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Calculation of CSP yields with probabilistic meteorological data sets: a case study in Brazil

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Abstract

Current practice for yield prognosis of solar thermal power plants simulates the average annual performance by using a typical meteorological year data set (TMY). This represents the long-term average or a 50 % probability of exceedance (P50) of direct normal irradiance (DNI) at the project's location. For more conservative risk evaluation it is common practice to calculate the 90 % yield exceedance level (P90) by estimating the uncertainty of the long-term DNI which depends on data set uncertainty and inter-annual variability. A simple approach to calculate the P90 yield is to assume a normal distribution for this uncertainty and a direct 1:1 relation of DNI averages to the yields. However, since the relation of DNI to energy yield is actually not linear it becomes more and more popular to calculate it from annual meteorological data sets (MY90), which are representing P90 DNI averages at a realistic distribution of actual values in the same time resolution as the P50 TMY. Applying such MY90 data sets still has the shortcoming that they are synthetic, while real years of data should lead to more realistic yields. Thus, this paper proposes the use of multiple years of weather input to realistically include the annual variability of DNI. To also represent the effect of the data set uncertainty, the time-series are modified in such a way that the annual DNI values follow a normal distribution with a 1-sigma width equivalent to the diagnosed data set uncertainty. The impact of this probabilistic approach on the energy yield of a CSP project is shown for the site Bom Jesus da Lapa in Brazil. Since the estimation of a realistic uncertainty of the long-term DNI at this location was challenging, several uncertainties between 3-9 % were assumed that could possibly be inherent in such a data set. Using these assumed data set uncertainties and the inter-annual variability of the data set, the deviations to the long-term mean of energy yield are shown for the current practice approaches and the new method. Hence for a data set uncertainty of 5 % the very basic risk analysis results in a single-year P90 yield 11.1 % below P50, while using a MY90 single year data set is resulting in a P90 yield 9.7 % below P50. The probabilistic approach introduced here is leading to P90 yields 8.5 % below P50.

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Keywords: DNI, Concentrating Solar Power, Energy yield, yield prognosis, probabilistic modeling

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1. Introduction

The method presented in Ho and Kolb [1] for the probabilistic modelling of solar thermal power plants includes uncertainties related to technical parameters and for the effect of DNI it considers the inter-annual variability. Inter-annual variability of DNI, however, does not cover uncertainties of deriving the DNI long-term average. According to [2] the uncertainty of DNI long-term averages is mainly influenced by three independent error sources for solar resource:

- uncertainty of ground-based measurements,
- uncertainty due to adaption of satellite-derived data to ground-based measurements,
- uncertainty due to the limited observation period and annual variability.

The overall uncertainty of the long-term average DNI resulting from the above error sources typically is in the range of 5 % to 15 % related to 1-sigma. This is of similar extent as the standard deviation of DNI annual values, which is expressing the inter-annual variability of DNI. Therefore the approach of Ho and Kolb [1] using simply the variability but neglecting DNI uncertainty gives a first idea about the effect of uncertainty. However, it is missing the combination of both independent effects on yields, which is of major interest for financing CSP plants. Thus, for CSP yield prognosis and risk analysis a method is needed which combines the effect of DNI uncertainty with the effect of DNI variability. Open questions are

- How such probabilistic data sets representing uncertainty on top of variability can be constructed and
- what is the effect on yield reduction compared to using a simple annual meteorological data set MY90 which should represent the P90 average value of DNI or
- what is the effect on yield reduction compared to using the even simpler approach of only calculating the P90 yield from a P90 DNI?

To answer these objectives a method is developed and applied to a site in Brazil. For the site Bom Jesus da Lapa in the northeast of Brazil a DNI data set from 1973 to 2001 covering 29 years is available. Such an exceptional long data set is an ideal playground to demonstrate the effects of inter-annual variability – especially because Brazil is having a relatively strong inter-annual variability of DNI. Also uncertainty of DNI is relatively high, because there is not much experience with DNI yet in this country. Further, Brazil's electricity system is dominated by hydroelectric power stations, which in the future may be accomplished by tapping its huge solar potential. Due to low potentials for further reservoir hydro plants, which provide favourable dispatchable power, concentrating solar power (CSP) applications are becoming an interesting option to fill this gap in the mid- or long-term. In energy deployment studies it should be shown how the potential CSP production might compensate low hydro production years, because hydro power is known for high inter-annual variability. For this purpose an approach using simple TMY and MY90 data set is not useful, but multi-annual data sets need to be taken.

