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Research paper

# Optimal Sizing and Placement of Renewable Energy Sources in Power System Connected Multi-Microgrids

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**ABSTRACT**

Large scale integration of distributed generation of medium and low voltage (LV) networks can be achieved by exploiting the Multi-Microgrid (MMG) concept, worldwide due to the increasing penetration of renewable energy sources. A modern technology based on the use of microgrids where DG penetration is beneficial if optimally placed. A new radial power system architecture allows the coordination between distributed generation units and Micrigrids (MGs) and thus the operation of such a system in islanded mode. Different microgrid models are developed for optimal location and capacity of renewable energy RES. In this context, this paper deals with an optimal approach to find the best location and sizing capacity of DG units in a radial electrical system (RDS) using metaheuristic optimization algorithms. The objective was to minimize the total active power losses with the assurance of a good voltage profile. The application of Particle Swarm Optimization (PSO) on the IEEE 33-bus network shows the validity of the proposed algorithm to minimize power losses and incorporate optimal micro-grid in the appropriate buses, which gives the optimal capacity and location of microgrid in the distribution network.

## 1. INTRODUCTION

In recent years, economic concerns, environmental pollution problems and global warming have led to significant changes in electrical network. Moreover, there is a novel trend of introducing clean energy resources and storage devices at the radial distribution system level for improvements. Energy consumers, engineers and industry owners have shown great interest in local connection of green energy resources at the distribution levels. With the increase in the penetration level of such resources, conventional distribution systems are transformed into multiple interconnected systems, and the

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evolution of local energy provisions gives rise to the conception of microgrid (MG) (Daryani at al., 2019; Hadidian-Moghaddam at al., 2017). MGs are mainly built from renewable energy sources (RES) focusing on the independence of local energy supplies (Phommixay, 2021). Microgrid consists of a low voltage network composed of loads, renewable energy sources and distribution generating units (DGs), energy storage devices, load and control devices together and supplies electricity to the consumer side (Yang et al.,2016). Meanwhile, microgrid is able to quickly respond to electricity demand, also enhance the reliability, efficiency, resilience and security of power supply against unexpected and critical events (Huang et al., 2008). Interconnecting multi-area MGs through AC and DC power flow tie-lines and building a resilient interconnected multi-microgrid (MMG) energy system has attracted more attention among researchers, linking MGs strengthens the system against extreme weather conditions and natural disasters and enhance the dynamic performances of the whole grid, while maintaining the flexibility to operate in model isolated areas and exploiting the advantages of MGs (Kargarian et al., 2015). However, the evolution of multi-Microgrids (MMGs) shows novel challenges in modern power systems. Specifically, the issue of synchronizing operations of systems that may function independently, interlinked with other Microgrids, and/or linked to primary grids, each with diverse objectives and constraints (e.g., cost optimization, reliability enhancement, emission reduction, etc.) emerges. This issue was framed by considering various facets of the distribution system, such as the stochastic and intermittent characteristics of green power resources and the probabilities or hourly load profile (Madureira et al., 2011). To have a practical design, a typical fuel mix of DER consisting of wind turbines, photovoltaic (PV) modules and diesel generators was considered. After designing the microgrids and assigning the DERs, as a public service action, to three different scenarios are followed to improve the operation of constructed microgrids (Arefifar et al., 2018). In the goal to combine both of the economic aspect and the technical issues related to the microgrid operation model, the employed strategy involves many fitness functions, where the optimization issue was modelled as a multi-objective problem to minimize at same time the energy losses and find the best capacity with optimal microgrid connection bus. The strategically positioned Distributed Generation (DG) could effectively minimize active power loss and improve the voltage profile. The optimization problem takes into account the voltage safety constraint, thereby significantly enhancing the operational efficiency of active distribution networks in grid-connected mode. This method not only boosts the performance of power grids but also fortifies the resilience of intelligent operation modes (Samala et al., 2017). However, the best location and capacity of DGs in the radial network is an important problem issue. A similar technique has been developed to solve the optimal problem of integrating microgrid containing photovoltaic, wind generator, battery, diesel generator and constant and variable load for the improvement of radial distribution network. The main difference between a microgrid and a distribution grid is that in microgrids, the distributed energy resources are directly connected and operate in a coordinated manner, whether in grid-connected or islanded mode. Meanwhile, since the microgrid often consists of a large number of devices, the nature-inspired PSO algorithm was used to solve the multi-objective issue and find the best solution for the optimal size and bus connection of the MGs with minimization of active power loss (Ramakrishnan et al., 2018). It has been demonstrated that the optimal positioning of Microgrids (MGs) in Radial Distribution Systems (RDS) utilizing the Particle Swarm Optimization (PSO) algorithm yields superior loss reduction and rapid convergence characteristics (Angalaeswari, 2015). The PSO algorithm has garnered significant attention from researchers owing to its efficacy and simplicity. Originating from the dynamics of bird flight and fish schooling, the PSO algorithm represents a versatile and robust population-based optimization technique that has been widely adopted by researchers for addressing engineering challenges and various engineering issues (Eberhart, 1995).

