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Distribution Network Loss Minimization by Incorporating DG Using Particle Swarm Optimization (PSO) Technique

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***Abstract*— The efficacy of transmitting energy from high voltage transmission power lines to low voltage distribution power lines is vital in electrical power networks. Nevertheless, distribution systems often encounter substantial I^2R losses as a result of elevated R/X ratios, heightened current levels, and insufficient voltage circumstances. Distribution power businesses are incentivized to minimize losses, since the financial repercussions are contingent upon the disparity between real and anticipated losses. Strategies to reduce losses include feeder grading, allocation of distributed generation (DG), reconfiguration of the network, allocation of capacitors, and novel methods for high voltage distribution systems. The purpose of this work is to use an evolutionary algorithm called particle swarm optimization to identify the optimal allocation of photovoltaic production, using a multi-objective function and many constraints. The efficacy of these algorithms was evaluated using MATLAB R2022a on standard radial 33 and 69 IEEE bus systems, offering a comprehensive assessment of their performance in real-world situations. The main objective is to improve strategies for minimizing losses in distribution networks by using advanced optimization methods to strategically place photovoltaic distributed generation.**

***Keywords*— DG allocation, Distribution network optimization, Solar PV, Decentralized generation, Evolutionary algorithm.**

I. Introduction

The shift from centralized to decentralized power production is driven by increasing energy demands and sustainable development goals. This involves integrating small electricity-generating units into distribution networks, offering benefits like reduced costs, reduced power dissipation, backup power, and enhanced network resilience. However, the optimal use of these benefits depends on the strategic positioning and scale of distributed generators.

The distribution networks are responsible for 70% of the power losses, highlighting the significance of decentralized generation in addressing technical, economic, and environmental obstacles [1-3]. This research aims to improve the performance, reliability, and environmental sustainability of power networks by integrating solar photovoltaic (PV) technology on standard radial 33 and 69 IEEE bus systems. The integration of distributed generators offers advantages such as decreased transmission and distribution expenses, minimized power dissipation, supply of backup power during outages, and enhanced network resilience [4]. Nevertheless, the optimal use of these benefits heavily relies on the strategic positioning and scale of distributed generators. Improper positioning may result in difficulties such as heightened power dissipation, voltage irregularities, and diminished power integrity. The increasing intricacy of distribution networks, along with varied client demands, requires the use of inventive solutions for optimization. Feeder reconfiguration is a crucial technique that improves the performance of a system by distributing loads evenly, enhancing feeder voltage, and reducing power losses throughout the whole system [5]. Merlin and Back first used optimization techniques to reduce losses, however later research suggested heuristic methods that relied on voltage differentials [6-8]. Civanlar used heuristics to minimize line loss, whereas Baran and Wu improved the approaches by including power flow equations and considering load balancing factors [9-11]. Chiang, Jean-Jumean, Jeon, Chen, Cho, Wagner, and other researchers suggested many optimization techniques [12-14]. The integration of distributed generation (DG) units into distribution networks presents issues because of the exact position ambiguity. Das, Loparo, and their colleagues used sensitivity analysis to optimize the size and placement of utility-operated DG units [15-16]. Reliability-focused optimization techniques, such as linear programming and evolutionary algorithms like particle swarm optimization (PSO), have been used to identify the most suitable location and scale of DG systems [17-19]. Ramos, Wang, Rugthaicharoencheep, and Sirisumrannukul used evolutionary algorithms and optimization approaches to enhance network efficiency and achieve load balancing [20-22]. In addition, research conducted by Ding, Kenneth, and other scholars has specifically examined the reconfiguration of unbalanced networks by the use of nonlinear programming and sensitivity analysis [23]. Various techniques such as loss sensitivity factor, linear programming, simulated annealing, particle swarm optimization, and fuzzy approaches have been used to ascertain the most efficient size and placement of DG systems [24-26]. Ochoa successfully achieved significant reductions in actual power loss and short circuit levels [27]. This extensive review establishes the context for the present investigation, highlighting the need for sophisticated optimization techniques

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in the changing environment of distribution networks. Fig. 1. depicted photovoltaic type DG incorporation into a distribution power line. Fig. 2. Advantages of integrating distributed generation in power distribution lines.

Based on the above discussion the contribution of this research are:

• This paper creatively combines fixed and unpredictable photovoltaic production by using PSO to reduce I^2R losses in distribution power lines.

• In contrast to conventional methods, the study specifically emphasizes the crucial significance of determining the place and size of distributed generation in order to tackle the issues associated with increased I^2R losses in distribution power lines.

• This research distinguishes itself by examining three simulation scenarios, thoroughly assessing the algorithm efficacy in maintaining power quality and reducing energy loss, hence improving the practical relevance of the research.

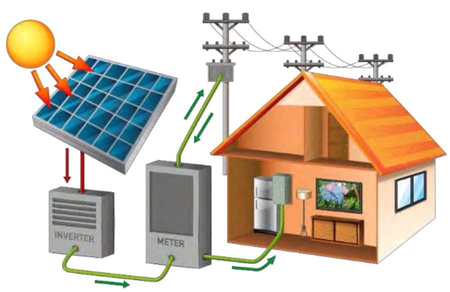

Fig. 1. Photovoltaic type DG incorporation into a distribution power line.

