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Establishing a Probabilistic Model of Extrapolated Wind Speed Data for Wind Energy Prediction

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Abstract**—**Wind is among the potential energy resources which can be harnessed to generate wind energy for conversion into electrical power. Due to the variability of wind speed with time and height, it becomes difficult to predict the generated wind energy more optimally. In this paper, an attempt is made to establish a probabilistic model fitting the wind speed data recorded at Makambako site in Tanzania. Wind speeds and direction were respectively measured using anemometer (type AN1) and wind Vane (type WD1) both supplied by Delta-T-Devices at a measurement height of 2 m. Wind speeds were then extrapolated for the height of 10 m using power law equation with an exponent of 0.47. Data were analysed using MINITAB statistical software to show the variability of wind speeds with time and height, and to determine the underlying probability model of the extrapolated wind speed data. The results show that wind speeds at Makambako site vary cyclically over time; and they conform to the Weibull probability distribution. From these results, Weibull probability density function can be used to predict the wind energy.

Keywords**—**Probabilistic models, wind speed, wind energy

I. Introduction

WIND is a highly promising energy resource such that the development of wind energy technology in the world has tremendously expanded in the last few years. With the increasing thrust on renewable energy sources, it is expected that the growth of wind energy use will continue in the future.

Reference [1] shows that an additional capacity of 25,500 MW is expected to be erected worldwide in the second half of 2011, which would bring new annual installations to 43,900 MW, compared with 37,642 MW in the year 2010. The total installed wind capacity is projected to reach 240,500 MW by the end of the year 2011. This capacity can cover almost 3% of the electricity demand all over the world. Due to the growing economic and increased social activities in Tanzania, the demand for electrical power has rapidly increased to exceed the actual generated electrical power. The projected growth of 10% per annum will bring the electricity demand to approximately 1105 MW in 2012 and 1219 MW in 2013 [2]. The potential energy sources in Tanzania are hydro and thermal power plants.

In reference [2], it is also reported that hydro power plants contributes the largest share of power generation of about 73% of total power generated from October 2009 to September 2010 while the remaining amount is contributed by natural gas and diesel power plants. Tanzania Electric Supply Company (TANESCO), a state-owned company, operates hydropower plants with a total installed capacity of 561 MW and gas-fired plants with the capacity of 145 MW [3].

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Independent power plants contribute to a total installed capacity of 282 MW. With comparison to the increasing electrical power demand, it is evident that Tanzania will continue to face a deficit of electrical power.

The dependence of hydro and thermal energy sources in Tanzania have also been subjected to environmental and socio-economical challenges. These include un-reliability and un-sustainability of power generation due to long-term droughts, sediment filling in water reservoirs, and water-consuming agriculture and livestock activities. Further to that, the frequent increase in oil price will limit the use of fossil fuel for electric power generation. However, the fossil fuel in general is associated with environmental pollution and destruction.

Tanzania is enriched with other energy sources which are yet to be exploited. These include coal, geothermal, nuclear, and tidal waves. However, the development of energy from these sources needs higher investment. In view of the above limitations, wind energy can be appropriate toward meeting the continually increasing demand for energy. For isolated systems such as rural electrification, wind energy has been considered as attractive and preferred alternative energy source [4]. Although wind energy development in Tanzania started in the 1970’s, it has been affected by lack of necessary wind data required for predicting the generated wind energy. For example, the underlying probability distribution of the wind speed data at meteorological stations in Tanzania is not well established. Due to the variability of wind speed with time and height, it becomes difficult to predict the generated wind energy if the underlying probabilistic model of the wind speed is not known. It is the purpose of this study to make an attempt to establish the underlying probability model that fits the wind speed data that were recorded at Makambako wind site in Tanzania.

