Investigation of Effects of Uncertain Weather Conditions on the Power Generation Ability of Wind Turbines

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Abstract

Wind energy is one of the abundant and renewable energy sources that can be harvested using wind turbines. Many factors affect the energy-yielding ability of wind turbines. The goal of this paper is to investigate the effects of uncertain weather conditions on the power generation ability of wind turbines. Uniquely, it presented the influence of the uncertain weather conditions and uncertain aerodynamic parameters of wind turbine on wind energy harvesting. The mathematical model of these factors and statistical analysis of their effects on the performance of wind turbines are presented using real-time data. It is found that the impact of uncertain weather conditions on annual average air density, and hence on the performance of wind turbines, is 1.33%. Whereas, the impact of variations of yearly average wind speed on the performance of wind turbines is found to be substantial. In particular, the annual uncertainty output power of wind turbines is found to be 32%. This investigation helps to find the mitigation mechanism and improve power generation efficiency from wind.

Keywords: wind turbine aerodynamics, uncertain weather conditions, wind energy conversion system, wind turbine energy conversion factor.

I. Introduction

Wind turbines convert wind energy to electric energy using generators. In 2019, 651 GW has been harvested globally [1]. The power harvesting ability of wind turbines is one of the key performance measures. Wind turbines must produce desired output power under stated conditions. Technically, variable-speed and variable-pitch regulated wind turbines have good power harvesting ability. However, it is easily affected by the unpredictability of weather conditions.

Most of the related researches consider only the reliability of facilities and physical components of wind turbines, variation in weather conditions are not considered as in [2], [3], and [4]. However, weather parameters variation reduce the reliability of wind turbines [5] by causing failure to components of wind turbines [6] or unable to drive the turbines, because weather is inconsistent.

Weather conditions are stochastic due to the unequal hotness of air on the surface of the earth. The Equator is hotter than polar areas. This varying surface temperature causes variations in atmospheric pressure. As temperature varies, pressure varies proportionally. Hence, around tropical regions, there is higher pressure than the polar. This initiates air blows from equatorial regions towards the poles. That means wind speed is higher around the equator than the polar region on the earth's surface. This indicates more wind energy is available around the equator than in the polar areas. Additionally, variations in temperature cause air humidity variations. This phenomenon gave rise to variations in air density. These fluctuations are called uncertain weather conditions. The variation in wind speed leads into variation aerodynamic parameters of wind turbine tip speed ratio, rotor speed, and power conversion coefficient. Fluctuations in wind speed, air density and aerodynamic parameters of wind turbine create fluctuations in output power of wind turbine.

The flow of atmospheric wind, and hence wind resource assessment, is affected by variations in the dispersion of solar energy, spatial inequalities in heat transfer on the earth's surface, and the earth's rotation [7]. The uncertain characteristic of wind speed is a vital factor in wind power harvesting [8]. Interesting facts like historic climate data accuracy of 1.5% to 4%, future variability accuracy of 1% to 3%, spatial variability accuracy of 1% to 4%, and energy loss accuracy of 1% to 3% are presented in [9]. Interfaces within wind turbines or wake effects create wind speed uncertainties [10], [11], and [12]. The amount of these uncertainties and their causes are presented in [13] and [14]. Every 10-meter vertical extrapolation of wind speed data results in a 1% uncertainty [15].

Wind speed is a stochastic variable that supplies energy and, at the same time, acts as a disturbance in wind energy harvesting systems. Wind speed models have four components; namely base, gust, ramp, and noise that characterize the variation in wind speed [16]. Another factor that affects the power harvesting ability of wind turbines is air thickness. The effect of temperature, pressure and humidity on air density is presented in [17]. These parameters also affect the power conversion coefficient of wind turbines. Varieties of uncertainties present in annual energy production from wind are presented in [18] and [19]. These studies indicated that wind speed uncertainty highly affects energy production from wind. For a 2.6% deviation in a 5 m/s annual average wind speed, there is 9.9% total uncertainty in annual energy production [20].

Power curve variability between the cut-in and the rated values of wind speed is another source of uncertainty in wind energy production [21]. Total wind power production can be varied seasonally or timely. For example, Simon Watson quantified hourly maximum change in wind power production using data derived from 1500 turbines in Germany. Accordingly, there is ± 50% variability in wind power production only within a four-hour duration [22]. Warren K. et.al concluded that there is 75–85% fluctuation in day-to-day maximum power produced by a wind plant in the USA in Texas [23]. The annual production of energy from the wind is varied by ± 40% in the USA at Lake Benton [24]. IEC 614400-12-1 stated there could be a 15.67% error in wind speed due to an error in site calibration [25].

Wind speed uncertainty reduces the output power of wind turbines. For instance, the uncertainty in tip speed ratio has a considerable effect on wind energy harvesting. For 5% uncertainty in the tip speed ratio of blades, there is a 1–3% energy loss while wind turbines run in a region below the rated wind speed [26], [27], and [28]. That means, a single-unit wind turbine of a 1.5 MW rating operates at a 32% capacity factor and produces 4.208 GWh energy annually. Suppose, the cheapest cost of energy is $0.09/kWh, a 1–3% loss of energy is equivalent to a $3787–$11361 loss annually.

This indicates how much money could be lost due to uncertainty alone due to the tip speed ratio of wind turbines. As a result, the power harvesting ability of wind turbines is degraded. Electric loads do not uniform throughout the day. Wind turbine-connected electric loads are another source of uncertainty in power generation [29].

Gaps and contributions: In the aforementioned literature, the influence of the uncertainty of air density and wind turbine aerodynamic on wind energy harvesting is not considered. Moreover, there is no comprehensive mathematical model relating these uncertainty parameters with wind turbine power harvesting capacity. Therefore, the major contributions of this study are

- Comprehensive and concise mathematical models that relate uncertain weather parameters and wind turbine power harvesting ability are formulated.
- The effects of these uncertain parameters on wind turbine performance are investigated.
- The impact of combined uncertainty is investigated by introducing a scaling factor.

This study, therefore, aims to extensively address these points using real-time data of a specific wind farm site. The next parts of this paper include; the research method, analytical model of uncertainty in wind power harvesting, results and discussion, and conclusions.

