.45	4.12	1.45	3.98
Annual	5.92	5.54	5.22	1.70	6.64	1.73	6.21	1.71	5.86

6.1 Monthly mean wind speed

Table 1 illustrates the monthly mean wind speed measured at three heights of 40, 60, and 80 m. The peak monthly wind speed average of 8.48 m/s was observed in July. On the other hand, the lowest monthly wind speed average occurred in December with a value of 3.92 m/s.

Variation of seasonal wind speed is presented in Table 2 to provide additional information regarding wind profile in Bam city. It can be concluded that while summer exhibit the peak seasonal mean speed, winter exhibit the lowest seasonal mean wind speed.

Table 3 illustrates monthly mean wind speed and Weibull parameters for three different heights.

As discussed previously, the two-parameter Weibull distribution function employed in this study. The shape parameter, k, demonstrates skewness rate of Weibull curve. Therefore, the curve is more skewed toward higher wind velocities for the higher values of k ($2 < k < 3$). On the other hand, values of k in range of $1 < k < 2$ means the curve is more skewed toward lower wind velocities. Such

observation indicates that lower wind velocities are more probable to happen. As it can be seen from the table, the variation of the shape parameters at a height of 80 m was in a range of 1.32 and 2.77. The scale parameter, c, illustrate the peak value of the Weibull curve. Therefore, higher values for c demonstrate a distribution over a wider range [4]. From the observed data, it can be seen that the scale parameters were observed to be in a range of between 4.91 and 9.54 m/s.

Table 4 illustrates Monthly power density and energy density for three heights in Bam. From the table, it can be seen that the peak values of power density and energy density occur during summer.

The highest values of power density and energy density are observed in July with values of 547 $\left(W/m^2\right)$ and 407 $\left(kWh/m^2\right)$, respectively. Bam region has a warm summer with a mean temperature of 40° during July. As a result of such weather, the energy demand for cooling purposes is at a peak during this period. Thus, it can be concluded the wind energy can be coupled with another source of energy to meet the additional energy demand during the summer season. On the other hand, the minimum wind power was observed during November with values of 110.4 $\left(W/m^2\right)$ and 79.5$\left(kWh/m^2\right)$, respectively.

The diurnal mean wind speed of Bam is illustrated in Table 5. From the table, the hours of the day which wind speed is at the peak are apparent. The peak means wind speed occurred at an interval of 14:00–20:00 throughout the year.

6.2 Wind speed distribution

Annual variation of the mean value of Weibull wind speed frequencies for Bam is illustrated in Figs. 3, 4, and 5 for three heights. Wind speed distribution is depicted with the Weibull distributions in the figures. Weibull parameters were estimated by employing three methods, namely maximum likelihood, Least squares, and WAsP algorithm. It can be seen from the figure that the statistical

	$P/A\left(W/m^2\right)$			$E/A\left(kWh/m^2\right)$		
	80 m	60 m	40 m	80 m	60 m	40 m
Jan	170.1	150.1	132.0	126.6	111.7	98.2
Feb	444.0	390.6	338.6	298.4	262.5	227.5
Mar	234.3	197.1	178.4	174.3	146.7	132.7
Apr	254.0	205.5	178.6	182.9	147.9	128.6
May	259.8	213.5	177.6	193.3	158.8	132.1
Jun	402.2	324.5	282.9	289.6	233.7	203.7
Jul	547.0	430.7	378.8	407.0	320.4	281.8
Aug	508.5	397.2	338.8	378.3	295.5	252.1
Sep	384.2	287.7	244.0	276.6	207.1	175.7
Oct	166.4	134.0	108.8	123.8	99.7	80.9
Nov	110.4	87.9	75.9	79.5	63.3	54.6
Dec	125.4	102.5	93.1	93.3	76.3	69.2

