Single-Site–Driven Synthesis of High-Frequency PV Power for Dispersed Portfolios

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***Abstract*—Minute-level photovoltaic (PV) power output time series are increasingly required for power-system operation studies such as regulation, ramping, and reserve sizing. Yet high-frequency irradiance (or PV) measurements are typically available at only a small number of locations, while the operational need is to represent PV variability over a dispersed fleet or a balancing area. This paper presents a single-site–driven framework that converts one high-frequency irradiance record into realistic PV power traces for dispersed PV portfolios by combining (i) a physically motivated PV power conversion model and (ii) an aggregation filter that reproduces the reduction of short-term variability with geographic diversity.**

***Index Terms*—photovoltaic power, geographic diversity, aggregation filter, irradiance variability**

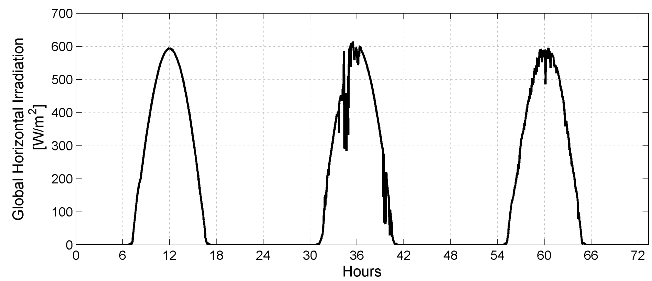

Fig. 1. Example of measured global horizontal irradiance (GHI) showing cloud-induced variability.

I. Introduction

Rapid growth of photovoltaic (PV) generation changes net-load variability and increases the need for flexibility in power-system operations. Many operational impacts—such as frequency regulation demand, intra-minute ramping, and short-term forecast errors—are driven by fast PV fluctuations caused primarily by cloud motion. As a result, operational studies increasingly require minute-level PV power time series that reproduce not only energy production but also short-term ramp statistics.

A practical obstacle is measurement availability. While PV and irradiance data at hourly (or coarser) resolution exist for many locations, high-frequency measurements are typically available at only a small number of stations. At the same time, system studies often require a geographically dispersed PV portfolio (e.g., rooftop PV in a distribution area or a balancing-area PV fleet), where aggregation reduces short-term variability relative to a single point measurement.

This paper focuses on the case where a single-site minute-resolution irradiance measurement is available and must be translated into a representative dispersed-portfolio PV power output. We propose a filter-based aggregation model that captures geographic smoothing and can be parameterized from portfolio geometry and correlation assumptions.

In contrast to purely data-driven approaches that require dense multi-site measurements, the proposed method targets a practical "one good sensor" setting: a high-quality reference irradiance record is used to generate a portfolio-equivalent variability driver, while the portfolio description (number of plants and spatial extent) provides the information needed to shape variability through an aggregation filter. This makes the approach suitable for planning and operational studies when the exact locations and capacities of individual PV systems are uncertain or when only coarse portfolio metadata are available.

A. Related work

High-frequency PV variability has been widely characterized in both time and frequency domains. Prior work shows that variability depends strongly on time scale and sky conditions, and that geographic dispersion produces smoothing in aggregated PV output [1]–[3]. Fig. 1 illustrates typical measured global horizontal irradiance (GHI) behavior, where cloud passages introduce fast ramps superimposed on the diurnal envelope.

Several approaches model aggregation either via explicit cloud advection/geometry or via statistical dependence across sites. Prior work has explored smoothing and spatial aggregation using (i) explicit cloud-motion/plant-geometry models for irradiance transients over large fields [4], [5], (ii) stochastic spatio-temporal models that capture distance-dependent dependence structure [6], [7], and (iii) data-driven or hybrid approaches that leverage satellite-derived irradiance and short-term downscaling methods [8], [9]. A broader overview of PV-plant variability simulation methods and their assumptions is provided in [10].

In this work we adopt a low-order filter representation that shapes high-frequency content with parameters tied to portfolio size and spatial extent [11], [12]. This choice provides a compact and transparent way to translate limited portfolio metadata into a target smoothing response, while remaining simple enough for sensitivity studies and integration into planning models.

A key practical challenge in filter-based aggregation is parameter selection: system studies typically know only approximate portfolio size and spatial footprint, while the underlying correlation structure depends on weather regime, cloud speed/direction, and sensor spacing. This sensitivity has been emphasized in studies of geographic diversity and short-term correlation structure [6]–[8], [13]. Our emphasis is therefore on a transparent procedure that links portfolio geometry to a target diversity curve and then to a fitted filter parameter, enabling sensitivity studies across plausible correlation assumptions without redesigning the full PV model.

