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Research Article

AI-optimization operation of biomass-based distributed generator for efficient radial distribution system

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Abstract. This research aims to optimize the size and location of biomass-based distributed generator (BMDG) units to enhance the voltage profile, reduce electrical losses, maximize cost savings, and decrease emissions from power distribution systems. Biomass-based distributed generator (BMDG) systems offer numerous advantages to enhance the efficiency of power distribution systems. However, achieving these benefits relies on determining the optimal size and position of the BMDGs. To achieve these objectives, the metaheuristic technique called particle swarm optimization (PSO) is employed to find the optimal placement and size of BMDGs. The proposed model was validated on MATLAB's IEEE-33 bus radial distribution system (RDS), confirming the aforementioned benefits. Comparative analysis between the PSO-based technique and other algorithms from previous research revealed better results with the proposed method. The results indicate that optimal placement and sizing of BMDG units have led to a reduction of more than 67.68% in active power losses and 65.90% in reactive power losses compared to the base case. Additionally, the reduction in active power loss was 40.44%, 11.39%, 42.85%, 1.81%, 0.85%, 29.83%, 5.82% and 28.38% more than artificial bee colony, backtracking search optimization algorithm, moth-flame optimization, Coordinate control, artificial Hummingbird algorithm, variable constants PSO (VCPSO), artificial gorilla troops optimizer (AGTO), and a jellyfish search optimizer respectively. Furthermore, the reactive power losses were reduced by 38.33% and 15.68% compared to VCPSO and AGTO respectively. Furthermore, this study revealed a cost reduction of 6.38% when compared to the AGTO and 1.30% when compared to the AHA. Moreover, the voltage profile of the power distribution system was improved by 7.28%. The presented methodology has demonstrated promising results for BMDGs in RDS across various applications.

Keywords: Biomass-based distributed generator (BMDG); particle swarm optimization (PSO); optimal placement and sizing; IEEE-33; radial distribution system (RDS).



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1. Introduction

The integration of renewable sources-based distributed generators to enhance the efficiency of radial distribution systems (RDS) is trending these days. A renewable energy source such as biomass has the advantage of lower electricity cost production as well as environmentally friendly energy. Biomass energy is derived from plants and their products, such as food, crops, wood, oil-rich algae, forestry or agriculture waste, and the biological portion of municipal and industrial surplus. The inherent process of photosynthesis harnesses solar energy to convert water (H₂O) and carbon dioxide (CO₂) into organic material, ultimately producing biomass (Britannica 2016). Compounds such as hemicellulose, lignin, lipids, simple sugar, water, cellulose, extractives, proteins, starches, ash, hydrocarbons, and other substances are found in biomass. Each type has a unique biomass composition with sugars or carbohydrates (75%) and Lignin (25%) (Álvarez *et al.* 2016; Demirbas 2010; Joshee 2012; Rezende *et al.* 2011). According

to (Administration 1 June 2016), the electrical energy generated through all sources was reported to be 21.53 trillion kilowatts hour (tkWh) in 2012 and it is expected to produce 39 tkWh globally in 2040 with a rise of 81% since 2012. Moreover, it has been predicted that 9.6 tkWh or 25% of the total electric power produced in the world in 2040 will be through renewable energy resources. The need to generate power using renewable sources like biomass, wind, hydro, solar, and geothermal has grown significantly. Although conventional sources of energy are extensively available worldwide, yet they are not only depleting quickly but have also become hazardous to the environment. Certainly, the source of biomass energy is widely available worldwide which is about 0.384(tkWh), or 2% of the total electric power generated in the world in 2012 (Administration 1 June 2016). Recent studies have estimated that biomass energy consumption would be able to provide up to 45% of global energy consumption in the coming years. These results have

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encouraged researchers to explore the potential of biomass energy (Keoleian & Volk 2005).

The energy generation at the grid side along with the generation at the distribution side through renewable sources is called cogeneration and it has gained momentum in recent years. This occurs as a result of improved co-generation and increased use of renewable resources. Small-scale power generation facilities known as distributed generators (DGs) are located close to the consumer load and also directly connected to the distribution network (DN) (Huda & Živanović 2017). Moreover, incorporating technology based on renewable resources can increase the size of the DN. There is an urgent requirement to transport reliable and reasonably priced services directly to consumers, including electrical loss reduction, emission of greenhouse gas mitigation, power quality improvement, peak load addressing, flexible voltage regulations, and enhancements in reliability (Ehsan & Yang 2018; Li *et al.* 2018). The researchers in (Widjaja *et al.* 2023) have developed a neural network model for accurately predicting the state-of-charge of battery cells in the Solar Dryer Dome, reducing overcharging and discharging, and includes a dashboard for monitoring battery status. The lowest mean absolute error has been achieved by Random Forest and support vector machine methods. In (Mladenova *et al.* 2023) Presents a carbon-free gas diffusion electrode design using a mixture of Co_3O_4 , NiCo_2O_4 , and polytetrafluoroethylene on stainless steel, enhanced with 70 wt.% Ni powder for improved oxygen reduction reaction performance, showing acceptable overpotentials and better stability, especially with Ni/ NiCo_2O_4 (70:30 wt.%).

The authors (Rao, Ravindra, Satish, & Narasimham 2012) Present a novel strategy for solving the network reconfiguration problem with the distributed generation that uses the Harmony Search Algorithm. The goal was to reduce real power loss and improve the voltage profile of a distribution system. A teaching-learning-based method was proposed by (Mohanty and Tripathy 2016) to determine the optimal place and size of DG to enhance voltage profiles and lessen the electrical loss in the network. In (Balu and Mukherjee 2023), researchers introduced a novel approach known as the Chaotic Student Psychology-Based Optimizer. This method was employed to determine the optimal locations and sizes of biomass, wind-battery, and PV-battery systems within RDS. The authors (Ali, Bhatti, Rasool, Farhan, and Esenogho 2023) presented an idea to deploy the particle swarm optimization (PSO) method for optimal PV-based DG size and location in RDS to reduce electrical losses, and enhance voltage, with 15.211% in terms of saving cost annually. The research in (Raut and Mishra 2023) utilized an improved equilibrium algorithm for the reconfiguration of a dynamic system featuring wind, PV, and biomass-distributed generators along with a multi-objective challenge to concurrently reduce electrical loss and increase financial gains. A Capuchin Search Algorithm was introduced by (Fathy, Yousri, Rezk, and Ramadan 2022) to determine the optimal placements, sizes, and power factors of BMDG units in RDS. The objective was to minimize active power loss while ensuring that power flow, bus voltage, and transmission line remained within normal operational ranges. An improved artificial ecosystem technique was presented in (Khasanov *et al.* 2023) to address the integration of a DG into an RDS, with a focus on the mitigation of active power loss.

