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A Data-driven Probabilistic Power Flow Analysis Considering Voltage-dependent Loads

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***Abstract*— Probabilistic power flow analysis (PPFA) stands as a promising method for assessing the steady-state performance of distribution networks (DNs) amidst uncertainties associated with renewable energy sources, particularly wind power units (WPUs). However, the reliability of the PPFA results hinges significantly on the accuracy of the power flow model. This paper proposes a new approach to PPFA that integrates voltage-dependent load (VDL). Although incorporating VDL in PPFA formulation enhances the precision of the model, it introduces additional computational complexity due to the introduction of new nonlinear terms into the optimization problem. Therefore, initially, a dataset of wind speed measurements is fitted to a Weibull probability distribution function (PDF). Subsequently, a new nonlinear model is developed, which integrates Monte Carlo (MC) simulation along with the specified PDF for PPFA, accounting for VDL effects. Finally, the proposed model is efficiently convexified using Newton's generalized binomial theorem, piecewise linearization, and appropriate approximations to extract the corresponding linear programming (LP) model. This LP model is then tested on a modified WPU-integrated 33-bus DN, revealing that the inclusion of VDL significantly influences the PPFA results. A comparative analysis between PPFA models with and without VDL incorporation illustrates that overlooking VDL can lead to underestimation of power losses and voltage drops in the analysis.**

Keywords*— *Data-driven analysis, distribution network, probabilistic analysis, power flow, Monte Carlo Simulation, voltage-dependent loads.

NOMENCLATURE

Acronyms	
DN	Distribution network
LP	Linear programming
MC	Monte Carlo Simulation
NGBT	Newton's generalized binomial theorem
PDF	Probability distribution function
PL	Power loss
PPFA	Probabilistic power flow analysis
VDL	Voltage-dependent load
WPU	Wind power unit
Indices	
k, i, j	Index for buses
ij	Index for lines
wu	Index for wind turbine units
ω	Index for pieces in piecewise linearization
Parameters	
$\alpha_0, \alpha_1, \alpha_2$	Coefficients of active VDL
$\beta_0, \beta_1, \beta_2$	Coefficients of reactive VDL
Λ^W	Wind speed
Λ^W_{ci}	Cut-in speed
Λ^W_{no}	Nominal speed
Λ^W_{co}	Cut-out speed
K	Shape parameter
S	Scale parameter
L_i^{PRAT}	Rated active power
L_i^{QRAT}	Rated reactive power
P_{no}^{WPU}	Nominal capacity of the wind turbine
R_{ij}, X_{ij}, Z_{ij}	Resistance, reactance, & impedance of lines
L_i^P, L_i^P	Active & reactive VDL
P_{wu}^{WPU}	Power generation of wind turbine
V_i^{est}	Estimated voltage
V^{RAT}	Rated voltage
V_{max}	Maximum voltage
V_{min}	Minimum voltage
$m_{ij,\omega}^{PQ}$	Slope of blocks in linearization of power
Δq_{ij}^{max}	Maximum discretization blocks of reactive power
Δp_{ij}^{max}	Maximum discretization blocks of active power
$\overline{\omega}$	Number of pieces in piecewise linearization
Variables	
p_{ij}, q_{ij}	Active & reactive power flowing in lines
v_i^{sqr}, i_{ij}^{sqr}	Square of voltage & current
$\Delta p_{ij,\omega}, \Delta q_{ij,\omega}$	Discretization blocks of power flowing in lines
$p_{bn,t}^{+}, q_{bn,t}^{+}$	Active & reactive power in line (positive direction)
$p_{bn,t}^{-}, q_{bn,t}^{-}$	Active & reactive power in line (negative direction)
p_i^{MG}, q_i^{MG}	Active & reactive power from the main grid

I. INTRODUCTION

The EU's strategy for bolstering renewable energy revolves around the implementation of the European Green Deal, which prioritizes reductions in fossil fuel consumption, improvements in energy efficiency, investments in renewable energy, and the promotion of sustainable resource management. This overarching plan aims towards achieving net-zero emissions by 2050 and embedding sustainability principles within economic frameworks [1]. High integration of renewable energy resources such as wind power units (WPUs), into the distribution networks (DNs) holds the potential to advance the environmental goals, diminish energy cost, and elevate energy efficiency at the distribution level. Nevertheless, the intermittent nature of WPU generation introduces uncertainties into DN operations, posing potential threats to their secure functioning by potentially violating voltage, current, and stability limits [2].

