A Probabilistic Forecasting Model for Accurate Estimation of PV Solar and Wind Power Generation

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***Abstract*— Wind and Solar power are the most promising and rapidly developing renewable energy technologies that exist in our world today. They are also termed variable energy resources since their natural resources, wind speed and solar irradiance, are intermittent in nature. This variability is a critical factor when estimating the annual energy of wind and solar sources. Capital and operational costs associated with their implementation are highly affected when inaccurate estimations are carried out. This paper presents a new forecasting model for solar irradiance and wind speed by utilizing historical hourly data to outline an annual eight-segment probabilistic model of wind and solar. The proposed methodology employs a probabilistic approach to estimate the hourly wind speeds and solar irradiance for a year. The model is used to estimate the annual energy produced by a 42.5 MW wind farm and a 1.5 MW PV array. The results are compared with a four-season estimation approach, which have shown a substantial improvement in the estimation accuracy of the total energy produced.**

Keywords—Wind energy, PV solar energy, Renewable energy variability, Forecasting of renewable energy resources.

I. Introduction

Renewable energy is the form of energy obtained from infinite natural resources because they are incessantly replenished upon usage. Benefits of using renewable energy over conventional non-renewable energy sources include mitigating global warming, removal of air and other forms of pollution, improved cost minimization, consumer independence with regards to energy supply etc. The emergence of renewable energy resource technologies has revolutionized over the past decade to become more reliable, efficient, cost effective, readily available and more environmentally friendly than the conventional energy resource technologies. Types of renewable energy resources include solar, wind, biomass, geothermal and hydro. The most promising types, wind and solar energy, are currently experiencing a rapid increase in installed capacity and usage, with solar power increasing from 8 GW in 2012 to more than 48 GW by 2040 while wind is estimated to increase from 60 GW in 2012 to 87 GW in 2040 [1].

Wind and solar energy utilization are dependent on the wind speed and solar irradiance available. These resources are inherently intermittent. As a result, appropriate resource forecasting methods are required for accurate output power estimation. There is currently a surge of research interest with a reasonable amount of literature review on methodologies used in modeling the random behavior of wind speed and solar irradiance in order to make accurate energy forecasts. Reference [2] uses Monte-Carlo numerical simulation procedure which employs probabilistic models to evaluate the annual energy output. Auto regression moving average model (ARMA) in [3] is another technique used to obtain annual behavioral pattern. The authors in [4] and [5] used three years historical data to estimate the hourly solar irradiance and wind speed with each year divided into four seasons to calculate the mean and standard deviation which are used to generate the Beta and Weibull probability density functions (pdf). Both the capability of finding ideal solutions using general algorithm (GA) and the nonlinear mapping capability of artificial neural network (ANN) were utilized in [6] and [7] in developing a hybrid model to forecast output energy from wind power stations. In [8], a least square based methodology was adopted utilizing wind speed spatial correlation of a wind farm to predict short term power. However, this methodology is dependent on the type of location terrain, which in this case was flat and affected the accuracy of the predicted power. In [9], solar irradiance states at different times of the day were modeled using a Markov approach based on the inter-dependency exhibited by solar states. Reference [10] utilized a normalized Beta pdf to generate the solar irradiance distribution for a typical day in a season while showing the variability in daily illumination times from season to season. A solar irradiance forecasting model was introduced in [11] that employs Artificial Neural Networks by Backpropagation algorithm. The model was used to forecast the consequent next-day solar irradiance patterns for every half-hour. For short-term solar forecasting, the authors in [12] used a network of wireless solar irradiance sensors located in close proximity to a PV array to predict its output power.

Based on ongoing research, more accurate estimation and prediction models need to be developed to achieve efficient and successful integration of the intermittent renewable energy resources. This paper proposes a better segmentation technique to model the hourly solar irradiance and wind speed data using Beta and Rayleigh pdfs based on a three year historical data documented for selected sites. Each year is divided into 8 segments with each segment representing one-half of a season to obtain more accurate means and standard deviations required for better forecasting of the extracted output energy.