An optimization approach utilizing the artificial bee colony (ABC) algorithm was presented in (Abu-Mouti and El-Hawary, 2011) to determine the optimal size, location, and power factor of DG units, aiming to minimize total system real power loss

only. The research (Das and Srivastava 2017) has utilized a Moth-Flame optimization (MFO) technique to determine the best placement and size of distributed generation units in a distribution system, aiming to minimize real power loss only. The Backtracking Search Optimization Algorithm (BSOA) is presented in (El-Fergany 2015) for efficient distributed generator placement in RDS. BSOA effectively decreases network losses and improves voltage profiles, but ignores other parameters like environmental concerns and annual cost savings. The research (Abo El-Ela, Allam, Shaheen, and Nagem 2021) presented an equilibrium technique for optimizing biomass-distributed generation units to improve distribution system performance, reduce environmental impact, and maximize power utility advantages but the performance is not better than the proposed system. In (Barik and Das 2020), the researchers integrated biomass DG into a 33-bus RDS to manage the remote bus by developing a new bus pair known as the Q-PQV bus pair. The study improves decentralized power generation by strategically deploying biomass-based units in a distribution system, focusing only on active power loss reduction. Additionally, authors (Roy, Bansal, and Bansal 2023) concentrated on enhancing the performance of RDS through the optimization of BMDG unit placements. It utilized a combination of the sensitivity index method and the AGTO algorithm to identify the optimal location and size of DG units within RDS. This approach caused improvements in voltage profile, minimization of power losses, and enhancement of voltage stability while adhering to the operational constraints of the system and performance parameters of RDS were not properly addressed. Further, in (Bhargava, Sinha, and Dave 2021), proposed that the dispatchable BMDG units when run at coordinated optimal size alongside solar DG units, reduce power losses and operational costs without additional installation and did not address the economic benefits due to the environmental penalty and active power loss reduction cost savings. The researchers proposed the Artificial Hummingbird Algorithm (AHA) (Fathy 2022) to determine the optimal locations and sizes of BMDG units within RDS, aiming to minimize the network's active power losses and voltage deviation, and other parameters like reactive power losses, emission reduction, and annual cost savings were not selected for improvement. The authors (Ranga *et al.* 2024) presented the effect of various DG unit integrations in RDS using a jellyfish search optimizer (JSO) for active power loss minimization only, without some other parameters that are not considered for improvement.

So, several studies have generally highlighted improving voltage profiles in power distribution systems, often neglecting economic considerations and environmental effects such as emissions. While some research has addressed these features, their primary focus persisted on voltage enhancement rather than simultaneously optimizing system losses and achieving cost savings. Additionally, efforts to mitigate global warming through decreased power losses have been explored by several scholars. In response to these gaps, this study presents a metaheuristic approach using the PSO technique to determine optimal locations and sizes for BMDG units within RDS. The contributions of this research include developing a model that integrates BMDG into distribution systems, thereby reducing both active and reactive power losses while enhancing the voltage profile. Moreover, it aims to increase annual cost savings through efficient operation, particularly in reducing emission penalties. The study focuses on the environmental benefits of reducing emissions during BMDG operation. It

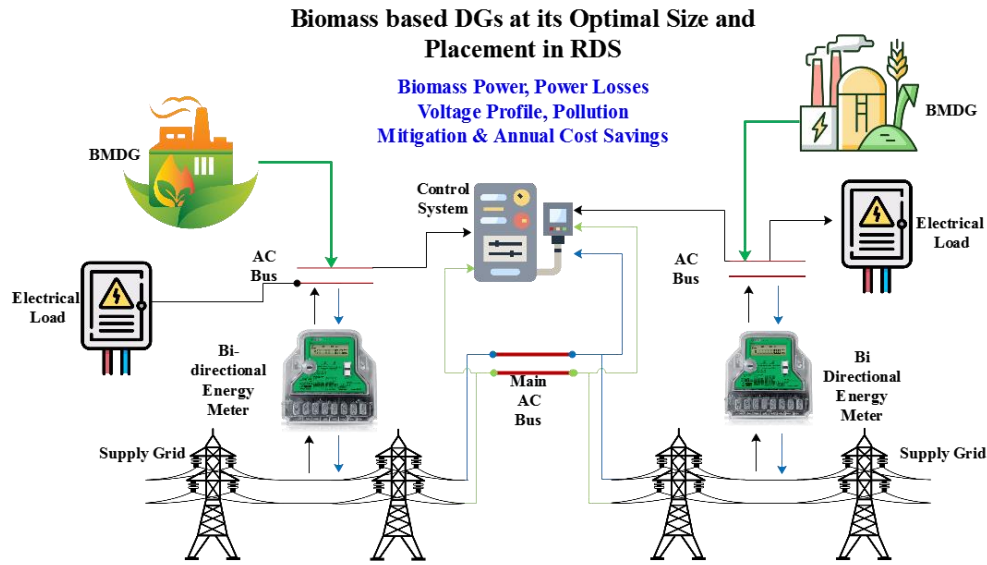


Fig 1. Power distribution system with BMDG.

specifically applies PSO to the IEEE-33 bus distribution system in MATLAB, comparing its simulation results with recent literature to demonstrate its effectiveness and improvement in enhancing overall power distribution systems.

2. Methodology

Biomass-based distributed generators at their optimal position and size within the RDS are shown in Figure 1. This shows that the control system obtains comprehensive records of IEEE-33 bus system data i.e. (power losses, voltage profile, emission values, energy cost), and BMDG capacity, enabling it to decide the best location and size of BMDG via the utilization of the PSO technique. Additionally, the control unit calculates voltage levels, power losses, emission reductions, and annual cost savings within the RDS, ensuring an efficient and sustainable power distribution system.

This study emphasizes the strategic integration of DG into the power distribution system, aiming to increase its technical performance and economic and environmental advantages. A thorough assessment of the current computation of numerous technical, economic, and environmental criteria is carried out. Subsequently, the PSO approach is applied to locate the optimal site and size of the BMDG unit in the distribution system. Upon obtaining the optimal position and size within the RDS, a

comparison has been presented among several methods to ensure the precision and reliability of the results generated by this proposed model. This validation process validates the robustness of the findings and provides actionable insights for practical implementation in power distribution systems.

3. Problem formulation

The aim of optimal location and sizing of biomass-based DGs (OLSBMDG) problem is to enhance annual cost savings, minimize active and reactive power loss, reduce the emission penalty, and improve the voltage profile while adhering to different equality and inequality constraints. Mathematically, the objective functions and constraints of OLSBMDG are given below.

3.1. Technical objective function

3.1.1. Total power losses formulation

The distribution line section coupled between two nodes i and j is displayed in Figure 2. This power system has a $P_i + jQ_i$ load connected to the i -th bus. The impedance of the transmission line is at $Z = R + jX$ and the RDS's active and reactive power losses are as follows (Hung, Mithulanathan, and Bansal 2013).

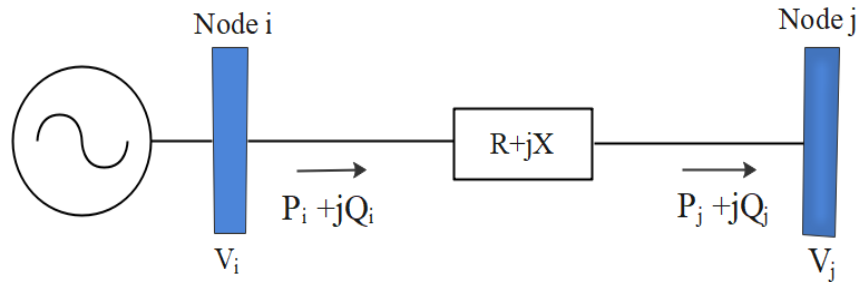


Fig 2. A simple distribution network

$$P_{Loss} = \sum_{k=1}^{N_b} |I_k|^2 R_k \quad (1)$$

$$Q_{Loss} = \sum_{k=1}^{N_b} |I_k|^2 X_k \quad (2)$$

P_{Loss} and Q_{Loss} are ARP losses, R_k and X_k are the resistance and reactance of the branch k , I_k is current for branch k and N_b is the number of total branches.

