



## **Benchmarking of Five Typical Meteorological Year Datasets Dedicated to Concentrated-PV Systems**

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## Benchmarking of five typical meteorological year datasets dedicated to concentrated-PV systems

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### Abstract

This paper presents the benchmarking of different Typical Meteorological Year (TMY) datasets applied to a Concentrated-PV (CPV) system. Using 18-years of high quality meteorological and pyranometric ground measurements, five types of TMY datasets were generated using variable time period and following different methods: the standard Sandia method or only considering the Direct Normal Irradiation (DNI) or a more sophisticated DNI-based driver considering the characteristics of the CPV system. The results show that the Sandia method is not suitable for CPV systems. The TMY datasets obtained using dedicated drivers are more representative to derive TMY datasets from limited long-term meteorological dataset.

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**Keywords:** Typical Meteorological Year; CPV; Filkenstein-Schafer statistics; driver; DNI

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## 1. Introduction

The awareness of the behavior of some meteorological parameters is essential for the conception, analysis, development and optimization of solar energy conversion systems, either photovoltaic (PV), concentrated solar power (CSP) or concentrated photovoltaic (CPV) systems. Accurate assessment of meteorological data for long-term prediction is the basis of decision making of banks and investors. Standard numerical simulations of solar energy conversion systems such as System Advisor Model or PVsyst require one year of meteorological data. Methodologies for the generation of Typical Meteorological Years (TMY) datasets representatives of the long-term solar resource of a given site have therefore been developed.

A TMY is a customized weather dataset of one-year of meteorological data that aims at representing climatic conditions deemed to be typical over a long-term period.

The most common method for solar energy conversion systems was proposed in 1978 by the Sandia National Laboratory [1], slightly modified by several researchers and well detailed in 2008 by Wilcox and Marion [2]. The resulting TMY dataset is composed of meteorological data of 12 calendar months selected from individual years from long-term record and concatenated to form a complete year, keeping the consistency across the different meteorological variables. In order to select the typical months in the long-term dataset, the method performs a specific weighted combination of the global, diffuse horizontal and direct normal irradiances (GHI, DHI and DNI), air temperature (Tamb), wind speed (WS) and relative humidity (DWT). Monthly data blocks are selected based on the smallest Filkenstein-Schafer (FS) distance measuring the difference of two cumulative distribution functions (CDF).

In 2012, a new approach was proposed in the framework of the European project FP7 ENDORSE [3]. It introduced the concept of “driver” that is defined by the user as an explicit function of the pyranometric and meteorological relevant variables to improve the representativeness of the TMY datasets with respect the specific solar energy conversion system of interest [4]. Similarly to the previous method, it calls upon the FS distance.

The overarching aim of this study is to benchmark the classical Sandia method with innovative methods based on the driver concept, in the particular case of a given CPV system in a given site.

## 2. Reference data used and CPV system used

The selected site is the meteorological station Desert Rock, Nevada, in the United States, which belongs to the Surface Radiation (SURFRAD) network [5]. SURFRAD has adopted the measurement standards set by the Baseline Surface Radiation Network (BSRN).

The data exploited here originates from high quality measurements with a 1-min resolution over an 18-year period from 1998 to 2015. The following meteorological variables were recovered from the SURFRAD network: GHI, DHI, DNI, DWT, Tamb, WS and atmospheric pressure.

An algorithm is used to check the quality of the meteorological data. Gap filling is performed to provide complete records, by the means of interpolation and mathematical formulas that link the various components of irradiance (GHI, DHI, DNI...). The position of the sun is calculated using the fast and accurate SG2 algorithm [6].

Regarding the system of reference, the Concentrix™ CPV technology developed by SOITEC was chosen due to its maturity in terms of product and modeling at the time the present work started. This system requires the use of a two-axis tracking system. The Concentrix technology uses optimized III-V-based multi-junction solar cells. The type of concentration is a point focusing silicone-on-glass Fresnel lenses. The model of the system selected is the CX-S540, with 2500 Wp of nominal DC power. The CPV system proposed for the simulations has an installed power of 750 kWp.