II. Materials and Methods

The study adopted wind data measured at Makambako site, one of the areas identified to have high annual average wind speed in Tanzania. Wind speed and direction were respectively measured by anemometer (type AN1) and wind Vane (type WD1) both supplied by Delta-T-Devices. The two wind sensors were positioned 2 m above the ground level. Wind measuring devices were part of the other sensors of the portable weather station including relative and temperature sensor type RH A1, soil temperature probe type ST1, rain gauge RG1 and solar energy sensor. The soil temperature probe was installed at 5 cm below the soil surface, whereas the rain gauge was just put on the ground surface. Electrical signals from these sensors were connected to a delta-T logger, the latter of which was powered by the battery whose voltage was enhanced using a solar panel. The logger can be configured in varieties of ways depending on the type of research needs and sensor characteristics.

For example, the data logger can be configured in such a way that data are collected after every one minute and the averages recorded after every hour. Most of the data used in this study are of this form. However, data for rainfall can be recorded on a longer time than one hour. The data were retrieved from the data logger to the computer using software called DL2e.

Wind speed data were measured 2 m above the ground level. The data were extrapolated from the measurement height to the wind turbine hub height of 10 m. The extrapolated wind speed was estimated using the power law equation [4], [5]:

$$\frac{u_z}{u_r} = \left(\frac{z}{z_r}\right)^{\alpha} \tag{1}$$

Where u_z is the wind speed (m/s) at height z (meters), and u_r is the known wind speed at a reference height z_r. The exponent α is an empirically derived coefficient that varies depending upon the stability of the atmosphere and the surface roughness length. The power law exponent of 0.47 for Makambako site was established to extrapolate wind speed to the hub height of wind turbine from measurement levels [5].

Data were analysed using MINITAB statistical software. The time series plot was constructed for visual observation of wind speed variation with time and height. The conformity of the wind speed data to theoretical probability distributions was determined using probability plotting technique. Four common probability distributions were tested to check their conformity to the wind speed data. These are normal, log-normal, exponential, and Weibull distributions.

The normal probability density function is expressed as:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}}, -\infty < x < \infty \tag{2}$$

The cumulative distribution function of the normal distribution is given as:

$$F(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(u-\mu)^2}{2\sigma^2}} du \tag{3}$$

The log-normal probability density function is expressed as:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma x} e^{\frac{-(\ln x-\mu)^2}{2\sigma^2}}, -\infty < x < \infty \tag{4}$$

The log-normal cumulative distribution function is:

$$F(x) = \int_{0}^{x} \frac{1}{\sqrt{2\pi}\,\sigma u} e^{\frac{-(\ln u-\mu)^2}{2\sigma^2}} du \tag{5}$$

The probability density function of exponential distribution is given by:

$$f(x) = \lambda e^{-\lambda x}, 0 \le x < \infty \tag{6}$$

The cumulative distribution function of the exponential distribution is:

$$F(x) = 1 - e^{-\lambda x} \tag{7}$$

The Weibull probability density function is presented by:

$$f(x) = \frac{\beta}{\delta}\left(\frac{x}{\delta}\right)^{\beta-1} e^{-\left(\frac{x}{\delta}\right)^{\beta}}, \quad x > 0, \delta > 0, \beta > 0 \tag{8}$$

The Weibull cumulative distribution function is given by:

$$F(x) = 1 - e^{-\left(\frac{x}{\delta}\right)^{\beta}} \tag{9}$$

Although the time series plot can show the variability of wind speed data with time, it cannot establish the true underlying probability distribution that generated the data and therefore the data values have to be assessed whether they follow to one of the theoretical probability distributions. The probability plotting technique can be used to determine the theoretical distribution fitting the wind speed data. It creates an estimated cumulative distribution function from the wind speed data by plotting each data against its estimated cumulative probability. In order to validate the probability distribution to be likely providing a reasonable model for the wind speed data, the plotted points will roughly form a straight line, the plotted points will fall close to the fitted distribution line, and the Anderson-Darling (AD) statistic will be small with the associated p-value being larger than the commonly α-level of 0.10.

