CHARACTERISTIC METEOROLOGICAL YEARS FROM GROUND AND SATTELITE DATA

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Abstract

Planning and due diligence of concentrating solar power plants needs high quality solar radiation data. The requirements are very different for the different planning phases. Economic calculations need data about the long term average expected yield from the available solar resource. Engineering of the power plant needs even more detailed site specific data covering all different states of operation and takes advantage also of time resolutions better than 60 min. These data should match the frequency distribution of the solar radiation at the specific site very well and should be of high temporal resolution to model transient states of the power plant. Two different methods which try to derive a characteristic meteorological year based on only limited data availability are described in this paper, the 365 day moving average method and the artificial average year. The latter implies manual modification of measurement data and may be subjective. Three independent operators have been asked to produce such a data set. The resulting data sets are applied for simulation of a parabolic trough solar thermal plant and the resulting electricity yields from all data sets are compared.

Keywords: solar resources, direct normal irradiation, simulation of CSP energy yields.

1. Introduction

Planning and due diligence of concentrating solar power plants needs high quality solar radiation data. The requirements are very different for the different planning phases. Economic calculations need data about the long term average expected yield from the available solar resource. When selling electricity to the market also hourly energy yields are relevant for estimating future revenues. Engineering of the power plant needs even more detailed site specific data covering all different states of operation and takes advantage also of time resolutions better than 60 min. These data should match the frequency distribution of the solar radiation at the specific site very well and should be of high temporal resolution to model transient states of the power plant.

For basic yield analysis and layout engineers like to work with so-called typical meteorological years (TMY), which shall represent the typical site-specific weather situation throughout one year. Typically TMYs have hourly resolution. They shall approach the long-term average conditions, but actual averaging of values should be avoided to prevent disturbance of distribution functions. Further, for the proper simulation and engineering of a CSP plant also auxiliary meteorological parameters like wind, air temperature and humidity are available and consistent with the solar irradiance data.

Ideally there would be qualified measurements at or very close to the site over decades. Then a high quality TMY according to [1] should be produced best from the 30 most recent years. However, almost nowhere on Earth such a long historic meteorological data set exists incorporating also direct normal irradiance (DNI), which for CSP is by far the most important parameter. Typically meteorological stations set up for qualification of CSP projects only measure over few years before construction of the plant begins.

Therefore alternate methods are required, which also make use of shorter measurement periods. Chapter 2 initiates, which type of data are typically available for CSP project development. Chapter 3 describes a method for deriving characteristic meteorological years for CSP, which usually could be applied when around 2 years of measurements are available. Chapter 4 describes a method, which can be applied as soon as a single year of measurements is available.

2. Available data

Usually available meteorological data for a site do not fulfill the requirements stated above. Satellite derived data can be analyzed in retrospect to cover long time series of solar radiation. Most data from early operational meteorological satellites date back to 1983. But the temporal resolution is typically hourly, which is not sufficient for modelling of transient processes, which are relevant for detailed analysis of energy yields and engineering. Satellite data also do not include the other meteorological parameters. They could be inferred from meteorological reanalysis data, but this has a much coarser spatial and temporal resolution.

A site specific ground measurement station can deliver high resolution data but the data is only available since the start of the measurement. Often the weather situation in the limited observation period differs significantly from the long term climatological average due to natural year to year variations. A single year of measurements may be at the margins of the distribution. According to [2, 3] in the worst case deviations of 15 % or more from the long-term value are possible only due to natural weather variability, without assuming inaccuracies from instruments or methodological shortcomings.

If the measurements have gaps or are flagged due to errors identified in the routine quality control, these must be filled first. For this the following gap filling methods shall be taken:

1. Gaps of up to 3 hours in all meteorological parameters should be interpolated for each parameter from the neighboring data.
2. Gaps up to 4 days should be filled by copying the missing hours from neighboring days including the auxiliary meteorological data.
3. Gaps with more than 4 days should be filled by copying the data of the same day of year from another year. A value of 4 days is taken as it is typical that in most weather regimes persistence is relatively high for such time periods. For more than 5 or more days the influence of variable sun elevation gets significant. Therefore it is assumed that data with identical sun geometry from other years likely lead to more realistic results.