The equations (5) can be utilized for calculating the annual cost savings of power losses.

$$C_{P_{Loss}} = W_{Loss} \times (T_{PL_{Without DG}} - T_{PL_{With BMDG}}) \times 8760 \quad (3)$$

The total annual cost savings in terms of active power loss reduction in RDS is $C_{P_{Loss}}$ and the power loss factor is W_{Loss} (0.06\$/kW) (Khasanov, Kamel, Xie, Zhou, & Li, 2019). $T_{PL_{Without BMDG}}$ denotes the total power losses when DG is not integrated, while $T_{PL_{With BMDG}}$ is the total power loss after the integration of BMDG.

3.1.2. Voltage profile

The voltage profile issues in distribution networks are directly related to power quality. Fluctuations in load and generating demand can cause voltage fluctuations across nodes. The increasing presence of highly intermittent renewable energy sources inside power distribution networks has piqued interest in distribution-level voltage profiles.

$$\Delta V = 1.05 \text{ pu} \leq v \leq 0.95 \text{ pu}$$

Where ΔV = Total change in voltage profile

3.1.3. Objective function formulation for pollution emissions

When biomass energy is used in DGs to fulfill the electricity demand, it emits CO₂, SO₂, and NO_x. The effect of emissions on the prices of BMDG units can be expressed (Niknam et al 2012).

$$E_{BMDG} = \sum_{i=1}^{N_{BMDG}} E(P_{BMDGi}) \quad (4)$$

$$E(P_{BMDGi}) = (CO_{2,BMDGi} + NO_{x,BMDGi} + SO_{2,BMDGi}) P_{BMDGi} \quad (5)$$

E_{BMDG} is total emission released from BMDG units and $CO_{2,BMDGi} + NO_{x,BMDGi} + SO_{2,BMDGi}$ are emissions generations of BMDG units. The following formula can be used to calculate the cost of BMDG units' emissions.

$$C_E = E_{BMDG} W_E \quad (6)$$

W_E is emission penalty factor (\$ per kilogram) and C_E is emission cost.

3.2. System operational constraints

There are two types of system operational constraints based on the proposed objective problems.

3.2.1 Equality Constraints

The power balance equations for the BMDG units in the distribution system are given below (Hassan et al 2017).

$$P_{Utility} + \sum_{i=1}^{N_{BMDG}} P_{BMDGi} = \sum_{j=1}^{N_l} P_d(j) + P_{Loss} \quad (7)$$

$$Q_{Utility} + \sum_{i=1}^{N_{BMDG}} Q_{BMDGi} = \sum_{j=1}^{N_l} Q_d(j) + Q_{Loss} \quad (8)$$

$P_{Utility}$ and $Q_{Utility}$ represent injected active and reactive power (ARP) from the utility, P_{BMDGi} & Q_{BMDGi} represent the generated ARP of the BMDG unit, $P_d(j)$ & $Q_d(j)$ represent the demand for ARP, and P_{Loss} & Q_{Loss} represent the total losses of ARP.

3.2.2 Inequality constraints

i. Voltage Limit Constraints

The voltage limitation for each bus in the electrical distribution could be defined as follows (Hassan et al. 2017).

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max} \quad (9)$$

$V_{Li}^{\min}$ and $V_{Li}^{\max}$ are the lowest and highest levels of voltage at load bus i respectively.

ii. DG Limit Constraints

In the RDS, the following equations can be used to define the lowest and highest permissible values for the ARP output of DG units.

$$P_{BMDGi}^{\min} \leq P_{BMDGi} \leq P_{BMDGi}^{\max} \quad (10)$$

$$Q_{BMDGi}^{\min} \leq Q_{BMDGi} \leq Q_{BMDGi}^{\max} \quad (11)$$

iii. BMDG Location Constraints

It is assumed that bus number 1 represents the slack bus or grid connection, therefore the placement of the BMDG is limited for other buses. The location of the bus for the BMDG unit is defined in Equation 12.

$$2 \leq \text{BMDG}_{\text{Position}} \leq n_{\text{Buses}} \quad (12)$$

iv. Feeder Constraints

Using the following equation, each branch of RDS's loading should be restricted.

$$S_{li} \leq S_{li}^{\max} \quad (13)$$

Where S_{li} represents the transmission line loading.

v. Thermal Rating

The thermal rating of the transmission lines can be found in the equation (14).

$$H_{li}^t = H_{li, \text{rated}} \quad (14)$$

Where H_{li}^t is the thermal rating of the line for t th hour and $H_{li, \text{rated}}$ is the valued thermal rating of the line.

4. Particle Swarm Optimization Algorithm

PSO method, commonly referred to as the bird's flock technique, was presented in 1995 by James Kennedy and Russell Eberhart (Kennedy 1995). It is based on the concept of artificial life, which is a research field that studies manmade systems and possesses the characteristics of life like ants building colonies or modeling the movement of birds. For

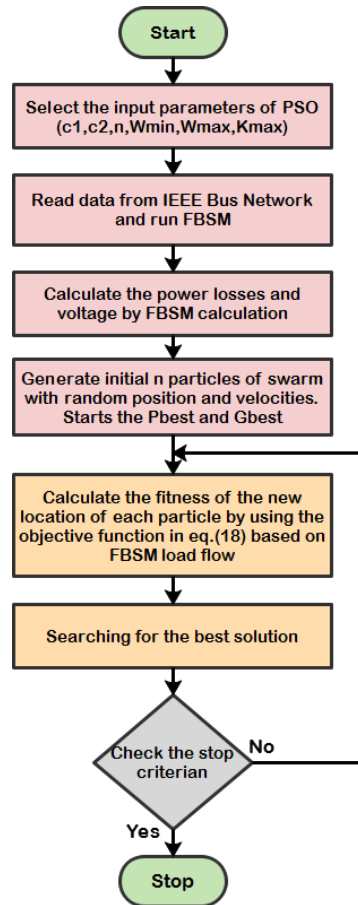


Fig 3. Proposed PSO method flow chart.

example, if a group of birds is looking for food in a specific region, the best method to find it is to disperse the birds and let them communicate with one another about their location. Within the algorithm, each bird is referred to as an element or particle, and each element has a related suitability value that indicates the fitness of its solution compared to that of the other elements. This process is carried out using a fitness function and each element has a speed that guides it on its foraging journey. Additionally, important variables such as personal best (pbest),

global best (gbest), and local best (lbest) are employed to handle information processing and identifying the best local position of the elements. Subsequently, the velocity and place of the elements undergo adjustments in each repetition. The proposed algorithm employs RDS to reduce loss, cost, environmental pollution, and voltage levels in the optimal location and size of BMDG units. Equations 17 and 18 can be employed to update a particle's position and velocity as it traverses an N-dimensional search space.

$$V_p^{k+1} = \omega V_p^k + c_1 * rand_1 * (p_{best} - S_p^k) + c_2 * rand_2 * (g_{best} - S_p^k) \quad (17)$$

$$S_p^{k+1} = S_p^k + \gamma * V_p^{k+1} \quad (18)$$

Where the current search point is S_k , and the altered search point is S_{k+1} , V_k is the current velocity, and V_{k+1} is the velocity that has changed. The weighting coefficients are c_1 and c_2 . The random numbers " $rand_1$ and $rand_2$ " are $[0,1]$; $c_1=c_2=2$; the inertia weight ω is equal to is $\omega_{max} - k(\omega_{max} - \omega_{min})/k_{max}$, with $\omega_{min}=0.4$ and $\omega_{max}=0.9$ (Eberhart & Shi, 2000). The present and maximum number of iterations is k and k_{max} .

The proposed PSO-based model has been demonstrated in Figure 3. This illustrates the process of finding the best position and size of the BMDG unit using the PSO optimizer. Initially, the input values for PSO were chosen, followed by the selection of line and bus data for the IEEE-33 bus network. The Forward/Backward Sweep Method (FBSM) was employed to determine power loss and voltage profile before integrating BMDG.

