Relations Between the Probabilities of Exceedance of Solar Radiation and Production of Concentrating Solar Thermal Systems

Miguel Larrañeta[1,a)], Daniel Álvarez-Zambrano[2], Manuel Antonio Silva-Pérez[2], Isidoro Lillo-Bravo[2]

[1)] Andalusian Association for Research and Industrial Cooperation (AICIA), Camino de los Descubrimientos s/n. 41092, Seville, Spain
[2)] Department of Energy Engineering, University of Seville, Camino de los Descubrimientos s/n. 41092, Sevilla, Spain

[a)]Corresponding author: mlarraneta@gter.es

Abstract. CSP feasibility analysis, bankability assessment and plant design are generally based in one-year meteorological series representative of "typical" o extreme conditions. There is a growing interest in accounting on the inherent variability of the performance of solar plants on their input variables in the plant model. In particular, for generating the probability distributions of annual energy yield, simulation tools require as input a large number of plausible meteorological years (PMYs). In this article we generate 100 synthetic years of DNI in the 1-min resolution for the location of Seville, Spain, and we estimate and evaluate the power produced by two CSP plants with similar configuration as two well-known parabolic trough and central receiver solar plants (Andasol 3 and Gemasolar) using System Advisor Model (SAM). We estimate that there is an almost linear relation between the Probabilities of Exceedance (PoE) of the DNI and the gross electricity generation of the solar plants but that for a given annual value that corresponds to a PoE of the DNI, there is a range of possible production values depending mainly on the monthly distribution of the solar radiation datasets.

INTRODUCTION

The common practice of using one-year meteorological series for long term evaluation may be living its last days since developers of solar projects are starting to understand the impact of the variability of the solar radiation in solar plants production. While a typical meteorological year may be useful for an average long-term performance in many applications, extreme time series for different extreme scenarios should be addressed through the multiyear approach. There have been many attempts in that direction [1], especially remarkable a recent approach by Larrañeta et al., [2] that joins different algorithms to extend and downscale solar radiation datasets generating 100 years of plausible meteorological years in the 1-min resolution that reproduce the annual probability distribution of the solar radiation in the location under study.

The annual probability distribution of the solar radiation has been addressed assuming that the annual DNI follows a Weibull distribution and the annual GHI follows a Normal distribution [3], but there is not much known about the annual probability distribution of the power supplied by CSP plants [4]. Furthermore, it is not clear that a given PoE of the solar radiation corresponds to the same PoE in terms of power production of a CSP plant. The annual probability of exceedance (PoE) describes the likelihood that a given solar radiation total accumulated over one year will be exceeded in any year. For 100 years, the probability of exceedance is complementary to the percentile (P). For instance, PoE90, which is complementary to the P10, indicates the annual DNI value that can be exceeded with 90% confidence. Comparing different PoEs to the PoE50, representative of the median of the annual DNI distribution, is a relative measure of the financial risk in CSP projects [5].

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In this article we generate 100 synthetic 1-min solar radiation datasets using the algorithm of Larrañeta et al. [2] obtaining 100 annual totals that corresponds to the probabilities of exceedance that define the probability distribution of the annual solar radiation in Seville, Spain. We then run simulations using SAM for the estimation of the production of two well-known CSP plants and we compare the results in terms of solar radiation versus power production.

METHODOLOGY

We use fourteen annual sets of DNI measurements recorded in Seville (37.40° N, 6.01° W) on the period 2002-2015 by the Group of Thermodynamics and Renewable Energies (GTER) of the University of Seville, to generate 100 synthetic DNI sets that would be used as input for the power production estimations.

Synthetic Solar Radiation Datasets

The implemented algorithm follows three steps. In step 1 we generate synthetic monthly data from the observed data. The input to the algorithm is the available fourteen annual series at the site. In step 2, both the output of the first step and the observed data are required as input to generate daily synthetic data. In the last step, we use the ND model [6] to generate 1-min synthetic data. Figure 1 shows the flow diagram of the implemented algorithm.