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A. Motivation

The interplay between electrical loads and voltage, encompassing constant impedance, constant current, and constant power load models, holds significant sway over power flow, voltage profiles, and power loss (PL) within DNs. Consequently, it is imperative to consider different load types when conducting PPFA. However, the inherent nonlinearity of these models poses challenges in solving optimization problems, as non-convex nonlinear problems are normally NP-hard, and commercial solvers may fall short of ensuring optimal solutions. Moreover, PL within DNs often exceeds that of the transmission system, primarily attributed to higher resistance per kilometer and the radial configuration of the networks. However, integrating renewable generation into DNs can improve both PL and voltage profiles, thereby reducing PL. Consequently, alongside incorporating voltage-dependent load (VDL), accurately modeling the uncertainty of wind power generation through leveraging available historical data is indispensable.

B. Literature

PPFA has been studied extensively in the literature as a means to effectively assess the steady-state performance of DNs in light of uncertainties linked with renewable energy generation. This section reviews recent studies to highlight the existing research gap. In [3], a tractable model for PPFA is presented, which integrates copulas and polynomial chaos expansion while considering correlations in renewable energy generation. Reference [4] contrasts parametric and non-parametric methodologies for estimating the probability density functions (PDFs) of uncertain parameters such as renewable generation and electric vehicles in PPFA. A novel hybrid method for PPFA is presented in [5], combining point estimates and interval-based approaches to address uncertainty. Despite their valuable contributions, these references primarily focus on uncertainty modeling of renewable generation without discussing VDL. Some prior studies have used PPFA to tackle allocation-sizing problems in DNs. For instance, [6] utilizes PPFA to determine the optimal placement and size of energy storage systems in wind-integrated DNs. Similarly, [7] proposes an adaptive metaheuristic algorithm alongside PPFA for the optimal allocation of distributed generation units in DNs. In [8], wind farm allocation and sizing are determined through clustering-based PPFA. While PPFA can indeed serve allocation and sizing purposes, these studies primarily emphasize using PPFA for these specific tasks rather than delving into the modeling of PPFA itself, along with its accuracy or challenges. Only a few studies previously considered the VDL in PPFA, in [9], a model is founded on semi-definite relaxation techniques applied to unbalanced power flow problems. Although it is a convex model, ensuring the optimality of solutions, it remains nonlinear and may encounter computational time challenges, particularly when utilizing a large dataset in Monte Carlo simulations. Additionally, it lacks a data-driven approach. In [10], at each iteration of the PPFA, after computing the probabilistic voltage profiles using the Gauss-Quadrature method, the power demand of VDLs is updated based on the new voltage levels. Therefore, VDL modeling and PPFA are not integrated as presented in our paper via optimization modeling.

C. Contribution

PPFA has been extensively discussed in the literature using various methodologies including Monte Carlo (MC) simulations. However, the current literature lacks exploration into the development of fast linear programming (LP) model for data-driven MC-based PPFA that incorporates VDL. In summary, this paper's contributions can be outlined:

- Development of a nonlinear model for PPFA that incorporates VDL and leverages wind speed data availability to enhance accuracy;
- Derivation of a linearized model using techniques such as Newton's generalized binomial theorem and piecewise linearization to ensure both optimality and time efficiency of the model;
- Validation of the effectiveness of the proposed model, as well as the influence of VDL on PPFA, through two case studies.

II. METHODOLOGY

The proposed methodology is outlined in a flowchart depicted in Fig. 1. Initially, real wind speed data [11] is used to estimate the parameters of the Weibull PDF. Subsequently, 5000 random wind speed samples are generated using this PDF, and these samples are used to determine the power generation of the WPUs. After that, the 5000 generation samples serve as input for the developed PPFA models.

A. Wind Speed and Weibull PDF

The Weibull PDF has been widely utilized in the literature to characterize the intermittent nature of wind speed. Its formulation is represented in (1). The power output of WPUs can be obtained in accordance to wind speed through (2) [12].