III. Results and Discussion

The time series plot in Fig. 1 shows the importance of time on variability of wind speed. The monthly average wind speeds at Makambako for the years 2004, 2005 and 2006 at measurement height and with extrapolated values varied at a large extent with time exhibiting a cyclic variation of data. There were consistent linear increases in wind speeds between March and October and sharp drops in wind speeds between October and December for years 2004, 2005 and 2006. The Figure also shows that the average extrapolated wind speeds for Makambako between March and December were above 6 m/s. In addition, significant extrapolated wind speeds at Makambako were observed between September and November with October recording the highest average wind speed of more than 10 m/s for all months of the years under consideration. The time series plot also shows that the year 2005 recorded the highest extrapolated wind speeds exceeding 13 m/s as compared to wind speeds in 2004 and 2006.

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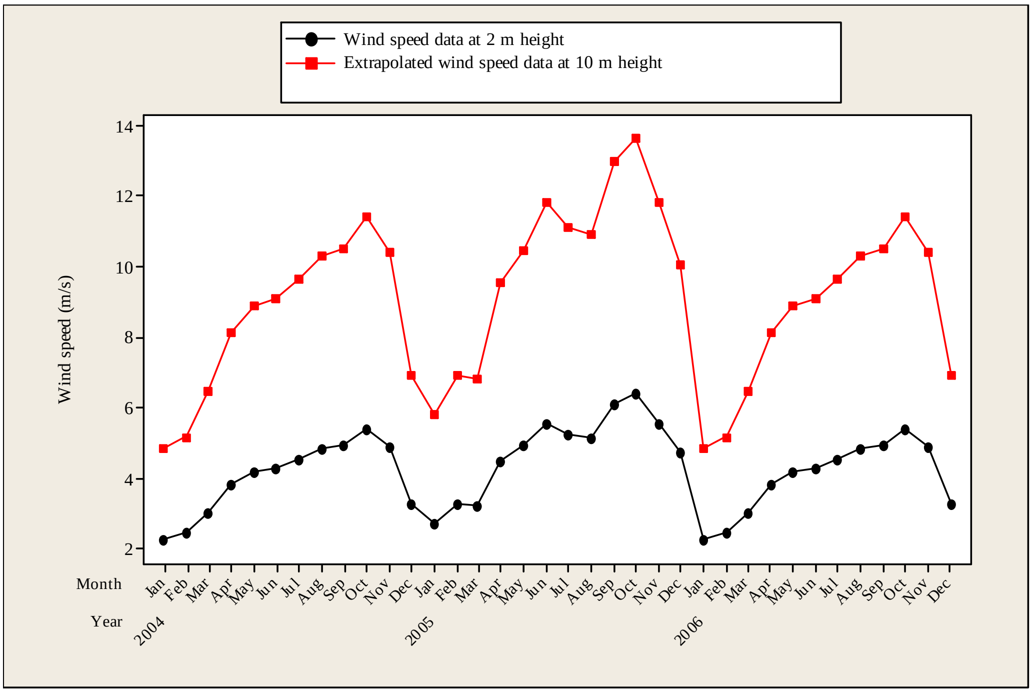

Fig. 1 Time series plot for wind speed data

In Fig. 2, MINITAB presents quantitative measures on how the wind speed data are described by the normal probability distribution. The plotted points form straight lines close to the fitted distribution lines. The Anderson-Darling (AD) statistics are 0.644 and the p-values for AD tests are 0.086. Since the p-values are below 0.10, the assumption for normal probability of the wind speed data for Makambako site is inappropriate.

Fig. 3 shows the MINITAB plots of lognormal probability. It can be observed from the figure that the plotted points fit straight lines close to the fitted distribution lines. The AD tests are equal to 1.15 and the p-values for AD tests are less than 0.005.

Since the p-values are below 0.10, it implies that the lognormal distribution does not fit the wind speed data at Makambako.

MINITAB exponential probability plots of wind speed data are shown in Fig. 4. As can be noted in the figure, the plotted points do not form straight lines closed to the fitted distribution lines. The AD tests are equal to 9.043 and the p-values for AD tests are less than 0.003. Since the plotted points do not form straight lines that are close to the fitted distribution lines and the p-values are below 0.10, it means that the exponential distribution is not a good probability measure for the wind speed data at Makambako.