If meteorological data from alternate stations within 5 km distance are available these shall be preferred for gap filling. Alternatively also DNI data from satellite may be taken. Each gap filling event and type has to be clearly indicated in the new data set by a flag. Leap days shall be excluded from the time-series.

3. Selecting a characteristic meteorological year through a moving 365 day average

The 365 day moving-average-method for derivation of CSP-specific characteristic meteorological years starts with deriving a long-term average DNI based on satellite and measurements. For this procedure the method of [4] may be applied to retrieve a best estimate with high reliability.

Then the daily average is calculated for each day for which continuous ground-based measurements are available. These daily average values now are convoluted with a moving average filter. A box-car filter with 365 days length is applied. Suitable periods, which shall represent characteristic meteorological years are then identified by those points, where the moving average equals the long-term average. To qualify for a matching time-window the average over the past 365 days shall meet the long-term average better than 0.5%.

If several time-periods are suitable the pattern of the monthly averages and the DNI distribution function should be inter-compared. The period with an annual distribution better matching the average distribution then shall be selected for yield assessments.

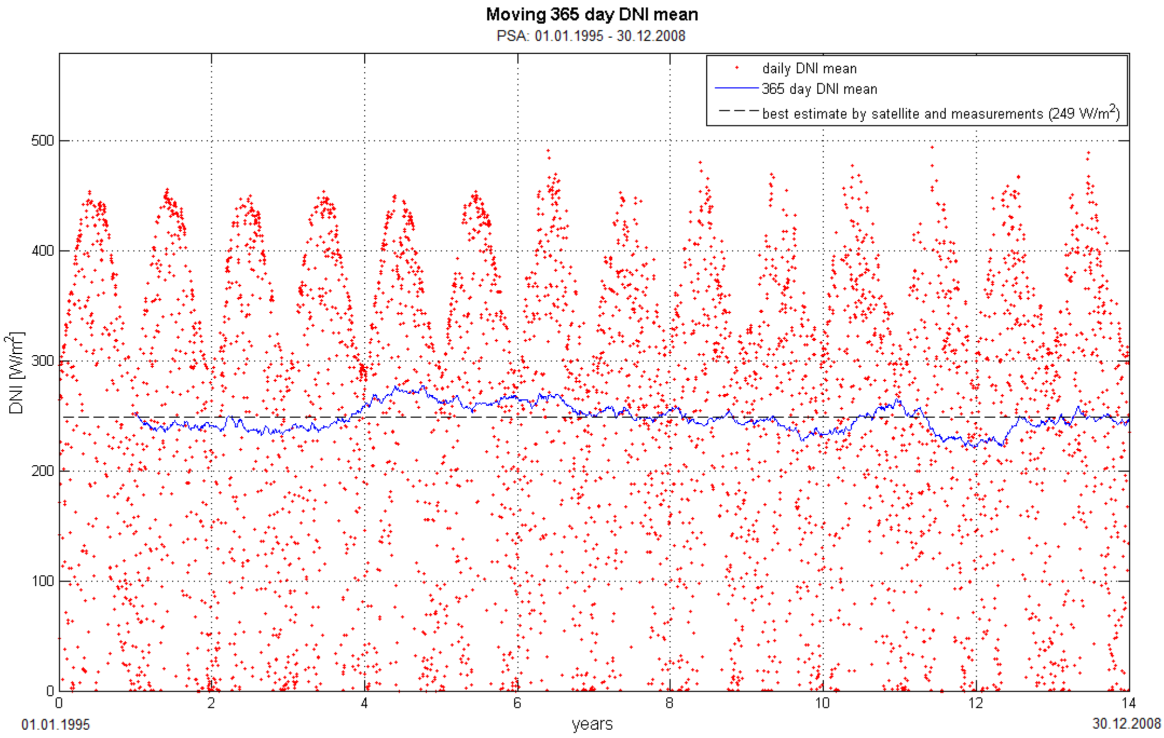


Figure 1: DNI time-series for a site in Spain (Plataforma Solar Almería) showing daily averages over a period of more 14 years. The horizontal line indicates the best-estimate for the long-term average of 249 W/m (equivalent to an annual sum of 2177 kWh/m). Crossings of the 365 day-moving average line indicate the end of periods, which match exactly the long-term annual sum. It is recommended to take such periods to extract characteristic meteorological data sets.

