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Research Article

Maintaining the electrical distribution grid network reliability with distributed photovoltaic generations

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Abstract: Green energy supply can be achieved by integrating intermittent renewable energy resources into the electrical distribution network. The intermittent nature of solar power generation presents significant technical challenges for integration that affect the network reliability and stability in relation to the grid power quality and voltage profile. Maximum utilization of photovoltaic in the electrical distribution network requires siting and sizing optimization. Distribution and transmission lines incur voltage drops and power losses due to their reactive and resistive properties. Application of evolutionary optimization techniques is adopted for optimal photovoltaic distributed generations placement in an electrical distribution network. Improved network voltage profile and system reliability was achieved by the application of particle swarm optimization algorithm to minimize the system's power losses in a radial distribution network-IEEE 33-bus system. This was achieved through a MATLAB code implementation, with validation of the solution techniques and the developed model realized through a genetic algorithm case study. The active and reactive total loads linked to the network test system were 3.720 MW and 2.310 MVAr, accordingly. The conversion of solar power was modeled at a constant power factor with cut-off solar radiation ≥ 4.0 kWh/m2/day under normal operating conditions. As an initial configuration, active and reactive power losses were found as 211.02 kW and 143.04 kVAr without photovoltaic distributed generation at 0.85 pf, respectively. Integration of solar distributed generations at optimal location and capacity resulted in reduction of the network power losses by 57.98% reactive and 61.60% active. Improvement in voltage profile attained was 8.46%, while the ASAI network reliability index value before integrating solar source was 0.99734 p.u. but improved by 1.82% on installation. In conclusion, the system's power losses reduced as acceptable voltage profile was maintained for sustained distribution network reliability.

Keywords: *Electrical network, Neural network, Objective Function, PSO, Photovoltaic, Real power loss*

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1. INTRODUCTION

A distributed generation is operated practically at the maximum rated output power; the power utilities have no direct control over the power the unit injects into the network. Intermittent renewable energy sources are not predictable [1]. Solar energy is available in day time while at night it is absolutely unavailable. The quality and supply of power in a distribution network can be maintained by optimally placing and sizing solar distributed generations (DGs) using their availability characteristics. The reliability golden rule must be adhered to in all solutions to distributed energy drawbacks pertaining to regulatory and technical issues. Extra load current is drawn from a source if the distribution network load increases, thus causing increased network power losses and voltage drops, which lowers the performances of grid networks [2,3]. Grid network reliability is the network's ability to supply load demand with no failure as the system's constraints are observed. The purpose of a grid distribution network is to supply the end users with electrical power within an entire electrical grid network. Small-scale power generation up to 5 MW represents a DG integrated in the electrical network for delivering electricity to local loads [4]. The minimization of network power loss generally offers a practical technique to achieve reliability assessment for DGs that are optimally placed and sized. Evolutionary optimization methods provide solutions, which suffer premature convergence when applied for optimal placement of DG, and therefore modifications and enhancement is required on them when adopted to solve optimization problems so as to obtain viable solutions for intermittent renewable energy sources installed to the electrical grid network. The extent to which variation of solar irradiance with regards to the weather and period of the day affects the electrical distribution network reliability, due to the intermittent nature of these renewable energy sources, it is not clear when the electrical energy demand share they supply is large. Solar photovoltaic (SPV) siting and capacity determination is a requisite for their integration into an electrical distribution network because of the uncertainties linked to their energy extraction in relation to solar radiation [5]. Solar PV productivity change with regards to the geographical siting. Optimal operation of a distribution network can only be realized when a reliable and exact solar energy prediction is availed for the subsequent days and hours [6,7]. A particle swarm optimization (PSO) technique is suggested in this research for the placement and sizing of intermittent renewable energy resources, solar, that represent spatially distributed generations. The distribution network reliability to supply load demand sustainably and attainment of improved voltage profile is enhanced by integrating distributed generation into the grid network [2,8]. A standard IEEE - 33 bus configured distribution network is provided by the proposed approach, which yields optimal capacity and site of the DG with reduced electrical power losses and improved voltage profile for sustained grid network reliability. The considered distribution system has no storing units; and its constraints and restrictions were disregarded, and the ART Suniva 245-60, 240 Wp solar PV characteristics were used to model the solar PV DG. The proposed method for solving the optimization problem was validated through software simulation with the aim of keeping the grid distribution system reliable when operated on intermittent sources, solar. It has been revealed by studies that there is a likely hood of increased network electrical losses if these sources are integrated having non-optimal capacities or when at non-optimal locations [9]. Applying PSO-approach [4] attained 51.40% reduction in power losses by appropriately sizing and locating the DGs in a radial network. Similarly, [2] used genetic algorithm (GA) technique and achieved 46.4% reduction in objective function for better radial network performance with regards to power loss minimization and voltage profile improvement. The network SAIFI and SAIDI reliability indices improved by 30.70% and 32.26% accordingly on the integration of the DG units [10]. Different reliability indices can be used to express reliability evaluation results with regards the application. In this research;

$$\textit{Average System Availability Index} = \frac{Load-hours-service-availability}{Customer-hours-service-demand}$$

was adopted in which the customer hours service demand is 8760 annually, with a standard target value for this index being 0.99983 [11]. A lower value implies that the delivered power is inadequate or insecure. The novelty of the proposed optimization algorithm is its ability to achieve optimal solutions with few iterations while giving consistent results as well as its versatility in integration with weather predictive software and can incorporate more intermittent DG sources.

