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Particle Swarm Optimisation-Based Optimal Placement And Sizing Of Distributed Generation System

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***Abstract*— In this work, the particle swarm optimisation-based optimal placement and sizing of distributed Generation (DG) system is presented. Specifically, detailed mathematical models along with the algorithm for the Particle Swarm Optimisation (PSO) are presented. Also, the parameters of the baseline scenario realized using the backward/forward sweep power flow analysis on the case study AKA 11kV radial distributed network (RDN) are presented. In the baseline case, total real power loss of 2108.68 kW and total reactive power loss of 776.5 kVar are realized and these constituted 13.23 % and 10.07% of the total real power and the total reactive power respectively. However, when the PSO algorithm for optimizing DG placement at 30% penetration was implemented, the results showed significant decrease in total real power loss from 2108.68 kW in the base case to 904 kW with 1 DG, 877 kW with 2 DGs, and 846 kW with 3 DGs, while the total reactive power loss reduced from 776.537 kVAR to 333 kVAR with 1 DG, 323 kVAR with 2 DGs, and 311 kVAR with 3 DGs. The percentage reduction in real power loss improved from 57.13% with 1 DG to 59.88% with 3 DGs, and the reduction in reactive power loss improved from 57.12% with 1 DG to 59.95% with 3 DGs. Essentially, the PSO can effectively be used to size and locate the DGs on the case study RDN.**

Keywords*— *Particle Swarm Optimisation, Distributed Generation System, Optimal Placement of Distributed Generation, Radial Distributed Network, Power Flow Analysis

1. INTRODUCTION

Over the years, the integration of distributed generation (DG) into the power distribution network has gained a lot of significant momentum among researchers and practitioners in the power industry, and this is mostly driven by concerns about climate and energy security as well as grid reliability [1, 2, 3,4]. The DG can be defined as the generation of electric energy from small power systems disseminated throughout the network near to the consumption centres [5, 6, 7]. Typical technologies of DG include solar, wind, and biomass power as well as fuel cells [8,9,10]. This evolution is driven by the evolution of greener energy generation and more modern power systems.

Although DG integration has numerous advantages, it also has some drawbacks [11,12]. Placement and sizing of DG units at the wrong locations or in too high numbers can increase power losses in distribution network (I^2 R losses due to increased current flow through the wires) and impact voltage stability, leading to voltage fluctuations and even blackouts [13,14]. Moreover, researchers are aware of the complexity of managing power losses, voltage stability and DG integration in complex distribution networks [16,16,17,18]. The use of traditional optimisation approaches to determine the optimal location and sizing of DG units might always give the best solutions considering the complexity of power systems [19,20]. To overcome these challenges, researchers have taken the initiative to integrate intelligent optimisation approaches, such as Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimisation (ACO) and Particle Swarm Optimisation (PSO), for optimising DG placement and sizing [21,22]. The key advantages of these modern optimisation approaches, known as metaheuristic algorithms, are high speed, good convergence, scalability and therefore they are suitable for tackling complex optimisation problems in general and power systems specifically. Accordingly, the PSO technique, which is a metaheuristic algorithms for optimal location and sizing of DG is presented in this paper.

2. METHODOLOGY

2.1 The mathematical model and flowchart for the PSO algorithm applied to optimal placement and sizing of distributed generation system

In this section. the Particle Swarm Optimisation (PSO) algorithm is developed using two methodologies which are the mimicking of the bird flocking and fish schooling (swarming theory) and evolution techniques. The Particle Swarm Optimisation (PSO) algorithm was originally proposed by Kennedy and Eberhart [23,24]. Basically, the PSO algorithm starts with initializing population randomly and solutions are assigned with randomized velocity to explore the search space. Each solution in PSO is referred to as particle and there are three distinct features of PSO, namely, the best fitness of each particle; the best fitness of swarm, and finally the velocity and position update of each particle.

The mathematical development of PSO is given the following steps:

i. Initialisation

Initialise a population of particles randomly within the search space.