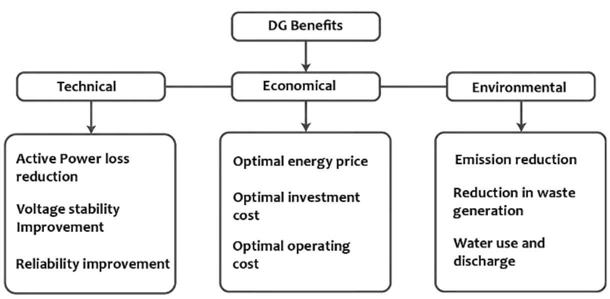

Fig. 2. Advantages of integrating distributed generation in power distribution lines.

I. METHODOLOGY

A. Evolutionary Algorithm:

PSO efficiently explores solution spaces by drawing inspiration from collective intelligence observed in fish and birds. This adaptive algorithm operates independently of target function attributes and accommodates diverse technologies. PSO construction involves a simple configuration with few adjustable parameters and no specific initial settings. Within the PSO framework, individuals form a swarm, traversing the solution space as particles. Collaboration among particles involves exploring paths and sharing information, facilitating dynamic solution enhancement. Velocity-based adjustments iteratively refine solutions until termination conditions are met, succinctly captured by a mathematical equation governing positional changes. PSO, rooted in collective search behavior, serves as a robust and adaptable optimization tool applicable across various contexts. Fig. 3. provides a visual representation of the PSO exploration process.

$$V_{new} = V_{old} + C_1 \times r_1 \times (P_{local} - P_{old}) + C_2 \times r_2 \times (P_{global} - P_{old}) \quad (1)$$

$$P_{New} = P_{Old} + V_{New}$$

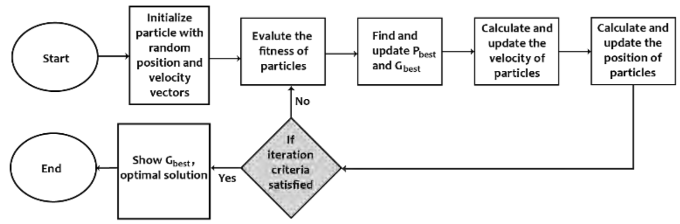

Fig. 3. The concept of searching PSO.

Here, P_{old} and P_{new} are the previous and updated particle values, V_{old} and V_{New} are the previous and new velocities, C_1, C_2 (1.2 and 0.12 respectively) are weighting factors, and r_1, r_2 are random numbers between 0 and 1. P_{Local} is the personal and P_{global} is the global best value within the group.

B. Load Flow Analysis:

The shift from passive to active states in distribution systems, driven by increased adoption of DG, demands a reevaluation of distribution analytic techniques. Accurate load flow forecasting becomes challenging with the integration of remote generations, especially when dealing with PV buses, requiring additional load flow calculation procedures. Fig. 4. outlines the successive stages in establishing an accurate load flow solution in a distribution system, emphasizing the challenges posed by dispersed generation. The evolving distribution system underscores the necessity for enhanced analytical methods to accommodate the dynamics introduced by widespread dispersed generation technologies. The inherent radial structure and elevated R/X ratios in distribution networks present challenges for traditional load flow methods commonly used in broader energy systems. Conventional approaches like LU factorization and Jacobian matrix substitution prove inefficient and time-consuming, particularly in networks with low strength, leading to convergence issues. These limitations highlight the demand for tailored load flow solutions capable of addressing the unique characteristics of distribution networks, ensuring precision and effectiveness in power flow analysis within these systems.

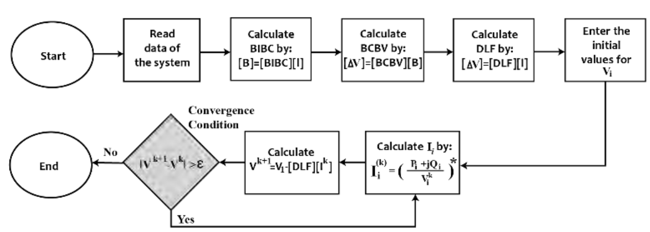

Fig. 4. The procedure for acquiring the load flow solution in distribution redial power lines.

