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MONTE CARLO–BASED PROBABILISTIC LOAD FLOW COMBINED WITH OPTIMIZED STATIC VAR COMPENSATORS SOLUTIONS FOR RADIAL DISTRIBUTION NETWORK

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Abstract:
This paper presents a Monte Carlo–based probabilistic load flow (PLF) framework combined with optimized multi–Static Var Compensator (SVC) integration for voltage stability enhancement in radial distribution networks under stochastic load variations. Load uncertainties are modeled using Gaussian probability distributions, and repeated backward–forward sweep load flow solutions are employed to quantify voltage profile distributions and voltage instability probabilities. A probabilistic voltage instability index is formulated to evaluate the likelihood of voltage violations at each bus. The proposed method is applied to an actual 11 kV, 34-bus Ayepe radial distribution network in Ibadan, Nigeria, enabling realistic assessment beyond standard IEEE test systems. Simulation results demonstrate that optimal SVC placement significantly improves mean voltage profiles and reduces voltage instability probabilities. While single SVC integration yields noticeable voltage support, coordinated multi-SVC deployment provides superior performance, reducing the total voltage instability probability from 16.04 in the base case to 0.1067 and raising the minimum mean bus voltage above acceptable limits. The study confirms the effectiveness of Monte Carlo PLF combined with optimized multi-SVC integration for robust voltage stability analysis in uncertain distribution network environments.
Keywords — **Static Var Compensator (SVC), Monte Carlo, Radial Distribution Network, Probability.**

I. Introduction

Monte Carlo–based probabilistic load flow has become an important tool for analyzing power distribution networks under uncertainty caused by stochastic load variations and changing operating conditions. Unlike conventional deterministic methods, probabilistic load flow quantifies the likelihood of voltage violations and instability by repeatedly solving the load flow problem using statistically generated load scenarios. Voltage instability is a major concern in radial distribution systems, particularly under heavy loading and high line impedance conditions. Static Var Compensators (SVCs) provide dynamic reactive power support to improve voltage profiles and stability; however, the use of multiple SVC units installed at optimal locations offers enhanced system-wide voltage regulation compared to a single compensator. Consequently, this study applies Monte Carlo probabilistic load flow analysis with multiple SVC stochastic load variations, thereby providing a more realistic and reliable assessment of distribution network operation. single compensator. Consequently, this study applies Monte Carlo probabilistic load flow analysis with multiple SVC integration to evaluate and improve voltage stability performance under stochastic load variations, thereby providing a more realistic and reliable assessment of distribution network operation.

II. Literature Review

Probabilistic load flow (PLF) methods have been widely developed to quantify the effects of uncertainty in power system planning and operation. Early foundational work on PLF highlighted the need to move beyond deterministic load flows by explicitly modeling random variations in generation and load conditions ([11]; [13]) to better assess system performance under stochastic influences. Traditional PLF approaches include Monte Carlo Simulation (MCS), analytical methods, and approximate techniques, with MCS being valued for its straightforward treatment of arbitrary probability distributions despite its computational cost [2]. Comprehensive reviews of PLF methods indicate that MCS remains a benchmark approach for capturing uncertainty in distribution networks, particularly with high penetrations of renewable generation and electric vehicle charging ([3], [12]).

Monte Carlo PLF has been applied in various contexts, such as voltage stability assessment under renewable integration [9] and probabilistic evaluation of load margins [13]. Its application for voltage stability analysis shows that random power injections and load variations directly influence voltage profile distributions, which deterministic methods cannot adequately capture [8]. Furthermore, improvements in sampling strategies, including low-discrepancy sequences or surrogate models, have been investigated to mitigate the computational burden of MCS while maintaining accuracy ([10], [7]).

Parallel to PLF research, studies on reactive power compensation using FACTS devices such as Static Var Compensators (SVCs) have underlined their importance in voltage regulation. SVCs improve voltage profiles and reduce reactive power imbalances, enhancing system stability under variable operating conditions ([1] [15]). According to [16], SVC significantly improved the voltage profile and the transient stability of Nigerian 330kV line connecting Afam to Port Harcourt. [17] applied SVC to 132/33kV network to show the effects of SVC on power network for voltage profile enhancement. Optimal placement and sizing of SVCs is critical to achieving these benefits; various optimization and planning methods, including mixed-integer programming and metaheuristic algorithms, have been proposed to determine the best locations under load uncertainty ([14], [4]). For example, combining Monte Carlo simulation with optimization techniques captures the stochastic nature of system conditions while identifying optimal reactive support locations [1].