Each particle has a position x_i and a velocity v_i.

ii. Objective Function Evaluation

Evaluate the fitness of each particle's position using the objective function: fx_i.

iii. Initialization of Particle's Best Position and Global Best

Set the particle's best position p_i initially equal to its current position x_i. Set the global best position g to be the position of the particle with the best fitness among all particles.

iv. Update Particle's Velocity

Update the velocity of each particle according to its current velocity, its cognitive component (tendency to move towards its own best position), and its social component (tendency to move towards the global best position). This can be expressed as:

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 \left(p_{i,lb}^{(t)} - x_i^{(t)}\right) + c_2 r_2 \left(p_{gb}^{(t)} - x_i^{(t)}\right) \quad (1)$$

Where i is the i^{th} particle, t is the generation counter or the iteration count, $v_i^{(t)}$ represents the present velocity of particle i at iteration t, $v_i^{(t+1)}$ is the updated velocity of particle i in the next iteration, ω is the inertia weight controlling the impact of the previous velocity, c_1 *and* c_2 are acceleration coefficients/constants controlling the impact of personal best and global best positions, r_1 *and* r_2 are random numbers uniformly distributed in the range $\in [0,1]$, $p_{i,lb}^{(t)}$ is the local best or personal best of the i^{th} particle, $p_{gb}^{(t)}$ is the global best position.

v. Update Particle's Position

Update the position of each particle using the new velocity calculated in the previous step:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (2)$$

Where, $x_i^{(t+1)}$ is the updated position of particle i at iteration t, $x_i^{(t)}$ represents the present position of particle i at iteration t, $v_i^{(t+1)}$ is the updated velocity of particle i at iteration t.

vi. Weight of inertia

In order to find the value of the weight of inertia the following expression is used;

$$\omega_{max} = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{t_{max}} * t \quad (3)$$

where $\omega_{max} - \omega_{min}$ represent the maximum and minimum values of the weight of inertia, and t and t_{max} represent the present iteration and total number of iterations, respectively;

vii. Objective Function Evaluation

Evaluate the fitness of each particle's new position using the objective function $f\left(x_i^{(t+1)}\right)$

viii. Update Particle's Best Position and Global Best

Update each particle's best position if its new position yields a better fitness value,

$$\text{if } f\left(x_i^{(t+1)}\right) < f\left(p_{i,lb}^{(t)}\right) \quad (4)$$

Update the global best position if any particle finds a better solution,

$$\text{if } f\left(x_i^{(t+1)}\right) < f\left(p_{gb}^{(t)}\right) \quad (5)$$

ix. Repeat

Repeat steps 4 to 7 until a termination condition is met (e.g., maximum number of iterations reached, convergence criteria met); and

x. Termination

Once the termination condition is met, return the best solution found.

This iterative process continues until a termination condition is satisfied, typically when a predefined number of iterations are completed or when the optimization process converges to a satisfactory solution.

The PSO flowchart algorithm for optimal location and sizing of DG is given in Figure 1.