This paper addresses a multi-objective optimization (MOO) method based on particle swarm optimization (PSO) was proposed to solve the optimal MG sizing and placement problem in a radial distribution power system with reliability considerations. The proposed method was implemented on the distribution networks of IEEE 16 bus and IEEE 33 bus systems, where obtained results are compared. The remainder of this document is structured as subsequent sections. Section 2 demonstrates the MG modelling. Section 3 presents the problem formulation. Section 4 was devoted to present the application study and numerical results. Finally, Section 5 concludes the chapter.

## 2. MICROGRID MODEL

Microgrids are mainly built from renewable energy sources (RES). The investigated MG in this work consists of Diesel Generator, Battery Storage, Solar PV Generator, Wind Generator, constant and variable Load as shown in Fig.1. The investigated microgrid was connected to the primary grid using the point of common coupling (PCC), where during the simulation, the MG was simulated as islanded and connected system using the breaker device.

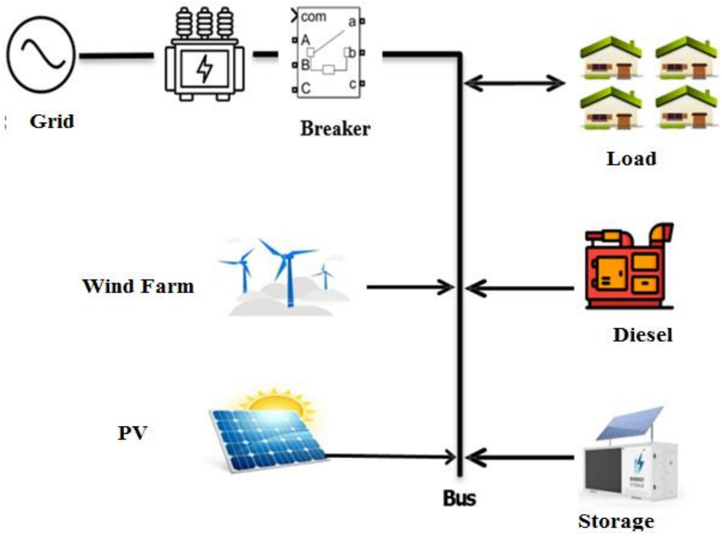


Fig 1. Proposed Microgrid Model.

### 2.1 Diesel Generator Model

The amount of fuel consumed and its cost can be calculated by using the following expressions:

$$C_{dg} = C_f \sum_{t=1}^{t=\frac{365j}{10min}=52560} F(t) \tag{1}$$

Where,

$C_f$ : the cost of fuel by liter.
$F(t)$: the amount of fuel consumed for each hour; and the formula for F(t)is shown below (Yimen et al., 2020):

$$F(t) = AP_{dg} + BP_r \tag{2}$$

Where, $P_{dg}$ represent the diesel engine power output and $P_r$ represent the diesel engine rated capacity. During the simulation the values of A and B are equal to 0.246 l/kWh and 0.0845 l/kWh respectively.

## 2.2 PV Panel Modeling

The electricity generated by each solar photovoltaic (PV) module is contingent upon the module's characteristics, the intensity of solar irradiation, and the ambient temperature (Liu et al., 2011). The following three equations present the mathematical model of a classical photovoltaic solar panel.

$$I_{pv} = n_p I_{ph} - n_p I_{sat} \times [exp\left(\left(\frac{q}{AKT}\right)\left(\frac{V_{pv}}{n_s} + I_{pv}R_s\right)\right) - 1] \tag{3}$$

$$I_{ph} = (I_{sso} + k_i(T - T_r))\frac{S}{1000} \tag{4}$$

$$I_{sat} = I_{rr}\left(\frac{T}{T_r}\right)^3 exp(\left(\frac{qE_{gap}}{kA}\right).\left(\frac{1}{T_r} - \frac{1}{T}\right)) \tag{5}$$

Where:

