The benefits of distributed grid production: An insight on the role of spatial scale on solar PV energy

EGU General Assembly 2024, Vienna, Austria, 14-19 April 2024; Session ERE2.3: *Spatial and temporal modelling of renewable energy systems*

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1. Abstract

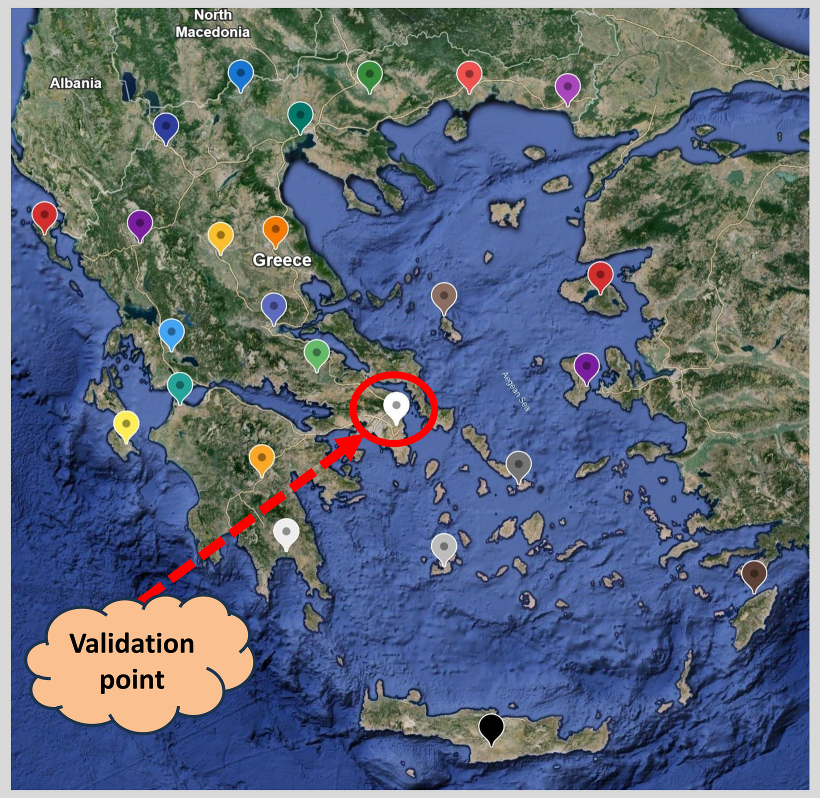
The hydrometeorological processes associated with renewables are characterized by substantial **spatiotemporal variability**, and thus uncertainty, which is addressed through **decentralized planning**, thus taking advantage of **scaling effects**. The objective of this work is to provide a comprehensive investigation of the role of scale regarding solar photovoltaic production in Greece, which is one of the predominant renewables. By implementing macroscopic criteria in terms of solar potential (e.g., topography radiation indices), we select a sufficient sample of **well-distributed locations** in Greece. For these points, hourly radiation and temperature data, derived from satellite products, are retrieved and validated against ground observations. Following this, we formulate a **detailed simulation** procedure that accounts for the two **physical drivers** and the **panel characteristics** (i.e., efficiency and temperature impacts due to heating), and we configure the baseline scenario by computing the individual production of each site. Next, to highlight the added value of distributed production and quantify the scaling effects in PV power production, we follow a Monte Carlo approach by **randomly distributing PVs across the selected locations**, to eventually provide a statistical analysis on the spatial and temporal domain and over different PV technologies.