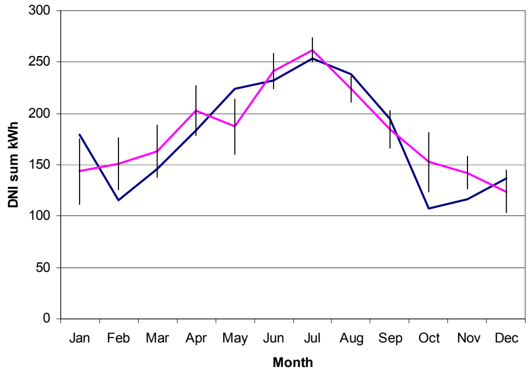
4. Concatenating a characteristic meteorological year from short-term measurements

The definition of an artificial average year tries to overcome these limitations. It is a combination of satellite data characterizing the long term situation and site-specific ground measurements, which give higher time resolution and provide the auxiliary meteorological data, which are required for proper simulation of solar thermal power plants.

The artificial average year takes at least one year of ground measurements and puts them into the context of a long term time series of solar radiation data from satellite images. It therefore tries to give something similar as a typical meteorological year as it gives values for a complete year which match the long term monthly averages of the satellite data set. It is artificial as it is not a direct but a manually modified measured time series. All the data in the artificial average year are taken from the ground measurement time series. It therefore contains all the auxiliary data the measurement station recorded.

The construction requires a long term time series from the satellite (at least 10 years are recommended) and a good quality ground measurement. To reach sufficient quality the measurements should not contain too many gaps. Less than 3-4 days missing per month are acceptable, but not more than 2-3 days in a row.

The construction of the artificial average year is based on the comparison of the average monthly sums of the satellite and the monthly sums of the ground measurements. First the average monthly sums and their standard deviation over the 10 years is calculated from the satellite data. This shows the natural variability of the values at the specific site.



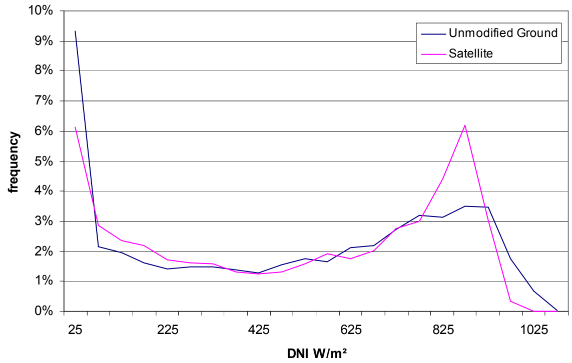


Figure 2: Monthly average of satellite and ground data with standard deviation of the monthly averages in the satellite data (top left. left figure pink curve with black bars), and the monthly averages from one year of measurements (2003, blue curve). The right figure shows the frequency distribution of the satellite and ground data.

Figure 2 shows a sample of the monthly sums of satellite and ground measurements. The black bars indicate the standard deviation of the monthly sums in the 10 year satellite data set.

There are two main reasons for the deviation of the curves. The first one is missing data in the ground measurements. This leads to a reduced total value of the ground data. The second reason for deviation is changing weather in each year. There may be more or less sunny days in a specific month each year.

The construction of the artificial year is done in two steps, first gap filling and second exchange of days to fit the monthly average.

4.1 General modification rules

A number of rules should be obeyed in modifying the data:

1. Each change has to be documented.
2. Only complete days are modified or copied. This avoids too many discontinuities in the data. Steps in auxiliary data appear only at midnight local time, when effect on CSP plants is usually neglectable.
3. All data fields of a day are copied. This keeps consistency of radiation components, temperature, pressure, etc.
4. The temporal distance of copied data should be kept within 5 days (e.g. data of July 10th, should only be copied to any data between July 5th and 15th.). This keeps errors due to variable sun paths in the solar data small.
5. Different weather patterns within a month should be conserved. (e.g. not all days with lower solar radiation should be eliminated, e.g. if there are five cloudy days, they can be reduced to two or three).
6. If the irradiation sum still is not met, solar data may be scaled by a constant factor. DNI values should not exceed 1100 W/m .