Table 4 Monthly power density and energy density for different heights

Table 5 Diurnal mean wind speed for three heights of 40, 60, and 80 m

Hour of Day	80 m	60 m	40 m
00:00—01:00	5.74	5.31	4.88
01:00—02:00	5.93	5.48	4.99
02:00—03:00	6.04	5.55	5.05
03:00—04:00	6.21	5.68	5.11
04:00—05:00	6.21	5.57	5.00
05:00—06:00	6.15	5.48	4.86
06:00—07:00	5.83	5.19	4.60
07:00—08:00	5.40	4.87	4.59
08:00—09:00	5.48	5.15	5.04
09:00—10:00	5.57	5.32	5.26
10:00—11:00	5.82	5.60	5.53
11:00—12:00	6.00	5.80	5.70
12:00—13:00	6.14	5.96	5.90
13:00—14:00	6.12	5.95	5.89
14:00—15:00	6.20	6.01	5.95
15:00—16:00	6.50	6.29	6.20
16:00—17:00	6.67	6.40	6.22
17:00—18:00	6.80	6.37	6.04
18:00—19:00	6.41	5.84	5.29
19:00—20:00	5.71	5.13	4.59
20:00—21:00	5.13	4.73	4.40
21:00—22:00	5.14	4.89	4.67
22:00—23:00	5.31	5.02	4.67
23:00—24:00	5.55	5.19	4.80

distribution methods for modeling real situations are close to each other. The wind speed bin of 3 to 25 m/s is crucial in the modeling of actual data the energy production range of commercial wind turbines lies within this range. From the figure, it is apparent that the Weibull distributions show good agreement with actual distribution data.

The performance and accuracy of these methods are investigated by performing an error analysis. Therefore, the coefficient of determination (R^2) is evaluated for all models and presented in Table 6. For a good model, the value of R^2 approaches to unity. The results demonstrated the suitability of all three models for approximating the measured wind data of Bam city.

Figure 6 illustrates the cumulative wind speed distribution for three heights. Cumulative distribution demonstrates the probabilities of a wind speed greater than a specific value. It can be observed that the probability of a wind speed at height 80 m is greater than other heights as the wind speed increases with height. It is apparent that the at heights of 40, 60, and 80 m wind speed greater than 4 m/s has a probability of 58%, 61%, and 64% of the year, respectively. This is a significant wind speed, as most commercial wind turbines have a cut-in speed of 4 m/s.
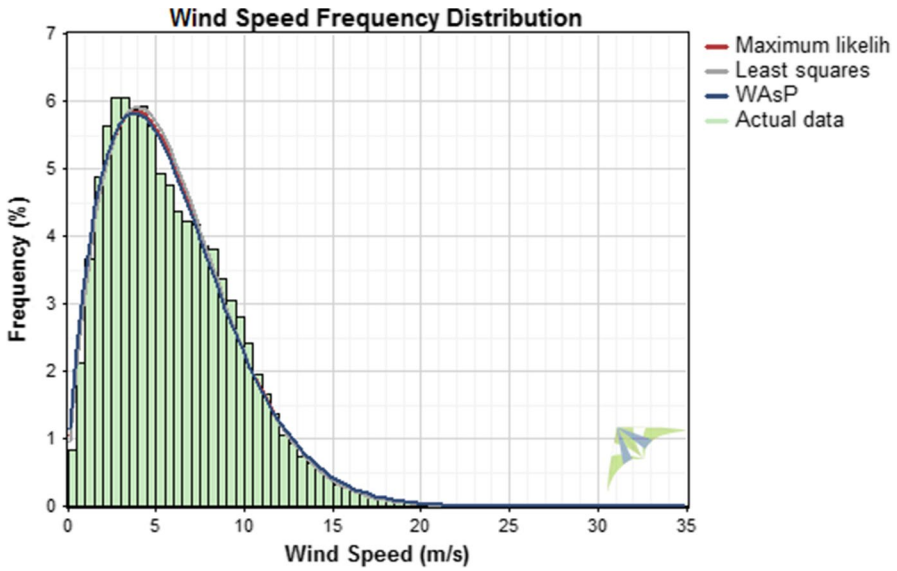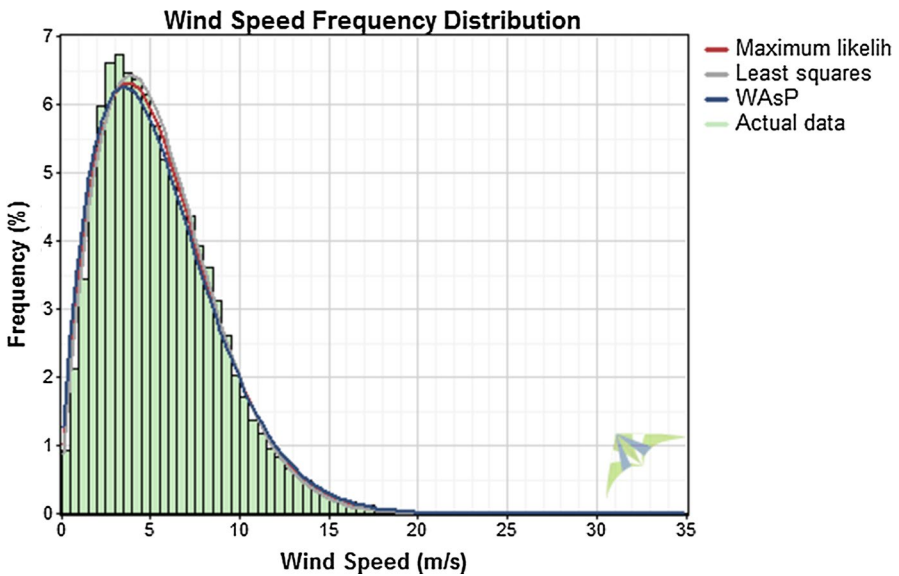
Fig. 3 Wind speed distribution at 80 m