2. METHODOLOGY

2.1. Distribution Network Dataset

The principal objective of this research was to carry out siting and capacity optimization of intermittent distributed generations such as solar, using PSO technique to achieve improved voltage profile and network reliability through minimization of network losses in a standard IEEE – 33 bus radial distribution network (RDN) system. The primary data was derived from the solar irradiance quantification profiles raw data obtained at selected meteorological department sites in Kenya. A MATLAB-coded program was developed to compute the solar power outputs from the sampled sites.

The PSO test flowchart shown in Fig. 1 was used to develop a particle swarm optimization algorithm on MATLAB software for optimizing placement and sizing of solar DGs installed into the RDN IEEE 33-bus system to minimize network losses, improve voltage profile and enhance system reliability. The dataset of solar irradiance indicated in Table 2 represent the direct normal irradiance. Bus data and line data were the required network characteristic data. The standard IEEE 33-bus loading is obtained from Table 1.

Table 1. Standard IEEE 33-bus distribution system loading data

Bn	BP (kW)	BQ (kVAr)
1	0	0
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20
7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80
15	60	10
16	60	20
17	60	20
18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40
BN - Bus number	BP - Bus Active Power	BQ - Bus Reactive Power

Table 2. Solar irradiance data of a normal day. Source: Lodwar Weather Station, Kenya

Time (Hours)	Solar irradiance data (kW/m^2)
1	0
2	0
3	0
4	0
5	0
6	0.02572
7	0.20358
8	0.41152
9	0.5726
10	0.67496
11	0.71254
12	0.84856
13	0.72082
14	0.73097
15	0.63798
16	0.5846
17	0.3584
18	0.14505
19	0.03584
20	0
21	0
22	0
23	0
24	0

2.2. The Particle Swarm Optimization Algorithm Testing Flowchart

The application of PSO has been successful in integrating renewable energy sources into electrical networks and in real power dispatch. While using PSO technique, the searching strategy to obtain the best solution is by following the particle nearer to the optimal solution known as global best solution, *g*Best, and computing the fitness of each solution, *p*Best, using the objective function. A flowchart to achieve improvement in voltage profile, network loss minimization, system reliability for optimally sized and placed SPV DGs in a radial distribution system is provided in Fig. 1. The solar DG optimization was realized with the parameters of the PSO being l = 50; population size, m = 2; members in a particle, and k_{max} = 1000.

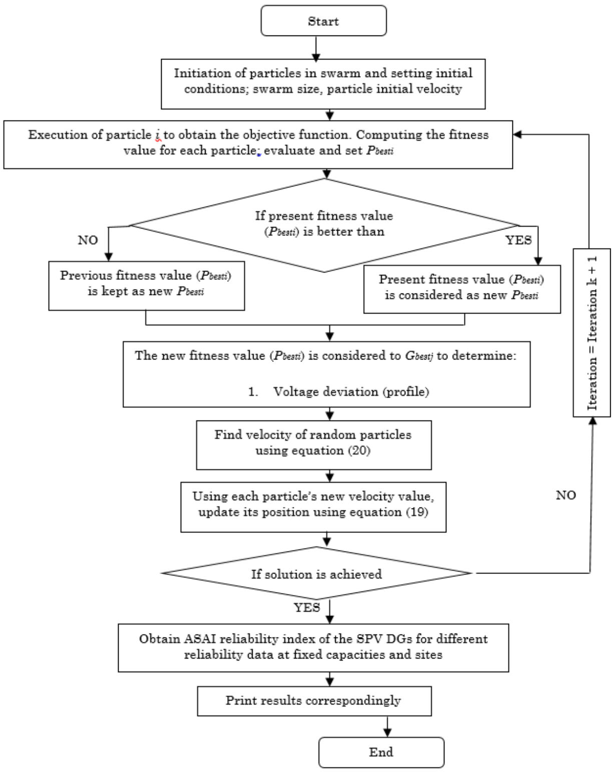

Figure 1. IEEE Standard 33-bus system PSO test flowchart

2.3.The RDN IEEE 33 – Bus Test Network

This study adopted a radial distribution system for its simplicity and is generally more preferred for distributed generations, additionally, it is not expensive to implement. A system constant load of reference voltage 12.660 KV and apparent power of 100.0 MVA are assumed. The total load on the network was set at 2.31 MVAr and 3.72 MW. The maximum real power output of the DG was adopted as 5 MW. The main components of test network include branches, loads, buses and utility grid; 32 loads, 32 branches and 33 buses.

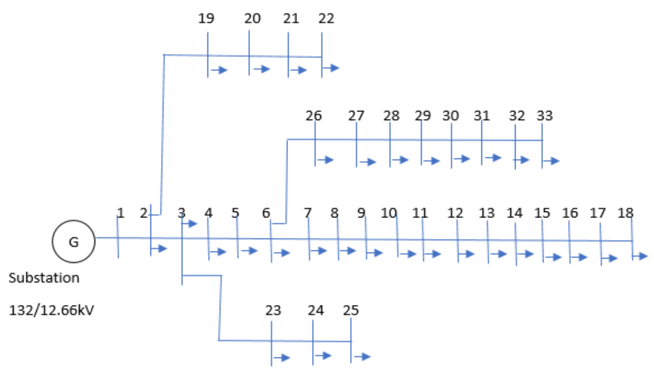

Figure 2. The RDN IEEE 33 – bus standard test network single line diagram.