The paper first introduces the method to generate populations of multi-annual data sets representing on top of the variability also the uncertainty. It is then applied to the Brazilian site. By comparison to the conventional risk analysis the advantages of the new methodology are shown.

2. Methodology

During the planning phase of a solar thermal power plant one of the main goals for financing is to derive a reliable value of the average annual energy production (AEP) and estimate the uncertainty and variability of this P50 AEP. An overview to the newly proposed method to do so is given in Fig. 1 where uncertainty is laid on top of long meteorological time series to represent potential error sources in P50 derivation.

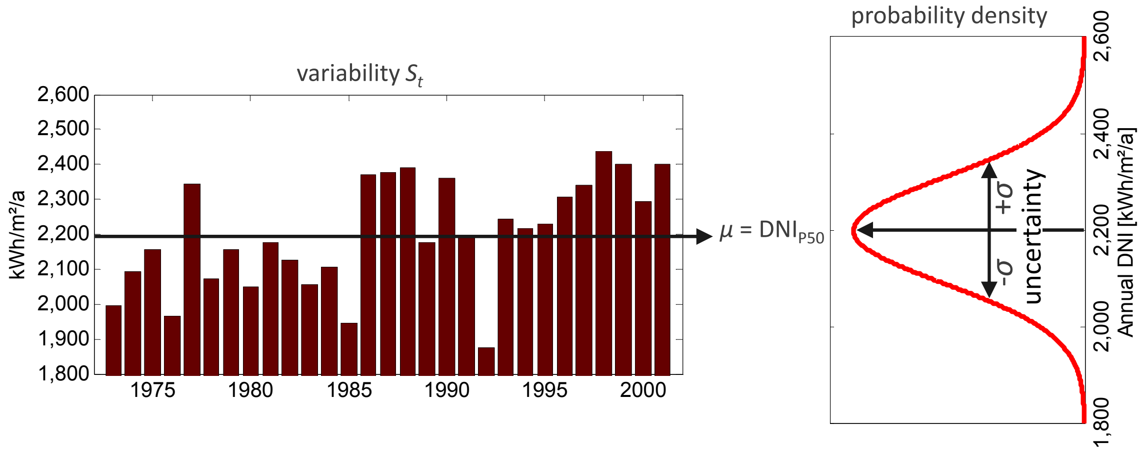

Fig. 1. New approach: laying data set uncertainty σ on top of annual variability S_t

The new approach promises to derive more reliable P50 values and much more realistic P90 values for risk analysis. It can be described by the following steps:

1. Selection of site-specific meteorological data sets
2. Estimation of an appropriate DNI data set uncertainty σ
3. Creation of additional sample data sets for all years of the historical weather data set. For each year, linearly increased and decreased DNI samples are created so that the total population represents the estimated σ
4. Execution of multiple performance simulations
5. Analysis of the simulation results: deriving P90 from cumulative distribution of AEP from all calculated energy yields.

2.1. Create/choose data set

In a first step, a meteorological data set has to be acquired that includes all necessary parameters for the simulation of a solar thermal power plant. This normally includes the components of solar radiation, global horizontal irradiance (GHI), DNI and diffuse horizontal irradiance (DHI), as well as other meteorological parameters like dry-bulb temperature, dew-point temperature, relative humidity, ambient pressure and wind speed. To derive reliable conclusions about the inter-annual variability of DNI, as many years as available should be chosen as raw data for the method. Furthermore it is of great importance to evaluate an appropriate data set uncertainty σ, which consists of sensor uncertainties inherent in the ground-measurement process ($\sigma_{measurement}$) and uncertainties due to the adaption of satellite-derived data to ground-measurement data ($\sigma_{adaption}$). $\sigma_{measurement}$ can be as low as 1-2 % for well-calibrated and well-maintained field pyrheliometers [3],[4]. $\sigma_{adaption}$ depends on the adaption method and the quality of the used data sets. For further information see [5] or [6]. σ is used to determine the distribution of the DNI samples for simulation, so an exact knowledge is crucial for the accuracy of the method.