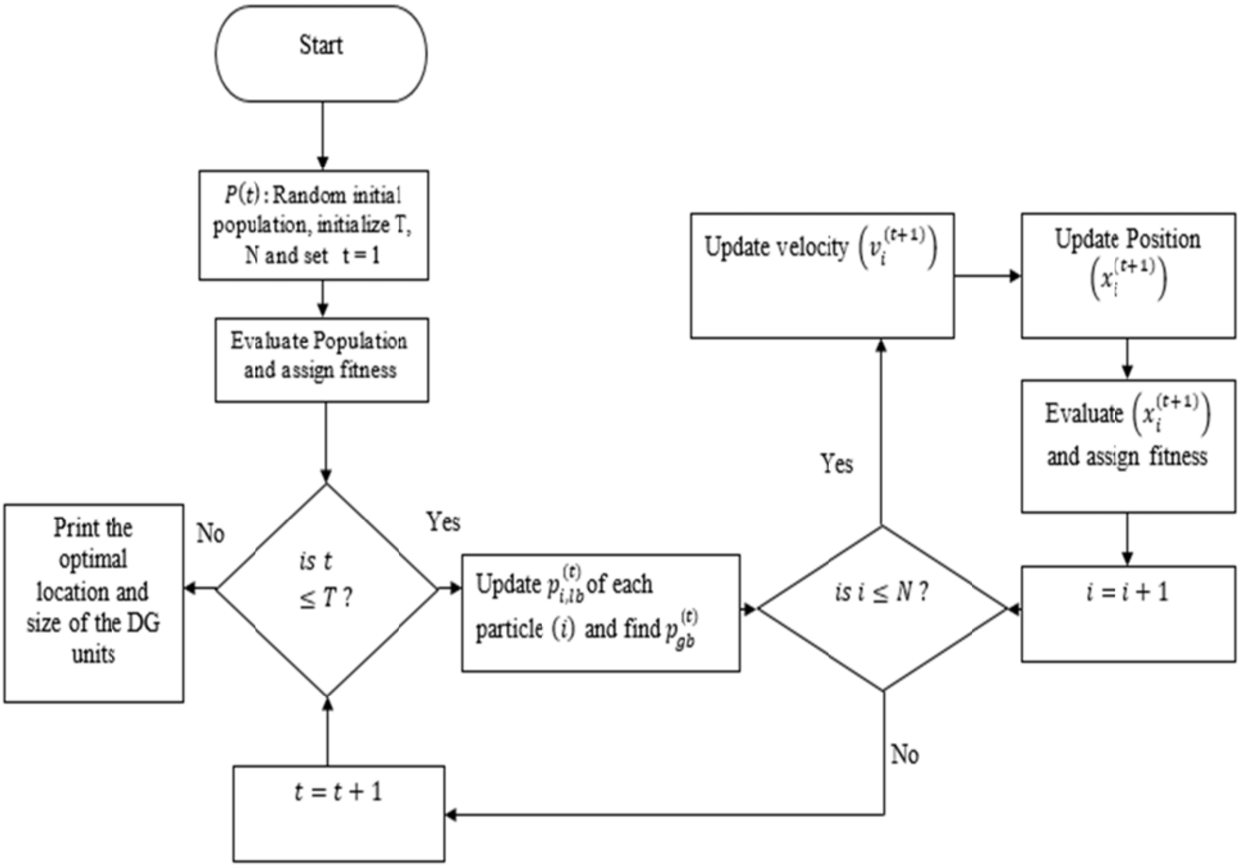

Figure 1: The PSO flowchart algorithm for optimal location and sizing of DG

3.2 The case study power distribution network and the parameters of the baseline scenario without distributed generators

The single-line diagram of the case study AKA 11kV distribution feeder network in Uyo Akwa Ibom State Nigeria is shown in Figure 2. The parameters of the baseline scenario realized using the backward/forward sweep power flow analysis on the AKA 11kV radial distribution feeder network are presented in Table 1. In the baseline case, total real power loss of 2108.68 kW and total reactive power loss of 776.5 kVar are realized and these constituted 13.23 % and 10.07% of the total real power and the total reactive power respectively.