II. Problem Statement and Methodology

A. Problem statement

Operational studies often require minute-level PV power time series, but high-frequency irradiance measurements are typically available at only a few locations. We consider the following problem:

Given a single-site minute-resolution irradiance measurement, generate a physically plausible PV power time series for a dispersed PV portfolio such that:

- the portfolio exhibits realistic smoothing relative to the single site, and
- operationally relevant short-term statistics are preserved.

In this paper, the key statistic we explicitly exploit to parameterize dispersion-driven smoothing is the correlation of ramps ("deltas") between locations. Empirically, correlations of irradiance/power deltas decrease with distance and this decay is stronger for shorter averaging windows [6], [7], [14]. This motivates a compact aggregation model that targets a desired variability reduction curve versus time scale.

B. Methodology

We assume a measured single-site minute global horizontal irradiance (GHI) record is available and use it as the variability driver for the portfolio. The objective is not to predict absolute irradiance at each location, but to synthesize a portfolio-equivalent signal whose short-term statistics match those of a geographically dispersed PV fleet.

The method takes as input the reference GHI time series together with a description of portfolio geometry (either explicit locations $\{(x_i, y_i)\}_{i=1}^{N}$ or an assumed spatial distribution over a footprint). Geographic smoothing is parameterized via the correlation of ramps ("deltas") between locations: for a time scale $\bar{t}$, we define $\Delta I^{\bar{t}}(t) = I^{\bar{t}}(t) - I^{\bar{t}}(t-\bar{t})$ and use a distance- and time-scale–dependent correlation model $\rho(d, \bar{t})$ to characterize how $\rho\big(\Delta I_i^{\bar{t}}, \Delta I_j^{\bar{t}}\big)$ decays with inter-site distance.

Fast PV and irradiance ramps are largely driven by the motion and evolution of cloud structures across a region. Even when cloud fields deform and change in time (i.e., the pattern is not perfectly translated by a constant wind), separated sites

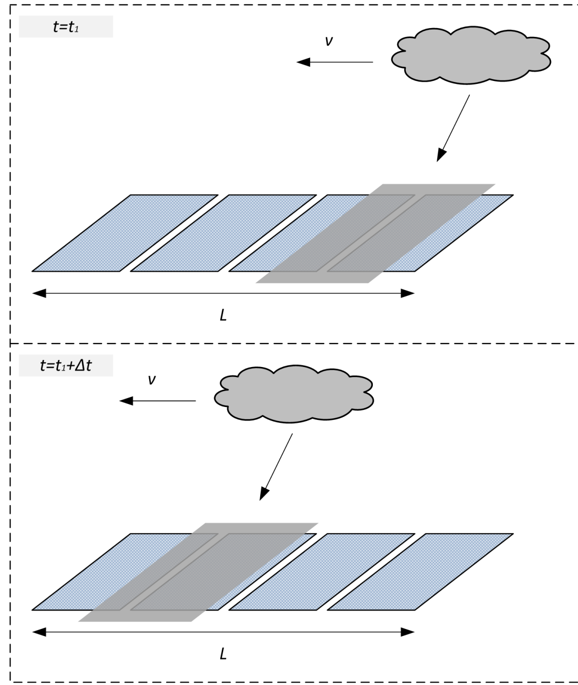

Fig. 2. Illustration of cloud movement (advection) producing time-shifted irradiance ramps across separated sites.

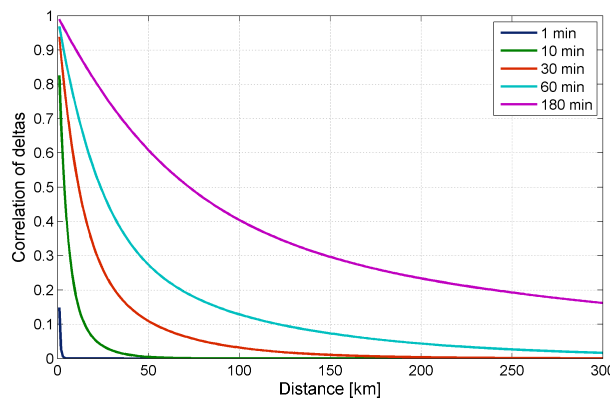

Fig. 3. Correlation of irradiance deltas versus distance for several averaging times (illustrative).

experience partially time-shifted and partially decorrelated ramps. As inter-site distance increases, the temporal overlap of rapid ramps decreases, which reduces the correlation of $\Delta I^{\bar{t}}$ and produces smoothing in aggregated PV output, especially at short time scales.

