ADAMA-II WIND FARM PERFORMANCE ASSESSMENT IN COMPARISON TO FEASIBILITY STUDY

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ABSTRACT

The objective of this paper was to assess the performance of the Adama-II Wind Farm in comparison to the feasibility study. Using one-year mast data, the site potential was reassessed by WAsP software and the performance of wind turbine generators was assessed by two years of SCADA data. The obtained mean annual wind speed was 7.75 m/s, and the mean wind power density was 462 w/m^2 while in the feasibility study, 9.55 m/s, and 634.6 w/m^2, which resulted in 18.8%, and 27.1% deviations. The prevailing and secondary wind directions obtained in this paper were ENE and NE with 35.7% and 19.1% but, in the feasibility study, ENE with 36.5% and E with 17.3%. From the SCADA data, the Capacity factor, Annual Energy Production (AEP), and Availability of wind turbines were determined as 30.5%, 396 GWh, and 95.1%. Therefore, the reasons for this deviation were long-term correction and weather impacts.

Keywords— Adama-II Wind Farm, Wind Farm performance, Wind characteristics, Annual Energy Production, Capacity Factor, Availability

INTRODUCTION

There is significant wind power potential in Ethiopia, which is estimated to be more than 10,000 MW, with a speed of 7 to 9 m/s. However, the current installed capacity is only 324 MW which is less than 5%. The Ethiopian government has a long-term plan of increasing the utilization of the resource by involving independent power producers. The case study farm here is Adama-II Wind Farm, located in the southeastern part of the country, 95 km from Addis Ababa and 7 km from Adama town. The farm's elevation ranges from 1741 to 2173 m, and its central location is at the latitude of N 008° 34' 18" and longitude of E 039° 12' 10'' (Tadesse 2014; Hydro China Corporation, 2013). Figure 1 shows the location map of the wind farm.

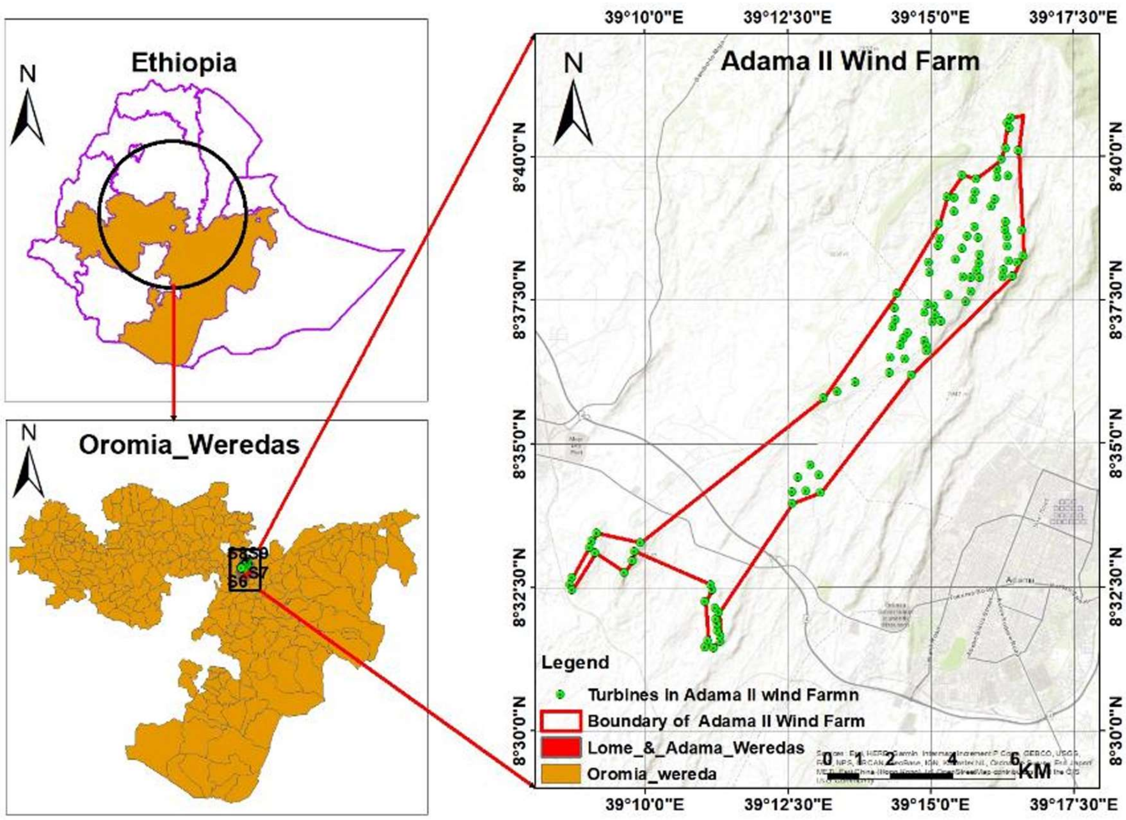


Figure 1: Location of Adama II Wind Farm (Generated by Arc Map 10.7)

Table 1: Parameters of the wind turbine at Adama-II wind farm

Parameters	Unit	Quantity
Blade number	Piece	3
Blade diameter	77 m	
WTG set	SANY SE7715	102
Rated capacity	1500 kW	
Rotating speed	10.6-21.1 rpm	
Cut-in	3.5 m/s	
Rated wins speed	11.25 m/s	
Cut-out wind speed	25 m/s	
Hub height	70 m	

Table 1 shows the summary of wind turbine parameters in Adama-II Wind Farm. The installed power capacity of the farm is 153 MW with 102 turbines with a rated capacity of each turbine, 1.5 MW. The farm has a 230 kV step-up substation with a total capacity of 180 MVA with two transformers rated 90 MVA each and a voltage level of 230/33 kV. The 230 kV outgoing line is connected to the Koka switch through a single circuit overhead line (Hydro China Corporation, 2013).

During the feasibility study, 4 years of mast data at wind speed measurement heights of 10 m and 40 m, wind direction measurement at 10 m. The wind data was extrapolated to the hub height of the turbines at 70 m. The wind data was corrected by 30 years of NCEP/NCAR (National Centers for Environmental Prediction/National Centers for Atmospheric Research) at the grid points of 7.5º N and 40 E which is 143 km from the central location of the wind farm. To verify these results, 9 months (in 2011) wind measurement at the hub height of 70 m was used and the wind potential of the site was estimated using these data.

Since the measurement period at the hub height was less than 1 year, there was an expectation that the results were prone to different uncertainties (Asian development bank, 2014). The uncertainties observed in the preconstruction period of wind resource assessment might be related to onsite measurement, long-term correction, and wind variability (Mönnich, et al., 2016). So, the main aim of this research is to compare production performance with the estimated values during the feasibility study. The paper addressed the following research questions.