Fig. 4 Wind speed distribution at 60 m

6.3 Wind shear profile

The vertical wind shear profile of Bam city is illustrated in Fig. 7. From the figure, it can be observed that the wind speed suppresses the speed of 6 m/s at a height of
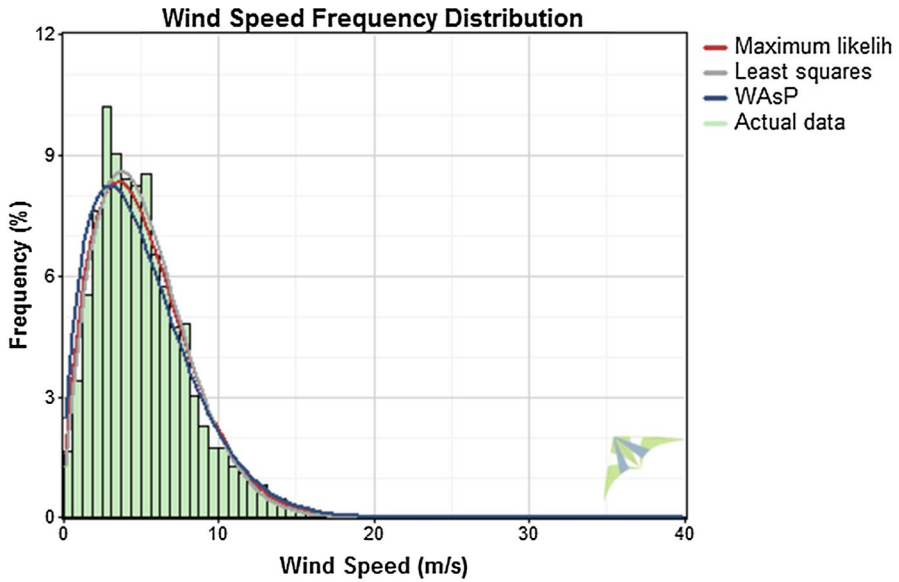
Fig. 5 Wind speed distribution at 40 m

Table 6 Wind speed distribution error analysis at three heights

	R^2		
	80 m	60 m	40 m
Maximum likelihood	0.9899	0.9938	0.9779
Least squares	0.9883	0.9936	0.9825
WAsP	0.9907	0.9916	0.9593

90 m. The power-law exponent (α) as well as a surface roughness (z_0) were computed with values of 0.179 and 0.217 m, respectively.

6.4 Wind rose diagram

Wind direction is an important parameter to obtain an optimum position for a wind farm.

