Analysis of the distribution of measured and synthetic DNI databases and its effect on the expected production of a parabolic trough plant

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Abstract

The generation of a Typical Meteorological Year (TMY) is a common practice in solar energy projects. Therefore it is desirable that the TMY provides not only a good estimate of the solar resource in the long term, but also an adequate input for the estimation of the performance of the project during its lifetime. The main goal of this work is to analyze and compare the effect of using synthetic and measured time series on the statistical relationships between the annual Direct Normal Insolation (DNI) values and the corresponding electricity generation of a Solar Thermal Electricity (STE) plant. For this purpose we have used two DNI databases: (a) terrestrial database with thirteen years (2000 to 2012) of 5-second measurements for the location of Seville, Spain, and (b) synthetic database generated with the Meteonorm® V 6.1.0.23 software, by applying GHI-DNI conversion models to the measured monthly values of GHI for the same location. We have used the EOS code to estimate the electricity generation of a 50 MW parabolic trough plant with 8 equivalent hours of thermal energy storage (TES) capacity. The results show that the use of synthetic series introduces an additional uncertainty that has to be analyzed for each project, being in this study the differences between the measured and synthetic data around a 2-3% for the annual values and for the main statistical parameters.

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1. Introduction

An accurate estimation of the electricity generation of a Solar Thermal Electric (STE) plant during its lifetime requires not only a precise model of the plant, but also accurate input data and the knowledge of the associated uncertainty. The solar resource data, usually provided as a Typical Meteorological Year, is the most significant contributor to the uncertainty of the results. The better the solar resource information available, the more accurately a project´s performance can be estimated, reducing uncertainty and risk for investors [1]. There are not many databases of measured DNI data, perhaps because of the high acquisition and operation costs of pyrheliometers [2] precluded the generalization of their use until very recent times. Alternative sensors have recently come into the market, but there is concern about their uncertainty [3]. In many cases, the estimation of the solar resource is based on the use of accepted databases of data derived from satellite images and conversion models.

The main objective of this paper is to analyze and compare the effect of using two different sources of solar radiation data on the statistical relationships between the annual DNI values and the corresponding electricity generation of a STE plant. The first source is a database collected at the meteorological station of the Group of Thermodynamics and Renewable Energies (GTER) installed at the roof of the Seville School of Engineering. Although the station has been measuring continuously since 1984, we have used the data collected from 2000 to 2012, because they have been carefully quality-checked and completed following well documented procedures. The second, a *synthetic* database of DNI has been generated from global horizontal measured values using Meteonorm®.

2. Methodology

2.1. Solar radiation datasets

The *basic DNI datasets* used for this study consist of: a) thirteen years of measurements, from 2000 to 2012, from the GTER database; and b) The corresponding synthetic series, generated with the computer tool Meteonorm® V 6.1.0.23 using the monthly values of GHI of the GTER selected years as input. The hourly DNI datasets are generated from the monthly values of measured GHI. This input is converted into daily and hourly values applying stochastic and time dependent, autoregressive, Gaussian models and finally the hourly values of DNI are obtained using a relational model [4].

We have also elaborated a Typical Meteorological Year (TMY) from the GTER database using the TMY3 NREL methodology [5], modified in the sense that only DNI and GHI values are taken into account; a second TMY for the same location has been obtained directly from Meteonorm.

In addition, we have generated two *extended DNI datasets* consisting of a total of 145 annual series each, by concatenating the monthly DNI series from the registered thirteen-year GTER database and from the thirteen synthetic years to have a bigger sample to work with. Every annual series consists of twelve consecutive months from the thirteen years (GTER or synthetic) and, consequently, there are only months from two different calendar years, as a maximum, in each annual series.

2.2. Statistical analysis of the solar radiation datasets

We have analyzed the yearly values of both, registered and synthetic, datasets to find out whether there are significant differences –and, if so, quantify them- from a statistical point of view.

