Reliability analysis of PV Strings along the years

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Abstract

The rapid expansion of utility-scale photovoltaic installations has shifted performance assessment focus from individual modules to system-level analysis, where string reliability becomes critical for operational efficiency. Module degradation presents a challenging modeling problem due to its gradual nature and heterogeneous patterns across large installations. While existing approaches include physical and data-driven models, stochastic modeling offers advantages for capturing inherent variability and uncertainty in degradation phenomena. This work proposes a novel stochastic framework for characterizing long-term photovoltaic string reliability. Building upon statistical degradation models for individual modules, we extend the analysis to evaluate PV string reliability evolution over operational lifetime. The approach accounts for series connection constraints where string performance is limited by the weakest module. The stochastic model uses time-dependent scaling functions to represent non-uniform degradation and growing performance uncertainty. Numerical analysis demonstrates that string reliability decreases significantly with both module count and power output uncertainty. The findings provide enhanced tools for optimizing string configurations and developing risk-informed maintenance strategies. Unlike conventional deterministic approaches, this probabilistic framework offers a methodology for quantifying uncertainty in PV string performance evolution, supporting improved energy yield forecasting and economic planning for solar installations.

Keywords: Degradation, PV string, reliability analysis, statistical modeling.

1. Introduction

The growing global demand for renewable energy, combined with the decreasing manufacturing costs of photovoltaic (PV) devices, has catalyzed a rapid and sustained expansion of the solar energy sector (Ndiaye et al. 2013). This remarkable trajectory has been further propelled by supportive government policies, technological advancements in PV cell efficiency, and increasing environmental awareness among consumers and industries. In the early stages of PV deployment, performance and reliability assessments were primarily conducted at the level of individual PV modules (Vázquez and Rey-Stolle 2008). This module-level approach was well-suited to small-scale residential and commercial systems, which typically comprised a limited number of components. At this scale, it was feasible to employ detailed diagnostic methods—such as current-voltage (I–V) curve tracing and electroluminescence (EL) imaging—to detect issues like hot spots, cell cracking, potential-induced degradation (PID), and increased series resistance (Liu and Wu 2025). These analyses offered a high degree of granularity, enabling precise identification of defects and performance losses at the component level (Ullah Khan et al. 2024). However, as the solar industry has matured, the scale and complexity of PV installations have grown dramatically, particularly with the emergence of utility-scale solar farms comprising thousands or even millions of modules (Ito et al. 2016). This transformation has rendered module-by-module assessment impractical and economically inefficient (Dhoke et al. 2018). Consequently, performance evaluations have shifted to higher system levels—such as the string or combiner box level—where faults can have broader operational impacts and centralized monitoring systems can provide more scalable and holistic oversight (Buerhop et al. 2023).

Among the many factors influencing PV plant performance, one of the most challenging to model and quantify is energy loss due to long-term module degradation (MacAlpine and Wolfrom 2019). Unlike transient issues such as soiling or shading—which can be readily identified and mitigated through maintenance—degradation is a gradual and irreversible decline in module efficiency (Lillo-Sánchez et al. 2021). It accumulates over the operational lifetime of the system and is driven by a complex interplay of environmental stressors, material aging, and operational conditions (Bora et al. 2021; Kaaya et al. 2019). The non-uniform nature of these influences often leads to heterogeneous degradation rates across modules within the same installation, introducing spatial and temporal variability that complicates traditional modeling approaches (IEA PVPS 2021).