Recent hybrid approaches integrate PLF with advanced control and optimization strategies to manage both uncertainty and reactive power device coordination. Deep learning–based control frameworks integrating PLF and hybrid FACTS controllers have been proposed for enhanced real-time voltage stabilization, indicating a trend towards intelligent probabilistic control synthesis in future grids [6]. Additionally, reliability studies employing sequential Monte Carlo simulation have demonstrated the impacts of SVC integration on broader system reliability metrics under multiple failure modes [5].

Overall, the literature indicates that Monte Carlo–based PLF combined with optimized SVC integration provides a powerful framework for voltage stability assessment and reactive power support in uncertain environments, though challenges remain in computational efficiency and integration with real-time control schemes.

Despite extensive global research on probabilistic load flow and reactive power compensation, their application to the Nigerian power distribution network remains limited. Most studies on Nigerian feeders still rely on deterministic load flow methods that do not adequately capture the pronounced load uncertainty arising from load shedding, seasonal demand variations, illegal connections, and frequent network reconfigurations. In addition, existing works largely focus on single reactive power compensation devices and steady-state voltage improvement, with little emphasis on coordinated multiple SVC integration or on quantifying voltage instability probabilities under stochastic operating conditions.

Furthermore, many probabilistic load flow studies are based on standard IEEE test systems, which fail to reflect the structural and operational characteristics of Nigerian 11 kV radial feeders, such as high R/X ratios, long feeder lengths, and weak voltage regulation. Consequently, there is a clear research gap in applying Monte Carlo–based probabilistic load flow to real Nigerian distribution networks with optimal multi-SVC integration to realistically assess and enhance voltage stability and reliability. This study therefore, focuses on the Monte Carlo–based PLF combined with optimized SVC integration into the 11kV 34-bus Ayepe radial distribution network in Ibadan, Nigeria.

III. Materials and Method

1) Monte Carlo Load Modeling

In the probabilistic load flow analysis, the uncertainties in load demand are represented using Monte Carlo Simulation (MCS). The real and reactive power demands at each load bus are assumed to follow a normal (Gaussian) distribution.

For bus i, the stochastic real and reactive power demands are modeled as:

$$P_i^{(m)} \sim N(\mu_{P_i}, \sigma_{P_i})$$

$$Q_i^{(m)} \sim N(\mu_{Q_i}, \sigma_{Q_i})$$

Where:

- $P_i^{(m)}, Q_i^{(m)}$ are the real and reactive power demands at bus i for the m^{th} Monte Carlo trail,
- μ_{P_i}, μ_{Q_i} are the nominal real and reactive load values,
- $\sigma_{P_i}, \sigma_{Q_i}$ are the corresponding standard deviations,
- $m = 1,2, \ldots, M, and\ M$ is the total number of Monte Carlo samples.

For each Monte Carlo sample, a deterministic load flow is solved using the backward/forward sweep algorithm, yielding the bus voltage vector:

$$V^{(m)} = \left[V_1^{(m)}, V_2^{(m)}, \dots, V_N^{(m)}\right]$$

Where N is the total number of buses.

2. Backward/Forward Sweep Load Flow Formulation

The injected current at bus i for the m^{th} Monte Carlo sample is calculated as:

$$I_i^{(m)} = \frac{P_i^{(m)} - jQ_i^{(m)}}{\left(V_i^{(m)}\right)^*}$$

During the backward sweep, branch currents are accumulated from the terminal buses towards the substation. In the forward sweep, bus voltage are updated as:

$$V_j^{(m)} = V_i^{(m)} - Z_{ij} I_{ij}^{(m)}$$

Where:

- $Z_{ij} = R_{ij} + jX_{ij}$ is the impedance of the line between buses i *and* j.
- $I_{ij}^{(m)}$ is the branch current from bus i to bus j.

3. SVC Control Law and Reactive Power Injection

The Static Var Compensator (SVC) is modeled as a voltage-regulating shunt compensator installed at a selected bus k. The reactive power injected or absorbed by the SVC is governed by a proportional control law:

$$Q_{SVC}^{(m)} = K_{SVC}\left(V_{ref} - \left|V_k^{(m)}\right|\right)$$

Where:

- K_{SVC} is the SVC gain,
- V_{ref} is the reference voltage,
- $\left|V_k^{(m)}\right|$ is the voltage magnitude at the SVC bus.