II. Methods

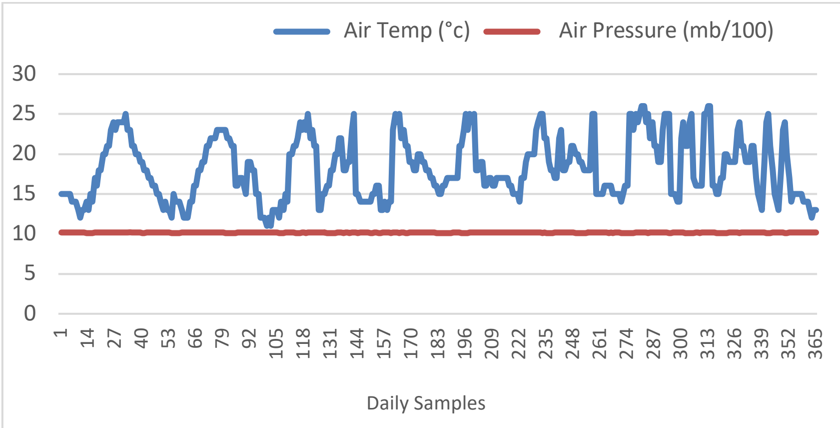
Real-time annual wind speed data and related weather parameters (temperature, air pressure, and air humidity) from June 2019 to May 2020 were collected at 10 meters above the surface of the earth in a Tropical Zone at the Adama II wind farm site of Adama, Ethiopia using the 10-channel logger, METRO-32. The data is logged every 10 minutes. Daily, socket 3 of the METRO-32 data logger stores 144 samples of wind speed. The METRO-32 data logger 4^{th} socket recorded weather parameters.

Uncertainty models of wind power harvesting are formulated considering a 1.5 MW wind turbine, whose technical specification is given in Table 1. The wind speed data is extrapolated to the 70 m hub height of the same model. Variations in the recorded daily average values of the weather parameters for the duration of June 2019 to May 2020 are depicted in Figure 1. The daily average temperature, pressure, relative humidity, wind speed, and wind turbine rotor speed variations are found to be 11–26 ^{0}c, around 1020 mb, 23% to 85%, 3 to 16 m/s, and 10 to19 rpm, respectively.

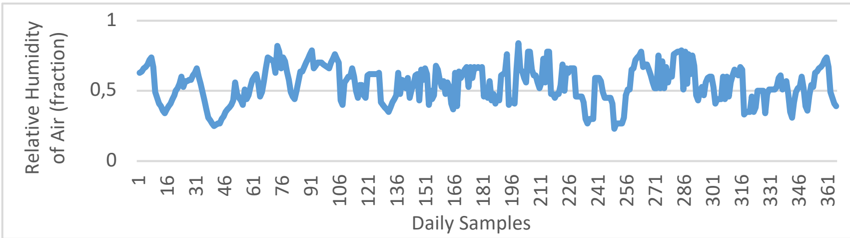
Analysis of the power conversion coefficient of the 1.5 MW wind turbine, the numerical computation of the uncertainties in the aforementioned parameters, and their effects on the wind power harvesting ability of the turbine are carried out.

Table 1: *Technical Parameters of the 1.5 MW Wind Turbine Rotor*

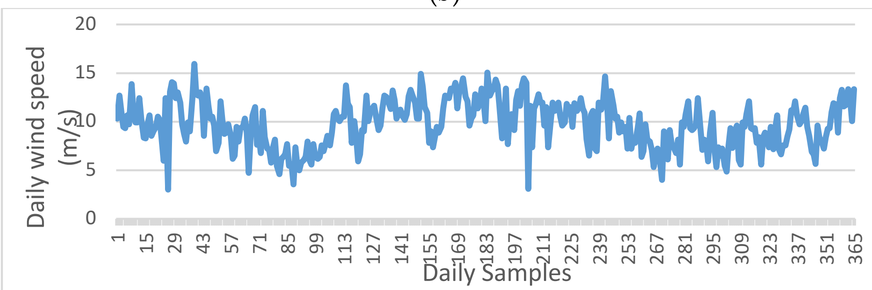
Parameter/Description	Value
Rated power	1500 kW
wind speed	Cut-in 3.5 m/s, Rated 12 m/s , Cut-out 25 m/s
Height of wheel hub center	77 m
Rotor radius	37.8 m
Rated rotating speed	19 rpm
Number of blades	3 blades with independent variable pitch controls



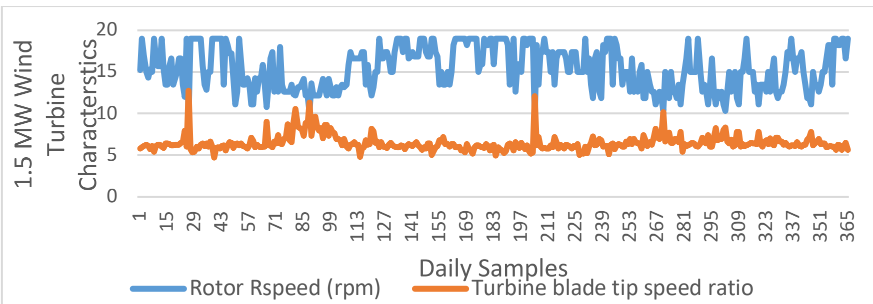
(a)



(b)



(c)



(d)

Figure 1: *Adama-II Windfarm annual measured data of (a) air temperature, (b) air pressure, and (c) air relative humidity (d) wind speed*

III. Analytical Model of Uncertainty in Wind Power Harvesting

The components of uncertainty affecting the performance of electric power-producing wind turbines are categorized as Type-A and Type-B uncertainties [28]. These categories of uncertainties are computed employing statistical methods. As stated in ISO/IEC Guide 98-3: 2008(E), estimation of the combined standard uncertainty of type-A and type-B errors is possible for each can be expressed in terms of standard deviation [30]. The basic mathematical model [7] for the conversion of wind power to mechanical power by a horizontal axis wind turbine is modified with a scale factor ($|\delta| \leq 1$) of the uncertainty in output power which is introduced and expressed in equation (1) for a wind turbine whose specifications are given in Table 1.

$$\mathrm{P}\big(v(t), \rho, C_p\big) = \begin{cases} 0;\ \text{for } v(\mathrm{t}) < 3\ m/s \\ 0.5\mathrm{A}\rho C_p(\lambda,\beta)v^3 \pm \Delta\mathrm{p}\big(v,\rho,C_p\big)|\delta|;\ \text{for } 3\ v(\mathrm{t}) \leq 12\ \mathrm{m/s} \\ \mathrm{P_{rated}}\ ;\ \text{for } 12\ \leq v(\mathrm{t}) < 25\mathrm{m/s} \\ 0;\ \text{for } v(\mathrm{t}) > 25\ m/s \end{cases} \quad (1)$$

Where A is the swept area of the rotor. A functional model between the turbine output power and measured variables such as wind speed-$v(t)$, air density-ρ and power conversion coefficient ($C_p(\lambda,\beta) = C_p$) is given in equation (2)

$$\mathrm{P}\big(v(t), \rho, C_p\big) = g(v, \rho, C_p) \quad (2)$$

Recognizing variations in the measured or computed variables (v, ρ, C_p), it is important to formulate a model of uncertainties in the functional relationship. For N samples of measured variables ($v_1, v_{2,\ldots}, v_{N;}\ \rho_1, \rho_{2,\ldots}, \rho_{N;}\ C_{p_1}, C_{p_{2,\ldots}}, C_{p_N}$), the averages of each measured variable is as in equation (3)

$$\overline{v} = \frac{1}{N}\sum_{i=1}^{N} v_i;\ \overline{\rho} = \frac{1}{N}\sum_{i=1}^{N} \rho_i;\ \overline{C_p} = \frac{1}{N}\sum_{i=1}^{N} C_{p_i} \quad (3)$$

