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Comparative Assessment of Deterministic and Probabilistic Load Flow Under Solar Irradiance Variability in PV-Integrated Distribution Networks

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Abstract

The increasing penetration of photovoltaic (PV) generation in modern distribution networks introduces considerable uncertainty due to the inherently fluctuating nature of solar irradiance. These fluctuations directly affect PV output power, resulting in significant variations in bus voltages, feeder currents, and power losses. Traditional deterministic load flow (DLF) analysis, which assumes fixed PV generation, is unable to capture this stochastic behavior and therefore may lead to inaccurate estimation of system conditions. This study presents a comparative assessment between deterministic load flow using the Backward–Forward Sweep (BFS) method and probabilistic load flow (PLF) based on Hong's Two-Point Estimate Method (PEM) to evaluate the impact of solar irradiance variability on the performance of PV-integrated distribution networks. Solar irradiance data are statistically characterized to obtain the mean and variance, which are then propagated into PV output power through a linear irradiance–power conversion model. The IEEE 34-bus radial distribution system is used as the test network, with multiple PV units installed at selected buses. The results show that deterministic analysis underestimates voltage deviations and fails to capture the range of power losses induced by PV uncertainty. In particular, the deterministic BFS solution yields a single operating point with real and reactive losses of 0.1582 MW and 0.0479 MVar, whereas the probabilistic 2PEM produces mean losses of 0.105 MW and 0.031 MVar with standard deviations of 0.057 MW and 0.016 MVar, respectively. In contrast to the fixed deterministic voltage curve, probabilistic voltage profiles form a bounded envelope around it, indicating non-negligible downstream voltage variability driven by irradiance fluctuations. Overall, the findings confirm that solar irradiance variability substantially influences distribution system performance, and incorporating probabilistic assessment is essential for more realistic, risk-informed planning and operation of PV-integrated distribution systems.

Keywords: Deterministic Load Flow, Probabilistic Load Flow, Backward-Forward Sweep, Point Estimate Method, Solar Irradiance Variability.

1. Introduction

The rapid growth of photovoltaic (PV) installations in modern distribution networks has significantly transformed the operational dynamics of electric power systems. As distribution feeders increasingly accommodate small- and medium-scale PV units, system operators face new challenges related to variability, intermittency, and uncertainty of renewable energy sources [1]. Unlike conventional generation, PV output is highly sensitive to environmental conditions especially solar irradiance which can fluctuate over seconds, minutes, hours, and across seasons [2]. These fluctuations propagate directly into real-time changes in power injections at distribution buses, causing variations in voltage profiles, feeder currents, and power losses. Such behavior introduces operational risks that traditional assessment tools may not adequately capture [3].

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Deterministic Load Flow (DLF) analysis remains the most widely adopted approach in utility planning and operation. However, it relies on fixed input parameters such as static PV output, constant load demand, and ideal operating conditions and therefore provides only a single operating point. While this is acceptable for conventional feeders dominated by predictable loads and dispatchable generators, it becomes insufficient when PV penetration reaches moderate to high levels. The main limitation of deterministic approaches is their inability to represent uncertainties associated with PV generation. When irradiance fluctuates rapidly due to cloud movements or atmospheric variations, PV output changes accordingly, affecting power system behavior in ways that deterministic load flow cannot predict. As a result, DLF may underestimate voltage deviations, misrepresent feeder losses, and overlook potential overvoltage or undervoltage events that occur in real operation [4]–[7].

In distribution networks, these challenges are exacerbated by the structural characteristics of the feeder. Radial networks commonly used for medium and low voltage distribution systems are characterized by high resistance-to-reactance (R/X) ratios, long line lengths, and limited reactive power support. Such conditions increase the sensitivity of bus voltages and line currents to changes in active power injections from PV units. Small fluctuations in solar irradiance can therefore result in noticeable voltage rise near PV buses, increased current flow through upstream branches, and unpredictable variation in technical losses [8]. This raises the need for analytical methods that can represent multiple possible operating states instead of a single deterministic snapshot.

To address the limitations of traditional DLF, probabilistic analysis has gained significant attention. Probabilistic Load Flow (PLF) methods aim to quantify not only the expected operating condition of a system but also its variability and the likelihood of extreme events [9]–[13]. Monte Carlo Simulation (MCS) [14]–[17] is generally considered the benchmark PLF method due to its accuracy; however, it is computationally demanding due to the large number of simulations required, especially when multiple uncertainties are considered. Analytical and hybrid approaches, such as cumulant-based methods [18] and Gaussian copula method [19], offer computational benefits but are mathematically complex and sensitive to assumed probability distributions. In contrast, the Point Estimate Method (PEM) has emerged as an attractive alternative due to its balance between computational efficiency and accuracy [20], [21]. Hong's Two-Point Estimate Method [22], in particular, requires only two deterministic load flow evaluations per random variable and can capture the effects of mean, variance, and skewness of uncertain inputs.