2.4. Mathematical Background

The research theoretical reference was inferred from the concepts of voltage drops and principle of power losses in an electrical distribution network due to its reactive and resistive properties.

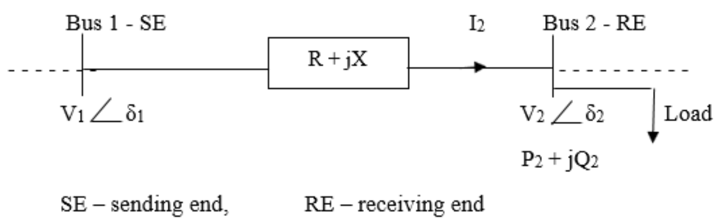

Figure 3. Two buses RDN section.

Here,

Impedance of the line (Z),

$$R + jX \tag{1}$$

Bus 2 through power,

$$P_2 + jQ_2 \tag{2}$$

Voltage drop between bus 2 and bus 1,

$$\begin{aligned} Vd &= V_1 \angle \delta_1 - V_2 \angle \delta_2 \\ &= I2Z = I2\,(R + jX) \end{aligned} \tag{3}$$

Bus 2 receiving end power is:

$$P_2 + jQ_2 = V_2^2 I_2^* \rightarrow I_2 = (P^2 - jQ^2)/V_2^* \tag{4}$$

Again,

$$V_d / Z = I_2 \quad \rightarrow \quad \frac{V_1 \angle \delta_1 - V_2 \angle \delta_2}{R+jX} \tag{5}$$

$$\delta_2 = \delta_1 - \tan^{-1}[(P_2X - Q_2R) / (V_2^{\,2} + P_2R + Q_2X)] \tag{6}$$

An expansion of electrical distribution network results to increased power losses and bus voltages that are not within the required range leading to reduction in system efficiency, reduced power quality and network instability [1,16]. Similarly, increased solar PV integration may cause negative impacts on distribution grids resulting to violation of standards and limits [7,17]. Solar PV penetration optimization in power networks has been a recent focus in maintaining power quality and acceptable bus voltage profiles [5,18].

A particle swarm optimization approach is developed in this study for optimizing the capacity and location of DG units, solar, in an RDN system to achieve an improved voltage profile through the reduction of voltage difference between the receiving and sending end buses, and minimization of network losses in order to enhance the system reliability [4].

In this research, the solar generating units modelling was based on constant - p.f. model. The considered average solar radiation cut-off for power generation in this case is ≥ 4.0 kWh/m²/day [12]. The research considered bus voltage, reliability, network loss, DG type and siting and capacity parameters of the DG. The classification of distributed generation technologies is shown in Fig. 4 [5].

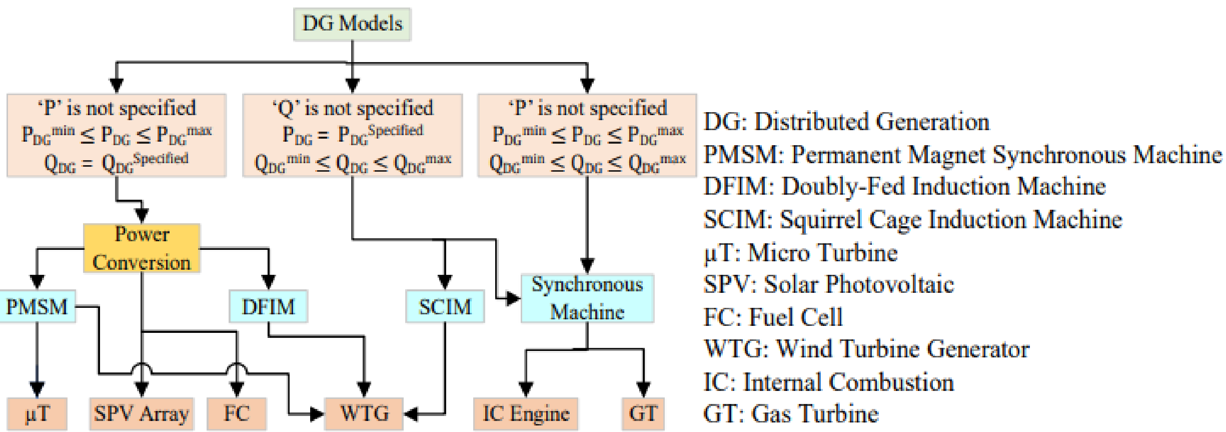

Figure 4. A model of distributed generation technology.