C. Problem Formulation:

The main objective of this research is to improve the technical and economic benefits obtained by integrating photovoltaic distribution generation (PV-DG) into the current standard radial distribution power lines, achieved via careful planning and deliberate design. The decision to use a three-year planning horizon is important due to the inherent fluctuations in consumer load and sun irradiation during the four seasons, each lasting about 91.25 days. The mathematical representation of this capability is expressed by the following formula.

$$\min F = \min(\omega_1 \times Obj_1 + \omega_2 \times Obj_2) \quad (2)$$

The main goals of Obj_1 and Obj_2 are to reduce voltage variations and improve the voltage stability index term. The values ω_1 and ω_2 denote the allotted weights allocated to each target, indicating the importance ascribed to specific objectives. The collective importance of these goals is shown by the act of adding them together, as described below.

$$|\omega_1| + |\omega_2| = 1 \quad (3)$$

$$Obj_1 = \frac{TVD_{with}}{TVD_{with\,out}} \quad (4)$$

$$Obj_2 = \frac{1}{\sum_{n=1}^{NB} VSI_n} \quad (5)$$

The term TVD_{with} is used to describe the whole collection of voltage deviations, except those related to PV-DG. The use of this terminology is crucial for distinguishing and measuring changes in voltage that are not influenced by photovoltaic distributed generation contributions. The mention equation defines the power loss experienced on each distribution power line, offering a numerical depiction of the effect on the electrical network.

$$P_{Loss} = R_{n,n+1}\left(\frac{P_n^2 + jQ_n^2}{|V_n|^2}\right) \quad (6)$$

The electrical output produced by the photovoltaic unit is represented as P_{PV}, and its mathematical expression may be stated as follows.

$$P_{PV} = \begin{cases} P_r\left(\frac{G_s^2}{G_{std} \times X_c}\right), & \text{for } 0 < G_s \le X_c \\ P_r\left(\frac{G_s}{G_{std}}\right), & \text{for } X_c \le G_s \le G_{std} \\ P_r, & \text{for } G_{std} \le G_s \end{cases} \quad (7)$$

Stands G_{std} refers to the standardised solar irradiance environment, which is defined as 1000 W/$m^2$and serves as a benchmark for solar irradiance. Simultaneously, G_s represents the sun irradiance measured in watts per square metre, indicating the real sun irradiance at a particular location, with X_c representing a single point of sun irradiance. The other goal function is to enhance the voltage profile by reducing voltage deviations. The purpose of this aim function is to strategically improve the stability and dependability of the power system by making specific modifications in response to changes in solar irradiance levels.

$$TVD = 91.25 \times \sum_{i=1}^{N_s} \sum_{h=1}^{24} \sum_{n=1}^{NB} |V_n - 1| \quad (8)$$

The calculation of voltage differences is crucial for determining the Total Voltage Deviation (TVD), with NB being the total number of buses. In the study, an important factor taken into account is the enhancement of the Voltage Stability Index (VSI_n), which is a function specifically developed to improve the overall stability of the system. The function's form is explained as follows, indicating a purposeful attempt to enhance the voltage stability index for increased power system resilience.

$$TVSI = 91.25 \times \sum_{i=1}^{N_s} \sum_{h=1}^{24} \sum_{n=1}^{NB} VSI_n \quad (9)$$

$$VSI_n = |V_n|^4 - 4\,(P_{mn+1}X_n - Q_{n+1}R_n)^2 - 4\,(P_{n+1}X_n + Q_{n+1}R_n)\,|V_n|^2 \quad (10)$$

The following equality constraints clarify the criteria for equilibrium that regulate the distribution of power within the system.

$$P_{Slack} + \sum_{i=1}^{NPV} P_{PV,i} = \sum_{i=1}^{NT} P_{loss,i} + \sum_{i=1}^{NB} P_{L,i} \quad (11)$$

$$Q_{Slack} + \sum_{i=1}^{NPV} Q_{PV,i} = \sum_{i=1}^{NT} Q_{loss,i} + \sum_{i=1}^{NB} Q_{L,i} \quad (12)$$

The variables P_L and Q_L indicate the active and reactive power demands of loads, respectively. On the other hand, P_{Slack} and Q_{Slack} represents the amount of active and reactive power being produced by the substation. In addition, NPV, in this particular situation, may include the number of photovoltaic units.

$$V_{min} \le V_i \le V_{max} \quad (13)$$

$$I_n \le I_{max,n} \; n = 1, 2, 3, \dots, NT \quad (14)$$

$$\sum_{i=1}^{N_{PV}} P_{PV,i} \le \sum_{i=1}^{NB} P_{L,i} \quad (15)$$

$$\sum_{i=1}^{N_{PV}} Q_{PV,i} \le \sum_{i=1}^{NB} Q_{L,i} \quad (16)$$

The term V_{min} refers to the minimum voltage limit, whereas V_{max} represents the highest voltage threshold. In addition, the notation $I_{max,n}$ precisely defines the maximum allowable current for the n^{th} distribution power line.

This section outlines the methodology for predicting uncertainty in Photovoltaic units and consumer demand. A comprehensive stochastic model is developed using three years of hourly historical data from a specific location. The temporal dimension is divided into four seasons, each comprising 96-time intervals to represent the 24-hour daily cycle. Probability distribution functions (pdfs) for each time are constructed by aggregating data from the same hour over three years. Hourly pdfs are derived from a dataset of 270 data points, encompassing sun irradiance and consumer demand for each time period over a 3-year span, organized into 3 months for each season with 30 days per month. The subsequent section provides a detailed explanation of the probabilistic model governing the behavior of both the photovoltaic system and electricity demand. Fig. 5. and Fig. 6. Shows the standard IEEE radial 33 and 69 distribution power system.