2.2. Sampling of DNI data values

With the evaluated σ, a distribution matrix that holds information on the deviations forming the determined uncertainty can be created and on this basis, sampling can be carried out. To obtain the distribution matrix, a normal distribution with a 1-sigma width equivalent to the diagnosed data set uncertainty has to be modelled. An example of the modelling is given in Fig. 2, which shows the probability density function (PDF) of a sampling with σ=5 %. While the red line represents a normal distribution with a sample number converging towards ∞ (steps on the x-axis with a sample weight $w_i > 0$ equal the sample number), a lower resolution has to be chosen for the sampling to model the distribution due to processing constraints. 0.5 % was chosen to be the resolution to model the uncertainty since it was considered a good compromise between adequate modelling accuracy and simulation effort. That means that for every deviation step of 0.05 % a sample is created and a sample weight w_i is calculated. In the example of σ=5 % in Fig. 2, the sample with a deviation of ±0 % is given a weight of 39, the samples with deviations of -7 % and +7 % are given a sample weight of 3, and so on. The samples lie on a distribution interval i around the average DNI value (x_i=±0 %) and build a normal distribution together with the sample weights w_i. Since samples have to maintain within a reasonable number for the following yield simulation and the sample weight w_i for each deviation x_i has to be an integer, normal distribution can only be approximated in an iterative process. Yet this approximation is generally very close (see Table 3 below).

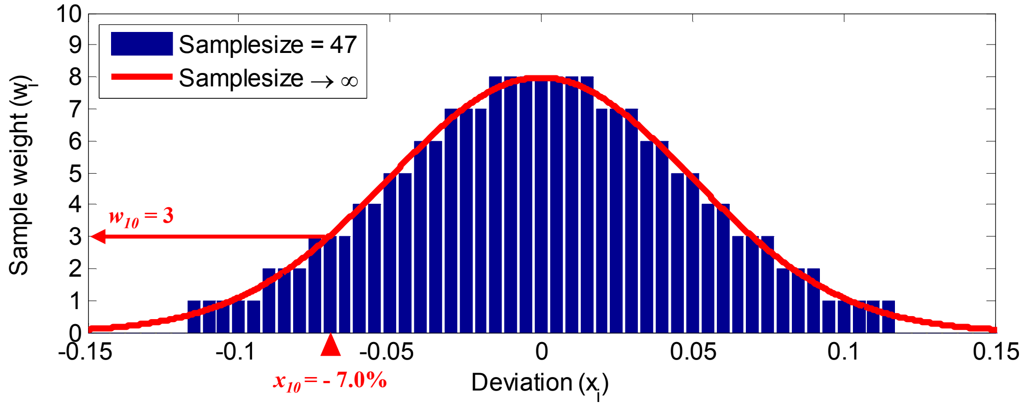

Fig. 2. Probability density function for σ = 5 %

When the most accurate sampling of σ has been found, the resulting distribution matrix is obtained. Comparing the PDF in Fig. 2 and the distribution matrix in Table 1 it shows that for each sample on the deviation interval i, a weighting w_i is saved for the corresponding deviation x_i. The total number of samples is 47 in the given example.

Table 1. Distribution matrix for σ=5 % and a resolution of 0.5 %

i	1	…	10	…	23	24	25	…	38	…	47
w_i	1	…	13	…	8	8	8	…	3	...	1
x_i	-11.5%	…	-7.0%	…	-0.5%	±0.0%	+0.5%	…	+7.0%	…	+11.5%

After the creation of the distribution matrix, the deviations x_i are applied to the average DNI value of each year. So according to the interval i, the average DNI value was multiplied with 0.885 to 1.115 in the given example of σ=5 %. The sample with the number i=10 for example was created by multiplying the average annual DNI with 0.93.