The wind direction can be affected significantly by the geographical feature of the region and also atmosphere circulation. A wind rose diagram is a useful diagram that illustrates wind speed frequency and wind direction altogether in one diagram. Thus, the relative wind speed and its corresponding wind direction can be shown in a wind rose diagram. Figure 8 demonstrates the wind rose diagram for Bam, measured at a height of 78 m. the graph plotted by employing Windographer software for 24 sectors with an arc of 15°. From the figure, it is apparent that the prevailing wind direction from North West.
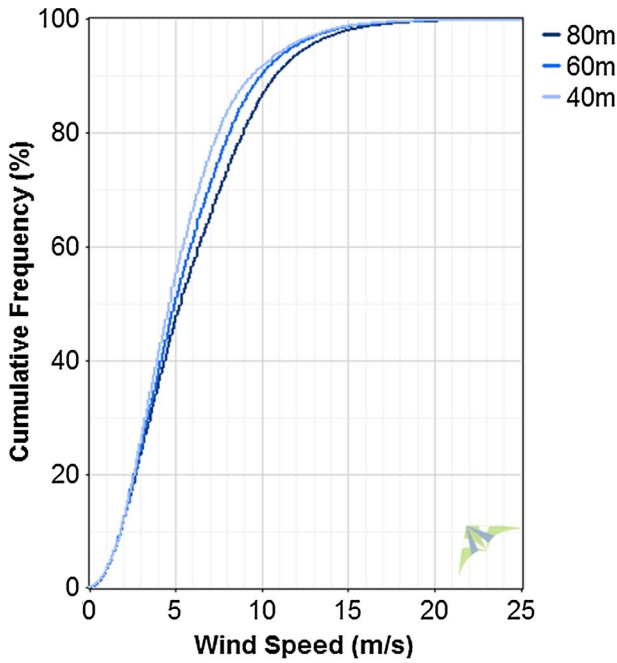
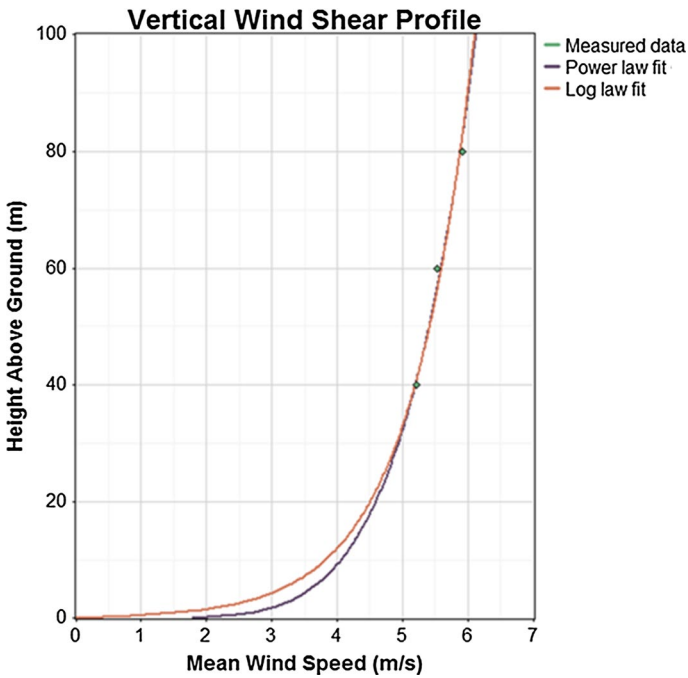**Fig. 6** Cumulative density of wind speed at three heights for Bam