The SVC reactive power is constrained within its operational limits:

$$Q_{SVC}^{(m)} \leq Q_{SVC}^{(m)} \leq Q_{SVC}^{(m)}$$

The effective reactive power demand at the SVC bus is therefore modified as:

$$Q_k^{(m)} = Q_{k,load}^{(m)} - Q_{SVC}^{(m)}$$

4. Voltage Instability Probability Index

Voltage instability is defined as a condition where the bus voltage magnitude falls below a predefined threshold V_{lim}. For each bus i, the probability of voltage instability is computed as:

$$P_{inst,\,i} = \frac{1}{M}\sum_{m=1}^{M} \mathbb{I}\left(\left|V_k^{(m)}\right| < V_{lim}\right)$$

Where:

- $\mathbb{I}(.)$ is the indicator function, equal to 1 if the condition is satisfied and 0 otherwise.

5. Objective Function for Optimal SVC Placement

The optimal SVC location is determined by minimizing the overall voltage instability probability across the network.

$$\min_{k \in \Omega} J_k = \sum_{i=1}^{N} P_{inst,i}^{(k)}$$

Where:

- Ω is the set of candidate buses for SVC installation,
- $P_{inst,i}^{(k)}$ is the instability probability at i when the SVC is installed at bus k.

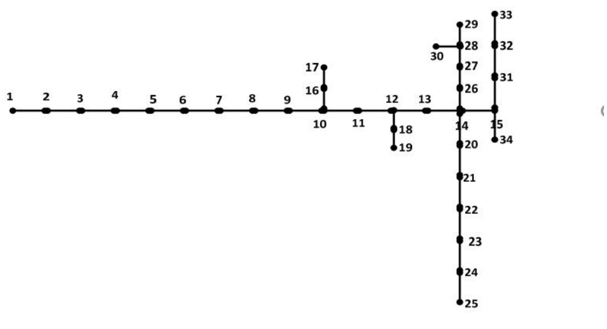

Fig. 1. Ayepe 34-bus radial distribution test network

Results and Discussion

To assess the effectiveness of the Monte-Carlo Probabilistic Load Flow algorithm with SVC integration, the 11-kV Ayepe

34-bus distribution network of the Ibadan Electricity Distribution Company (IBEDC), illustrated in Fig. 1, was adopted as the test system. The network comprises 34 buses, with Bus 1 designated as the substation supplying power to the remaining buses. The aggregate real and reactive power demands of the system are 4.12 MW and 2.05 MVAr, respectively.

To simulate the Monte-Carlo Probabilistic Load Flow algorithm in the radial distribution system, the parameters used are according to the data provided in Table 1. In the simulation, all the buses of the system have been considered as candidate for installation of SVC except the first bus which is represented as in-feed of electric power from transmission system.

TABLE 1. SIMULATION PARAMETER SETTINGS

Parameters	Value
Monte Carlo simulations	1500
Voltage instability threshold	0.9
SVC reference voltage	1pu
Qsvc_max	600
Qsvc_min	-600
SVC gain	25
Number of SVC	2
Real power standard deviation	25
Reactive power standard deviation	5
Base KV	11
Base MVA	1000

This study investigates three distinct test cases, which are outlined as follows:

Case 1: Base Case (No SVC installed)

A Monte Carlo–based probabilistic load flow was conducted for the base case in order to obtain the mean voltage profile and the corresponding voltage instability probability bar chart. As shown in Fig. 2, Buses 1–8 and 19–27 were identified as non-critical, exhibiting instability probabilities below 5%. This is attributed to their proximity to the substation, which provides adequate voltage support. In contrast, Buses 9–18, which supply relatively heavy loads, recorded instability probabilities exceeding the 5% threshold and were therefore classified as critical buses and selected as potential locations for SVC installation. Additionally, Buses 28–34 were also identified as critical due to their elevated voltage instability risk, resulting from their location at the feeder ends, where higher line impedances and significant voltage drops are present.