During sampling, the problem occurred that with high σ, physically impossible DNI values may be sampled. Hence, a threshold was established to set an upper limit of DNI. While the solar constant (I_0 = 1,367 W/m²) could be a possible, though probably very high upper limit, a lower threshold should be chosen to set a reasonable maximum that could occur under clear sky conditions. For the case study the upper threshold was set to 1,100 W/m², since this is the maximum value in the used TMY2 files and it also represents a likely value for hourly DNI data. Furthermore the maximum hourly DNI value of all 29 years in the historical weather data set was 1,047 W/m².

2.3. Multiple performance simulations

In the case study of Bom Jesus da Lapa, the performance simulation is conducted with NREL's System Advisor Model (SAM). The software offers a wide spectrum of parameters to model a CSP power plant. Parabolic-trough, power tower, linear-fresnel and also dish-stirling power stations can be simulated. To simulate the large number of weather files used in the method, a small script was written in the integrated SamUL programming environment to process the files and save simulation outputs automatically.

2.4. Analysis / interpretation of results

After yield simulation, the obtained simulation results are sampled according to the uncertainty σ with the help of the distribution matrix (see Fig. 3). The sample weights are applied to the simulated AEP samples to build the distribution function. The result of this process is shown in Fig 4. Then, standard deviation, relative standard deviation (RSD), mean, and percentile values of the sampled energy yields can be obtained and analysed.

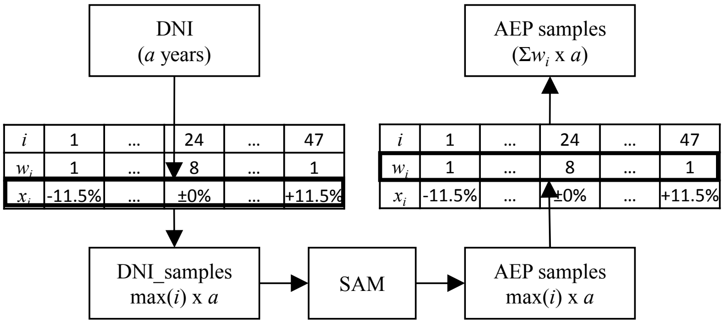

Fig. 3. Overview of the probabilistic model and the application of the sample weights to the simulated AEP samples

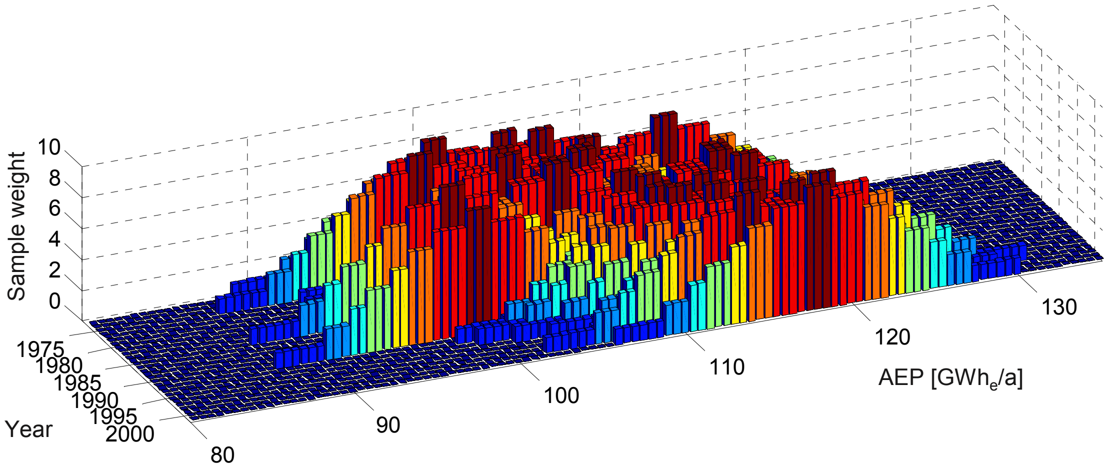

Fig. 4. Illustration of AEP sample distribution in Bom Jesus da Lapa (1973 – 2001) with σ=5 %

3. Case study in Bom Jesus da Lapa

Bom Jesus da Lapa, in the northeast of Brazil, was chosen as the location for the case study. The region of the São Francisco river basin is one of the areas with the highest potential for solar thermal electricity generation in the country because of its favourable solar conditions and low precipitation (see [7]).