As outlined in IEA PVPS (2021), Kaaya et al. (2021), and Lindig et al. (2018), several modeling strategies have been

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developed to characterize PV module degradation. Physical models aim to simulate the underlying degradation mechanisms by representing the electrochemical, thermal, and mechanical processes occurring within PV cells. While these models offer a rigorous theoretical foundation, they often demand detailed knowledge of system parameters and may struggle to capture the simultaneous influence of multiple degradation pathways in real-world conditions. Data-driven models, on the other hand, leverage historical performance data and machine learning algorithms to identify degradation patterns and forecast future trends. These models are capable of capturing system-specific behaviors but typically require large volumes of high-quality data and may lack generalization across varying climatic regions or technologies (Ullah Khan et al. 2024). Stochastic models constitute a third category that introduces probabilistic elements to account for the inherent variability and uncertainty in degradation phenomena (Wu et al. 2020). These models provide a flexible framework that can accommodate the heterogeneous nature of degradation observed in large-scale PV installations. By representing performance deterioration as a probabilistic process, stochastic approaches enable the modeling of uncertainty bounds, facilitate risk assessment, and support reliability analyses (Vázquez and Rey-Stolle 2008). This probabilistic perspective is particularly advantageous for long-term energy yield forecasting, financial planning, and maintenance optimization, as it moves beyond deterministic point estimates to offer distributions of potential outcomes that better reflect real-world operational conditions.

In this context, our work proposes a novel stochastic modeling framework to characterize the long-term PV module degradation at the system level. Recognizing the limitations of deterministic and purely data-driven approaches—particularly when dealing with the variability and uncertainty inherent in large-scale photovoltaic systems—this study aims to develop a probabilistic model that better captures the heterogeneous nature of degradation. Building on the statistical degradation model for PV modules proposed by Jiménez et al. (2025), we extend the analytical framework to evaluate the reliability and performance evolution of PV strings over their operational lifetime. This extension represents a crucial advancement, as PV strings constitute the fundamental building blocks of larger photovoltaic systems, and their collective behavior determines overall plant performance.

2. Preliminaries

2.1 Photovoltaic Module Degradation Model

This section describes the underlying stochastic degradation model for individual PV modules that serve as the foundation for our system-level analysis. According to Vázquez and Rey-Stolle (2008), the power output of a PV module at any given time can be statistically characterized as following a Gaussian (normal) distribution with mean μ and standard deviation σ. Building upon this foundation, Jiménez et al. (2025) extend the model by incorporating time-dependent degradation effects that influence both the mean and standard deviation of the distribution.

This acknowledges that degradation affects modules in two ways: it reduces their average performance and makes their individual behavior more variable over time. This occurs because degradation mechanisms do not progress uniformly different cells within the same module and different modules within the same installation degrade at different rates, causing performance to become more dispersed as the system ages. Specifically, degradation manifests as a gradual proportional reduction in the mean power output (μ) over time, reflecting the expected decline in module efficiency. Conversely, the standard deviation (σ) increases with time, capturing the growing variability in performance due to factors such as material aging, environmental stresses, and manufacturing inconsistencies. In mathematical terms, the power output of the i-th PV module at year y, denoted as $P_i(t)$, is modeled as:

$$P_i \sim \mathcal{N}(\mu_i \times \lambda_i(t), \sigma_i \times \epsilon_i(t)) \quad \text{(eq. 1)}$$

where $\sim$ denotes "distributed as", $\mathcal{N}(\mu, \sigma)$ represents a normal distribution with mean μ and standard deviation σ, and μ_i and σ_i correspond to the initial mean and standard deviation of the power output distribution of the i-th PV module, respectively. The functions λ_i and $\epsilon_i(t)$ are time-dependent scaling factors that account for the temporal evolution of PV module degradation by modifying the distribution parameters. The degradation scaling function λ_i typically exhibits values less than unity for $t > 0$, representing the decline in expected power output and it is modeled by Jiménez et al. (2025)

$$\lambda_i(t) = \begin{cases} 1, & t = 0 \\ 0.98, & t = 1 \\ 0.98(1-\delta)^{t-1}, & t \geq 2 \end{cases} \qquad \text{(eq. 2)}$$

where δ is annual degradation rate[1]. The uncertainty scaling function $\epsilon_i(t)$ generally increases with time, reflecting the growing variability in module performance as degradation processes accumulate and diversify across the module population and is modeled by Jiménez et al. (2025)

$$\epsilon_i(t) = \begin{cases} 1, & t = 0 \\ 1 + \dfrac{\zeta\, P_{nom}}{\varpi_i} t & t > 1 \end{cases} \qquad \text{(eq. 3)}$$

where ζ represents a percentage of P_{nom} and ϖ_i denotes the non-homogeneous degradation of the modules and takes random values between 0.5 and 1[2].