Considering the operational characteristics of distribution feeders, the deterministic portion of the analysis in this study employs the Backward–Forward Sweep (BFS) method [23]. BFS is well established as the most suitable and stable load flow technique for radial and weakly meshed distribution systems, offering rapid convergence and computational efficiency even in systems with high R/X ratios [24]. Its compatibility with repeated load flow executions also makes BFS ideal for integration with probabilistic methods such as PEM. The combination of BFS for deterministic analysis and PEM for uncertainty propagation forms a robust framework for evaluating the impact of solar irradiance variability on network performance.

Although research on load-flow analysis and PV uncertainty has grown rapidly, important gaps still remain. Probabilistic load-flow formulations are frequently presented without a direct, quantitative baseline comparison to deterministic load flow under identical irradiance driven PV operating conditions, which makes it difficult to interpret the practical benefit of probabilistic modeling. Monte Carlo simulation and cumulant-based approaches are widely used to represent irradiance uncertainty, but they are often applied in ways that do not explicitly show how uncertainty described by simple statistical moments (mean and variance) propagates into PV output and affects feeder performance. In this context, moment-based methods such as Hong's Two-Point Estimate Method (2PEM) provide a computationally efficient alternative. However, their application to PV-integrated radial distribution feeders remains limited. To address these gaps, this study provides a quantitative comparison between deterministic and probabilistic load-flow methods under solar irradiance variability. The aim is to assess how irradiance uncertainty affects bus voltages, power losses, and overall system accuracy when analyzed using the BFS deterministic method versus the PEM probabilistic approach. Solar irradiance is statistically characterized using its mean and variance from real insolation data, and these moments are propagated through a linear irradiance PV output model. The IEEE 34-bus radial distribution feeder is used as the case study due to its realistic structure and suitability for PV integration, with several PV units installed at selected buses to reflect typical distributed generation deployment.

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This study highlights how changes in solar irradiance directly influence PV output and, in turn, affect the overall behavior of a distribution network. By comparing deterministic BFS load flow with the probabilistic PEM approach, the results show clear differences that are not captured when solar conditions are assumed to be constant—such as hidden voltage variations and shifts in power losses that emerge under uncertainty. The analysis also provides a broader view of system performance, covering voltage profiles, loss patterns, and operational risks across the feeder. Overall, the findings show that relying solely on deterministic methods is not enough to understand the real behavior of networks with significant PV penetration. Incorporating probabilistic analysis gives a more realistic and risk-aware picture of system conditions, which is essential for better planning and decision-making in modern distribution systems.

2. Methodology

2.1 Solar Irradiance Data and Statistical Characterization

Solar resource characterization plays a crucial role in accurately modeling photovoltaic (PV) output for probabilistic power-flow studies. Solar energy is generally described using two interrelated metrics: solar insolation and solar irradiance. Solar insolation represents the total solar energy accumulated on a unit surface over a full day (kWh/m²/day) and is widely reported in global renewable-energy databases. In contrast, solar irradiance refers to the instantaneous solar power intensity (kW/m²) incident on a surface at any given moment and serves as the fundamental input for PV power estimation and uncertainty modeling [25].

In this study, monthly solar-resource inputs for the geographical location of Universitas Negeri Medan, Indonesia (3.46° S, 98.76° E) are obtained from the NASA Surface meteorology and Solar Energy (SSE) database [26]. Since NASA SSE provides long-term climatological monthly averages (historical averages) rather than measured time-series for a single specific year, the monthly values used in this work should be interpreted as climatological monthly average daily insolation statistics for January–September at the study location as presented in Table 1.

Table 1. Monthly Average Solar Insolation (kWh/m²/day) for Universitas Negeri Medan based on NASA SSE Dataset

January	February	March	April	May	June	July	August	September	Mean
4.5	5.0	5.5	5.7	5.5	5.2	5.23	5.18	5.12	5.21

Because PV power models require irradiance rather than insolation, the monthly average daily insolation values are converted into an equivalent average irradiance under an effective sunshine-duration assumption. For equatorial/tropical regions such as Indonesia, an effective sunlight period of approximately 12 hours/day is commonly adopted as a practical simplification for irradiance-based PV modeling [27]. Thus, the conversion is performed as:

$$I_{avg}(kW/m^2) = \frac{H\,(kWh/m^2/day)}{h_s\left(\frac{h}{day}\right)},\ h_s = 12 \tag{1}$$

Applying (1) yields the monthly average irradiance values summarized in Table 2.

