Algarve, Portugal, June 11-13, 2008

Probability Analysis of Weather Data for Energy Assessment of Hybrid Solar/Wind Power System

G. TINA, S. GAGLIANO D.I.E.E.S University of Catania V. le A. Doria 6, 95125 Catania ITALY

Abstract: - In this paper a procedure for the probabilistic treatment of irradiance and wind meteorological data is reported in order to evaluate the energy potential of a given site as well as the generation of electricity from photovoltaic systems (PVSs) and wind systems (WECSs). In particular the aim of the proposed analysis of recorded meteorological data is twofold: first of all to check if the real probability distribution functions (PDF) of both clearness index and wind speed are respectively overlapped with Hollands-Huget distribution and Weibull distribution then to find the parameters of these two distributions.

The results of this procedure stands for the input of an algorithm for the optimized design of grid-connected Hybrid Solar Wind Power Systems (HSWPS). The core of this algorithm is a probabilistic model based on the convolution technique, that allows to assess the long-term performance of a hybrid solar–wind power system for both stand-alone and grid-linked applications.

In this paper, the applicability of this procedure has been tested for a site, Acireale (Italy), finding the fitting parameters of the probabilistic models.

Key-Words: - Solar radiation, wind speed, probability analysis, Hybrid Solar Wind Power System, Solar Energy System, Wind Energy conversion System

1 Introduction

Solar and wind energy is non-depletable, sitedependent, non-polluting, and potential sources of alternative energy. Utilization of solar and wind power has become increasingly significant, attractive and cost-effective, since the oil crises of early 1970s [1]. However, common drawback with solar and wind energy is their unpredictable nature. In general, the variations of solar and wind energy do not match with the time distribution of demand. The independent use of both the systems results in considerable over-sizing for system reliability, which in turn makes the design costly [1]. As the advantages of solar and wind energy systems became widely known, system designers have tarted looking for their integration. In this scenario Hybrid Solar Wind Power System (HSWPS) can be considered as a viable option for the energy market.

The HSWPS design is mainly dependent on the performance of an individual system. In order to predict performance, individual components should be modeled and then their mix can be evaluated to meet the demand reliably. Various modeling techniques are developed by researchers to model components of HWPS. Performance of individual component is either modeled by deterministic or probabilistic approaches [2].

Many attempts have been tried to explore a relatively simple method for designing hybrid energy systems. An algorithm based on energy concept to optimally size solar photovoltaic (PV) array in a PV/wind hybrid system was reported [3]. Different system developments in hybrid energy system for Thailand were published [4]. A simple numerical algorithm was used for unit sizing and cost analysis of a stand-alone wind, solar PV hybrid system [5]. A linear programming technique was developed for optimal design of a hybrid wind/ solar PV power system for either autonomous or grid-linked applications [6].

In [7] Salerno et al. propose a new method for the optimized design of grid-connected HSWPS. The system's model of HSWPS is an analytical model using statistical approach and in particular convolving the PDFs of power generated by Solar Energy System (SES) and Wind Energy Conversion System (WECS) [8].

The hypothesis assumed in [8] to calculate the probabilistic model of HSWPS and in particular to calculate the PDFs for HSWPS are the following: 1) the expression used for the PDF of clearness index (k_r) is the one proposed by Hollands and Huget [9], 2) the expression used for the PDF of the wind speed is the Weibull Distribution. In order to calculate the performance of an existing system or energy generated from a system in the design stage, appropriate weather data has required. On this regard both the analysis of the influence of the measurement interval of solar radiation and wind speed and a good fit for the data measured in a typical hybrid energy system are of paramount importance not only with regard to technical reliability but also in the minimization of total system cost (kWh costs).

In this paper a procedure for the probabilistic treatment of irradiance and wind meteorological data is reported so as to evaluate the energy potential of a given site as well as the generation of electricity from photovoltaic systems (PVSs) and wind systems (WECSs). The paper is organized as follows : in sections 2 the formulation of the problem for the optimal sizing of an HSWPS is reported, in section 3 and 4 the models of two energy sources (solar and wind energies) are described, finally in section 5 a case study is included to illustrate the validity of this approach and to analyze the influence of measurement interval on the long term performance of HSWPS.