Subsequently, the PSO optimizer was executed to find the optimal site and size of BMDG. In each iteration, electric loss and voltage level were computed using FBSM. Upon obtaining the optimal position and size of BMDG, the model effectively reduced electric losses, minimized annual cost savings, reduced global warming, and improved the voltage profile for the specified objectives. The suitability value for the confirmed BMDG indicates the enhancement achieved for the stated objectives.

5. Performance Analysis

Figure 4 presents the architectural framework encompassing key design considerations for this study. The research focuses on an analysis of the IEEE-33 bus network

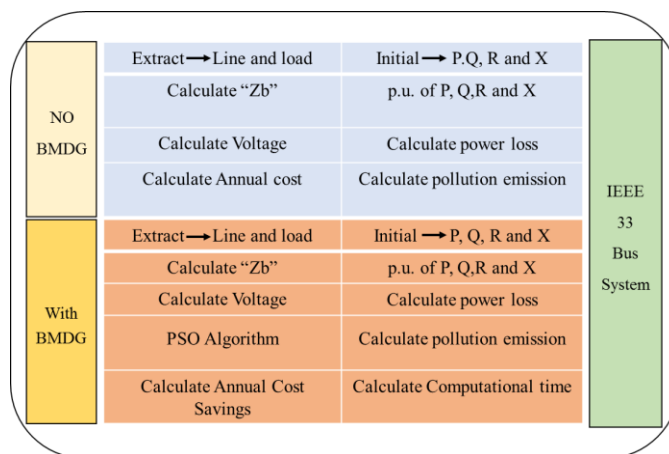


Fig 4. Proposed BMDG system.

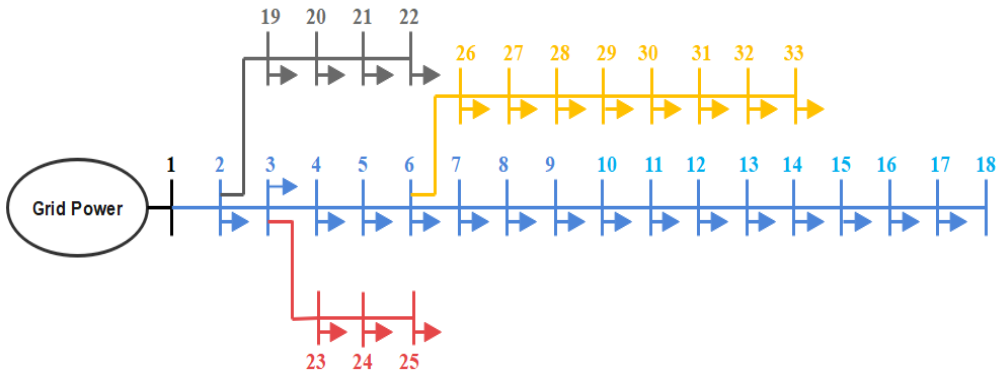


Fig 5. Single line drawing of the IEEE-33 bus system.

under two scenarios: one without Distributed Generation (No DG) and one with BMDG. To establish initial values for resistance (R), reactance (X), active power (P), and reactive power (Q), a comprehensive dataset from both the load and line databases has been considered.

The process begins with the calculation of the base impedance (Zb), which takes into account the rated MVA (Mega-Volt-Ampere) and kilovolt (kV) ratings of the IEEE-33 network. Subsequently, per-unit values for ARP, resistance, and reactance are determined using Zb as the reference. The study then calculates voltage levels for both the without-DG and biomass-DG scenarios. In the case of the biomass DG system, a PSO method is used to optimize the DG unit's placement and size, to minimize electrical losses in the network. Finally, a performance analysis is conducted, comparing the power system's behavior without DG to that with BMDG. This analysis offers OLSBMDG the advantages and integration into the electrical power distribution network.

The PSO-based model has been employed to determine the optimal place and size of distributed generations. Figure 5 shows the RDS network, and the data is taken from (Tan *et al.* 2013). Two different scenarios (absent of BMDG, with BMDG) were utilized to illustrate the PSO algorithm's effectiveness in solving OABMDG issues. Subsequently, a comparative analysis of all circumstances has been conducted.

5.1 No DG power system

The IEEE-33 system configuration comprises 33 buses and 32 lines, providing a comprehensive test system for this research analysis. Particularly, the end nodes of this IEEE bus network are designated as buses 18, 22, 25, and 33. These

particular buses are characterized by base voltage values of 12.66 kV and a steady state power rating of 100MVA, accompanied by a power factor of 0.8.

The choices of these buses for examination are pivotal in this study, as they represent critical points within the power distribution system. Understanding the impact of BMDG integration at these nodes is crucial for assessing the system's overall performance and stability. The real power distribution within the system, alongside the associated load, is visually represented in Figure 6. This figure vividly explains the progression of active power (Pi) and reactive power (Qi) within the system, with their initial values recorded at zero for bus 1 and subsequent changes occurring from bus 2 through to bus 32.

To provide a comprehensive overview, it is important to note that the cumulative active power load across the network stands at 3715 kW, while the total reactive power load amounts to 2300 kVAR. Among the various bus nodes, buses 24 and 25 emerged as the nodes with the highest active power demands, each registering a substantial 420 kW. In terms of reactive power, the peak demand has been observed at bus 30, which required 600 kVAR. Conversely, the minimum values for both ARPs were observed at bus one, where they remained at zero.

Figure 7a presents the impedance characteristics of the IEEE-33 bus network, presenting the R and X values for the network's lines. The maximum resistance of 1.542 ohms is observed at line 19, while the highest reactance value of 1.7210 ohms is found at line 16. In contrast, the minimum resistance and reactance values are at line 1, measuring 0.0922 ohms and 0.0470 ohms, respectively (T.A, 2020).

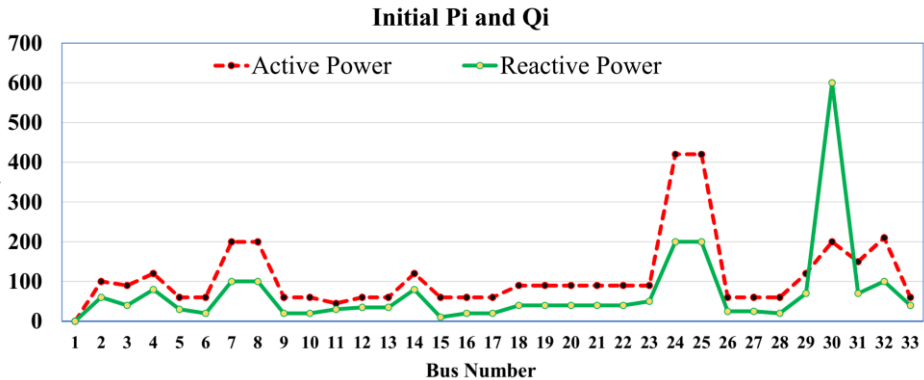


Fig 6. A graphical illustration of the load data of the IEEE-33 bus system.