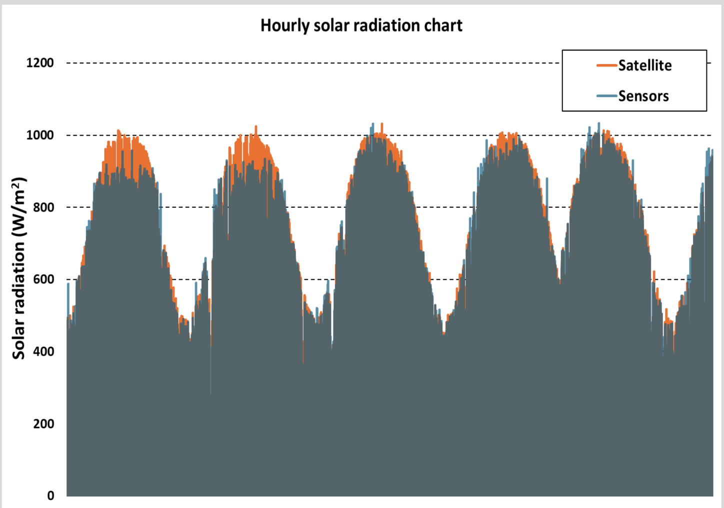
2. Why distributed?

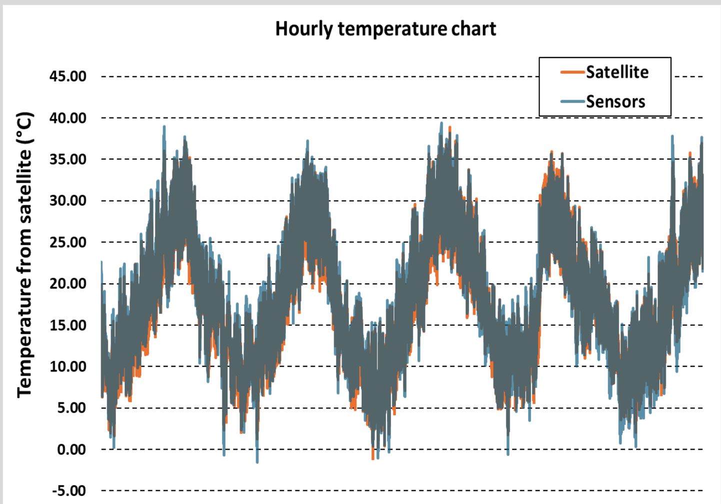
- Distributed energy systems (DES) have emerged as promising solutions towards the delivery of key electricity services, including, but not limited to, power production, having the potential to reduce reliance on centralized infrastructure (cf. Burger *et al.*, 2019).
- DES, if sited at the right locations and operated under the right conditions, not only deliver the same services as centralized systems, but also provide additional locational value.
- Their benefits, especially when combined with centralized systems, include reducing operating (e.g., transmission) costs and energy losses, and increasing reliability and resilience both by relieving network congestion and in the occasion of network outages.

