Article

# Modified analytical approach for PV-DGs integration into radial distribution network considering loss sensitivity and voltage stability

**Oludamilare Bode Adewuyi[1*], Ayooluwa Peter Adeagbo[2], Isaiah Gbadegesin Adebayo[3*], Harun Or Rashid Howlader[4*], Yanxia Sun[5]**

[1] Department of Electrical and Electronic Engineering, First Technical University, Ibadan, 200255, Nigeria; oludamilare.adewuyi@tech-u.edu.ng; adewuyiobode@gmail.com (O.B.A.)
[2] Department of Electrical and Electronic Engineering, Adeleke University, Ede, 232101, Nigeria; ayooluwaadeagbo@yahoo.com (A.P.A.)
[3] Department of Electrical and Electronic Engineering, Ladoke Akintola University of Technology, Ogbomoso, 210214, Nigeria; igadebayo@lautech.edu.ng (I.G.A.)
[4] Graduate School of Science and Engineering, University of the Ryukyus, Okinawa 903-0213, Japan; harun340@yahoo.com (H.H.)
[5] Department of Electrical and Electronics Engineering Science, University of Johannesburg, Guateng, 2006, Johannesburg, South Africa; ysun@uj.ac.za (Y.S.)
* Correspondence: oludamilare.adewuyi@tech-u.edu.ng; igadebayo@lautech.edu.ng; harun340@yahoo.com

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**Abstract:** Achieving the goals of distribution systems operation often involves taking vital decisions with adequate consideration for several but often contradictory technical and economic criteria. Hence, this paper presents a modified analytical approach for optimal location and sizing of solar PV-based DG units into radial distribution network (RDN) considering strategic combination of important power system planning criteria. The considered criteria are total planning cost, active power loss and voltage stability, under credible distribution network operation constraints. The optimal DG placement approach is derived from the modification of the analytical approach for DG placement using line loss sensitivity factor and the multiobjective constriction factor based particle swarm optimization is adopted for optimal sizing. The effectiveness of the proposed procedure is tested on the IEEE 33-bus system modeled using Matlab considering three scenarios. The results are compared with existing reports presented in literature and the results obtained from the proposed approach shows credible improvement in the RDN steady state operation performances for line loss reduction, voltage profile improvement and voltage stability improvement.

**Keywords:** solar PV DG; line loss sensitivity; voltage stability; project cost; PV capacity factor; backward/forward sweep algorithm; particle swarm optimization with clerc's constriction

## 1. Introduction

The power system is a complex network that consist of three operation levels namely generation, transmission and distribution and each of these levels of operation has its peculiar challenges. However, in recent times, optimal planning at the distribution levels have been an issue of great priority for utilities. This is mainly because it is the most vulnerable component in the power system network by the virtue of its closeness to the end users which makes it account for a greater percentage of loss in the entire power system. With investment in new electrical facilities continuing to be very expensive, techniques and methods for improving the performance of existing distribution systems infrastructure vis-a-vis reduction in losses, improved reliability of supply, enhanced security of operation and profit maximization, have been developed by researchers and adopted by utility companies over the years[1].

In recent times, consumers' load demand pattern is changing and the amount of electricity demand is increasing beyond the existing power system capacity. Hence, the power system's operation dynamics is becoming even more complex to monitor, control and effectively dispatched [2]. More so, several countries, especially the developing countries, are faced with the problem of shortage of electricity supply as a result of continuously increasing load demand necessitated by the drive for industrialization and modernization. However, the generation and transmission facilities are not growing at equal rates and also most of these facilities are old and inefficient. Hence, electric utilities in the developing part of the world are forced to operate very close to their loadable limits (allowed capacities) due to geographical, economical and technical reasons. Consequently, in the recent time, the need for adequate planning and scheduling of large interconnected power system is becoming more pronounced due to the need for economical operation and compliance with current clean environment-oriented policies [3,4].

Introduction of localized renewable energy-based generators has been identified as a way to improve the steady state operating condition of power system. Harnessing the renewable energy resources properly can help bridge the gap that exists between load demand of customers and the supply capacity in a way that is economical and ensure compliance with environmental sustainability needs. Several renewable energy-based power generation technologies have been deployed in the concept known as distributed generation. Distributed generators (DGs) are rapidly developing and gradually changing the face of power generation in the world due to the cheap source of primary fuel and their closeness to the load centers. Hence they are often referred to as on-site generation, dispersed generation, embedded generation or decentralized generation [5]. Properly designed DG systems can reduce the risk of stressing the already overloaded transmission lines [6]. DG-enabled microgrids are usually designed to provide power supply systems for communities by ensuring on-site/local power generation for loads in either grid connected or off grid configuration [7].

Dispersed generation (DG) is a concept where smaller, highly efficient power plants would be built along the existing grid, close to the customers [8]. DG can provide grid quality power supply for different customer types (residential, commercial and sometimes, industrial) at significantly low cost. In 2013, 19.1 % of world energy consumption was met by renewable energy-based technologies [9], and these includes both off-grid and grid-connected dispersed generation. Dispersed generation setup, at mini-grid level, is a decentralized power plant, feeding into either the sub-transmission or the distribution level of power grid. The concept behind decentralized/dispersed generation is to inject reliable and high quality power using efficient power conversion technologies which are to be built along the existing grid close to the energy end-users. Apart from their techno-economical benefits such as transmission loss reduction and reduced cost of primary fuel, these generators promotes environmental sustainability in terms of reduced greenhouse gases emission and less noise [10,11].

Depending on the goal of the system planner, different DG types can be incorporated into the grid to either inject or/and absorb active or/and reactive power. Some of the crucial goals of DG inclusion in power systems are loss minimization, voltage regulation, security/stability enhancements, reduction of green house gas pollution that are common with the burning of fossil fuels in conventional generators *etc*. Several works have been done on the optimal sizing and siting of DGs in power systems, especially for distribution systems. The optimal planning of DGs into distribution systems involve two significant aspects namely optimal siting/location/placement and optimal sizing/techno-economic analysis of injected capacity. Though both are often considered together in a DG planning project, what they entails are significantly different. Often time, siting precedes sizing because proper placement of DGs has the capacity to avert oversizing the DGs at the point of injection.

Significant efforts have been dedicated to DG placement as contained in existing literature and the differences in the methodologies are seen in the criteria considered (technical, economic and environmental), as well as the models used for placement/siting of DG and the optimization algorithm deployed for sizing of the DGs. The main economic criteria is investment and operation cost reduction which is a very common objective to all such research study reported. The common technical criteria includes voltage profile improvement, power loss minimization, supply reliability improvement, flexibility management requirement, system security/voltage stability improvement etc. The environmental criteria are usually the need to mitigate climate change through active decarbonization of the power system and this is achieved by decommissioning of conventional fossil fuel-based generators and increasing the percentage contribution from renewable resources.