2.5. PQ Type Constant Power Factor Model

Real power and p.f values in this case are specified. reactive power and current injection equivalent calculations is achieved by the application of Eqs. (7,8) respectively.

$$Q_{i,\,source}, (Reactive\ power) = P_{i,\,source} \tan[\cos^{-1}(p.f_{i,\,source})] \tag{7}$$

$$I_{i,\,source}, (Equivalent\ injected\ current) = \frac{P_{i,source} + jQ_{i,source}}{V_{i.source}} \tag{8}$$

2.6. Modelling of Solar Power

A direct current power output is obtained from solar power generating plant, which produces electrical power from converting solar energy; grid-tie inverters are used to change such output to AC power for grid compatibility. The module surface area, solar irradiance and efficiency of the module determine the SPV module power output. The solar module maximum output power at instant of time *t is* expressed as:

$$P\,(t)_{solar\ DG\ power} = A\mu(t)\,\beta \tag{9}$$

Whereby;
A - surface area of the module (m^2)
μ - intensity of solar irradiance (W/m^2)
β - efficiency of the solar module

Normally, the solar power is produced at rated maximum capacity within the day in periodic intervals. The power output of a SPV module into a distribution network is determined using Eq. (10) during the implementation of the proposed PSO technique, whereby;

AC_{SPV} output power to grid = Inverter efficiency x SPV_{max} power out, at instant time *(t)*.

$$P_{AC\text{-}SPV}(t) = \eta_{inverter}\ x\ P_{SPV\text{-}max\ output}(t) \tag{10}$$

The maximum power rating of a solar farm is computed by obtaining the cumulative day averages of the AC powers calculated from Eq. (9). The elementary specifications and features of the SPV module in consideration in this case, for the solar DG unit modelling, are provided in Table 3. The module efficiency is 14.75%. Suniva BYD company solar PV manufactured module, BYD240P6-30, is adopted with regards to its output power rating; with cell's temperature of 25 ^{0}C, A.M 1.5 global and the module cell is rated 1000 W/m^2, and on standard test conditions, the module performance is proportional to the solar radiation falling perpendicularly on its surface.

Table 3. Specifications of the BYD240P6-30 Suniva BYD solar panel.

Parameters	Unit of Rating	Parameters	Unit of Rating
Nominal power (P_{nom})	240.0 Wp	Maximum series fuse	25.0 A
Tolerance of power	±3/0%	Temperature range	-40.0 ^{0}C to 85.0 ^{0}C
Efficiency	14.750%	Power temperature coefficient	-0.340%/^{0}C
Rated voltage	27.840 V	Voltage temperature coefficient	-0.280%/^{0}C
Rated current	8.120 A	Current temperature coefficient	0.060%/^{0}C
Open circuit voltage (V_{oc})	37.54 V	Weight	21.50 kg
Short circuit current(I_{sc})	8.90 A	Solar cells	Monocrystalline
Maximum system voltage (IEC)	1500.0 V	L x B x H mm^2	2362.0x1092.0x35.0

Table 2 shows an annually averaged solar irradiance data over 24 hours. Applying Eq. (9) for every solar irradiance level, the power generated is computed. On average, the solar farm in this analysis yields 1.0268 p.u of the real power generated.

2.7. The Electrical Distribution Network Optimization Objective Function Formulation

The set of constraints that the optimization objective function (OF) is subjected to are given in Eq. (11). The single-objective optimization problem mathematical expression is often given by:

$$\text{Optimize } [F(x_0)], \text{ under constraints: } \begin{cases} g(x) = 0 \\ h(x) \leq 0 \\ x_i^{min} \leq x \leq x_i^{max} \\ x = \{x_1, x_{2,\dots\dots\dots} x_n\} \end{cases} \tag{11}$$

Whereby, $F(x_0)$ is the single-objective function for optimization, and vector x of n variables represents the problem parameters required for optimization and include $g(x_i)$ and $h(x_i)$ representing constraints set of inequality and equality respectively, with x_i^{max} and x_i^{min} being domains constraints [9,13]. The improvement in the attributes of the system is achieved by determining voltage profile (VP), total network power loss, maximum MVA capacity of the conductor, distributed energy resources sizing and siting, and system reliability, by applying a multiple-objective optimization process in all the sub-problems. The optimum size and location of the SPV array are computed for electrical loss reduction and voltage deviation in this optimization technique. Studies have indicated that a distribution network system incurs power losses close to about 13.0% of the total power generated injected into the electrical network [14]. The basis of undertaking this study is on this fact given that power demand continues to increase resulting in more loading of the distribution network; Solar, being an intermittent distributed generation, needs to be appropriately placed and sized in a radial distributed network for reduced power line losses; distributed generations offer a solution to the increasing grid power demand. The network line current is expressed as:

$$I_i = \left[\frac{Pi+Qi}{Vi}\right] \tag{12}$$

The reactive and real/active system power losses (i.e. RPL and APL) are both computed as:

$$\textit{Reactive power, } Q_{loss} = \left[\frac{P_{i+1}^2 + Q_{i+1}^2}{V_i^2}\right] X_i \tag{13}$$

$$\textit{Real power, } P_{loss} = \left[\frac{P_{i+1}^2 + Q_{i+1}^2}{V_i^2}\right] R_i \tag{14}$$

$$\textit{Index of the MVA Capacity, } C_I = max_{j=1}^{nl}\left[\frac{Sj}{SCj}\right] \tag{15}$$

$$\textit{Index of the Voltage profile, } V_{PI} = max_{i=2}^{n}\left[\frac{V1-Vi}{V1}\right] \tag{16}$$

With;
n - is the number of buses in the grid
V_1 - substation bus voltage; the reference voltage
V_i - the i^{th} bus voltage

This study has an OF intended to achieve system power loss reduction, for both RPL and APL. ASAI reliability assessment is then undertaken by fitting the optimal location and size of the Solar PV DGs in the proposed PSO technique. The principal purpose of any OPF in an electrical network is to reduce the network's real power loss.