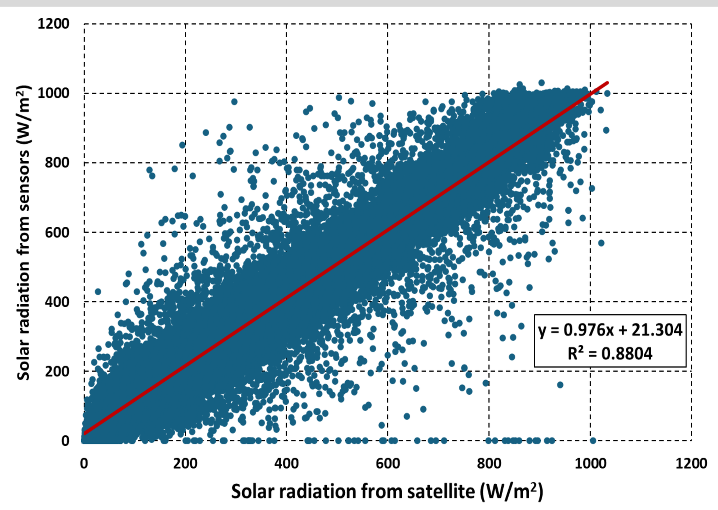
3. Data collection and validation

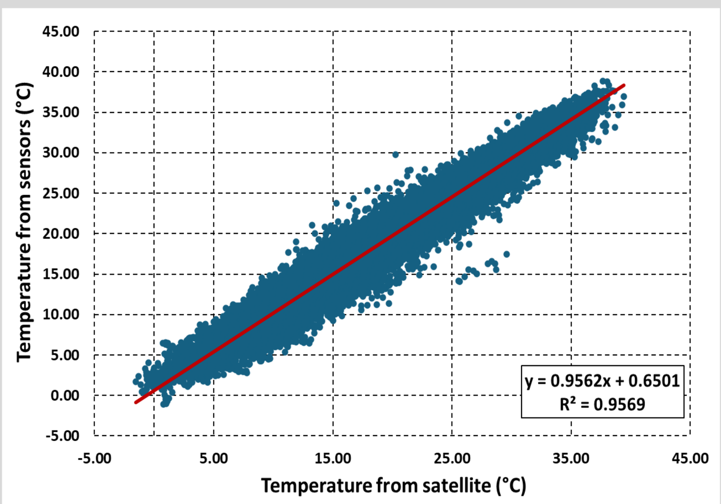
- 25 well-distributed locations all over Greece are selected to investigate their PV power potential;
- Hourly solar radiation and air temperature data for 15 years are retrieved from the **Photovoltaic Geographical Information System (PVGIS)** tool (cf. Huld *et al.*, 2012) using the Surface Solar Radiation Data Set Heliosat-2 (SARAH-2);
- To assess the **predictive capacity** of satellite data, we contrast them with ground observations of hourly solar radiation and temperature time series, in one of the selected locations (telemetric meteorological station @ NTUA campus, Zographou, Athens).











Remark: The satellite-derived time series exhibit sufficient similarity with ground data.

4. Outline of solar PV system simulation procedure: Data, parameters & processes

- The simulation accounts for the two driving meteorological processes, i.e., solar radiation, $\boldsymbol{R}$ (W/m²) and temperature, $\boldsymbol{T}$ (°C), and two technical parameters, associated with panel technology (i.e., efficiency, power temperature coefficient).
- At each location, the hourly power production is calculated for 15 years (2005-2020) as follows:

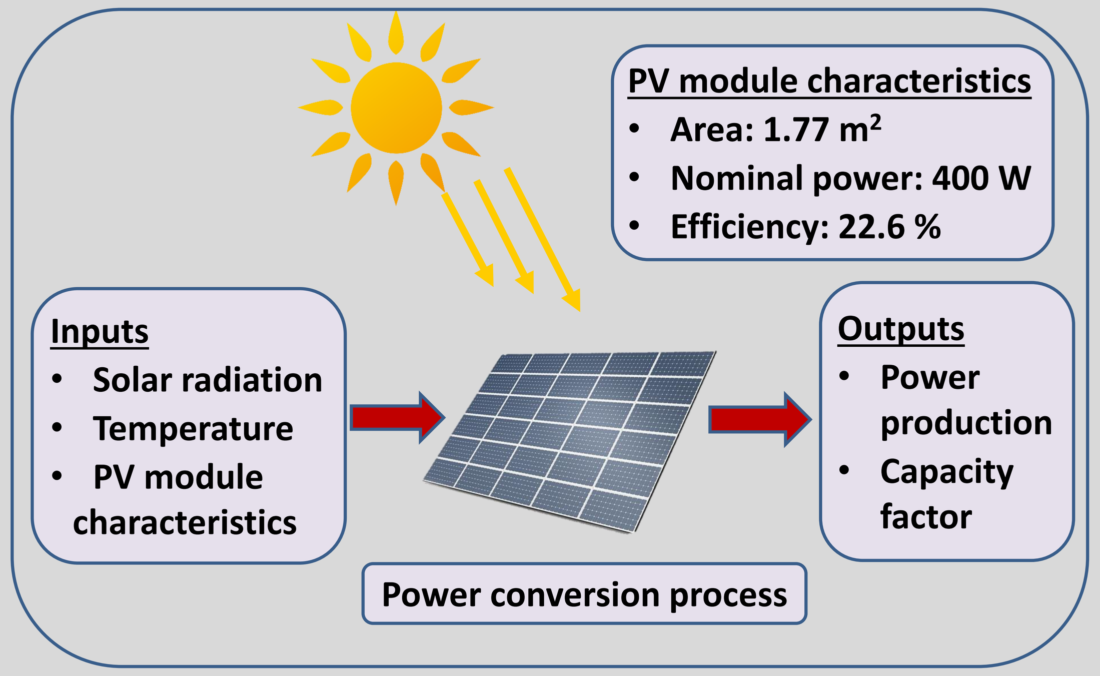
$$P_{hourly} = \frac{n_{act}}{n_{nom}} min[n_{nom} \cdot R \cdot A_{panel}, P_{nom}]$$