### 3. Methodology

In this study, five types of TMY were generated with the following methods:

- TMY Sandia: meteorological year built according to the Sandia National Laboratory methodology. The following meteorological variables on the hourly basis are used with specific weighting factors: GHI, DNI, Tamb, WS and DWT.
- TMY simplified driver: in that case, the FS-based method is applied only using DNI as a simple driver for the construction of the typical meteorological year. Two simplified drivers have been created, one using hourly data and another using 1-min data.
- TMY filtered driver: in that case, the driver is defined as a function depending not only on the DNI but also on the meteorological and mechanical limitations and constraints of the CPV system. As before two filtered drivers have been considered, one using hourly data and another one using 1-min data.

The last two approaches are special cases of the driver methodology proposed by the ENDORSE project, with an increasing degree of complexity to refine the representativeness of the energy production of the targeted energy conversion system.

The CDF for each variable used, depending on the TMY generation method, is determined. In all five cases, the construction of the meteorological year is done by comparing the CDF of each block of data for a given month to the CDF of the concatenation of all blocks of data for this month over the long-term. The FS distance is used to select the 12 typical months of meteorological data. The most representative block of monthly data for each calendar month is thus selected.

Since, in practical, it is not always possible to obtain long-term data with 18 years of meteorological and pyranometric measurements, we have applied the five TMY approaches by varying the amount of years by windows between 5 to 18 consecutive years in order to keep real situations of inter-annual correlations. For example, in the case of a 5-year windows, there are 13 periods of data from [1998-2002] to [2011-2015].

Fig. 1 presents the schematic of the methodology used to compare the five TMY methods considering different numbers of years. The energy generation output of the CPV system over the long-term 18-years period is the quantity used for the comparison between the different TMY datasets. This energy output has been chosen since it is directly related to the profitability of the system and thus to its bankability and its associated decision making.

A simulation tool was then used with each TMY as input to calculate the yield of the CPV system. This tool is an internal tool developed and validated by SOLAÏS. In order to assess the relevance of the TMY datasets generated with each methodology and each historical period, two analyses are performed: one comparing the long-term average yield with the yield associated to the TMY datasets and another comparing the corresponding CDFs through the Kolmogorov-Smirnov test Integral parameter (KSI) [7]. This KSI test is used to compare two statistical samples, i.e. to measure the distance between two CDFs. It is possible to normalize this parameter to obtain a relative value of KSI (KSIr); a value greater than 100 % indicates a significant difference between the two CDFs with a confidence level of 95 %.