*Iph* : Photocurrent
*Isat*: Module reverse saturation current
*Ipv*: PV current
*np*: number of cells parallel
*q*: Electron charge
*Rs*: series resistance of PV cell
*T*: Reference temperature
*Tr*: Temperature
*S*: solar radiation level
*Isso*: short-circuit current
*ki*: short-circuit current temperature coefficient

## 2.3 Wind Power Generation Model

The wind turbine is a device that converts the kinetic energy of the wind into mechanical energy. The power generated by the air mass passing through the active surface S of the wing is derived from the kinetic energy of the moving air particles. The efficiency of a wind turbine is influenced by various factors, including the design of the blades and the wind speed. The shape and length of the blades determine how much energy can be extracted from the wind. Additionally, the wind speed plays a crucial role in the power output of the turbine. Higher wind speeds result in more kinetic energy being available for conversion. Moreover, the location of the wind turbine also impacts its performance. Placing turbines in areas with consistent and strong winds can significantly increase their energy production. Proper maintenance and regular inspections are essential to ensure the longevity and optimal functioning of wind turbines. By monitoring performance metrics and addressing any issues promptly, the overall efficiency and reliability of wind energy systems can be maximized. The wind turbine power is determined by:

$$p_w = \frac{1}{2} c_p(\lambda, \beta) \rho A v_{wind}^3 \tag{6}$$

Where:

$p_w$ describes the wind turbine mechanical power.
$c_p$ presents the power coefficient.
$\lambda$ is the optimal tip speed ratio.
$\beta$ is the blade pitch angle (*deg*).
$\rho$ is the air density (*kg/m3*).
$A$ :is the wind turbine swept area (*m2*).
$v_{wind}$ is the wind velocity (*m/s*).

## 2.4 Battery Energy Storage Modeling

Energy storage (ES) devices operate in two states, namely charging and discharging modes. ES units would act as a load when operating in charging mode and would be energy generators during the discharging time (Daryani at al., 2019). Two important parameters to represent the state of a battery are terminal voltage and state of charge (SOC) as follows (Liu et al., 2011).

$$V_b = V_0 + R_b . i_b - Kb \frac{Q}{Q + \int i_b dt} + Ab . \exp(Bb \int i_b dt) \tag{7}$$

$$soc = 100(1 + \frac{\int i_b dt}{Q}) \tag{8}$$

Where:
The internal resistance of the battery is given by $R_b$
$V_0$ represents the voltage when no charge is connected to the circuit.
$i_b$ describes the battery current.
$Kb$ is the bias voltage.
Q is the battery capacity.
$Ab$ represents the exponential voltage and $Bb$ is the exponential capacity.

## 2.6 Load Model

Load characteristics have a major influence on system stability and dynamics, which is modeled as follows:

$$S_L = P_L + Q_L \tag{9}$$

## 3. PROPOSED OPTIMIZATION PROBLEM

An optimization problem was based on the formulation of the objective function, decision variables, and constraints. The objective function represents the quantity to be maximized or minimized, the decision parameters are the gains under control, and the constraints are the limitations or conditions that the solution must adhere to. Once these components are defined, various optimization techniques can be applied to find the best solution (Naimi & Salhi, 2015). The function f represents the function to be minimized according to the optimization case, in our case it represents the power losses. It is shown that the optimal energy production of MG at the desired bus has the capability to effectively diminish the active power loss of a distribution system (Acharya, 2006). Therefore, the main goal of the presented study was framed as a minimization of the power loss in the distribution system, with the precise formula for active power loss PL being denoted by:

$$Minimize P_L = \sum_{i=1}^{n}\sum_{j=1}^{n}\left[\alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j - P_iQ_j\right)\right] \tag{10}$$

Where,

$$\alpha_{ij} = \frac{r_{ij}}{V_iV_j}cos\left(\delta_i - \delta_j\right) \tag{11}$$

$$\beta_{ij} = \frac{r_{ij}}{V_iV_j}sin\left(\delta_i - \delta_j\right) \tag{12}$$

$$Z_{ij} = r_{ij} - jx_{ij} \tag{13}$$

$$P_{Gi} - P_{Di} = \textstyle\sum_{j=1}^{n} V_iV_j\left[G_{ij}cos\left(\delta_i - \delta_j\right) + \beta_{ij}sin\left(\delta_i - \delta_j\right)\right] \tag{14}$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{n} V_iV_j\left[G_{ij}sin\left(\delta_i - \delta_j\right) - \beta_{ij}cos\left(\delta_i - \delta_j\right)\right] \tag{15}$$

