Kernel Density Estimation of Solar Radiation and Wind Speed for South Africa

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Abstract

Accurately determining the amount of daily solar irradiance is of paramount significance before commencing on any solar energy projects. Similarly, precise approximation of wind speed probability distribution is essential and significant important in renewable applications and as a result a study was performed. The paper offers a nonparametric density estimation technique for solar irradiance and wind speed probability distribution. In literature, several probability distribution functions (pdfs) are tested both for solar irradiance and wind speeds and compared with the proposed nonparametric kernel density estimation method. To judge the performance and correctness of the appropriate modelling distributions, the root mean square error (rmse) and mean bias error (mbe) are used as performance test criteria for pdfs. The results firstly demonstrate that the proposed nonparametric kernel density estimator gives more accurate estimation with better adaptability than the commonly used conventional parametric distribution for both solar and wind. Moreover, the study shows that the commonly used Gaussian and Epanechnikov kernel methods were the most adaptable methods for all stations. This study will play an in important role in the country as the first-hand information in prediction of future renewable projects.

Keywords:

Statistical distribution, kernel density estimator, root mean square error, mean bias error.

1. Introduction

With Africa's potential to renewable energy investment and fast growing renewable energy technology, Africa has a significant share in energy production in the future. This will assist in minimizing the high dependence on traditional ways of energy generation and in turn help with job creation. Currently, the composition of energy mix in South Africa shows a great dependence on fossil fuels with approximately 80% of the country's electricity produced from coal. South Africa is relatively in an infant stage in terms of renewable energy systems however, it is growing and according to the country's medium-long term goals set in 2010, renewables will account about 17 500 MW of the total energy mix by 2030. About 7 000 MW of this renewable target is expected to be phased in and operating by the end of 2020. Moreover, solar energy seems to have a potential for massive roll out for both small scale and large scale in many regions of South Africa and thereby having a significant share in energy production in the future.

Renewable energy system has a major role to play in alleviating this high reliance on fossil fuels and other disadvantages as discussed according to department of energy. In modelling these renewable energy generating system, meteorological data for both wind and solar is required. Evaluating the wind and solar energy characteristics together with their ability is the utmost important step for economic viability of these renewable energy projects. Actually, the pdfs of wind speeds and solar irradiance constitute the wind speeds and solar irradiance gathered over a long period. As a result, their information is important for evaluating the wind and solar energy ability of a certain location.

A broad literature examination shows that several parametric probability distribution functions have been tested to predict both wind speeds and solar irradiance, which are applied in reliability evaluation of these renewable resources. Probability distribution for modelling global solar radiation of Ibadan, Nigeria was conducted by Ayodele and concluded that logistic distribution presents the best probability distribution in modelling global solar radiation of Ibadan. In a similar fashion, four distribution methods were examined and all four probability functions showed similar results for Hualien and Taitung by Tian Pau Chang in Taiwan. Many other solar radiation probability distributions have been investigated around the different parts of the continent with Weibull distribution function proving to be best distribution model for M'sila region, Algeria Razika and Nabila (2016), Akuffo and Brew-

Hammond (1993), (Ettoumi et al 2002), (Arthur et al 2013). In similar manner, an extensive literature study has been done for wind speed around the world. These distribution functions include Weibull, Gamma, Generalized Extreme Value, Inverse-Gaussian Rayleigh, Lognormal and many others Lum and Lam (2000), (Celik 2004), (Pobocokova et al 2016), Li and Shi (2010), (Lo Brona et al 2011). From these studies, it is observed that Weibull distribution function with two parameters is the favoured function for wind estimation (Zhilong et al 2011).

Theory coupled with experience, shows that there is a substantial difference showing between the assumed theoretical distribution function and the actual performance or characteristics of wind or solar irradiance. This means, a presumed pdf does not necessarily constantly result in an acceptable best outcomes. This uncertainty is caused by the method of selecting an appropriate pdf from one region to the other. Thus, there does not exist a theoretical criteria for selecting probability distribution functions and, also projected parameters for a certain presumed distribution might not adequately fit historical data of wind speed and solar irradiance and hence result in failure to satisfy the statistical evaluation for parameter approximation caused by unpredictability of wind speed and solar radiation.