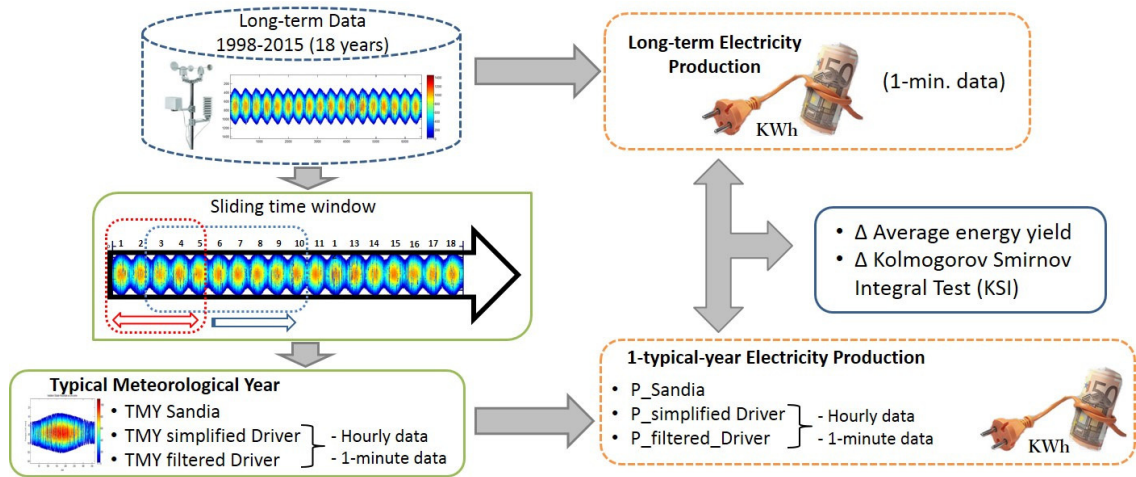


Fig. 1. Schematic of the methodology implemented to analyze the representativeness of the driver methodology using 18 years data [1998-2015].

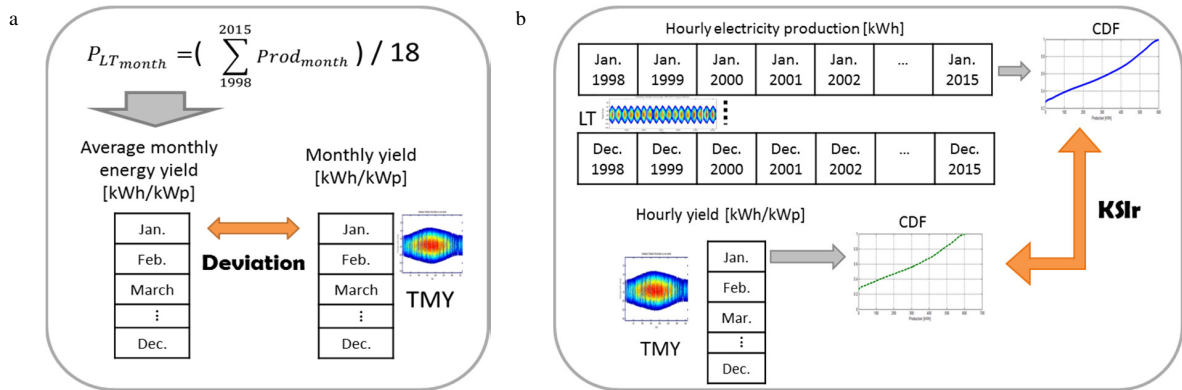


Fig. 2. (a) Monthly analysis comparing the average yields; (b) Monthly analysis applying the KSI test.

### 3.1. Performance indicators

Firstly, the monthly yield obtained from each meteorological year per historical periods is compared to the monthly yield of the reference long-term 18-year period. The maximum absolute values of monthly deviation per number of years of the historical period and per method of TMY generation corresponds to the worst-case for each method. Fig. 2a illustrates the procedure followed for this analysis. The same analysis is applied to the annual yield.

Secondly, the KSI test is used to compare the CDF of the long-term yield to the CDF of the yield resulting from the TMY datasets. For that purpose, hourly production data is used. Both monthly and annual data is analyzed. Fig. 2b presents the procedure followed for this analysis. The maximum values of KSIr per number of years of the historical period and per method of TMY generation corresponds to the worst-case for each method.

### 3.2. Driver

As mentioned previously, several drivers are used. The so-called “simplified driver” only uses the raw DNI as representative variable. The “filtered driver” integrates the limitations and constraints of the CPV system of reference by applying a coefficient factor to the DNI values to be used for the construction of the TMY.

Regarding the constraints due to spectral sensitivity, following [8, 9], a utilization factor (UF), dimensionless, has been applied to the DNI to properly consider the effective fraction of solar spectrum used for photocurrent generation for the solar cells of the studied system. The total UF depends on the air mass (AM), Tamb and DNI, as shown in equation (1):

$$UF = \alpha_{AM} * UF_{AM} + \alpha_{Tamb} * UF_{Tamb} + \alpha_{DNI} * UF_{DNI} \quad (1)$$

The alpha coefficients ( $\alpha_{AM}$ ,  $\alpha_{Tamb}$  and  $\alpha_{DNI}$ ) used for each parameter, for the model of reference, are respectively 0.35, 0.25 and 0.4. The profile of each individual UF are derived from research projects conducted by SOITEC and PVSyst [10, 11].