Wind turbine mechanical output power (P_i) can be computed at any wind speed (v_i), air density (ρ_i), and power conversion coefficient (C_{p_i}) which is $g\big(\overline{v}, \overline{\rho}, \overline{C_p}\big)$ at average values of the measured variables. Using the Taylor series, P_i can be expanded by centering the average values as in equation (4).

$$P_i = g\big(\overline{v}, \overline{\rho}, \overline{C_p}\big) + (v_i - \overline{v})\frac{\partial \mathrm{P}}{\partial \mathrm{v}}\Big|_{\overline{v}} + (\rho_i - \overline{\rho})\frac{\partial \mathrm{P}}{\partial \rho}\Big|_{\overline{\rho}} + \Big(C_{p_i} - \overline{C_p}\Big)\frac{\partial \mathrm{P}}{\partial C_p}\Big|_{\overline{C_p}} + \text{ higher} - \text{order terms} \quad (4)$$

Averaging the measured values, the higher-order terms can be dropped as expressed in equation (5).

$$P_i - \mathrm{P}\big(v(t), \rho, C_p\big) = (v_i - \overline{v})\frac{\partial \mathrm{P}}{\partial \mathrm{v}}\Big|_{\overline{v}} + (\rho_i - \overline{\rho})\frac{\partial \mathrm{P}}{\partial \rho}\Big|_{\overline{\rho}} + \Big(C_{p_i} - \overline{C_p}\Big)\frac{\partial \mathrm{P}}{\partial C_p}\Big|_{\overline{C_p}} \quad (5)$$

Now, we can define the uncertainty (variation or standard deviation) in the output power of wind turbines as

$$
\begin{aligned}
[\Delta p(v,\rho,C_p)]^2 &= [\Delta_P]^2 = \frac{1}{N}\sum_{i=1}^{N}[P_i - P(v(t),\rho,C_p)]^2 \\
&= \frac{1}{N}\sum_{i=1}^{N}\left[(v_i-\overline{v})\frac{\partial P}{\partial v}\Big|_{v,\overline{\rho},\overline{C_p}} + \left(C_{p_i}-\overline{C_p}\right)\frac{\partial P}{C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}} + (\rho_i-\overline{\rho})\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right]^2 \\
&= \frac{1}{N}\sum_{i=1}^{N}(v_i-\overline{v})^2\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 + \frac{1}{N}\sum_{i=1}^{N}\left(C_{p_i}-\overline{C_p}\right)^2\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 \\
&\quad + \frac{1}{N}\sum_{i=1}^{N}(\rho_i-\overline{\rho})^2\left(\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 \\
&\quad + \frac{2}{N}\sum_{i=1}^{N}(v_i-\overline{v})(\rho_i-\overline{\rho})\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right) \\
&\quad + \frac{2}{N}\sum_{i=1}^{N}(v_i-\overline{v})\left(C_{p_i}-\overline{C_p}\right)\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right) \\
&\quad + \frac{2}{N}\sum_{i=1}^{N}(\rho_i-\overline{\rho})\left(C_{p_i}-\overline{C_p}\right)\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right) \\
&= [\Delta_v]^2\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 + [\Delta_\rho]^2\left(\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 + [\Delta_{Cp}]^2\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)^2 \\
&\quad + 2\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\Delta_{v(t)\rho} \\
&\quad + 2\left(\frac{\partial P}{\partial v}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\Delta_{v(t)Cp} + 2\left(\frac{\partial P}{\partial \rho}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\left(\frac{\partial P}{\partial C_p}\Big|_{\overline{v},\overline{\rho},\overline{C_p}}\right)\Delta_{\rho Cp}
\end{aligned} \tag{6}
$$

Equation (6) combines the effects of individual uncertainties of wind speed, air density, and wind energy conversion coefficient. The variances (standard deviations) of wind speed, air density, and power conversion coefficient are expressed as in equation (7a).

$$
\begin{cases}
[\Delta_v]^2 = \frac{1}{N}\sum_{i=1}^{N}(v_i(t)-\overline{v})^2 \\
[\Delta_{Cp}]^2 = \frac{1}{N}\sum_{i=1}^{N}\left(C_{p_i}-\overline{C_p}\right)^2 \\
[\Delta_\rho]^2 = \frac{1}{N}\sum_{i=1}^{N}(\rho_i-\overline{\rho})^2
\end{cases} \tag{7a}
$$

For correlated measured variables, co-variances among the wind speed, air density, and power conversion coefficient are expressed as in equation (7b).

$$
\begin{cases}
\Delta_{v\rho} = \frac{1}{N}\sum_{i=1}^{N}(v_i-\overline{v})(\rho_i-\overline{\rho}) \\
\Delta_{\rho Cp} = \frac{1}{N}\sum_{i=1}^{N}(\rho_i-\overline{\rho})\left(C_{p_i}-\overline{C_p}\right) \\
\Delta_{vCp} = \frac{1}{N}\sum_{i=1}^{N}(v_i-\overline{v})\left(C_{p_i}-\overline{C_p}\right)
\end{cases} \tag{7b}
$$

In the case of uncorrelated variables, equation (7b) shows the modifications. In this study, real-time data of wind speed and air density are independently recorded. The power conversion coefficient is a function of wind turbine blade tip speed ratio and pitch angle. According to IEC 61400-12-1 [23], no air density normalization to its actual average value is required as the average of the recorded data is in the range of 1.225 ± 0.05 kg/m^3. That is confirmed in section IV. Thus, the combined uncertainty in the wind power conversion system expressed in equation (6) can be rewritten as in equation (8).

$$
[\Delta_P]^2 = \left[\Delta_{v(t)}\frac{\partial P(v(t))}{\partial v(t)}\Big|_{\overline{v},\overline{\rho},\overline{Cp}(\lambda,\beta)}\right]^2 + \left[\Delta_{Cp(\lambda,\beta)}\frac{\partial P(v(t))}{\partial Cp(\lambda,\beta)}\Big|_{v\overline{\rho},\overline{Cp}(\lambda,\beta)}\right]^2 + \left[\Delta_\rho\frac{\partial P(v(t))}{\partial \rho(t)}\Big|_{\overline{v},\overline{\rho},\overline{Cp}(\lambda,\beta)}\right]^2
$$

$$+ 2\Delta_{\rho Cp(\lambda,\beta)} \frac{\partial P(v(t))}{\partial \rho} \frac{\partial P(v(t))}{\partial Cp(\lambda,\beta)}\Big|_{\bar{v},\bar{\rho},\overline{Cp}(\lambda,\beta)} + 2\Delta_{v(t)Cp(\lambda,\beta)} \frac{\partial P(v(t))}{\partial v(t)} \frac{\partial P(v(t))}{\partial Cp(\lambda,\beta)}\Big|_{\bar{v},\bar{\rho},\overline{Cp}(\lambda,\beta)} \quad (8)$$