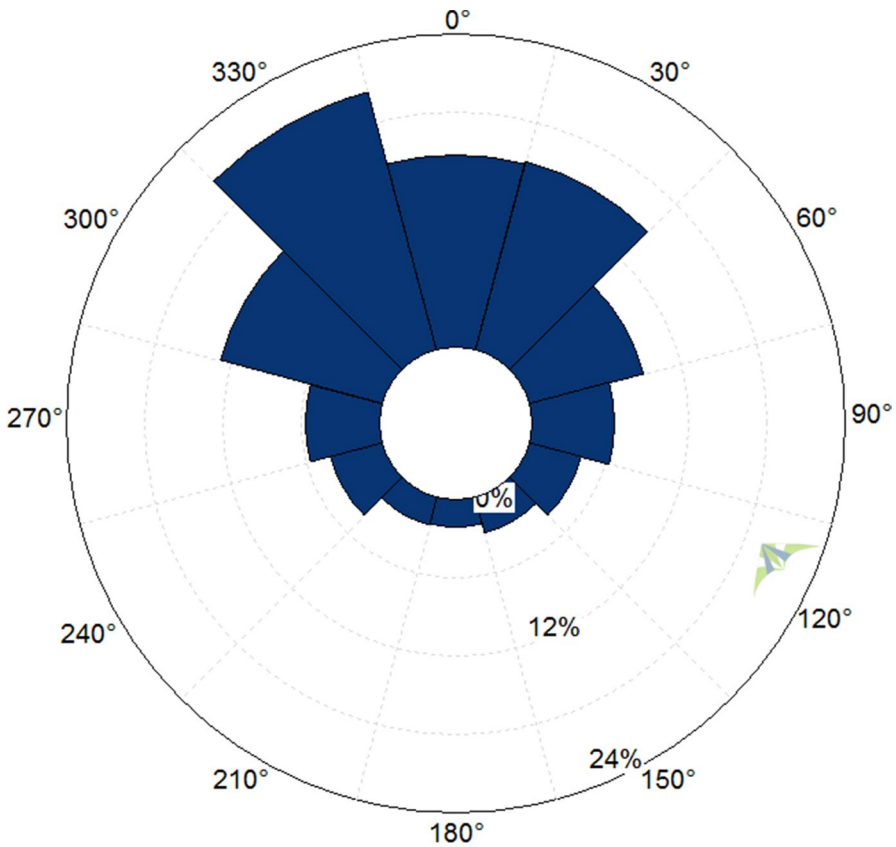

Fig. 7 Vertical wind shear profile for Bam

Fig. 8 Wind rose diagram of Bam city

6.5 Economic evaluation

To evaluate the wind energy potential and investigate the feasibility of harvesting the wind power in Bam, six different wind turbines are selected and their performance is investigated in terms of Annual Energy Production (AEP), Capacity Factor (CF), and Unit Cost of Energy (UCE).

Windographer software has been employed to compute capacity factor C_f and annual energy output AEP of the selected wind turbines. Several parameters such as awake, power curve hysteresis, and connection grid downtime were considered to evaluate the production losses due to wind turbine downtime with 10% production losses. To perform the economical assessment, initial costs, C_I, including costs such as transportation, installation, and grid integration are taken to be 40% of the turbine cost [34, 40]. Also, annual operating and maintenance costs, C_{OM}, together with land are assumed to be 5% of the wind turbine cost [34]. Other parameters such as discount rate and expected useful life cycle of the turbines are taken as 10.5% [41] and 20 years, respectively.

Table 7 Technical specification and performance of the selected wind turbines

Turbine name	Turbine cost (USD) [29]	Hub height	Grid type (m)	AEP (kWh/yr)	CF (%)	UCE (USD/kWh)
Bergey XL.1	9500	18	Off-grid	1509	17.23	1.512
Endurance E-3120	350,000	42.7	Grid-connected	111,844	23.21	0.751
Endurance G-3120	280,000	42.7	Grid-connected	82,869	27.03	0.811
Proven 2.5 kW	25,000	6.5	Off-grid	5274	24.08	1.138
Proven 15 kW	77,000	25	Grid-connected	37,678	28.67	0.491
Raum 1.3 kW	10,000	14.5	Off-grid	1918	16.84	1.252

Table 7 shows specifications of the selected turbines, AEP, C_f and UCE. In terms of AEP Endurance E-3120 (Grid-connected) and Proven 2.5 kW (Off-grid) produces the highest amount of energy. On the other hand, C_f is an important parameter for analyzing wind turbine performance which also affects the cost of electricity generation. From the presented results, it can be seen that wind turbine Proven 15 kW demonstrates the highest efficiency in terms of a capacity factor with a value of 28.67%. From the table, it is apparent that the unit cost of energy in Bam ranges from 0.491 to 1.512 (USD/kWh). The grid-connected Proven 15 kW demonstrates the cheapest energy production.