Table 2. Monthly average solar irradiance (kW/m²) for Universitas Negeri Medan converted from NASA SSE insolation data

January	February	March	April	May	June	July	August	September	Mean
0.375	0.417	0.458	0.475	0.458	0.433	0.436	0.432	0.427	0.435

For probabilistic load flow using Hong's Two-Point Estimate Method (2PEM), irradiance is treated as a stochastic input characterized by its first two moments. The sample mean and sample standard deviation of irradiance are computed from the monthly values as:

$$\mu_I = \frac{1}{n}\sum_{i=1}^{n} I_i\,,\ \sigma_I = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(I_i - \mu_I)^2}, \qquad \gamma_1 = \frac{\mathbb{E}[(X-\mu)^3]}{\sigma^3} \tag{2}$$

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At the aggregated monthly time scale, irradiance variability can be reasonably approximated by a Normal-type distribution [28], [29]:

$$I \sim \mathcal{N}(\mu_I, \sigma_I^2). \tag{3}$$

Although Eq. 3 is convenient for 2PEM which requires mean variance inputs, a Normal model may theoretically generate negative values, which are physically infeasible. Therefore, non-negativity is enforced via a simple rectification (clipping) rule as follow,

$$I^* = \max(0, I). \tag{4}$$

This introduces only a minor approximation because the probability mass below zero under the fitted monthly distribution is negligible as follows,

$$P(I < 0) = \Phi\left(\frac{0-\mu_I}{\sigma_I}\right) = \Phi\left(-\frac{\mu_I}{\sigma_I}\right) \approx 1.37 \times 10^{-51} \approx 0 \tag{5}$$

where Φ denotes the standard Normal cumulative distribution function. Hence, the processed irradiance I^*remains physically valid while preserving the mean variance characterization required for Hong's 2PEM-based probabilistic assessment of distribution-system voltages and losses.

2.2 PV Output Modeling Under Irradiance Variability

Photovoltaic generation is directly influenced by the level of incident solar irradiance, therefore, accurately modeling PV output under varying irradiance conditions is essential for probabilistic analysis of distribution networks. In this study, the relationship between irradiance and PV power is represented using a linear transformation model in accordance with standard PV performance characterization practices. Under Standard Test Conditions (STC), irradiance of 1 kW/m² and cell temperature of 25°C, the rated power of a PV module is defined as:

$$P_{\text{rated}} = G_{\text{STC}} \cdot A \cdot \eta \tag{6}$$

where $G_{\text{STC}}$is the reference irradiance (1 kW/m²), $A$is the active panel area (m²), and $\eta$is the module conversion efficiency. For real operating conditions, the actual PV output is obtained by replacing the STC irradiance with the measured or estimated irradiance level:

$$P_{\text{rated}} = G_{\text{STC}} \cdot A \cdot \eta \tag{7}$$

where G denotes the actual solar irradiance (kW/m²). Because the PV power rating is typically known in system planning studies, the active area Acan be expressed as:

$$A = \frac{P_{\text{rated}}}{\eta \cdot G_{\text{STC}}} \tag{8}$$

which, when substituted into Eq.3, yields the commonly used normalized PV output model:

$$P_{\text{PV}} = n \cdot P_{\text{rated}} \cdot \frac{G}{G_{\text{STC}}} \tag{9}$$

Here, n denotes the number of PV modules or the scaling factor associated with the installed PV capacity at a given bus. Eq.5 demonstrates that PV power output varies linearly with irradiance, making the transformation from irradiance variability to PV output variability mathematically straightforward. This is a key advantage when integrating PV uncertainty into the probabilistic load-flow evaluation, as the statistical moments of PV output can be directly obtained from the irradiance moments:

$$\mu_P = k\mu_G \tag{10}$$

$$\sigma_P = k\sigma_G \tag{11}$$

$$\gamma_P = k\gamma_G \tag{12}$$

where $k = n\left(\frac{P_{\text{rated}}}{G_{\text{STC}}}\right)$, and μ_G, σ_G, and γ_G denote the mean, standard deviation, and skewness of irradiance, respectively.

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2.3 Deterministic Load Flow Using Backward–Forward Sweep (BFS)

The Backward–Forward Sweep (BFS) algorithm is employed in this study to perform deterministic load-flow analysis for radial distribution systems. This method leverages the radial topology of distribution feeders to obtain voltage and current solutions with significantly higher numerical stability and computational efficiency. As a result, BFS is widely recognized as the most appropriate deterministic load-flow technique for distribution networks with high R/X ratios and unbalanced loading conditions.