D. Solar Irradiance Modeling:

The sun radiation data for each hour was used to create a Beta probability density function customized for the particular time period being studied. The accompanying discourse will clarify the creation of this probability density function.

$$f_b(g_s) = \begin{cases} u\,\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)}\, g_s^{(\alpha-1)}.\, u(1-g_s)^{(\beta-1)}, u0 \le g_s \le 1;\ \ \alpha,\beta \ge 0 \\ 0, \qquad\qquad\qquad \text{Otherwise} \end{cases} \tag{17}$$

The Beta probability density function for solar irradiance, $f_b(g_s)$, is defined using the gamma function, Γ, with α and β as the parameters that distinguish each phase of the Beta distribution. The process of obtaining these parameters from past data is explained in detail in the following technique.

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1\right) \tag{18}$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \tag{19}$$

The average (μ) and variability (σ) of solar irradiation for each specific time period are given in reference [28]. Dividing Beta probability density functions into several intervals results in respective average values and probabilities of occurrence. The probability of a certain segment occurring during a given hour is calculated using the following formula:

$$prob_i^{g_s} = \int_{g_{s,i}}^{g_{s,i+1}} f_b(g_s)\, dg_{s,i} \tag{20}$$

The parameters $g_{s,i}$ and $g_{s,i+1}$ provide the starting and ending points of the interval, which are identified by the index i. The notation $prob_i^{g_s}$ represents the likelihood of interval i occurring within the solar irradiance distribution. The output power of Photovoltaic (PV) systems during certain states may be calculated using equation (7), which utilises the Beta probability density function for solar irradiance during a specified time.

E. Load Demand Modeling:

Since To account for the random behavior of the load demand, a normal probability density function is used to represent its fluctuation at each bus. The approach described in reference [11] enables the calculation of the average probability density function for the intrinsically uncertain load demand.

$$f_n(l) = u\,\frac{1}{\sigma_l\sqrt{2\pi}} \times exp\left[-\left(\frac{l-\mu_l}{2\sigma_l^2}\right)\right] \tag{21}$$

The probability of a segment occurring during a certain hour is measured by the following equation: The function $f_n(l)$ represents the probability density function that describes the load demand. The parameters μ_l and σ_l represents the mean and variability of the load demand for each specific time.

$$prob_i^l = \int_{l_i}^{l_{i+1}} f_n(l)\, dlu \tag{22}$$

The probability of interval i happening is represented as $prob_i^l$, wherein l_i and l_{i+1} represent the initiation and conclusion of the interval, respectively.

F. Combined Model:

The probabilistic models for solar irradiance and load demand, explained in subsections A and B, are combined to provide a unified probability model called ($P_{com,i}$) for Photovoltaic (PV) load. To calculate this integrated model for each unique time, the probabilities related to solar irradiance and load demand are convoluted, as explained in reference [29].

$$P_{com,i} = prob_i^{g_s} \times prob_i^l \tag{23}$$

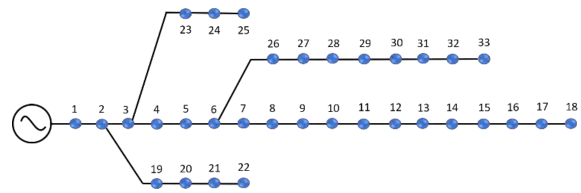

Fig. 5. Standard IEEE radial 33 distribution power system.

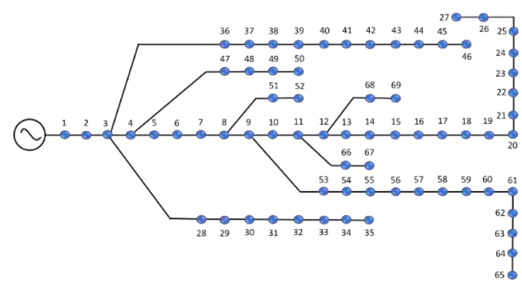

Fig. 6. Standard IEEE radial 69 distribution power system.

II. RESULTS AND DISCUSSIONS

The preliminary findings, excluding sunlight exposure and load demand uncertainties, are displayed in Table 1 for the standard 33 redial distribution bus system when the evolutionary algorithm is implemented and when it is not. In a similar vein, the results for the standard 69 redial distribution bus system in the presence and absence of the evolutionary algorithm are detailed in Table 2.

Table 1: Comparative results under certainty for the standard 33 redial distribution bus system with and without PSO.