The constraints of the embedded tracking system are the azimuth and elevation angles limits, the wind stow issue and the focusing losses both due to excessive wind speed. Each constrain is translated into derating coefficients, respectively  $D_{angles}$  and  $D_{stowage}$ , both equal to 0 or 1, along with  $D_{focusing}$ , ranging between 0.989 and 1.

The tracker focusing loss is calculated using a post-processing file of the PVSyst output data, delivered by SOITEC. The tracker goes into its stow position when the 1-min wind speed is above a certain threshold. For the model selected in the study, the maximal tracking wind speed is 14 m/s with a hysteresis period of 10 min.

The DNI used by the simplified driver and the one used by the filtered driver is presented in equation (2) and equation (3) respectively:

$$DNI_{Simplified\ driver} = DNI \quad (2)$$

$$DNI_{Filtered\ driver} = DNI * [UF * D_{angles} * D_{stowage} * D_{focusing}] \quad (3)$$

## 4. Simulation based results

### 4.1. Monthly averages

The monthly average yield is calculated for the 18 years used as the long-term period of reference. The results are presented in Table 1. The monthly values are considered as the reference to be compared with the values obtained from the different TMY datasets used as inputs to the CPV yield simulations.

Fig. 3 shows the worst case per number of years of the historical period as explained in section 3.1. The results at the monthly basis obtained from the drivers, with hourly and 1-min data, are significantly better than those obtained with the Sandia method. The deviations obtained with the drivers, for the worst month, are reduced up to 77 % compared with those obtained with the Sandia method. The results for the simplified and filtered drivers are equivalent with stable results between 6- and 13-year data, and significant improvements from 14-year data, with a deviation below 6.7 %.

Table 1. Average yield for the 18-year period [1998-2015] of the reference CPV system in Desert Rock.

	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	YEAR
Yield [kWh/kWp]	129	126	171	186	216	233	206	207	195	168	140	117	2093

#### 4.2. Annual averages

The average annual yield for the 18-year period of Desert Rock is 2093 kWh/kWp, as presented in Table 1, with a standard deviation of inter-annual variability equal to 2.8 %. Fig. 4 illustrates the absolute values of maximum annual deviations per number of years of the historical period obtained for each TMY methodology.

The maximum annual deviations obtained with the Sandia method and with the drivers have no consistent pattern. Nevertheless, the simplified and filtered drivers exhibit better results than the Sandia method. From 9-year data, the results obtained with the simplified and filtered drivers are always under 1.7 %, whereas with the Sandia method deviation up to 3.6 % may be observed with 14-year data.

#### 4.3. Monthly KSI test

The KSI test is implemented for hourly data of electricity generation. Fig. 5 presents the maximum monthly KSIr for each TMY generation methodology, for the different number of years of the historical period. The maximum monthly KSIr over the 18 years present the same behavior than the results obtained with the analysis of monthly averages. The maximum monthly deviations obtained with the Sandia method approach or exceed twice the deviations obtained with the drivers. The results obtained with the simplified and filtered drivers are similar and always better than the Sandia method.

#### 4.4. Annual KSI test

Each block of years obtained with each method were analyzed as previously done for the monthly KSI test. Fig. 6 presents the worst annual KSIr obtained for each window length for each TMY generation methodology. Even if the annual results obtained with the Sandia are close to the long-term behavior, the performances obtained with the drivers are better than those obtained with the Sandia method. The simplified and filtered drivers provide KSIr values systematically less than 45 % from 8-year data. This performance can only be reached with 13- and 17-year data with the Sandia method.