In the deterministic framework, all system inputs including load demand, feeder impedances, and PV generation are treated as fixed quantities without uncertainty. PV units are modeled as negative active loads, such that the net power demand at each PV-connected bus is:

$$P_{net,i} = P_{L,i} - P_{PV,i} \tag{13}$$

The BFS algorithm consists of two iterative stages Backward Sweep and Forward Sweep which are executed until voltage convergence is achieved. In the backward sweep, branch currents are calculated starting from the terminal (leaf) nodes toward the substation (slack bus). The load current at bus i is expressed as:

$$I_{L,i} = \frac{P_{net,i} - jQ_{L,i}}{V_i^*} \tag{14}$$

where V_i is the bus voltage from the previous iteration. For each branch connecting buses i and j, the branch current is obtained by aggregating all downstream load currents:

$$I_{ij} = \sum_{k\in\Omega_{ij}} I_{L,k} \tag{15}$$

where Ω_{ij} denotes the set of buses downstream of branch *i–j*. This bottom-up current accumulation inherently aligns with radial feeder structures.

In the forward sweep, updated bus voltages are computed from the slack bus toward downstream buses using:

$$V_j = V_i - Z_{ij} I_{ij} \tag{16}$$

where:

V_i: upstream bus voltage

$Z_{ij} = R_{ij} + jX_{ij}$: branch impedance

I_{ij}: branch current obtained from the backward sweep

The backward and forward sweeps are repeated iteratively until voltage convergence is achieved:

$$\max_i \mid V_i^{(k+1)} - V_i^{(k)} \mid < \epsilon \tag{17}$$

with ϵ set to 10^{-4} p.u. in this study. Upon convergence, bus voltages, branch currents, and real power losses are recorded as the deterministic load-flow solution.

$$P_{loss,ij} = \mid I_{ij} \mid^2 R_{ij} \tag{18}$$

2.4 Probabilistic Load Flow Using Hong's Two-Point Estimate Method (PEM)

The probabilistic load-flow analysis in this study is carried out using Hong's Two-Point Estimate Method (2PEM), a moment-based uncertainty quantification framework that propagates stochastic PV power fluctuations to system performance metrics with significantly fewer evaluations than Monte Carlo Simulation (MCS). Instead of generating a large number of random samples, 2PEM reconstructs the probabilistic behavior of network outputs by evaluating the deterministic load-flow model at two statistically representative concentration points derived from the mean, standard deviation, and skewness of the input distribution.

To provide a clearer understanding of this combined workflow, the complete integration sequence of BFS and 2PEM is illustrated in the Figure 1, which visualizes the stages of moment extraction, concentration-point generation, deterministic BFS execution, and probabilistic output reconstruction.