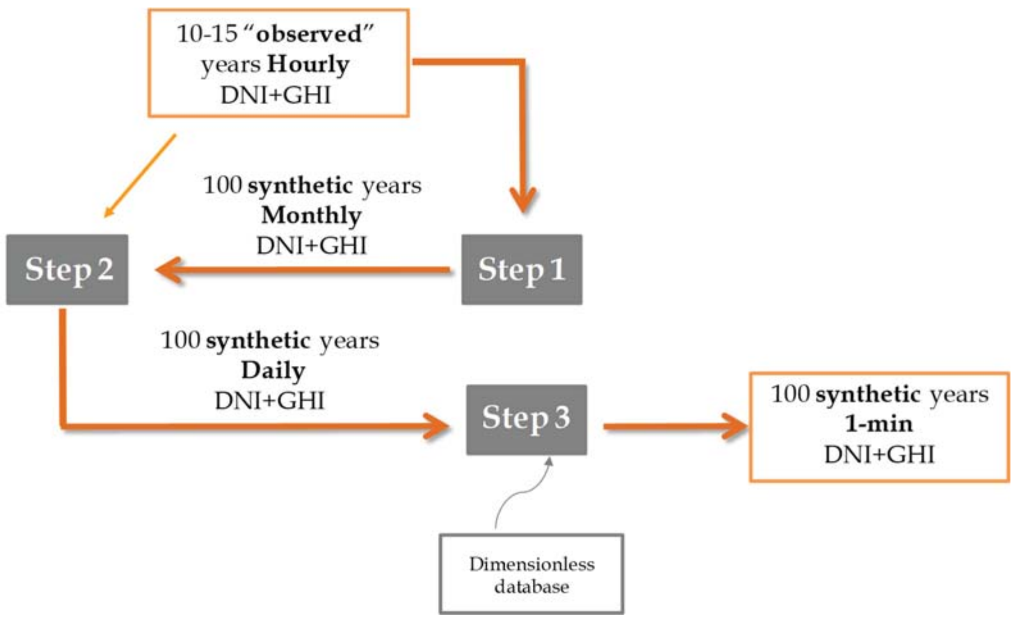

FIGURE 1. Flow diagram of the implemented algorithm for the multiyear synthetic generation.

As output, we generate 100 annual series at 1-min time resolution for the location of Seville, corresponding to the annual probability of exceedance from 1 to 100.

Power Production Estimation

We use the synthetic data to estimate the production of two CSP plants using SAM. We also simulate the CSP plants performance using the fourteen annual observed sets as input. We select two PT plants similar to operational plants with parabolic trough and central receiver technologies sited in the South of Spain as reference models: Andasol 3 (A3) and Gemasolar (GS), respectively. Both plants have thermal energy storage (TES) system. The main characteristics of these plants are summarized in Table 1.

TABLE 1. Main technical data used in SAM to model the plants. A3 and GS models are based on the characteristics of ANDASOL 3 and GEMASOLAR, respectively, both plants located in Spain.

Parameter	A3	GS
Net output at design (MWe)	50	20
Collector/Heliostat type	EuroTrough ET150	Sener
Receiver type/Tower Height (m)	Schott PTR70 2008	140
Number of loops/Heliostats	156	2650
Solar field aperture area (m^2)	510,120	304,750
HTF	Therminol VP-1	Molten salts
Design loop/receiver outlet Temp (ºC)	391	565
TES Capacity (full-load equivalent hours)	7.5	15

Observed and synthetic sets have been integrated into the hourly resolution for the simulations since we have found irregularities in the performance of SAM for high temporal resolution and in order to reduce the computational cost. The operation strategy has been defined to provide full power output during the maximum possible time.

RESULTS AND DISCUSSION

In order to compare the distributions of observed and synthetic data, in Figure 2 we represent the observed annual DNI (blue dots) together with the CDF of the synthetic annual DNI values (blue line). In the same figure we represent the estimated annual gross net production obtained from the observed datasets (GP_{obs}, red dots) together with the CDF of the of the production obtained with the synthetic sets (GP_{synth}, red line). We perform this exercise for A3 (left) and GS (right).