As a first step, we have compared the registered and synthetic 13-year datasets to find possible similarities and differences between them. The statistics in which we have focused have been the mean value and several percentiles (P10, P50 or P90), but we have also included other statistics like the standard deviation or the maximum and minimum values. We have done a similar analysis with the extended databases (145 years), calculating the same statistics and comparing them with the previous ones.

2.3. Electricity generation calculation using EOS software

EOS [6], a parabolic trough model that have been validated against actual data from two operating stations with TES system in Spain, is the result of the collaboration established in 2006 between AYESA and the Group of Thermodynamics and Renewable Energies of the University of Seville. In general terms, the main goal of the EOS simulator is to calculate the instantaneous power plant output by solving the mass and energy balances. EOS is based on the fragmentation of the plant model in interconnected modules that represent different functional parts of the plant, as shown in Figure 1.

Every simulation is preceded by a design definition phase, necessary to define plant systems features. Once the plant is completely defined, the simulations are carried out as a function of the meteorological data.

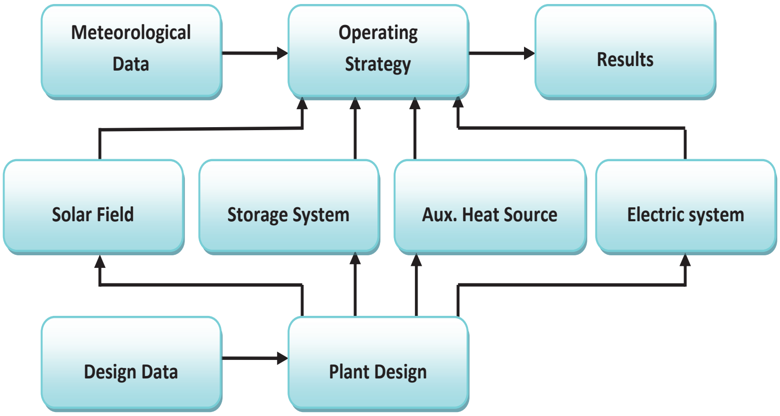

Fig. 1. EOS flow diagram.

The strategies implemented to simulate the operation of the TES system and the natural gas burner are aimed to:

- Operate at full load and with the highest possible continuity of the power block.
- Extend operation after sunset.
- Avoid energy dumps as a consequence of the use of natural gas.

Other considerations that affect the operation of these subsystems are:

- Storage System: During the night or in overcast periods, it extends the operation of the plant by operating alongside the natural gas burner.
- Natural Gas Burner System: Avoids interruptions in plant operation and supplements the turbine load ratio when it is not possible to achieve the rated power with energy from the solar field or the TES system. The natural gas burner is located in the oil side, in parallel to the solar field and it is designed to generate 15MW of electricity in nominal conditions. A maximum contribution level of 15% is permitted for the natural gas back-up.

The reference plant has a rated power of 50 MW with 8 equivalent hours TES. Table 1 shows some relevant characteristics of the reference plant.

Table 1. Main data of the reference plant [7], [8]

Parameter	Value	Unit	Parameter	Value	Unit
Turbine Gross Power	55	MW	Reflectance	0.93	-
Latitude	37.41	º	Interception factor	0.94	-
Longitude	-6.0	º	Transmittance	0.95	-
Mirror Aperture Area	5.731	m^2/m	Absorptance	0.95	-
Module Longitude	11.9	m	Cleanliness	0.96	-
Modules per SCA	12	MW	Thermal Fluid	VP-1	-
SCA per Loop	4	-	HTF Outlet Temperature	393	ºC
Number of Loops	160	-	Storage Capacity	8	hours

2.4. Statistical analysis of the electricity generation estimates

The annual electricity generation of the reference plant has been estimated, using EOS, for each of the registered and synthetic DNI annual series of the basic and extended DNI datasets described above. The relevant statistics of the results have been compared to those of the DNI series to analyze the correspondence between the statistics of annual DNI (both measured and synthetic) and electricity generation estimates.