It is shown that to compute the uncertainty in the output power of wind turbines, computation of partial derivatives (sensitivities) of the turbine output power concerning wind speed, air density, and power conversion coefficient is a must. These sensitivities are expressed in equation (9).

$$\begin{cases} \frac{\partial P(v(t))}{\partial v(t)} = \frac{3A\rho v^2 C_p(\lambda,\beta)}{2} \\ \frac{\partial P(v(t))}{\partial \rho} = \frac{A v^3 C_p(\lambda,\beta)}{2} \\ \frac{\partial P(v(t))}{\partial C_p(\lambda,\beta)} = \frac{\rho A v^3}{2} \\ \frac{\partial P(v(t))}{\partial v(t)} \frac{\partial P(v(t))}{\partial Cp(\lambda,\beta)} = \frac{3A^2\rho^2 v^5 C_p(\lambda,\beta)}{4} \\ \frac{\partial P(v(t))}{\partial \rho} \frac{\partial P(v(t))}{\partial Cp(\lambda,\beta)} = \frac{A^2 \rho v^6 C_p(\lambda,\beta)}{4} \end{cases} \quad (9)$$

The major causes of uncertainty in the output power of wind turbines are uncertainties of weather parameters (temperature, pressure, and humidity that affect air density and wind velocity) and uncertainties of wind turbine aerodynamic parameters (wind turbine blade tip speed ratio and pitch angle that affect blade lift and drag coefficients and power conversion coefficient). Therefore, to compute the uncertainty in the wind turbine output power, first, computation of individual uncertainties in weather and aerodynamic parameters is essential as described below.

I. Computation of Uncertainties in Weather Parameters Related to Wind Energy Harvesting

Real-time annual temperature, air pressure, air humidity, and wind speed collected during the aforementioned duration are used to compute the effect of uncertainties in air density and wind speed on energy harvesting from the wind.

i. Computation of Uncertainty in Wind Speed

As discussed earlier in this paper at least three categories of uncertainties exist in this data. These are measurement uncertainty, inter-annual wind speed uncertainty, and wind shear model uncertainty. Whatever the type of uncertainty ($\Delta_{v(t)}$) it's computed using the statistical model of equation (10) on the real-time data shown in Figure 1 (c). Where $\bar{v}$ is the yearly average wind speed of i = 1, 2… N (N = 365) and daily wind speed measurement ($v_i(t)$.

$$[\Delta_{v(t)}]^2 = \frac{1}{N}\sum_i^N (v_i(t) - \bar{v})^2; \text{for } \bar{v} = \frac{1}{N}\sum_i^N v_i(t) \quad (10)$$

ii. Computation of Uncertainty in Air Density

Air density is another main parameter that affects power harvesting from the wind. Air is composed of dry air and water steam. As the atmospheric temperature of the considered location varies, water vapor in the air, i.e. air humidity, varies too. This affects air density. According to the IEC-Wind

Turbines part-12-2 documents [13], [31], and [32] considering the effect of air humidity variations, air density is expressed as

$$\rho(T_{em}, P_a, H) = \frac{1}{T_{em}}\left[\frac{P_a}{\mathcal{R}} - \varphi_w\left(\frac{1}{\mathcal{R}} - \frac{1}{R_w}\right)H\right] \tag{11}$$

Where T_{em} is absolute temp (K) = ^{0}C+273.15, P_a is barometric pressure (Pascal), H is relative humidity between 0 and 1, $\mathcal{R}$ is the gas constant of dry air which equals 287.01 J/kg.K, and R_w is the gas constant of water vapor which equals to 461.5 J/kg.K, the vapor pressure in Pascal (φ_w) which equals to 0.0000205exp (0.0631846T). Substituting these constants and equation (11), we get

$$\rho = \rho(T_{em}, P_a, H) \quad = \frac{1}{T_{em}}\left[\frac{P_a}{287.01} - 2.6995 * 10^{-8} H.\exp\left(0.0632 T_{em}\right)\right] \tag{12}$$

Due to variations in temperature, air pressure, and air humidity air density varies. There is some contribution of the measuring instruments (thermometer, barometer, and hygrometer) error in calibration or resolution. In a similar fashion in equation (6), the variation in air density can be computed as

$$[\Delta_\rho]^2 = \left[\left.\frac{\partial\rho}{\partial T_{em}}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_{T_{em}}\right]^2 + \left[\left.\frac{\partial\rho}{\partial P_a}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_{P_a}\right]^2 + \left[\left.\frac{\partial\rho}{\partial H}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_H\right]^2 + 2\left.\frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial P_a}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_{T_{em}P_a}$$

$$+ 2\left.\frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial H}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_{T_{em}H} + 2\left.\frac{\partial\rho}{\partial P_a}\frac{\partial\rho}{\partial H}\right|_{(\bar{T}_{em},\overline{P_a},\bar{H})}\Delta_{P_aH} \tag{13}$$

In equation (12), putting $2.6995 * 10^{-8} = \gamma_1$ and $0.0632 = \gamma_2$, the sensitivities of air density concerning temperature, pressure, and humidity is presented as in equation (14).

$$\begin{cases} \frac{\partial\rho}{\partial P_a} = \frac{1}{\mathcal{R}T_{em}} \\ \frac{\partial\rho}{\partial H} = \frac{-\gamma_1}{T_{em}} exp(\gamma_2 T_{em}) \\ \frac{\partial\rho}{\partial T_{em}} = \frac{-P_a}{\mathcal{R}{T_{em}}^2} + (1-\gamma_2 T_{em})\frac{\gamma_1 H}{{T_{em}}^2} exp(\gamma_2 T_{em}) \\ \frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial P_a} = \frac{-P_a}{\mathcal{R}^2{T_{em}}^3} + (1-\gamma_2 T_{em})\frac{\gamma_1 H}{\mathcal{R}{T_{em}}^3} exp(\gamma_2 T_{em}) \\ \frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial H} = \frac{P_a\gamma_1}{\mathcal{R}{T_{em}}^3}\exp(\gamma_2 T_{em}) - (1-\gamma_2 T_{em})\frac{{\gamma_1}^2 H}{{T_{em}}^3}(exp(\gamma_2 T_{em}))^2 \\ \frac{\partial\rho}{\partial P_a}\frac{\partial\rho}{\partial H} = \frac{-\gamma_1}{\mathcal{R}{T_{em}}^2} exp(\gamma_2 T_{em}) \end{cases} \tag{14}$$

The uncertainties in temperature, pressure and humidity in (13) are found from their measured data employing the statistical relations in (15).