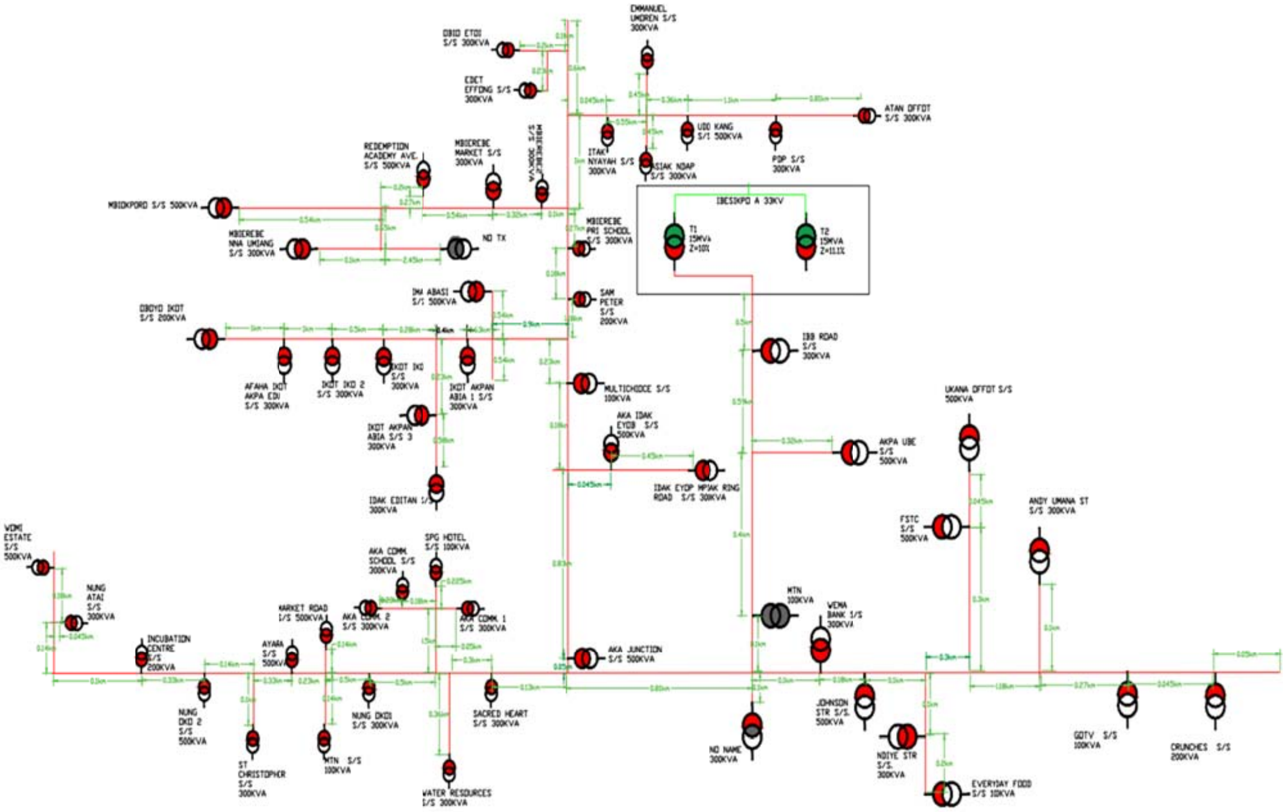

Figure 2: The Single-line diagram of the case study AKA 11kV distribution feeder network (DFN).

Table 1 The parameters of the baseline scenario realized using the backward/forward sweep power flow analysis on the AKA 11kV radial distribution feeder network

Parameters	Base Case
Total real power demand (kW)	15938.62
Total reactive power demand (kVar)	7715.29
Total real power loss (kW)	2108.68
Total reactive power loss (kVar)	776.5
Minimum voltage (pu)	0.8621
Minimum voltage bus number	56
Maximum Voltage (pu)	0.9834
Maximum voltage Bus number	2
Voltage deviation index (%)	11.28

3. RESULTS AND DISCUSSIONS

The PSO algorithm was used to determine the optimal size and placement of distributed generators in the AKA 11kV DFN. Three scenarios were conducted, namely, one DG, two GDs and three DGs. The key performance metrics obtained through simulations using PSO algorithm for a scenario with 30% DG penetration is presented in Table 2. Also, the voltage profile at each bus for the base case and with 1, 2, and 3 DGs is shown in Figure 3, illustrating the impact of DG on voltage stability and power quality. The impact of DG on power losses is illustrated in Figure 4.

From the results in Table 2, the PSO algorithm for optimizing DG placement at 30% penetration showed a significant decrease in total real power loss from 2108.68 kW in the base case to 904 kW with 1 DG, 877 kW with 2 DGs, and 846 kW with 3 DGs, while the total reactive power loss reduced from 776.537 kVAR to 333 kVAR with 1 DG, 323 kVAR with 2 DGs, and 311 kVAR with 3 DGs. The percentage reduction in real power loss improved from 57.13% with 1 DG to 59.88% with 3 DGs, and the reduction in reactive power loss improved from 57.12% with 1 DG to 59.95% with 3 DGs. The minimum voltage increased from 0.8621 pu in the base case to 0.914 pu with 1 DG, while with 2 and 3 DGs it was slightly lower at around 0.9095 pu. The maximum voltage remained fairly constant around 0.9834 to 0.989 pu across all scenarios.