2 Optimization HSWPS Problem Formulation

In the system under study a Wind Energy Conversion System (WECS) is connected to the control unit through an appropriate electrical interface. In parallel a Photovoltaic System (PVS) is also connected to the control unit. Interaction with the grid is assumed to be bi-directional: excess of energy generated by the HSWPS is conditionally supplied to the grid. On the other hand, deficit of energy will be drawn by the grid in the low generating phase to supply the local demand.

Due to the stochastic nature of the solar and wind sources, the performance of the HSWPS under study can be assessed by employing suitable probabilistic models for both WECS and PVS.

In a good design of HSWPSs the objectives which must be reached are the minimization of the overall cost and the maximization of the energy performance of the system.

In [7] has been developed an algorithm for the optimized design of grid-connected HSWPS based on a probabilistic model.

The control variables are: surface and tilt angle for the PVS and rated power and hub height for the WECS. In particular it is important to observe as the parameters of the PDFs for energy sources will vary depending on:

- the control variables such as tilt angle (PVS), rated power and hub height (WECS);
- the time frequency of the measured data (solar radiation and wind speed).

3 Wind Speed Probabilistic Model

Since the wind speed "v" is a random variable, a long term meteorological data is desirable to describe wind energy potential of the sites. In [10] Youcef Ettoumi et al. show the statistical features of the wind at Oran (Algeria). The three-hourly wind data have been modelled by means of Markov chains. First-order nine-state Markov chains are found to fit well the wind direction data. whereas the related wind speed data are well fitted by first-order three-state Markov chains. The Weibull PDF has also been considered and found to fit the monthly frequency distributions of wind speed measurements. In this paper based on historic recordings of mean hourly wind velocity the analysis shows the importance to incorporate the variation in wind energy potential during diurnal cycles. In order to assess the variability of wind speed, during the j^{th} hour (j=1,..,24) of the mth month (m=1,..,12), the measured data [11] are well fitted by a Weibull distribution with a scale parameter $\alpha_{wm,i}$ and a shape parameter $\beta_{wm,i}$. Density and PDFs are given by (hereafter for legibility's sake the variables that depend on the hour of the day and on the month will be written in boldface):

$$f_{\nu}(\nu) = \frac{\beta_{w}}{\alpha_{w}} \cdot \nu^{\beta_{w}-1} \cdot \exp\left[-\left(\frac{\nu}{\alpha_{w}}\right)^{\beta_{w}}\right]$$
(1)

$$F_{\nu}(\nu) = 1 - \exp\left[-\left(\frac{\nu}{a_{\nu}}\right)^{\beta_{\nu}}\right]$$
(2)

Wind energy assessments that are based on Weibull distribution using average daily/seasonal wind speeds fail to acknowledge that wind speed probabilities can vary significantly during day and night.

The wind speed distribution for selected sites as well as the power output characteristic of the chosen wind turbine are the factors that have to be considered to determine the WECS power output. We can extrapolate the overall mean wind speed to a common height using the following relationship [12]:

$$\frac{v}{v_o} = \left(\frac{h}{h_o}\right)^{a'} \tag{3}$$

where v is the wind speed at the required common height, v_0 is wind speed at the original height, h is Algarve, Portugal, June 11-13, 2008

the required common height, h_0 is the original height, and *a* is the power law exponent (taken as 0.14 for smooth, grass-covered terrain). We can extrapolate the Weibull's parameters to a common height using the relationship (3) and replaced in (1). The PDF for the wind speed will vary with the height, with the maximum value for the Weibull distribution shifted versus the highest wind speed and around a new mean value and with a new scale parameter. The distribution modified will have the same value for the interval measure (8760 hours) and it is possible only if the new scale parameter α has the expression reported in (4).

$$\alpha' = \frac{\alpha_w}{\left(\frac{h}{h_o}\right)^{a'}} \tag{4}$$

The equation (4) has been obtained to introduce in equations (1) and (2) the dependency of wind speed from hub height.