$$\begin{cases} [\Delta_{\mathrm{Tem}}]^2 = \frac{1}{N}\sum_i^N \left(T_{em_i} - \overline{\mathrm{T}}_{em}\right)^2;\ \text{for } \overline{\mathrm{T}}_{em} = \frac{1}{N}\sum_i^N \mathrm{T}_{\mathrm{em}_i} \\ [\Delta_{\mathrm{Pa}}]^2 = \frac{1}{N}\sum_i^N \left(\mathrm{Pa}_i - \overline{\mathrm{Pa}}\right)^2;\ \text{for } \overline{\mathrm{Pa}} = \frac{1}{N}\sum_i^N \mathrm{Pa}_i \\ [\Delta_{\mathrm{H}}]^2 = \frac{1}{N}\sum_i^N \left(\mathrm{H}_i - \overline{\mathrm{H}}\right)^2;\ \text{for } \overline{\mathrm{H}} = \frac{1}{N}\sum_i^N \mathrm{H}_i \end{cases} \tag{15}$$

Where $\overline{\mathrm{T}}_{em}$, $\overline{\mathrm{Pa}}$ and $\overline{\mathrm{H}}$ are averages of N measurements T_{em_i}, Pa_i and H_i which are temperature, pressure, and humidity, respectively. Naturally, the meteorological parameters are correlated with each other. Hence the effects of one parameter on others (co-variances) are found from their measured data employing the statistical models of equation (16).

$$\begin{cases} \Delta_{\mathrm{TemPa}} = \frac{1}{N}\sum_i^N (T_{em_i} - \overline{\mathrm{T}}_{em})\,(\mathrm{Pa_i} - \overline{\mathrm{Pa}}) \\ \Delta_{\mathrm{TemH}} = \frac{1}{N}\sum_i^N (T_{em_i} - \overline{\mathrm{T}}_{em})\,(\mathrm{H_i} - \overline{\mathrm{H}}) \\ \Delta_{\mathrm{P_aH}} = \frac{1}{N}\sum_i^N (H_i - \overline{\mathrm{H}})\,(\mathrm{P_{a_i}} - \overline{\mathrm{P}}_{\mathrm{a}}) \end{cases} \tag{16}$$

Where $\Delta_{\mathrm{TemP_a}}$, Δ_{TemH} and $\Delta_{\mathrm{P_aH}}$ are co-variances between temperature and pressure, temperature and humidity, and pressure and humidity, respectively.

II. Computation of Uncertainties in Aerodynamic Parameters of Wind Turbine Related to Wind Energy Harvesting

The ratio of wind turbine mechanical output power to its input wind power is the power conversion coefficient. The empirical models of this coefficient ($C_P(\lambda,\beta)$) are deliberated in [33], [34], [35], and [36] in terms of turbine tip-speed ratio (λ) and rotor blade pitch angle (β). One of such models is

$$\mathrm{C_p}(\lambda,\beta) = 0.73((\frac{151}{\lambda_i}) - 0.58\beta - 0.002\beta^{2.14}) \exp(-\frac{18.4}{\lambda_i}) \tag{17a}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.02\beta} - \frac{0.03}{1+\beta^3} \tag{17b}$$

The variation of $C_P(\lambda,\beta)$ with λ and β is depicted [37]. As indicated in equation (8), uncertainty ($\Delta_{\mathrm{C_p(\lambda,\beta)}}$) in power conversion coefficient results in uncertainty of wind turbines' output power. It combines uncertainties in turbine blade tip speed ratio and pitch angle. This is shown in (17a). The uncertainty in $\mathrm{C_P}(\lambda, \beta)$ is expressed in (18) where $\bar{\lambda}$, and $\bar{\beta}$ are the averages of N measurements of λ_i and β_i of turbine blade tip speed ratio and pitch angle, correspondingly. Δ_λ is uncertainty in λ, Δ_β is uncertainty in β, and $\Delta_{\lambda\beta}$ is the covariance between λ and β.

$$[\Delta_{\mathrm{C_p(\lambda,\beta)}}]^2 = \left[\frac{\partial \mathrm{C_p}(\lambda,\beta)}{\partial\lambda}\bigg|_{(\bar{\lambda},\bar{\beta})} \Delta_\lambda\right]^2 + \left[\frac{\partial \mathrm{C_p}(\lambda,\beta)}{\partial\beta}\bigg|_{(\bar{\lambda},\bar{\beta})} \Delta_\beta\right]^2 + 2\frac{\partial \mathrm{C_p}(\lambda,\beta)}{\partial\lambda}\frac{\partial \mathrm{C_p}(\lambda,\beta)}{\partial\beta}\bigg|_{(\bar{\lambda},\bar{\beta})} \Delta_{\lambda\beta} \tag{18}$$

While wind speed is lower than its rated value, the blade pitch angle is set to zero degrees to harvest more power from wind. In this case Δ_β and $\Delta_{\lambda\beta}$ are zero. Thus, (17a) was replaced by (19).

$$\begin{aligned} \mathrm{C_p}(\lambda, 0) &= 0.73((151/\lambda_i) - 13.2).\exp(-18.4/\lambda_i) \\ &= 0.73(\frac{151 - 17.73\lambda}{\lambda})\exp(\frac{-18.4}{\lambda} + 0.552) \end{aligned} \tag{19}$$

As a result, (18) is replaced by (20).

$$[\Delta_{\mathrm{Cp(\lambda,0)}}]^2 = \left[\frac{\partial \mathrm{C_p}(\lambda,0)}{\partial\lambda}\bigg|_{(\bar{\lambda},0)} \Delta_\lambda\right]^2 \tag{20}$$

The sensitivity of $\mathrm{C_P}(\lambda, \beta)$ of the blade tip speed ratio is

$$\left.\frac{\partial C_p(\lambda,0)}{\partial \lambda}\right|_{(\overline{\lambda},0)} = 0.73\left(\frac{2778.4-477.232\lambda}{\lambda^3}\right)\exp\left(\frac{-18.4}{\lambda}+0.552\right) \tag{21}$$

To compute (20), the computation of uncertainty in tip speed ratio is expressed as in (22).

$$[\Delta_\lambda]^2 = \left[\left.\frac{\partial\lambda}{\partial\omega}\right|_{(\overline{\omega},\overline{v})}\Delta_\omega\right]^2 + \left[\left.\frac{\partial\lambda}{\partial v}\right|_{(\overline{\omega},\overline{v})}\Delta_v\right]^2 + 2\left.\frac{\partial\lambda}{\partial\omega}\frac{\partial\lambda}{\partial v}\right|_{(\overline{\omega},\overline{v})}\Delta_{\omega v} \tag{22}$$

Where $\overline{\omega}$, and $\overline{v}$ are the averages of N measurements of ω_i and v_i of wind turbine rotor speed ($\omega(t)$) and wind speed ($v(t)$), respectively. Δ_ω and Δ_v are the variances of $\omega(t)$ and $v(t)$, respectively, and $\Delta_{\omega v}$ is co-variance of $\omega(t)$ and $v(t)$.