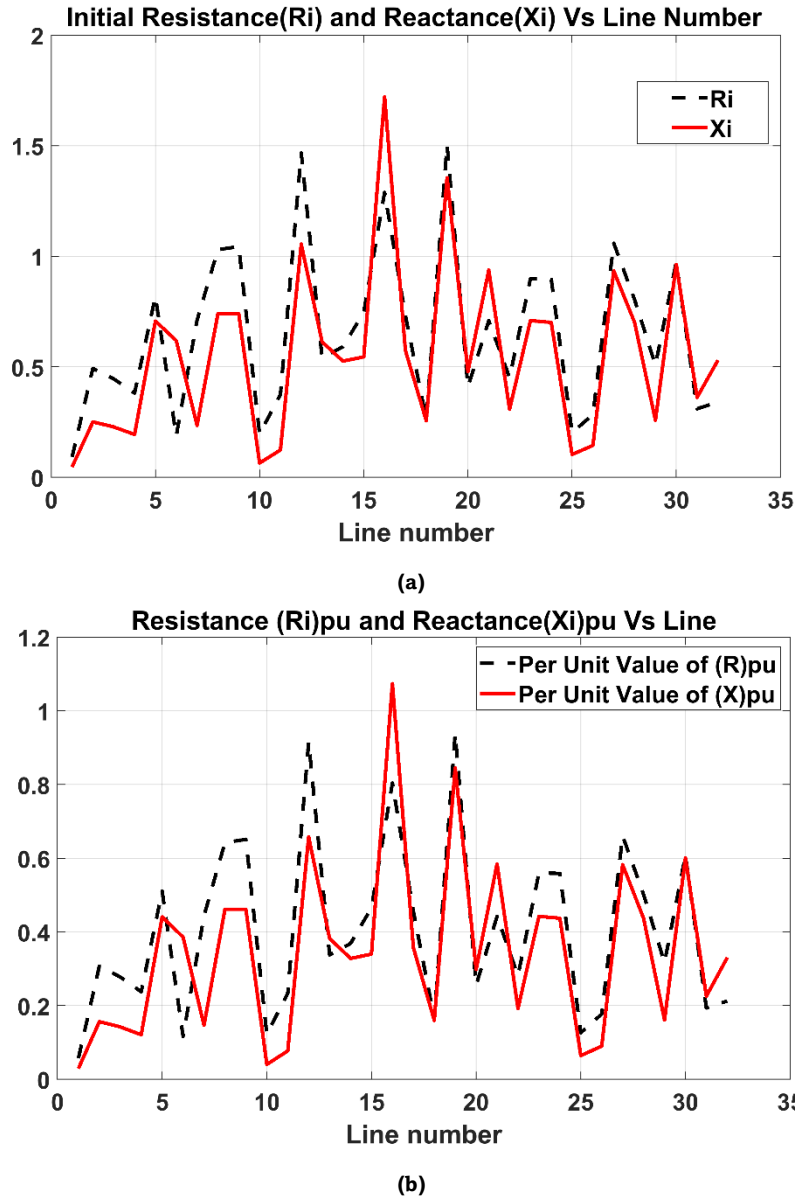


Fig 7 (a) A plot of resistance and reactance of take-out from load data of the IEEE-33 bus network, (b) Per-unit values of resistance and reactance for each line in the IEEE-33 bus network.

The calculation of the base impedance (Z_b) is a crucial step in our analysis and has been carried out by considering the specified kilovolt (kV) and Mega-Volt-Ampere (MVA) rating of the IEEE-33 bus system. The formula for determining the base impedance (Z_b) is derived from equation (21), providing a fundamental reference point for our impedance analysis.

$$Z_b = V^2 / \text{MVA} \quad (21)$$

Additionally, the per-unit values (p.u.) for resistance, denoted as " $(R)_{p.u.}$ " and reactance denoted as " $(X)_{p.u.}$ " for each line are computed using the equations provided in 22 and 23.

$$(R)_{p.u} = R_i / Z_b \quad (22)$$

Here, " $(R)_{p.u.}$ " represents the initial resistance value extracted from the system's line database.

$$(X)_{p.u} = X_i / Z_b \quad (23)$$

Here, " $(X)_{p.u.}$ " represents the initial reactance value, which is likewise extracted from the network's line database.

Figure 7b depicts a graph illustrating the per-unit values of resistance " $(R)_{p.u.}$ " and reactance " $(X)_{p.u.}$ " for 32 lines within the 33-bus network. Upon examining the plot, it becomes evident that the line with the maximum resistance reaching 0.93851, corresponds to line number 19. Similarly, the line exhibiting the maximum reactance, registering 1.073775, is identified as line 16. In contrast, the line with the lowest resistance, measuring 0.057525912, is denoted as line number 1, and it also features the lowest reactance value at 0.029324.

5.2. Biomass-Based Distributed Generator Model

Biomass resources can be converted into syngas (Syngas from biomass gasification is a flexible fuel including hydrogen and carbon monoxide. It is derived from renewable sources such as agricultural leftovers and is used in the production of electricity and biofuel) through various processes like direct combustion, gasification, and mixed combustion, contributing

Table 1

Parameters of energy calculation used in the Ceibales landfill.

Parameters	Values
ICM engine efficiency (η)	40%
Plant availability factor (CF)	85%
Recoverable efficiency (γ)	71%
LHV	18 MJ/m ³
An exchange factor of MJ to kWh(γ_1)	3.57

to the fight against climate change and reducing dependence on fossil fuels. According to (Zhao & Feng, 2014), gasification systems may generate power between 0 and 6 MW, whereas direct and mixed combustion can generate up to 25 and 140 MW. Biomass generators, particularly in rural areas, offer an eco-friendly alternative to conventional diesel generators, utilizing abundant biomass feedstock. Implementing green energy not only ensures food and water security but also enhances environmental quality in rural communities. Biomass-power generation systems, employing the steam cycle, convert biomass materials into steam, which powers a turbine connected to a generator, producing electricity effectively (Akorede, Hizam, & Pouresmaeil, 2010). Despite Methane (CH₄) combustion producing Carbon dioxide (CO₂) in internal combustion engines, it's a better option than releasing CH₄ directly into the atmosphere, which is significantly more harmful. However, ineffective allocations can impact the efficiency of a distribution system (Barragán-Escandón *et al.* 2020).

Equation (15) is defined to calculate the potential electric power that could be generated by biogas. This formula relates the production of biogas usable energy in the form of electric power and heat (Barros, Tiago Filho, & Da Silva, 2014).

$$E_{dis} = \frac{LHV \cdot Q_{br} \cdot \eta}{\gamma_i} \quad (15)$$

Where, E_{dis} is the obtainable electric power in (kWh/year) and LHV is the lower calorific value of biogas. Q_{br} is the recoverable flow (m³/y) of biogas, η is the generating element's electrical efficiency at converting heat into electricity (Turbine, Microturbine, or internal combustion engine (ICM), and γ_i is the change feature MJ into kWh (MJ/0.28kWh).

The electricity produced by the generator can be calculated from equation (18).

$$P = \frac{E_{dis}}{8760 \cdot CF} \quad (16)$$

Where, P represents the amount of electricity produced by the generator in (kWh/year) and the capacity (CF) or plant accessibility factor, which is typically taken into between 80% and 90% (Blanco, Santalla, Córdoba, & Levy, 2017).

Table 1 outlines the parameters used to calculate the energy in the Ceibales landfill (Barragán-Escandón *et al.*, 2020). The ICM efficiency (η) is set to 40%. The plant availability factor (CF) is estimated to be 85 percent. The recoverable efficiency (γ) is set at 71%. The lower heating value (LHV) is set at 18 MJ/m³. In addition, an exchange factor (γ_1) of 3.57 is used to convert MJ to kWh. These factors are critical in the energy evaluation of the Ceibales dump, as they help to determine its potential for energy generation

The emission factor values for various pollutants are taken into account and presented in Table 2. Additionally, the table indicates that the emission penalty for each pollutant is 0.000008745 \$/g. The CO₂ emission factor is higher than any other pollutant (Ahmed OY)

Table 2

Important parameters considered for BMDG's emission of pollutants calculation.