In Figure 1 for different hub height it is possible to observe some wind speed PDFs.



Fig. 1. PDF for the wind speed varying the hub height.

For a typical WECS, the power output characteristic can be assumed in such a way that it starts generating at the cut-in wind speed V_C , the power output increases linearly as the wind speed increases from V_C to the rated wind speed V_R . The rated power P_R is produced when the wind speed varies from V_R to the cut out wind speed V_F . at which the WECS will be shut down for safety. Thus,

$$\boldsymbol{P}_{w}(v) = \begin{cases} \left(\frac{P_{R}}{V_{R} - V_{C}}\right) \cdot \left(v - V_{C}\right) & \text{for } V_{C} \leq v \leq V_{R} \\ \\ P_{R} & \text{for } V_{R} \leq v \leq V_{F} \\ \\ 0 & Otherwise \end{cases}$$
(5)

The PDF $f(P_w)$ for the power output of the WECS can be obtained using Equations (1) and (5) by the application of the transformation theorem [13].

4 Solar Radiation probabilistic model

The amount of solar radiation that reaches the ground, besides on the daily and yearly apparent motion of the sun, depends on the geographical location (latitude and altitude) and on the climatic conditions (e.g. cloud cover). Many studies have proved that cloudiness is the main factor affecting the difference between the values of solar radiation measured outside the atmosphere and on earthly surface. To account for the difference between these two values, a daily clearness index, K_t , has been defined as the ratio of daily solar radiation, H_t [MJ/m²], to the extraterrestrial daily solar radiation, H_o [MJ/m²], for that day, both referred to a horizontal surface. We can also define an hourly clearness index, $k_{\rm t}$, as the ratio of the irradiance on horizontal plane, I_t [kW/m²], to the an extraterrestrial total solar irradiance I_0 [kW/m²]:

$$\boldsymbol{k}_t = \frac{\boldsymbol{I}_t}{\boldsymbol{I}_o} \tag{6}$$

Since k_t is a random variable it is possible to describe it by means of an appropriate pdf. Liu and Jordan [14] first proposed a "generalized family of distribution functions" of the daily clearness index, depending only on the monthly mean of the clearness index. These functions are then independent of the geographical location and of the month considered. Later on, several works have shown that these functions are not as universal as initially thought and there are several functional forms for the density of the clearness index that consider other local variables. ([15], [16], [17]).

Usually the same density functions are used for hourly and daily data, as both densities are unimodal. Olseth and Skartveit [18] found "Ushaped" densities with daily data in temperature storm belt climates. In [19] using global irradiance data measured at 1 min intervals in Western Australia, the authors found a bimodal density function for the clearness index and use a mathematical model related to the Boltzman statistics. This distribution is dependent on the air mass (m) and on the mean of the clearness index (k_t) , and they proposed to find out if the density $f(k_t)$ will also be bimodal in other latitudes and climates. Jurado et al. [20] confirm the bimodal shape of the distribution but $f(k_t)$ is dependent on k_t and on the hour angles w_s. In this paper based on historic recordings of hourly mean monthly solar radiation data are well fitted by Hollands and Huget distribution, C and λ are Hollands and Huget distribution parameters [15]. The distribution's parameters will vary with the nature of the recorded data (monthly, hourly, yearly etc...).

The Hollands and Huget distribution is well approximated by a Gamma distribution, where x is the hourly clearness index k_t .

$$f(x) = \frac{1}{b^{a} \Gamma(a)} x^{a-1} e^{\frac{x}{b}}$$
(7)

Gamma distribution is implemented in Matlab[®] library and related with the Hollands and Huget parameters through the following relations:

$$b = \frac{C \cdot k_{tu} \cdot (2\overline{k}_{t}^{2} + k_{tu}^{2}) \cdot e^{\lambda k_{tu}}}{\overline{k}_{t} \cdot 12 \cdot 10}$$

$$a = \frac{\overline{k}_{t} \cdot 12 \cdot 10}{C \cdot k_{tu} \cdot (2\overline{k}_{t}^{2} + k_{tu}^{2}) \cdot e^{\lambda k_{tu}}}$$
(8)
$$(9)$$

Where:

 k_t is the hourly monthly mean value for the clearness index $k_t k_{tu}$ is the upper bound for k_t .