This study argues for the use of kernel density estimator concept which does not require prior knowledge of parameters, for estimation of wind speeds and solar radiation probability distributions in South Africa. This method does not require any assumption of theoretical distribution for either wind speed or solar radiation and there is no need to estimate any characteristic parameters of distribution. Thus, the proposed concept avoids the uncertainties experienced when using probability distribution functions that require prior knowledge of parameters. This nonparametric method is used in surveillance systems, econometrics, computer vision and many other fields, and for that reason it is an acceptable idea for applying to renewable systems (Elgammal et al 2002), (Pagal 2009), Wang and Sutter (2004).

Wind speeds and solar radiation data at seven specific locations covering the major provinces in South Africa, are utilised to make distinct evaluations between the suggested nonparametric concept and three traditional parametric probability distribution functions applying statistical evaluation as an estimator. The process further utilizes measured wind and solar data instead of satellite data as the later showed some deficiencies resulting in over estimation of solar irradiance in case of (Dekker et al 2012).

The rest of this paper is structured as follows: Section 2 describes the experimental set-up together with data collection zones. The probability density functions employed for modelling both the wind speed and solar radiation probability distribution are discussed in Section 3. In Section 4, the comparative analysis of estimated distribution and the statistical parameters applied to evaluate the performance of the employed probability distribution functions are discussed. In Section 5, the results and discussion are presented with conclusions being drawn in Section 6.

2. Experimental Set-up and Data Collection Zones

2.1 Location Overview

The study presented take place in South Africa found in the African continent on Latitude (-28° 28' 44.35" S) and Longitude (24° 40' 22.77" E) with an estimated human population of over 59 million people (June, 2020). It is in the southern tip of continent Africa with nine provinces forming this sub-tropical region. As a country it experiences different climatic conditions varying from the western Mediterranean climate to interior dry cold semi-desert conditions and to subtropical humid conditions of the east coast. Seven sites across the country have been identified and used as experimental places, with them covering most of the nine provinces.

2.2 Renewable Energy Resources

As a determining factor for the applicability of these renewable resources for modelling wind speeds and global solar irradiance in South Africa, monthly average wind speeds and global solar irradiance were used. Two methods of measuring the amount of solar radiation at surface area are possible, namely ground measured data and satellite based estimations. There are numerous number of satellite based solar irradiation data sources including NASA SSE, Meteo-norm, EnMerSol, Helioclim, Solemi and etc. The data from these sources partially differ from one source to the other due to changing in quality control procedures applied to each. NASA SSE satellite derived data was used to compare with the ground measured data and showed discrepancies in the overall modelling as can be seen on table 1. These inaccuracies are as a result of cloud effect in satellite measurements and also quality control procedures (Dekker et al 2012). It is imperative that this solar irradiation will differ based on the instrument used.

In this paper, both solar irradiation and wind speed data were measured using ground monitoring equipment in all the seven different geographical stations which represent South Africa. These seven geographical sites are currently monitoring the solar irradiance and wind speeds using ground monitoring stations for research and are freely available to the general public. The data collection campaign is under an umbrella of the Southern African Universities Radiometric Network (SAURAN). The data provided global horizontal irradiance in kWh/m^2/day and wind speeds (m/s). The solar radiation and wind speeds data presented in this paper span for three years (2014-2016). Four of these SAURAN data sites are located on university campuses in Stellenbosch University (SU) data site at (33.9281S, 18.8654E) representing the Western Cape winelands area, University of Free State (UF) (29.1107S, 26.1850E) in the Free State, University of Pretoria (UP) in the Gauteng Province (25.7531S, 28.2286E) representing Gauteng and surrounding Mpumalanga and North West Areas and University of KwaZulu Natal, (UZ) located in Durban (29.8709S, 30.9769E) representing the KwaZulu Natal Province. The other three stations are found on rural farms near the town of Graaff-Reinet (GR)(32.4854S, 245858E) in the Eastern Cape, Alexander Bay (AL) (28.5608S, 16.7615E) in the Richveld region of the Northern Cape and SAURN Vryheid (VR) (27.8282S, 30.5000E) representing the Northern parts of Kwazulu Natal together with surrounding Mpumalanga areas.