3. Results

3.1. Statistical analysis of the solar radiation datasets

3.1.1 Basic DNI datasets (2000 – 2012)

Table 2 shows the annual DNI values from both, measured and synthetic datasets for the selected thirteen years (2000 to 2012), for the TMY developed by GTER and for the Meteonorm TMY for Seville. Most of the annual synthetic DNI values, but the last two, are lower than the corresponding to the measured years (the differences are positive when measured values are higher than the synthetic ones). The difference between the maximum value (2230.2 kWh/m^2 in 2012) and the minimum value (1939.6 kWh/m2 in 2002) for measured years is about a 13%, while for synthetic years this difference is slightly higher than 17% (with a maximum of 2277.9 in 2012 and a minimum of 1884.1 in 2010). Finally, the annual DNI value of the synthetic TMY is significantly lower (10.27 %) than the one developed from the GTER measurement database.

Table 2. DNI values from 2000 to 2012 for measured and synthetic annual series

Year	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)	Year	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)
2000	2132.3	2100.8	1.48	2007	2076.4	2029.5	2.26
2001	1987.8	1931.9	2.81	2008	2145.5	2059.4	4.01
2002	1939.6	1918.6	1.08	2009	2121.1	1987.9	6.28
2003	2031.7	1997.6	1.68	2010	1953.4	1884.1	3.55
2004	2069.9	1996.6	3.54	2011	2057.7	2117.1	-2.89
2005	2228.9	2184.0	2.01	2012	2230.2	2277.9	-2.14
2006	1968.7	1912.9	2.84	TMY	2072.6	1859.7	10.27

Some of the main statistical parameters for both datasets are summarized in Table 3. All percentiles are around a 1.5-3.5% lower for the synthetic years, with a difference of 3.49% for the P50, while these differences are somewhat lower, 2.18% and 1.88%, for P10 and P90 respectively. There is a greater dispersion of the synthetic values for these thirteen years, as it can be observed in the ranges shown on the right side of the table. Finally, it should be noted that the GTER TMY, the mean value and the P50 of the measured datasets are very close to each other.

Table 3. Main statistics parameters of the 13 years from measured and synthetic databases.

Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)	Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)
Mean	2072.5	2030.6	2.02	Maximum	2230.2	2277.9	-2.14
P10	1956	1913.9	2.18	Minimum	1939.6	1884.1	2.86
P25	1987.8	1931.9	2.81	Range (Max-Min)	290.6	393.8	-35.49
P50	2069.9	1997.6	3.49	Percentile Range (P90-P10)	255.8	256.8	-0.38
P75	2132.3	2100.8	1.48	IQ Range (P75-P25)	144.5	168.9	-16.87
P90	2212.2	2170.6	1.88	Standard Deviation	96.7	115.3	-19.22
(P25+P75)/2	2060.0	2016.3	2.12	Variation coefficient (%)	4.67	5.68	-1.01

3.1.2 Extended DNI datasets (145 years)

The values of the P90 and P10 for the extended datasets (Table 4) are quite similar (differences around 1%) to those obtained for the thirteen years (Table 3), but the dispersion increases for both datasets –compare the maximum and minimum values and the percentile ranges-, especially for the synthetic one. The histograms in Figure 2 highlight the similarities and differences between the frequency distributions of both datasets.

Table 4. Main statistics parameters of the 145 years from GTER and Meteonorm datasets

Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)	Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)
Mean	2065.3	2020.3	2.18	Maximum	2312.1	2446.5	-5.81
P10	1953.4	1910.4	2.20	Minimum	1914.5	1868.4	2.40
P25	1991.5	1937.8	2.70	Range (Max-Min)	397.6	578.0	-45.36
P50	2031.7	1980.3	2.53	Percentile Range (P90-P10)	287.3	272.8	5.02
P75	2132.3	2067.2	3.05	IQ Range (P75-P25)	140.7	129.5	7.99
P90	2240.7	2183.2	2.56	Standard Deviation	103.8	125.0	-20.35
(P25+P75)/2	2061.9	2002.5	2.88	Variation coefficient (%)	5.03	6.19	1.16