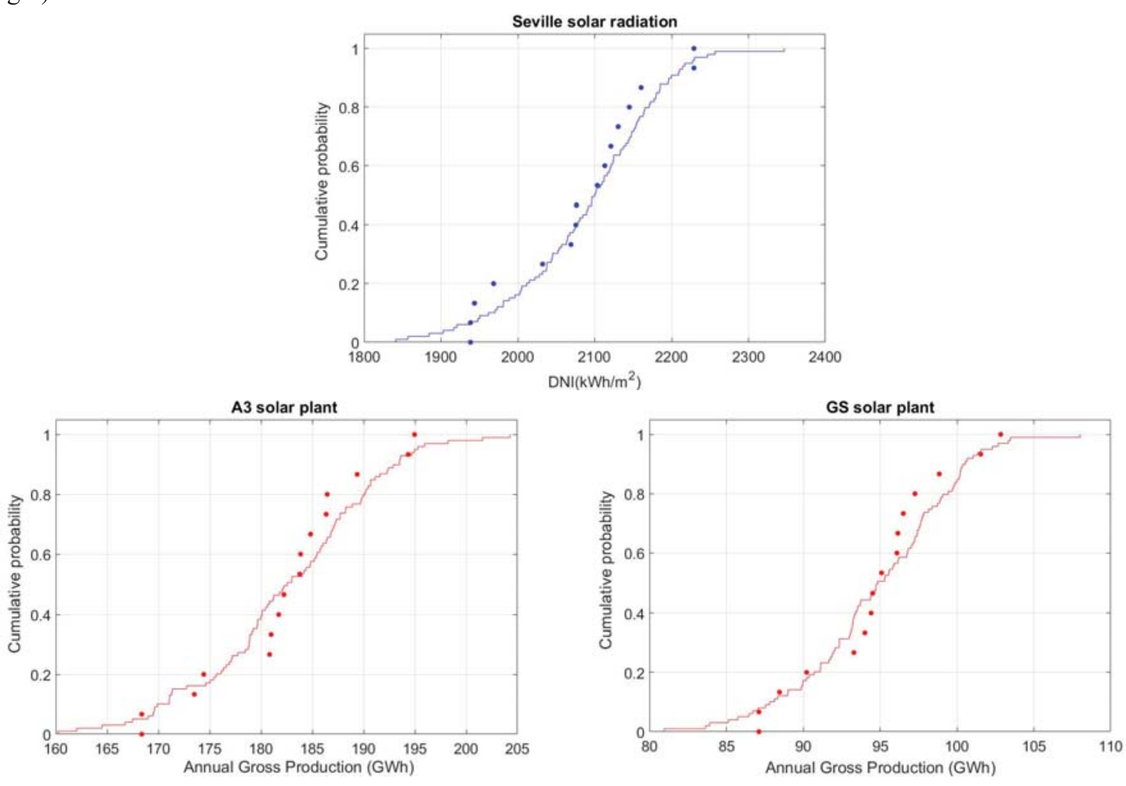

FIGURE 2. CDFs of the observed annual values of DNI (blue dots) and the GP_{obs} (red dots) together with the CDF of the synthetic annual values of DNI (blue line) and the GP_{synth} (red line)

In Figure 2 we observe that the CDF of the synthetic annual DNI values (blue line) are closely fitted to the observed values. The fit is slightly offset for annual GP values (red) in both cases A3 and GS. In Figure 3 we present the estimated annual gross power versus the annual DNI. Synthetic data is presented in blue circles and observed data is presented in red triangles. We present the results for A3 (a) and GS (b).