From the geometry and $\rho(d, \bar{t})$ we compute a target diversity-factor curve $D^{\bar{t}}$ over a grid of time scales, and then fit the time constant T of the first-order shaping filter (2) so that $|H(j\omega)|$ matches this target (Algorithm 1). The fitted filter is applied to the single-site irradiance to obtain a portfolio-equivalent irradiance driver, which is then converted to PV power.

Fig. 3 illustrates the delta-correlation decay with distance (the key statistic exploited). Fig. 4 summarizes the overall workflow.

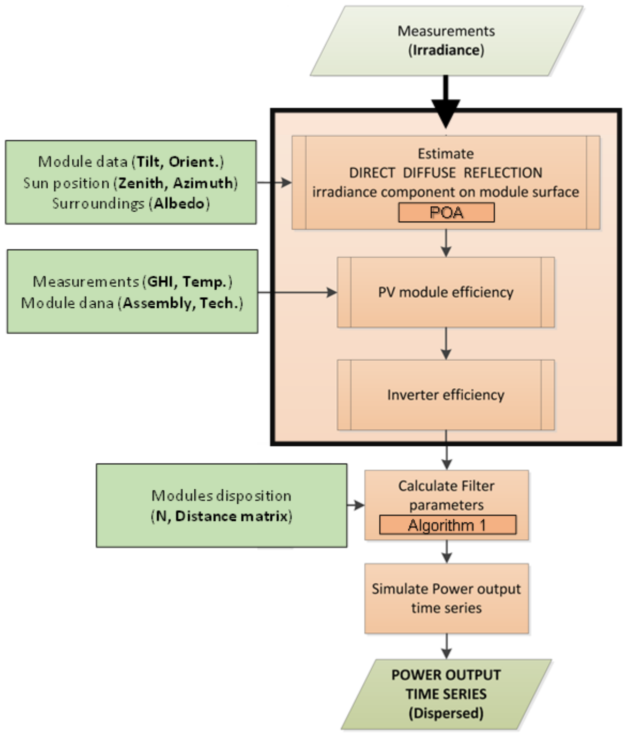

Fig. 4. Workflow for single-site high-resolution synthesis of dispersed PV portfolio power (data inputs on the left, processing steps on the right).

We quantify smoothing via the diversity factor

$$D^{\bar{t}} = \frac{\sigma^{\bar{t}}_{\Delta P_{\text{total}}}}{N\sigma^{\bar{t}}_{\Delta P}} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho\big(\Delta P_i^{\bar{t}}, \Delta P_j^{\bar{t}}\big)}, \qquad (1)$$

and represent aggregation with the first-order shaping filter

$$H(s) = \frac{1 + s\left(\frac{T}{\sqrt{N}}\right)}{1 + sT}, \qquad (2)$$

where T is fitted to match $|H(j\omega)|$ to the target $D^{\bar{t}}$ curve.

Fig. 5 shows an example Bode magnitude response of the fitted aggregation filter for different footprint areas and numbers of PV plants, illustrating how increased geographic dispersion and larger N primarily attenuate higher-frequency (short time-scale) variability.

In implementation, the fitted filter is applied to the single-site irradiance to obtain a smoothed irradiance driver consistent with the target dispersed portfolio.

C. PV power conversion

Given (filtered) irradiance, we compute PV AC power using standard components.

a) POA transposition and orientation.: Let θ denote the angle of incidence between the sun vector and the module normal. The beam component on a tilted surface can be approximated by

$$I_{\text{tilt},b} = I_{h,b}\,\frac{\cos(\theta)}{\sin(\beta_s)}, \qquad (3)$$

Algorithm 1 Filter fit for dispersed-portfolio aggregation

Require: Plant locations $\{(x_i, y_i)\}_{i=1}^{N}$, time-scale grid $\{\bar{t}_m\}$, correlation model $\rho(d, \bar{t})$, and filter structure $H(s; T, N)$.
Ensure: Fitted time constant T.
Compute all pairwise distances d_{ij} for $i, j \in \{1, \ldots, N\}$.
for each time scale $\bar{t}_m$ **do**
  Compute target diversity factor $D^{\bar{t}_m}$ using $D^{\bar{t}_m} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\rho(d_{ij}, \bar{t}_m)}$.
  Map $\bar{t}_m$ to angular frequency ω_m (e.g., $\omega_m = 2\pi/\bar{t}_m$).
  Evaluate $|H(j\omega_m; T, N)|$.
end for
Define an objective, e.g., weighted least squares $J(T) = \sum_m w_m \left(D^{\bar{t}_m} - |H(j\omega_m; T, N)|\right)^2$ with weights $w_m \geq 0$.
Solve $\min_{T>0} J(T)$ (1-D search/line search).
return T.