To illustrate how the power distribution of a PV module evolves over time, Figure 1 presents the density function $f_{P_i}(\cdot)$ of the random variable P_i across different years. In this analysis, we adopt the degradation model proposed by Jiménez et al. (2025), assuming a PV module with a nominal power of 500 W, a constant degradation rate δ of 0.4% per year, and a yearly increase in the standard deviation ζ equal to 0.2% of the nominal power. The figure highlights the temporal shift and dispersion of the power distribution due to aging effects, providing insights into the progressive performance decline of individual modules over the system's lifetime.

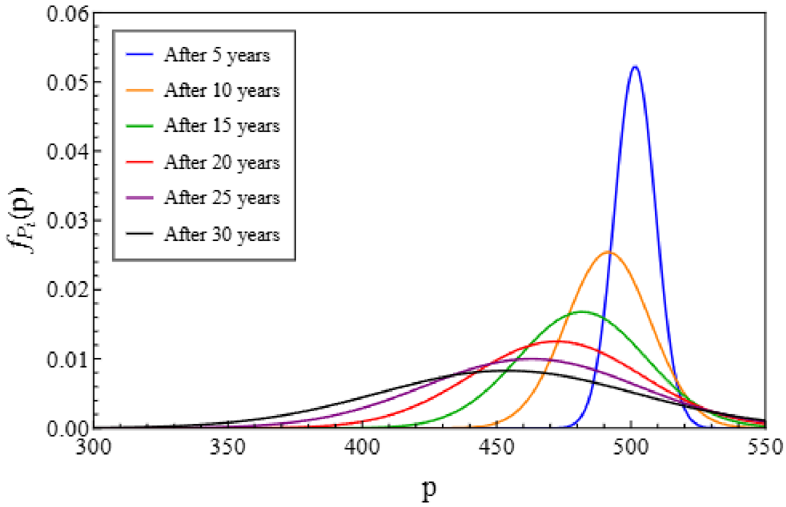

Figure 1: Pv module power output distribution alonf the years.

2.2 Probabilistic String Modeling

A PV string consists of a series connection of N individual PV modules. In an idealized scenario—assuming perfect uniformity among modules and no electrical mismatch—the total power output of the string can be expressed as the product of the number of modules, the operating current, and the voltage across each module, i.e., $P_{string} = N \times V \times I$. However, real-world conditions deviate significantly from this ideal. In practice, due to factors such as manufacturing variability, partial shading, soiling, and degradation, the current output of individual modules can vary within the same string. Because PV modules connected in series must operate at the same current, the overall current of the string is constrained by the module producing the lowest current. Meanwhile, the total string voltage remains approximately equal to the sum of individual module voltages, as each module contributes its respective voltage drop across the series connection. Consequently, the power output of the PV string is governed by the most limiting module in terms of current. Assuming every module operates at an (approximately) constant voltage the string power can thus be expressed as:

$$P_{string} = N \times V \times \min\{I_i\}_{\mathrm{i}=1}^{N} \qquad \text{(eq. 4)}$$

where V denotes the voltage of each module and $\min\{I_i\}_{\mathrm{i}=1}^{N}$ represents the minimum current among the N modules

[1] For newer PV module technologies, a typical value for δ is around 0.4%. In contrast, older and less efficient modules, which experience faster degradation, are generally associated with higher δ values.