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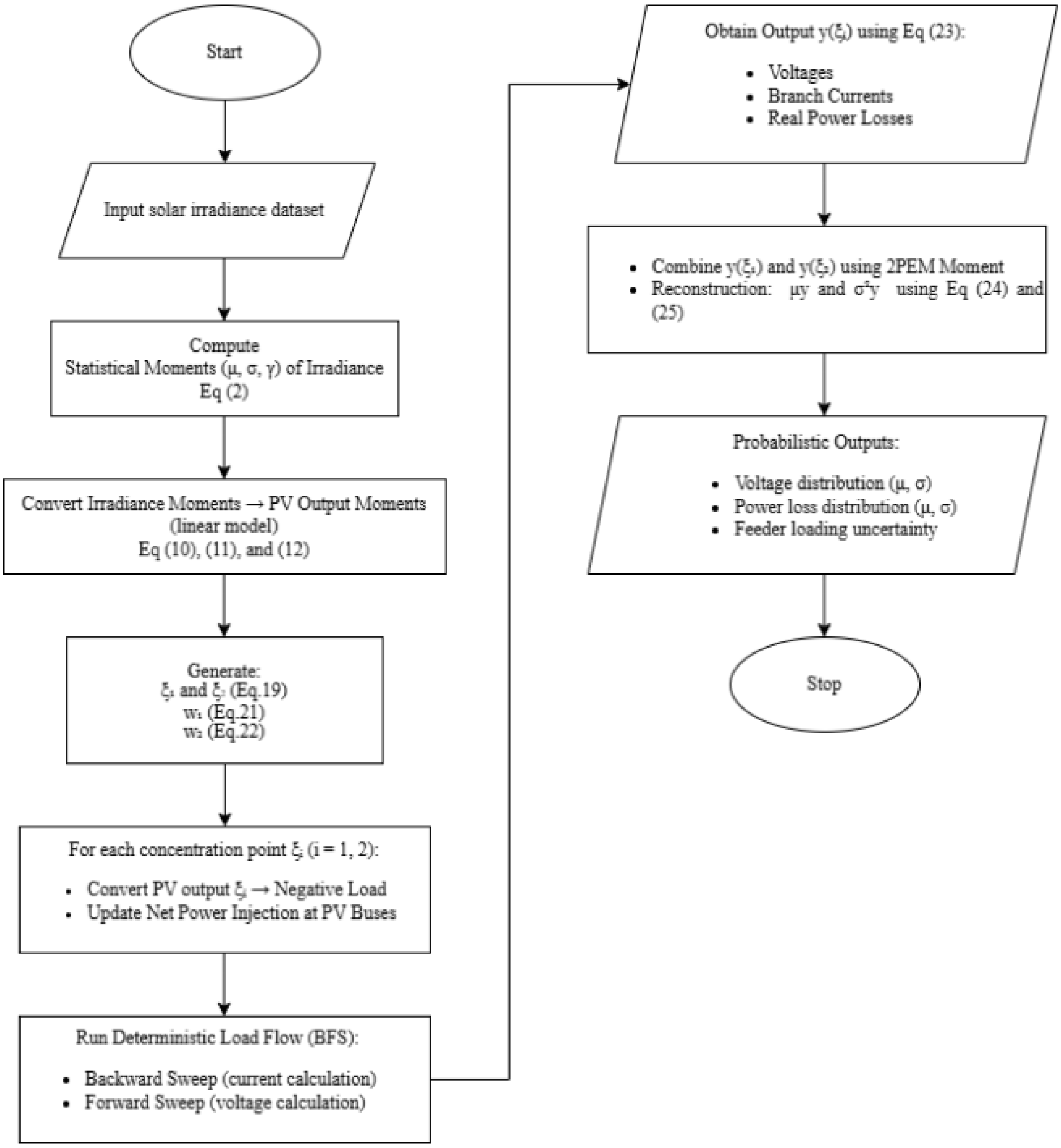

Figure 1. Flowchart of the Integrated Probabilistic Load Flow Procedure Combining Hong's Two-Point Estimate Method (2PEM) with the Backward–Forward Sweep (BFS) Algorithm

Solar irradiance is modeled using Normal distribution yields the PV mean μ_{PV}, standard deviation σ_{PV}, and skewness γ_{PV}, 2PEM constructs the two concentration points as:

$$\xi_{1,2} = \mu_{PV} \pm \lambda \sigma_{PV} \tag{19}$$

where,

$$\lambda = \frac{\sqrt{\gamma_{PV}^2 + 4}}{2} \tag{20}$$

with corresponding probability weights:

$$w_1 = \frac{1}{2}\left(1 + \frac{\gamma_{PV}}{\sqrt{\gamma_{PV}^2 + 4}}\right) \tag{21}$$

$$w_2 = 1 - w_1 \tag{22}$$

These concentration points reflect higher than average and lower than average PV production conditions, fully capturing the skewness and boundedness of the irradiance distribution.

A key component of the proposed method is the integration of the Backward–Forward Sweep (BFS) load-flow algorithm into the 2PEM evaluation cycle. For each concentration point ξ_i, the

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corresponding PV output is modeled as a negative load and injected at the PV-connected buses. The BFS algorithm is then executed for each scenario to compute the resulting node voltages, branch currents, and feeder real-power losses. Since 2PEM requires only two deterministic evaluations for a single uncertain variable, the BFS routine is executed exactly twice once for $\xi_1$and once for ξ_2. The outputs produced by these two deterministic load-flow solutions are denoted as:

$$y(\xi_1), y(\xi_2) \tag{23}$$

where each $y(\xi_i)$represents the full set of system responses under the irradiance scenario ξ_i, including: bus voltage magnitudes, branch current flows, total real-power losses, minimum/maximum node voltage, and other operational metrics.

In other words, $y(\xi_1)$is the deterministic solution when the PV output represents the upper statistical scenario (higher irradiance), while $y(\xi_2)$ is the deterministic solution when PV output corresponds to the lower statistical scenario (lower irradiance).

These two deterministic load-flow results are then combined using the 2PEM output-reconstruction formulas:

$$\mu_y = w_1 y(\xi_1) + w_2 y(\xi_2) \tag{24}$$

$$\sigma_y^2 = w_1\big(y(\xi_1) - \mu_y\big)^2 + w_2\big(y(\xi_2) - \mu_y\big)^2 \tag{25}$$

This reconstruction yields the expected value and variance of voltages, power losses, and branch currents, thereby quantifying the extent to which solar irradiance variability influences distribution network performance.