Table 1. Average monthly solar radiation for UP

Month	Solar Irradiance (KWh/m^2/d) Average			
	2014	**2015**	**2016**	**NASA SSE**
January	6.60	6.62	6.58	6.79
February	5.95	7.00	6.77	6.34
March	4.27	5.80	5.51	5.75
April	4.85	4.63	5.17	5.03
May	4.50	4.68	4.08	4.58
June	4.21	3.50	3.84	4.15
July	4.41	4.13	4.20	4.51
August	5.00	5.01	4.78	5.13
September	6.22	5.44	5.70	6.05
October	6.89	6.64	6.80	6.23
November	5.70	7.42	6.47	6.47
December	6.36	7.14	6.54	6.78
Average	**5.42**	**5.67**	**5.54**	**5.65**

3. Methodology

3.1 Parametric Distribution Models

In the use of parametric distribution functions, three statistical distribution functions were tested for all the stations, evaluated and reported based on their performance. The three parametric distribution functions employed are Gamma, Weibull and Lognormal. All these distribution functions had three parameters namely; location, shape and scale parameters. The three parametric distribution functions tested were randomly selected based on theoretical literature using the popular preferred pdfs for renewable estimations.

3.1.1 Gamma Distribution Function

Literature shows that Gamma distribution function with two parameters is widely used in the field of renewable energy for fitting global solar radiation, however three parameter distribution function is used in this modelling as mentioned before (Ayodele 2015), Razika and Nabila (2016). This function is given by equation (1),

$$f_{Gamma}(x)=\left[\frac{1}{\alpha\Gamma(\beta)}\right]\left[\frac{(x-\gamma)}{\alpha}\right]^{\beta-1} exp\left[-\frac{(x-\gamma)}{\alpha}\right] \tag{1}$$

where, γ is represents the parameter for location, α representing pparameter for scale and β as a shape parameter. Maximum likelihood was used to estimate these parameters for gamma distribution.

3.1.2 Weibull Distribution Function

Weibull distribution function with three parameters was also tested in fitting the measured wind speeds and global solar radiation. Equation (2) represents this three parameter distribution function.

$$f_{WB}(x)=\left(\frac{m}{l}\right)\left(\frac{x-k}{l}\right)^{m-1} \exp\left[-\left\{\frac{(x-k)}{l}\right\}^{m}\right] \tag{2}$$

where, $f_{WB}(x)$ presents the function for Weibull distribution, k as a parameter for location, l a parameter for scale and m representing a shape parameter.

3.1.3 Lognormal Distribution Function

Lognormal distribution probability density function with three parameters is expressed by equation (3) below:

$$f_{LN}(x;\sigma,\rho,\tau)=\left[\frac{1}{\sqrt{2\pi}\tau(x-\sigma)}\right]\exp\left(-\frac{\left\{\ln\left[\frac{(x-\sigma)}{\rho}\right]\right\}^2}{2\tau^2}\right) \tag{3}$$

where, $f_{LN}(x)$ is the lognormal distribution function, σ is a location parameter, ρ is a scale parameter and τ is a shape parameter.

3.2 Non-parametric Kernel Density Model

Kernel density estimation is a technique of approximating an unknown probability density function for a given data that does not require necessity of parameters. It utilizes the given data sample excluding the need of approximating the characteristic parameters in a theoretical distribution. In addition to this none requirement of characteristic parameters, it provides a curve smoothing option by utilising bandwidth adjustment. This nonparametric density method is explained by equations 4 and 5 below;

$$f(x)=\tfrac{1}{N}\sum_{i=1}^{N}K(x-x_i) \tag{4}$$

where, (N) is the sample size and (K) is called the kernel function. This kernel function vary and typically requires the following properties;

- It should be non-negative: $K(x)\geq 0$ for every value of (x) as the probability is always non-negative.
- It should be symmetric: $K(x)=K(-x)$ for every value of (x)
- It should be decreasing: $K'(x)\leq 0$ for every $x>0$.

In controlling the bandwidth for this kernel function, b is introduced to the equation and thus;

$$f(x)=\tfrac{1}{Nb}\sum_{i=1}^{N}K\left(\frac{x-x_i}{b}\right) \tag{5}$$

The accuracy and best estimation of this function depends on optimal selection of the bandwidth. A small bandwidth will result in a rough curve as a result of some points which occur outside the fitted curve as the data is random. Inversely, a large bandwidth may result in an over smoothed curve.