Sr. No.	Emission Parameters	Values
01	CH ₄	22 g/kWh
02	CO ₂	3000 g/kWh
03	SO ₂ (Sulfur dioxide)	0 g/kWh
04	CO (Carbon Monoxide)	25 g/kWh
05	SOOT (Amorphous Carbon)	0.700 g/kWh
06	NO _x (Nitrogen Oxides)	5 g/kWh
07	Unburned hydrocarbons	0 g/kWh
08	Particular matters	0 g/kWh
09	Penalty for each emission pollutant	0.8745

6. Results and Discussion

This research utilizes the PSO algorithm and evaluates its performance on the IEEE-33 bus network in MATLAB to assess its effectiveness in optimizing the position and size of one or more BMDG units for voltage profile and electric power loss reduction. The planned optimization technique is applied using MATLAB-2018a software. The simulations have been conducted on a laptop equipped with an Intel® Core™ i7-3720QM CPU operating at 2.60GHz and 16GB RAM. The results are provided in detail for further analysis in the following sections.

6.1 Performance Analysis of the Proposed System without BMDG

The absence of DG units clearly impacts the overall efficiency of the power distribution network. The high losses at specific buses, such as bus 33, underscore the challenges in maintaining an efficient power flow without supplementary DG

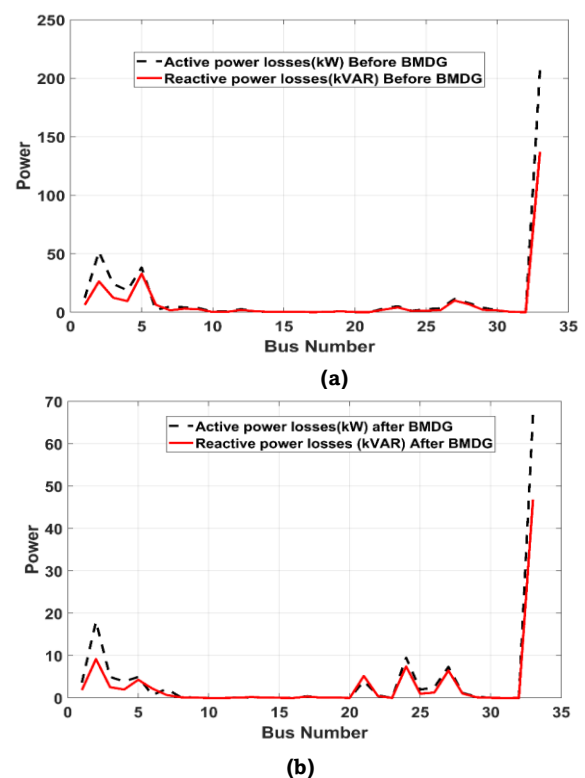


Fig 8. (a) Active and reactive power losses without BMDG, **(b)** Active and reactive power losses with the integration of BMDG.

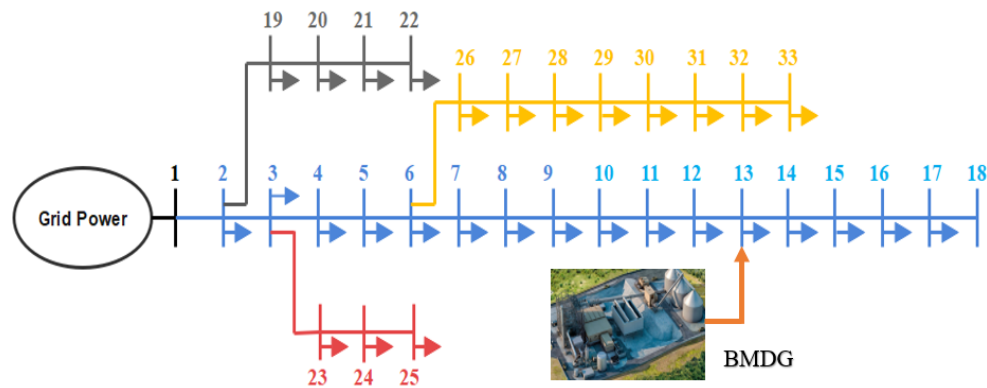


Fig 9. Standard IEEE-33 RDS system with integration of OLSBMDG.

sources. Biomass-based DG units play a crucial role in reducing such losses, thereby enhancing the performance and reliability of the power system.

In Figure 8a, the analysis of (ARP) in the absence of a biomass-based distributed generation DG unit is illustrated. The chart highlights significant power losses across various buses in the system. Notably, bus 33 stands out with the highest active power loss, amounting to 206.95 kW. In addition to active power losses, bus 33 also experiences substantial reactive power losses, totaling 137.13 kVAR. The lowest voltage (0.9116 per unit) was recorded at bus 18, while the highest voltage (0.9970 per unit) was observed at bus 2.

This performance analysis indicates the potential benefits of integrating biomass-based DG units. Without them, certain areas of the power distribution network experience considerably higher power losses, which can lead to inefficiencies and increased operational costs. Therefore, the inclusion of biomass-based DG units is vital for improving energy efficiency, reducing losses, and ensuring a more robust and reliable power distribution system.

6.2 Performance Analysis of the Proposed System with BMDG

DG systems can be categorized into two broad kinds: renewable and non-renewable DG. In this research, our focus is on the analysis of BMDG as a represented renewable energy resource. This investigates the impact of OLSBMDG within an RD system. All bus bars, with the exception of bus-1, are investigated in this study as viable possibilities for incorporating BMDG; bus-1 acts as a slack bus meant to be connected to an external utility.

The proposed PSO-based model has been applied to find the OLSBMDG in a distribution system to increase the efficiency of RDS. The optimized results show that integrating the BMDG unit at node 13 and sizing it at 2981 kVA produces optimal outcomes. In this manuscript, Figure 9 illustrates the optimal location and size for a BMDG within a 33-bus system. The best location and size considerably reduce ARP losses, enhancing the system's voltage profile. Furthermore, the BMDG integration not only improves electrical efficiency but also helps to reduce global warming impacts and achieve annual cost savings. This overall improvement highlights the efficiency of the PSO-based strategy in optimizing the distribution networks.

The strategic positioning and sizing of BMDG resulted in considerable reductions in both active and reactive power losses. The active power loss reduced from 206.95 kW to 66.90 kW, while the reactive power loss decreased from 137.13 kVAR to 46.88 kVAR, as illustrated in Figure 8b. These results reflect a significant improvement in limiting real power losses over the

base case findings provided in Section 6.1. The significant reduction in both types of power losses demonstrates the efficacy of the optimal BMDG method in improving the distribution network. This reduction not only reduces energy waste but also improves overall system reliability, demonstrating the efficacy of the proposed approach in optimizing power distribution and improving sustainability.

The voltage levels at the end terminals (nodes 18, 22, 25, and 33) of the IEEE 33-bus distribution system are much lower than at other nodes due to their distance from the substation, distribution line impedance, load distribution, and radial network layout. The integration of BMDG has significantly improved these voltage levels. BMDG enables localized generating, lowering the distance power has to travel and minimizing voltage inclines. In addition, BMDG provided voltage support and regulation to counteract inductive load effects, as well as reduce line losses by supplying power locally. This improved the overall voltage profile. Specifically, BMDG integration increased the voltage at node 18 by 7.304%, while the average voltage enhancement across the terminal nodes (18, 22, 25, and 33) was 3.5088%. These improvements are clearly depicted in the per-unit voltage levels illustrated in Figure 10, demonstrating BMDG's effectiveness in improving voltage stability and quality in an IEEE 33-bus system.