1. Is the feasibility study of the Adama-II Wind Farm comparable to the production data?

2. If the is a deviation from the feasibility study, what could be the main reasons behind that deviation?

3. What should be considered to alleviate such problems?

To answer the above research questions, the site potential was reassessed using one-year mast data by WAsP 10 and Weibull probability density functions (Weibull pdf), then the performance of wind turbine generators was assessed using two years of SCADA data, and KPIs were calculated and compared with the feasibility study.

2. Literature Review

The review of the state of art on this paper has two parts. The first one is about the pre and post-construction wind resource estimation uncertainties and the second part is about the performance evaluation matrices of the operational wind farms.

Wind resource assessment before the construction of a wind farm is vulnerable to various uncertainties that are related the wind variability, long-term correction, turbine power curve. Kwon (2010) showed that wind energy uncertainties do arise from wind resources and energy production. The first one comes from the calibration problem of measuring instruments, which includes the uncertainties associated with the type of sensor, installation, calibration of sensors, location of the towers, etc. Annual energy production uncertainties related to the power curve of a wind turbine. Grünbaum (2010) stated that wind energy is so unstable and indeterminate in its very nature that energy extraction is highly reliant on the weather. This variability introduces a challenge in predicting and handling the resource. Such uncertainties will be prevalent as the penetration level is getting higher and higher. Padhee et.al. (2017) stated that variations of wind power and system load have a great impact on the power system voltage profile. So, the study preferred a season-focused modeling approach from a season-independent modeling approach to effectively analyze the impacts of the variations in wind power output and system load on the voltage profiles. Wind resources at the west coast of Ireland showed substantial change at a seasonal scale (Ren, 2018) and the winter season was characterized by high wind speed than the rest of the three seasons which results create uncertainties. Lira et al. (2016) used probabilistic models, Monte Carlo simulation, and MCP methods to determine the uncertainties due to wind inconsistency. Therefore, these methods assessed the risk of power output deviance. Abolude & Zhou, (2018) compared actual and theoretical power curves by doing an inspection of time series of wind turbine performance and energy yield has been done under three different situations using two seasons (i.e., winter and summer). The detected data displayed that wind direction might substantially affect turbine power output; likewise, turbine momentum may withstand wind power production despite low wind speed. So, the researcher proposed Effective Power Curve (EPC) based on turbine performance over a given period and makes fewer estimation errors relative to the theoretical power curve when used for the prediction of 15-minute ranged power production (Abolude & Zhou, 2018).

The second part of the literature review is about the performance metrics of wind farms. There various performance indicators as stated by different researchers, for instance, Pfaffel, et.al. (2019) divided wind farm KPIs into maintenance, reliability, health, safety and the environment (HSE), and Finance KPIs. Here, the capacity factor, time-based and, production-based availabilities fell under maintenance KPIs. Pfaffel, et.al. (2017) also reported that Availability and capacity factors are key performance indicators of various wind farms worldwide. Conroy, et.al.,(2011) compared time-based and energy-based wind farm availability and stated that time-based availability is the most commonly utilized by turbine manufacturers and power producers. The study also demonstrated that energy-based availability is preferable to time-based availability if the power producers have enough monitoring wind speed and SCADA data. Among the commonly used wind farm operational KPIs, capacity factor, time-based availability, energy-based availability, and wind energy index were described in (IEC TS 61400-26-1,2011; Bocard, 2009). The capacity factors cannot necessarily show the long-term wind potential of the site. They would rather indicate yearly output because they can evolve. For that reason, a low observed capacity factor might be due to low wind conditions, below their long-term potential (Rimple & Westerhellweg, 2013). There is also wind index which is considered as wind farm KPI which depends on the production of several reference wind turbines over a wide geographic area. Power system operators can identify a normal period of annual wind energy, expressed as 100%. This is also ideal in distinguishing underperforming turbines and wind strengths below expected levels. It also opens comparison room for the production of a wind farm with the available wind resource (Ritter, et.al.,2015; IEC TS 61400-26-2, 2014).

3. Materials and Methods

3.1 Available data

For post-construction assessment of the wind farm potential, a one-year mast data was used and after preprocessing, this data was input to Wasp Climate analyst.

Table 2: Information of Mast 10357#

Mast 10357#		Tower height (m)	Elevation (m)	Speed measurement height (m)	Direction measurement height (m)
Latitude	Longitude				
8°34.646'N	39°13.152'E	70	1885	70/50/30/10	70/10

As shown in the above Table the location of Mast 10357# is at a latitude of 8°34.646'N and a longitude of 39°13.152'E. The height of the tower is 70 m with 4 speed measuring heights m, (10 m, 30 m,50 m, and 70 m) and wind direction measuring heights of 10 m and 70 m. The types of sensors that are used on this mast are wind vanes, anemometers, pressure sensors, temperature sensors humidity sensors. Table 2 shows the location of the mast with the nearest turbine sites.

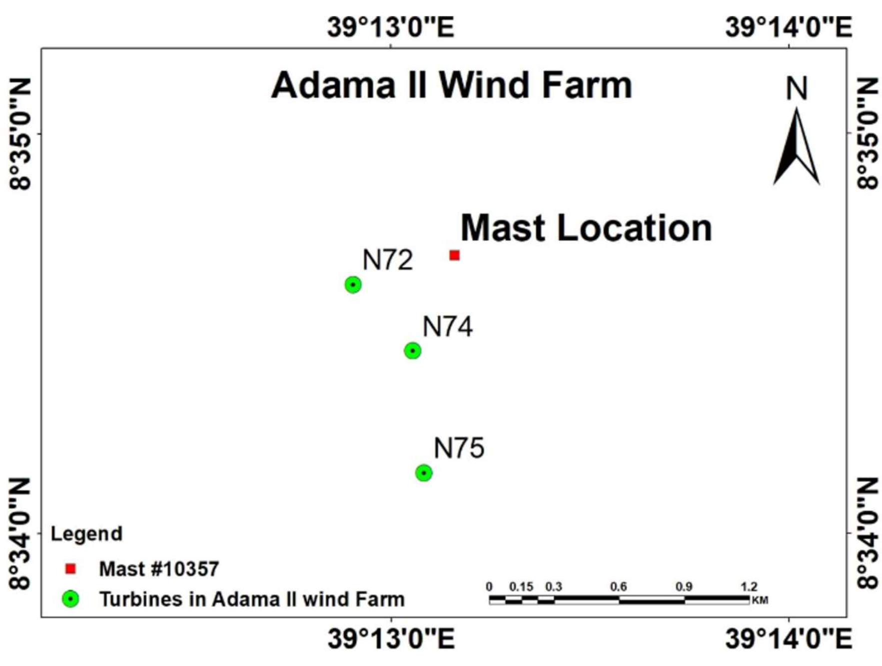


Figure 2: Location of Mast 10357#

As shown in the above figure, N74 and N72 are turbines near the mast.10357#

Long-term correction

There were 1164 wind speed records at 70 m which were lower than speeds at 10 m (-ve wind shear). After identifying and replacing them with the 10 m records, 30 years of MERRA-2 data was applied for long-term correction. The reason for choosing this data is its better spatial resolution and temporal resolution than NCEP/NCAR.