3.1. Case study definition

The historical weather data set was compiled by NREL using the METSTAT (Meteorological/Statistical solar radiation model) model and covers 30 years (1973-2002) of hourly data as well as a TMY2 data set. The year 2002 had to be excluded due to missing data, so a total number of 29 years was available. Table 2 gives an overview of the data set. It can be observed that yearly DNI values are very variable at this location, with a minimum of 1,882 kWh/m²/year, a maximum of 2,437 kWh/m²/year and a relative standard deviation (RSD) of 7.05 %. This value represents the annual variability of DNI S_t. Excluding wind speed, DNI is the most volatile parameter in the data set, especially more volatile than GHI with a standard deviation of the annual sums of only 2.66 %.

Table 2. Overview of meteorological data set for Bom Jesus da Lapa

Parameter	Unit	TMY	Mean	Minimum	Maximum	RSD [%]
GHI	kWh/m²/a	2,143	2,151	2,033	2,239	2.66
DNI	kWh/m²/a	2,199	2,203	1,882	2,437	7.05
DHI	kWh/m²/a	672	675	610	785	6.65
Dry-bulb Temp.	°C	26.1	26.2	25.0	27.4	2.16
Dew-point Temp.	°C	18.0	17.9	17.3	18.5	1.84
Rel. Humidity	%	64.4	58.1	68.8	63.4	3.93
Ambient pressure	mbar	961	961	961	963	0.05
Wind speed	m/s	1.6	1.5	1.1	1.9	13.83

The plant configuration in SAM was set to the Gemasolar molten-salt power tower according to [8]. The plant has a capacity of 19.9 MW_e (gross), 15 h of full load hours of TES and a solar multiple of 2.5. The simulated annual energy yield at the plant site in Sevilla, Spain, is 107.4 GWh_e. The annual DNI of the TMY in Sevilla lies at 2,089.7 kWh/m², which is a little less than the TMY value of Bom Jesus da Lapa (2,198.5 kWh/m²). Yield simulation with the TMY of Bom Jesus da Lapa consequently resulted in a slightly higher annual energy yield of 109.7 GWh_e.

3.2. Case study results

The RSD of DNI given in Table 2 (S_t=7.05 %) quantifies the possible deviation from the long-term mean for any particular year. It is in good accordance with the average for regions below a latitude of 45° (7.6% according to [9]). By using equation 1 (see e.g. [2], [6]) the long-term average for a consecutive years of the annual variability can be calculated. For the case study this led to S_{29} = 1.31 %. Thus annual variability for 29 consecutive years is almost averaged out completely. Consequently, uncertainty of energy yields derived from multi-year approaches would be much lower than from single-year approaches, so the new method will only be compared to current practices calculated with annual variability referring to a single year.

$$S_a = \frac{S_t}{\sqrt{a}} \tag{1}$$

To include all sources of uncertainty to the evaluation in the case study, uncertainties from dataset correlation and instrument error have to be included via σ. According to [10] and [11], the overall model bias of satellite data can be corrected with available measurement data to the uncertainty level of well-maintained ground instruments. Assuming high quality ground measurements under optimal conditions, σ of a best practice DNI data set would be in the range of 1-2 %. Less accurate ground data or inappropriate adaption methods are likely to produce a much higher σ. For this case study, σ between 3 % and 9 % were simulated. Due to modelling constraints concerning sampling mentioned above, the deviations in Table 3 occurred between $\sigma_{theoretical}$ and $\sigma_{resulting}$. Consequently, σ was set to $\sigma_{resulting}$ during the method.