4. Comparative Analysis of Estimated Distribution

4.1 Statistical test

In determination of correctness and performance of the predicted data for these three parameter probability distribution functions, a performance analysis was performed. Two tests that were done are, root mean square error (RMSE) and mean bias error (MBE). The two tests are respectively expressed as below where, n is the number of data points; x_{meas} is the measured data for either global solar radiation or wind speed and $x_{mod\,el}$ is the modelled data for either of them as mentioned.

$$RMSE=\sqrt{\left[\frac{1}{n}\sum_{i=l}^{n}(x_{\mathrm{mod}\,el}-x_{meas})^2\right]} \tag{6}$$

The root mean square error will inform about the accuracy of each model to the true value. The results will indicate the performance whether the pdf overestimated or underestimated. These values will help in selecting the best pdf for a certain region.

$$MBE=\sum_{i=l}^{n}\frac{x_{mod\,el}-x_{meas}}{n} \tag{7}$$

The mean bias error is used to show the average bias for each pdf. The combination of these two statistics errors will assist with better interpretation. Table 2 show the parameters used for each distribution model for all the sites studied.

Table 2. Distribution parameters for each model

Models	Site Name						
	A L	UZ	VR	GR	SU	UF	UP
Gamma							
γ	-10,94	-6,9194	-11,692	-7,2405E-26	-3,0110E-19	-6,8979	-1,7262
α	65,606	31,3	109,36	1,9414	3,2472	35,348	13,196
β	0,2599	0,36858	0,1608	2,8091	2,0156	0,3601	0,55266
Weibull							
k	-0,515	-0,34443	-0,5483	1,8000E-42	2,4106E-35	-0,95069	1,7728
l	3,61	2,6081	4,3716	0,26322	0,22587	3,653	4,7697
m	7,3916	5,5869	7,0643	54,209	1,3750E-5	7,5706	7,9932
Lognormal							
σ	-29,291	-14,234	-34,686	-2,3880E-24	-2,0600E-17	-20,098	-21,414
ρ	0,05898	0,10894	0,04102	3,0645	1,5387	0,08112	0,06465
τ	3,5656	2,9307	3,7023	1,7141	1,8396	3,2551	3,2922

4.2 Kernel Density Estimator

As a testing measure of the correctness for the data used, non-parametric kernel density estimator was used. In determination of correctness and performance of the predicted data for these six KDE functions, a performance analysis was done using Integral Squared Error, ISE.

$$ISE = \int_{-\infty}^{\infty} \left[f(x) - f^*(x) \right]^2 dx \tag{8}$$

Six kernels that were used are Gaussian kernel, Uniform kernel, Triangular kernel, Quatric kernel, Triweight kernel and Epanechnikov kernel. Results from these kernels will show the accuracy of the data used and ISE will indicate the performance of the model considered with values showing either overestimation or underestimation of the global solar radiation values and wind speed values. Modelling of renewable data will assist by developing a design which will have the similar behaviour as the actual data of the location as envisage.

5. Results and Discussion

An evaluation study between raw measured data and estimated model using the three proposed models was done, the performance tests carried out using RMSE and MBE methods as shown in Table 3. This evaluation was done for all seven sites with the purpose of identifying the best performing model and also the least performing one. In interpreting the results, a low RMSE shows a good presentation of the proposed model whilst an MBE results informs us about the estimation of the model. The positive MBE aids to identify the amount the model overestimates the global solar radiation while the negative MBE aids in determining the underestimation of the model.

In terms of RMSE, the University of Free State presents the lowest value which is replicable for both gamma and lognormal distributions with the amount of 0.0405. This low RMSE value shows a good estimate of the technique presented for all distribution functions. In addition, a picture presentation of the three pdf for six of the sites used is illustrated by figures 1 to 6. It can be seen in figure 4 that Weibull probability function has the best representation of the data for UP. This better presentation was observed for both solar radiation and wind speeds in this site.

In terms of the proposed nonparametric method, the results are demonstrated firstly by statistical analysis of ISE for six kernels of each site as demonstrated by table 4. The initial estimate is the first estimate obtained using values from the measured pdf using probabilistic approach while the final estimate represents the error estimate from the different kernels. It is observed firstly that all kernels performed better for all the sites when compared to normal traditional pdf. The individual kernels when compared against each other, it is observed that Gaussian KDE performed best for three of the seven sites namely UF, VR and UZ. Moreover, results show that all six kernels are adoptable in most sites. Figures 7 to 12 show the modelling results for six of the seven sites due to space considerations. In addition, the results were only for Gaussian KDE for all six sites. It can be clearly observed from the modelling results that the use of kernel density estimation method gives better adaptability and with the option of bandwidth adjustment it fits all sites data appropriately.