In the Hollands and Huget distribution the value of k_{tu} was constant along the year and equal to 0.864. In the case study the maximum data recorded and related upper bound for k_t have been compared with the same obtained through an estimation of clear sky radiation (CSR) [21].

Once the hourly clearness index k_t is known it is possible to determine the irradiance on a surface with inclination β to the horizontal plane, I_{β} [kW/m²] [8]. Since the PVS is usually equipped with a maximum power point tracker (MPPT) and the relationship between the maximum power per unit area of array surface available from PVS and I_{β} is linear [22], the power output of PVS (P_{pv}) is given by:

$$\boldsymbol{P}_{pv} = A_C \cdot \boldsymbol{\eta} \cdot \boldsymbol{I}_{\beta} = A_C \cdot \boldsymbol{\eta} \cdot \left(\boldsymbol{T} \cdot \boldsymbol{k}_t - \boldsymbol{T'} \cdot \boldsymbol{k}_t^2 \right)$$
(10)

where:

 A_C is the array surface area [m²];

 I_{β} the irradiance on a surface with inclination β to the horizontal plane [kW/m²];

 η is the efficiency of the PVS in Realistic Reporting Conditions. (RRC) [23];

T and T' are parameters that depend on inclination β , declination δ , reflectance of the ground ρ , latitude φ , hour angle ω , sunset hour angle ω_s , day of the year n [8].

From (10), if the PDF for the random variable k_t is known ($f(k_t)$), it is possible to obtain the PDF for $\mathbf{P}_{pv}(\mathbf{f}_{pv}(\mathbf{P}_{pv}))$ by applying the fundamental theorem for function of a random variable [13].

Depending on the sign of the parameters T and T', the PDF has four different expressions but only two have a physical meaning [8], therefore the expressions will vary with the nature of recorded data. In particular the expression for $f(P_{pv})$ is related with k_{tu} . So if this value is variable and not fixed the expressions for $f(P_{pv})$ and the related power generated by PVS will vary.

Of course, quite often, the hourly radiation data are not available, so it may be necessary to start with daily data and estimate hourly values from daily numbers. Since the estimation of diffuse from total radiation is not an exact process, there is no way to determine these circumstances from daily totals. However the method proposed in [24], can be applied although it works best for clear days, and those are the days that produce most of the output of solar processes. Further it tends to produce conservative estimates of long-time process performance. The equation that expresses the ratio of hourly total to daily total radiation, as function of a day length and the hour in question is [22]:

$$r_{t} = \frac{I_{t}}{H_{t}} = \frac{\pi}{24} (c + d \cdot \cos \omega) \cdot \frac{\cos \omega - \cos \omega_{s}}{\sin \omega_{s} - \frac{2\pi \cdot \omega_{s}}{360} \cos \omega_{s}}$$
(11)

The coefficients c e d are given by [22]

$$c = 0.409 + 0.5016 \cdot \sin(\omega_s - 60)$$

$$d = 0.6609 - 0.4767 \cdot \sin(\omega_s - 60)$$
 (12)

5 Experimental Data

The data set used in this study were recorded in a radiometric station on the top of the meteoric and seismic observatory of Pennisi college in Acireale (Italy). The data sets had been gathered over the period from 1961 till 1966 and they comprise daily and hourly daily of wind speed, wind direction, and daily solar radiation. For the wind speed the data are related to three hourly range (8:00,14:00,19:00). The geographical data and the characteristic of the instrumentation on the meteorological station are reported in table 1. In table 2 the Monthly average daily solar radiation

In table 2 the Monthly average daily solar radiation recorded [MJ/m²day] are shown and the results are compared to the ones indicated in the Italian standard UNI 10349 for the nearest site that is

Catania (Latitude 37° 31' 0'' N Longitude 15° 4' E Altitude 7 m), that is 10 km far from Acireale. Also as far as the wind speed is concerned, the comparison has been made with CNR reference [26] (see table 3).