3. Result and Discussion

3.1 System Data

The probabilistic performance evaluation in this study is conducted on the IEEE 34-bus radial distribution test feeder, as illustrated in Figure 2. This feeder is characterized by long radial sections, unbalanced loading, and relatively high *R* / *X*. For the solar irradiance is derived directly from the NASA SSE dataset as for the study location. The monthly averaged irradiance values presented in Table 2 serve as the basis for computing the mean and variance, which are required inputs to the PEM framework.

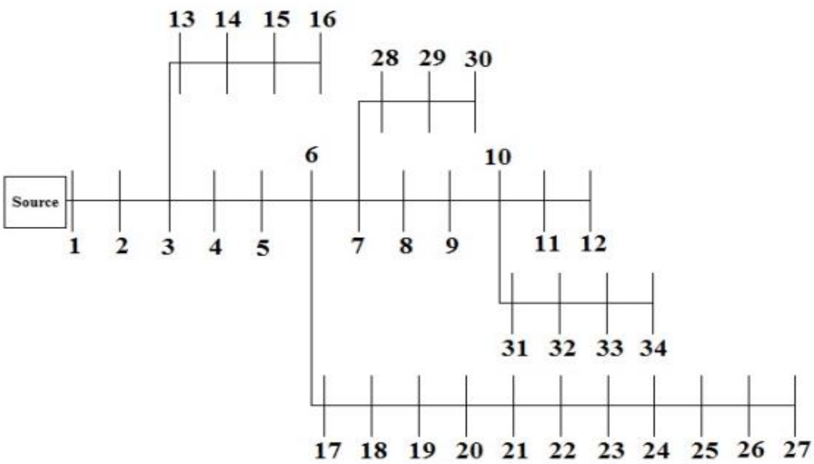

Figure 2. The test system of IEEE 34 bus

Since this study does not incorporate load uncertainty, the load data are modeled as fixed deterministic values corresponding to the system's peak-demand condition. During this peak period, the IEEE 34-bus feeder exhibits a total real power demand of 4.64 MW and a reactive-power demand of 2.87 MVar.

3.2 Deterministic Load Flow Using Backward–Forward Sweep

In this scenario, six photovoltaic units are installed at buses 23, 24, 25, 26, 27, and 33 of the IEEE 34-bus radial feeder. A rated capacity of 270 kW of PV will be installed in each site. Based on the solar

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resource characteristics at the study location, the average expected PV output at each site is approximately 116 kW. When aggregated across all six locations, the effective PV penetration level corresponds to roughly 15% of the system peak load. The primary objective of this penetration level is to observe the extent to which PV-DG can contribute to feeder loss reduction.

The Backward–Forward Sweep method is performed for the deterministic case, yielding a total active power loss of 0.1582 MW and a reactive power loss of 0.0479 MVar. These deterministic loss values correspond to a single operating point in which PV generation is fixed at the mean irradiance (average) output (≈116 kW per PV unit), providing the baseline for comparison with the 2PEM-based probabilistic assessment.

The resulting voltage profile obtained from the deterministic BFS analysis is shown in Figure 3. As expected for a long radial feeder, the voltage magnitude decreases progressively along the feeder path; however, the presence of PV injections at intermediate buses contributes to slight voltage support in the surrounding sections.