The general objective function optimization expression is given by:

$$OF = W_a \frac{Tploss;with\ IRES}{Tploss;without\ IRES} + W_b \frac{Tqloss;with\ IRES}{Tqloss;without\ IRES} + W_c\, max_{j=1}^{nl}\left[\frac{Sj}{SCj}\right] + W_d\, max_{i=2}^{n}\left[\frac{V1-Vi}{V1}\right]$$

$$OF = [W_a.R_{PLI} + W_b.Q_{PLI} + W_c.C_I + W_d.V_{PI}] \tag{17}$$

The PSO parameters setting up involved the number of particles 'ℓ', C_2 and C_1 weighting factors. The initial population is established by randomly selecting the DG location and size from the original population set. C_2 and C_1, acceleration weights were determined from [14]. The DG location variable is represented by L while P_g represents the DG size. The expression for the proposed particles is:

$$\chi_{particle} = [P_{g1}, P_{g2}, \ldots P_{g\gamma}, L_1, L_2, \ldots L_\delta],$$

where δ represents number of locations and γ is the number of DGs.

In this study, the inertia weights are adopted as; $W_a = 0.40$, $W_b = 0.20$, $W_c = 0.250$, $W_d = 0.150$ according to [15,19], and the expression of the constraints maintained is,

$$\sum_{x=1}^{4} Wx = 1 \tag{18}$$

Whereby, W_x represents the space within [0,1]. The implementation of optimizing algorithms follows after the optimization problem (see Appendixes A1). It is defined in order to establish a near-optimal or optimal result for the problem. The proposed PSO approach algorithm computes these optimal results. The movement of the particles depend on both their experiences with the other members and their own experience within the swarm; Q_{bestj} and P_{besti} respectively. The current velocity and position; V_i^{k+1} and X_i^{k+1} for the particle is updated in accordance with Eqs. (19,20) respectively and in relation to G_{bestj} and P_{besti}.

After every iteration, the particles' updating, for the two best solutions linking the cognitive factor-personal best value and social factor-global best value, is therefore done through the PSO tracking.

$$V_i^{k+1} + X_i^k = X_i^{k+1}, j = 1, 2, \ldots m \text{ (swarm) and } i = 1, 2, \ldots. l \text{ (particle)} \tag{19}$$

$$C_2\, rand_2\, (G_{bestj} - X_i^k) + C_1\, rand_1\, (P_{besti} - X_i^k) + \omega V_i^k + = V_i^{k+1} \tag{20}$$

whereby particles' i_0 current velocity and searching position are V_i^k and X_i^k at iteration k_0, $rand_2$ and $rand_1$ representing random values within the range of 1 to 0, on equal distribution. P_{bestio} is the particle's i function's finest value the particle has achieved; the best position of particle i_0 before iteration k_0, while G_{bestj} is the function's fitness best value achieved so far by any particle; the best position of particles' global in the swarm amongst all particles prior to iteration k_0, C_2 and C_1 are the random positive acceleration terms weighting factor constants whose values are in the range between 2 to 1, although 2 is mostly adopted in many cases [14,15]; and therefore their values are normally set to 2.0.

The particle's i updated velocity is V_i^{k+1} while X_i^{k+1} is the updated position. m is the total members within a particle and l represents the total particles within a group. The particle's i function of velocity weight, which typically represents inertia weight ω, is set in accordance with the equation given below [2]:

$$\omega_{max} - \left\lfloor \frac{\omega\, max - \omega min}{kmax} \right\rfloor k = (k+1)\, \omega \tag{21}$$

where the new iteration number is k and k_{max} represents the highest number of iterations. ω_{max} and ω_{min} indicates the inertia weights highest and lowest values respectively, having recommended values of 0.90 and 0.40 accordingly.

The accomplishment of the system reliability assessment (i.e. RA) follows after computing the reduced system's power loss and improved bus voltage. The performance analysis of the chosen distribution network and the grid's RA are obtained for integrated SPV DGs and without. The reliability assessment of the electrical distribution system (EDS) observes the IEEE standard number 1366-2012 guide that provides the requirements for the analysis of different reliability indices for an EDS [5].

2.8. Optimal Placements for IEEE-33 Bus RDN System

In minimizing power system line losses, it is critical to determine the location and size of the distributed generation to be integrated into the EDS [20]. Therefore, integration of DGs in an electrical distribution network, it is important to carry out techno-economic analysis in order to lower the system's overall operational and investment cost.

The proposed power loss reduction technique is implemented on the 33-bus RDN system. The optimal locations of the SPV DGs are established based on the power loss index (PLI) values shown in Table 4, at upf and 0.85 pf lagging, with the best SPV placements at bus 24 on the 33-bus RDN system.

Table 4. IEEE 33-bus RDN system PLI values for the locations.