Table 1 Meteorological station: geographical dat	a
--	---

and instrumentation characteristics [11]					
Place	Acireale (Italy)				
Latitude	37° 36' 28''				
Longitude	E 15° 09' 45''				
Altitude s.l.m.	194 [m]				
Height anemometer	22 [m]				
Height anemometer	22 [m]				
Anemometer	S.I.A.P. VT 127				
Height Piranometer	18.5 [m]				
Piranometer	S.I.A.P. SO 20				

Table 2 Monthly average daily solar radiation \overline{H}_t recorded and related value reported in UNI

10349 for Catania								
	\overline{H}_t [MJ/m ² ·day]							
Month	1961	1962	1963	1964	1965	1966	Aver age	UNI 10349
Jan	6.13	7.65	7.01	5.38	5.67	6.93	6.46	9.00
Feb	11.89	9.35	9.32	9.02	9.81	10.4	9.96	11.90
Mar	14.38	11.35	13.26	13.34	13.31	12.1	13	16.00
Apr	18.12	18.12	15.22	17.84	17.26	14.9	16.9	20.70
May	21.96	22.05	17.48	19.80	21.70	17.90	20.2	25.50
Jun	22.00	21.96	21.25	20.32	22.73	21.1	21.6	28.20
Jul	23.05	23.74	20.15	20.77	21.93	21.1	21.80	28.20
Aug	21.32	21.88	20.23	16.89	18.40	19.5	19.70	25.40
Sep	16.81	17.33	14.97	16.30	13.97	15.30	15.8	19.50
Oct		10.19	10.11	12.00	8.29	9.91	10.10	13.70
Nov		8.14	8.40	8.88	7.66	7.14	8.04	10.00
Dec		6.97	5.33	6.32	5.94	6.55	6.22	8.00

The advantages of combining the use of wind and solar energy for renewable electricity supply systems depend on a seasonal anti-correlation in the time pattern of the wind and solar resources. Fig. 2 shows that solar and wind sources are complementary over that year. The summer provides good solar irradiance but poor wind conditions, whilst a relatively good wind source but poor solar radiation occurs in the winter.

Whereas the hourly measurements were available it could be possible to check also the daily cross correlation due to for example the presence of breezes.

By means of a mathematical function implemented in Matlab[®] library it is possible to compute the sample cross correlation function (XCF) between the two stochastic time series, the mean monthly values for wind speed and solar radiation (Fig.3), where Lags is a vector of periods (month) corresponding to XCF (-nLags,...,+nLags)

				\overline{v}	[m/s]		
Month	1961	1962	1963	1964	1965	1966	Aver age	CNR
Jan	3.86	3.55	4.08	3.70	4.06	5.13	4.06	3.42
Feb	4.30	4.08	4.66	3.76	4.54	3.62	4.16	3.75
Mar	2.94	4.10	4.03	4.23	3.37	3.55	3.70	3.45
Apr	2.81	3.32	2.72	3.37	3.13	3.20	3.09	3.50
May	3.11	2.25	3,07	2.73	3.23	3.03	2.90	2.86
Jun	2.67	2.92	2,85	2.64	2.92	2.64	2.77	2.88
Jul	2.89	3.04	2,69	2.74	3.05	2.65	2.84	2.77
Aug	2.60	3.17	2,84	2.82	2.77	2.81	2.83	2.58
Sep	2.59	2.86	2.93	2.89	2.72	2.26	2.71	2.63
Oct		3.33	3,25	4.48	3.37	2.96	3.48	2.88
Nov		4.80	3,43	3.88	4.42	4.55	4.22	3.07
Dec		5.19	4.59	5.25	4.07	4.38	4.70	3.19

Table 3 Monthly average daily solar radiation Wind speed $\overline{\nu}$ recorded and related value reported in Italian official data base (CNR) for Catania



Fig. 2 Monthly average daily solar radiation and wind speed values (1961-1966 years)





The Weibull pdf parameters assume different values depending on the nature of available data (Hourly, daily, monthly...). These results can be observed in tables 4 and 5 that show the Weibull pdf parameters α and β considering the following three hypothesis: 1) hourly daily recording data in the three hourly steps (8:00, 14:00, 19:00), β 8- β 14- β 19 and α 8- α 14- α 19; 2) mean daily recording data $\overline{\beta}$ and $\overline{\alpha}$ (obtained averaging respectively β 8, β 14, β 19 and α 8, α 14, α 19); 3) wind speed

recorded data treated as a whole (independently of time of the day), β^* and α^* .