$$PDF(\Lambda) = \frac{K}{S}\left(\frac{\Lambda}{S}\right)^{K-1} e^{-\left(\frac{\Lambda}{S}\right)^{K}} \tag{1}$$

$$P^{WPU} = \begin{cases} 0 \quad if\ \Lambda_{co}^{W} < \Lambda^{W}\ or\ \Lambda^{W} < \Lambda_{ci}^{W} \\ P_{no}^{WPU}\left(\frac{(\Lambda)^2 - (\Lambda_{ci}^{W})^2}{(\Lambda_{no}^{W})^2 - (\Lambda_{ci}^{W})^2}\right)\ if\ \Lambda_{ci}^{W} \le \Lambda^{W} \le \Lambda_{no}^{W} \\ P_{no}^{WPU} \quad if\ \Lambda_{no}^{W} < \Lambda^{W} \le \Lambda_{co}^{W} \end{cases} \tag{2}$$

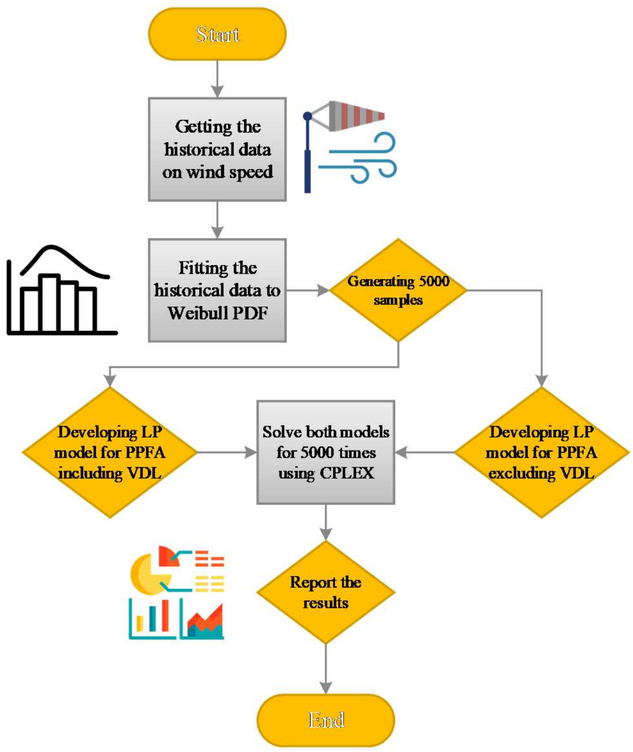

Fig. 1. Flowchart of proposed Fast Data-oriented Probabilistic Power Flow Analysis

B. Voltage-dependent Presentation of Active and Reactive Power Demand

Active and reactive power demands can be classified into three groups based on their dependence on the magnitude of voltage. The first group is known as constant power loads, indicating that the amount of demand remains unaffected by voltage fluctuations. The second group, termed constant current loads, exhibits a linear correlation between power demand (both active and reactive) and voltage. The final group, constant impedance loads, experiences a direct impact on power due to variations in the square of voltage. The expressions for active and reactive power of loads considering voltage dependency are presented in (3) and (4), respectively [13].

$$L_i^P = L_i^{PRAT}\left(\alpha_O + \alpha_1\left|\frac{v_i}{V^{RAT}}\right| + \alpha_2\left|\frac{v_i}{V^{RAT}}\right|^2\right) \tag{3}$$

$$L_i^Q = L_i^{QRAT}\left(\beta_O + \beta_1\left|\frac{v_i}{V^{RAT}}\right| + \beta_2\left|\frac{v_i}{V^{RAT}}\right|^2\right) \tag{4}$$

$$\alpha_O + \alpha_1 + \alpha_2 = \beta_O + \beta_1 + \beta_2 = 1 \tag{5}$$

C. Nonlinear Nonconvex Model of PPFA

As previously discussed, integration of renewable energy resources can mitigate PL in DNs. However, it remains crucial to evaluate the DN operation under uncertainty to ensure smooth operation without breaching technical constraints. In (6), the nonlinear objective function, aimed at minimizing active power loss, is introduced.

$$\text{Min}\sum_{ii} R_{ij} i_{ij}^2;\ \ \forall ij|ij \in L \tag{6}$$

The bidirectional nonlinear nonconvex AC power flow formulation, considering VDL, is presented in (7)–(10). Equations (7) and (8) show the active and reactive power balances, respectively. The relationship between voltage, current, and power is modeled by (9) and (10) [14].