7 Conclusion

Electricity generation from wind energy as clean and sustainable energy increasing significantly. Hence, to harvest energy by employing wind turbines, it is required to evaluate the wind characteristics of the region. In this study, the wind potential of Bam city has been investigated by employing wind speed data acquired by the Renewable Energies Organization of Iran for one year with ten minutes intervals. The annual wind speed at 80 m was observed to be 5.92 m/s with maximum and minimum monthly wind speed average that occurred in July and December, respectively. Hence, in July power density and energy density reached a peak value of 547 (W/m^2) and 407 (kWh/m^2), respectively. On the other hand, the minimum seasonal wind speed occurred was observed during winter. Such variation provided an opportunity for harvesting wind energy to meet the domestic demand of the region. Thus, during warm summer with peak demand of energy for cooling purposes, wind energy can be utilized to meet the additional energy demand.

The result demonstrated the prevailing wind direction was observed from North West in this region, which must be considered for development future wind farm. Finally, the performance of 6 Grid-connected and Off-grid small-scale wind turbines has been assessed. The feasibility investigation revealed that the UCE in Bam for small-scale wind turbines ranges from 0.491 to 1.512 (USD/kWh). Future work will include the IoT System to communicate and collect data with the server to be used for further processing of data. In this way, it is envisaged to investigate the

possibility of improving wind energy production by integrating the classical production site with new IoT systems, and the application of the expert system, as well as statistics to reach better results and performance.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Teimourian A et al (2020) Assessment of wind energy potential in the southeastern province of Iran. Energy Sour, Part A: Recovery, Util, Environ Eff 42(3):329–343
2. Ouammi A et al (2010) Monthly and seasonal assessment of wind energy characteristics at four monitored locations in Liguria region (Italy). Renew Sustain Energy Rev 14(7):1959–1968
3. Tizpar A et al (2014) Wind resource assessment and wind power potential of Mil-E Nader region in Sistan and Baluchestan Province, Iran-Part 1: Annual energy estimation. Energy Convers Manage 79:273–280
4. Mostafaeipour A et al (2013) Evaluation of wind energy potential as a power generation source for electricity production in Binalood Iran. Renew Energy 52:222–229
5. Morgan VT (1995) Statistical distributions of wind parameters at Sydney Australia. Renew Energy 6(1):39–47
6. Chang TP (2011) Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application. Appl Energy 88(1):272–282
7. Mostafaeipour A et al (2011) Wind energy feasibility study for city of Shahrbabak in Iran. Renew Sustain Energy Rev 15(6):2545–2556
8. Eskin N, Artar H, Tolun S (2008) Wind energy potential of Gökçeada Island in Turkey. Renew Sustain Energy Rev 12(3):839–851
9. Wais P (2017) Two and three-parameter Weibull distribution in available wind power analysis. Renewable Energy 103:15–29
10. Tuller SE, Brett AC (1985) The goodness of fit of the Weibull and Rayleigh distributions to the distributions of observed wind speeds in a topographically diverse area. J Climatol 5(1):79–94
11. Bowden G, et al. (1983) *The Weibull distribution function and wind power statistics.* Wind Engineering, p. 85–98.
12. Keyhani A et al (2010) An assessment of wind energy potential as a power generation source in the capital of Iran, Tehran. Energy 35(1):188–201
13. Mohammadi K, Mostafaeipour A (2013) Economic feasibility of developing wind turbines in Aligoodarz, Iran. Energy Convers Manag 76:645–653
14. Mostafaeipour A (2013) Economic evaluation of small wind turbine utilization in Kerman Iran. Energy Convers Manag 73:214–225
15. Mostafaeipour A (2010) Feasibility study of harnessing wind energy for turbine installation in province of Yazd in Iran. Renew Sustain Energy Rev 14(1):93–111
16. Mostafaeipour A, Abarghooei H (2008) Harnessing wind energy at Manjil area located in north of Iran. Renew Sustain Energy Rev 12(6):1758–1766
17. Alhmoud L, Al-Zoubi H (2019) IoT Applications in Wind Energy Conversion Systems. Open Engineering 9(1):490–499
18. Al-Turjman F et al (2020) Feasibility analysis of solar photovoltaic-wind hybrid energy system for household applications. Comput Electr Eng 86:106743
19. Alhaddad M, et al. (2019) Aiming for smart wind energy: A comparison analysis between wind speed forecasting techniques. Transactions on Emerging Telecommunications Technologies, p. e3749.
20. Dimililer K, Dindar H, Al-Turjman F (2020) Deep learning, machine learning and internet of things in geophysical engineering applications: an overview. Microprocessors Microsyst 103613.