PLI value @upf	PLI value @0.85 pf	Bus number
0.4798	0.6262	6
0.5802	0.7143	13
0.6718	0.8572	24

3. RESULTS AND DISCUSSION

The following four system cases are considered:

Case 0: NO Solar DGs,
Case 2: TWO Solar DGs,
Case 1: ONE Solar DG,
Case 3: THREE Solar DGs

3.1. Real and Reactive Power Loss Results

The reduction in both APL and RPL in the electrical distribution system were realized by optimizing the location as well as the capacity of the distributed Solar PV generations through their integration onto the radial distribution network. After estimating the values of VP, RPL, and APL, the network's reliability assessment is done. Hence, the network's reliability assessment is carried out at optimized sites and capacities for the distributed generations, and with minimal network losses and improved voltage profile. Table 4 shows network losses after and before solar PV distributed generation at upf.

Table 5. Network loss after and before Solar PV distributed generation integration at upf.

Test system	Without DG power loss		On DG integration power loss		% Power loss reduction		Optimal location	DG size x 10kW/ x 10kVAr
	Ploss (x100kW)	Qloss (x 100kVAr)	Ploss (x 10kW)	Qloss (x10kVAr)	Ploss (W)	Qloss (VAr)		
Without DG	2.026	1.351						
1-Solar DG			10.74	7.825	47.98	43.14	6	40.31
2-Solar DGs			8.308	5.873	58.02	55.56	13	64.982
3-Solar DGs			6.852	4.947	67.18	64.43	24	257.644

On operating the RDN with no DGs at 0.85 power factor, the overall power loss, real and reactive, was observed to be 143.04 kVAr and 211.02 kW respectively. When SPV DG that has optimal capacity and placement is integrated, the total network loss reduced by 56.98% and 62.62%, both reactive and real power line losses accordingly, Table 5. Again, the network losses reduced by 68.46% and 71.43% reactive and real on installation of 2-solar DGs that are optimally sized and placed. Similarly, integration of 3-Solar PV DGs onto the distribution network further reduces the network losses by 83.56% and 85.72% for RPL and APL accordingly.

Table 6. Power loss after and before Solar PV integration at 0.85 power factor

Test system	Without DG power loss		On DG integration power loss		% Power loss reduction		Optimal location	DG size x 10kW/ x 10kVAr
	Ploss (x100kW)	Qloss (x 100kVAr)	Ploss (x 10kW)	Qloss (x10kVAr)	Ploss (W)	Qloss (VAr)		
Without DG	*2.1102*	*1.4304*						
1-Solar DG			*8.13*	*6.011*	*62.62*	*56.98*	*6*	*40.321*
2-Solar DGs			*5.82*	*4.368*	*71.43*	*68.46*	*13*	*64.983*
3-Solar DGs			*2.81*	*2.20*	*85.72*	*83.56*	*24*	*257.646*

When the proposed PSO technique is applied in case 3, 2, 1 and 0 at 0.85 power factor, the amount of network line loss reduced from 211.02kW to 81.3kW; approximation of 61.62% reduction for 1-solar DG. It is noted that when a similar network is applied on Genetic Algorithm technique, it results to a less network power loss reduction of 13.73% (201.1kW to 175.4kW). Therefore, the proposed particle swarm optimization algorithm in this research leads to a better system power loss improvement in comparison to Genetic Algorithm approach; with a total power loss improvement of 85.72% for 3-solar DGs. The PSO approach presents a superior capability of having better performance and giving faster solutions than the known conventional methods. In respect to that, the superiority of the technique is manifested in the configuration of SPV DGs integration in an electrical distribution grid system.

3.2. Improvement of the Bus Voltages

Achievement of the system's voltage profile improvement was accomplished when the distribution network run on optimally sized and sited Solar PV distributed generations on their installation. Variation of bus voltages depends on the power losses for both active and reactive in the distribution grid network. Fig. 7 illustrates these results; which show the voltage profile improvement results on locating and sizing of the solar distributed generations in the RDN system as obtained through the application of the proposed particle swarm optimization algorithm. Further improvement of the network buses' voltage profile at the connections can be achieved when reactive power support is higher; notably by operating the distribution system at 0.85 power factor.

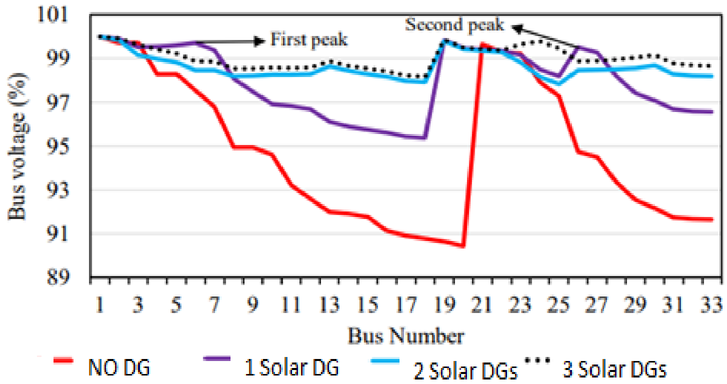

Figure 5. RDN 33-bus system improvement of voltage profile on PV DGs at 0.85 power factor.