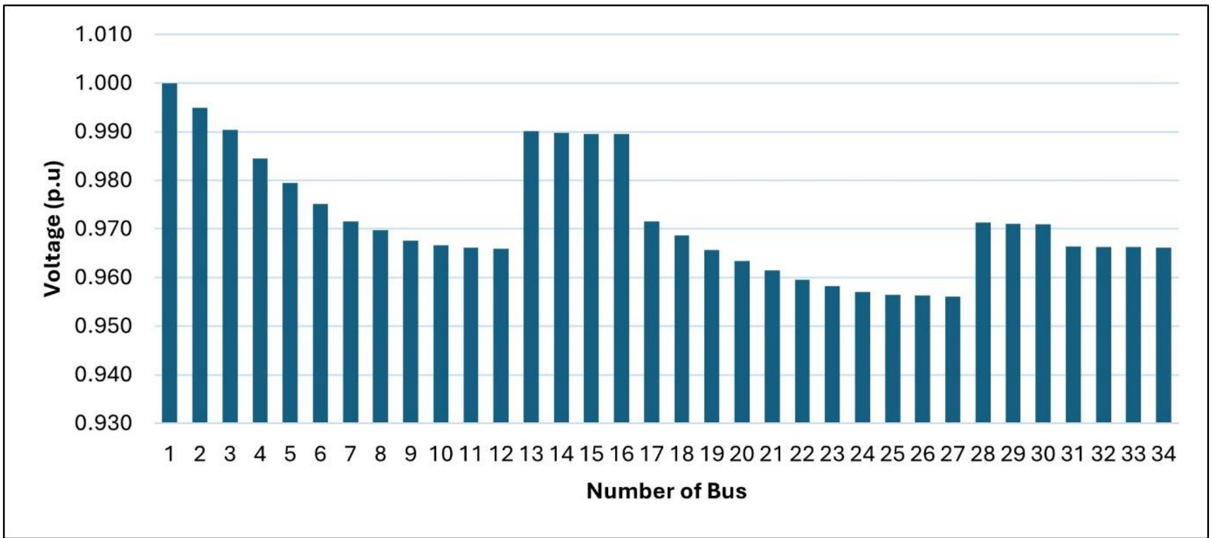

Figure 3. Voltage Profile of Deterministic Load Flow Using Backward–Forward Sweep

3.3 Probabilistic Load Flow Using Hong's Two-Point Estimate Method

The probabilistic load flow analysis is performed for the same PV installation scenario, but this time incorporating solar irradiance variability (Figure 4). The uncertainty in irradiance is propagated through Hong's Two-Point Estimate Method (2PEM), resulting in two characteristic irradiance levels that represent low- and high-generation scenarios. These concentration points are individually processed using the deterministic BFS algorithm, and the final probabilistic results are computed through weighted aggregation.

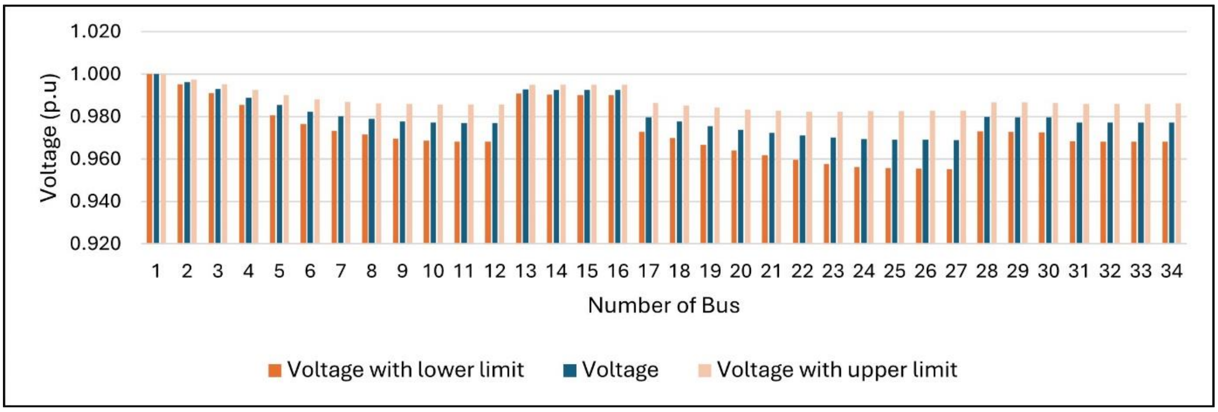

Figure 4. Probabilistic Voltage Profile Using Hong's Two-Point Estimate Method

In contrast to the deterministic profile, which provides a single operating point, the probabilistic voltage profile represents an envelope of possible voltage values. The upper boundary of this envelope

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corresponds to high-irradiance conditions, while the lower boundary reflects low-irradiance cases. The width of this band widens toward the end of the feeder, illustrating the increased sensitivity of downstream buses to PV generation uncertainty.

3.4 Comparison Between Deterministic and Probabilistic Results and Impact of Irradiance Variability on Network Performance

A direct comparison between deterministic and probabilistic load-flow outcomes reveals how the inclusion of solar irradiance uncertainty fundamentally alters the interpretation of feeder operating conditions. While the deterministic analysis based on the Backward–Forward Sweep (BFS) algorithm yields a single operating point for system voltages and feeder losses, the probabilistic framework introduces a spectrum of possible outcomes driven by fluctuating photovoltaic (PV) generation. This difference provides a more comprehensive understanding of the network's behavior under real operational conditions.