Table 3. Difference between $\sigma_{theoretical}$ and $\sigma_{resulting}$

$\sigma_{theoretical}$	%	3.00	5.00	7.00	9.00
$\sigma_{resulting}$	%	3.00	4.99	6.99	9.05
$\lvert \sigma_{theoretical} - \sigma_{resulting} \rvert$	%	0.00	0.01	0.01	0.05

Knowing the dataset uncertainty σ, and annual variability S_t, the DNI uncertainties in Table 4 can be calculated using equation 2 (see [2]) and then be compared to $\sigma_{DNI,method}$, which was calculated from the generated DNI samples (including the sampling weight w_i). Comparing $\sigma_{DNI,method}$ and σ_{DNI} shows that the sampling method accurately models the normal distributed DNI uncertainty for each single year.

$$\sigma_{DNI} \approx \sqrt{{S_t}^2 + \sigma^2} \tag{2}$$

Table 4. Overview of DNI uncertainties in the raw data set

σ	S_t	σ_{DNI}	$\sigma_{DNI,method}$
3 %	7.1 %	7.7 %	7.6 %
5 %	7.1 %	8.6 %	8.6 %
7 %	7.1 %	9.9 %	9.9 %
9 %	7.1 %	11.4 %	11.4%

This can also be seen in Fig. 5a, where annual DNI exceedance values and CDFs of current practices, and the presented method are shown. The small deviations of the method's CDF to the CDF that was calculated assuming a normal-distribution can be explained by comparing the CDFs in Fig. 5b. It shows the CDF, both normally-distributed and empirically derived, for the 29 years. It can be derived that for the case study in Bom Jesus da Lapa, the annual variability is not perfectly normally-distributed during the observed time period. The presented method simulates the years individually, without assuming a distribution function for annual variability, which leads to a difference to the simple approach. Hence, the method promises a better estimate of the P90 yield, using the actual multi-year DNI datasets.

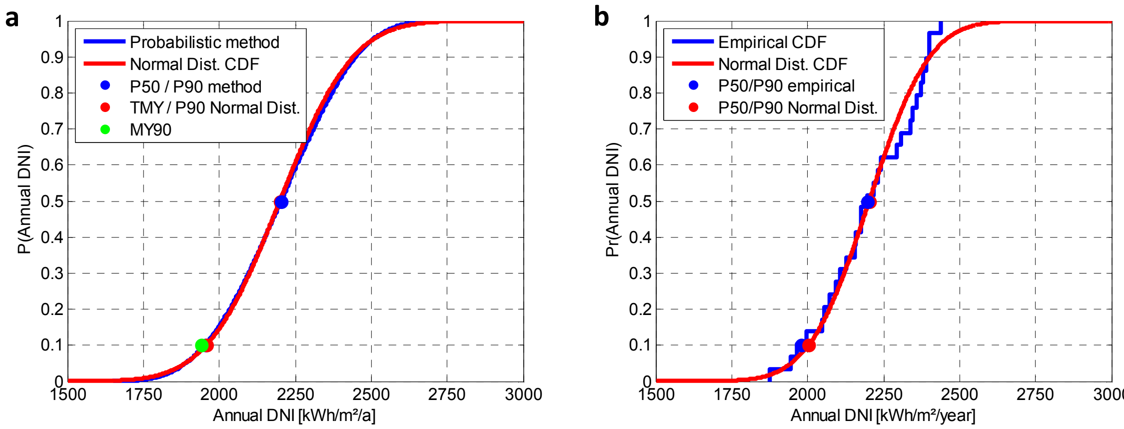

Fig. 5. (a) CDF & P50/P90 values of annual DNI including σ = 5 % for the years 1973-2001;
(b) CDF & P50/P90 values of annual DNI for the years 1973-2001

A simple approach to estimate a P90 energy yield would be to simulate the TMY, which represents the P50 value of the multi-year dataset, and then calculate the 90 % exceedance level, assuming a normal distribution and a direct 1:1 relation of DNI averages to the yields. For a σ of 5 % for example, this leads to a single-year-P90 value of AEPP90,simple=97.5 GWhe.