Table 3. Statistical analysis for each pdf

Site Name	Gamma		Weibull		Lognormal	
	RMSE	*MBE*	*RMSE*	*MBE*	*RMSE*	*MBE*
VR	0.0598	-0.005	0.0598	-0.004	0.0603	-0.005
UZ	0.0743	-0.0076	0.0746	-0.0061	0.0735	-0.0076
AL	0.0610	-0.0134	0.1070	-0.0781	0.1075	-0.0613
SU	0.0600	-0.0136	0.1151	-0.0990	0.0957	-0.0384
UF	0.0405	-0.0024	0.0417	-0.0011	0.0405	-0.0023
UP	0.0479	-0.0031	0.0458	-0.0003	0.0432	-0.0011
GR	0.0532	-0.0062	0.0531	-0.0044	0.0537	-0.0058

Table 4. Vanrhynsdorp Statistical Error Results for Solar Irradiance

SITE	ISE	Kernel					
		Gaussian	**Uniform**	**Triangular**	**Quatric**	**Triweight**	**Epanechnikov**
AL	**Initial**	0.00361299	0.00361299	0.00361299	0.00361299	0.00361299	0.003613676
	Final	0.000410871	0.000439622	0.000413461	0.000433584	0.000351298	0.000487451
UZ	**Initial**	0.001290591	0.001290591	0.001290591	0.001290591	0.001290591	0.001290591
	Final	0.000208879	0.000177459	0.000378044	0.000424804	0.000507099	0.000301052
VR	**Initial**	0.001083273	0.001117895	0.001121174	0.001129164	0.001121174	0.001121174
	Final	-0.00068744	-0.00154401	-0.00219905	-0.00213786	-0.00213827	-0.002235941
GR	**Initial**	0.001381076	0.001608114	0.001608114	0.001608114	0.001608114	0.001608114
	Final	0.00026581	-3.15087E-05	-0.00019357	-0.00018237	-0.00016849	-0.000170563
SU	**Initial**	0.005424434	0.005424434	0.005424434	0.005424434	0.005424434	0.005424434
	Final	0.001950812	0.001198444	0.000978001	0.000959787	0.000906345	0.0010322
UF	**Initial**	0.00129295	0.00129295	0.00129295	0.00129295	0.00129295	0.00129295
	Final	-0.000110961	-0.000147578	-0.00057969	-0.00065302	-0.00093005	-0.000390814
UP	**Initial**	0.001047326	0.001047326	0.001047326	0.001047326	0.001047326	0.001047326
	Final	-0.000864355	-0.001052116	-0.00067703	-0.00061818	-0.00043509	-0.00085152