The remainder of this paper is structured as follows. Section II discusses the uncertainties associated with renewable energy generation and its adverse effects in grid-connected schemes. The proposed forecasting model and its related mathematical

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expressions are presented in Section III. The validated results are compared with that obtained from a forecasting method used in previous work. Section IV explains the results and the conclusions follow in Section V.

II. Uncertainty of Renewable Energy Resources

Renewable energy resources are referred to as variable energy resources due to the dependency of their output energy on various variable parameters. Wind speed and solar irradiance are major variable parameters of wind and solar power respectively. Cloud formation and landscape also contribute greatly to PV and wind output power variability respectively. Studies have shown that correlations can be found in PV output power variability between sites in close proximity (20 km or less) [13]. Due to the already existing load demand uncertainty on the power grid, a more complex uncertainty analysis is required when wind and solar generation units are deployed in distributed generation [14]. Accordingly, regulation reserves are required to compensate for these uncertainties to ensure there is a balance between load generation and demand [15]. Furthermore, the uncertainty of grid connected wind and solar resources have a significant impact on the power system performance and efficiency, necessitating advanced planning and operation of electric grids.

Power curtailment is one of the negative impacts on the power grid when wrong output power forecasting is carried out on grid-connected variable energy systems [16]. This can result in significant increase in capital and operational costs allocated. Power reserve and recovery resources are usually put in place for dealing with power generation and load demand uncertainties. However, the capability of these protection schemes is overburdened when the generation or load demand variability threshold predicted by uncertainty forecasting is exceeded.

III. Proposed Model

This section explains how the probability density functions (pdfs) are generated and utilized in estimating hourly wind speeds and solar irradiance for the sites under study. In the proposed model, the data processing is based on three years of historical hourly data to forecast the random behavior of wind speeds and solar irradiance at different times of the year. The aim of this proposed methodology is to minimize error margins in the means and standard deviations by representing the year in shorter segments thereby creating an eight-segment year (eight minor seasons).

For the selected sites, Beta and Rayleigh probability density functions are utilized to estimate the hourly irradiance and wind speed based on three years of historical hourly data. The segmentation approach applied here divides each year into eight minor seasons with each minor season being represented by any day within that season. From the historical measurements, the frequency distribution of a typical day in a minor season is derived. The whole year is therefore represented by 192-hr time-segments since each typical day consists of 24-h time segments. As a result, for the three year period, each time-segment has a total of 135 irradiance and wind speed data points with the assumption that one month is made up of 30 days (3 years × 30 days per month × 1.5 months per minor season). The Beta and Rayleigh pdfs for each hour are generated based on the means and standard deviations calculated.

A. *Solar Irradiance Modeling and PV Array Output Power*

Beta Probability Density Functions is widely used in solar irradiance probabilistic modeling. It can be used to model the optimal curve fit for the unimodal behavior that solar irradiance exhibits over a 24-hour period. To obtain a typical day in a minor season's solar irradiance behavior for a 24-hour period, a Beta pdf is adopted [4]. The Beta pdf equation is given as:

$$fb(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} * s^{(\alpha-1)} \\ * (1-s)^{(\beta-1)}, \text{ for } 0 \le s \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 \qquad\qquad , \text{ otherwise} \end{cases} \tag{1}$$

Where s is the solar irradiance in kW/m^2, $fb(s)$ is the Beta distributed function of s and α, β are computed as shape parameters of the Beta distribution function [17].