Table 3: Comparison of MERRA-2 and NCEP/NCAR

Long-term Reanalysis data	Spatial resolution	Temporal resolution	Distance from the center (km)	Remark
MERRA-2 Nearest X and Y	0.5°X 0.625° 541273 m	1 Hr. 939594 m	20.5	Used in this paper
NCEP/NCAR Nearest X and Y	2.5° X 2.5° 610335	6 Hr. 829148	143	Used in the feasibility study

NCEP/NCAR showed a strong up-wind long-term speed trend for the period of 1980-2009 while the MERRA-2 showed a lower long-term wind speed trend (Liléo & Petrik, 2011). The report also showed a 16% improvement of MERRA-2 over NCAR/NCEP and properly representing the site-specific data. So, the hourly mean wind speed of 30 years long-term data was used in this paper is 3.46 m/s

To evaluate the performance of wind turbine generators, two years of 5-minute SCADA data were used. The wind index method is used for long-term correction because it is directly related to the energy production of a wind turbine (Thøgersen, et al., 2007).

$$\text{WIndex} = \frac{Mean\ wind\ speed\ of\ the\ mon}{Mean\ annual\ wind\ speed} \qquad (1)$$

AEP long-term = 12 * MEP (month i) / Windex (month i)

Where, MEP = Monthly Energy Production.

So we can get 12 estimates of AEP in a year, the average of these all will be the long-term corrected value of AEP (Lindvall, et al., 2016).

3.2. Methods

After the long-term adjustment, the mast data was input to WAsP 10 to reassess the site potential and the following equations were used to obtain the characteristics of the site.

Table 4: Wind Mast data analysis and Weibull equivalent.

Characteristics	Meteorological Data	Equivalent Weibull
Mean wind speed	$V_m = \sum_{i=1}^{n} V_i f(V_i)$	$V_m = A.\gamma(1 + \frac{1}{k})$
Most frequent speed	$V_f = V[f(V)_{max}]$	$V_f = A.(1 + \frac{1}{k})^{\frac{1}{k}}$
Most energetic speed	$V_e = V[P_d(V)_{max}]$	$V_e = A.\left(1 + \frac{2}{k}\right)^{1/k}$
Standard deviation	$\sigma = \left[\sum_{i=1}^{n} (V_i - V_m)^2 f(V)_i\right]^{\frac{1}{2}}$	$\sigma = A^2\left[\gamma\left(1 + \frac{2}{k}\right) - \gamma^2\left(1 + \frac{1}{k}\right)\right]$

The power production of wind turbine generators is also compared with the site predicted values in this paper and the feasibility. To study the performance of the wind farm, the performance KPIs used here are: capacity factor, Annual Energy production, Availability, capacity factors, and they are defined by the following equations.

$$\mathrm{CF_{farm}} = \frac{\mathrm{AEP}}{8760\sum_{j=1}^{N} \mathrm{P_i}} \quad (2)$$

Where AEP is Annual Energy Production,

P_{rj}, rated power of each turbine, and N is the number of turbines

The following equation shows that AEP is dependent on installed capacity (IEC TS 61400-26-2, 2014).

$$\mathrm{AEP} = \mathrm{N_h}\sum_{i=1}^{N}[\mathrm{F(V_i)} - \mathrm{F(V_{i-1})}]\left(\frac{\mathrm{P_{i-1}} + \mathrm{P_i}}{2}\right) \quad (3)$$

$$\mathrm{F(V)} = 1 - \exp\left(-\frac{\pi}{4}\left(\frac{V}{Vave}\right)^2\right) \quad (4)$$

Where AEP is Annual Energy Production in MWh,

N_h is the total number of hours in a year, 8760 hrs,

F(v) is the Rayleigh frequency distribution function and

Pi is power reading from the power curve.

The summary of the methodology followed in this paper is shown in the Figure below.

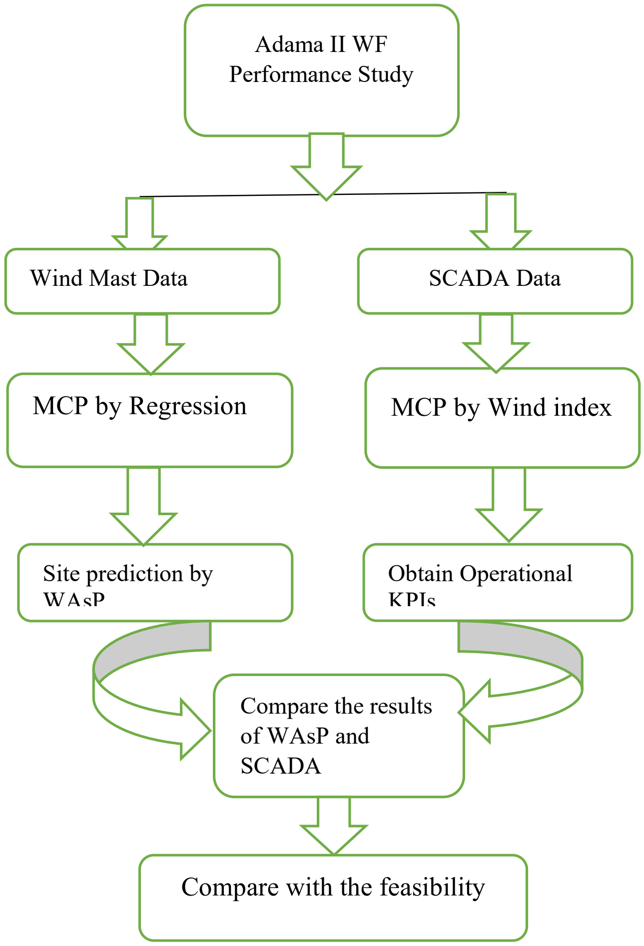


Figure 3: Flow diagram of the proposed study

4. Result and Discussion

4.1 Long-term correction

The monthly correlation between MERRA-2 and mast 10357 at 10 m resulted in a correlation coefficient (R) of 0.8556, for the concurrent period of 2017. So, to correct the mast data with MERRA-2, a long-term correction coefficient is calculated and applied to each 10-minute data of the mast. The monthly correlation of wind speeds between the mast and the MERRA-2 in 2017 is given in the Figure