The complexity involved in DG sizing problems have been notably simplified by using tested and verified evolutionary (nature-inspired) algorithms, such as Genetic Algorithm , Particle Swarm Optimization, Chaotic Artificial Bee Colony, Imperialistic Competitive Algorithm,Plant Growth Simulation Algorithm, Modified Cuckoo Search Algorithm for fuel cost reduction, ant lion optimization algorithm for optimal reactive power solution and more [10,12–16]. Evolutionary algorithms are population-based optimization techniques that are easy to adopt for solving non-linear optimization problems [17,18]. However, they may be limited in accuracy due to the problem of early convergence at local optimal point for complex optimization problems, especially those with non-linear relationships. A notable multi-criteria decision making research study based on evolutionary algorithm deployment for optimal sizing of DG units in distribution networks is proposed in [19]. The target was to improve the voltage profile and reduce the network's real and reactive power losses using the IEEE 33-bus radial network as the test system. The biogeography-based optimization approach for DG units location and sizing in radial distribution systems was proposed in [20] using the IEEE 33-bus and 69-bus radial systems and the obtained results was compared with the results of genetic algorithm, particle swarm optimization and artificial bee colony algorithm. A hybrid approach that combines grasshopper optimization and cuckoo search technique for DG sizing was reported in [21], with the target of improving the voltage profile and minimize losses and cost. In [22], the DG sizing optimization is achieved for power loss minimization and voltage stability improvement using particle swarm optimization algorithm. Similar problem on IEEE 33 and IEEE 69 bus distribution system have been solved using more recent evolutionary approach such as the differential evolution [23] and improved Elitist-JAYA [24], algorithm. The challenges of solving complex non-linear optimization problems with other techniques led to the evolution of the several evolutionary algorithms (EA) reported in the literature. Generally, EA are easy to use tool for providing good approximate solutions to quite a number of real life optimization problems that may be too computationally-intensive to solve deterministically.

The vital and remarkably demanding aspect of electrical distribution system planning with DG injection is the placement (siting); this is the hub of the planning problem which determines whether the different contrasting objectives of the planning problem can be met at minimal economic and computational requirements. Depending on the network configuration and steady state parameters of interest, several models have been developed for efficient DG placement in power systems. A novel voltage stability index-based DG placement approach under a load growth condition was reported in [25]; the load demand are continually increased across all the buses and the effect on each bus is monitored to determine the most sentive bus for DG placement. Sensitivity factors approach for DG placement based on loss reduction and voltage improvement was described in [26]. In the paper, new sensitivity factors that can be useful for selecting the best locations for DG injection are discussed. The authors in [27] presented a detail comparison of different sensitivity approaches for efficient DG allocation in radial network. Some of the developed sensitivity approaches for DG placement in distribution network that are reported in the literature are power stability index [28], novel Q-PQV bus pair method [29], chaotic maps integrated with stochastic fractal search [30], zero bus flow approach [31], power loss sensitivity (PLS) on GAMS [32], pareto optimality with game theory [33], static and dynamic network reconfiguration [34], combined power loss index [35], node voltage deviation sensitivity [36], probabilistic generation with time-varying load models [37]. All these methods mentioned above are obtained from direct approximation of the voltage stability condition derived from the two bus transmission line model that has been widely reported in different works on steady-state voltage stability analysis [38]. The idea behind the reported approaches is to determine the best loading point as well as the best injection point (bus or node) for additional power from DG units by ensuring that the power system security is not compromised. This goal is achieved by monitoring specific steady-state parameters of the power system using different indices and sensitivity analysis.

One specific drawback of most of the existing approaches especially for loss minimization is that they really do not consider the effect of the injected power at a selected point of injection on the power loss along the associated branch/lines. More so, improper placement of DGs in a distribution network can increase the criticality of the lines as seen in the violation of the loadable limit which can be consequently reflected on their effective voltage stability margins. In another way, most sizing approach discussed in the literature do not give specific attention to solar irradiation for solar PV-based DGs. Hence, researchers often employ an estimate DG size based on load demand at the identified injection point. However, for real/actual case studies, there is a need to consider the solar irradiance of the specific location of interest. In this research work, a new attempt was made towards solving the problem associated with the impact of DG placement on line losses by adopting a modified model of loss sensitivity factor presented by Tah and Das in [39] and an absolute voltage stability margin index introduced by Furukakoi *et*. *al*. in [40] for monitoring the system stability condition. In order to factor in the effect of the time-dependent solar irradiance, the instantaneous PV output model is adopted with a capacity factor approach introduced in [4] for estimating the per hour equivalent power injection from the solar PV-based DGs to ensure compliance with the requirement for the load flow analysis using the backward/forward sweep algorithm [41–43], which is the basic tool deployed for distribution system parameter estimation in this study.

Voltage stability has been widely explained as the ability of a power system to maintain steady acceptable voltage levels at all buses within the system under normal operating conditions and after being subjected to a disturbance [44]. Heavily loaded (stressed) power systems are at the risk of voltage instability due to insufficient capacity to provide reactive power (VAR) support at the local load points. This can be empirically noticed by the dip in the voltage profile at critical buses within the power system. If this situation persists, it can lead to voltage collapse and wide-area power system blackouts; which is a common experience in many developing countries. Hence, increasing the share of DGs especially at the low and medium voltage sub-transmission/distribution level of the power system can help to improve the voltage stability [45]. The significant of voltage stability analysis in power system operation is seen in the fact that voltage stability indicates how quickly the power system can return to within the safe operating limit after a sudden change in the operating condition either due to disturbance or planned activities such as DG inclusion. The voltage stability level of a power system is totally different from the voltage magnitude levels which can be easily monitored by watching the fluctuations of the bus voltages [46]. Thus, the significant contributions of the study reported in this manuscript is the modification of the analytical approach reported in Tah and Das in [39] with the inclusion of voltage stability condition considering the effect of injected power from solar PV DGs and also, the consideration of site capacity factor in the determination of the effective power injected from the solar PV DGs.

For the optimization procedure, an enhanced multiobjective particle swarm optimization algorithm with constriction factor reported in [47] is used due to its proven enhanced capacity for handling non-linear problems, improved exploratory ability for solution accuracy with better convergence performance [48,49]. Three objective functions are considered and combined to produce three scenarios of optimal DG sizing problem formulation; these functions are minimization of total investment cost, minimization of power loss and maximization of voltage stability margin. The remaining section of this paper are organized as follows: the adopted mathematical models and methods are described under section 2. The optimization problem formulation which includes the objective function and constraints for DG placement and sizing are described in section 3. The simulation results are discussed in section 4 and the report is concluded in section 5.

## 2. Mathematical models and research methods

The different mathematical models employed at different stage of this research work are discussed in this section.

### 2.1. Backward/forward sweep load flow for radial distribution system

This work takes into consideration the inherent characteristics of radial network as analyzed using the backward/forward sweep (BFS) load flow algorithm. Considering a simple two nodes distribution network of Figure 1, the real and reactive power flows and losses are as expressed by equations 1 - 4.

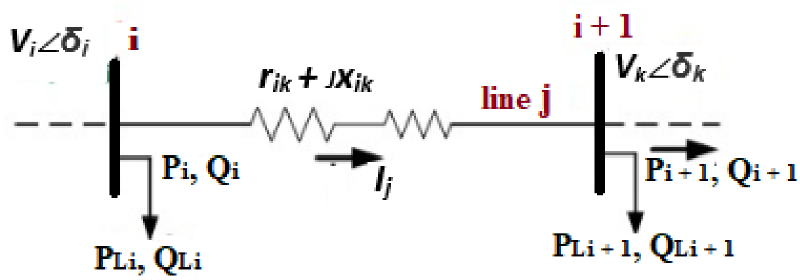


**Figure 1.** Two nodes distribution network [49]

$$P_i = P'_{i+1} + r_{ik}\frac{(P'^2_{i+1} + Q'^2_{i+1})}{V'^2_{i+1}}, \tag{1}$$

$$Q_i = Q'_{i+1} + x_{ik}\frac{(P'^2_{i+1} + Q'^2_{i+1})}{V'^2_{i+1}}, \tag{2}$$

Equations 1 and 2 represent the active and reactive powers ($P_j$ and $Q_j$) flowing through the branch 'j' from node 'i' to 'i+1' calculated backwards.