$$\begin{aligned}\sum_{ki|ki\in L} p_{ki} - \sum_{ij|ij\in L}\left(p_{ij} + R_{ij} i_{ij}^2\right) + \sum_{i|i=b_{sub}} p_i^{MG} + \sum_{wu|b_{wu}=i} p_{wu}^{WPU} \\ = L_i^{PRAT}\left(\alpha_O + \alpha_1\left|\frac{v_i}{V^{RAT}}\right|\right. \\ \left. + \alpha_2\left|\frac{v_i}{V^{RAT}}\right|^2\right);\ \ \forall i\end{aligned} \tag{7}$$

$$\begin{aligned}\sum_{ki|ki\in L} q_{ki} - \sum_{ij|ij\in L}\left(q_{ij} + X_{ij} i_{ij}^2\right) + \sum_{i|i=b_{sub}} q_i^{MG} + \\ = L_i^{QRAT}\left(\beta_O + \beta_1\left|\frac{v_i}{V^{RAT}}\right|\right. \\ \left. + \beta_2\left|\frac{v_i}{V^{RAT}}\right|^2\right);\ \ \forall i\end{aligned} \tag{8}$$

$$v_i^2 - v_j^2 = 2\left(R_{ij} p_{ij} + X_{ij} q_{ij}\right) + Z_{ij}^2 i_{ij,}^2;\ \ \forall ij|ij \in L \tag{9}$$

$$v_i^2 i_{ij}^2 \geq \left(p_{ij}^2 + q_{ij}^2\right);\ \ \forall ij|ij \in L \tag{10}$$

D. Convexification

Nonconvex and nonlinear problems often offer high accuracy in modeling real-world phenomena. However, due to computational burden and the absence of optimality guarantees, it is common practice to convexify these models. In this section, firstly, the Newton's generalized binomial theorem (NGBT) is used to reformulate the VDL nonlinear equations. Subsequently, piecewise linearization and smooth approximations are utilized to derive the corresponding LP model. In (11), the NGBT formula is presented. By setting $y = 1$, (11) can be simplified as (12). Moreover, if $r = 0.5$ and $|x| \ll 1$, (12) can be rewritten as (13).

$$(x+y)^r = \sum_{k=0}^{\infty}\binom{r}{k} x^{r-k} y^k \tag{11}$$

$$(x+1)^r = \sum_{k=0}^{\infty}\binom{r}{k} x^{r-k} \tag{12}$$

$$\sqrt{x+1} = 1 + \frac{x}{2} \tag{13}$$

By defining new auxiliary variables $v_i^{sq} = {v_i}^2$ and $V^{RATsq} = {V^{RAT}}^2$ the equations (3) and (4) can be rewritten as (14) and (15), respectively. By comparing (13) with (14) and (15), and by considering the fact that $\left|\frac{v_i^{sq}}{V^{RATsq}} - 1\right| \ll 1$, it is straightforward to linearize (14) and (15) by reformulating them as (16) and (17).

$$L_i^P = L_i^{PRAT}\left(\alpha_O + \alpha_1\sqrt{\frac{v_i^{sq}}{V^{RATsq}}} + \alpha_2\frac{v_i^{sq}}{V^{RATsq}}\right) \tag{14}$$

$$L_i^Q = L_i^{QRAT}\left(\beta_O + \beta_1\sqrt{\frac{v_i^{sq}}{V^{RATsq}}} + \beta_2\frac{v_i^{sq}}{V^{RATsq}}\right) \tag{15}$$

$$L_i^P = L_i^{PRAT}\left(\alpha_O + \frac{\alpha_1}{2}\left(\frac{v_i^{sq}}{V^{RATsq}} + 1\right) + \alpha_2\frac{v_i^{sq}}{V^{RATsq}}\right) \tag{16}$$

$$L_i^Q = L_i^{QRAT}\left(\beta_O + \frac{\beta_1}{2}\left(\frac{v_i^{sq}}{V^{RATsq}} + 1\right) + \beta_2\frac{v_i^{sq}}{V^{RATsq}}\right) \tag{17}$$

Similarly, by defining a new auxiliary variable $i_{ij}^{sq} = i_{ij}^2$, it can be noticed that the objective function and all constraints are linearized except for (10). By replacing v_i^2 with its approximated value (v_i^{est}) on the left-hand side and using piecewise linearization for p_{ij}^2 and q_{ij}^2 on the right-hand side of (10), the non-convex constraint (10) can be replaced by (18) as presented and explained in [15].