The mathematical model discussed in [38] that relates blade tip speed ratio to wind speed and turbine rotor speed is depicted in equation (23). The sensitivities of the tip speed ratio of wind speed and turbine rotor speed are derived as in equation (24).

$$\lambda = \omega(t)R/v(t) \tag{23}$$

$$\begin{cases} \dfrac{\partial\lambda}{\partial\omega(t)} = \dfrac{R}{v(t)} \\ \dfrac{\partial\lambda}{\partial v(t)} = \dfrac{-\omega(t)R}{v^2(t)} \\ \dfrac{\partial\lambda}{\partial\omega(t)}\dfrac{\partial\lambda}{\partial v(t)} = \dfrac{-\omega(t)R^2}{v^3(t)} \end{cases} \tag{24}$$

Variations in wind speed and turbine rotor speed are evaluated employing statistical tools on real-time measured data. These are

$$\begin{cases} [\Delta_\omega]^2 = \frac{1}{N}\sum_i^N (\omega_i - \overline{\omega})^2; \text{ for } \overline{\omega} = \frac{1}{N}\sum_i^N \omega_i \\ \Delta_{\omega v} = \frac{1}{N}\sum_i^N (\omega_i - \overline{\omega})(v_i - \overline{v}) \end{cases} \tag{25}$$

The co-variances among wind speed, air density, and power conversion coefficient in the model shown in equation (8) are evaluated using real-time data and computed data employing the statistical relations of equation (7a), which are rewritten as in equation (26) as $\overline{C_P}(\lambda,0) = \frac{1}{N}\sum_i^N C_P(\lambda,0)_i$.

$$\begin{cases} \Delta_{v(t)Cp(\lambda,0)} = \frac{1}{N}\sum_i^N (v_i(t) - \overline{v})(C_P(\lambda,0) - \overline{C_P}(\lambda,0)) \\ \Delta_{\rho Cp(\lambda,0)} = \frac{1}{N}\sum_{i=1}^N (\rho_i - \overline{\rho})(C_P(\lambda,0) - \overline{C_P}(\lambda,0)); \end{cases} \tag{26}$$

IV. Results

To compute uncertainties in the output power of wind turbines, sensitivities and individual uncertainties in wind energy associated with weather conditions and wind turbine aerodynamic variables are investigated and presented. Using the real-time data shown in Figure 1, first, air density was computed employing equation (12). The variation in air density because of variations in air temperature, pressure, and humidity is depicted in Figure 2. Accordingly, air density at the Adama-

II wind farm site varies between 1.18 and 1.24 kg/m³. To compute the uncertainty in it and its sensitivities to the correlated parameters, the variance, and covariance of the measured data in Figure 1 of the weather condition parameters are required. These are computed by employing equation (15) and tabulated in Table 2. From Table 2, variation in temperature is more influential.

Table 2: *Variations in the air temperature, pressure, and humidity*

Δ_{Tem}	Δ_{Pa}	Δ_{H}	Δ_{TemPa}	Δ_{TemH}	Δ_{PaH}
3.815	2.147	0.129	-0.340	-0.0116	0.119

Where temperature (T_{em}), pressure (P_a), and humidity (H) are in ⁰C, mb, and % (a fraction), respectively. Using equation (14), the sensitivities of air density concerning temperature, pressure, and humidity are evaluated at average values ($\bar{T}_{em}$,$\bar{P}_a$, $\bar{\mathrm{H}}$) = (18.1778 ⁰C, 1016.333 mb, 0.4849) of the real-time data which are tabulated in Table 3. From Table 3, air density is more sensitivities to temperature. Inserting the values of Table 2 and Table 3 into equation (13), the uncertainty in air density (Δ_ρ) is equal to 0.0161.

Table 3: *Air density sensitivities to temperature, pressure, and humidity at*($\bar{T}_{em}$,$\bar{P}_a$, $\bar{h}$)

$\frac{\partial\rho}{\partial T_{em}}$	$\frac{\partial\rho}{\partial P_a}$	$\frac{\partial\rho}{\partial \mathrm{H}}$	$\frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial P_a}$	$\frac{\partial\rho}{\partial T_{em}}\frac{\partial\rho}{\partial \mathrm{H}}$	$\frac{\partial\rho}{\partial P_a}\frac{\partial\rho}{\partial \mathrm{H}}$
4.44E-3	1.2E-5	-0.0092	-5.32E-8	-3.59E-5	-1.1E-07

The uncertainty in $C_P(\lambda,0)$ is the second factor that affects energy harvesting from the wind. $C_P(\lambda,0)$ of the 1.5 MW wind turbine is analytically computed using its tip speed ratio and equation (19). The result is presented in Figure 2. This figure shows the computed $C_P(\lambda,0)$ varies in the range of 0.0265 – 0.4412. The uncertainty in $C_P(\lambda,0)$ is computed employing equation (20). It depends on variations of tip speed ratio. The tip speed ratio is attuned with wind speed status to maintain rotor speed within the limits. To compute the uncertainty in tip speed ratio, first, the uncertainties in wind speed and rotor speed, and the required sensitivities were computed using real-time data as depicted in Figure 1 (c) and (d). The average values and uncertainties in wind speed, turbine rotor speed, and the covariance between these two variables are tabulated in Table 4.

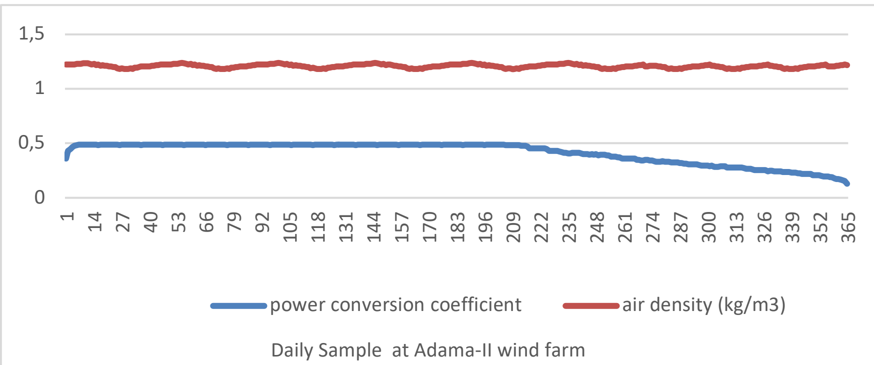


Figure 2: *Annual air density at Adama II Windfarm and power conversion coefficient of the 1.5 MW wind turbine.*

Table 4: *The average value and uncertainty in wind speed and rotor speed.*

$\bar{v}$	$\bar{\omega}$	$\Delta_{v(t)}$	Δ_{ω}	$\Delta_{\omega v}$
9.7335	1.5792	2.3895	0.3473	0.8122

Next, employing equation (22), the uncertainty and the sensitivities of tip speed ratio concerning wind speed and rotor speed are carried at average values of ($\bar{v}, \bar{\omega}$) is equal to (9.7335 m/s, 1.57922 rad/s) based on the wind speed data and the 1.5 MW wind turbine rotor speed characteristics shown in Figure 1 (c) and (d). The results are tabulated in Table 5. The results in Table 5 indicates tip speed ratio is more sensitive to turbine rotor speed.