In the deterministic case, PV units are assumed to operate at a fixed output derived from the average irradiance level. This assumption results in total system losses of 0.1582 MW for active power and 0.0479 MVar for reactive power, with a voltage profile that progressively declines toward the remote buses. Such results represent the network under a nominal condition and do not capture the influence of temporal variability in PV generation. Consequently, the deterministic profile reflects only one point on the potential performance curve of the feeder.

When uncertainty is incorporated through Hong's Two-Point Estimate Method, the resulting power-flow outputs exhibit a range of feasible values rather than a single deterministic solution. The probabilistic evaluation yields mean losses of 0.105 MW for active power and 0.031 MVar for reactive power, with non-negligible standard deviations, indicating that feeder losses vary noticeably across different irradiance realizations. This lower probabilistic mean does not imply that high-irradiance periods occur more frequently than low-irradiance periods under the assumed (approximately symmetric) irradiance model. Instead, it reflects the nonlinear relationship between irradiance-driven PV injection, network voltages/currents, and feeder losses, such that the expected loss over multiple feasible operating conditions may differ from the loss computed at a single mean-irradiance operating point. In addition, irradiance is constrained to be physically feasible using clipping ($I^* = \max(0, I)$), which slightly modifies the lower tail of the input distribution. At the same time, the standard deviations confirm that the system may operate near or above the deterministic loss values during low-irradiance realizations. Thus, while the expected performance improves, the probabilistic framework reveals inherent variability and operational margins that a deterministic single operating-point method cannot capture.

The voltage characteristics observed in the probabilistic analysis further emphasize the limitations of deterministic modelling. Instead of a single voltage curve, the probabilistic results present a voltage band that envelopes the mean profile. The upper region of this band corresponds to high PV output conditions, during which local voltage support increases, sometimes exceeding the deterministic values. Conversely, the lower region captures periods of diminished irradiance, where PV contribution decreases and feeder voltages approach more critical levels. These variations become increasingly pronounced toward the end of the feeder, where the cumulative impedance amplifies the effect of fluctuating injections.

The combined interpretation of losses and voltage behaviour highlights the operational significance of irradiance variability. Deterministic results suggest a stable and predictable feeder condition, but probabilistic outcomes show that actual system states may deviate substantially depending on solar conditions throughout the day. This deviation affects power quality, risk of undervoltage during low generation periods, and potential overvoltage during high generation periods. Moreover, the probabilistic model uncovers intermediate operating states scenarios that the deterministic analysis overlooks thereby offering a more realistic representation of network performance across different irradiance conditions.

The probabilistic results show that the mean active power loss of the system is 0.105 MW, with an associated standard deviation of 0.057 MW. Similarly, the mean reactive power loss is 0.031 MVar, with a standard deviation of 0.016 MVar. These values demonstrate that the system exhibits noticeable variability in losses depending on the realizations of solar irradiance. In particular, low-irradiance scenarios lead to higher feeder loading and thus increased losses, whereas high-irradiance scenarios

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cause loss reduction due to enhanced PV contribution. The probabilistic voltage profile obtained from the 2PEM analysis is depicted in Figure 4.

4. Conclusion

This study investigated the impact of solar irradiance variability on the operational performance of the IEEE 34-bus radial distribution feeder by comparing deterministic load-flow analysis using the Backward–Forward Sweep (BFS) method with a probabilistic load-flow framework based on Hong's Two-Point Estimate Method (2PEM). The deterministic analysis produced a single operating point with real and reactive power losses of 0.1582 MW and 0.0479 MVar, respectively, and yielded a fixed voltage profile along the feeder. However, this representation proved insufficient for capturing the operational uncertainty introduced by fluctuating PV generation. When solar irradiance was modeled as a stochastic variable and propagated through 2PEM, the results showed a substantial deviation from deterministic predictions. The mean real and reactive losses decreased to 0.105 MW and 0.031 MVar, while the associated standard deviations (0.057 MW and 0.016 MVar) highlighted the feeder's sensitivity to irradiance fluctuations. Similarly, probabilistic voltage profiles formed a bounded envelope around the deterministic curve, indicating that downstream buses experience significant variability driven by changes in PV output. Overall, the comparative analysis demonstrates that irradiance uncertainty plays a critical role in shaping feeder performance and cannot be adequately represented by deterministic methods alone. The probabilistic approach provides a more realistic and risk-aware characterization of voltage behavior, loss variability, and operational margins. These findings underscore the importance of incorporating probabilistic assessment in planning and operating distribution networks with high PV penetration, particularly in regions with substantial solar intermittency such as tropical climates. Also, this broader perspective is essential for planners and operators seeking to evaluate hosting capacity, manage voltage regulation equipment, and ensure reliable operation under increasing penetration of stochastic renewable energy sources.

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