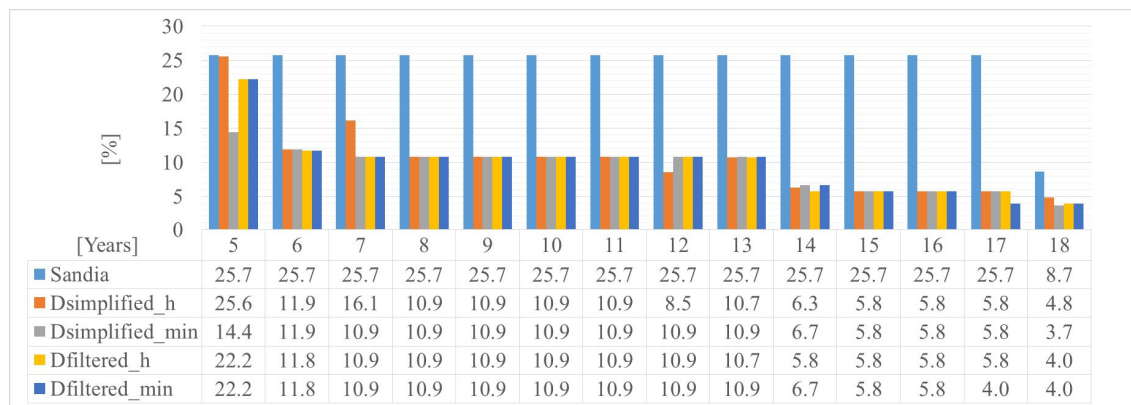


Fig. 3. Maximum deviation of monthly yields per time window compared to the long-term data [1998-2015], for each TMY generation methodology.



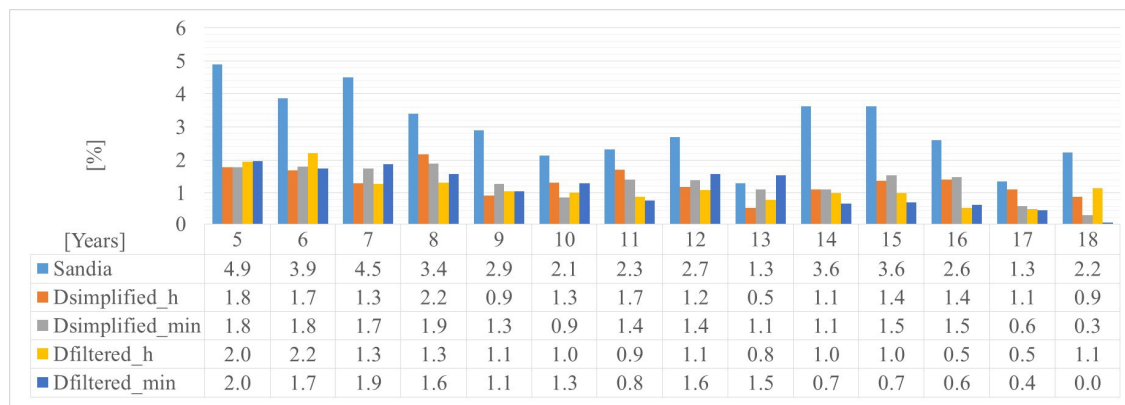


Fig. 4. Maximum deviation of annual yields per time window to the long-term data [1998-2015], for each TMY generation methodology.