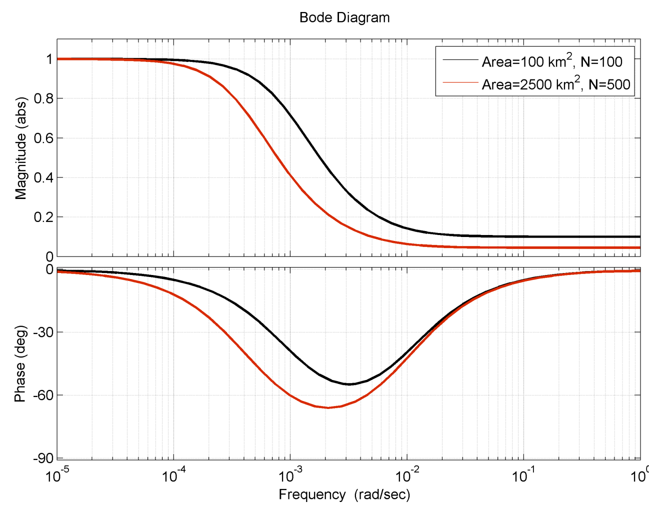

Fig. 5. Bode magnitude response of the aggregation filter for different portfolio footprint areas and numbers of PV plants.

where $I_{h,b}$ is the direct beam on horizontal and β_s is the solar elevation angle. The diffuse component is modeled with an anisotropic transposition model (e.g., the Klucher model) [15], [16]. The POA irradiance G is obtained by combining beam, diffuse, and ground-reflected components.

b) Module temperature.: We use the widely adopted linear temperature model

$$T_{\text{mod}} = T_{\text{amb}} + c_T\,G, \qquad (4)$$

where c_T depends on mounting configuration and technology [17].

c) Efficiency and inverter mapping.: Module efficiency depends on (G, T_{mod}); inverter efficiency depends on loading. In this paper we represent both with parametric curves calibrated to the technology under study and clip the output at the inverter AC rating.

The output of this stage is an AC power time series for an individual plant; applying (2) yields a portfolio- or footprint-consistent trace.

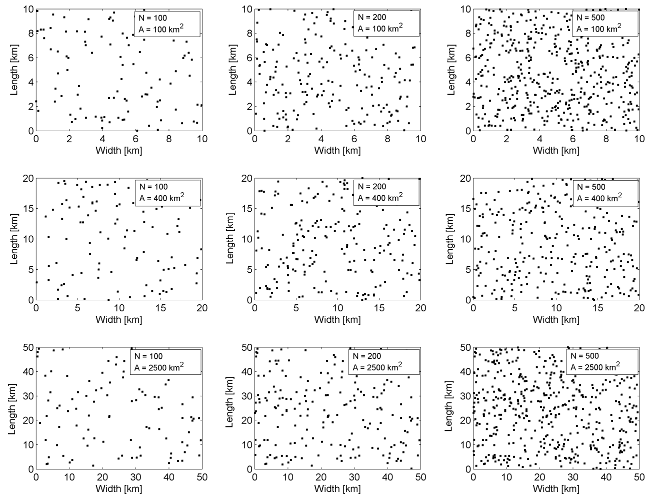

Fig. 6. Illustrative random distributions of PV units over different geographic footprints (case study setup).

III. Results and Discussion

A. Case study description

To illustrate the proposed aggregation filter design, we consider a synthetic dispersed PV portfolio defined by a geographic footprint and a number of PV units N. For illustration purposes, PV unit locations are assumed to be randomly distributed over the footprint (uniform placement), as shown in Fig. 6. This choice allows the behavior of the aggregation model to be demonstrated without requiring detailed asset data. To demonstrate the model capabilities, we vary the portfolio footprint area and the number of PV plants:

- Footprint area: $100\,\mathrm{km}^2$, $400\,\mathrm{km}^2$, and $2500\,\mathrm{km}^2$.
- Number of PV plants: $N \in \{100, 200, 500\}$.

In a real-world application, the same procedure applies but the portfolio geometry would be built from actual PV locations (and, if available, capacities/weights).