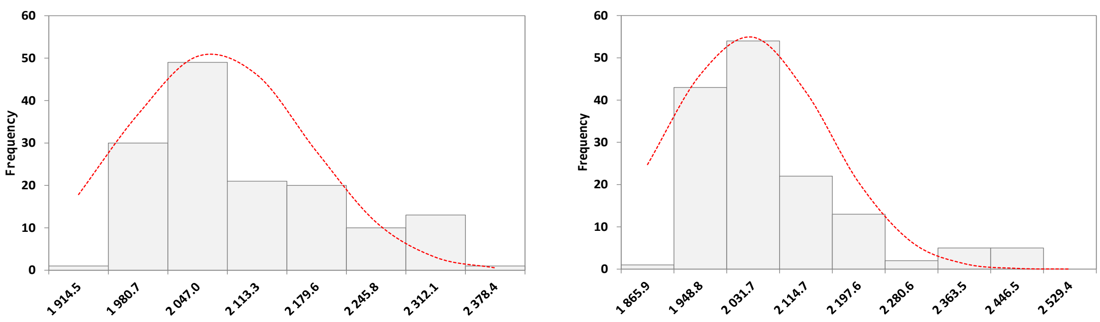

Fig. 2. (a) GTER DNI frequency histogram; (b) Meteonorm DNI frequency histogram.

3.2. Statistical analysis of the electricity generation estimates

We have used the EOS code, described above, to estimate the annual electricity generation of the reference plant for each of the annual series, both measured and synthetic, of the basic and extended datasets.

3.2.1 Electricity generation estimates form the basic DNI datasets (2000 -2012)

The differences between the gross electricity generation estimates for measured and synthetic annual series (Table 5) are slightly higher than those for the corresponding DNI series, this is, the differences are somewhat amplified. The production obtained for every measured year, but 2011 and 2012, is higher than the production obtained for the corresponding synthetic years, accordingly to the relation between the respective DNI values. Regarding the TMYs, the difference in terms of production (12.16%) is higher than the difference in DNI (10.27%).

Table 5. Gross expected electricity generation from 2000 to 2012

Year	Measured (GWh)	Synthetic (GWh)	Difference (%)	Year	Measured (GWh)	Synthetic (GWh)	Difference (%)
2000	220.713	217.242	1.57	2007	211.91	206.828	2.40
2001	206.072	201.209	2.36	2008	217.933	210.907	3.22
2002	198.11	194.186	1.98	2009	221.537	206.87	6.62
2003	212.233	209.262	1.40	2010	204.761	198.054	3.28
2004	211.957	203.017	4.22	2011	212.245	216.315	-1.92
2005	226.822	223.943	1.27	2012	227.042	234.672	-3.36
2006	201.523	192.459	4.50	TMY	212.941	187.037	12.16

The statistical analysis of the generation estimates for the basic datasets shows that the percentiles (Table 6) for the synthetic dataset are between 1.40 - 3.57 % lower than the percentiles for the measured dataset, in accordance with the percentiles for the DNI series, but the dispersion shows a significant increase for the estimates from synthetic DNI series. Once again, the mean value and P50 of the generation estimates from measured series percentile are very close to the result for the GTER TMY, indicating that the TMY is not only 'typical' from the point of view of the estimation of the solar resource in the long term, but also an adequate time series (input) for the estimation of the performance of a CSP plant in the long term.