The voltage deviation index, indicating voltage uniformity, improved from 11.28% in the base case to 6.87% with 3 DGs. With 1 DG, it was placed at bus 54 with a real power size of 4779 kW and a reactive power size of 2315 kVAR; with 2 DGs, they were placed at buses 23 and 53, each with a real power size of 2390 kW and a reactive power size of 1157 kVAR; and with 3 DGs, they were placed at buses 40, 47, and 54, each with a real power size of 1593 kW and a reactive power size of 772 kVAR. The addition of DG units significantly reduced both real and reactive power losses while improving the voltage profile and reducing voltage deviation in the system, with these benefits becoming more pronounced as the number of DG units increased.

Table 2: The results of the PSO-optimized DG placement at 30% Penetration

Parameters	Base Case	One DG	Two DGs	Three DGs
Toal real power loss (kW)	2108.68	904	877	846
Total reactive power loss (kVAR)	776.537	333	323	311
Real power loss reduction (%)	-	57.13	58.41	59.88
% Reactive power loss reduction	-	57.12	58.41	59.95
Minimum voltage (pu)	0.8621	0.914	0.9095	0.9094
Minimum voltage bus number	56	24	50	50
Maximum Voltage (pu)	0.9834	0.989	0.986	0.989
Maximum voltage bus number	2	2	2	2
Voltage deviation index (%)	11.28	7.15	7.04	6.87
DG location (Bus No.)	-	54	23, 53	40, 47, 54
DG real power size (kW)	-	4779	2390, 2390	1593, 1593, 1593
DG reactive power size (kVAR)	-	2315	1157, 1157	772, 772, 772

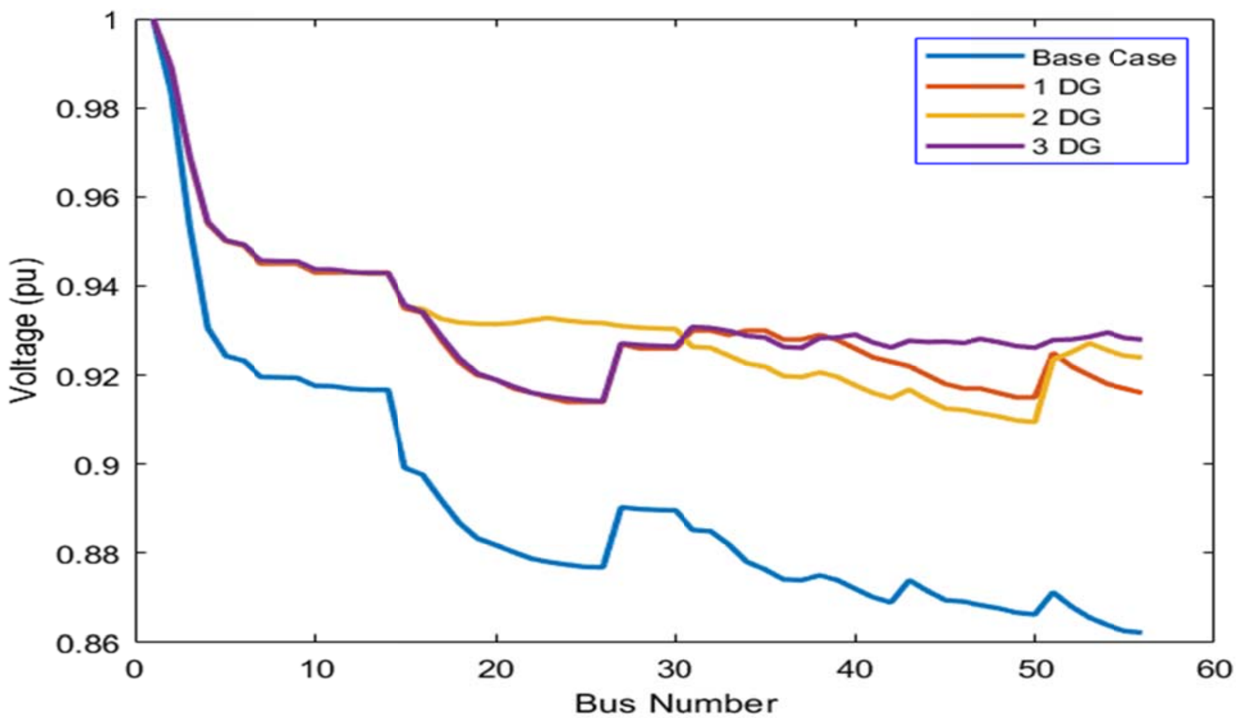

Figure 3: Voltage profile comparison with increasing DG penetration using PSO.