The influence of the BMDG on enhancing the voltage profile of the proposed network is visually presented in Figure 11. This graphical representation offers a distinct and persuasive comparison between the voltage profiles of the network with and without the integration of the BMDG system. Significantly, the introduction of the biomass-based DG to the 33-bus system has resulted in substantial improvements in the voltage profile. Notably, at node 18, the voltage level has shown a notable increase from 0.9116 p.u to a more resilient 0.9780, when the BMDG unit has been seamlessly incorporated. The maximum voltage within the system remained constant at 1 per unit, occurring at node one. With the implementation of the BMDG system, an overall enhancement of the system's voltage profile by 7.28% was observed, resulting in notably improved system performance and 51.67% higher improvement presented in (Alajmi *et al.* 2023)

Table 3 summarizes the model's results, and reveals the substantial improvements achieved after the addition of a 2981 kVA BMDG unit at 13 bus. The data indicates a prominent reduction in total active power losses by 67.68% and a corresponding decrease of 65.90% in reactive power losses from the base case (without integration of BMDG in the IEEE 33 bus system). These findings underscore the effectiveness of the BMDG system in improving the overall efficiency of the

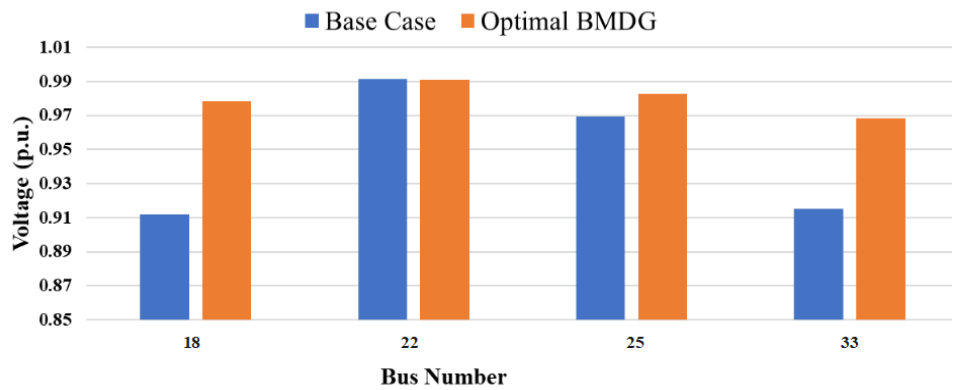


Fig 10. Far-end bus voltage enhancement with optimal BMDG

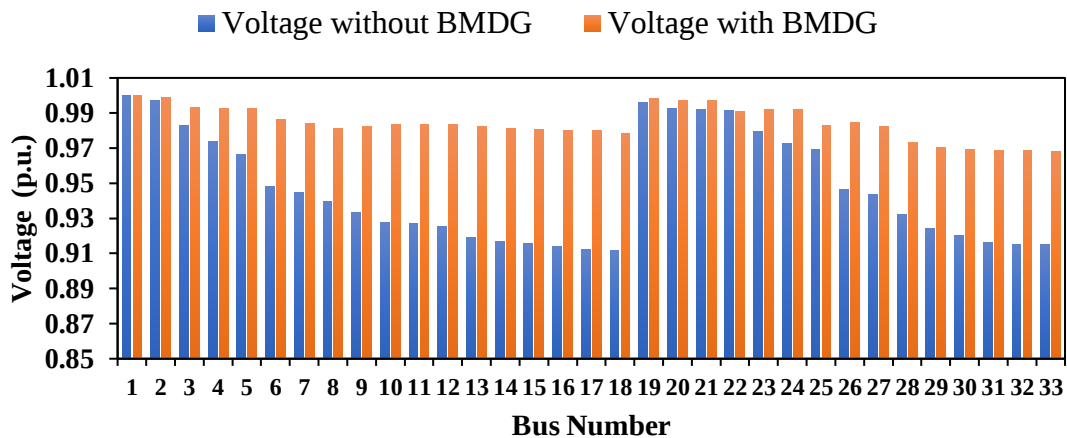


Fig 11. Voltage profile without BMDG and with BMDG.

distribution system. Beyond the enhancements observed in the voltage profile and power loss reduction, the system has undergone a positive transformation. Before integration, the voltage level stood at 0.9116 p.u. but with the inclusion of the BMDG unit, it rose to an improved 0.9780 p.u. This boost in voltage levels not only signifies an improvement in system stability but also contributes to better overall performance and reliability. Moreover, the cost of loss has been reduced from 108772.92\$ to 35162.64\$ by the integration of BMDG.

Figure 12 shows the annual energy cost savings for the proposed study, indicating a significant rise in savings as a result of lower power losses. Based on a \$0.06 unit cost, the annual

savings total \$73,606.28, which is more than the amount that was found in earlier research by (Fathy, 2022) (Alajmi *et al.* 2023; Roy *et al.* 2023). This substantial improvement demonstrates how well the suggested PSO-based approach works to optimize BMDG allocation and development in a 33-bus system.

The integration of BMDG at node 13 with a capacity of 2981 kVA has significantly decreased ARP losses while improving the voltage profile. The planned positioning and sizing of BMDG not only improves electrical efficiency but also helps to reduce global warming impacts by lowering emissions related to power generation. Furthermore, the incorporation of

Table 3
Main results obtained with BMDG and without BMDG by the proposed system.

Sr. No.	Parameters	Without BMDG	With BMDG
01	Active Power loss (kW)	206.95	66.90
02	Reactive Power loss (kVAR)	137.13	46.88
03	Loss reduction in Pi (%)	-	67.68
04	Loss reduction in Qi (%)	-	65.90
05	Lowest voltage (p.u) @ bus	0.9116 @ 18	0.9780 @ 18
06	Highest voltage (p.u) @ bus	0.9970 @ 2	0.9989 @ 2
07	Cost of losses (\$)	108772.92	35162.64
08	Saving (\$/year)		73606.28
09	Total BMDG (Size @ Location)	-	2981kVA @ bus 13

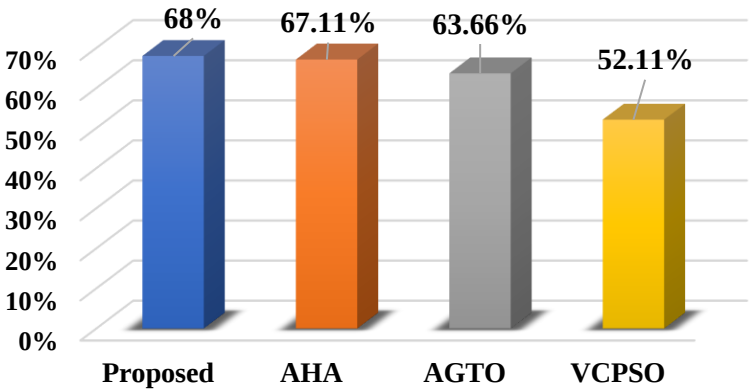


Fig 12. Comparison of annual cost savings with the BMDG system.

Table 4.
The estimated emission values and penalty expenses results of the proposed model.