The mean (μ) and standard deviation (σ) are utilized to calculate the parameters of the Beta Distribution function as follows:

$$\beta = (1-\mu) * \left(\frac{\mu*(1+\mu)}{\sigma^2}\right) - 1 \tag{2}$$

$$\alpha = \frac{\mu*\beta}{1-\mu} \tag{3}$$

After the beta distribution for each time segment has been generated, the probability of possible solar irradiance states (i.e. from 0 – 1 kW/m^2, with increments of 0.1) is derived and compiled to determine the average solar irradiance for that time segment. The output power of the PV array for one time segment is calculated using [18]:

$$P_{st}(s_{a\,t}) = N * FF * V_t * I_t \tag{4}$$

$$FF = \frac{V_M*I_M}{V_{oc,STC}*I_{sc,STC}} \tag{5}$$

Where N is number of PV modules and FF is the filling factor calculated from PV manufacturer specifications. For simplicity, open circuit voltage, V_t and short circuit current, I_t, are computed at each time segment to obtain the output power at that time segment, P_{st}. V_M, I_M, $V_{oc,STC}$, $I_{sc,STC}$ are voltage and current at maximum power point, open-circuit voltage and short circuit current at Standard Test Conditions respectively.

B. *Wind Speed Modeling and Wind Turbine Output Power*

In this paper, a special case of Weibull probability density function (pdf) is used to model the wind speed behavior. The Wiebull pdf, as expressed in (6) below gives a probabilistic representation of a minor season's wind speed frequency distributions and behavior for a 24-hour period of a typical day [19], [20]. The Rayleigh PDF in (7) is a unique type of Weibull pdf in which the shape parameter, k in (6) is equal to 2 [21]. It is the most pragmatic and commonly used pdf to obtain optimal estimation of wind speed and output power behavior.

$$f(v) = (\tfrac{k}{c})\left(\tfrac{v}{c}\right)^{k-1} \exp[-(\tfrac{v}{c})^{k}] \tag{6}$$

Substituting Rayleigh scale index approximation [4],

$$c = 1.128\bar{v}$$

into (6) gives;

$$\begin{aligned} fr(v) &= \left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right] \\ &= \left(\frac{\pi v}{2v^2}\right)\exp\left[-\left(\frac{v}{4}\right)\left(\frac{v}{\bar{v}}\right)^2\right] \end{aligned} \tag{7}$$

Where $fr(v)$ = Rayleigh pdf, $f(v)$ = Weibull pdf, v = wind speed, $\bar{v}$ = average wind speed and scale index, c.

After generating the Rayleigh distribution for each time segment, the probability of possible wind speed states (i.e. from 0 – 25 m/s, with increments of 1m/s) is derived and compiled to determine the average wind speed for that time segment. Assuming Rayleigh statistics, the output power in the wind turbine at each segment is given by equation (8) [21].

$$P_{vt}(v_{at}) = \begin{cases} P_r * \frac{v_{at}-v_{ci}}{v_r-v_{ci}} & v_{ci} \le v_{at} \le v_r \\ P_r & v_r \le v_{at} \le v_{co} \\ 0 & otherwise \end{cases} \tag{8}$$

Where P_{vt} is the output power of the wind turbine at each time segment, P_r is Rated Power, V_{at}, V_{ci}, V_r and V_{co} are average wind speed of each segment, cut-in speed, rated speed and cut-out speed of the wind turbine respectively.

IV. Simulation Results

The proposed eight-segment model is compared with the four-season model adopted in previous work [4] and [5]. For comparison, 24 time segments represent a season for the four-season model while 48 time-segments represents a season in the proposed model. In this study, PV rated output power of 1.545 MW is considered by using 20,600 PV modules with a rated capacity of 75 W each. Fig.1. compares the forecasted output power using both models. As shown in Fig.1, the output power forecast using the proposed model shows the peak contributions from both early and late season. For example, a peak output power of 1.4 MW can be seen to occur during a typical day in late spring as compared to the 1.3 MW peak observed when using the four-season model. Results in Table I show that the estimated annual energy using the 4 segment model is 15,542.9 GWh while the 8 segment model yielded a forecasted annual energy of 15,744 GWh. The difference in the estimated annual energy of 201.1 GWh shows the improvement in the total annual energy forecast.