Parameters	Base Case	With PV PSO
Active Power Loss (kW)	202.6771	96.7132
Reactive Power Loss (kVAR)	135.141	67.8457
Minimum Voltage	0.91306	0.95
Minimum Voltage Bus No.	18	7
Maximum Voltage	0.99703	0.99706
Maximum Voltage Bus No.	2	2
Optimal PV Location	NIL	14, 15
Optimal PV Size (kW)	NIL	445, 453
VSI (p.u)	25.595	27.1364
VD (p.u)	1.7013	1.2298

Moreover, the results are displayed herein post-consideration of uncertainties related to sun irradiance and load. Table 3 delineates the results for the standard 33 redial distribution bus system, comparing scenarios with and without the application of Particle Swarm Optimization (PSO). Correspondingly, Table 4 portrays the simulation results for the standard 69 redial distribution bus system under conditions where PSO is absent and present.

Table 2: Comparative results under certainty for the standard 69 redial distribution bus system with and without PSO.

Parameters	Base Case	With PV PSO
Active Power Loss (kW)	224.9606	129.97
Reactive Power Loss (kVAR)	102.147	53.3081
Minimum Voltage	0.90901	0.95
Minimum Voltage Bus No.	65	57
Maximum Voltage	0.99997	0.99997
Maximum Voltage Bus No.	2	2
Optimal PV Location	NIL	20, 23
Optimal PV Size (kW)	NIL	315, 296
VSI (p.u)	60.645	61.6304
VD (p.u)	1.8385	1.5314

Table 3: Comparative results under uncertainties for the standard 33 redial distribution bus system with and without PSO.

Parameters	Base Case	With PV PSO
Active Power Loss (kW)	125.2216	118.9791
Reactive Power Loss (kVAR)	80.1132	76.1253
E_{loss} (MWh)	0.53495	0.44502
E_{grid} (MWh)	40.5349	40.445
Optimal location	NIL	18, 16
Optimal size (KW)	NIL	2639, 939
VD (p.u)	10523.8643	9125.8153
VSI (p.u)	238991.3695	250042.0161

Table 4: Comparative results under uncertainties for the standard 69 redial distribution bus system with and without PSO.

Parameters	Base Case	With PV PSO
Active Power Loss (kW)	127.5364	120.5134
Reactive Power Loss (kVAR)	62.023	58.0508
E_{loss} (MWh)	0.51276	0.45194
E_{grid} (MWh)	40.5128	40.4519
Optimal location	NIL	64, 18
Optimal size (KW)	NIL	2479, 945
VD (p.u)	12619.523	10820.7753
VSI (p.u)	546037.3176	562010.8104

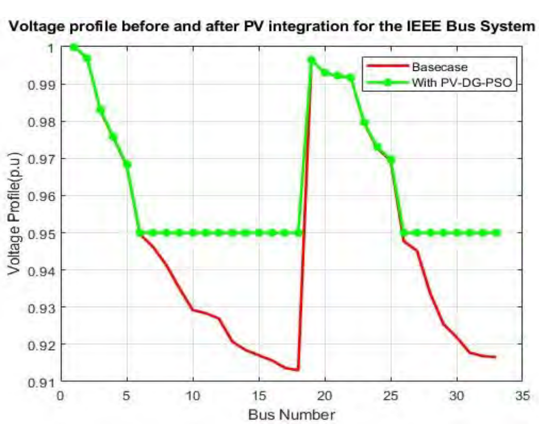

Fig. 7. Pre and post photovoltaic integration voltage profiling on the standard 33 redial distribution bus system.

The subjoined output graphs from fig. 7. to fig. 12. depict a scenario wherein uncertainties associated with load demand and solar irradiance are omitted from consideration.

The ensuing statistical graphs from fig. 13. to fig. 24. illustrates the conditions wherein uncertainties associated with load demand and solar irradiance are factored into the analysis.

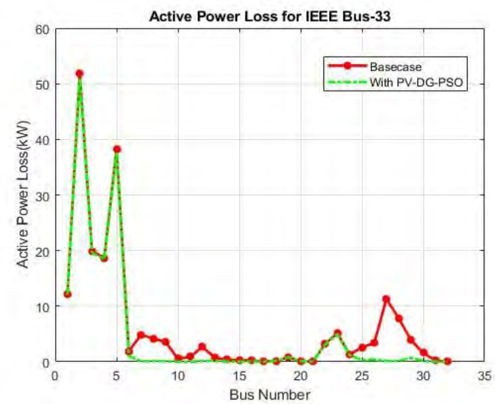

Fig. 8. Active power loss occurs both before and after photovoltaic integration in a standard 33 redial distribution bus system.

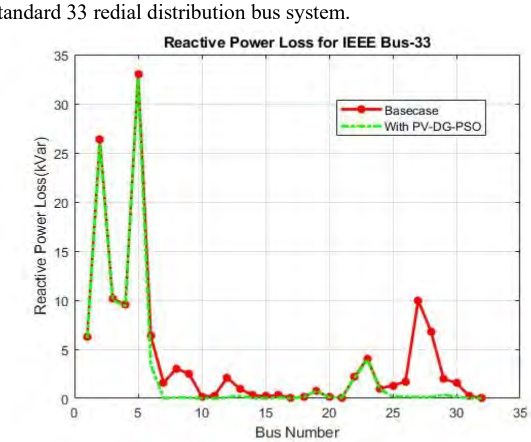

Fig. 9. Reactive power loss occurs both before and after photovoltaic integration in a standard 33 redial distribution bus system.