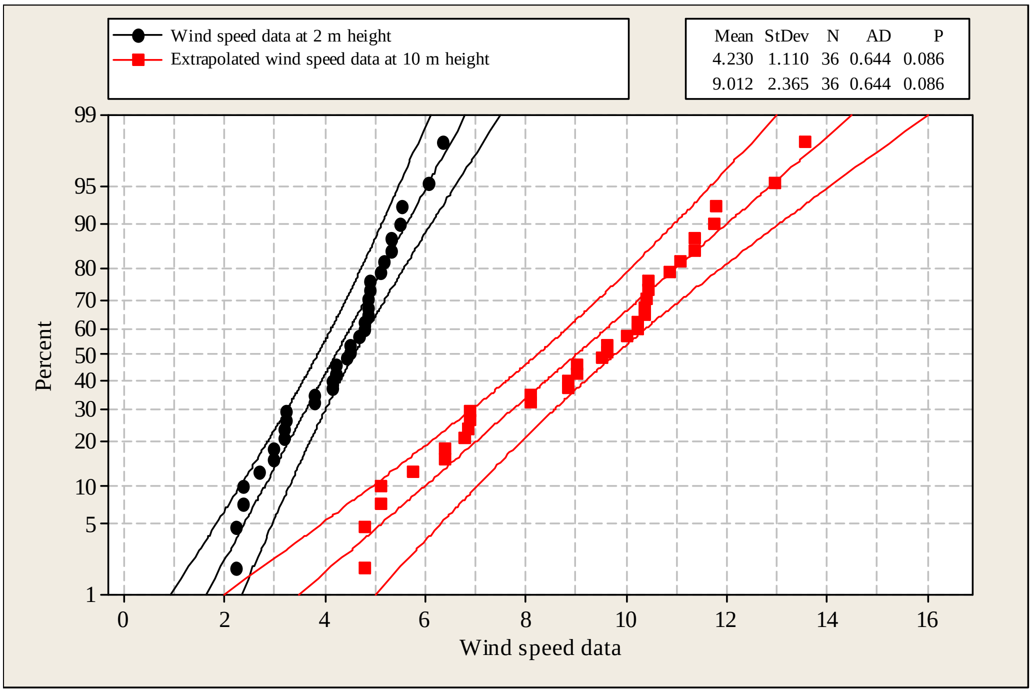

Fig. 2 Normal probability plot for wind speed data

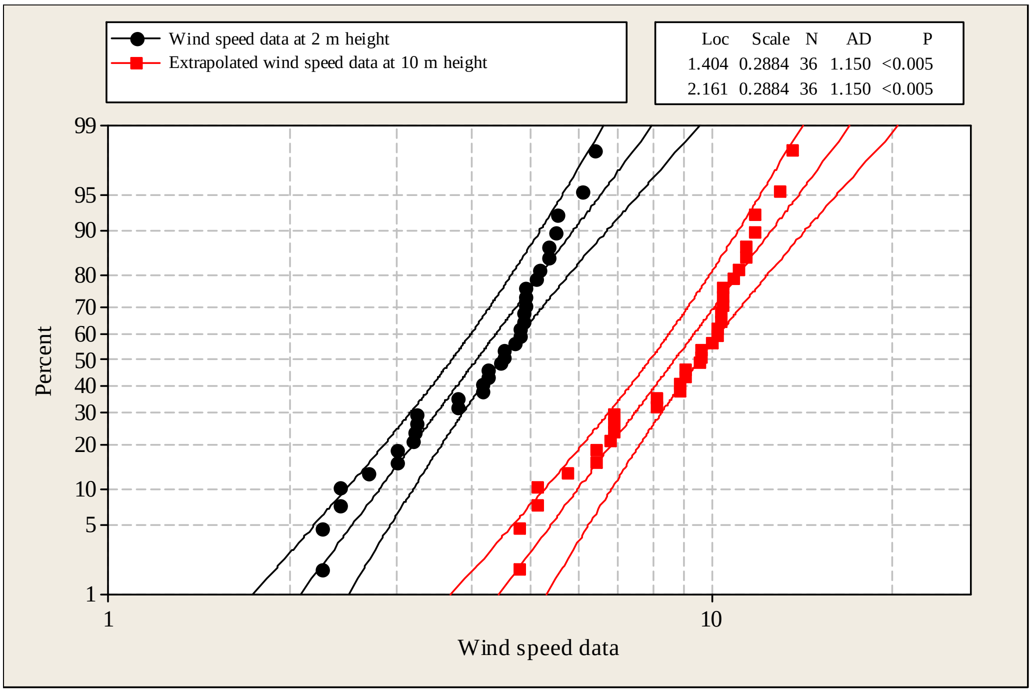

Fig. 3 Lognormal probability plot for wind speed data

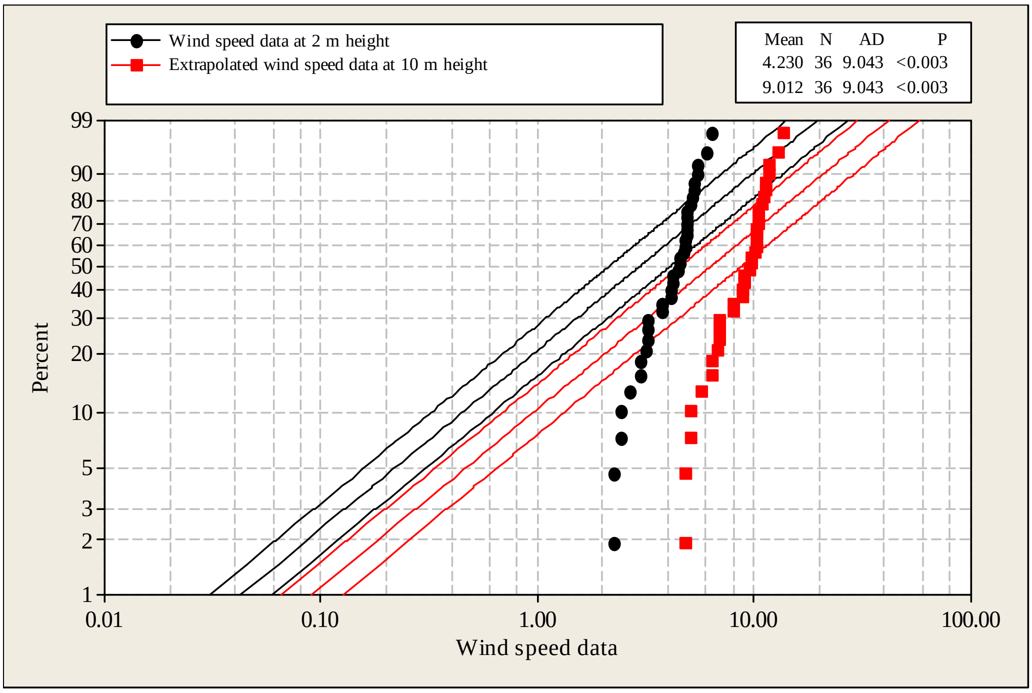

Fig. 4 Exponential probability plot for wind speed data

Fig. 5 shows Weibull probability plots generated by MINITAB. The plotted wind speed data in the figure form straight lines being close to the fitted distribution lines. The AD statistics are 0.554 and the p-values for AD are 0.16 which are above 0.10. Since the plotted data form reasonable straight lines that are close to the fitted distribution lines and the p-values obtained are above 0.10, it clearly suggests that Weibull probability is the right model for the wind speed data at Makambako site. With Weibull probability distribution, MINITAB also provided the maximum likelihood estimates of the shape parameter β=4.512 and the scale parameter δ=4.646 for wind speed data at measurement height of 2 m; and β=4.512 and δ=9.899 for extrapolated wind speed at 10 m with 0.47 exponent at Makambako site.