where n_{act} is the adjusted PV efficiency against temperature effects, n_{nom} is the nominal efficiency, A_{panel} is the PV area, and P_{nom} is the nominal power, which is achieved under the so-called Standard Test Conditions (i.e., for cell temperature of 25°C, solar irradiance of 1000 W/m² and air mass of 1.5)

- The adjustment of efficiency is employed by the following formula that accounts for temperature effects:

$$n_{actual} = n_{nom} - a_T \cdot max(T - 25, 0)$$

where a_T is a **power temperature coefficient** (%/°C), denoting the rate of PV efficiency decrease for every unit increase of temperature above 25°C.



- To evaluate the PV potential of each location in dimensionless means, we express it in terms of **annual capacity factor**:

$$CF = \frac{E_{mean,annual}}{P_{nom} \cdot 8760}$$

- The CF values at all locations are quite high (min 17.4%, max 21.4%, for the conventional temperature factor), which in turn, confirms that their solar potential is high. This verifies the site selection criteria utilized in our analysis.

Remark: Each location's PV performance is evaluated for three power temperature coefficient values (i.e., 0.0, 0.2, 0.4%/°C). The first value corresponds to a theoretical setting, where temperature has no effect on PV power production, the second refers to state-of-the-art technologies that are less susceptible to temperature effects, while the last one is a typical value, concerning conventional modules.

5. Probabilistic assessment of centralized production

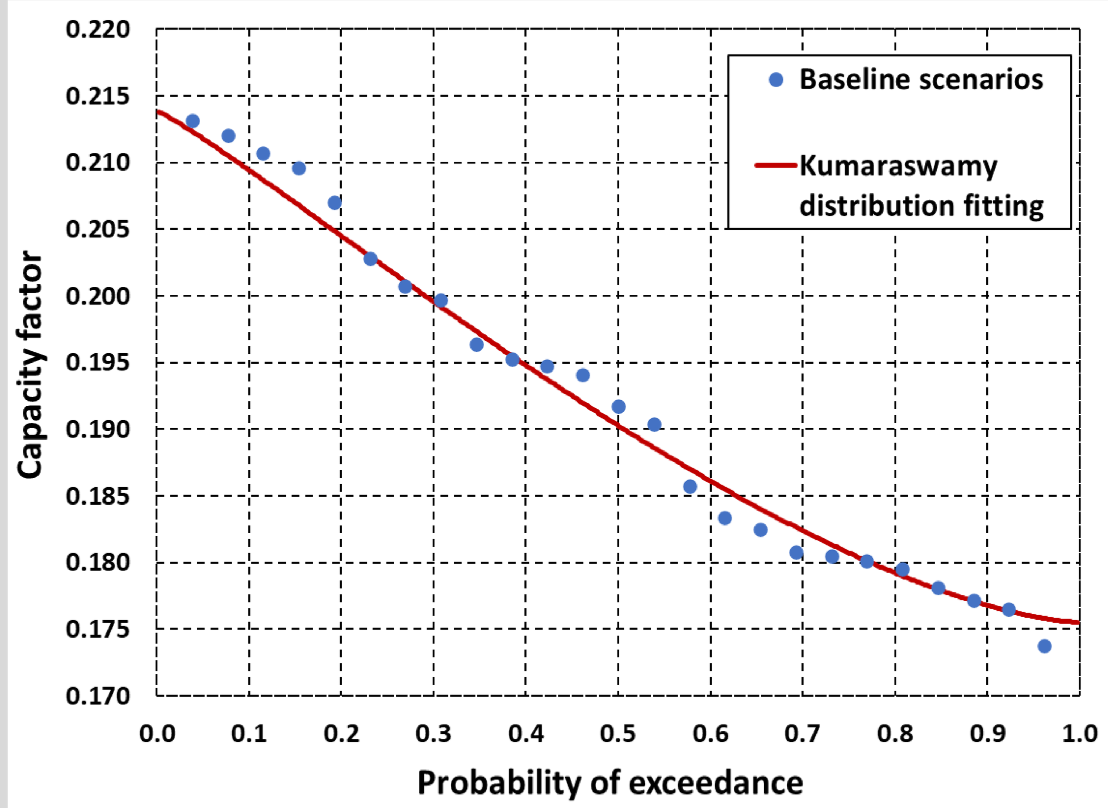
- The spatial variability of the **centralized production** is visualized through the **empirical probability curve** (inverse CDF) of the annual capacity factors across the 25 selected locations.
- The curve data are derived by sorting the CF values in descending order and assigning an empirical exceedance probability (cf. Efstratiadis *et al.*, 2021) to each value. If n is the size of data, the probability of exceeding the sorted value at position i is estimated through the Weibull plotting position, i.e.:

$$p_i = i \,/\, (n + 1)$$

- To provide a continuous spatial variability model, we fit the formula derived by the Kumaraswamy distribution function (cf. Kumaraswamy, 1980) to the empirical probability values:

$$CF = CF_{min} + \left(1 - (1 - p^a)^b\right)(CF_{max} - CF_{min})$$

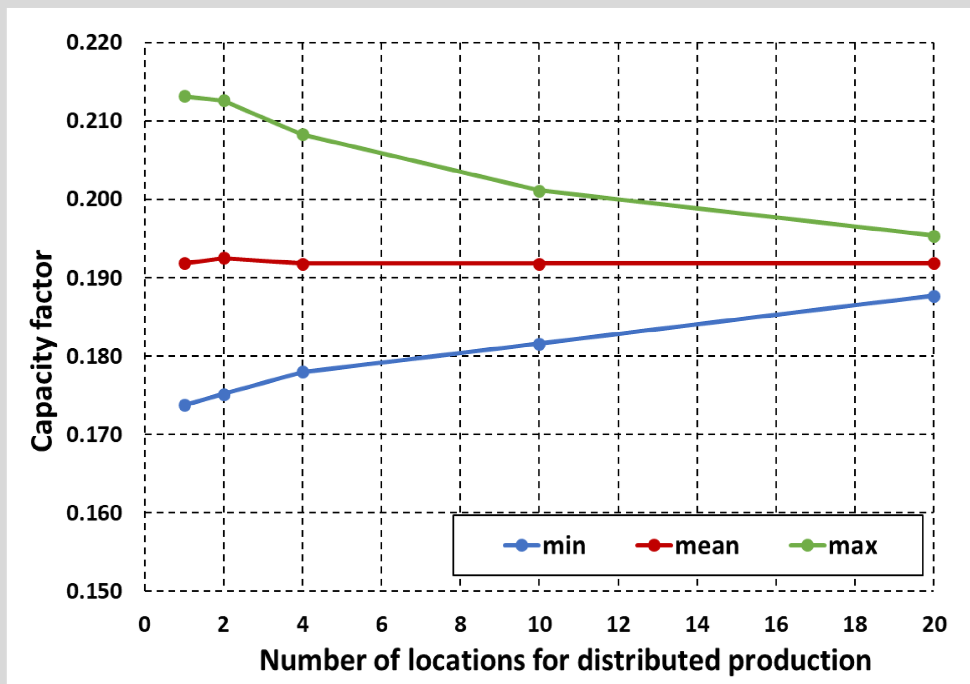
where CF_{min} and CF_{max} are the theoretical lower and upper limits of the capacity values, respectively, $\boldsymbol{a}$ and $\boldsymbol{b}$ are shape parameters, and $\boldsymbol{p}$ is the probability of exceedance.