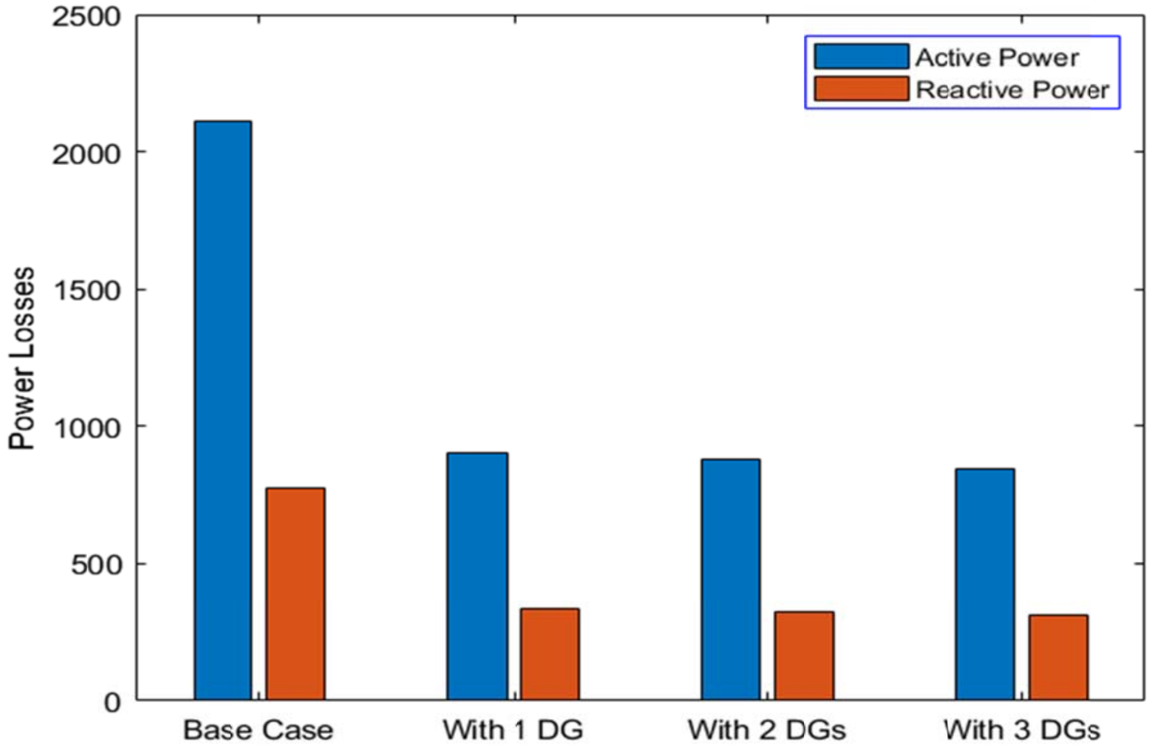

Figure 4: Real and reactive power losses for all scenarios using PSO

4. CONCLUSION

The study presented an approach to optimally size and locate distributed generators (DG) on a case study Radial Distributed Network (RDN). Specifically, Particle Swarm Optimisation (PSO) algorithm is used in the optimal DG sizing and placement. The details of the mathematical models along with the algorithm for the PSO are presented along with the base line scenario of the case study RDN without DG. The PSO algorithm is implemented based on the RDN data and the results show that the optimally sized DG using the PSO significantly reduced the real and reactive power and the reduction in the losses improved as the number of DGs increase. Essentially, the PSO can effectively be used to size and locate the DGs on the case study RDN.

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