21. Khan M et al (2021) A new hybrid approach of clustering based probabilistic decision tree to forecast wind power on large scales. J Electr Eng Technol 16(2):697–710

22. Khan M, Liu T, Ullah F (2019) A new hybrid approach to forecast wind power for large scale wind turbine data using deep learning with TensorFlow framework and principal component analysis. Energies 12(12):2229

23. Batcha RR, Geetha MK (2020) A survey on IOT based on renewable energy for efficient energy conservation using machine learning approaches. in 2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE). IEEE.

24. Almonacid-Olleros G et al (2020) A new architecture based on IoT and machine learning paradigms in photovoltaic systems to nowcast output energy. Sensors 20(15):4224

25. Yeh C-H et al (2019) Machine learning for long cycle maintenance prediction of wind turbine. Sensors 19(7):1671

26. Demircan B, Akyüz E (2019) IoT and cloud based remote monitoring of wind turbine. Celal Bayar Univ J Sci 15(4):337–342

27. Alamdari P, Nematollahi O, Mirhosseini M (2012) Assessment of wind energy in Iran: A review. Renew Sustain Energy Rev 16(1):836–860

28. Wikipedia (2018) Bam Wiki.

29. Nedaei M (2014) Wind resource assessment in Hormozgan province in Iran. Int J Sustain Energ 33(3):650–694

30. Chang T-J et al (2003) Assessment of wind characteristics and wind turbine characteristics in Taiwan. Renew Energy 28(6):851–871

31. Mohammadi K, Mostafaeipour A (2013) Using different methods for comprehensive study of wind turbine utilization in Zarrineh, Iran. Energy Convers Manag 65:463–470

32. Diaf S, Notton G (2013) Technical and economic analysis of large-scale wind energy conversion systems in Algeria. Renew Sustain Energy Rev 19:37–51

33. Mirhosseini M, Sharifi F, Sedaghat A (2011) Assessing the wind energy potential locations in province of Semnan in Iran. Renew Sustain Energy Rev 15(1):449–459

34. Mostafaeipour A et al (2014) An analysis of wind energy potential and economic evaluation in Zahedan, Iran. Renew Sustain Energy Rev 30:641–650

35. Bahrami A et al (2019) Technical and economic analysis of wind energy potential in Uzbekistan. J Clean Prod 223:801–814

36. Bahrami A et al (2019) Assessing the feasibility of wind energy as a power source in Turkmenistan; a major opportunity for Central Asia's energy market. Energy 183:415–427

37. Çakmakçı BA, Hüner E (2020) Evaluation of wind energy potential: a case study. Energy Sour, Part A: Recov, Util, Environ Effects 1–19.

38. Khlaifat N et al. (2020) Evaluation of wind resource potential using statistical analysis of probability density functions in New South Wales, Australia. Energy Sour, Part A: Recov, Util, Environ Effects 1–18.

39. Kandpal TC, Garg HP (2003) Financial evaluation of renewable energy technologies: MacMillam India Limited.

40. IRENA, R.P.G.C.i., (2017) International Renewable Energy Agency, Abu Dhabi

41. Iran, (2018) C.b.o.t.I.R.o.

42. Ahmadi A, Nabipour M, Mohammadi-Ivatloo B, Amani AM, Rho S, Piran MJ (2020) Long-term wind power forecasting using tree-based learning algorithms. IEEE Access 8:151511–151522. https://doi.org/10.1109/ACCESS.2020.3017442