Remark: The shape parameters and the limits CF_{min} and CF_{max}, corresponding to $p \approx 1$ and $p \approx 0$, are inferred via calibration

6. Monte Carlo approach for distributed production

- A Monte Carlo analysis is carried out to highlight the benefits of distributed solar PV production, thus accounting for alternative sites and production capacities.
- The **"joint" power potential** is assessed by distributing PVs in equally-probable combinations of locations. To handle *combinatorial explosion*, we employ a **Monte Carlo** approach to calculate the capacity factor from 1,000 randomly selected combinations. Each combination is configured by sampling the number of PV installation sites within the range [2, N − 1], where N is the total number of feasible locations (25 in our case).
- Since solar radiation exhibits quite significant fluctuations across Greece, we argue that **by distributing PVs across the predefined locations, the uncertainty in PV power production will be reduced**. This is because, unlike centralized production, factors that typically induce power curtailment, such as cloud coverage, temperature effects, and atmospheric aerosols (cf. Kambezidis, 2021) are less likely to simultaneously impact different geographic regions.

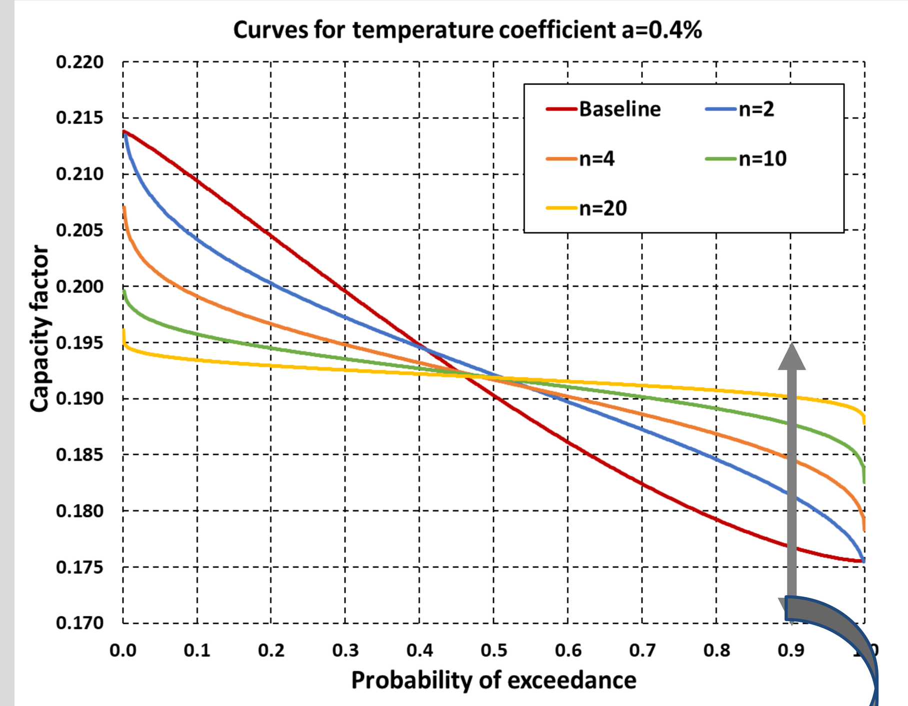


Remark: As the spatial spread of PVs across the Greek territory increases, the uncertainty of power performance (in terms of CF) decreases