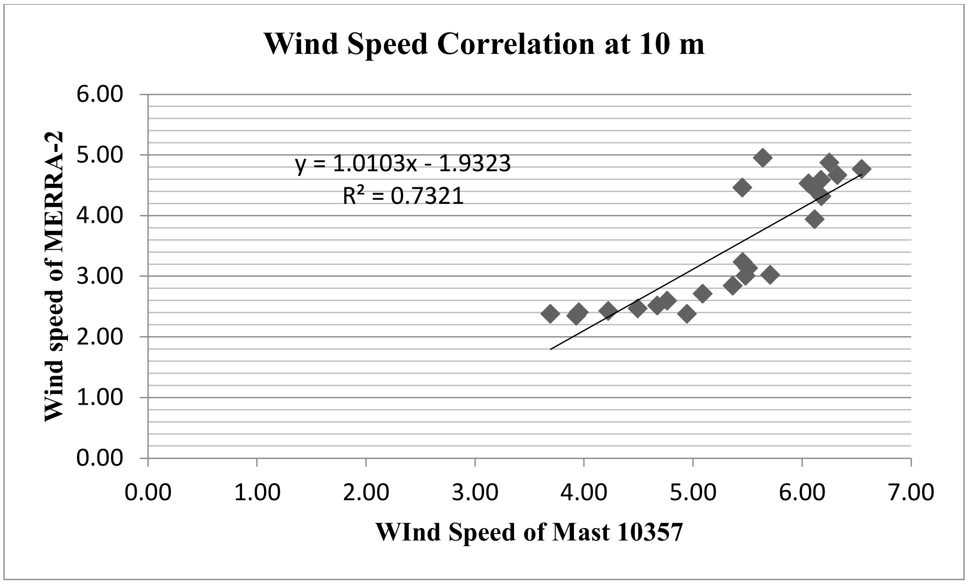


Figure 4: Monthly wind speed Correlation at 10m

Clt= Mean wind speed of MERRA-2 (30yrs)/Mean wind speed of MERRA-2 (2017)

Clt=3.461/3.460= 1.00028 which is equal to 1 so, we can use the mast data wind speed as a long-term corrected wind speed. So, the mean wind speed of the site is taken as the values recorded at 10 m is 5.34 m/s at 7.68 m/s at 70 m.

For long-term correction of wind direction at 10 m, 30yrs wind direction of MERRA-2 data is obtained as shown in the table below with primary and secondary directions of ENE and NE (32.4% and 20.7%) respectively.

Table 5: Long-term wind direction of MERRA-2

E	ENE	ESE	N	NE	NNE	NNW	NW	S	SE	SSE	SSW	SW	W	WNW	WSW
23418	85251	10508	727	54408	3267	1500	1004	2944	5796	3319	5187	31792	4528	1603	27716
8.9%	32.4%	4.0%	0.3%	20.7%	1.2%	0.6%	0.4%	1.1%	2.2%	1.3%	2.0%	12.1%	1.7%	0.6%	10.5%

The hourly wind rose of the MERRA-2 in 2017 is shown in the following rose plot below.

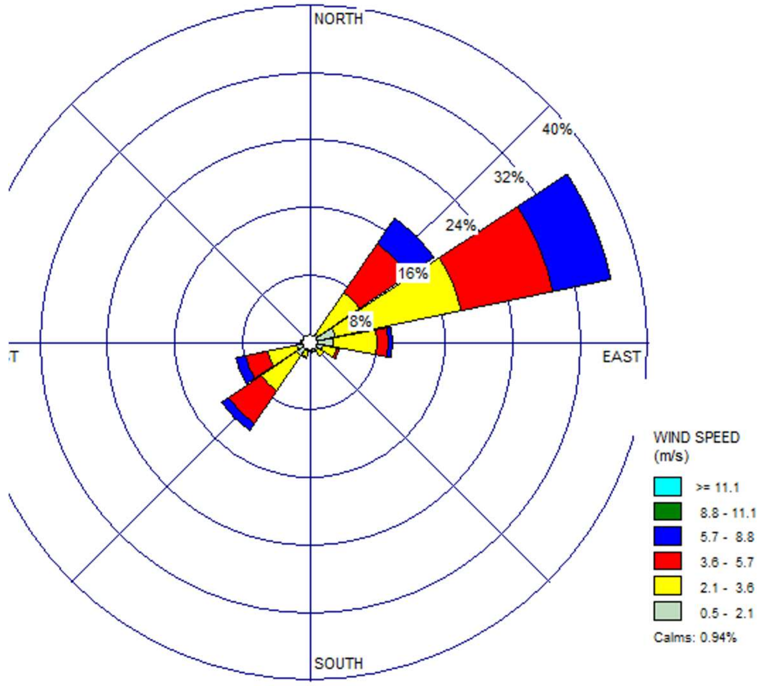


Figure 5: Rose plot of MERRA-2 at 10 m in 2017

The wind direction of MERRA-2 shows that the prevailing and secondary wind directions are ENE and NE. The mean hourly wind direction in the 30 years was 118° and in 2017, it was 116°, so the long-term coefficient is equal to Cltd=118/116=1.0172, applying this coefficient to the 10-minute direction data of Mast 10357 gives, the following table,

Table 6: Wind direction of Mast 10357# at 10 m

E	ENE	ESE	N	NE	NNE	NNW	NW	S	SE	SSE	SSW	SW	W	WNW	WSW
6345	21069	762	597	3070	1180	2244	2873	470	345	292	585	1647	4187	3165	3729
12.1%	40.1%	1.5%	1.1%	5.8%	2.3%	4.3%	5.5%	0.9%	0.7%	0.6%	1.1%	3.1%	8.0%	6.0%	7.1%

As shown in the above table, primary and secondary wind directions are ENE and E with wind direction frequencies 40.1% and 12.1% respectively.

As there is no wind direction measurement in MERRA-2 data at 70 m, the monthly wind direction of the mast at 70 m was correlated with the long-term adjusted direction of the wind mast at 10 m. The correlation coefficient obtained is 0.9112, which shows a strong correlation. Applying MCP, the wind direction at 70 m is shown in the table below.