The real and reactive power losses of branch 'j' are calculated using equations 3 and 4 as follows:

$$P_{lossj} = r_{ik}\frac{(P_i^2 + Q_i^2)}{V_i^2}, \tag{3}$$

$$Q_{lossj} = x_{ik}\frac{(P_i^2 + Q_i^2)}{V_i^2}, \tag{4}$$

The above equations represent the active and reactive power losses along the branch 'j' ($P_j$ and $Q_j$) from node 'i' to 'i+1' using the backward calculation. $V_i$ is the voltage at node 'i', $r_{ik}$ and $x_{ik}$ are the resistance and reactance of the branch 'j' between any two nodes 'i' and 'k'.

The superiority of this load flow analysis method is such that regardless of the original network topology, the distribution network is first converted to a radial network. Also, a node and branch-oriented approach is incorporated using an efficient numbering scheme to enhance the numerical performance of the solution method as described with details in [43].

### 2.2. Solar PV system output dynamics and DG net power injection

In order to consider the effect of the time-varying solar irradiance in the solar PV DG sizing, the capacity factor approach is deployed to get an estimate of the net power injectable from the solar PV DGs. The output power of the PV system at time, $t$, for each DG at any injection point (bus) $i$ is calculated as a function of the size/rated power of the DG for each injection point [4]:

$$P_{pvi}(t) = \begin{cases} P_{pvratedi}\left(\frac{G_t^2}{G_{std}R_c}\right) & \text{for } 0 \leq G_t \leq R_c \\ P_{pvratedi}\left(\frac{G_t}{G_{std}}\right) & \text{for } G_t > R_c. \end{cases} \tag{5}$$

$P_{pvratedi}$ is the optimal size of the PV system at each identified injection point $i$ which is the decision variable to be estimated in the optimization procedure, $G_t$ is the instantaneous solar radiation, $G_{std}$ is standard radiation and $R_c$ is the radiation threshold.

By definition, the capacity factor of a solar PV facility is a measure of the energy production efficiency of that facility over a period of time, usually a year, based on the solar resource potential of the site. The power flow analysis is often calculated as per hour simulation of the steady-state condition of the power system; thus, the maximum available a.c. power injection into the distribution system from the solar PV DG units in per hour equivalent can be obtained as a function of the site's capacity factor ($Cf_{pv}$) and inverter's efficiency ($\eta_{inv.}$) as described [50]:

$$P_{DGi} = \eta_{inv.} \times P_{pvratedi} \times Cf_{pv} \tag{6}$$

The capacity factor of a good site with sufficient solar potential is estimated to be from 20% and above [51]. The solar data of a typical location with moderate solar potential is used for analysis in this study and the site capacity factor is assumed to be 25%.

### *2.3. Modified analytical approach for solar PV DGs placement based on line loss sensitivity*

The analytical method for DG placement adopted in this study recognizes that the rate of change of power loss along a branch against the injected power at the sending end is a parabolic function which is known as the loss sensitivity factor, $L_f$. This approach is an adaptation of the analysis of DG placement using the exact loss equation reported in [39,52]. The main difference between the reported approach and the modified approach being proposed in this study is the priority given to individual line loss with respect to the injected power by a DG placed at its sending end bus and the corresponding effect on the loading at the receiving end. The exact line loss for distribution network is calculated using the equation below:

$$P_{L_j} = \sum_{i=1}^{N_b}\sum_{k=1}^{N_b}[\alpha_{ik}(P_iP_k + Q_iQ_k) + \beta_{ik}(Q_iP_k - P_iQ_k)] \tag{7}$$

where

$$\alpha_{ik} = \frac{r_{ik}}{V_iV_k}cos(\delta_i - \delta_k); \tag{8}$$

$$\beta_{ik} = \frac{r_{ik}}{V_iV_k}sin(\delta_i - \delta_k) \tag{9}$$

The active and reactive powers from the DG injected into the network at the sending end buses of each branch can be represented as $P_{DGi}$ and $Q_{DGi}$, respectively as given below.

$$Q_{DGi} = \wp P_{DGi} \qquad \left(\equiv \sqrt{S_{inv}^2 - P_{DGi}^2}\right) \tag{10}$$

where

$$\wp = \tan(\cos^{-1}(pf)) \tag{11}$$

$S_{inv}$ is the inverter's ratings and $\wp$ is a function of the system's power factor and $N_b$ is the total number of nodes (buses) in the distribution system. The modification of the exact loss equation using the negative load model for DG power injection [50,53] gives:

$$P_{L_j} = \sum_{i=1}^{N_b} \sum_{k=1}^{N_b} \{\alpha_{ik}[(P_i - P_{DGi})P_k + (Q_i - Q_{DGi})Q_k] + \beta_{ik}[(Q_i - Q_{DGi})P_k - (P_i - P_{DGi})Q_k]\} \tag{12}$$

The active power loss along a line increases as the partial derivative of the line loss with respect to the active power injected from DG connected at its sending end bus $i$ rises up to a maximum point as illustrated in the Figure 2. Thus, for any branch/line $j$, the loss sensitivity factor $L_{fj}$ due to power injected by a DG at its sending end bus $i$ is described as:

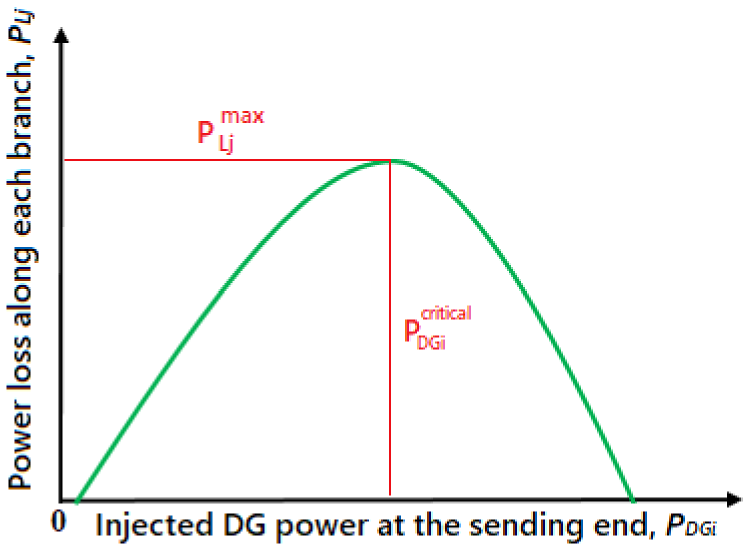


**Figure 2.** Illustration of loss sensitivity factor as a function of injected power, $L_{fj}$

$$L_{fj} = \frac{\partial P_{L_j}}{\partial P_{DGi}} = -\sum_{k=1}^{N_b} [\alpha_{ik}(P_k + \wp Q_k) + \beta_{ik}(\wp P_k - Q_k)] \tag{13}$$

Hence, to determine the candidate buses, the line sensitivity factor, $L_{fj}$ is sorted in descending order prioritizing the branches with high $L_{fj}$ values; and the candidate buses for DG injection are the sending end buses (as long as it is not the main feeder which is the bus 1) of the selected branches/lines.