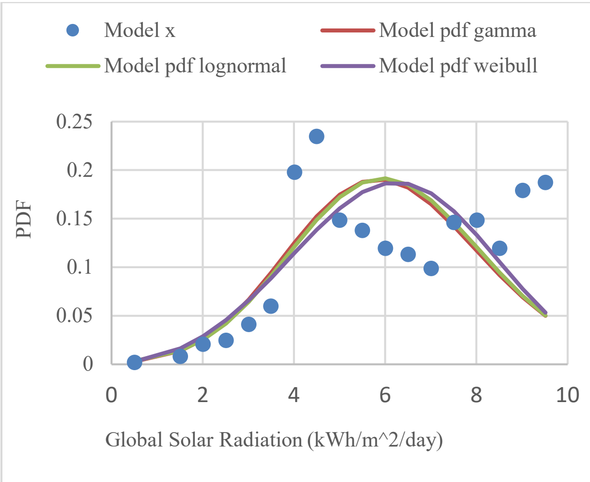

Figure 1. Fitting of pdfs for AL

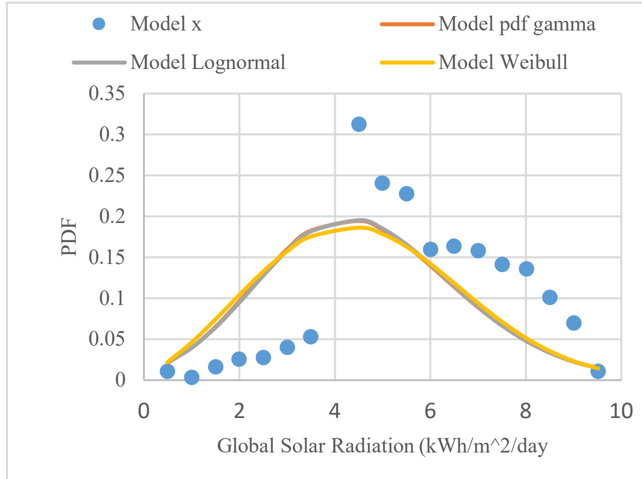

Figure 2. Fitting of pdfs for UZ

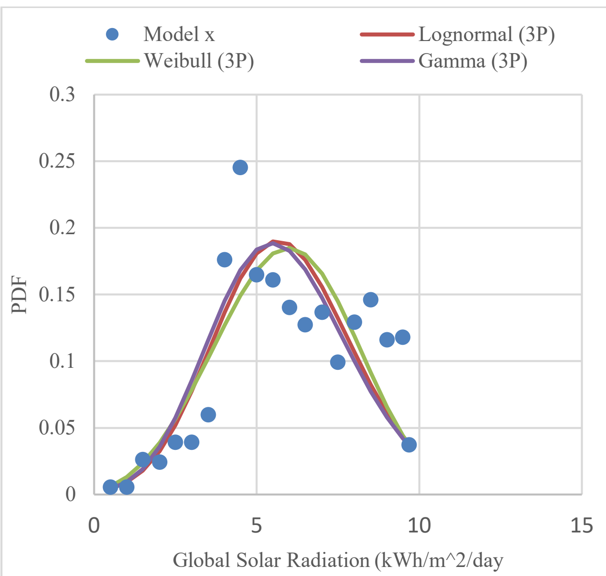

Figure 3. Fitting of pdfs for UF

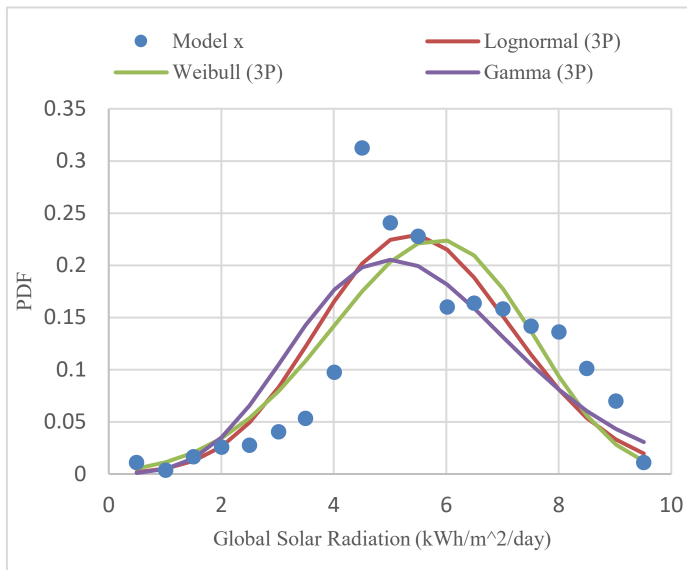

Figure 4. Fitting of pdfs for UP

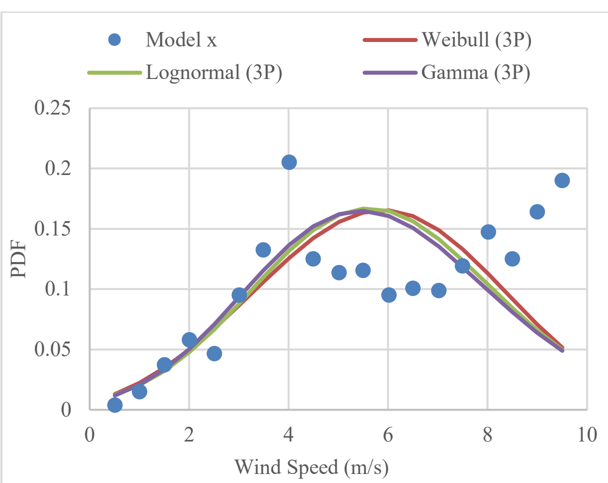

Figure 5. Fitting of pdfs for GR

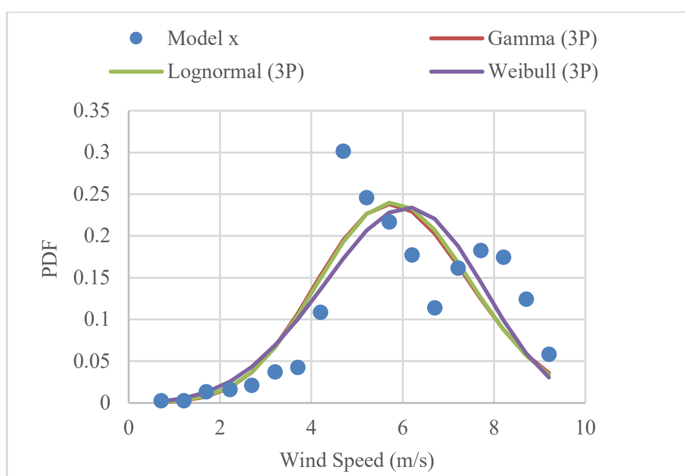

Figure 6. Fitting of pdfs for VR

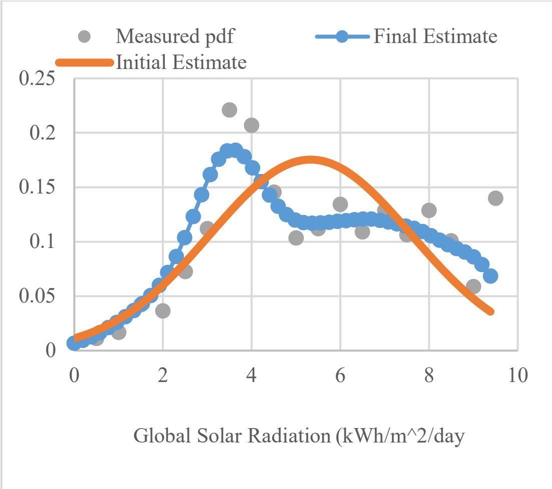

Figure 7. Gaussian kde for AL

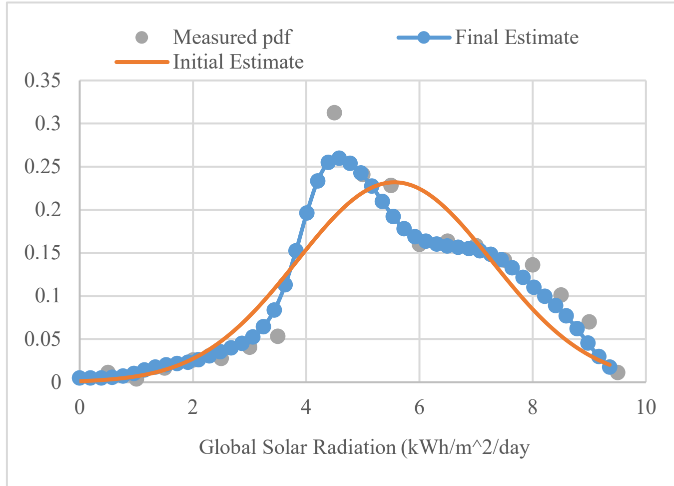

Figure 8. Gaussian kde for UZ

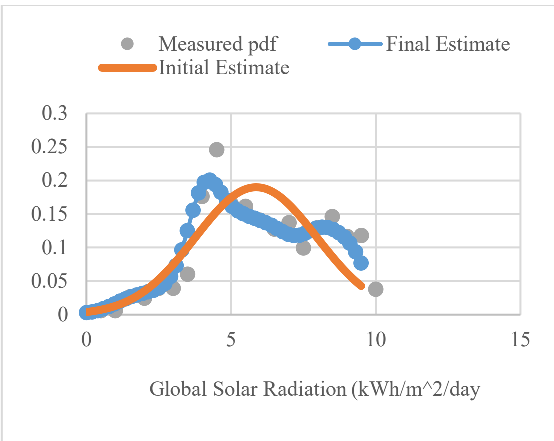

Figure 9. Gaussian kde for UF

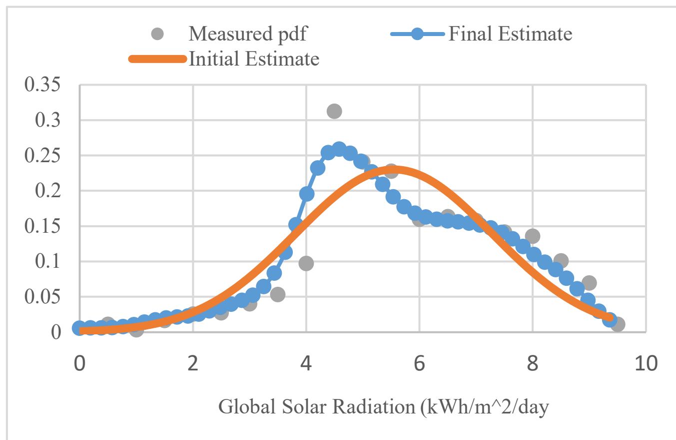

Figure 10. Gaussian kde for UP

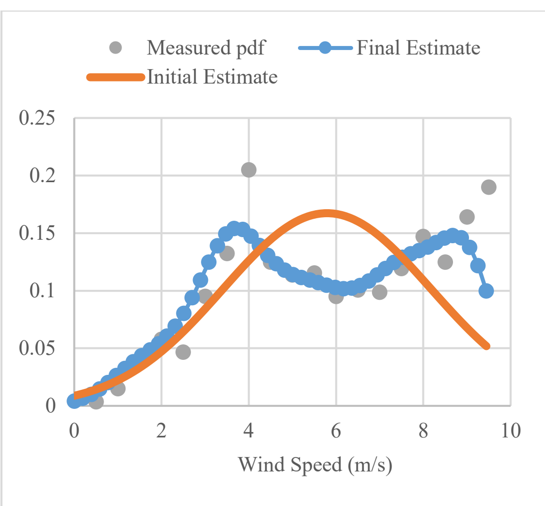

Figure 11. Gaussian kde for GR