In the case of wind and for simulation purposes, a windfarm with a rated output power of 42.5 MW using 50 wind turbine units with rated capacity of 850 kW each is adopted. Fig. 2 compares the estimated output power from the wind farm using both models.

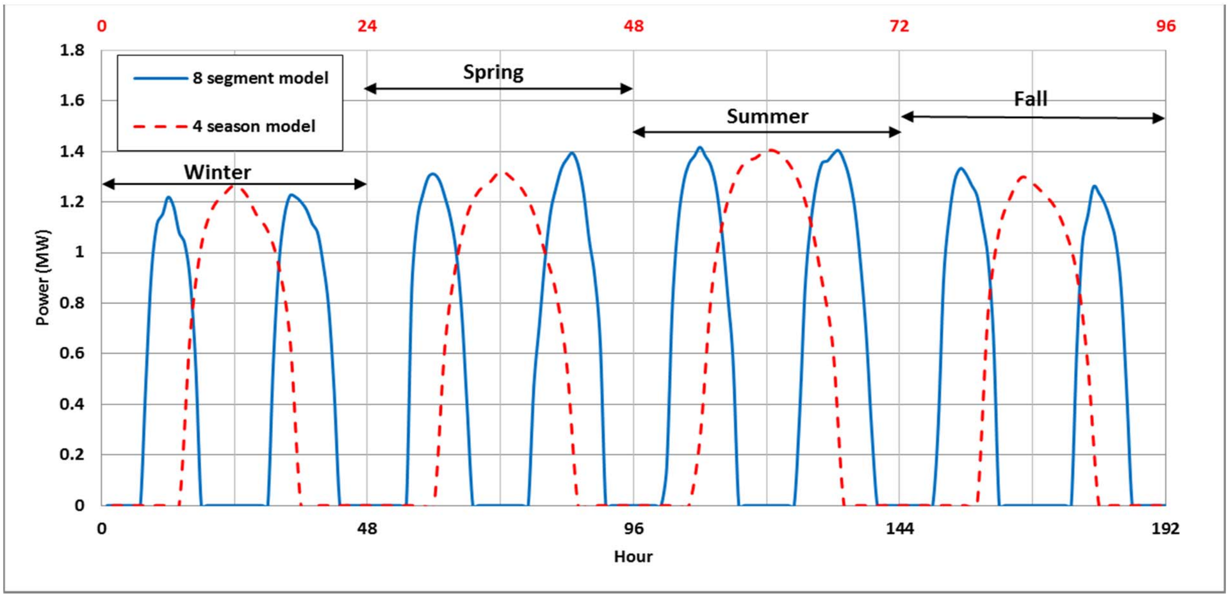

Fig. 1. Forecasted output power from PV using both models

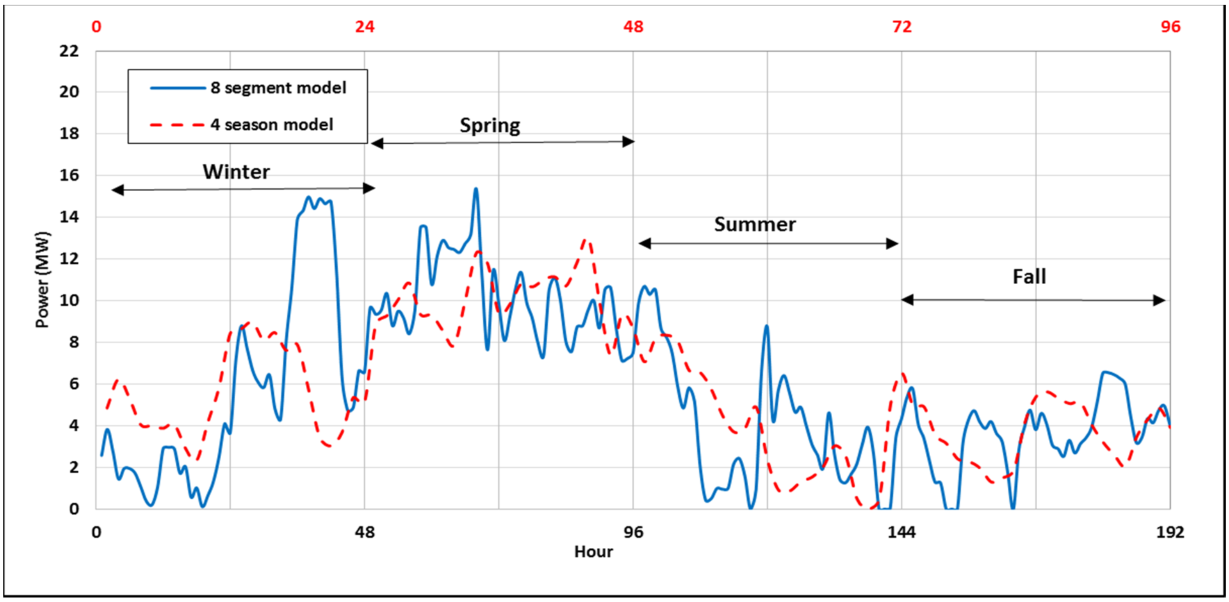

Fig. 2. Forecasted output power from Wind using both models

It was found that the peak output power of 13 MW is generated for a typical day in late spring in the case of the four-season model. Conversely, the proposed model shows that an output peak power of 15.4 MW is delivered in early spring and not late spring. It is noteworthy that when the wind speed is lower than the cut-in speed, a low output power is produced. For example, from Fig.2, the wind farm in the four-season model produces low output power for a short period in the summer while the eight-segment model shows more details on other periods where low output power from the wind farm was observed. The total estimated annual energy produced based on the proposed model is 180,643.9 GWh as shown in Table I. This value is significantly higher by 217 GWh when compared to the 180,426.9 GWh produced in the reference four-season model. In conclusion, the new model presents more accurate details of the generated power at different periods of the year.

TABLE I

COMPARISON OF ANNUAL ENERGY USING BOTH MODELS

	Proposed Model			4 season model	
	Solar Energy (GWh)	Wind Energy (GWh)		Solar Energy (GWh)	Wind Energy (GWh)
Early Winter	1559.805	7358.479	Winter	3382.309	42908.662
Late Winter	1918.938	35473.896			
Early Spring	1881.848	43091.460	Spring	4105.086	78494.009