### *2.4. Voltage stability margin and optimal DG sizing*

One crucial feature of power system security vis-a-vis voltage stability analysis are the assessment of lines voltage stability condition as related to the critical loading limit (stability margin) of the branches. This critical security criteria is defined as the ability to maintain a stable voltage profile under all credible contingencies, *i.e.* no fault, faulty, fault-cleared, as well as, normal load and overload conditions. This is often analyzed as a function of the maximum load increase that the system can withstand without violating its stability expectations. This loading margin can be graphically portray by the relationship between the real and reactive loading as shown in the Figure 3. The voltage stability margin can also be a crucial parameter for determining the limit of extra generation that the power system has the capacity to take, especially with the variable renewable DGs, as illustrated in the Figure 4. At a point, though the VSM is enhanced, the system can become overcompensated and this also threatens the power system stability condition.

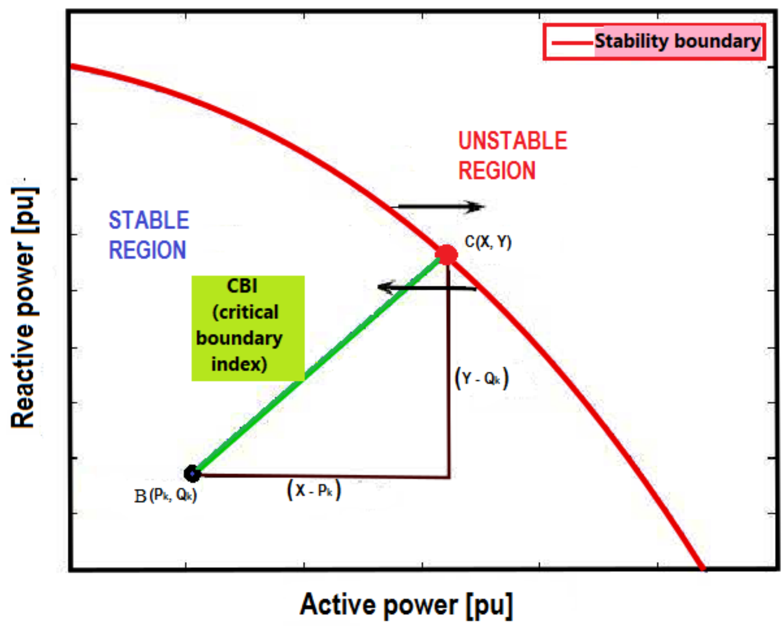


**Figure 3.** P-Q curve showing the voltage stability margin

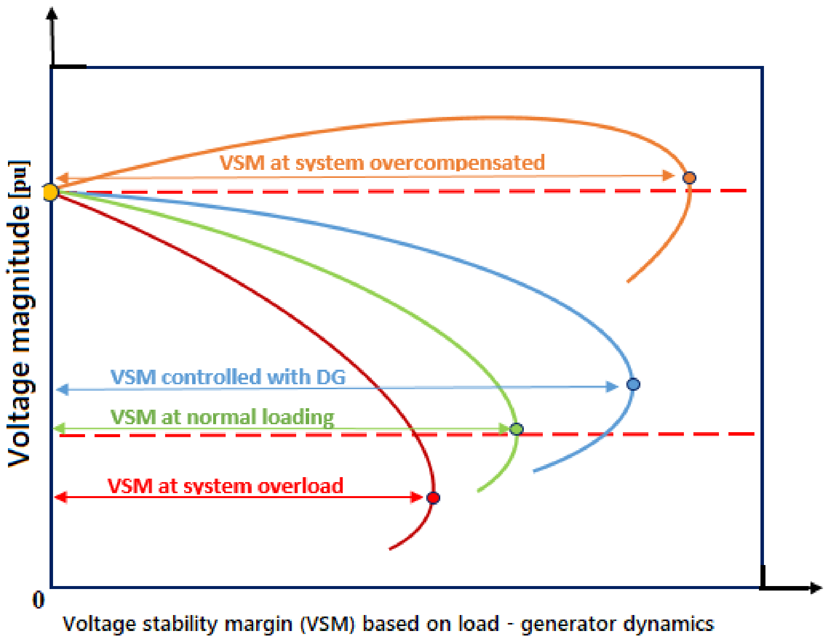


**Figure 4.** Voltage stability margin at different system conditions

245 The estimation model used for evaluating the stability margin in this study is the critical boundary
246 index, CBI, which is derived from the simple transmission line model described in [40]. The condition
247 for a power system at steady state to be within the voltage stability range is expressed as:

$$\sqrt{\left(P_k r_{ik} + Q_k x_{ik} - \frac{V_i^2}{2}\right)^2} - \left(r_{ik}^2 + x_{ik}^2\right)\left(P_k^2 + Q_k^2\right) \leq 0. \tag{14}$$

248 Thus, the locus of a point $C(X, Y)$ on the stability boundary can be obtained as:

$$C(X,Y) = \left(r_{ik}X + x_{ik}Y - \frac{V_i^2}{2}\right)^2 - \left(r_{ik}^2 + x_{ik}^2\right)\left(X^2 + Y^2\right). \tag{15}$$

The real and reactive load powers are $Q_k$ and $P_k$, respectively. $V_i$ and $V_k$ are the branch sending and receiving end voltage, respectively. $x_{ik}$ and $r_{ik}$ are the line reactance and resistance. Applying, the distance between two points approach, the current operating point, $B(P_k, Q_k)$ from any point, $C(X,Y)$ on the stability boundary is:

$$D = \sqrt{(X - P_k)^2 + (Y - Q_k)^2}. \tag{16}$$

Subject to the stability criteria defined by equation 15.

Hence, the non-linear problem is defined below using Lagrange constant method to obtain $X$ and $Y$.

$$F(X,Y,\lambda) = D(X,Y) + C(X,Y) \tag{17}$$

Hence, the critical boundary index, CBI is calculated as:

$$CBI = \sqrt{(X - P_k)^2 + (Y - Q_k)^2}. \tag{18}$$

As CBI approaches zero, the stability of the power system is threatened/compromised.

## 3. Problem formulations

For analysing the consistency of the proposed approach for DG siting and optimal sizing of DGs, three relevant objectives are considered and combined comparatively in a three scenarios arrangement, as described in this section. The considered objectives are the minimization of the total investment cost, the minimization of the total active power loss and the maximization of the voltage stability margin. The result of the three scenarios is compared with results from relevant literature on loss minimization and voltage stability enhancement in the succeeding section.

### 3.1. Objective functions

Three fitness functions are considered and compared in the designed optimization procedure based on different decision scenarios. This includes the total cost minimization, which is consistent with all considered scenario, power loss minimization and voltage stability margin maximization [4,50].