It is observed that there is a voltage peak at buses 26 and 7 since these two buses are connected directly to bus 6 at which there would be optimal siting of the Solar PV DG, Table 4. Integration of spatial generations has a greater effect at buses of low voltage; 33, 25, 22, and 18, whereby the voltage improvement rate is notably observed to decrease when the number of connected distributed generations are increased. The low voltage buses had voltage that was lower than the permissible limit prior to optimum sizing and siting of the SPV distributed generations but after the installation of the distributed generations, the voltage at all the buses was within the acceptable levels. The distribution grid system bus voltages are required to be sustained within maximum and minimum limits. The upper and lower limits of bus voltage are set at 1.05 and 0.95 p.u. accordingly with reference to the base bus voltage. The bus 18 base case voltage is 0.9038 per unity. as observed from Table 6; this voltage is lower than the acceptable distribution system limit of 0.95 per unity. The installation of solar DGs of optimal placement and size improves this low-voltage; a voltage profile improvement of 8.45% is achieved by integrating solar onto the distribution system.

Table 7. % Minimum voltage at unity power factor, and 0.85 power factor

pf	% Min voltage			
	Testing system			
	Without DG	1-Solar DG	2-Solar DGs	3-Solar DGs
1.0		93.16	95.77	97.75
0.85	91.38	96.62	97.02	99.11

3.3. Network Reliability Assessment

The radial distribution network testing system reliability index is calculated by applying the MATLAB code while inferring the reliability data from the reliability library. Four scenarios were simulated to establish the average system availability index (ASAI) reliability index improvement. Before installation of the solar DGs, the ASAI value was 0.99736p.u., and it improved by 1.83% after their integration.

Improvement of the network reliability is best obtained when RT, $_{\text{repair time}}$, is 12h and λ_{ρ}, $_{\text{failure rate}}$, is 0.2. The reliability data values are given as:

Scenario a: 12h, 0.2f/yr Scenario d: 24h, 0.2f/ty
Scenario b: 12h, 0.4f/ty Scenario e: 48h, 0.2f/yr
Scenario c: 12h, 0.6f/yr Scenario f: No failure

The ASAI index determination is carried out by manually fitting these values of reliability data into the particle swarm optimization algorithm which establishes the network's reliability improvement.

Table 8. The per unity computation of ASAI index for the 6 scenarios

Network configuration	Scenario 'a'	Scenario 'b'	Scenario 'c'	Scenario 'd'	Scenario 'e'	Scenario 'f'
NO DG case	0.99734	0.99734	0.99734	0.99734	0.99734	0.99734
1-Solar DG – case 1	0.99776	0.99763	0.99746	0.99763	0.99731	0.99793
2-Solar DGs – case 2	0.99814	0.99808	0.99800	0.99808	0.997921	0.99823
3-Solar DGs – case 3	0.99916	0.99908	0.99901	0.99908	0.99897	0.99923

It is noted that the ASAI index increases when 3SPV DGs are integrated into the distribution network, and thus the network reliability improves. Similarly, its value reduces with increased repair time and rate of failure; hence the distributed generations are recommended to have a lower λ_p and RT adopted. Consequently, the electrical power service availability will increase in all the system loads when multiple distributed generations are integrated onto the distribution network. It is evident that for an enhanced network reliability, the ASAI value is desirably increased.

3.4. Cost-benefit Analysis for the Implementation of the Proposed PSO Algorithm

The voltage profile, RPL and APL, and the energy loss cost together with the cost of power obtained from the SPV DGs are provided for the IEEE 33-bus RDN test system at 0.85 pf lagging and upf. These values were computed as follows:

$$\text{Annual Energy Loss Cost, ELC} = \$(TAPL)\ x\ [(K_e\ L_{sf}\ 8760) + K_p] \tag{22}$$

In which, TAPL → total active power loss, K_e → annual energy loss cost ($/kWh), L_{sf} → power loss factor, K_p → annual power loss demand cost ($/kW). The load factor ($L_f$) is used to express the system's loss factor from the equation below:

$$L_{sf} = [(1\text{-}K)\ L_f^2] + (K\ L_f) \tag{23}$$

In calculating the power loss factor, the coefficient values adopted are: K → 0.2, L_f → 0.469, K_e → 0.00961539 $/kWh, and K_p → 57.6922 $/kW. The SPV DG cost component for the RP and AP is given by:

$$\text{For the AP supplied by the SPV DGs, } S(P_{sdg}) = (aP_{sdg}^2 + bP_{sdg} + c)\ \$/MWh \tag{24}$$

Whereby, the cost coefficients chosen are: $c \rightarrow 0.250$, $b \rightarrow 20.0$ and $a \rightarrow 0.0$

$$\text{For the RP cost supplied by the SPV DGs, } C(Qsdg) = \{(Sgmax)\,cost - (\sqrt{Sgmax^2 - Qg^2})\,cost * k\} \quad (25)$$

The value of the maximum apparent power generated is:

$$S_{gmax} = {Pgmax}/{Cos\theta} \quad (26)$$

And, $P_{gmax} \rightarrow 1.10 * P_g$,. The pf used have been considered at 0.85 and 1 for the analysis. Normally, the range of K is 0.1 – 0.05. This study adopts 0.1 as the value factor of K.

The energy loss cost (*ELC*), active power cost (P_{sdg}) and the reactive power cost (Q_{sdg}) are shown in the Table below.