The second current practice approach is the creation of meteorological years that model the P90 exceedance value of DNI (MY90). Based on this approach, different MY90s were constructed on a monthly basis, using Finkelstein-Schafer statistics comparable to the creation of a TMY (see [12]), yet taking into account the relative difference between the DNI sum of the month and the P90 value of all respective months. The weighting of different parameters was taken from the best practice example in [6] where 0.6 was given to DNI, 0.4 to GHI, and 0.1 to air temperature, divided by the total of 1.1. A cross check between the DNI sums of the MY90s and the P90-DNI sums assuming a normal distribution around the TMY, showed that the representative years were created in good accordance (see also Fig. 5a). For a σ of 5 % the MY90 resulted in AEPMY90=99.1 GWhe.

Fig. 6b shows the exceedance values and the CDF of the simulated AEPs during the method for σ=5 % as well as the corresponding values for the current practice methods. Since the first method assumes a normal distribution of DNI uncertainty and 1:1 relation to AEP, its CDF of the AEP is identical to the CDF of DNI (compare Fig. 6a and Fig. 6b). The method's CDF for energy yields however differs from the normal distribution around the TMY since it seems to show a reduced uncertainty in AEP. For a σ of 5 % for example the AEP uncertainty was 30 % lower than DNI uncertainty. For all σ the relation between DNI uncertainty and AEP uncertainty was about σAEP ∝ 0.7 σDNI, which is consistent with the relation found in Meyer et al. (2009) [2]. The P90 values of the energy yield are consequently higher for the presented method and also for the method using the representative MY90.

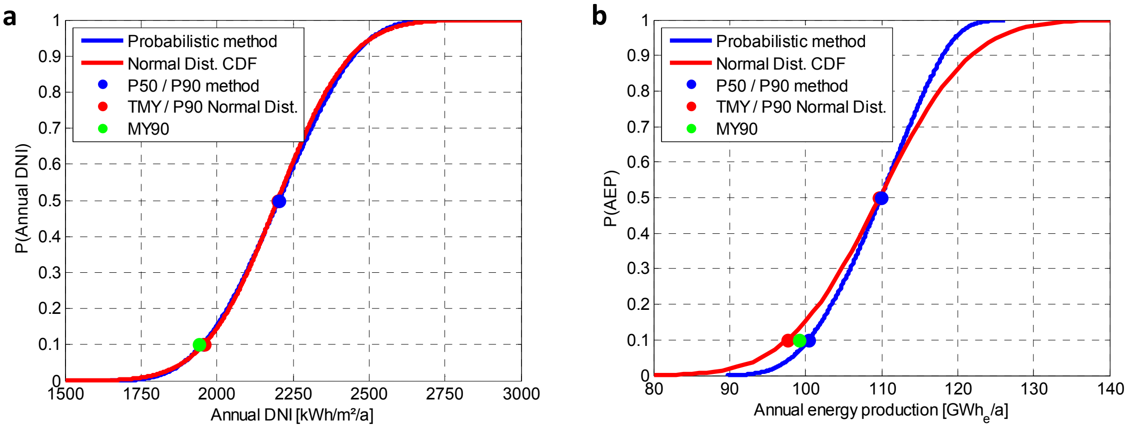

Fig. 6. (a) CDF & P50/P90 values of annual DNI including σ = 5 % for the years 1973-2001;
(b) CDF & P50/P90 values of AEP including σ=5 % for the years 1973-2001

Table 5 gives an overview of the different P90 exceedance values derived from current practices and the presented method. The simulated AEP derived from the presented method is generally higher than the simple single year P90 calculation. This is due to the fact that the simple estimation approach assumes a 1:1 relation between DNI and AEP uncertainty, while simulation showed that relation is lower. The creation of a MY90 already leads to more realistic results than the simple approach, yet has the shortcoming that it is synthetic and does not use multiple real years of weather data.