(a.) $F_1$: **Total system cost**

$$PV_{cost}^{total} = C_{inv.} + C_{o\&m} - C_{sal} \tag{19}$$

(i.) Cost of investment:

$$C_{inv} = \sum_{i=1}^{N_{pv}} \left(P_{pvrated} \times Inv_{cost}\right) \tag{20}$$

(ii.) Cost of operation and maintenance:

$$C_{o\&m} = \sum_{i=1}^{N_{pv}} \left(P_{pvrated} \times o\&m_{cost} \times \sum_{n=1}^{N_y} \left(\frac{1+\epsilon}{1+\mu}\right)^n\right) \tag{21}$$

(iii.) Resale cost of salvageable component (after project lifetime):

$$C_{sal} = \sum_{i=1}^{N_{pv}} \left(P_{pvrated} \times sal_{cost} \times \left(\frac{1+\epsilon}{1+\mu}\right)^{N_y}\right) \tag{22}$$

where $\epsilon$ is the inflation rate, $\mu$ is the interest rate, $N_y$ is the project lifetime, $Cf_{pv}$ is the site capacity factor, $N_{pv}$ is the number of the identified/selected PV sites, $\eta_{inv.}$ is the converter's efficiency, $Inv_{cost}$ is the unit cost of investment, $o\&m_{cost}$ is the unit operation and maintenance cost and $sal_{cost}$ is the unit salvage cost. The full details of all parameters and their values are provided in Table 1.

(b.) $F_2$: **Total active power loss**

$$P_{loss}^{total} = \sum_{j=1}^{N_{br}} Ploss_j \tag{23}$$

(c.) $F_3$: **Voltage stability margin**

$$CBI_{min} = \text{minimum}\ (\text{CBI}_j), \quad \forall j \in N_{br} \tag{24}$$

$N_b$ and $N_{br}$ are the number of buses/nodes and number of branches, respectively. The optimization problem scenarios solved and compared are thus described:

- **Scenario 1**: Total cost minimization and power loss minimization - minimize [$F_1$, $F_2$]
- **Scenario 2**: Total cost minimization and stability margin maximization - minimize [$F_1$, -$F_3$]
- **Scenario 3**: Total cost minimization, power loss minimization and stability margin maximization - minimize [$F_1$, $F_2$, -$F_3$].

For consistency with simulation model, the maximization problem is converted to the minimization equivalent by expressing it as negative during initialization of optimization process.

### 3.2. Network constraints

The following constraints are considered alongside the power balance equations [48].

(i.) Power flow constraint: Power flow constraint in each line($S_{flow_j}$) must be less than the maximum limit of power flow on each line ($S_{flow_j}^{max}$) as:

$$S_{flow_j} < S_{flow_j}^{max} \tag{25}$$

(ii.) Bus Voltage constraint The voltage at each bus $V_i$ must be within their permissible minimum and maximum limit as:

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{26}$$

(iii.) Voltage stability limit The critical boundary index value for each branch should be greater than a specific limit:

$$CBI_j \geq CBI_{limit} \tag{27}$$

The critical stability limits is considered to be at least 10% of the line's thermal limit [54]

### 3.3. Overview of Multi-objective Particle Swarm Optimization Algorithm

Classical Particle Swarm Optimization algorithm was developed based on the emergent motion of a flock of birds searching for food. It is a population-based, self - adaptive search optimization technique first introduced by Kennedy and Eberhart in 1995. The PSO algorithm performance is based on the social behavior and interaction of particles within the swarm, therefore the global best solution is achieved by adjusting the trajectory of each individual toward its own best location and toward the best particle of the entire swarm at each time generation [55]. The movement of each individual particle in the search space is adjusted by dynamically changing the velocity of each particle based on its movement with respect to that of its neighbours in the search space. The velocity is the additive factor for updating the position of each particle. The position and velocity vectors of the $i$th particle of a search space with $d$-dimension can be represented as: $X_i = (x_{i1}, x_{i2}, ..., x_{id})$ and $V_i = (v_{i1}, v_{i2}, ..., v_{id})$, respectively. Based on the fitness function value, if the best position of the particle at a particular time (known as the local best) is obtained as $Pbest_i = (p_{i1}, p_{i2}, ..., p_{id})$ and the best position so far (known as the global best) is $Pbest_g = gbest = (p_{g1}, p_{g2}, ..., p_{gd})$, the positions of the particles for the next fitness evaluation are calculated using the following equations:

$$V_{id}^{t+1} = w \times v_{id}^{k} + c_1 \times rand_1 \times (Pbest_{id} - X_{id}) + c_2 \times rand_2 \times (gbest_d - X_{id}) \tag{28}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{29}$$

Here, $w$ is the inertia weight that is linearly varying over the generation (iteration).

$$w = w_{damp} \times \frac{iter_{max} - iter}{iter_{max}} + w_i \tag{30}$$

$iter$ is the current iteration number, $iter_{max}$ is the maximum number of iterations. $w_i$ and $w_f$ are the lower and upper boundary values of the inertia weight which are 0.4 and 0.9 respectively. $c_1$ and $c_2$ are the cognitive and social factors for the swarm interactions, respectively. In the conventional PSO, $c_1$ and $c_2$ are both chosen to be constant (usually 2.0). In this study, however, a variant of PSO with improved convergence capability known as the constriction PSO factor [47], is adopted. The algorithm involves introducing a weighting coefficient, $\chi$ to the dynamic velocity as illustrated below [56].

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{31}$$

$$V_{id}^{t+1} = \chi(w \cdot v_{id}^{k} + c_1 \cdot rand_1 \cdot (Pbest_{id} - X_{id}) + c_2 \cdot rand_2 \cdot (gbest_d - X_{id})) \tag{32}$$

where ($\varphi = c_1 + c_2$ and $\varphi \geq 4$).

The multiobjective optimization problems described in this study are solved using the multi-objective PSO algorithm defined in [57,58]. The use of secondary repository particles helps to guide our search towards obtaining an *efficient, non - inferior* and *admissible* pareto front, by sorting out the non-dominated vectors. A special mutation operator was employed to reinforce the exploratory capacity of the algorithm; this resembles that of genetic algorithm. If $\vec{f}(\vec{x})$ consists of $n$ objective functions each with $m$ decision variables, then the multiobjective problem can be defined as finding the vector $\vec{x}^* = [x_1^*, x_2^*, ..., x_m^*]^T$ which minimizes $\vec{f}(\vec{x})$:

$$\min \ \vec{f}(\vec{x}) = [f_1(\vec{x}), f_{\vec{2}}(x), ...f_n(\vec{x})] \quad for \vec{x}^* \in \varepsilon \tag{33}$$

$$\vec{g}(\vec{x}) \leq 0 \tag{34}$$

$$\vec{h}(\vec{x}) = 0 \tag{35}$$

$\vec{g}$ and $\vec{h}$ are sets of inequality and equality constraints, respectively. Set of optimal solutions, called pareto solutions, are obtained based on the concept of non-dominated sorting. A point $\vec{x}^* \in \chi$ is pareto optimal if for every $\vec{x} \in \chi$
and $I = 1, 2, ..., k$ either

$$\forall i \in I(f_i(\vec{x}) = f_i(\vec{x}^*)). \tag{36}$$

or at least there is one $i \in I$ such that

$$f_i(\vec{x}) > f_i(\vec{x}^*)). \tag{37}$$

## 4. Simulation conditions, results and discussion

The method proposed in this study is tested on the standard IEEE 33 bus distribution network [59] which is strictly a radial network with no tie line requirement as seen in Figure 5. The system consists of 33 buses/nodes and 32 lines/branches and it is operated at a voltage of 12.66 kV with a load size of 3.715 MW of active power and 2.300 MVAr of reactive power [6,53]. The location/number of the distributed generation unit is limited to three with total size of about 40% of the total load, in consistent with standard practice as reported in several literatures. All simulations reported in this work are performed with the steady state analysis approach using the load flow methods designed on Matlab.