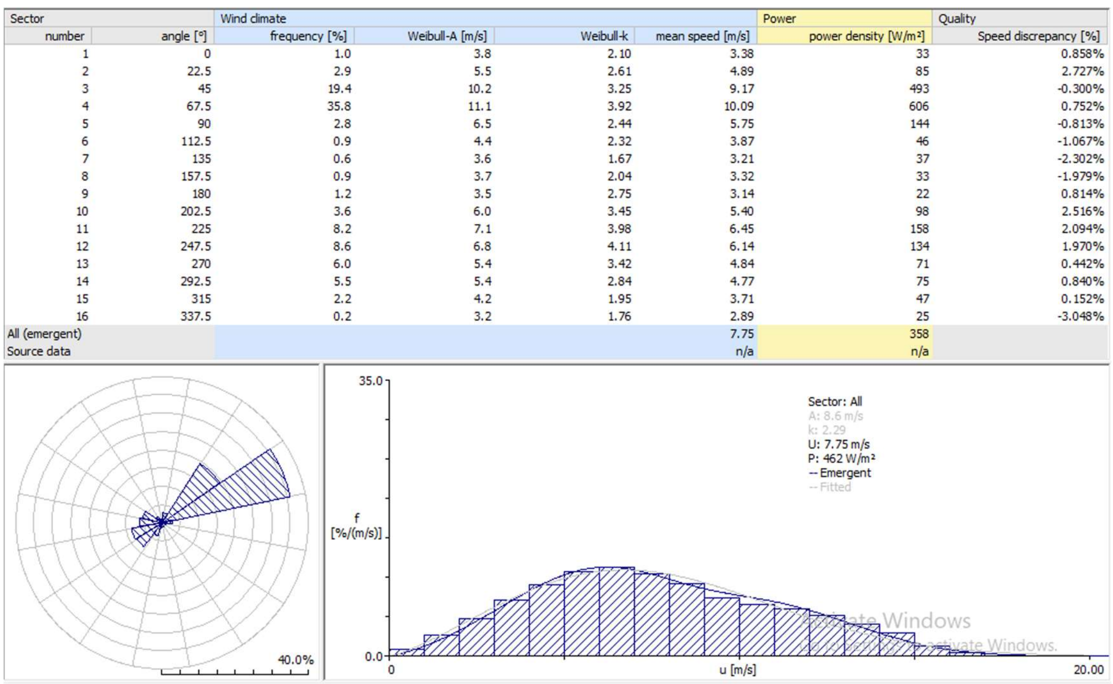
Table 7: Wind direction frequencies of the site at 70 m

E	ENE	ESE	N	NE	NNE	NNW	NW	S	SE	SSE	SSW	SW	W	WNW	WSW
1453	18778	478	505	10057	1678	301	1128	618	301	485	2068	4156	3152	2897	4505
2.8%	35.7%	0.9%	1.0%	19.1%	3.2%	0.6%	2.1%	1.2%	0.6%	0.9%	3.9%	7.9%	6.0%	5.5%	8.6%

As sown in the above table, the prevailing wind direction is found to be ENE with 35.7% and secondary wind direction is NE with 19.1 %.

4.2 Observed Wind Climate (OWC)

The observed wind climate of a site describes the site-specific wind climate and is the first step in wind resource assessment using WAsP. The input to this module is wind mast location and the measured wind data.



Sector		Wind climate				Power	Quality
number	angle [°]	frequency [%]	Weibull-A [m/s]	Weibull-k	mean speed [m/s]	power density [W/m²]	Speed discrepancy [%]
1	0	1.0	3.8	2.10	3.38	33	0.858%
2	22.5	2.9	5.5	2.61	4.89	85	2.727%
3	45	19.4	10.2	3.25	9.17	493	-0.300%
4	67.5	35.8	11.1	3.92	10.09	606	0.752%
5	90	2.8	6.5	2.44	5.75	144	-0.813%
6	112.5	0.9	4.4	2.32	3.87	46	-1.067%
7	135	0.6	3.6	1.67	3.21	37	-2.302%
8	157.5	0.9	3.7	2.04	3.32	33	-1.979%
9	180	1.2	3.5	2.75	3.14	22	0.814%
10	202.5	3.6	6.0	3.45	5.40	98	2.516%
11	225	8.2	7.1	3.98	6.45	158	2.094%
12	247.5	8.6	6.8	4.11	6.14	134	1.970%
13	270	6.0	5.4	3.42	4.84	71	0.442%
14	292.5	5.5	5.4	2.84	4.77	75	0.840%
15	315	2.2	4.2	1.95	3.71	47	0.152%
16	337.5	0.2	3.2	1.76	2.89	25	-3.048%
All (emergent)					7.75	358	
Source data					n/a	n/a	

Figure 6: Observed wind climate of the site

The obtained result from this analysis is a mean wind speed of 7.75 m/s, and the values of shape and scale parameters were 2.29 and 8.6 m/s at a height of 70 m. The average power density was 462 w/m^2. This proved that the annual wind speed and mean wind power density at 70 m from feasibility estimation were less by 18.8% and 27.1%. The primary and secondary wind directions are ENE with 35.7% and NE with 19.1% respectively.

The seasonal variation from the mast data can be seen in the table below.

Table 8: Seasonal wind Resource Variation at 70m

Season	Daytime	Nighttime	Average
Autumn	6.7	8.0	7.4
Winter	9.2	11.1	10.2
Spring	6.6	8.3	7.5
Summer	6.4	5.6	6.0

Table 8 shows that nighttime wind speeds were higher than daytime except in the summer. The winter season had a maximum mean speed of 10.2 m/s, and in the summer, it was 6 m/s. This means that the average value of wind speeds in winter was larger than the other three seasons. The average wind speed in autumn and spring were almost similar.