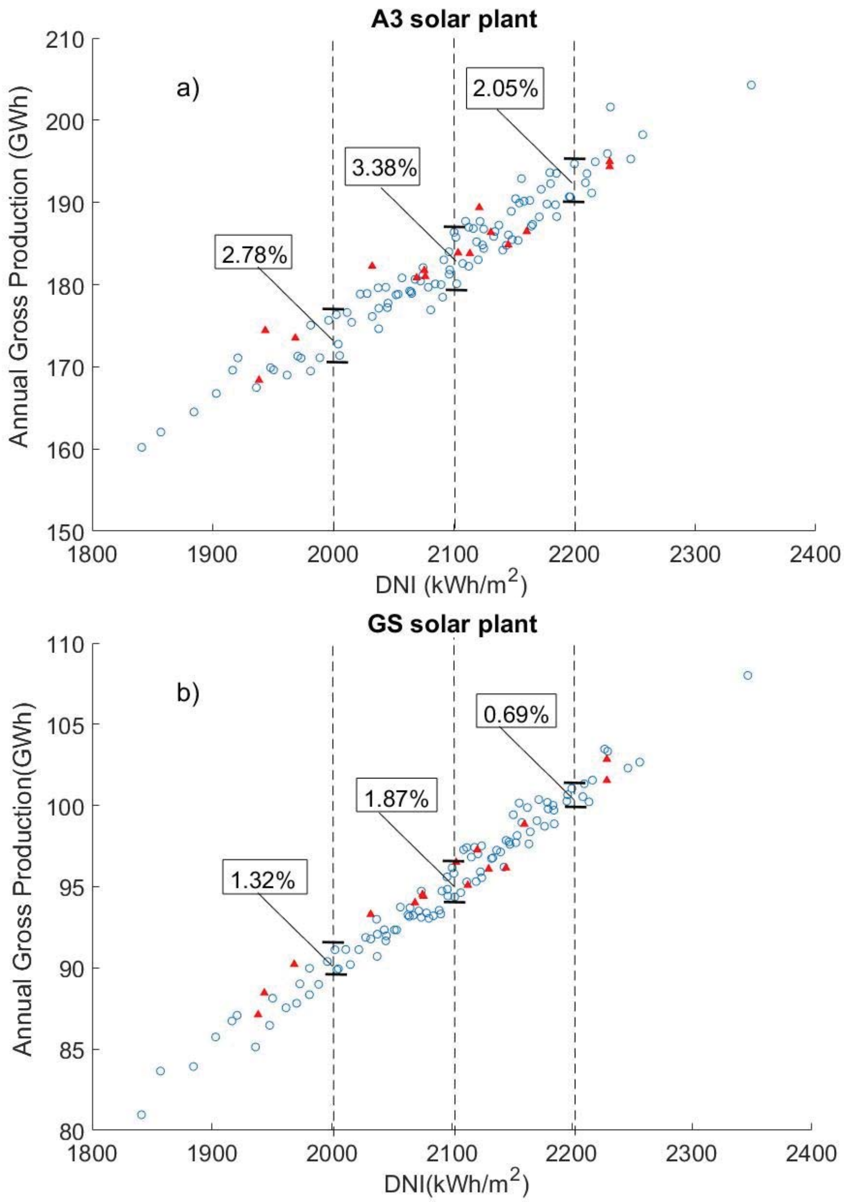

FIGURE 3. Estimated annual gross production versus the annual DNI. Synthetic sets in blue, observed sets in red. A3 (a) and GS (b).

There is an almost linear relation between the annual gross production and the annual DNI that can be quantified through the Pearson correlation coefficient (PCC). We obtain a PCC of 0.972 and 0.987 for A3 and GS solar plants. It should be noticed that a PCC value of 1 is a total positive linear correlation. We also observe in Figure 3 that there is a significant dispersion in the cloud points meaning that for a similar annual DNI value, we can obtain different annual gross productions. This dispersion is related to the monthly, daily and intra-daily variability of the solar radiation. We approach a relative value of dispersion for three levels of solar radiation that could be related to the uncertainty of the inherent variability of the solar radiation when estimating solar plant performance with a single annual set as input. We obtain that for A3 and average levels of solar radiation for the location under study ≈ 2100 kWh/m^2, there is a variation in the possible values of gross production of 3.4%. For high and low levels of annual DNI, the dispersion is lower, 2.1% and 2.8% respectively. This is a reasonable reduction since the greater the number of sunny and cloudy days, the lower the intra-daily variability, that has a negative impact in the production of CSP plants. We observe that for GS solar plant, the dispersion is lower, reaching values of 1.9%, 0.7% and 1.3% for mid, high and low levels of annual DNI for the location under study.

In Figure 4 we present the annual gross production as a function of the annual DNI synthetic sets. We group ten annual sets into boxes that represent ten PoEs in terms of DNI. For instance, the box representing the PoE50 corresponds to the annual GP_{synth} obtained with the DNI sets from PoE46 to PoE54. We present the results for A3 (a) and GS (b). We also present in discontinuous lines the PoEs 20, 50 and 80 in both terms, gross annual production and annual DNI.