Figure 6 shows the estimated loss sensitivity factor for all the lines as described in the previous section and the candidate buses are selected to be buses 8, 30 and 24, considering maximum DGs to be three in line with the siting/selection criteria previously described.

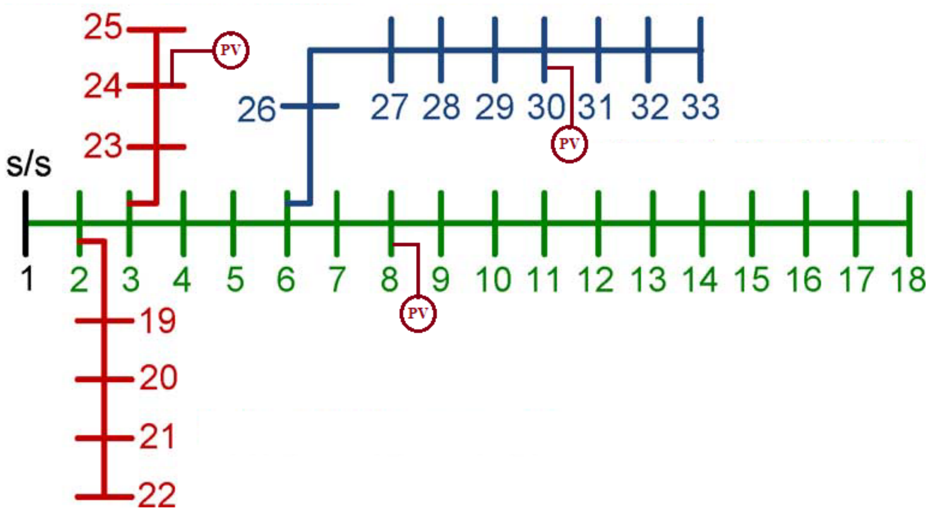


**Figure 5.** IEEE 33 radial distribution network

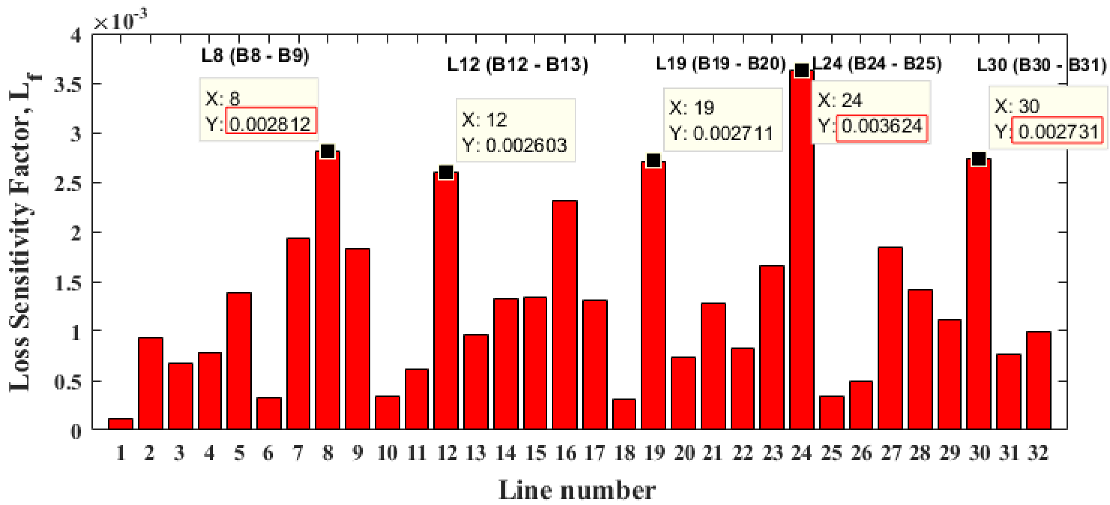


**Figure 6.** Line sensitivity factor ranking for the transmission lines

For the optimization procedure for DG sizing, the operating voltages is constrained to be between 0.95 p.u. and 1.05 p.u. which is a safe voltage magnitude margin for distribution network [53]. The cost and technical parameters adopted in the simulation procedures are given in Table 1 and simulation parameters for PSO algorithm are provided in Table 2:

**Table 1.** Cost and technical parameters for solar PV system [4,50,53]

| Symbol | Meaning | Value | Unit |
|---|---|---|---|
| $\epsilon$ | Inflation rate | 4% | |
| $\mu$ | Interest rate | 10% | |
| $N_y$ | Project lifetime | 25 | years |
| $Cf_{pv}$ | Site capacity factor | 25.50% | |
| $\eta_{inv.}$ | Converter's efficiency | 95% | |
| $Inv_{cost}$ | Unit investment cost | 1695 | $/kW |
| $o\&m_{cost}$ | Unit oper. and maint. cost | 26 | $/kW/year |
| $sal_{cost}$ | Unit salvage cost | $0.25 \times Inv_{cost}$ | $/kW |

**Table 2.** PSO Parameters [47]

| Parameter | Values |
|---|---|
| Population size | 200 |
| Repository Particles | 200 |
| Number of Iterations | 500 |
| Cognitive factor, $C_1$ | 2.05 |
| Social factor, $C_2$ | 2.05 |
| Inertia weight, $w$ | 0.9 - 0.4 |

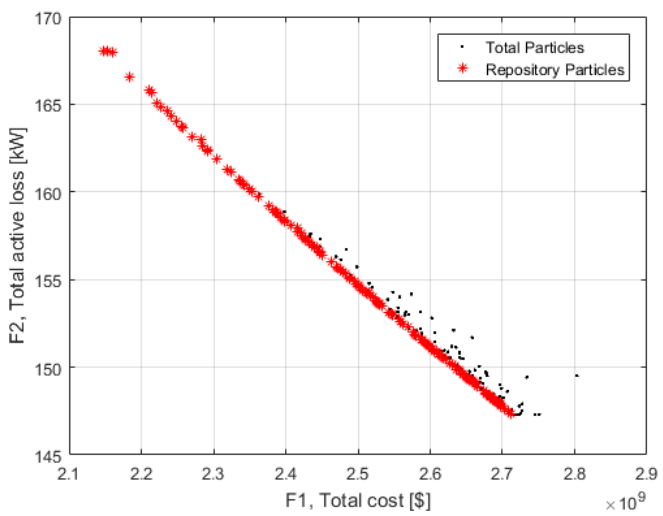


**Figure 7.** Pareto optimality (Scenario 1)

The simulation was performed for the three scenarios described in the previous section towards establishing the consistency of the proposed approach for effective DG placement based on line loss sensitivity and optimal sizing considering the time-varying dynamics of the PV system output. The pareto optimality plots for the three scenarios are shown in Figures 7, 8 and 9; and the summary of the obtained results is presented in Table 3 and this is compared, as summarized in Table 4, with available results from some relevant literature on loss minimization and voltage stability enhancement in radial distribution network using IEEE 33 bus system.