In Figure 4 it is possible to observe the PDF that better fit the recorded wind speed data (Weibull) for January in the hourly range 1961-1966 at 8:00.



Fig. 4 PDF for the wind speed data and experimental data in January at 8:00 for the period 1961-1966

For the solar radiation we can see that the measured data are well fitted by a Hollands and Huget distribution. In Table 6 are reported the monthly values for *a* and *b* obtained through the recorded data for the solar radiation $[MJ/m^2day]$ in the period 1961-1966.

Table 6 Monthly values of Gamma distribution

parameters for k_t in the period 1961-66						
Month	a	b	С	Λ		
Jan	2.97	0.12	0.22	9.87		
Feb	5.12	0.09	0.19	8.21		
Mar	3.58	0.12	0.48	4.65		
Apr	5.37	0.09	0.43	4.45		
May	9.59	0.05	0.32	4.88		
Jun	23.06	0.02	0.26	5.28		
Jul	31.97	0.02	0.25	5.16		
Aug	19.97	0.03	0.09	8.09		
Sep	12.06	0.04	0.15	7.36		
Oct	2.72	0.15	0.42	6.04		
Nov	6.25	0.07	0.1	10.77		
Dec	4.07	0.1	0.04	15.21		

Where a and b are the Gamma parameters distribution that we have been described in (8, 9). By means of the CSR model the daily upper bounds for the clearness index can be determined and these values can be compared with the same that have been recorded in Acireale (Table 7).

Table 7 Comparison between the daily maximum
clearness index k_{tu} with recorded data and with
Clear Shar Madal (CSM)

Clear Sky Model (CSM)					
Month	k _{tu} (CSM)	k _{tu} (recorded in Acireale)			
Jan	0.728	0.560			
Feb	0.764	0.668			
Mar	0.796	0.798			
Apr	0.825	0.846			
May	0.844	0.873			
Jun	0.853	0.871			
Jul	0.853	0.894			
Aug	0.842	0.778			
Sep	0.820	0.766			
Oct	0.789	0.693			
Nov	0.752	0.610			
Dec	0.726	0.520			

It is worth observing that in CSR model k_{tu} is computed at midday for a typical day of the month. In Figure 5 it is possible to observe experimental data for July and the PDF (Gamma distribution) that better fits the k_t In this case the PDF has been calculated with the real k_{tu} recorded in Acireale.



Fig. 5 PDF for the the clearness index and experimental data in January for the period 1961-1966

6 Conclusion

The analysis of local weather data patterns shows that solar power and wind power can compensate well for one another, and can provide a good capacity factor for hybrid renewable energy applications. As the first step in developing HSWPS, weather data recorded in Acireale from Algarve, Portugal, June 11-13, 2008

1961 to 1966 were used to analyze both the availability of energy sources (solar radiation and wind speed) and their complementary characteristics The results show that detailed modeling for the energy conversion system and for energy sources should be undertaken before designing an HSWPS.

The numerical example presented illustrates the versatility of the approach developed especially in the perspective of the optimal unit sizing of an HSWPS including economical objectives (i.e. electric contract demand, expected values of annual total cost and annual energy consumption).