Table 5. Overview of derived AEP-P90 values for different probabilistic approaches

σ	$AEP_{P90,simple}$	AEP_{MY90}	$AEP_{P90,method}$
	GWh_e/a	GWh_e/a	GWh_e/a
3 %	98.9	100.5	100.9
5 %	97.5	99.1	100.4
7 %	95.7	97.6	99.2
9 %	93.6	96.8	97.5

The deviations to the long-term mean of energy yield for the different probabilistic approaches are shown in Fig. 7 for a data set uncertainty of σ=5 %. P90 derived from the new method is 3.5 GWhe/a or +3.0 % higher than the basic approach assuming a 1:1 relation between DNI and AEP, and 2.4 GWhe/a or +1.6 % higher than the MY90 method, when taking the energy yield of the TMY as a reference.

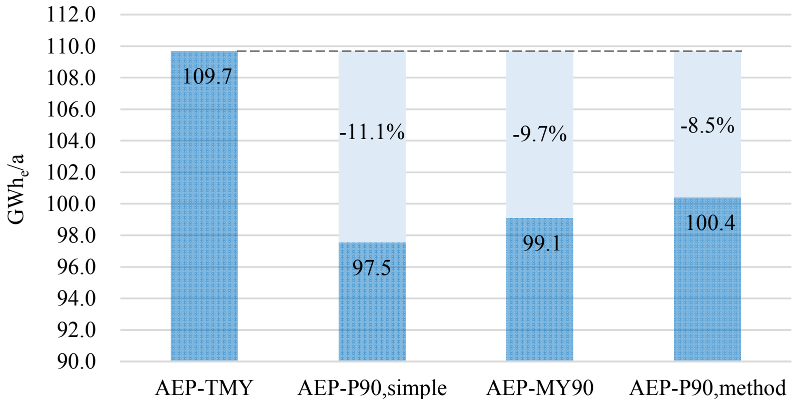

Fig. 7. AEPs of the TMY and different probabilistic approaches (σ=5 %)

4. Conclusion

Current practices for risk evaluation of CSP plants have several critical shortcomings. They tend to underestimate yields compared to probabilistic modelling, and they do not allow to analyse effects of inter-annual variations on cash flows or the power mix from other sources. Furthermore, they are difficult to apply to non-uniform DNI distributions.

The case study showed that P90 values derived from the new method have advantages compared to simple methods that assume a normal distribution for annual variability, since this assumption is not always valid. Also the 1:1 relation of DNI to AEP is unlikely, since the simulations showed that the uncertainty of the energy yield is generally lower than DNI uncertainty, with a correlation factor of about 0.7 for different assumed uncertainties. In the case study, the derived P90 of the probabilistic method leads to 3 % higher yields than the simplistic P90 approach.

Compared to the risk evaluation of creating an artificial meteorological year (MY90) representing the P90 exceedance value of DNI, the new method also shows a higher P90 yield. The difference, however, is less than the very basic approach with 1.6 % in the case study. The combined representation of variability and uncertainty effects by the population of the prepared meteorological data files is having more smoothing effects than represented by the P90 yield value of the MY90, and thus seems to behave friendlier concerning energy output. However, it needs to be evaluated further how realistic the linear variation of DNI is really representing the uncertainty of the DNI values. A different modulation might lead to a higher or lower sensitivity.

The newly introduced probabilistic method includes the aspects of uncertainty and variability in solar resource assessment and performance modelling. It considers all independent uncertainties of a DNI dataset and shows their impact on the energy yield of a solar thermal power station. Various indicators as standard deviation, PDF, CDF or exceedance values for the bankability of a CSP plant can be derived. This can help decision-makers or project developers to better evaluate the future energy production. Firm Energy Certificates for Brazilian energy auctions for example, which specify the maximum amount of energy a generation project can sell in a contract, could be defined according to exceedance values derived from the method. Enhanced confidence into the yield predictions and higher transparency of the forecasts could give an impulse for lower investment costs. Furthermore, it can provide real-time data, which is also required when feed-in-prices vary and for grid-integration. For all the reasons above, the new method should be introduced as new best practice for financing CSP plants.

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