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Carlos D. Zuluaga-Ríos^{*} and [Paola M. Ortiz-Grisales](#)

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Article

Distribution-Matching Likelihood-Free Importance Sampling for Probabilistic Power Flow

Carlos D. Zuluaga-Ríos ^{1,*} and Paola M. Ortiz-Grisales ²

¹ Department of Electromechanical and Mechatronics, Faculty of Engineering, Institución Universitaria ITM, 050036, Colombia

² Department of Electrical Engineering, Faculty of Engineering, Institución Universitaria Pascual Bravo, 050036, Colombia

* Correspondence: carloszuluaga5756@correo.itm.edu.co

Abstract

The increasing penetration of renewable generation and electrified loads introduces non-Gaussian and strongly nonlinear uncertainty in power system operation. Probabilistic power flow (PPF) methods based on Monte Carlo simulation provide accurate uncertainty propagation but remain computationally demanding, while many analytical and approximation-based approaches rely on restrictive distributional assumptions. This letter proposes a Distribution-Matching Likelihood-Free Importance Sampling (DM-LFIS) framework for PPF. The method avoids explicit likelihood construction and posterior sampling, and instead propagates uncertainty by reweighting candidate operating states according to a discrepancy between simulated and observed power injection distributions. Data-driven and physics-informed proposals guided by DC and Newton–Raphson power flow solutions are used to improve sampling efficiency. Numerical results on standard IEEE test systems show that DM-LFIS accurately captures voltage and angle uncertainty with reduced computational cost compared to conventional Monte Carlo-based PPF methods.

Keywords: probabilistic power flow; likelihood-free inference; importance sampling; renewable energy integration

1. Introduction

The increasing penetration of renewable generation and electrified loads is making power system uncertainty more non-Gaussian and harder to propagate through nonlinear power flow equations. Probabilistic power flow (PPF) is therefore key to quantify operational risk and characterize the variability of voltage magnitudes and phase angles. Conventional Monte Carlo simulation (MCS) remains the reference due to its accuracy, but its computational burden often prevents large-scale or online use [1]. Most PPF techniques can be grouped into simulation-based, analytical, and approximation-based methods [2]. Simulation variants improve efficiency but may still require many power-flow evaluations [3], whereas analytical and approximation approaches reduce cost at the price of linearization or sensitivity to the dimension and shape of the uncertainty space [4,5]. Surrogate, data-driven or likelihood-free models further speed up computations, yet their performance can depend on modeling assumptions or data coverage, which may weaken tail reliability under rare operating conditions [1,5–7]. To address these limitations, this letter proposes a Distribution-Matching Likelihood-Free Importance Sampling (DM-LFIS) framework for PPF. Instead of threshold-based accept/reject rules or explicit posterior construction, DM-LFIS assigns importance weights by matching the distributions of simulated and observed power injections, and it uses data-driven and physics-informed proposals (DC and Newton–Raphson guided) to sample efficiently. Notably, DM-LFIS avoids repeated deterministic power flow solutions, which reduces computational burden in large-scale systems. The resulting weighted-resampled ensemble provides accurate voltage and angle marginals with reduced computational effort, while avoiding sensitivity to tolerance tuning under non-Gaussian uncertainty.

2. Distribution-Matching Likelihood-Free Importance Sampling

2.1. Problem Formulation

Let $\mathbf{x}$ collect bus voltage angles and magnitudes, and let $\mathbf{b}$ denote uncertain active/reactive injections. The power flow equations are [8]

$$\mathbf{f}(\mathbf{x}, \mathbf{b}) = \mathbf{0}. \quad (1)$$

PPF aims to characterize the uncertainty of $\mathbf{x}$ induced by uncertainty in $\mathbf{b}$.