Table 6. Main production statistics parameters of the 13 years from GTER and Meteonorm datasets

Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)	Parameter	Measured (kWh/m^2)	Synthetic (kWh/m^2)	Difference (%)
Mean	213.297	208.843	2.09	Maximum	227.042	234.672	-3.36
P10	202.171	194.960	3.57	Minimum	198.110	192.459	2.85
P25	206.072	201.209	2.36	Range (Max-Min)	28.932	42.213	-45.90
P50	212.233	206.87	2.53	Percentile Range (P90-P10)	23.594	27.643	-17.16
P75	220.713	216.315	1.99	IQ Range (P75-P25)	14.641	15.106	-3.18
P90	225.765	222.603	1.40	Standard Deviation	9.204	11.992	-30.08
(P25+P75)/2	213.393	208.762	2.17	Variation coefficient (%)	4.32	5.74	1.42

This is illustrated in the box and whiskers diagrams below (Figure 3) for both the annual DNI values and their corresponding annual gross electricity generation estimates for the basic datasets. The synthetic data exhibit higher dispersion and increased asymmetry with respect to the measured data.

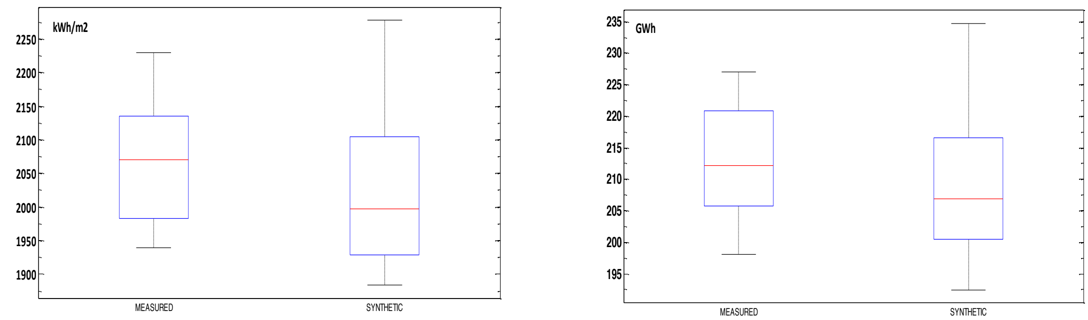

Fig. 3. (a) Radiation whisker and box diagrams; (b) Production whisker and box diagrams.

3.2.2 Electricity generation estimates form the extended DNI datasets (145 years)

Table 7 shows the main statistical parameters of the generation estimates for the extended datasets. The values of the different percentiles are, once again, nearly identical to those showed in Table 6 (differences smaller than 1% in most cases). The range increases slightly for both the estimates from measured and synthetic datasets. Figure 4 shows the respective frequency histograms.

Table 7. Main statistical parameters of the electricity generation estimates from the extended DNI datasets (measured and synthetic).

Parameter	Measured (GWh)	Synthetic (GWh)	Difference (%)	Parameter	Measured (GWh)	Synthetic (GWh)	Difference (%)
Mean	212.673	207.789	2.30	Maximum	233.175	249.760	-7.11
P10	201.234	195.749	2.75	Minimum	194.061	190.558	1.80
P25	205.977	199.568	3.11	Range (Max-Min)	39.114	59.202	-51.36
P50	211.631	205.835	2.74	Percentile Range (P90-P10)	25.838	27.637	-6.96
P75	219.005	212.137	3.14	IQ Range (P75-P25)	13.028	12.570	3.51
P90	227.132	223.386	1.65	Standard Deviation	9.063	12.106	-33.58
(P25+P75)/2	212.491	205.852	3.12	Variation coefficient (%)	3.44	1.43	-1.09

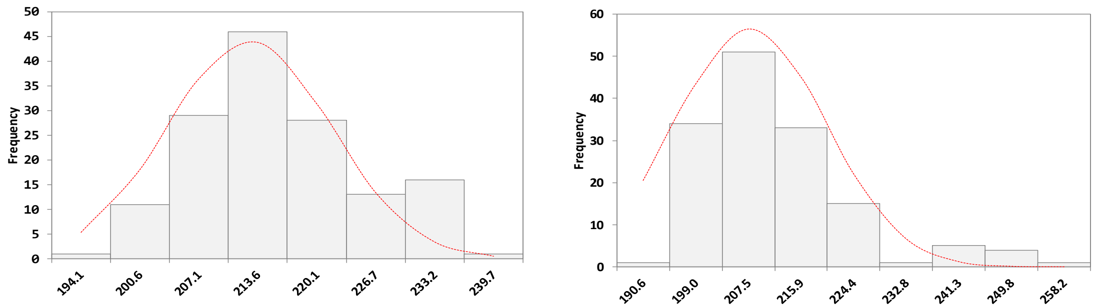

Fig. 4. Frequency histograms of the estimated annual electricity generation for the extended datasets: (a, left) from measured DNI series; (b, right) from synthetic DNI series.