[2] For newer PV module technologies ζ typically ranges between 0.1% and 0.3%, whereas for older technologies, ζ is generally assumed to lie between 0.5% and 1%.

in the string. The voltage is assumed to be equal across all modules, as voltage variations within a series-connected string are typically small under most practical operating conditions. Therefore, for modeling purposes, the power output of the string can be rewritten as:

$$P_{string} = N \times \min\{P_i\}_{\mathrm{i}=1}^{N} \qquad \text{(eq. 5)}$$

Since each module's power output P_i can be modeled as a Gaussian random variable, the authors in Jiménez et al. (2025) proposed modeling the total power output of a PV string as the minimum of N such Gaussian variables. This approach reflects the practical behavior of series-connected modules, where the overall performance is constrained by the weakest (i.e., lowest-performing) module in the string. Let us formally define the total string power as

$$Z = N \times \min\{P_i\}_{\mathrm{i}=1}^{N} \qquad \text{(eq. 6)}$$

Under the assumption that the P_i are independent and identically distributed (i.i.d.) Gaussian random variables, the probability density function (PDF) and cumulative distribution function (CDF) of Z can be derived as follows:

$$\begin{aligned} f_Z(z) = \left(\frac{1}{2}\right)^{N-1} \sum_{j=1}^{N} \frac{\exp\left(-\frac{\left(\frac{z}{N} - \mu_j \lambda_j(t)\right)^2}{2\,\sigma_j^2 \epsilon_j(t)}\right)}{N\sqrt{2\,\pi}\sigma_j\,\epsilon_j(t)} \\ \times \prod_{\substack{i=1 \\ i \neq j}}^{N} \operatorname{erfc}\left(\frac{\left(\frac{z}{N} - \mu_i \lambda_i(t)\right)}{\sqrt{2}\,\sigma_i^2 i(t)}\right) \end{aligned} \qquad \text{(eq. 7)}$$

$$f_Z(z) = 1 - \prod_{i=1}^{N}\left(1 - \frac{1}{2}\operatorname{erfc}\left(\frac{\left(\mu_i \lambda_i(t) - \frac{z}{N}\right)}{\sqrt{2}\,\sigma_i^2 \epsilon_i(t)}\right)\right) \qquad \text{(eq. 8)}$$

where erfc(·) is the complementary error function (Wolfram Research, Inc. 2022) (eq. 06.27.02.0001.01).

3. Long-Term Reliability of Photovoltaic Strings

To model the long-term reliability of PV strings, a novel formulation is derived to assess the reliability of a PV string over time. In the context of statistical reliability analysis, the reliability of a system is defined as a time-dependent function that quantifies the probability that the system continues to perform above a specified performance threshold throughout its operational lifetime. Specifically, this can be expressed as:

$$\begin{aligned} R(t) &= \mathbb{P}(Z \geq \gamma_{th}) \\ &= \int_{\gamma_{th}}^{\infty} f_Z(z)\; dz \end{aligned} \qquad \text{(eq. 9)}$$

where $R(t)$ represents the reliability of the PV string at year t, and γ_{th} denotes the minimum acceptable power output level. The right-hand side of (eq. 8) expresses the probability that the random variable Z exceeds this threshold, i.e., that the string continues to deliver adequate performance at time t. By substituting the PDF from (eq. 7) into (eq. 9) we obtain:

$$R(t) = \prod_{i=1}^{N}\left(1 - \frac{1}{2}\operatorname{erfc}\left(\frac{\left(\mu_i \lambda_i(t) - \frac{z}{N}\right)}{\sqrt{2}\,\sigma_i^2 \epsilon_i(t)}\right)\right) \qquad \text{(eq. 10)}$$

In real-world PV systems it is common practice to define the performance threshold γ_{th} at 80% of the nominal power. Accordingly, the reliability analysis focuses on determining the probability that the string continues to operate above this threshold after t years. To the best of the authors' knowledge, the formulation presented in (eq. 10) is novel in the literature and represents a significant contribution, as it enables the reliability of a PV string to be modeled in a simple yet effective and analytically tractable manner.

4. Numerical Results

This section presents numerical results based on the stochastic reliability analysis framework developed in the previous sections. The simulation parameters and their corresponding values are summarized in Table 1.