2.2. Relation to ABC-Based PPF

Likelihood-free PPF methods such as JABC [5] approximate an ϵ -posterior by accepting simulated reactive and active powers injections $\mathcal{D}'$ close to observations $\mathcal{D}$:

$$p_\epsilon(\mathbf{x} | \mathcal{D}) \propto p(\mathbf{x}) \int \mathbb{I}(d(\mathcal{D}, \mathcal{D}') \leq \epsilon) p(\mathcal{D}' | \mathbf{x}) d\mathcal{D}', \quad (2)$$

where $\mathcal{D}'$ is computed by using $\mathbf{b}$ in Eq. (1); and $d(\mathcal{D}, \mathcal{D}')$ is the discrepancy metric. A smooth alternative replaces the hard indicator ($\mathbb{I}(\cdot)$) by a kernel [9],

$$p_\epsilon(\mathbf{x} | \mathcal{D}) \propto p(\mathbf{x}) \int K_\epsilon(d(\mathcal{D}, \mathcal{D}')) p(\mathcal{D}' | \mathbf{x}) d\mathcal{D}', \quad (3)$$

but the resulting distribution remains approximate and depends on discrepancy and bandwidth choices. DM-LFIS avoids accept/reject decisions and instead performs likelihood-free importance sampling driven by distribution matching.

2.3. DM-LFIS: Discrepancy, Weights, and Proposals

Given a candidate state $\mathbf{x}^{(n)} \sim q(\mathbf{x})$, we simulate injections $\mathcal{D}_{\text{sim}}$ and compute a distribution-level discrepancy using Parzen-smoothed kernel distances [9],

$$d(\mathcal{D}, \mathcal{D}') = \gamma_k^2(\mathbf{P}_{\text{obs}}, \mathbf{P}_{\text{sim}}). \quad (4)$$

Importance weights are assigned as

$$w^{(n)} \propto \exp\left(-\frac{d(\mathcal{D}, \mathcal{D}')}{\tau}\right), \quad (5)$$

with τ set to the median of unnormalized discrepancies to obtain a robust, data-adaptive scaling and to mitigate weight degeneracy. To improve efficiency, $q(\mathbf{x})$ is defined as a mixture of physics-informed and exploratory proposals, that is,

$$q(\mathbf{x}) = \alpha q_{\text{DC}}(\mathbf{x}) + \beta q_{\text{NR}}(\mathbf{x}) + (1 - \alpha - \beta) q_{\text{RW}}(\mathbf{x}), \quad (6)$$

where q_{DC} and q_{NR} are physics-informed proposals derived from DC and Newton–Raphson power flow solutions, respectively, and q_{RW} is a random-walk component. The coefficients α and β are *mixture weights* allocating sampling effort across proposal mechanisms.

2.4. Residual Resampling

From the weighted empirical measure $\hat{\pi}_S(d\mathbf{x}) = \sum_{i=1}^S w_i \delta_{\mathbf{x}_i}(d\mathbf{x})$, we obtain an equally weighted ensemble via residual resampling [10]. Each particle gets $N_i^{(0)} = \lfloor Sw_i \rfloor$ deterministic copies, and the remaining $S_r = S - \sum_i N_i^{(0)}$ samples are drawn from residual probabilities

$$r_i = \frac{Sw_i - \lfloor Sw_i \rfloor}{S_r}. \quad (7)$$

This step reduces Monte Carlo variance relative to multinomial resampling and concentrates samples on distribution-consistent solutions without threshold tuning. The DM-LFIS algorithm can be summarized as follows,

Algorithm 1: DM-LFIS

- 1 Sample $\mathbf{x}^{(n)} \sim q(\mathbf{x})$ in (6).
 - 2 Simulate $\mathcal{D}_{\text{sim}} \sim p(\mathcal{D} | \mathbf{x}^{(n)})$.
 - 3 Compute $d(\mathcal{D}_{\text{obs}}, \mathcal{D}_{\text{sim}})$ in (4) and $w^{(n)}$ in (5).
 - 4 Residual-resample [10] to obtain $\{\mathbf{x}_j^*\}_{j=1}^S$.
-