Again, the values corresponding to the different percentiles of the electricity generation estimates from the extended datasets are very close, especially for the measured series, with differences below 1% to those corresponding to the basic datasets. We can observe some outliers in the DNI and electricity generation estimates from synthetic values in the whisker and box diagrams of Figure 5 , suggesting that the models used to generate the synthetic series may generate 'atypical' DNI series from correct, measured, monthly values of GHI. This has to be further explored to assess the performance of the distribution and conversion models used for this purpose.

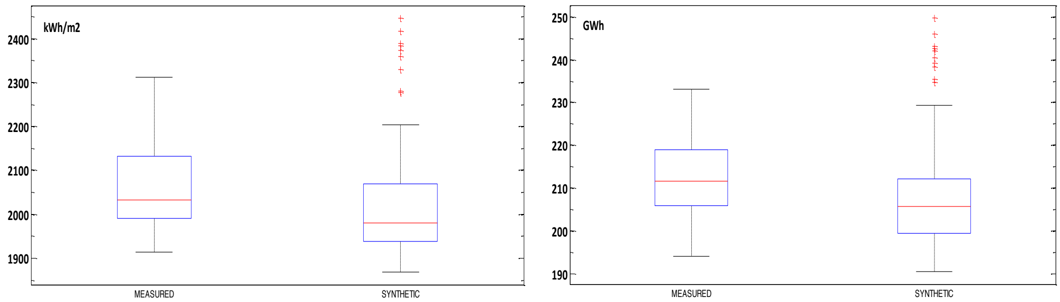

Fig. 5. Box and whisker diagrams, extended datasets: (a) annual DNI values; (b) Electricity generation estimates.

Figure 6 compares the annual DNI values (left) and electricity generation estimates (right) for the extended datasets. One interesting observation is that, both for measured and synthetic datasets, there are some years where an increase in DNI does not result in the corresponding increase of electricity generation. This emphasizes the need to assess the DNI not only in terms of annual values of DNI, but also in terms of its temporal distribution (monthly, daily, hourly).

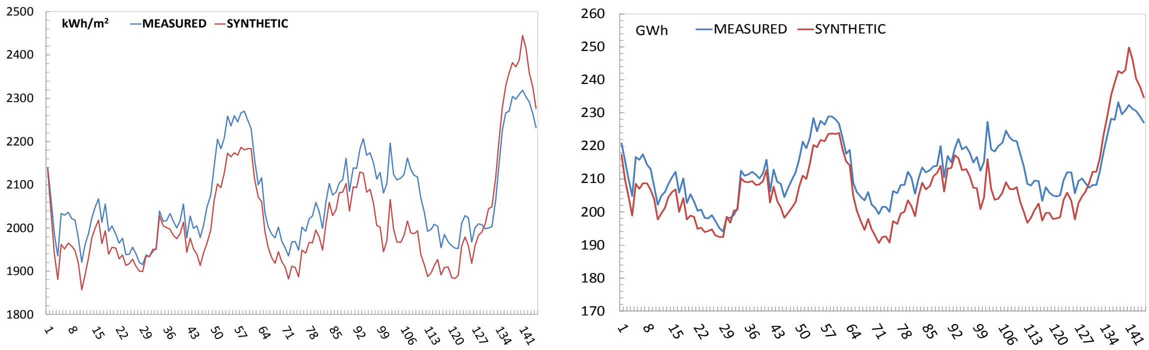

Fig. 6. Annual values for the extended dataset: (a, left) DNI; (b, right) Electricity generation estimates