where,

$r_{ij}$ represents the power line resistance;
$x_{ij}$ is the power line reactance;
$Z_{ij}$ is the power line impendence;
$V_i$ is the voltage magnitude at bus *i;*
$\delta_i$ is the voltage angle at bus *i;*
$V_j$ is the voltage magnitude at bus *j;*
$\delta_j$ is the voltage angle at bus *j;*
$P_i$ is the active power at bus *i*;
$Q_i$ is the reactive power at bus *i* ;
$P_j$ is the active power at bus *j*;
$Q_j$ is the reactive power at bus *j*;
*n* is the total number of power system buses.
$P_{Gi}$ is the active power generated by the MG at bus i ;
$Q_{Gi}$ is the reactive power generated by MG at bus *i* ;
$P_{Di}$ is the load active power at bus *i*;
$Q_{Di}$ is the load reactive power at bus *i* ;
$G_{ij}$ is the conductance of the power line;
$\beta_{ij}$ is the susceptance of the power line.

The energy production limits is given by:

$$P_{GK\,min} \leq P_{GK} \leq P_{GK\,max} \tag{16}$$

where $P_{GK\,min}$&$P_{GK\,max}$ are the minimum & maximum power production limits of MG $k$ respectively. The bus Voltage Limits are given by:

$$V_{i\,min} \leq V_i \leq V_{i\,max} \tag{17}$$

where $V_{i\,min}$&$V_{i\,max}$ is minimum & maximum voltage limits of bus i respectively.

## Particle Swarm Optimization Algorithm (PSO)

Artificial intelligence methods refer to techniques and algorithms used to enable machines to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making (Brunette al., 2009). These methods often involve the use of algorithms like machine learning, neural networks, natural language processing, and computer vision to analyze data and make predictions or decisions (Oke, 2008). AI is used in a wide range of applications, from autonomous vehicles to medical diagnosis to personal assistants (Yang, 2010). ON the other hand, bio-inspired and nature-inspired optimization methods are algorithms that are based on the behavior of natural processes or phenomena. These algorithms mimic the evolutionary processes seen in nature, such as Simulated Annealing (SA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). By harnessing the power of nature-inspired algorithms, researchers and engineers are able to solve complex optimization problems efficiently and effectively (Nanda & Panda, 2014). These algorithms are used in a variety of applications, including engineering design, logistics, and financial modeling (Kouba et al., 2019). Particle Swarm Optimization (PSO) is basically based on the behavioral attributes of natural drift developed by a particle in a swarm of birds or of fish. In the 1995, PSO algorithm was developed by Eberhart & Kennedy (1995) to solve engineering problems (Acharya, 2006). These algorithms are inspired by insect swarms (or schools of fish or flocks of birds) and their coordinated movements, search for solutions for an optimization problem. The individuals of the algorithm are called particles and the population is called a swarm (Brik et al., 2024). PSO algorithm explores the best optimal global solutions in an engineering optimization challenge by interacting with the particles within a population. Each agent of the population possesses crucial characteristics in the form of particle position and velocity. Theoretically, within an optimization scenario, the particle's position denoted as "x" and its velocity denoted as "v" represent the current solution and incremental distance for subsequent iterations respectively. The adjustment of the position and velocity of the ith particle for successive iterations is accomplished by leveraging its existing velocity and the step length between the global optimal position and the local optimal position. This adjustment can be mathematically formulated as given (Eberhart & Kennedy, 1995).

$$v_{id}^{t+1} = \omega . v_{id}^{t} + \varphi_1 \left( P_{gd} - x_{id}^{t} \right) + \varphi_2 \left( P_{id} - x_{id}^{t} \right) \tag{18}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{19}$$

where,
$\omega$ is inertia weight;
$c_1$ & $c_2$ are the acceleration coefficients;
$t$ is the iteration count.

The diagram of the PSO algorithm is shown in Fig.2.