6. Key simulation outcomes

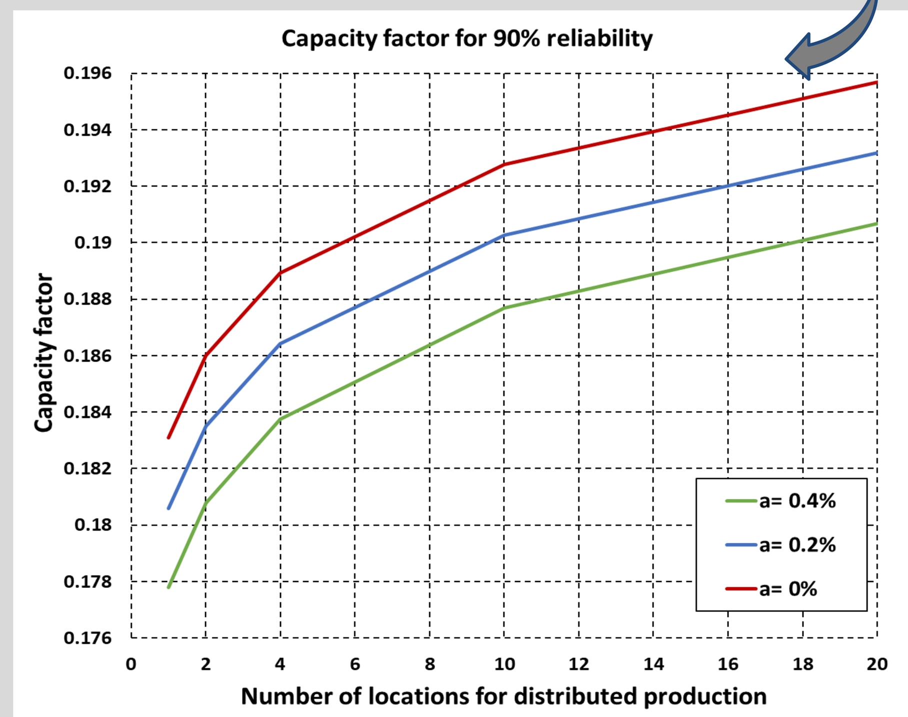
By contrasting the capacity factor probability curves of the centralized production (benchmark scenario) against the distributed settings, derived through stochastic combinations of PVs (**upper panel**), the following conclusions are drawn:

- The probability of exceedance can be interpreted as a metric of **spatial reliability**, thus the increase of PV spatial distribution leads to increased **guaranteed power production**;
- As the number of locations increases, the curves become smoother, thus increasing the spatial spread of PVs leads to decreased variability, and eventually **less uncertainty in PV power production**;
- Notably, the ratio of the underlying area of the $n = 2$ curve to the baseline one is 1.8/1.0 (the two curves are crossed at $p = 40\%$).



To provide better understanding of the **scaling law** derived by the distributed production setting, we plot the CF values that correspond to 90% probability of exceedance against n (**lower panel**). Key conclusions are:

- For the given spatial reliability level, the distributed power production increases as more locations are accounted for;
- **Temperature effects** are also contrasted, where, as expected, as the temperature coefficient increases, so does the PV power curtailment.
- The distance between the probability curves practically equals the difference of associated power temperature coefficients, i.e. 0.2%.



7. Conclusions & future research perspectives

- Distributing solar PVs across different locations exhibits a shift of the relationship between power production and spatial reliability. As the spatial distribution of PVs increases, so do the higher-reliability capacity factor values, while lower-reliability values decrease;
- Distributed PVs can ensure higher power production with increased reliability, compared to that of centralized configurations;
- The variance of PV production practically converges to zero as more locations are accounted for, meaning that highly **distributed layouts are significantly less vulnerable to power curtailment factors**;
- The effects of temperature on PV power production are not negligible, especially during the summer months;
- Future research will be focused on:
  - Including more components in the estimation of solar potential, e.g., diffuse radiation, cloud coverage, effects of topography (cf. Mamassis *et al.*, 2012);
  - Investigating seasonality effects on spatially-distributed capacity factors;
  - Validation of theoretical power potential with real-world cases.

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