Subjects	With centralized BMDG					At the optimal location and size of BMDG				
Active Power loss (kW)	206.95					66.90				
Pollutant	CO ₂	NO _x	CO	CH ₄	SOOT	CO ₂	NO _x	CO	CH ₄	SOOT
Emission (g)	620850	1304.75	5173.75	4552.9	144.865	200700	334.5	1672.5	1471.8	46.83
Emission Penalty (\$)/kWh	0.552706969					0.178595313				
Emission cost penalty in year (\$)	4839.6					1564.5				
Emission penalty cost savings in a year (\$)	-					3275.1				

BMDG results in significant annual cost savings, demonstrating the system's advantages over earlier techniques. This overall improvement in cost savings and system performance highlights the PSO-based strategy's potential to improve distribution network sustainability and efficiency

The anticipated pollution emissions and corresponding penalty expenses for the proposed system are represented in Table 4. This tabulated data presents the emission details for each pollutant generated by the BMDG over different hours and in the initial year. Additionally, the table includes the associated penalty costs for each pollutant during both hourly intervals and the first year. Notably, the results show that CO₂ exceeds other pollutants, resulting in a proportionately bigger impact on overall penalty expenses, as seen in the table. The results show that when the BMDG is integrated at a centralized point, both emissions and penalties are higher compared to its optimal position and size. This emphasizes the importance of strategically placing and sizing BMDG units to minimize emissions and associated costs. Optimal placement and sizing significantly reduce the environmental and financial impact, enhancing the system's efficiency and sustainability

The proposed PSO based model significantly enhanced the performance of the RDS when compared to various other optimization algorithms. The key parameters evaluated include voltage improvement, reduction in active and reactive power losses, execution time, and annual cost savings. The execution time for the proposed system is impressively short, completing in just 5.70 seconds to yield optimized results. The execution time in this research is much lower than compared to existing techniques in the literature (Fathy, 2022) (El-Fergany 2015) (Roy *et al.* 2023) (Alajmi *et al.* 2023) (Ranga *et al.* 2024). This study has demonstrated the efficacy of the BMDG unit, especially when strategically placed at the 13th bus with a capacity of 2.981 MW.

The magnitude of the improvement achieved in power loss reduction is outstanding, with active power losses reduced by 67.68% and reactive power losses dropping by 65.90% from the base case. This considerable achievement places in proposed results ahead of other techniques, as exemplified by the comparison with the AGTO method (Roy *et al.* 2023), presented in Table 5. The efficiency of the proposed result in terms of active power losses demonstrates a more significant reduction of 67.68% from the base case and existing literature ABC (Abu-Mouti and El-Hawary 2011), BSOA (El-Fergany 2015), MFO (Das and Srivastava 2017), Coordinate control (Bhargava *et al.*, 2021), AHA (Fathy, 2022), VCPSO (Alajmi *et al.* 2023), AGTO (Roy *et al.* 2023), and JSO (Ranga *et al.* 2024) have been reduced 48.19%, 60.76%, 47.38%, 66.48%, 67.11%, 52.13%, 63.96%, and 52.72% respectively from the base case. Additionally, the reactive power losses of 65.90% from the base case also have been compared with the existing literature algorithms, such as the VCPSO (Alajmi *et al.* 2023) and AGTO (Roy *et al.* 2023) which have been reduced by 47.64% and 56.97% respectively from the base case

For voltage improvement, the proposed method has obtained a voltage level of 0.9780 at bus 18, which is the highest among the compared techniques. This specifies a better voltage profile in the RDS. In contrast, methods such as the AHA (Fathy 2022) and Coordinate Control (Bhargava *et al.* 2021) have demonstrated the voltage improvements of 0.9761 and 0.9684 respectively at bus 18, which are slightly lower than the PSO method

Regarding annual cost savings, the proposed model has achieved the highest annual cost savings of \$73,606.28. This surpasses the cost savings of other approaches such as AGTO (\$69,571.16) and VCPSO (\$56,703.32) (Roy *et al.* 2023) (Alajmi *et al.* 2023). The significant annual cost savings are the result of

Table 5
Performance Comparison of the PSO-based model results with the existing literature techniques

References	Method	Improvement in Lowest Voltage @ Bus	Active Power Loss Reduction %	Reactive Power loss reduction %	Execution Time (Sec)	Maximum Cost Savings (USD)
(Abu-Mouti & El-Hawary, 2011)	ABC	-	48.19	-	-	-
(El-Fergany, 2015)	BSOA	-	60.76	-	36.87	-
(Das & Srivastava, 2017)	MFO	-	47.38	-	-	-
(Bhargava <i>et al.</i> , 2021)	Coordinate control	0.9684 @ 18	66.48	-	-	-
(Fathy, 2022)	AHA	0.9761 @ 18	67.11	-	409.92	72997.51
(Alajmi <i>et al.</i> , 2023)	VCPSO	0.948 @ 18	52.13	47.64	29	56703.32
(Roy <i>et al.</i> , 2023)	AGTO	0.9580 @ 18	63.96	56.97	21.2	69571.16
(Ranga <i>et al.</i> , 2024)	JSO	0.9522	50.72	-	12	-
Proposed System	PSO	0.9780 @ 18	67.68	65.90	5.70	73606.28

the efficient decrement in power losses and the associated pollutants penalties.

It is seen that the proposed PSO-based system demonstrated better performance in all evaluated parameters. It achieved the best voltage improvement, the highest reductions in active and reactive power losses, the fastest execution time, and the greatest cost savings. These results highlighted the PSO method's effectiveness and efficiency in optimizing the performance of power distribution systems with biomass-based distributed generators. The comprehensive improvements in technical, economic, and environmental characteristics highlighted the proposed technique as a leading solution for increasing the sustainability and dependability of power distribution networks

7. Conclusion

This study harnessed the effect of the PSO algorithm to strategically position and optimize the size of a biomass-based distributed generator within the IEEE-33 bus system, with a primary objective of minimizing power losses, reducing the emission penalty cost, increasing the annual saving cost, and improving the voltage level. The results obtained from the proposed analysis, conducted on this established benchmark, demonstrated significant improvements across multiple key aspects.

The BMDG unit is integrated into the 33-bus system at its optimal location and sizing. The proposed analysis demonstrated a considerable reduction in energy losses, encompassing power (active and reactive). Active power losses have been notably decreased by 67.68%, while reactive power losses have been reduced by 65.90 % when compared to the base case. Moreover, active power loss reduction has been achieved by 40.44%, 11.39%, 42.85%, 1.81%, 0.85%, 29.83%, 5.82% and 28.38% compared to the values achieved by using ABC, BSOA, MFO, Coordinate control, AHA, VCPSO, AGTO, and JSO respectively. Additionally, the reactive power losses of 65.90% have been reduced from the base case. More so this loss reduction was compared with the existing literature algorithms, such as the VCPSO and AGTO and found to be reduced by 38.33% and 15.68% respectively. With the integration of the BMDG unit, an overall enhancement of the voltage profile was 7.28%, resulting in notably improved system performance from the base case and also higher improvement was achieved as compared to existing literature. The computational time of the algorithm was recorded as 5.70 seconds for PSO. The annual cost saving of the BMDG model is \$73606.28 which is more than

the previous proposed model. The penalty cost of emission from BMDG is reduced from \$4839.6 to \$1564.5 at its optimal location and size and the annual emission penalty cost savings achieved is \$3275.1.

In summary, the proposed technique results confirm that optimizing BMDG with the PSO method proves to be a viable solution for mitigating electrical power losses, improving voltage profiles, reducing emission costs, and enhancing annual cost savings within the RDS. Furthermore, this integration contributes to an overall boost in the efficiency of the RDS network and can reduce dependency on the central utility system during periods of peak demand.

The future perspective of the proposed research could be extended with the integration of various sources i.e. fuel cells, wind, photovoltaic, and battery storage. Furthermore, conducting comparative studies between biomass and wind DGs would provide valuable insights. Lastly, addressing the challenges posed by load requirement uncertainties remains an important aspect of future research in this domain.

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