3. Numerical Results and Discussion

The proposed DM-LFIS method is benchmarked against MCS, JABC, and standard ABC using the IEEE 6, 39, and 118-bus test systems under renewable-driven uncertainty. In the 6-bus system, a solar and a wind farm are integrated at nodes 5 and 6, respectively. For the 39-bus system, a solar farm is connected at node 13 and a wind farm at node 2. In the 118-bus system, both solar and wind generation are considered at nodes 3 and 4. Wind speed and solar irradiance are modeled using Weibull and Beta distributions, respectively, with parameters adopted from [5]. All simulations were conducted using a sample size of 1000, consistent with the experimental setup in [5]. For ABC, we have set ϵ in all experiments so that an acceptance rate of around 0.5% was obtained. For JABC, we have used all the parameters set out in [5]. For DM-LFIS, $\alpha = 0.1$ and $\beta = 0.7$ were used in the physics-informed proposal. MCS was implemented using MATPOWER.¹

3.1. Distributional Accuracy of State Variables

In the absence of an analytical ground truth, distributional accuracy is assessed by comparing the marginal distributions of voltage magnitudes and phase angles against MCS results. Figure 1 contrasts the distributions obtained with MCS, ABC, JABC, and the proposed DM-LFIS for the IEEE 6, 39, and 118-bus systems. As shown, standard ABC exhibits pronounced deviations from MCS under non-Gaussian and multimodal uncertainty, while JABC improves agreement but retains noticeable tail bias. In contrast, DM-LFIS accurately reproduces the voltage and angle marginal distributions obtained by MCS while avoiding explicit deterministic power flow computations. By obviating threshold-based accept/reject mechanisms, the proposed framework eliminates sensitivity to tolerance parameters

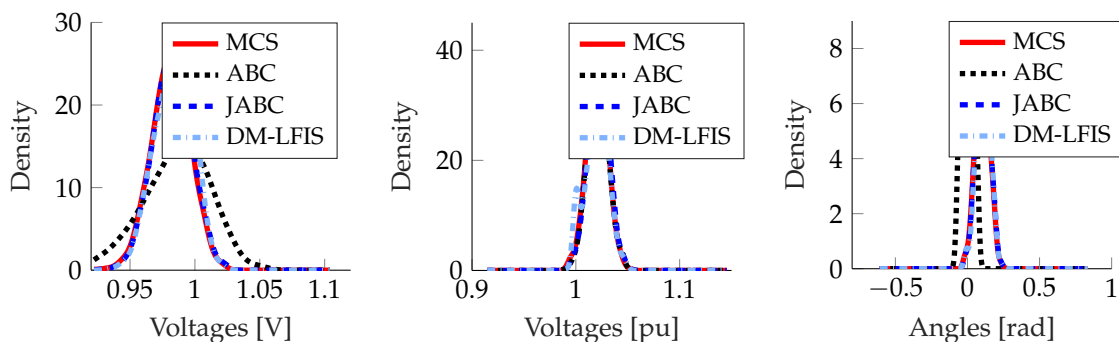


Figure 1. Probability distributions of selected state variables for the IEEE 6, 39 and 118-bus test systems. The solid red line corresponds to MCS, while the dotted black, blue, and light-blue lines represent the distributions obtained using ABC, JABC, and DM-LFIS, respectively. Left: shows the distribution of V_4 for the 6-bus system. Middle: shows the distribution of V_{25} for the 39-bus system. Right: shows the distribution of θ_{111} for the 118-bus system.

In contrast, DM-LFIS accurately reproduces the voltage and angle marginal distributions obtained by MCS while avoiding explicit deterministic power flow computations. By obviating threshold-based accept/reject mechanisms, the proposed framework eliminates sensitivity to tolerance parameters

¹ It is available at <http://www.pserc.cornell.edu/matpower/>

and demonstrates improved robustness under non-Gaussian uncertainty, particularly in large-scale systems where standard ABC methods tend to discard physically plausible samples.

3.2. Residual Error Analysis

Since an analytical ground-truth solution was unavailable, the accuracy of ABC-based methods and proposed method was assessed by comparing the mean and standard deviation of voltage magnitudes and phase angles against those obtained from MCS, which were used as reference values.² Table 1 reports the relative errors (RE) of the mean and standard deviation of voltage magnitudes and phase angles obtained using ABC, JABC, and the proposed DM-LFIS framework, with MCS used as reference. Several relevant observations can be drawn when these numerical indicators are jointly interpreted with the distributional results shown in Figure 1.