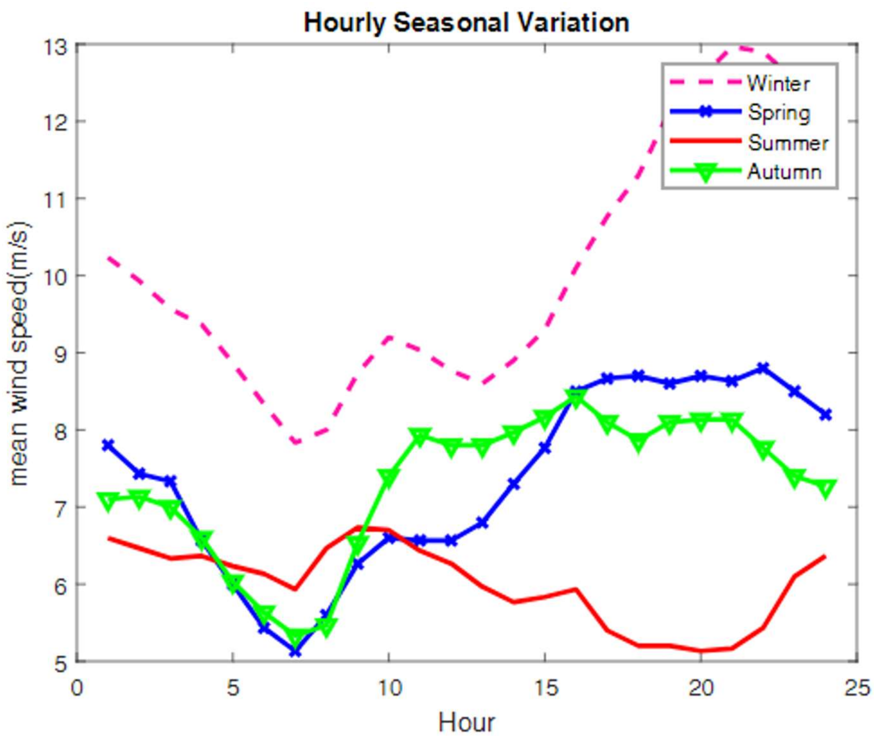


Figure 7: Seasonal wind speed variation (hourly)

Figure 7 shows the hourly variation of mean wind speed by season. In all seasons, daytime wind speeds were lower than nighttime speeds. Winter has an ample amount of wind speed than the other seasons and it had lower wind speed during the day, reached a peak in the evening. And in the summer, low average wind speeds with no particular trend observed during hours of the day.

To manage the power generated during peak hours, peak loads, and energy trading aught be used during that time.

The following table gives the wind characteristics of the Adama-II wind farm based on 2017 mast data.

Table 9: Wind characteristics of Adama II site

Wind characteristics.	$\overline{u}$**@70m**	$\overline{u}$**@50m**	$\overline{u}$**@30m**	$\overline{u}$**@10m**
Mean speed($\overline{U}$**)**	**7.7**	**7.1**	**6.6**	**5.3**
SD(m/s)	3.5	3.2	3.1	2.7
Wind power density (W/m^2)	**460**	**333**	**267.6**	**161.2**
Most-frequent wind speed (Vf) (m/s)	6.6	6.3	5.1	2.8

As per Table 9, the mean annual wind speed and most frequent wind speeds at the height of 70 m were 7.7 m/s and 6.6 m/s. The predicted annual average wind speed during the feasibility study was 9.55 m/s at the height of 70 m.

Farm-level resource categorization depending on mean wind speed(u), most frequent speed (uf), cut-in speed(uc), rated speed (ur), and cut-out wind speed (uo) are given in Table 10.

Table 10: Duration of wind speed distribution

u<$\overline{u}$	**u≥**$\overline{u}$	**u=**$\overline{u}$	**u<uf**	**u≥uf**
53.46%	45.43%	1.11%	32.51%	67.49%
u<uc	**uc<u<ur**	**u>uc**	**u>ur**	**u≥uo**
11.40%	71.60%	87.9	17.70%	0%

As per the table, 52.6% of the wind speeds were lower than the average value (7.7 m/s), which implies 47.4% of the wind speeds were greater than or equal to the mean value. 67.5% of the speeds are greater or equal to the most frequent wind speed which means that the resource availability in the power productive range was higher. It is also shown that 72.5% of the speeds were producing power since they were in between the cut-in and rated speed. There are also speeds beyond rated speed (15.3%). By relating the site's wind potential with wind power classes, the wind farm falls in a wind power class of 4 because wind speed and wind power density at 50 m were 7.1 m/s, 333 W/m^2, and at 30 m, 6.6 m/s, 267.6 W/m^2. However, during the feasibility study, the wind farm was supposed to be of wind power class 6.

4.3 Wind Atlas (Generalized wind climate) of the area

Wind Atlas of the site describes the general wind climate of the area, and it is obtained by using the observed wind climate of a site and adding a roughness class. The wind farm is characterized by an open agricultural area with a roughness ranging from 0.03 to 0.04. So, five roughness classes are considered with a roughness length of (0.000, 0.033, 0.036, 0.038, 0.04) at the heights of 10 m 30 m, 50 m, 70 m, and 100 m (Tadesse, 2014).

		R-class 0 (0.000 m)	R-class 1 (0.030 m)	R-class 2 (0.036 m)	R-class 3 (0.038 m)	R-class 4 (0.040 m)
Height 1 (z = 10 m)	U [m/s]	7.30	5.14	5.05	5.02	4.99
	P [W/m²]	323	121	115	113	111
Height 2 (z = 30 m)	U [m/s]	8.13	6.34	6.25	6.22	6.19
	P [W/m²]	437	215	206	203	201
Height 3 (z = 50 m)	U [m/s]	8.56	7.02	6.93	6.90	6.88
	P [W/m²]	503	280	269	266	263
Height 4 (z = 70 m)	U [m/s]	8.86	7.55	7.46	7.43	7.40
	P [W/m²]	562	335	323	320	316
Height 5 (z = 100 m)	U [m/s]	9.23	8.21	8.11	8.08	8.05
	P [W/m²]	637	428	412	407	404