Table 9. Results of the IEEE 33-bus RDN system with SPV DGs at upf and 0.85 pf.

	Without SPV DG	At upf		At 0.85 pf	
		Method (Hari et al 2019)	Proposed method	Method (Hari et al 2019)	Proposed method
SPV DG location	-	30	24	30	24
SPV DG size (kW)	-	1544.5	2576.44	1939.3	2576.46
Total active power loss (TAPL); kW	211.02	125.2	68.52	78.4	28.1
Total reactive power loss (TRPL); kVAr	143.04	89.3	49.47	58.97	22.0
Minimum voltage (V_{min}); pu	0.9138	0.9272	0.9775	0.9386	0.9911
Energy loss cost (ELC); $	16982.6	10067.3	9030.56	6308.8	4700.02
P_{sdg} cost ($/MWh)	-	31.15	29.05	35.108	31.5
Q_{sdg} cost ($/MVArh)	-	-	-	3.928	3.3

The energy loss cost, as shown from table Table 9, reduced from $ 16982.6 to $ 4700.02 when the SPV DGs are operating at 0.85 pf lagging while it reduced to $ 9030.56 when the network operated at upf. The energy loss cost is lower when the RDN is operating at 0.85 pf and therefore when compared with the results of Hari et al, better results are obtained with the proposed method.

3.5. PSO and GA Performance Comparison

Performance comparison of PSO and GA for the cases considered is by examining the performance of each algorithm in reaching the optimal solution in terms of computing time, number of iterations and accuracy percentages. Regarding achieving of the optimal solution, the difference in iterations is 1657, with PSO algorithm being superior and of better speed. The PSO always obtained the solution 100% accuracy while GA average accuracy was 99% as more SPV DGs are integrated.

Table 10. PSO and GA performance comparison

Method	1SPV DG		2SPV DGs		3SPV DGs	
	Average accuracy	Best iteration	Average accuracy	Best iteration	Average accuracy	Best iteration
PSO (Proposed)	1.0	62	1.0	3564	1.0	43850
GA (Wihartiko et al, 2018)	1.0	49	0.99	5221	0.93	56743

In Table 10, it is observed that there is no significant difference when applying PSO and GA for the case of 1SPV DG. The GA decreases in accuracy when the number of DGs increase as it demonstrates less stable condition compared to PSO in finding the optimal solution. Generally, the PSO technique is superior in finding the optimal solution in terms of iterations and accuracy.

4. CONCLUSIONS

There are issues of network power losses, reliability and voltage drops in a RDN system. In optimizing placement and sizing of solar energy sources, improvement of the RDN reliability was significantly realized on application of the proposed PSO technique. The BYD240P6-30power output Suniva SPV module was adopted to perform the results analysis. SPV uncertainties in their reliability data were considered for further analysis so as to obtain better RA results; these factors are the rate of failure and time of repair. The distribution network bus voltage profile and power loss reduction were enhanced by optimally placing and sizing the SPV DGs for their installation, as opposed to a network with no distributed solar generations. Integration of numerous DGs provides better results compared to a mono-installation. The APL value was observed to reduce by 0.00178MW at upf for 1SPV and by 0.00126MW for 3SPV cases, in comparison to results of GA approach. There was an improvement in minimum value of the bus voltage by 7.07_0% for 3SPV case at upf in comparison to NO DG case. At 0.85 p.u., further improvement was achieved, yielding to 8.45%. Adopting scenario 'a' with three SPV case; a more favored configuration, results to an acceptable network reliability improvement that yields to 0.99917 ASAI reliability index, that is ~ 0.99982 recommended by other studies. The proposed technique implementation is simple and has a potential of having capability to compute near optimal and desirable solutions on few iterations. Further study is required on complex distribution systems; the IEEE 69 or 118-bus distribution grids on factors concerning network reconfiguration and emission of carbon in order to establish the network's reliability.

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APPENDIX

A1. The Particle Swarm Optimization Algorithm

```
clc;
clear all;
format short;
tic
m=load('loaddata33bus.m');
l=load('linedata33bus.m');
disp('%-----Solar Based DG------%');
% m=load('loaddata33bus.m');
% l=load('linedata33bus.m');
.
.
    % --Position of Swarms---
    for uu=1:Swarms;
        Swarm(uu,1)=Swarm(uu,1)+Swarm(uu,5)/1.2; % update u Position
        Swarm(uu,2)=Swarm(uu,2)+Swarm(uu,6)/1.2; % update v Position
.
.
                % ---updating velocity vectors
                for vv=1:swarms
                  swarms(vv,5)=rand*inertia*swarm(vv,5)+correction_factor*r
                  and*(swarm(vv,3)...
                       -swarm(vv,1))+correction_factor*rand*(swarm(qbest,3)-
                        swarm(vv,1)); % u velocity parameters
                  swarm(vv,6)=rand*inertia*swarm(vv,6)+correction_factor*ra
                  nd*(swarm(vv,4)...
                       -swarm(vv,2))+correction_factor*rand*(swarm(qbest,4)-
                        swarm(vv,2)); % v velocity parameters
.
.
Sprintf('Power-Loss=%d KW, Power-Loss=%d KVAr', PL,QL')
Sprintf('DG Location=%d, DG Power=%d KVA', DG_Location, DG_Size')
```