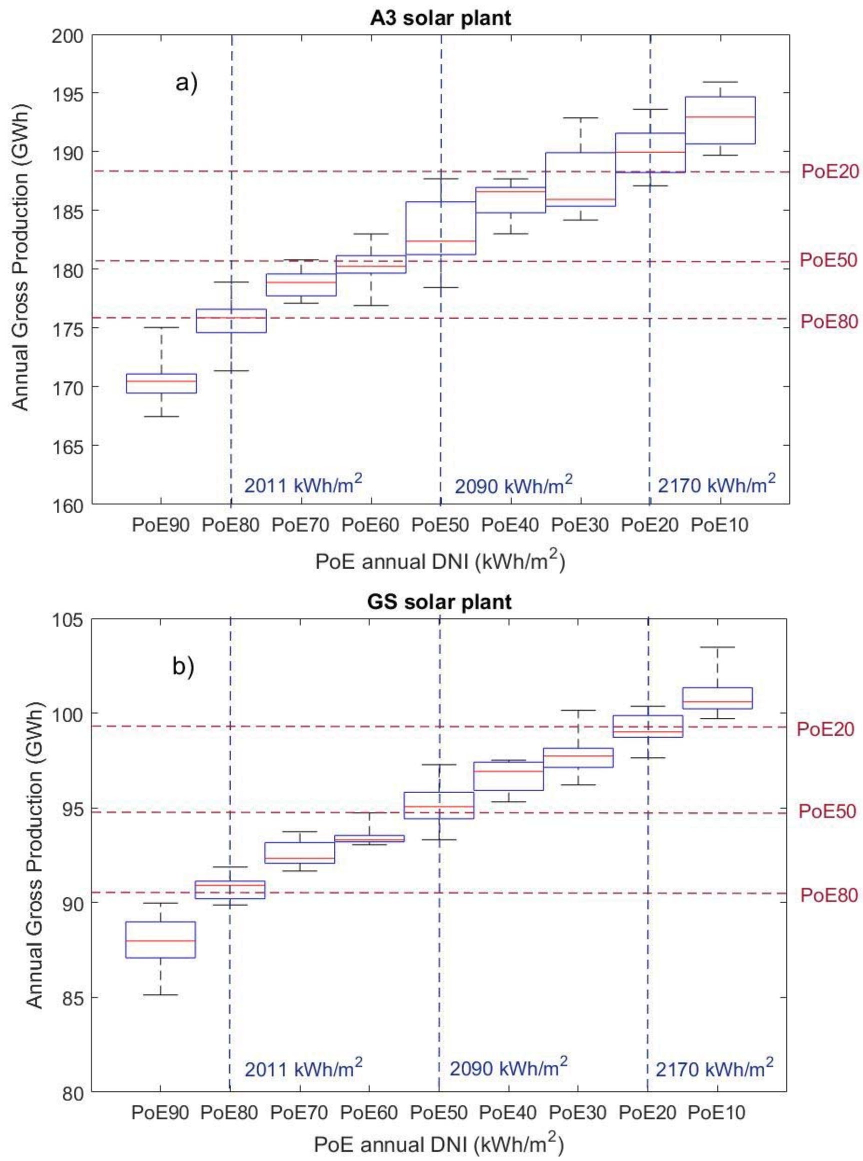

FIGURE 4. Boxplots of the annual gross power as a function of the annual DNI synthetic sets. A3 (a) and GS (b).

Each box presents the P25 and P75 limits. The red line within each box represent the P50. Maximum and minimum values are represented with black horizontal lines. We can observe the wide range of possible annual gross production values for similar annual DNI values. We can observe that the boxes are smaller in GS than in A3 solar plants. We focus on PoE50 box of A3 and we extract the sets leading the maximum and minimum GP_{synth} values. Results are presented in Table 2.

TABLE 2. Maximum and minimum GP_{synth} values of PoE50 boxes and their corresponding annual DNI values.

	PoE 50 box			
	Year	**DNI (kWh/m^2)**	**A3 GP_{synth} (GWh)**	**GS GP_{synth} (GWh)**
Max	PoE46	2109	187.7	97.3
Min	PoE54	2090	178.4	93.3

It is noticeable that the maximum and minimum values of GP_{synth} correspond to the maximum and minimum values of annual DNI. However, differences in terms of solar radiation are very small. We find differences of 1% in terms of solar radiation while in terms of gross power we find differences of 5% for A3 and 4% for GS. In Figure 5 we represent the monthly distribution of PoE46 and PoE54 sets in terms of solar radiation on top and in terms of gross production for A3 and GS on the bottom.