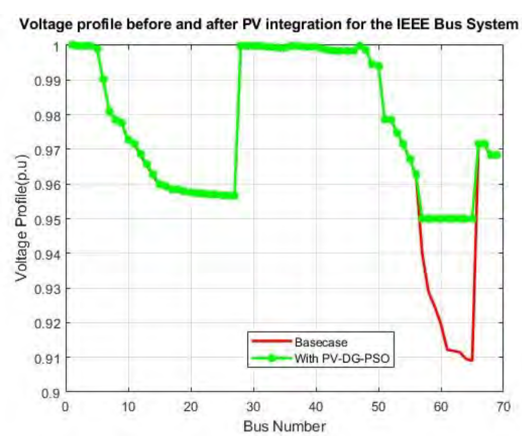

Fig. 10. Pre and post photovoltaic integration voltage profiling on the standard 69 redial distribution bus system.

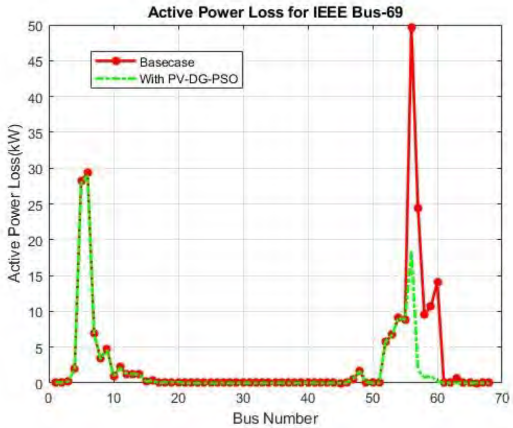

Fig. 11. Active power loss occurs both before and after photovoltaic integration in a standard 69 redial distribution bus system.

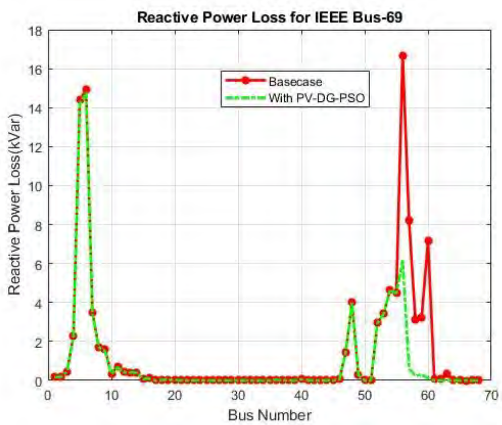

Fig. 12. Reactive power loss occurs both before and after photovoltaic integration in a standard 69 redial distribution bus system.

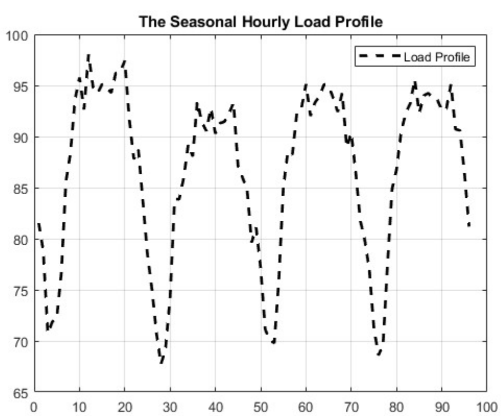

Fig. 13. Variations in seasonal hourly demand for the standard 33 redial distribution bus system.

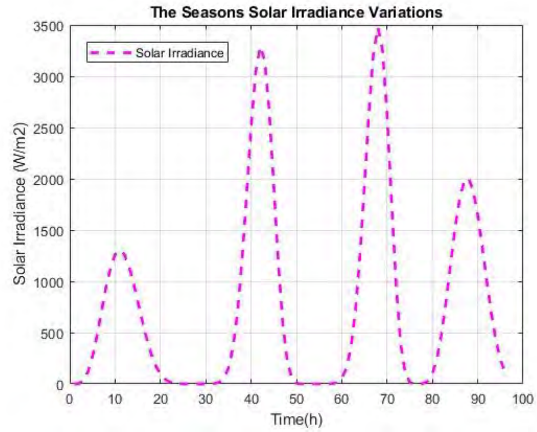

Fig. 14. Solar irradiation fluctuations throughout the seasons for the standard 33 redial distribution bus system.

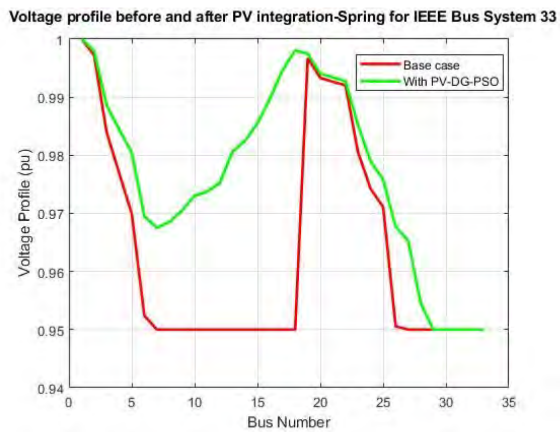

Fig. 15. Spring voltage profile for a standard 33 redial distribution bus system pre and post photovoltaic integration.