The results obtained are presented in Table 3. The proposed approach yielded significant performances for the three simulated scenario in terms of total active power loss with 74.44 kW, 74.34 kW and 74.33 kW obtained for scenario 1, scenario 2 and scenario 3, respectively. The obtained

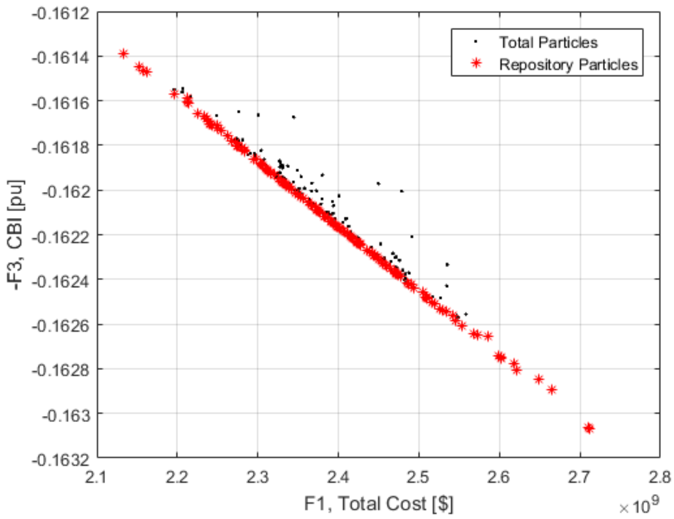


**Figure 8.** Pareto optimality (Scenario 2)

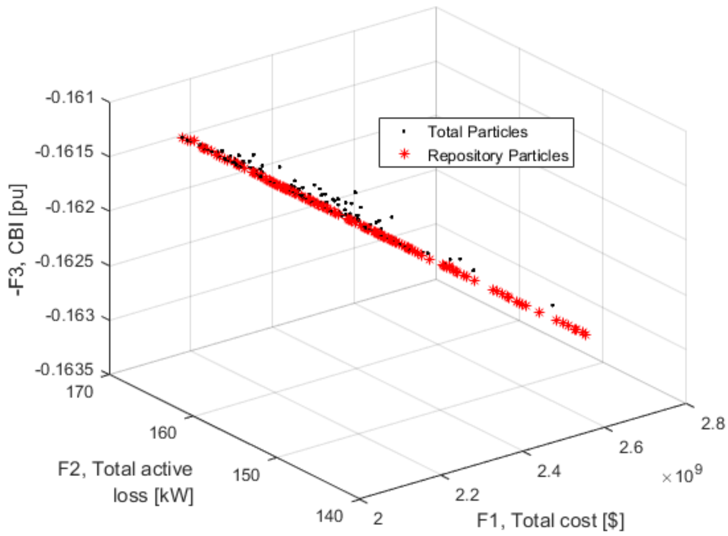


**Figure 9.** Pareto optimality (Scenario 3)

**Table 3.** RESULT

| **PARAMETERS** | | **No DG** | **Scenario 1** | **Scenario 2** | **Scenario 3** |
|---|---|---|---|---|---|
| Optimal size [MW] Location/Bus number | (Bus 8) | n/a | 0.7503 | 0.7506 | 0.7542 |
| | (Bus 30) | n/a | 0.7501 | 0.7504 | 0.8354 |
| | (Bus 24) | n/a | 1.4611 | 1.2179 | 1.4608 |
| Total DG size [MW] | n/a | n/a | 2.9615 | 2.7189 | 3.0504 |
| Total investment cost [$] | | n/a | $2.4839 \times 10^9$ | $2.4576 \times 10^9$ | $2.5528 \times 10^9$ |
| Total active power loss [kW] | | 202.66 | 74.44 | 74.34 | 74.33 |
| Total reactive power loss [kVAR] | | 135.22 | 51.17 | 50.94 | 50.63 |
| Minimum CBI [pu] | (Line 16) | 0.1591 | 0.1492 | 0.1702 | 0.2311 |
| Minimum voltage [pu] | (Bus 18) | 0.9131 | 0.9345 | 0.9408 | 0.9467 |

values agreed with the one found in existing literature as shown in Table 4. Though no literature standard for investment cost comparison was found due to the site capacity factor and cost estimation models deployed, however the total investment cost obtained for the three scenarios shows remarkable consistency *i.e.* $2.4839 \times 10^9$, $2.4576 \times 10^9$ and $2.5528 \times 10^9$ for scenario 1, scenario 2 and scenario 3, respectively. The selected location for DG placement agrees to reasonably well with the one obtained by other researchers; this can be seen with the consistency of buses 24 and 30 in most of the referenced result. Moreover, the total DG size of 2.9615 MW, 2.7189 MW and 3.0504 MW for scenario 1, scenario 2 and scenario 3, respectively is significantly consistent with the results of other methods reported in literature as presented in Table 4.

**Table 4.** RESULT

| METHOD | DG location and (size in MW) | | | Total DG size (MW) | Total loss (kW) |
|---|---|---|---|---|---|
| SFS [30] | 13 (0.8020) | 24 (1.0910) | 30 (1.0530) | 2.9470 | 72.7850 |
| CMSFS [30] | 13 (0.8020) | 30 (1.0540) | 24 (1.0910) | 2.9470 | 72.7850 |
| EA [60] | 13 (0.7980) | 24 (1.0990) | 30 (1.0500) | 2.9470 | 72.7870 |
| EA-OPF [60] | 13 (0.8020) | 24 (1.0910) | 30 (1.0540) | 2.9470 | 72.7900 |
| AM-PSO [61] | 13(0.7900) | 24(1.0700) | 30(1.0100) | 2.8700 | 72.8900 |
| TLBO [62] | 10 (0.8246) | 24 (1.0311) | 31 (0.8862) | 2.7419 | 75.5400 |
| QOTLBO [62] | 12 (0.8808) | 24 (1.0592) | 29 (1.0714) | 3.0114 | 74.1010 |
| **Scenario 1** | 8 (0.7503) | 30 (0.7501) | 24 (1.4611) | 2.9615 | 74.4400 |
| **Scenario 2** | 8 (0.7506) | 30 (0.7504) | 24 (1.2179) | 2.7189 | 74.3400 |
| **Scenario 3** | 8 (0.7542) | 30 (0.8354) | 24 (1.4608) | 3.0504 | 74.3300 |