Late Spring	2240.703	35393.063			
Early Summer	2250.355	18790.508	Summer	4616.692	30766.35
Late Summer	2409.651	12067.249			
Early Fall	1866.540	11649.726	Fall	3438.904	28257.888
Late Fall	1616.190	16819.604			
TOTAL ENERGY	**15744.030**	**180643.986**		**15542.991**	**180426.909**

V. CONCLUSION

A new method for estimating hourly wind speed and solar irradiance has been proposed. By implementing the frequency distribution in shorter time frames, this method provides more accurate results when estimating the output power and annual energy delivered by the renewable energy-based generation units. The newly proposed model is used to generate accurate annual forecasts of wind speed and solar irradiance which are in turn used to estimate the output power and annual wind and solar energy. The simulation results obtained from the proposed model are compared with the commonly used 4 segment forecasting model to demonstrate the improvement in forecasting accuracy.

Despite the complexity involved in processing the data for the proposed model, better output power and annual energy estimations are obtained which is emphasized by the significant improvement in total estimated annual energy. In addition, a more informative description of periods when peak power is delivered can be obtained. The output power and energy obtained using this new model can be utilized by transmission system operators to maintain system stability and balance between electricity demand and generation by ensuring the demand is always met. This also helps in minimizing costs associated with energy curtailment and reserve strategies.

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