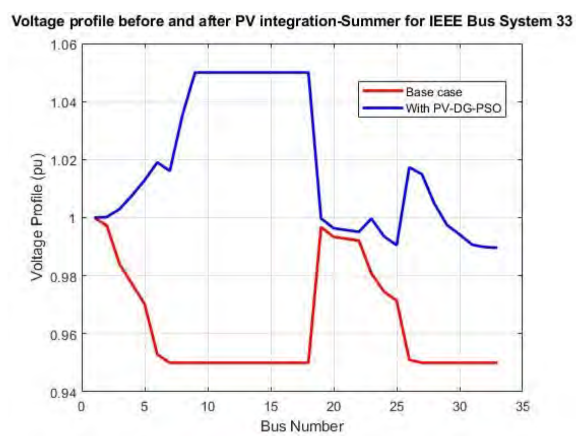

Fig. 16. Summer voltage profile for a standard 33 redial distribution bus system pre and post photovoltaic integration.

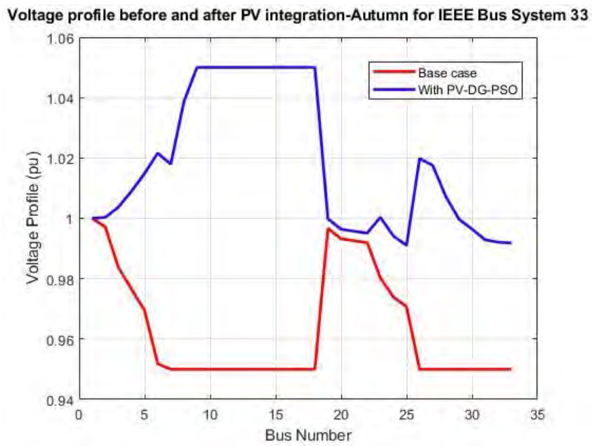

Fig. 17. Autumn voltage profile for a standard 33 redial distribution bus system pre and post photovoltaic integration.

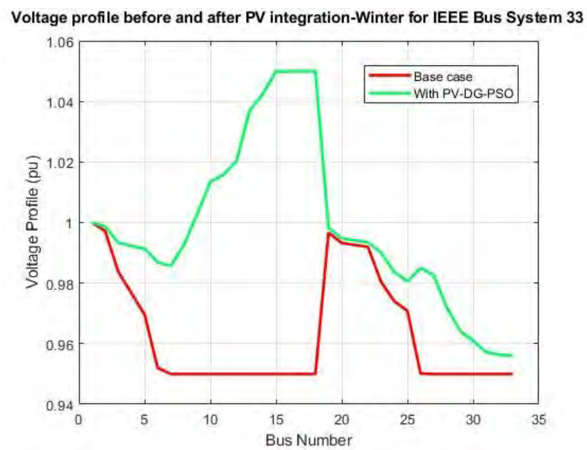

Fig. 18. Winter voltage profile for a standard 33 redial distribution bus system pre and post photovoltaic integration.

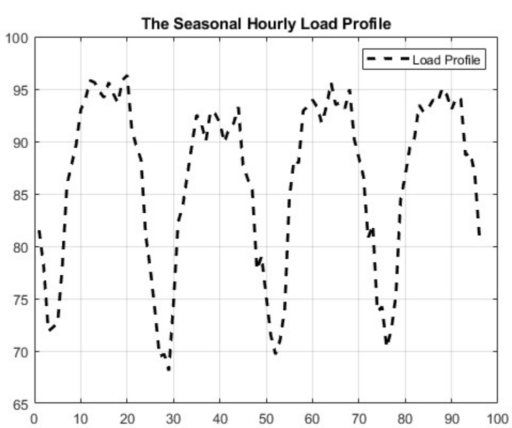

Fig. 19. Variations in seasonal hourly demand for the standard 69 redial distribution bus system.

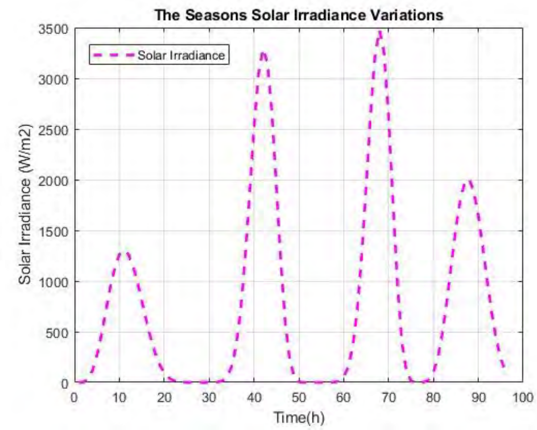

Fig. 20. Solar irradiation fluctuations throughout the seasons for the standard 69 redial distribution bus system.