From Table 1, standard ABC exhibits large RE for angle statistics across all test systems, consistent with the pronounced mismatch observed in the corresponding probability density functions. This behavior confirms the sensitivity of threshold-based ABC to non-Gaussian and multimodal uncertainty, which leads to premature rejection of physically plausible samples. JABC significantly improves mean estimation for both voltages and angles; however, noticeable errors in standard deviation remain for larger systems, particularly for angle variables. While JABC improves mean estimation, Figure 1 shows that noticeable discrepancies remain in the distribution tails. DM-LFIS consistently achieves the lowest mean RE, especially for angles, while maintaining competitive accuracy for voltage magnitudes. Although its standard deviation errors are not always minimal, DM-LFIS provides closer alignment with MCS across the full distribution support. Overall, DM-LFIS offers a robust compromise between accuracy and stability by emphasizing distribution-level matching through likelihood-free importance weighting, avoiding hard rejection and improving robustness under non-Gaussian uncertainty.

Table 1. Relative error for voltages and angles using the IEEE 6, 39 and 118-bus test systems

Method		IEEE 6		IEEE 39		IEEE 118	
		ε_θ [%]	ε_V [%]	ε_θ [%]	ε_V [%]	ε_θ [%]	ε_V [%]
ABC	μ	176.3694	0.7203	5.5335	0.0407	137.28	2.3301
	σ	32.390	70.816	52.646	18.492	41.377	1530.7
JABC	μ	1.1556	0.0714	5.1204	0.1103	4.4494	0.0236
	σ	0.0348	0.1184	0.7064	0.4557	0.0719	3.3562
DM-LFIS	μ	0.3022	0.1604	2.6504	0.1545	3.7770	0.0318
	σ	6.8465	3.3173	2.5520	17.551	2.3389	11.084

3.3. Computational Efficiency

Finally, Table 2 compares the average computation times required by MCS, ABC, JABC, and the proposed DM-LFIS method for the three standard grids.³

Table 2. Computation time obtained by MCS, JABC, ABC and DM-LFIS, in the solution of the PPF problem using the IEEE 6-bus, 39-bus and 118-bus test system.

Computation time [s]	MCS	JABC	ABC	DM-LFIS
IEEE-6	5.2431	0.4572	17.271	4.0863
IEEE-39	7.0106	1.2812	16.671	5.4375
IEEE-118	9.1253	2.5895	20.752	8.5739

Table 2 shows that MCS incurs the highest computational cost due to the large number of power flow solutions required, while ABC also exhibits relatively high runtimes as a consequence of low acceptance rates. JABC achieves the lowest execution times by leveraging Jacobian-based corrections;

² Relative errors were computed with respect to the MCS reference using the metrics $\varepsilon_x^\mu = \left| \frac{\mu_x - \mu_x^*}{\mu_x} \right|$ and $\varepsilon_x^\sigma = \left| \frac{\sigma_x - \sigma_x^*}{\sigma_x} \right|$ [8], where ε_x^μ and ε_x^σ denote the relative error of the mean and standard deviation, respectively. Here, μ_x and σ_x were obtained from MCS, while μ_x^* and σ_x^* correspond to the estimates computed by ABC methods and proposed method.

³ All simulations were conducted on an Intel Core i7 PC with a 2.1GHz processor.

however, this efficiency is accompanied by residual distributional bias, particularly in the tails for larger systems. The proposed DM-LFIS method consistently outperforms MCS and ABC in terms of computation time, while remaining slightly more expensive than JABC due to the evaluation of distributional discrepancies and resampling. Overall, DM-LFIS offers a favorable trade-off between computational efficiency and distributional accuracy under non-Gaussian uncertainty.

4. Conclusion

This letter presented a Distribution-Matching Likelihood-Free Importance Sampling framework for probabilistic power flow. By avoiding explicit likelihood construction and posterior sampling, the proposed method provides a flexible and computationally efficient approach for uncertainty propagation in power systems with complex, non-Gaussian uncertainties. Future work will explore adaptive proposal strategies and online implementations for real-time operational assessment.

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