$$V_i^{est} i_{ij}^{sqr} = \sum_{\omega} m_{ij,\omega}^{pq}\left(\Delta p_{ij,\omega} + \Delta q_{ij,\omega}\right);\forall ij \tag{18}$$

$$V_i^{est} = \left(V_{max}^2 + V_{min}^2\right)/2;\ \forall i \tag{19}$$

$$p_{ij} = p_{ij}^+ - p_{ij}^-;\ \forall ij \tag{20}$$

$$q_{ij} = q_{ij}^+ - q_{ij}^-;\ \forall ij \tag{21}$$

$$\sum_{\omega}\left(\Delta p_{ij,\omega}\right) = p_{ij}^+ + p_{ij}^-;\ \forall ij \tag{22}$$

$$\sum_{\omega}\left(\Delta q_{ij,\omega}\right) = q_{ij}^+ + q_{ij}^-;\ \forall ij \tag{23}$$

$$\Delta p_{ij,\omega} \leq \Delta p_{ij}^{max};\ \forall ij,\omega \tag{24}$$

$$\Delta q_{ij,\omega} \leq \Delta q_{ij}^{max};\ \forall ij,\omega \tag{25}$$

$$\Delta p_{ij}^{max} = \Delta q_{ij}^{max} = \left(V_{max} I_{max}\right)/\overline{\omega};\ \forall ij \tag{26}$$

III. RESULTS AND DISCUSSION

The parameters K and S are determined by fitting actual wind speed data spanning from June 1, 2020, to May 31, 2021, to the Weibull PDF using the SciPy package and the Weibull_min.fit function in Python, as illustrated in Fig. 2. The shape parameter, scale parameter, and mean wind speed are found to be 2.02, 5.38, and 4.75, respectively. The resulting PDF is then used to randomly generate 5000 samples, as illustrated in Fig. 3. To evaluate the efficiency of the proposed fast data-driven PPFA model, a modified IEEE 33-bus network integrated by two 1.5 MW wind turbines [16] at Bus 18 and Bus 33 is considered. It is noteworthy that The proposed LP mathematical models are implemented in GAMS software [17] and solved using CPLEX [18], utilizing a computer with an Intel i7-6500U processor and 8 GB of RAM.

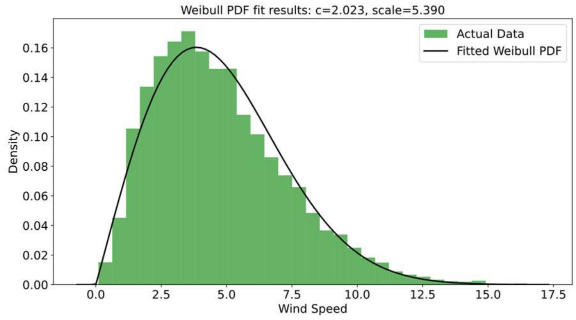

Fig. 2. Data-based Weibull probably density function compared to histogram of the real wind speed data

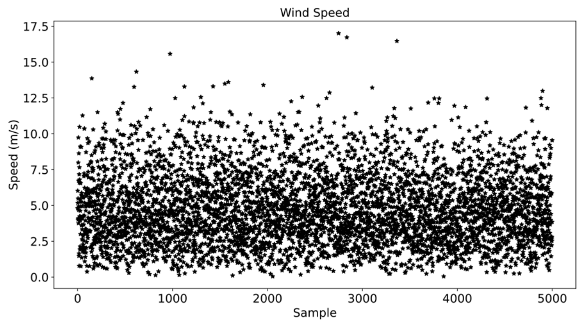

Fig. 3. Wind speed samples

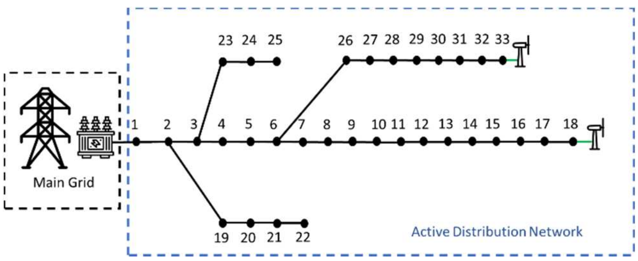

Fig. 4. Schematic diagram of the distribution network

A. Case I: PPFA Excluding VDL

The PPFA is performed using MC simulation with 5000 samples, assuming that both active and reactive power demands remain unaffected by voltage levels (i.e., $\alpha_1 = \alpha_2 = \beta_1 = \beta_2 = 0$). Table 1 presents the highest, average, and lowest values of power loss and voltage. Additionally, voltage profiles are illustrated in Fig. 5, highlighting that Bus 18 and Bus 33 experience the most significant voltage fluctuations. In contrast, buses which are closer to substation show marginal variation. This occurrence is expected due to the connection of WPUs to these buses.