4.2 Step 1: Gap filling

The first step is the filling of gaps in the data by copied data from neighbouring days according to the rules above. Data with different daily patterns should be used if the data around the gap shows corresponding variability. If partial days are missing they should be copied with complete days.

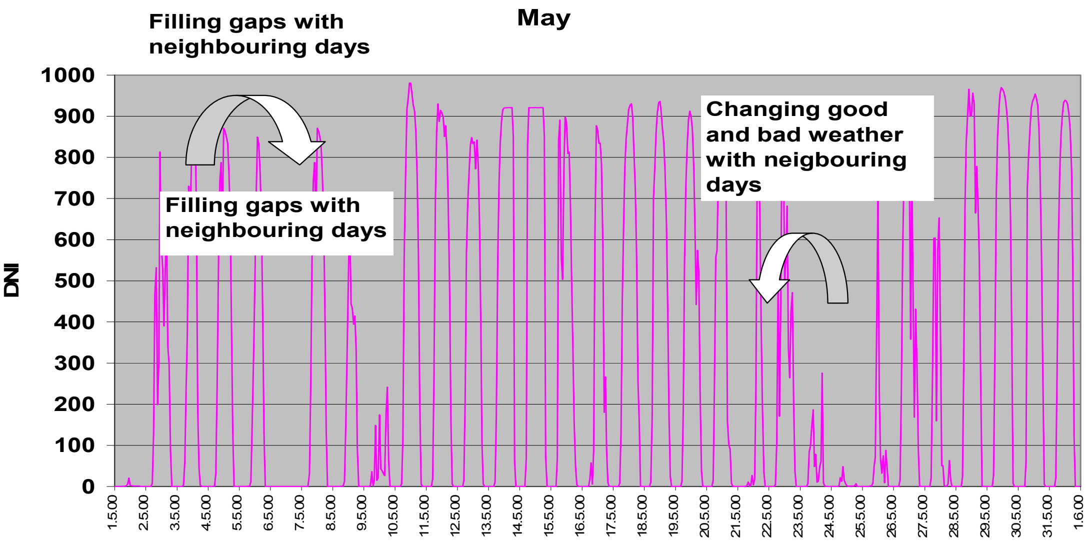


Figure 3: Modifications to the ground data, gaps are filled by neighbouring days, sunny and cloudy days are exchanged to modify the monthly average.

4.3 Step 2: Exchange of days to modify monthly sums.

The construction of new data is done by "changing the weather". This is done by copying neighboring days (see figure 2). If the measured month is below the average, days with cloudy weather are replaced by sunny days. If a month is above the average, cloudy days are copied over sunny days. The modifications are done until the monthly sum is at least within the standard deviation of satellite data for this month. A difference of less then 5 % is targeted.

The result is a complete data set with an annual sum of radiation corresponding to the long term mean, but with high time resolution. This data set can be used as input to transient system performance modelling. As all the data is measured, solar radiation and auxiliary parameters as temperature, wind speeds, humidity and pressure are consistent, if they are recorded together with the radiation data set.

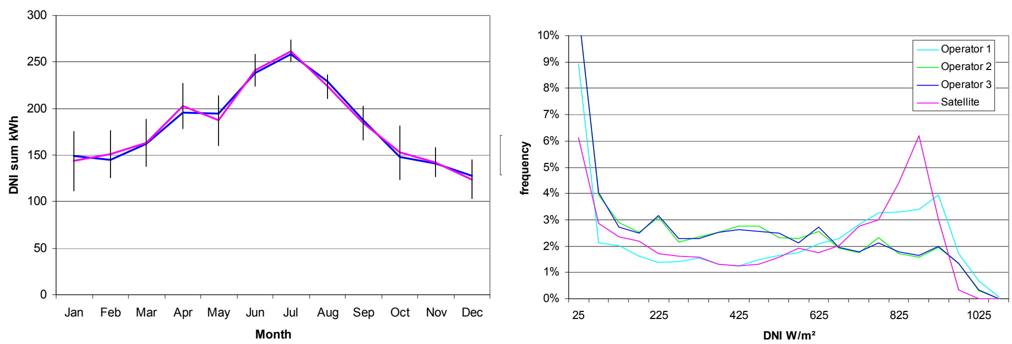


Figure 4: Monthly average of satellite and modified ground data (left) and associated frequency distributions by three different operators constructing the artificial average year.