References:

- [1] Elhadidy MA, Shaahid SM, Parametric study of hybrid (wind+solar+diesel) power generating systems, *Renew Energy*,21(2),2000, pp.129–39.
- [2] Karaki SH, Chedid RB, Ramadan R, Probabilistic performance assessment of autonomous solar-wind energy conversion systems, IEEE *Trans Energy Convers* 14(3), 1999, pp. 766–72.
- [3]Borrowsy BS, Salameh ZM. Optimum photovoltaic array size for a hybrid wind/PV systems. *IEEE Trans Energy Conver*, 9(3), 1994, pp. 482–8.
- [4] Kruangpradit P, Tayati W. Hybrid renewable energy system development in Thailand. *Renewable Energy*, 8(1-4), 1996, pp. 514–7.
- [5] Kellogg WD, Nehrir MH, Venkataramana G, Gerez V. Generation unit sizing and cost analysis for stand alone wind, photovoltaic and hybrid wind/PV systems. *IEEE Trans Energy Convers* 13(1), 1998, pp. 70–5.
- [6] Chedid R, Rahman S. Unit sizing and control of hybrid wind-solar power system. *IEEE Trans Energy Conversion*, 112(1), 1997, pp. 79–86.
- [7] E. Dilettoso, S. Gagliano, N. Salerno G. Tina, Optimization of Hybrid Solar Wind Power Systems, OIPE 2006, *IJAEM* Issue 26/3-4, 2007.
- [8] Tina et al. Hybrid solar/wind power system probabilistic modelling for long-term performance assessment, *Solar Energy*, Vol.80, Issue 5, May 2006, pp. 578-588.
- [9] Hollands K. T. G. and Huget R. G., A probability density function for the clearness index, with applications. *Solar Energy*, 30, 1983, pp. 195-209.
- [10] F. Youcef Ettoumi, H. Sauvageot and A. E. H. Adane Statistical bivariate modelling of wind using first-order Markov chain and Weibull distribution, *Renewable Energy*, Vol. 28, Issue 11, September 2003, pp. 1787-1802

- [11] Bollettino meteorico mensile dell'osservatorio Meteorico Sismico, Collegio A. Pennini, Acireale (1961-1966) (in Italian)
- [12] Gipe P. Wind power for home and business: renewable energy for the 1990s and beyond (Chapter 3). Vermont: Chelsea Green Publishing Company, 1993.
- [13] Papoulis A., *Probability, Random Variables* and Stochastic Processes, McGraw Hill, 2001.
- [14] Liu B. Y. H. and R. C. Jordan, The Interrelationship and Characteristic Distribution of Direct, Diffuse and Total Solar Radiation, *Solar Energy*, Vol. 4 No. 3, issue 1, 1960.
- [15] Hollands K. T. G. and Huget R. G., A probability density function for the clearness index, with applications. *Solar Energy*, 30, 1983, pp. 195-209.
- [16] Bendt et al. The frequency distribution of daily insolation values, *Solar Energy*, Vol. 27, Issue 1, 1981, pp. 1-5.
- [17] Saunier et al. A monthly probability distribution function of daily global irradiation values appropriate for both tropical and temperate locations, *Solar Energy*, Vol. 38, Issue 3, 1987, pp. 169-177
- [18] Olseth J. A. and Skartveit A., A probability density function for daily insolation within the temperate storm belts, *Solar Energy*, Vol. 33, 1984, pp. 533-542.
- [19] Suehrcke, H., and McCormick, P. G., The Frequency Distribution of Instantaneous Insolation Values, *Solar Energy*, Vol.40, 1988, pp.413–422.
- [20] Jurado et al. Statistical distribution of the clearness index with radiation data integrated over five minute intervals, *Solar Energy*, Vol. 55, Issue 6, December 1995, pp. 469-473.
- [21] Kroposki et al. Photovoltaic module energy rating methodology development. *Photovoltaic Specialists Conference*, Conference Record of the Twenty Fifth IEEE, 13-17 May 1996.
- [22] Duffie J. A., Beckman W. A., Solar engineering of thermal processes, John Wiley & Sons, New York, 1991.
- [23] Kroposki et al. Photovoltaic module energy rating methodology development. *Photovoltaic Specialists Conference*, Conference Record of the Twenty Fifth IEEE, 13-17 May 1996.
- [24] Collares-Pereira M. and Rabl A., The average Distribution of Solar Radiation –Correlations between Diffuse and Hemispherical and between Daily and Hourly Insolation values, *Solar Energy*, Vol. 22, 175, 1979