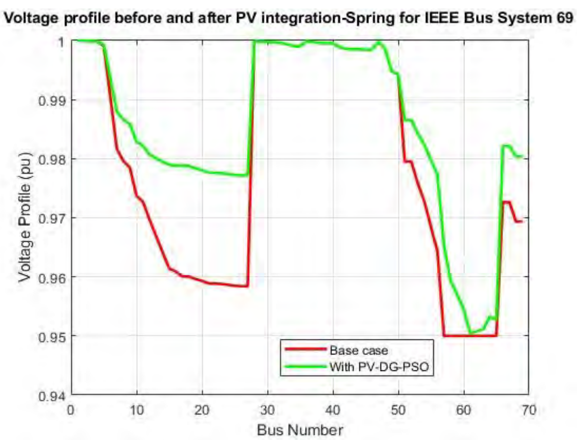

Fig. 21. Spring voltage profile for a standard 69 redial distribution bus system pre and post photovoltaic integration.

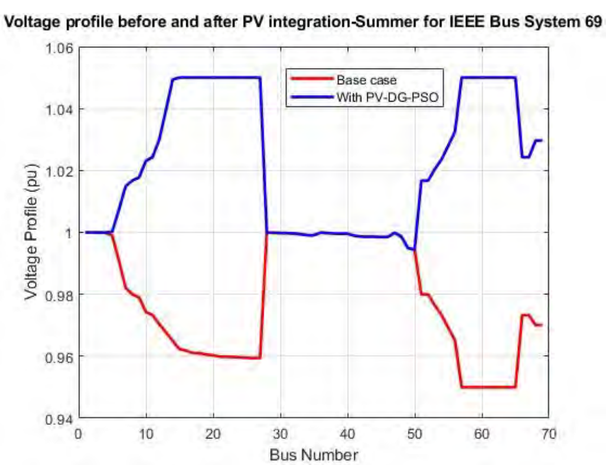

Fig. 22. Summer voltage profile for a standard 69 redial distribution bus system pre and post photovoltaic integration.

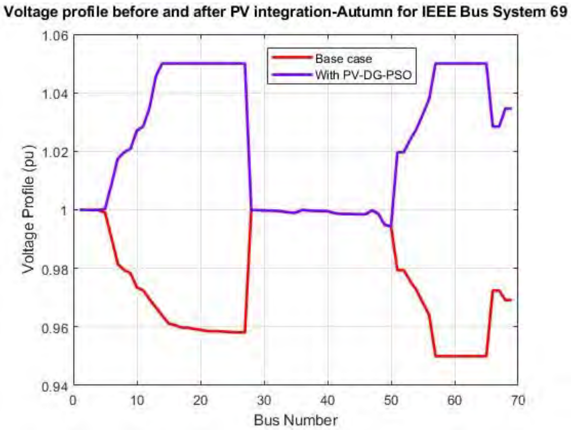

Fig. 23. Autumn voltage profile for a standard 69 redial distribution bus system pre and post photovoltaic integration.

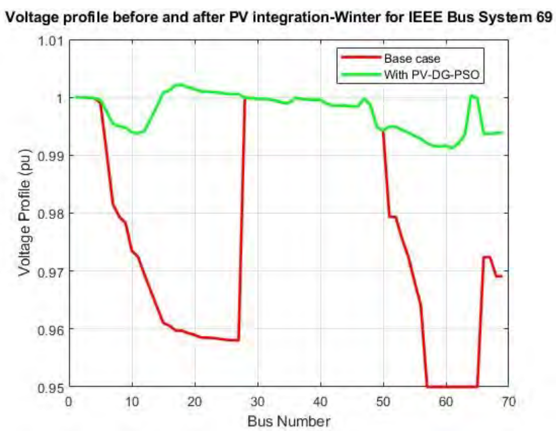

Fig. 24. Winter voltage profile for a standard 69 redial distribution bus system pre and post photovoltaic integration.

III. CONCLUSION

To summarize, this research emphasizes the need for effective power distribution in electrical systems, with a specific focus on reducing I^2R losses in distribution power lines. Certain methods, such as high voltage distribution systems, distributed generation allocation, line grading, network reconfiguration, and capacitor allocation, have been investigated with the intention of lowering losses. In this research PSO optimization technique was used to evaluate the capability and positioning of photovoltaic generators in radial distribution power lines. Our analysis focuses on mitigating voltage drops, achieving phase voltage balance, and minimizing energy loss. The comparison of IEEE standard redials bus systems, which are 33 and 69, reveals that the PSO method outperforms in terms of solution quality and convergence time. Subsequent studies will include several evolutionary algorithms such as Artificial Bee Colony, Grasshopper optimization and Ant Colony techniques to improve the suggested system. This research not only decreases power losses but also improves voltage stability in simulations of both IEEE standard redial bus systems, providing useful insights for study in power system optimization. The use of distributed generation and loss reduction enhances the novelty and durability of energy distribution networks.

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