4. Conclusions

The analysis of the basic (13 calendar years) and extended (145 annual series obtained by concatenating monthly time series of 10-minute values) datasets of DNI leads to the following conclusions:

1) The mean value, the P50 and the TMY of both the basic and the extended datasets of measured data are very close to each other, with negligible differences for the basic dataset (less than 0.02%) and somewhat larger for the extended dataset (less than 2%). This result suggests that 13 years of on-site measurements are sufficient to characterize the solar resource to a very good accuracy.
2) The annual value of the TMY provided by Meteonorm is 11% lower than the one obtained form the basic datasets.
3) The differences between the synthetic P50 and mean values with respect to the corresponding values of the measured series are -2% and -3.5%, respectively.

4) There are some outliers in the extended series of synthetic DNI values, indicating that in some cases the methodology used to generate the DNI series form the GHI may result in the generation of 'atypical' months. This fact has to be explored in deeper detail in future studies.
5) These results show that the use of conversion models to estimate the annual DNI from monthly values of measured GHI provides acceptable results for the assessment of the DNI, although the uncertainty of the results increase and should be always carefully checked.

The analysis of the electricity generation estimates datasets obtained by simulating the annual DNI series of the basic and extended datasets and the TMY's for a reference plant with the EOS code shows that:

1) There is a very good correspondence between the mean value and the different percentiles of the electricity generation estimates with those of the measured DNI datasets (both basic and extended). The same occurs for the TMY. This is, the statistical distribution of the DNI and electricity generation estimates are very similar.
2) The correspondence between the synthetic annual DNI values and the electricity generation estimates is also good, although both show a greater dispersion than the above-mentioned series (measured), including the presence of outliers in the distribution of the values form the extended datasets.
3) It has been observed that, for a few of the extended series, both measured and synthetic, an increase of the annual DNI value does not result in the corresponding increase of estimated electricity generation, suggesting that there is a significant effect of the intra-annual temporal distribution of the DNI.

References

[1] Vignola, F., Michalsky, J., Stoffel., T. Solar and infrared radiation measurements. Chapter 1. CRC Press 2012. ISBN: 1439851891 / 9781439851890
[2] Quaschning, G. Soiling of irradiation sensors and methods for soiling correction . Solar Energy, Volume 80, Issue 11, November 2006, Pages 1402-1409N.
[3] Eltbaakh, Y.A., Ruslan, M.H.,Alghoul, M.A., Othman, M.Y.,Sopian, K., Fadhel, M.I. Measurement of total and spectral solar irradiance: Overview of existing research. Renewable and Sustainable Energy Reviews Volume 15, Issue 3, April 2011, Pages 1403-1426.
[4] Meteonorm. Handbook: Part II: Theory, Version 7.0.20. February 2013.
[5] Wilcox, S., Marion, W. (2008). User's Manual for TMY3 Data Sets, National Renewable Energy Laboratory (NREL/TP-581-43156), Golden, Colorado, April 2008.
[6] Silva, M. A., Barea, J.M., Vélez, J.A., Barón, A., Gavilán, A., "EOS, a Computer Code for the Analysis of Parabolic Trough Solar Thermal Power Plants", 16th International SolarPACES Symposium on Solar Thermal Concentrating Technologies, Perpignan, 2010.
[7] Zarza, E. (2003). "Generación directa de vapor con colectores solares cilindro parabólicos". Ed. Ciemat. ISBN: 84-7834-472-1.
[8] Patnode, A. (2006). "Simulation and Performance Evaluation of Parabolic Trough Solar Power Plants". Thesis; University of Wisconsin-Madison.
[9] Barea, J.M, Moreno, S., Silva, M. A., "Analysis of the influence of the monthly distribution of direct normal radiation in the production of parabolic trough plants using EOS". 16th International SolarPACES Symposium on Solar Thermal Concentrating Technologies, Perpignan, 2010.