Case 2: Single Svc Unit Installed in the Test System

Following the determination of the optimal SVC location, a Monte Carlo–based probabilistic load flow was carried out to evaluate the resulting mean voltage profile and voltage instability probability bar chart in comparison with the base case. Table 2 presents a comparative assessment between the base case scenario and the system with a single SVC integrated. As illustrated in Fig. 3, the installation of a single SVC led to a significant enhancement in the mean voltage profile and a noticeable reduction in the voltage violation probabilities of buses identified as critical in the base case. In particular, the instability probabilities of Buses 10–18 and 28–30, which previously exceeded the 5% threshold, were substantially reduced. Notably, the probabilities at Buses 10, 11, and 28 were lowered below the 5% limit, thereby reclassifying them as non-critical under stochastic load variations. This demonstrates the strong effectiveness of the SVC in improving voltage performance under probabilistic load flow conditions. However, although Buses 12–18 and 29–30 also experienced considerable reductions in instability probability, their values remained above the 5% threshold, indicating that they continue to be classified as critical buses.

TABLE 2: COMPARATIVE BASE CASE AND OPTIMAL SINGLE SVC RESULTS

Optimal SVC Location	18
Minimum Mean Voltage (Base)	0.8607p.u.
Minimum Mean Voltage (SVC)	0.8813p.u.
Total Instability Probability (Base)	16.1353
Total Instability Probability (SVC)	7.4107

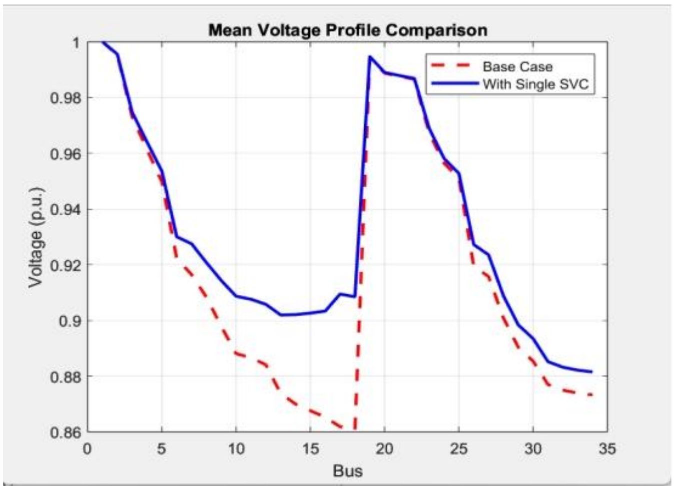

Fig. 2: **Ayepe 34-bus Mean Voltage Profile Comparison- Base Case VS Single SVC Case**

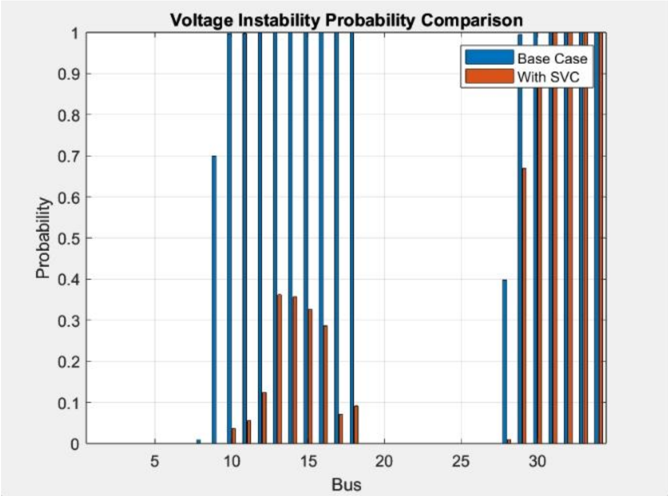

Fig. 3: **Ayepe 34-bus Voltage Instability Probability Comparison- Base Case VS Single SVC Case**

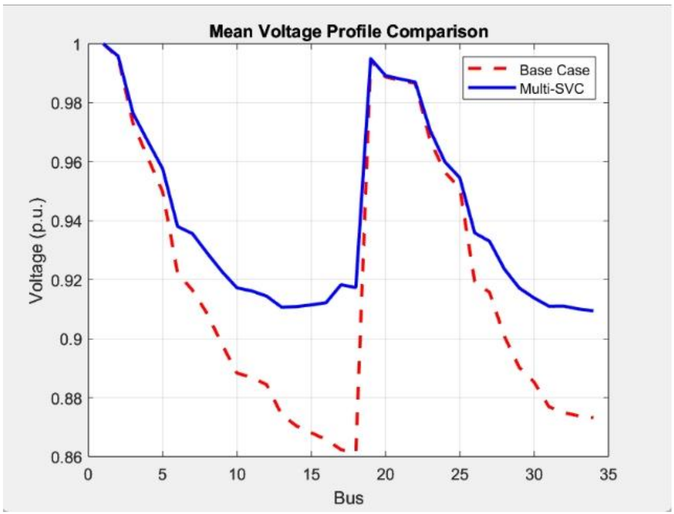

Fig. 4: **Ayepe 34-bus Mean Voltage Profile Comparison- Base Case VS Multi-SVC Case**