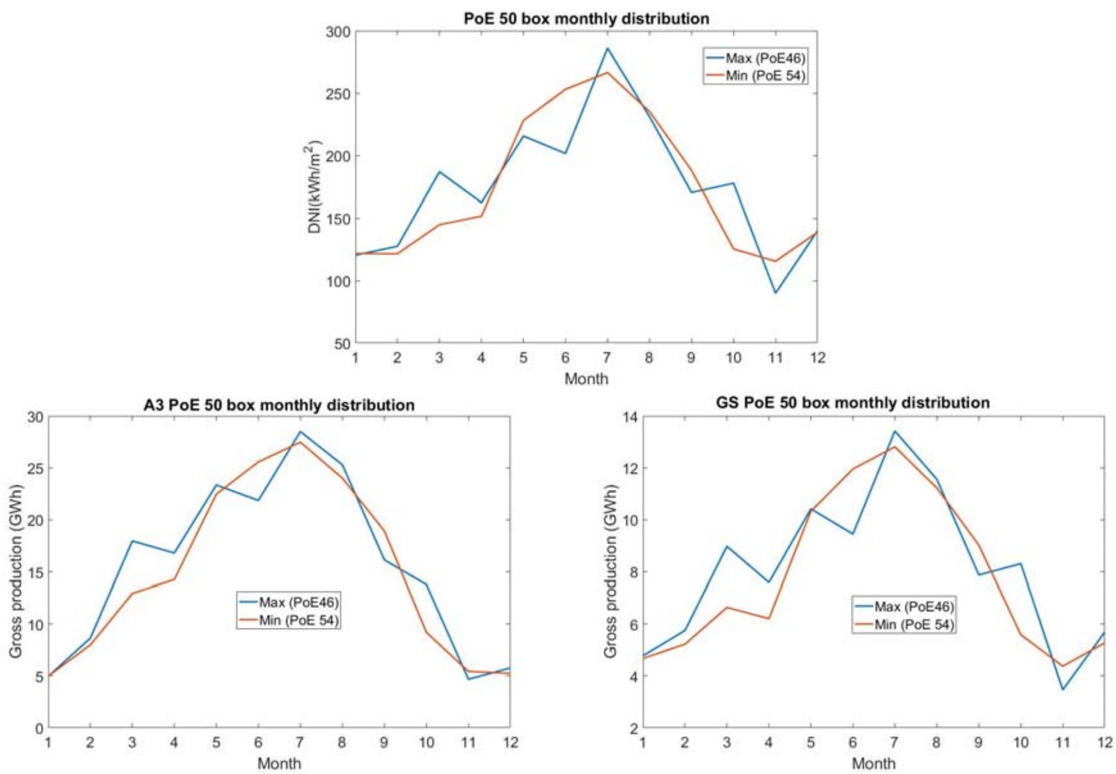

FIGURE 5. Monthly distribution of maximum and minimum annual sets represented in PoE50 box for A3 and GS

In this figure we don´t intend to analyse the optical performance of CSP plants, but to empathise on the relevance of the monthly distribution of the solar radiation on the production of CSP plants. We can observe that high levels of solar radiation in summer months may not be as effective in terms of gross power because of curtailment, and in winter because of the low optical efficiency levels.

CONCLUSIONS

In this research we put the spotlight on the relevance of the multiyear approach on the feasibility assessment of CSP projects. For two annual sets with similar annual DNI, there can be found significant differences in terms of CSP production caused mainly due to different monthly DNI distribution. We can suggest an uncertainty value between ± 1-1.7% for parabolic trough and ± 0.4-0.9% for central receiver due to the use of a single year in feasibility assessments and/or risk evaluations. This results have been obtained for the location of Seville. A similar approach for different climates will be faced in future works.

There is an almost linear relation between DNI and gross production. This relation is strongest for GS solar plant possibly because the greater storage system softens the impact of the variability of the solar radiation.

We believe the multiyear approach is more comprehensive than classical approaches in the feasibility assessment of CSP projects since the impact of the monthly, daily and intra-daily variability of the solar radiation is taken into account in the CSP plant production estimations. Future works will focus on the improvement of the multiyear synthetic generator algorithm.

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