B. Results: impact of area and number of PV units

Figs. 7 and 8 show the aggregation effect produced by the proposed filter design. Each figure compares the original single-site signal with its filtered (portfolio-equivalent) counterpart, demonstrating reduced high-frequency variability in the time domain and attenuation of high-frequency content in the frequency domain.

a) Impact of geographic area.: Fig. 7 considers a fixed number of PV units and varies the geographic footprint size. As the footprint grows, typical inter-site distances increase and delta correlations decrease, which leads to stronger smoothing over a wider range of time scales. In other words, a larger geographic spread reduces the coincidence of fast fluctuations across sites, and the aggregate exhibits lower short-term ramps.

b) Impact of the number of PV units.: Fig. 8 considers a fixed footprint and varies the number of PV units. Increasing N increases the achievable smoothing at the shortest time scales, consistent with the limiting behavior of the aggregation model (high-frequency attenuation approaching $1/\sqrt{N}$). For longer time scales, the aggregated signal remains closer to the single-site signal, since slower variability is more coherent across a region.

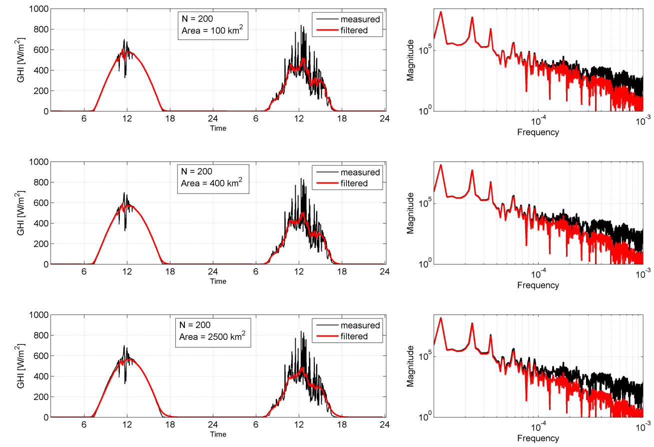

Fig. 7. Aggregation effect for fixed N and varying geographic area (time and frequency domain).

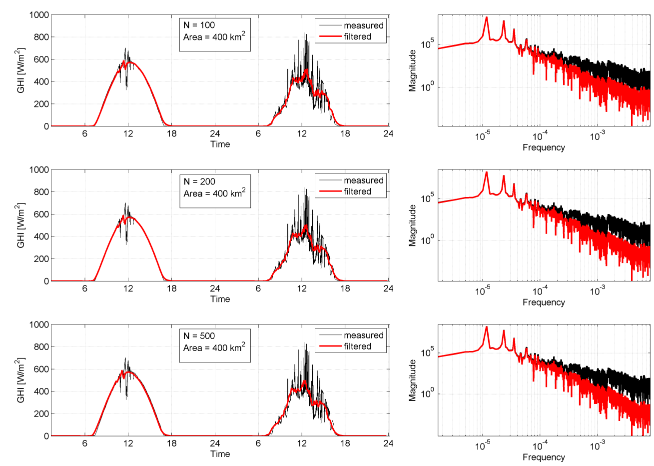

Fig. 8. Aggregation effect for fixed geographic area and varying number of PV units (time and frequency domain).

IV. Conclusion

This paper presented a single-site–driven framework for synthesizing minute-level PV power output representative of dispersed PV portfolios when only one high-frequency irradiance measurement is available. The proposed workflow couples a physically motivated PV conversion chain with a compact, parameterized aggregation filter that reproduces the reduction of short-term variability with geographic diversity.

A case study with varying footprint area and number of PV plants demonstrates the expected smoothing trends: increasing geographic extent reduces the coincidence of fast cloud-induced fluctuations across sites, while increasing N strengthens attenuation at the shortest time scales. The resulting portfolio-equivalent traces preserve the diurnal envelope while exhibiting reduced intra-minute and multi-minute ramping consistent with dispersed aggregation.

The main limitation of the approach is the reliance on an assumed (or externally estimated) distance- and time-scale–dependent delta-correlation model to parameterize the target diversity curve; addressing this and extending validation are the focus of the future work outlined in the next section.

V. FUTURE WORK

Future work will focus on improving parameterization and validation of the proposed single-site–driven synthesis framework. Key directions include:

- **Correlation calibration:** estimate $\rho(d,\bar{t})$ parameters across weather regimes, seasons, and climate zones, and quantify uncertainty bands for sensitivity studies.
- **PV-plant heterogeneity:** extend the aggregation step to capacity-weighted portfolios and heterogeneous PV plants (orientation, clipping, and temperature response).
- **Multi-site validation:** benchmark synthesized portfolio traces against multi-site measurements using ramp-rate distributions, spectral metrics, and reserve-sizing proxies.
- **Extensions to forecasting studies:** integrate the synthesized traces into short-term forecast error and flexibility assessments at different spatial aggregation levels.

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