5. Results

To check the reproducibility of the concatenating method a blind test was executed with three persons. Everyone got the same unmodified set of measurement data and the satellite-derived results with error bars indicating the goal and the monthly and annual sums as goals, which should be matched. Every test person further received the set of rules for modifying the original ground-based measurements as described in this paper. The results can be seen in figure 4. First observation is that it takes an untrained person around 4 hours to prepare one data set.

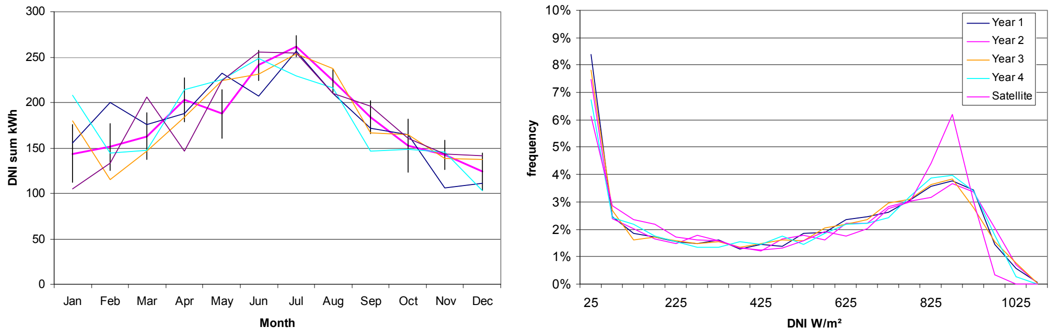


Figure 5: Monthly averages (left) and frequency distribution (right) of the 365d moving average method.

parameters	units	samples op. 1	samples op. 2	samples op. 3	arith-metic mean	relative std.dev.	relative min. dev.	relative max. dev.
DNI annual sum	[kWh/m²]	2178	2177	2176	**2177**	0,1%	-0,1%	0,1%
DNI annual averaqe	[W/m²]	249	249	248	**249**	0,1%	-0,1%	0,1%
DNI max	[W/m²]	1073	1073	1073	**1073**	0,0%	0,0%	0,0%
DNI standard deviation	[W/m²]	346	343	344	**345**			
net electricity yield layout 1	[GWh]	132	130	130	**130**	0,8%	-0,6%	0,9%
net electricity yield layout 2	[GWh]	191	191	191	**191**	0,2%	-0,2%	0,2%
net electricity yield layout 3	[GWh]	210	210	209	**210**	0,3%	-0,3%	0,2%

Table 1: Summary results for the concatenating method produced by 3 independent operators. .

All candidates managed to approach the long-term average almost exactly (see table 1). As a rough indicator for temporal variability the standard deviation is calculated over all time-series. This shows no noticeable differences for all operators.

To analyze the effect of the somehow subjective concatenating method on energy yields all 3 modified data sets are taken as input for simulating energy yields of parabolic trough plants. Results in form of net electricity yields are given in table 1. To check the influence of plant layout three different 50 MW plants are assessed:

1. 100 loops, 2 h storage,
2. 134 loops, 7.3 h storage,
3. 154 loops, 7.3 h storage.

In all layouts SKAL-ET loops with Schott PTR70 absorber tubes and outlet temperatures of 395°C with 15% co-firing are assumed. Despite the very different distribution functions the electricity yield are almost the same for all operators.