In the table, the parameter $\boldsymbol{\vartheta}$ represents the manufacturing tolerance, indicating that each module delivers a power output $\boldsymbol{P_i}$ within a range of $\pm\boldsymbol{\vartheta}$ relative to the nominal power $\boldsymbol{P_{nom}}$. Moreover, the initial mean of each module's power output distribution was sampled from a normal distribution $\boldsymbol{\mathcal{N}(P_{nom}, P_{nom} \times \vartheta)}$, while the initial standard deviation was randomly selected from the range $\boldsymbol{0.1\% \times P_{nom}}$ to $\boldsymbol{0.5\% \times P_{nom}}$.

Table 1: Simulation parameters.

Parameter	Figure 2	Figure 3	Figure 4
P_{nom}	500W	500W	500W
ϑ	5%	5%	5%
N	20	varies	20
δ	0.4%	0.4%	0.4%
ϖ	0.5 to 1	0.5 to 1	0.5 to 1
ζ	0.3%	0.3%	varies

Figure 2 presents the probability distributions of the string power output at 5-year intervals from year 5 to year 25, based on the parameters described in Table 1. Over time, the distributions exhibit both a declining mean power and an increasing standard deviation, reflecting the growing dispersion among module powers. Unlike the symmetric distribution observed for an individual PV module, the string distributions are distinctly skewed. This asymmetry results from the minimum constraint applied to the set of 20 series-connected modules, whereby the lowest-performing module governs the entire string

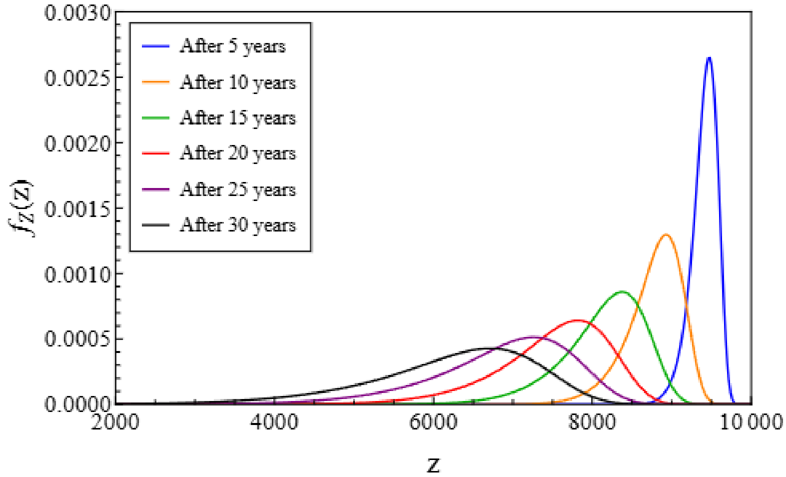

Figure 2: String´s power output distribution, $f_Z(z)$, along the years.

Figure 3 shows the progressive reliability decrease of PV strings over time due to degradation. However, a significant finding emerges regarding the influence of string configuration on long-term performance. The number of PV modules within a string demonstrates a pronounced impact on reliability evolution over the operational lifetime. This effect is clearly observed when comparing different string sizes. For instance, examining the curves for $\boldsymbol{N = 5}$ and $\boldsymbol{N = 10}$ modules reveal substantial differences: at $\boldsymbol{t = 30}$ years, the string with $\boldsymbol{N = 5}$ modules maintain reliability of $\boldsymbol{R(30) = 0.5}$, while the $\boldsymbol{N = 10}$ string shows degraded reliability of $\boldsymbol{R(30) = 0.2}$. This behavior occurs because series-connected strings are governed by their weakest-performing module, and larger strings have higher probability of containing at least one significantly degraded module. Consequently, strings composed of more modules tend to exhibit faster reliability degradation.