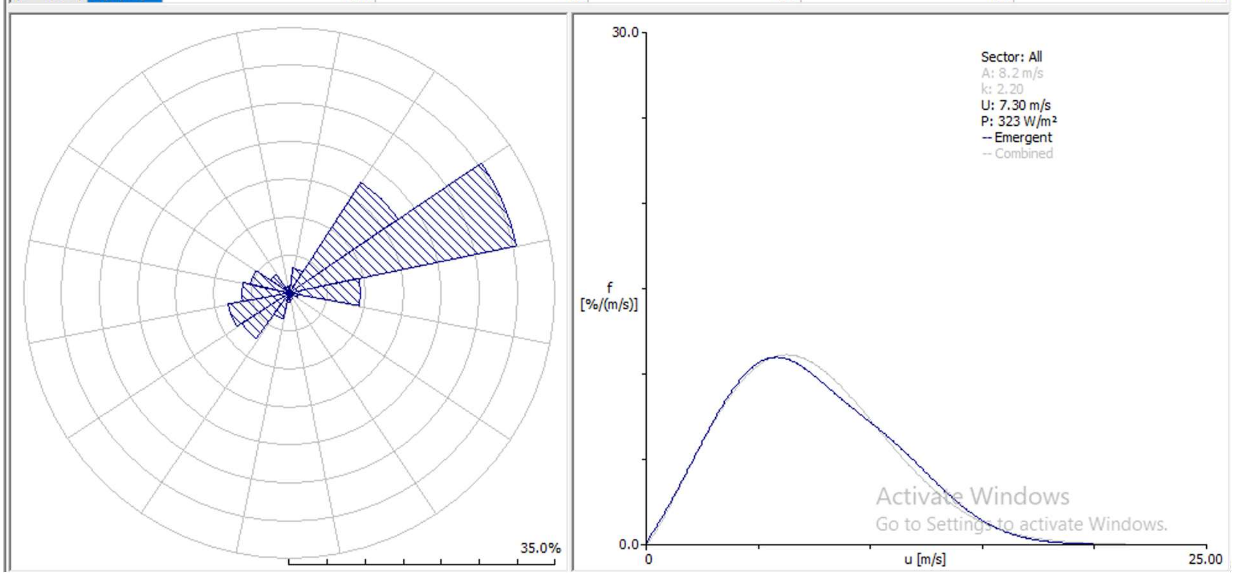


Figure 8: Generalized wind climate (Wind atlas)

The general wind climate of the Adama area (GWC) shows that the mean wind speed at the height of 70 m is 7.3 m/s with a mean power density of 323 w/m^2.

The following figure shows the sitting of all wind turbines in the wind farm site.

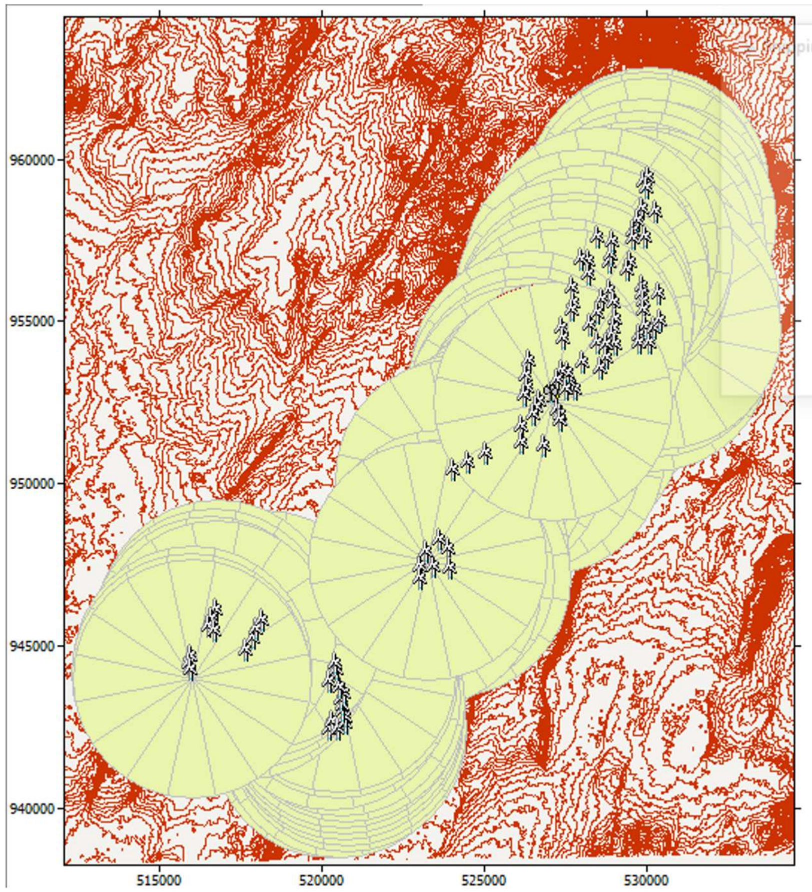


Figure 9: Wind turbine sites as proposed by the feasibility

Table 11: summary statistics of wind farm production estimation

Variable	Total	Mean	Min	Max
Total gross AEP [GWh]	570....	5.648	4.669	6.892
Total net AEP [GWh]	534....	5.297	4.363	6.736
Proportional wake loss [%]	6.21	-	0.9	16.02
Mean speed [m/s]	-	8.47	7.65	9.69
Power density [W/m2]	-	478	340	710
RIX	-	-	0.3	5.0

As shown in Table 11, the gross annual energy production was 570 GWh with 6.21 % of wake loss, which tends the net AEP to be 534 GWh. The mean speed of the site is to be 8.47 m/s and the mean annual wind power density of 478 w/m^2. However, the gross production obtained during the feasibility study was 730.833 (Hydro China Corporation, 2013) which results in a deviation of 22 %.

4.4 Power performance of Wind Turbine Generators

Five-minute SCADA data of 2016 and 2017 were used for assessing the energy yield performance of each turbine. As per the determination of these parameters, the average values for wind speed varied from 6 m/s to 8.1 m/s, and wind power from 300 kW to 500 kW. Moreover, the standard deviation of wind speed and power ranged from 2.8 to 3.2 m/s and 300 kW to 400 kW respectively. The range of the maximum wind speed and wind power is from 17 m/s to 26.1 m/s and 1500 kW to 1581 kW respectively. These values were shown in the following box plots.

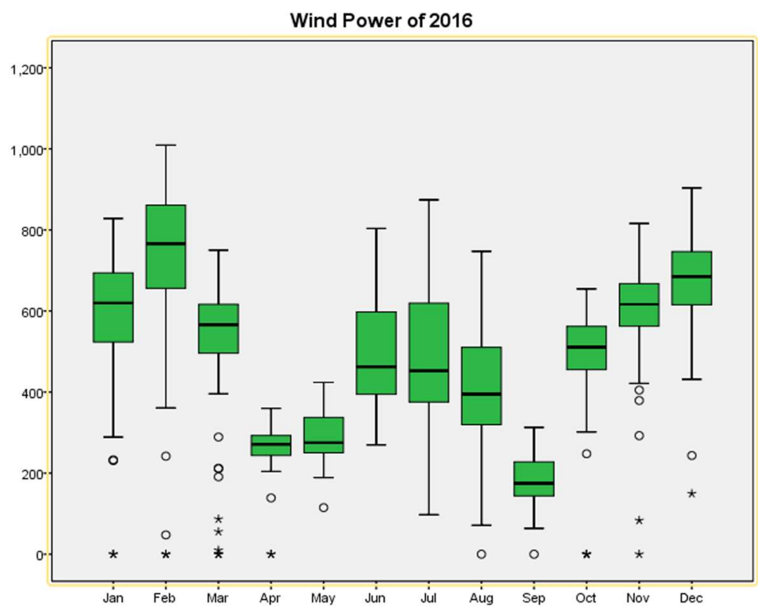


Figure 10: Monthly SCADA data of wind power (2016)