Case 3: Multi-Svc Integration

Two SVC units, each rated at 600kVar, were integrated into the network and their optimal installation locations were subsequently determined. A Monte Carlo–based probabilistic load flow analysis was then conducted to evaluate the resulting mean voltage profile and voltage instability probability bar chart, with comparisons made against the base case and the single SVC configuration. The simulation outcomes for the multi-SVC integration are presented in Table 3, which provides a comparative evaluation between the base case and the multi-SVC scenarios. As depicted in Fig. 4, the deployment of multiple SVC units resulted in a substantial enhancement of the mean voltage profile and a further reduction in voltage violation probabilities across the network relative to both the base case and single SVC cases. Following optimal multi-SVC installation, Buses 1–8, 13–16, 18–27, and 30–34 exhibited instability probabilities below the 5% threshold as shown in Fig. 5, highlighting the effectiveness of SVCs in improving voltage stability under probabilistic load flow conditions. Overall, the multi-SVC configuration achieved greater voltage profile improvement than both the base case and the single SVC unit scenarios

TABLE 3: COMPARATIVE BASE CASE AND OPTIMAL MULTI - SVC RESULTS

Optimal SVC Location	17, 32
Minimum Mean Voltage (Base)	0.8613p.u.
Minimum Mean Voltage (SVC)	0.9094p.u.
Total Instability Probability (Base)	16.04
Total Instability Probability (SVC)	0.1067

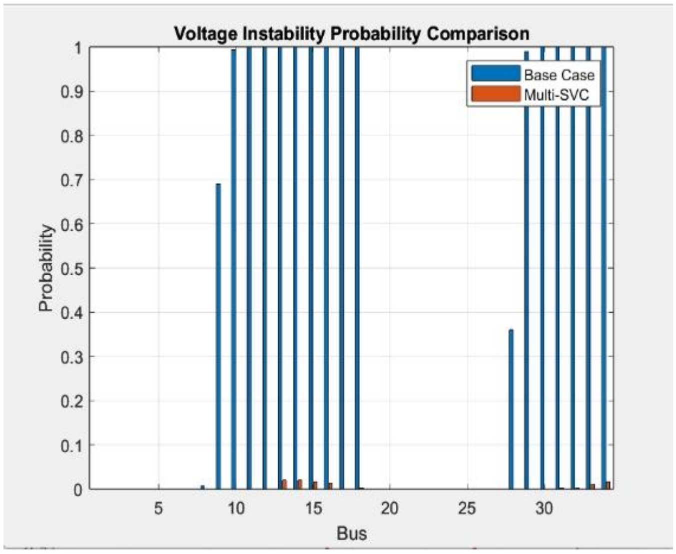

Fig. 5: **Ayepe 34-bus Voltage Instability Probability Comparison- Base Case VS Multi-SVC Case**

CONCLUSION

This study has demonstrated the effectiveness of Monte Carlo–based probabilistic load flow analysis combined with optimized multi-SVC integration for voltage stability enhancement in radial distribution networks subject to load uncertainty. By explicitly modeling stochastic variations in real and reactive power demands, the proposed framework provides a more realistic assessment of voltage behavior compared to conventional deterministic methods. Application to the 11 kV Ayepe 34-bus distribution network reveals that voltage instability risks are significant under probabilistic operating conditions, particularly at heavily loaded and remote feeder buses. The integration of SVCs at optimally selected locations substantially improves mean voltage profiles and reduces voltage violation probabilities. While a single SVC offers meaningful voltage support, the coordinated deployment of multiple SVC units delivers markedly superior performance, virtually eliminating voltage instability across the network. The results highlight the importance of probabilistic analysis and coordinated reactive power compensation for effective planning and operation of weak radial distribution systems. The proposed approach is therefore well suited for practical deployment in developing power networks characterized by high uncertainty and weak voltage regulation.

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