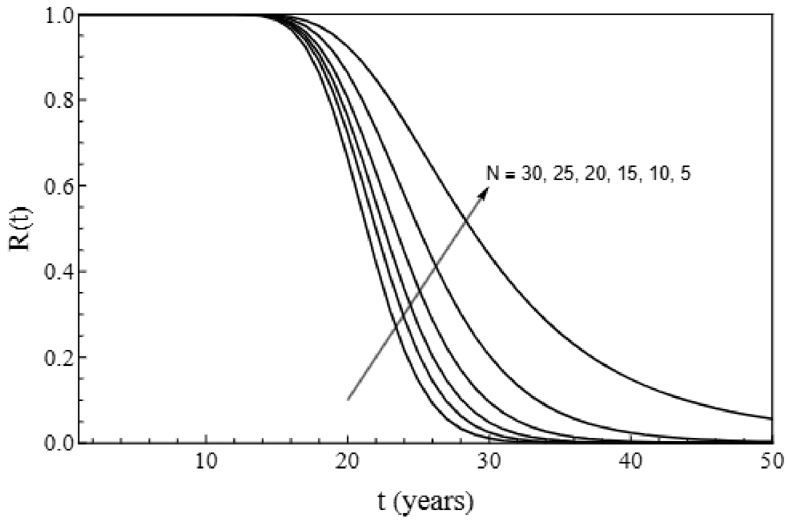

Figure 3: String reliability over time for different numbers of PV modules within the string.

Turning to Figure 4, the results show that for a fixed number of modules $\boldsymbol{N = 20}$, higher values of the standard deviation scaling parameter ζ lead to reduced reliability performance. This behavior aligns with the theoretical foundations of the proposed model, where increased standard deviation in individual module performance translates to greater uncertainty in string output. Specifically, as the component $\boldsymbol{\sigma_i \times \epsilon_i(t)}$ increases, the overall dispersion of the power output distribution becomes more pronounced, resulting in higher probability that the string performance falls below the specified threshold. This finding indicates that installations with greater performance variability will experience accelerated reliability degradation.

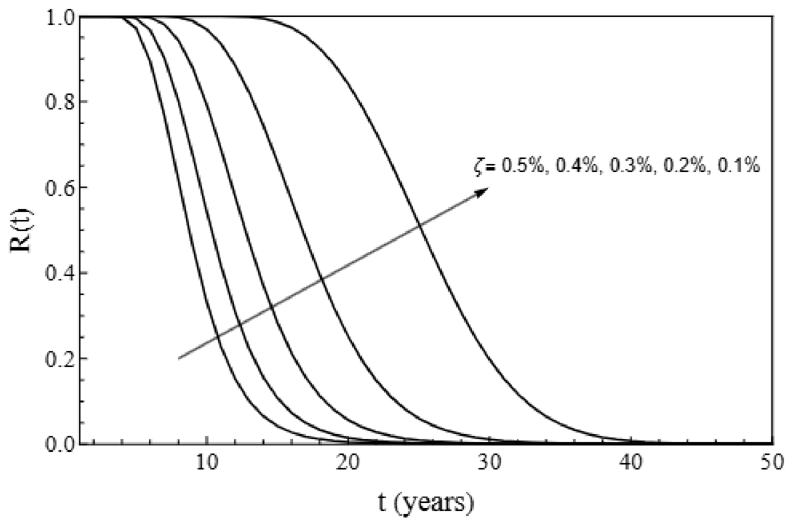

Figure 4: String reliability along the years along the years for different values of ζ.

These findings represent novel contributions within the existing photovoltaic reliability literature. The proposed stochastic framework provides an alternative approach for assessing the inherent uncertainty in PV string degradation, offering system designers enhanced tools for optimizing configurations and developing risk-informed maintenance strategies. This methodology supports improved decision-making for long-term performance prediction and economic planning of solar energy installations.

5. Conclusion

This study presents a concise probabilistic framework for quantifying how degradation—arising from environmental stressors, and natural ageing—progressively reduces the power output and reliability of photovoltaic strings. By combining analytical degradation models with statistical modelling, we show that power output steadily falls and becomes less predictable over time, especially in longer strings or in systems with greater variation among modules. These insights offer practical guidance for limiting string length, tightening quality-control tolerances, and planning maintenance to sustain long-term energy production. Future work may extend this framework by fitting the distribution parameters to real-world scenarios using field data, enabling more accurate and site-specific analysis.

6. References

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