B. Case II: PPFA Inlcuding VDL

In this case, the evaluation of electric load dependency on voltage variation (i.e., $\alpha_1 = \alpha_2 = \beta_1 = \beta_2 = 0.3$) and its impact on the PPFA is conducted. The comparison of results between the two cases in Table 1 shows that neglecting VDL may lead to significant underestimation of power losses. Voltage profiles are illustrated, similar to Case I, Bus 18 and Bus 33 experience the most significant voltage fluctuations. For instance, the highest, average, and lowest values of power losses are approximately 51%, 54%, and 57% higher, respectively, compared to when VDL is considered. This disparity is highlighted in Fig. 7, illustrating the power losses for both cases. Similarly, modeling VDL indicates a reduction of 2%, 2%, and 1% in the highest, average, and lowest values of voltage, respectively. Therefore, accurately modeling the VDL is essential for estimating the voltage profile and PL of the DNs in PPFA.

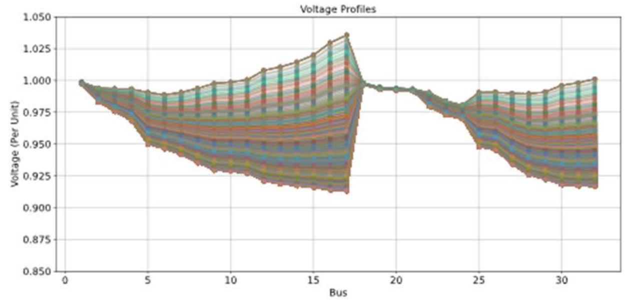

Fig. 5. Voltage profile in Case I

TABLE I. POWER LOSS AND VOLTAGE

Variable	Case I	Case II
V^{max}(p.u.)	1.03	1.01
V^{min} (p.u.)	0.91	0.89
V^{mean} (p.u.)	0.95	0.94
$Loss^{max}$ (kW)	191.22	288.79
$Loss^{min}$ (kW)	101.83	160.42
$Loss^{mean}$(kW)	162.06	250.64

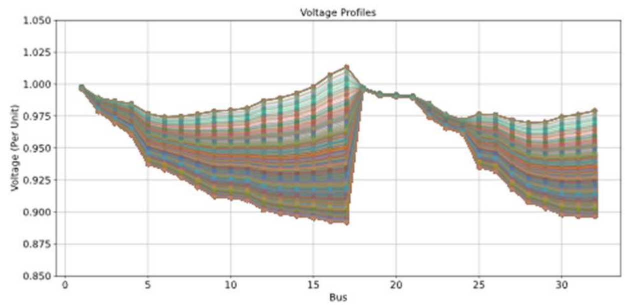

Fig. 6. Voltage profile in Case II

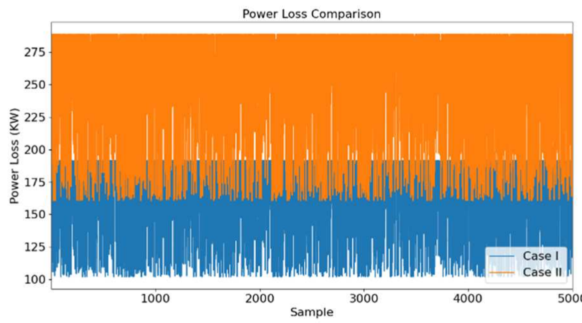

Fig. 7. Power loss for Case I and Case II

IV. CONCLUSION

Probabilistic power flow analysis or PPFA serves as a valuable tool for comprehending steady-state performance of distribution networks amidst intermittent renewable generation. Nevertheless, the accuracy of such analysis hinges on precise modeling and the availability of historical data. To address this, real-data for wind speed has been used to derive the corresponding Weibull probability distribution function or PDF. Subsequently, this PDF, alongside Monte Carlo simulation, has been used to generate samples (i.e., input parameters) for the PPFA. In addition, to refine the accuracy of the mathematical model, the impact of voltage-dependent loads or VDL on the PPFA has been evaluated. The findings demonstrate that incorporating VDL can significantly alter the maximum, minimum, and average power losses, as well as voltage profiles.

For future research endeavors, the proposed PPFA will be extended to encompass photovoltaic generation as well as electric vehicle charging, aiming to establish a comprehensive framework for data-driven PPFA that includes various electric load types in distribution networks.

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