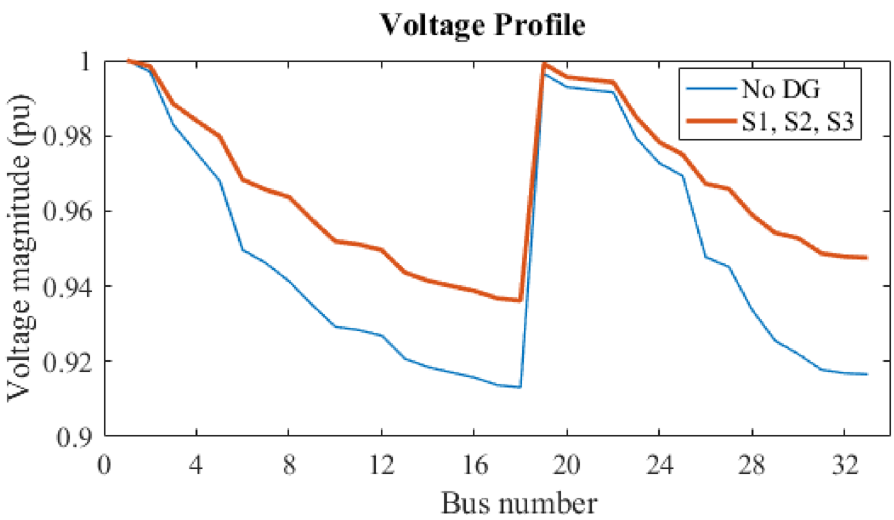


**Figure 10.** Voltage magnitude at each bus

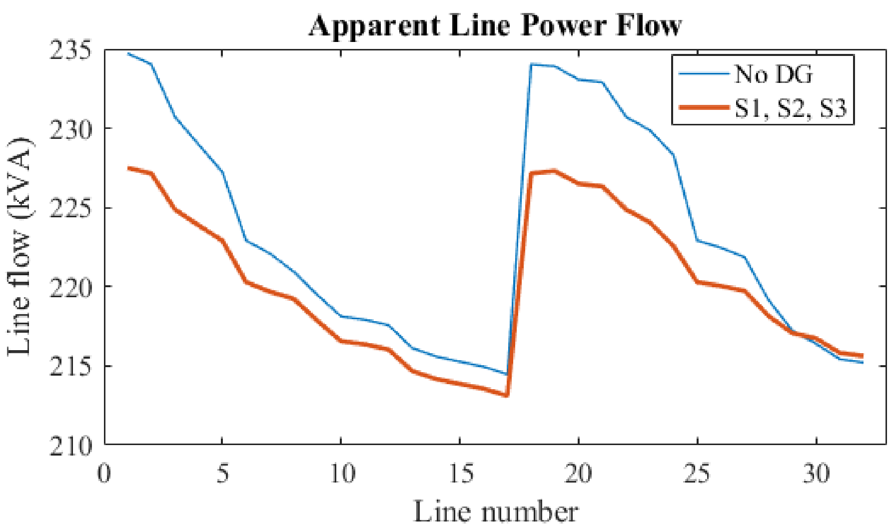


**Figure 11.** Power flow along each brance

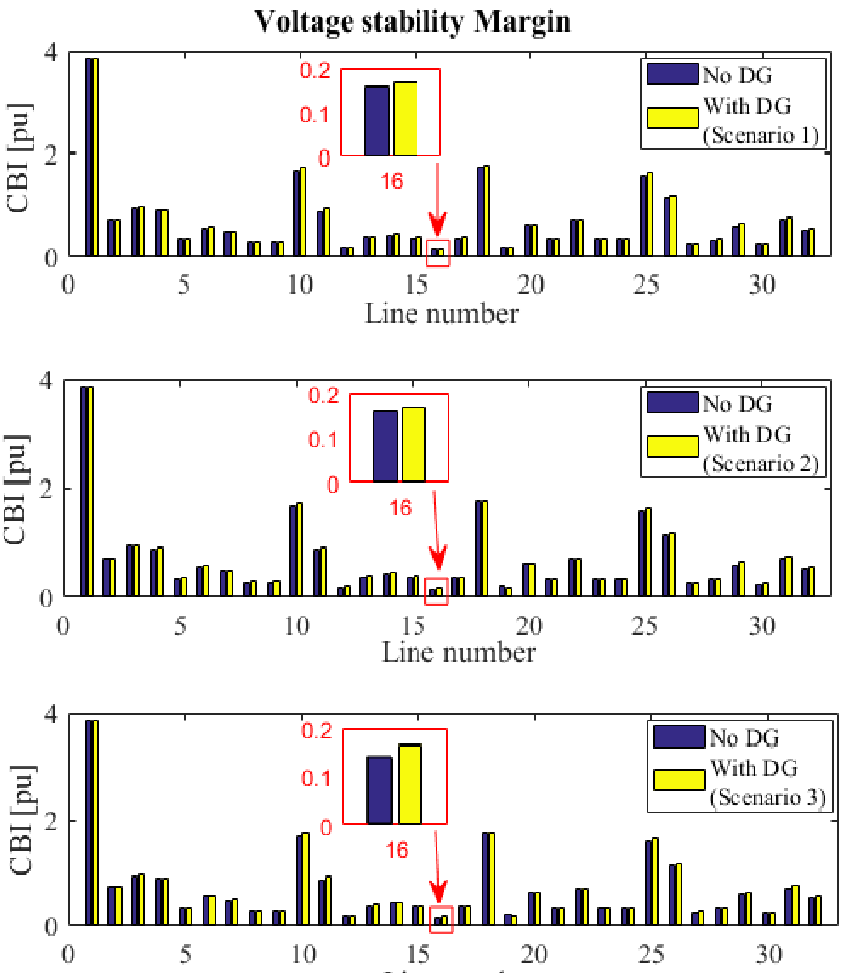


**Figure 12.** Voltage stability margin without and with DGs

The performance of the approach with respect to the voltage magnitude, line flow and the voltage stability margin is presented in Figures 10, 11 and 12, respectively. The figures show consistency of the proposed DG siting and sizing approach with remarkable improvement in the voltage magnitude, line flow and the voltage stability margin. Not much difference is observed in the results obtained for the three scenario, however, it is clearly noticed that there is a significant improvement in the distribution network performance using the proposed methods under the three considered scenarios. The significance of this improvement under each scenario is clearly indicated in Table 3 as reflected in the improvement of the minimum bus voltage at bus 18 from 0.9131 pu to 0.9445 pu, 0.9408 pu and 0.9467 pu under the scenario 1, scenario 2 and scenario 3, respectively. The voltage stability margin as measured using CBI shows an improvement of the least CBI value (at line 16) from 0.1591 pu to 0.1702 pu and 0.2311 pu for scenario 2 and 3, respectively while there is a slight reduction in the least CBI value to 0.1492 pu under scenario 1. The trend can be explained by the fact that the formulation of the objective function for scenario 2 and 3 involves CBI maximization directly.

## 5. Conclusions

In conclusion, the increasing desire to increase the uptake of alternative energy resources especially the variable renewable energy sources calls for improvement in the methods of power system planning downstream. The concept of DG is directed towards ensuring adequate management of available power system infrastructure *i.e.* the grid, by locating modular generating unit close to the load points along the distribution end. Hence, in this work, a new and more efficient approach for injecting power from renewable energy-based DGs into radial distribution network (RDN) with goals of ensuring cost-effective planning and improved technical performances of the power system in terms of power loss minimization and voltage stability improvement have been investigated and discussed. The new loss sensitivity-based analytical approach for DG siting have been derived and its influence on the optimal sizing of the DG units have been verified in a three scenario approach using a combination of three important objective functions namely total investment cost minimization, total active power loss minimization and voltage stability margin maximization. Finally, the results obtained using the proposed methods are compared with available results in literature that are focused on similar objectives from system planning and operation perspectives. The future research direction is to look at the possibility of merging the flexibility needs and voltage stability criteria for radial distribution network with high renewable energy integration especially for large radial distribution network as well as mesh distribution system which includes tie line requirements.

## Conflict of Interest

The authors declare no conflict of interest

## Author Contributions

OBA conceptualized and provided resource, as well as modeling and writing of the paper; APA provided resource data and writing; IGA validated and supervised the work; HOR.H provided resource and editing; YS supervised and validated the results.

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## Availability of Data

The main data used for this work is the bus and line parameters for the standard IEEE 33 bus system model [59].

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