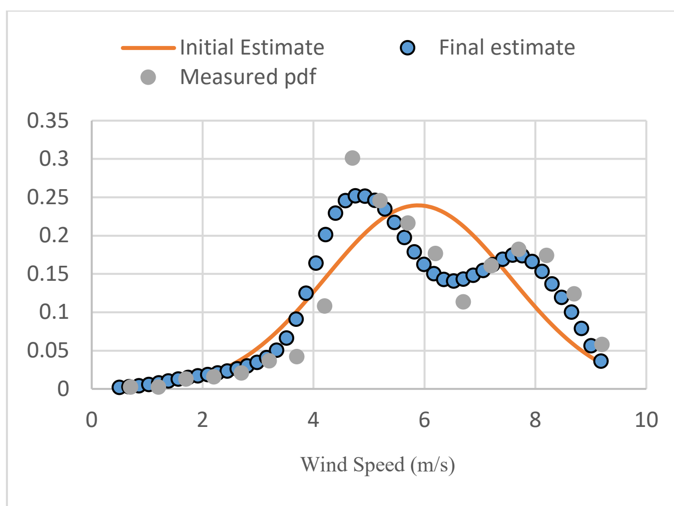

Figure 12. Gaussian kde for VR

6. Conclusion

In this paper, parametric and non-parametric data modelling of global horizontal solar irradiance and wind speed recorded for seven sites in South Africa from 2014 to 2016 were investigated using three distribution functions namely, Gamma, Weibull and Lognomal for parametric modelling while kernel density estimator was used for non-parametric modelling. The data used to for appropriateness of the three parametric distributions and proposed nonparametric kernel estimation method for modelling these seven sites was the actual measured data. An evaluation study was performed using three statistical tests, root mean square error, mean bias error for appropriateness of the parametric distributions. An integral squared error, ISE was used for the performance comparison of the proposed nonparametric method with the conventional parametric normal distribution.

Using a parametric distribution method depends highly on acquiring the site solar and wind characteristics in advanced. Moreover, the parametric distribution functions are not adaptable for all sites which means one needs to use a trial and error method to obtain the best suitable function for any site. In terms of adjusting to the available data and smoothing the curve representation accordingly, these parametric distribution functions do not possess such option. The use of the proposed nonparametric kernel density method can overcome all the mentioned drawbacks. The results of this study are utmost important to potential use of solar and wind energy in South Africa.

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