Table 5: *Blade tip speed ratio sensitivities to rotor speed and wind speed at ($\bar{v}, \bar{\omega}$).*

$\frac{\partial\lambda}{\partial\omega}$	$\frac{\partial\lambda}{\partial v(t)}$	$\frac{\partial\lambda}{\partial v(t)}\frac{\partial\lambda}{\partial\omega}$
3.8853	-0.63068	-2.45044

From the results in Tables 4 and 5 and applying equation (22), the uncertainty in turbine rotor blade tip speed ratio(Δ_λ) is equal to 0.330804. Via equation (21a), the sensitivity of $C_P(\lambda,0)$ concerning blade tip speed ratio at its average values is $\partial C_p(\lambda, 0)/\partial\lambda\big|_{(5.063,0^0)}$ which equals 0.0938. Therefore, inserting these two values in equation (20), the uncertainty in $C_P(\lambda,0)$ becomes

$$\Delta_{C_p(\lambda,0)} = ((0.330804 * 0.0938)^2)^{1/2} = 0.0325.$$

The co-variances between wind speed and power conversion coefficient, and between air density and power conversion coefficient are evaluated using data in Figure 1 and Figure 2 and the models in equation (26). The summary of the investigated uncertainties is depicted in Table 6.

Table 6: *Summary of uncertainties in wind speed, air density, power conversion coefficient, and covariance.*

$\Delta_{v(t)}$	$\Delta_{Cp(\lambda,0)}$	Δ_ρ	$\Delta_{v(t)Cp(\lambda,0)}$	$\Delta_{\rho Cp(\lambda,0)}$
2.3882	0.0325	0.0161	0.1199	9.51E-05

The sensitivities in equation (8) of wind turbines output power concerning wind speed, air density, and power conversion coefficient are evaluated at average values of ($\bar{v}, \overline{\rho}, \bar{C}_p$) = (9.7335 m/s, 1.2111 kg/m^3, 0.4156) of the real-time data where the result is tabulated in Table 7. These are indicators of changes in output power of wind turbines at the average values of the associated parameters.

Table 7: *The sensitivities of power concerning wind speed, air density, and power conversion coefficient at ($\bar{v}, \overline{\rho}, \bar{c}_p$).*

$\frac{\partial P(v(t))}{\partial v(t)}$	$\frac{\partial P(v(t))}{\partial C_p(\lambda,\beta)}$	$\frac{\partial P(v(t))}{\partial\rho}$	$\frac{\partial P(v(t))}{\partial v(t)}\frac{\partial P(v(t))}{\partial C_p(\lambda,\beta)}$	$\frac{\partial P(v(t))}{\partial\rho}\frac{\partial P(v(t))}{\partial C_p(\lambda,\beta)}$
253907	1073675	937212	6.94191E+11	8.42E+11

From Table 7, output power of wind turbines is more sensitivities to power conversion coefficient. Finally, inserting the results of Tables 6 and 7 into equation (8), the uncertain components ($\Delta P(v(t),\varrho,C_P)$) and ($P(v(t),\varrho, C_P)$) of the output power of the 1.5 MW wind turbine are evaluated at ($\bar{v}, \overline{\rho}, \bar{C}_p$) using equation (1). The results are presented in Table 8.

Table 8: *Uncertain and certain output powers of the 1.5 MW wind turbine rotor at ($\bar{v}, \overline{\rho}, \bar{c}_p$).*

$P(v(t),\varrho,C_P)$	1097007 W
$\Delta_P = \Delta P(v(t),\varrho,C_P)$	351042.24 W

At any values of wind speed (v(t)), air density (ρ), and wind power to mechanical power conversion coefficient (C_P), the uncertainty in output power of wind turbine can be expressed in percentage which is maximum at scale factor $|\delta| = 1$. For instance, at the average values of wind speed, air density, and power conversion coefficient ($\bar{v}, \overline{\rho}, \bar{C}_p$), it is

$$\% \text{ uncertainty in power } = \left.\frac{\Delta P(v(t), \rho, Cp)}{P(v(t), \rho, Cp)}\right|_{(\bar{v}, \overline{\rho}, \bar{C}_p)} * 100 \%$$

$$= \frac{351042.24}{1097007} * 100 \% = 32 \% .$$

This can be rewritten as 1097007*(1 ± 0.32|δ|) watt. For δ = 0.1, the uncertainty could be 32%*0.1 which is 3.2 % above or below the $P(\bar{v}, \overline{\rho}, \bar{C}_p)$ value. In the case of δ =1, the value 32 % will be included in the annual output power and hence the output power fluctuation interval is defined as

$$745965 \leq P(\bar{v}, \overline{\rho}, \bar{C}_p) \leq 1448049 \text{ Watt.}$$

Similarly, the uncertainties in wind speed, air density, and power conversion coefficient represented in Table 6 are in percentage and/or relatively at the annual average values of ($\bar{v}, \overline{\rho}, \bar{C}_p$) as 24.55% or $7.3440 \leq v(t) \leq 12.1230$ m/s, 1.33% or $1.1950 \leq \rho \leq 1.2272$ kg/m^3 and 7.82% or $0.3831 \leq Cp(\lambda,0) \leq 0.4471$, respectively.

V. Discussion

The results obtained in this study can be compared to the IEC61400-12-1 standard [20]. Accordingly, air density uncertainty is ± 0.05 kg/m^3 around 1.225kg/m^3. That is $1.175 \leq \rho \leq 1.275$ kg/m^3. The air density variation result of this study is within the international standard range. Moreover, the wind turbine power conversion coefficient was indicated by the aforementioned standard as $0.03 \leq Cp \leq 0.45$ when the air density is 1.225kg/m^3. This shows the investigated variation of the power conversion coefficient is within the standard range. The same standard describes that a 1 MW rated wind turbine produces 396.5 kW with an uncertainty of 224.8 kW at a wind speed of 21.5 m/s, air density of 1.225 kg/m^3, and Cp of 0.03. This is equivalent to a maximum of 56.69% uncertainty in power production. Also, according to a study presented in references [21] – [23], the variability of annual total energy production from the wind is more than +/- 40%. These indicated the maximum investigated uncertainty of the power produced from the wind at the Adama wind farm site is acceptable.