The same exercise has also been done with the 365-day-moving average method. Table 2 shows the simulation results.

parameters	units	year 1	year 2	Year 3	year 4	**arith. mean**	**std. dev.**	**min. dev.**	**max. dev;**
start date		2001-09-24	2002-09-12	2004-06-30	2005-05-07				
end date		2002-09-24	2003-09-12	2005-06-30	2006-05-07				
DNI annual sum	[kWh/m²]	2177	2177	2177	2177	**2177**	0,0%	0,0%	0,0%
DNI annual average	[W/m²]	249	249	249	249	**249**	0,0%	0,0%	0,0%
DNI max	[W/m²]	1084	1073	1065	1046	**1067**	1,5%	-2,0%	1,6%
DNI standard deviation	[W/m²]	343	345	343	344	**344**			
net electricity yield layout 1	[GWh]	126	121	123	124	**123**	1,5%	-1,8%	1,8%
net electricity yield layout 2	[GWh]	181	178	179	181	**180**	0,8%	-1,0%	0,8%
net electricity yield layout 3	[GWh]	198	194	195	196	**196**	0,9%	-1,0%	1,2%

Table 2: Summary results for the 365-day-moving average method. The annual sums or averages must match per definition. The standard deviation of the hourly DNI values indicates very similar variability among the samples.

Here the deviation between the different selected years is larger than in the concatenating method. The may due to the very different distribution of the DNI over the year (see also figure 5 left). Second the energy yields are lower than from the concatenating method. Table 3 compares the two methods. The differences in DNI characteristics are neglectable but data from both methods show significant deviation in the energy yields.

	Methodolgy	method 1	method 2	arithm.	rel. deviation
parameters	**Units**	365 d	concatenating	mean	(m1 - m2)/av
DNI annual sum	[kWh/m²]	2177	2177	2177	0,0%
DNI annual average	[W/m²]	249	249	249	0,0%
DNI max	[W/m²]	1067	1073	1070	-0,5%
DNI standard deviation	[W/m²]	344	345	344	-0,3%
net electricity yield layout 1	[GWh]	123,4	130,5	126,9	-5,6%
net electricity yield layout 2	[GWh]	179,7	191,0	185,3	-6,1%
net electricity yield layout 3	[GWh]	195,6	209,8	202,7	-7,0%

Table 3: Inter-comparison of the two methods.

6. Conclusions & Outlook

Two methods for creating characteristic meteorological years for CSP based on site-specific measurements are introduced. The 365 day-moving-average-method has the advantage of requiring less man power for creation of characteristic meteorological years. If the measurement period covers at least 18 months and falls into a period with average conditions, chances are good, that at least one continuous 365 day long period can be found, which meets the long-term average. If this method is successful the selected time-period has the advantage of being continuous and consisting mostly of real data. Electricity yield results derived by this method can easily be matched with market prices. However individual month of the characteristic meteorological year derived by this method can significantly deviate from the long-term average. This can lead to wrong assumptions for the distribution of energy yields across the year. Due to changing sun height, the effective DNI may stronger deviate stronger from the long-term situation. This can – as the 4 sample years show - lead to underestimations of electricity yields.

In case the 365 day-moving-average-method fails, which the concatenating-method is an alternative to derive site-specific characteristic meteorological time-series for CSP assessments. The samples provided by 3 independent operators indicate, that the long-term average can be easily matched. However the method leaves room for subjective decisions, which may have significant impact on the energy output, when used for yield prognosis of CSP plants. The sample in this paper shows good agreement between 3 independent operators.

The maximum observed deviation in terms of energy yields is approximately 1% for the concatenating method and almost 2% for the moving average method relative to the samples created with the same method. The inter-comparison of methods reveals that the distribution of DNI across the year is rather sensitive. Here the moving average method on average leads to 6% lower energy yields than the concatenating method based on the same annual DNI sum. This represents another source of uncertainty in the yield prediction process, which so far usually is not accounted for. Unfortunately the sample size of 3 concatenated years and 4 moving average years still is too small to derive sound conclusions. More sample studies should be undertaken to analyze this uncertainty more thoroughly.

Both methods show promising approaches to derive characteristic meteorological years where only limited data is available unsuitable for the construction of typical meteorological years (TMY). Effects of varying annual and frequency distribution need further investigation.

Acknowledgements

Work for this paper was co-funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) within the research project SESK (Standardisierung der Ertragsprognose für Solarthermische Kraftwerke – standardization of yield prognosis for solar thermal power plants; grants 0325084A, 0325084B). We thank Norbert Geuder for preparing the ground-based meteorological measurements data. Responsibility for the contents keep the authors.

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