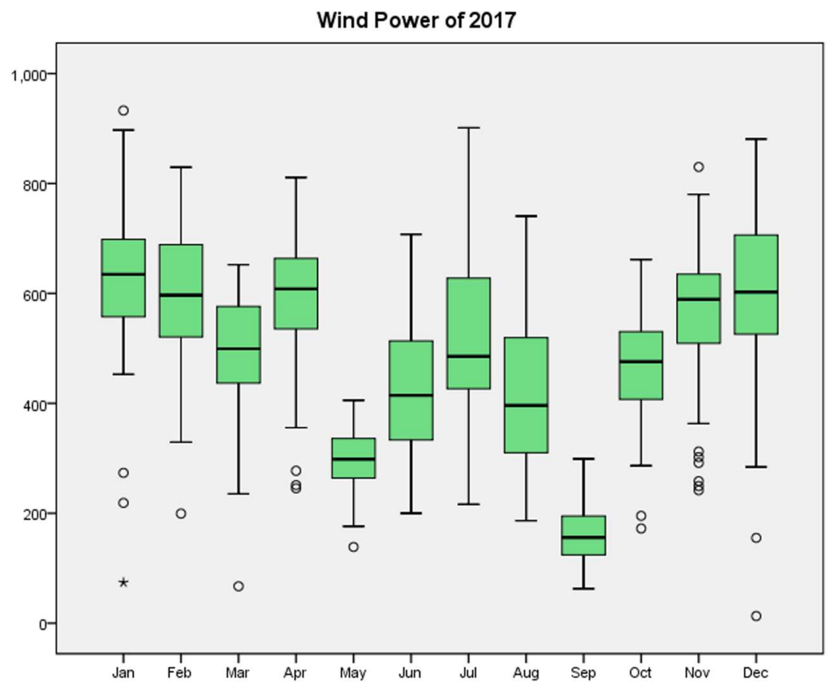


Figure 11: Monthly wind power production in 2017

For evaluating the power performance of all turbines, monthly SCADA data of each turbine was considered.

As the main part of this performance study, the annual variation of performance indices for 2016 and 2017 was determined and shown in Table 12.

Table 12: Annual variation of performance indices before long-term correction

Year	AEP(GWh)	U (m/s)	Pav (kW)	A-Time (%)	A-Energy (%)	CF (%)
2016	409	7.4	481.2	96.68	79.26	30.5
2017	408.5	7.7	478.9	93.57	76.2	30.5
Average	**408.8**	**7.6**	**480.1**	**95.1**	**77.73**	**30.5**

Where A-Time is Time based Availability or turbines' availability and A-Energy, is energy-based Availability. The table shows that the time-based availability is 95.1% while energy production availability was 77.73%. This means that the turbines were available as per the warranty of the manufacturer. The average wind speed of the farm was 7.6 m/s. When this value is compared with the feasibility study's annual wind speed (9.55m/s), it showed a deviation of 20.4%. Annual Energy

Production for the two years was 408.8 MWh. After applying the wind index on the monthly production of the two years, the long-term annual energy is given in the tables below.

Table 13: Long-term Corrected AEP for 2016

Months	AEP long-term for 2016				AEP long-term for 2017			
	Speed(m/s)	Wind Index	MEP/WI	MEPi*12	Speed	Wind Index	MEP/WI (GWh)	(MEP/WI)*12 GWh
1	8.00	1.10	38.20	458.20	9.30	1.20	38.80	465.40
2	8.90	1.20	40.00	479.70	8.70	1.10	34.10	409.10
3	7.50	1.00	36.40	436.70	7.60	1.00	37.00	444.40
4	5.40	0.70	23.00	275.40	8.30	1.10	38.90	467.30
5	5.70	0.80	26.10	312.90	5.70	0.70	30.30	363.20
6	7.40	1.00	35.00	420.10	7.00	0.90	34.20	410.30
7	7.40	1.00	36.10	433.20	7.80	1.00	35.60	426.90
8	7.00	1.00	32.10	385.00	7.10	0.90	32.00	384.50
9	5.00	0.70	19.10	229.50	4.90	0.60	17.50	210.00
10	7.90	1.10	34.50	413.80	7.80	1.00	33.60	403.20
11	8.80	1.20	36.70	440.90	9.30	1.20	32.70	392.60
12	9.60	1.30	38.80	465.80	9.10	1.20	35.30	423.10
Average	7.40	1.00	33.00	395.90	7.70	1.00	33.30	400.00

The long-term corrected AEP for 2016 and 2017 were 395.9 GWh and 400 GWh this gives the average of the two years to be 398 GWh.

Reasons of deviation from the feasibility study

The reason for the deviation in the wind climate estimation is the long-term correction data used in the feasibility study. Because the feasibility study used the reference point 143 km from the center of the wind farm. However, in this paper, the long-term MERRA-2 reanalysis data used which, better temporal and spatial resolution, distance is around 20.5 km from the center of the wind farm. From the SCADA data, the average environmental disenabled time was 971 Hrs. in 2016 (11.1%) and 821 Hrs. in 2017 (9.3%).

CONCLUSION

This study addressed the Adama II wind farm performance by reassessing the wind potential of the site and the energy production of wind turbine generators compared to the feasibility. Using one-year mast data, the site's mean annual wind speed found to be 7.75 m/s while, in the feasibility study, it was 9.55 m/s at 70 m. The prevailing and secondary wind directions obtained were ENE by 35.7% and NE 19.1%. But in the feasibility study, these figures were ENE and E with a frequency of 35.3% and 17.3% at 70 m. From the energy performance evaluation aspect, two years of SCADA data were used. The gross annual energy predicted in the preconstruction of the wind farm was 730.833GWh but in this study, it was 570 GWh, which shows a deviation of 22%. The capacity factor determined was 30.5%, but in the feasibility study, it was 35%. The average wind farm availability of turbines was 95.1%, and in the feasibility, it was 95%. The reason for the deviation was the long-term correction and environmental dis-inability for the turbines to produce power. The weather influence considered in the feasibility was only 2 % while in this production years, 10.2 %.

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Appendix

Appendix 1: **Satellite data descriptions**

Date of acquisition	Sensor	Spatial Resolution	Data Type	Format	Source
2014	SRTM(DEM)	30m	Elevation/Contour map	Raster	USGS

Appendix 2: The software used to process the data

Software Name	Version	Application in the Process
ArcGIS	10.7	Mapping study area and Contour map
Global Mapper	2020	Exporting contour into Wasp map file
Wasp map editor	10	Roughness mapping

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