The real-time wind speed data shown in Figure 1(c) is arranged in ascending order with corresponding air density and power conversion coefficients shown in Figure 2. Using these data and for δ equal to 0.1 and 1, the certain and uncertain output powers of the 1.5 MW wind turbine are computed and presented in Figure 3 and Figure 4. Figure 3 describes 3.2% uncertainty in the power captured by the 1.5 MW wind turbine at δ is 0.1. The rated output power of the wind turbine is 1.5 MW at nominal input variables (wind speed and air density). Whereas, in the case of uncertain input variables, the output power is also uncertain. For instance, at 3.2% uncertainty in the output power, it is 48 kW above or below the rated value at nominal inputs. This causes the wind energy conversion system to be overloaded or stressed. That is for a negative value of $\Delta P(v(t), \rho, Cp)|\delta|$, the output power of the wind turbine is smaller than the rated power of the turbine. Thus, the turbine output power cannot cover the demand overloading the wind turbine. This forces it to operate only under partial load or even it may shut down. This indicates the degraded output power of the wind turbine and resulting in a low return of the system. At higher wind speeds where $\Delta P(v(t), \rho, Cp)|\delta|$ is positive, it causes more power generation stressing the wind turbine. In this case, the pitch control system of the wind turbine can regulate the power to the rated value safeguarding the turbine from damage. The worst-case uncertainty is depicted in Figure 4. That is at $\delta = 1$, the annual output power of the wind turbine is 32% uncertain. At rated inputs, it varies between 1.02 and 1.98 Mega Watts. The effect of the positive value of the uncertain component is regulated by the turbine blade pitch mechanism, but the negative value of the uncertain component results in the same effect as discussed before.

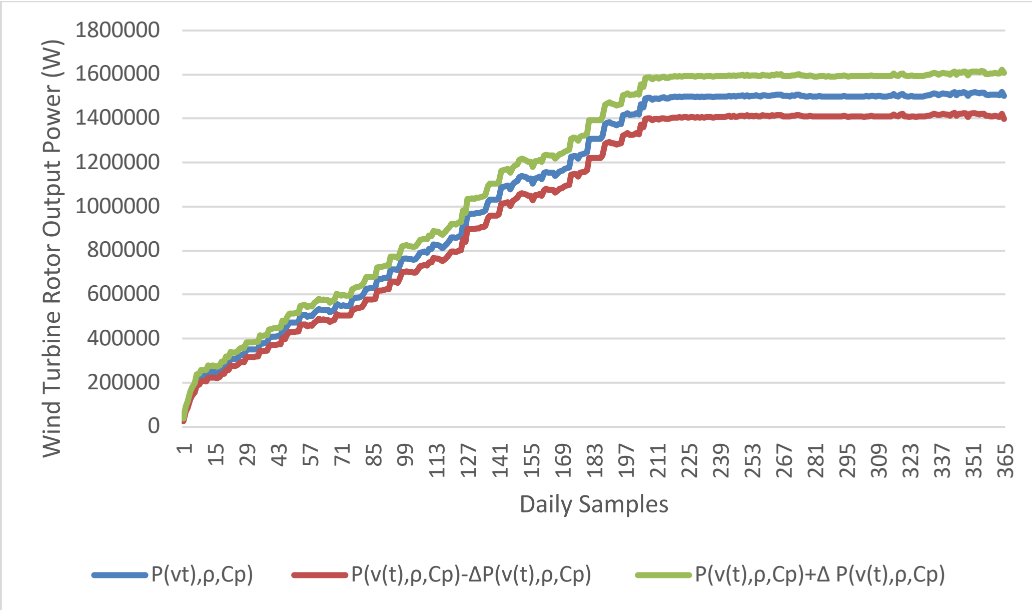


Figure 3: *Uncertainty in the 1.5 MW Wind Turbine Rotor Output Power for δ is equal to 0.1.*

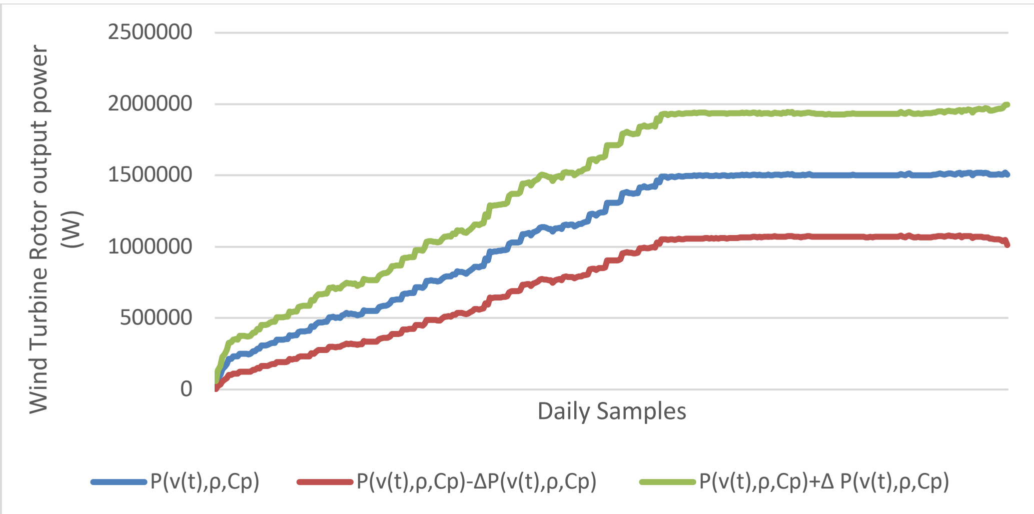


Figure 4: *Uncertainty in the 1.5 MW Wind Turbine Rotor Output Power for δ is equal to 1.*

In conclusion, mathematical modelling of wind turbine rotor output power uncertainties is done. The effect of uncertain weather parameters at Adama-II wind farm, found at Adam, Ethiopia on the wind turbine is examined. Real-time data of weather parameters of the mentioned site and the turbine rotor output power are recorded. Uncertainties in weather parameters and output power are computed according to the formulated models. The annual variation in air temperature and pressure causes 24.55% uncertainty in the annual wind speed, 1.33% uncertainty in air density, and 7.82% uncertainty in power conversion coefficient of the wind turbine. The output power of wind turbine is more sensitive to varying power conversion coefficient. The annual uncertainty in the turbine rotor output power is 32%. The computed uncertain power is compared to the expected output power of the turbine. This uncertainty percentage in power is either added or subtracted from the expected output power. The additive case is regulated by the wind turbine blade pitch system. Due to the uncertainty effects, the turbine output power becomes unreliable and economically impacts the system's return. The effects of air density and wind speed uncertainties are natural, and hence technical regulation of fluctuation in air density may not be possible. The fluctuation in wind speed and power conversion coefficient of wind turbines can be reduced by advancing the wind turbine blade pitch system and its control techniques. This study results helps as base and guide for wind energy assessing and forecasting, wind turbine control designers and operation professionals to maintain performances of wind turbines well consistent.

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