Reference [6] reports that many studies have confirmed that the Weibull probability distribution of two parameters is successfully in describing the wind speed variation as it has been validated in this study. The Weibull probability density function was provided in Equation (8) as:

$$f(v)=\frac{\beta}{\delta}\left(\frac{v}{\delta}\right)^{\beta-1}e^{-\left(\frac{v}{\delta}\right)^{\beta}}, \quad v>0, \delta>0, \beta>0$$

Wind energy per time transported by the air stream with speed v can be calculated using the following expression [6]-[8]:

$$P_v=\frac{1}{2}A\rho v^3 \tag{10}$$

Where A is the swept area perpendicular to the direction of the wind speed, and ρ is the air density. The Weibull probability density function of wind energy per time may therefore be expressed as a function of P_v [6]:

$$f(P_v)=\frac{\beta}{3A\rho\delta^3}\left(\frac{2P_v}{A\rho\delta^3}\right)^{\frac{\beta}{3}-1}e^{-\left(\frac{2P_v}{A\rho\delta^3}\right)^{\frac{\beta}{3}}} \tag{11}$$

With parameters

$$\delta'=\frac{1}{2}A\rho\delta^3;\ \beta'=\frac{\beta}{3} \tag{12}$$

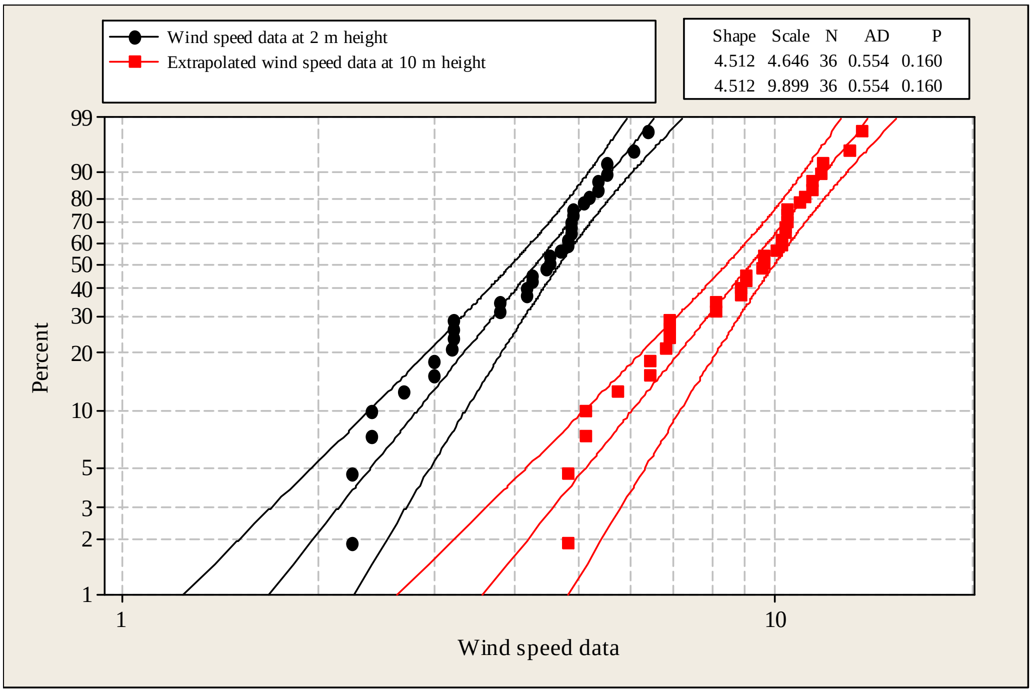

Fig. 5 Weibull probability plot for wind speed data

IV. Conclusions

Wind speeds vary cyclically from instantaneous, hourly, and daily to seasonal at measurement height as well as at estimated hub height. The presence of these variations makes it necessary to describe wind speeds by a probabilistic model. In this study, four probabilistic models were tested to examine which model describes the measured wind speed at Makambako site in Tanzania. Weibull probability distribution has confirmed to fit the wind speed data at measurement height and the extrapolated wind speeds at hub height of 10 m for Makambako site. Subsequently, the Weibull probability density function can be used to predict the wind energy conversion chain more optimally.

Acknowledgment

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