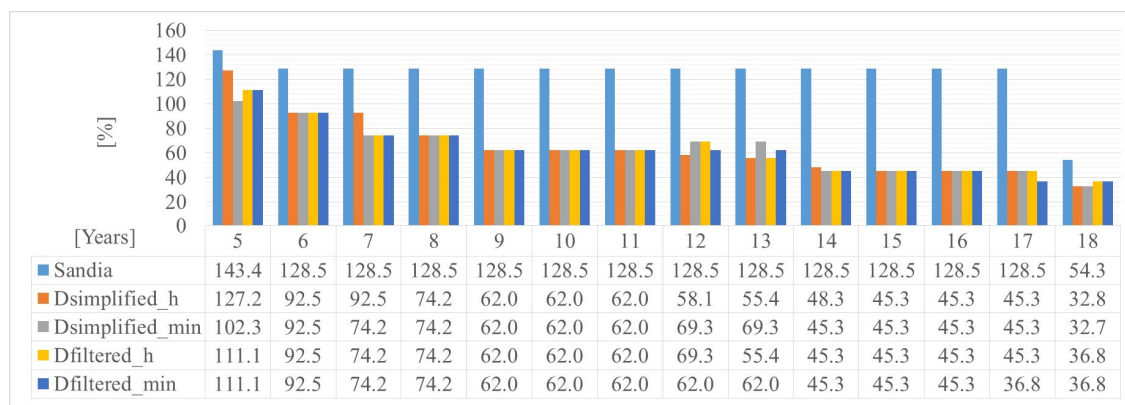


Fig. 5. Maximum monthly KSIR per time window for each TMY generation methodology, resulting from the comparison of the electrical production per TMY with the long-term yield [1998-2015].

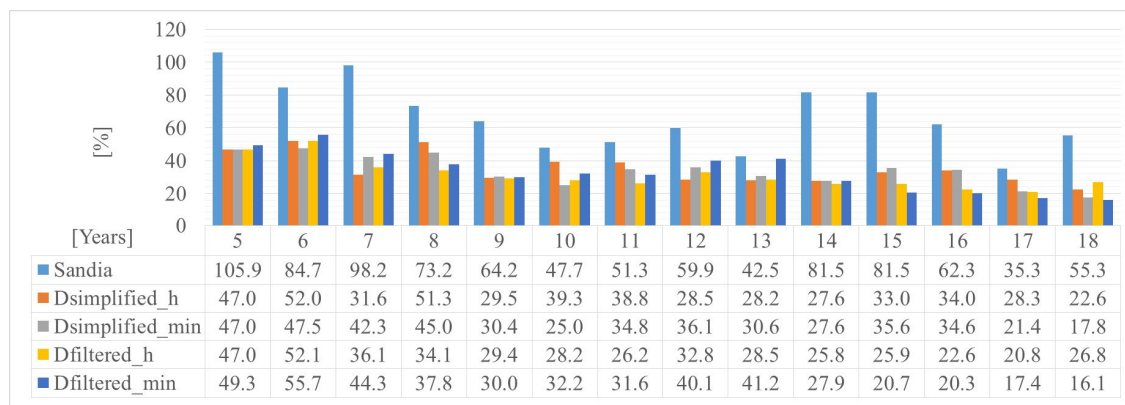


Fig. 6. Maximum annual KSIR per windows length for each TMY generation methodology, resulting from the comparison of the electrical production per TMY with the long-term yield [1998-2015].



## 5. Conclusions and perspectives

The results obtained with the analysis at the monthly basis, compared with the average long-term yield so as with the application of the KSI test, indicate that the TMY datasets generated with the simplified and filtered drivers are more representative to the long-term energy production than those generated with the Sandia method for CPV systems at the site of study.

The lack of representativeness at the monthly basis observed for the Sandia method seems to balance over the year. Thus, the annual results are close to the long-term reference behavior. However, the performances obtained with the simplified and filtered drivers are better than those obtained with the Sandia method.

Regarding the average yield, an annual deviation less than 1.7 % was found with the simplified and filtered drivers from 9-year data, whereas the Sandia method yields greater deviations. The TMY dataset obtained using dedicated drivers are thus more representative to derive TMY from limited long-term meteorological dataset.

The added value of the non-linear behavior brought by the filtered driver is not significant compared to the simplified driver in this particular hypothetical study case. In addition, the difference between the TMY datasets obtained using dedicated drivers with 1-min data and hourly data are not significant. The simplified driver using hourly data seems a good compromise to obtain a typical meteorological year, due to its simplicity and good performance of the resulting TMY.

The present conclusions are applicable to Desert Rock site, for which the historical time series of wind speed does not have a significant impact on the tracking system performance. Therefore, it would be interesting to perform the same study in more constraining conditions comprising wind historic and tracker stowage algorithm in order to confirm the added value of the filtered drivers with 1-min data.

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