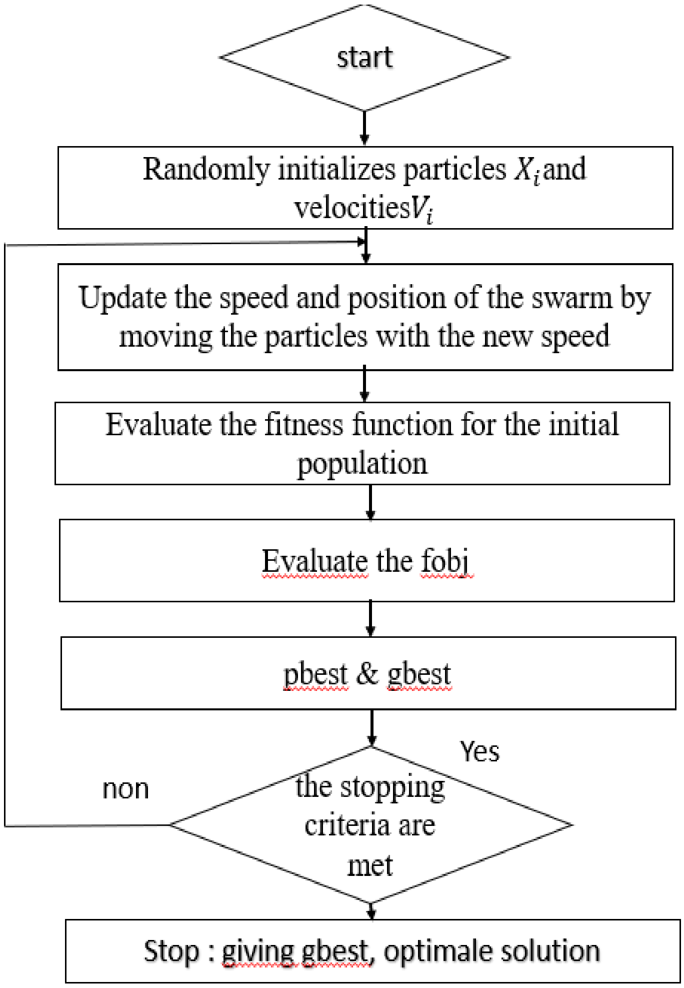


Fig 2. Flowchart of PSO algorithm.

## 4. SIMULATION RESULTS AND DISCUSSIONS

### 4.1 Analysis of a Hybrid Multi-Source System

Fig. 3 shows the schematic of the proposed microgrid system connected to the utility grid, which was chosen as the study system used for static and dynamic analysis. Then, a radial distribution grid was connected to the microgrid which is consisting of diesel engine, a wind farm, photovoltaic generator, storage battery, and two constant and variable loads. The microgrid is connected to the public power grid at the chosen bus via the PCC.

To show the impact of integration renewable energy sources on static and dynamic power system stability during faults, two scenarios have been simulated and presented as shown in Fig.4.

- Event 1: change of operating mode from On-Grid to OFF-Grid or isolated mode. The circuit breaker was opened at t=12 sec, changing system operating mode, the MG switches from connected operation mode to stand alone operation mode.
- Event 2: at t=35 sec a load variation was simulated via the connection of an extern variable load.

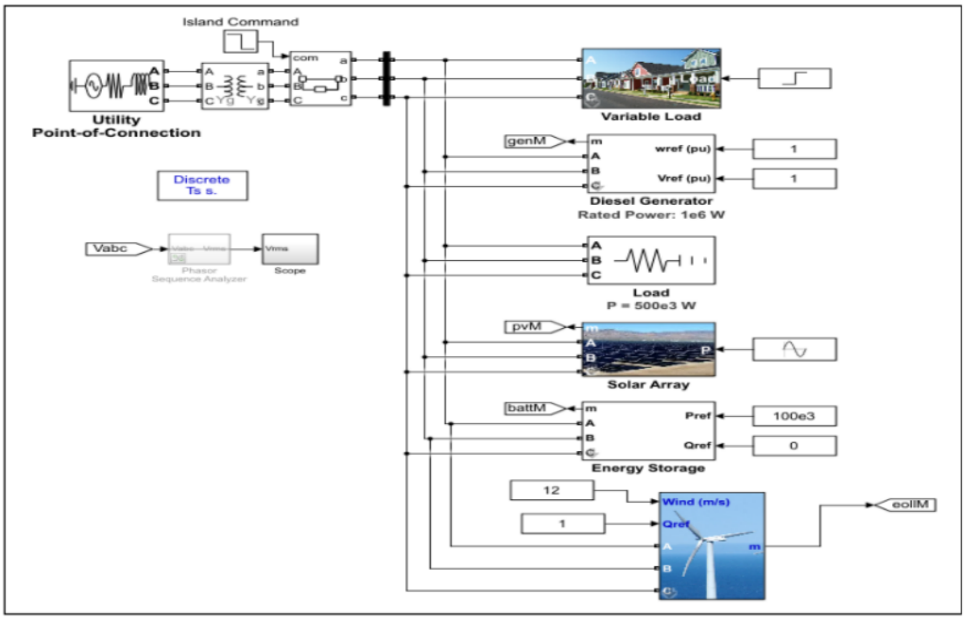


Fig 3. Grid-Connected Microgrid.

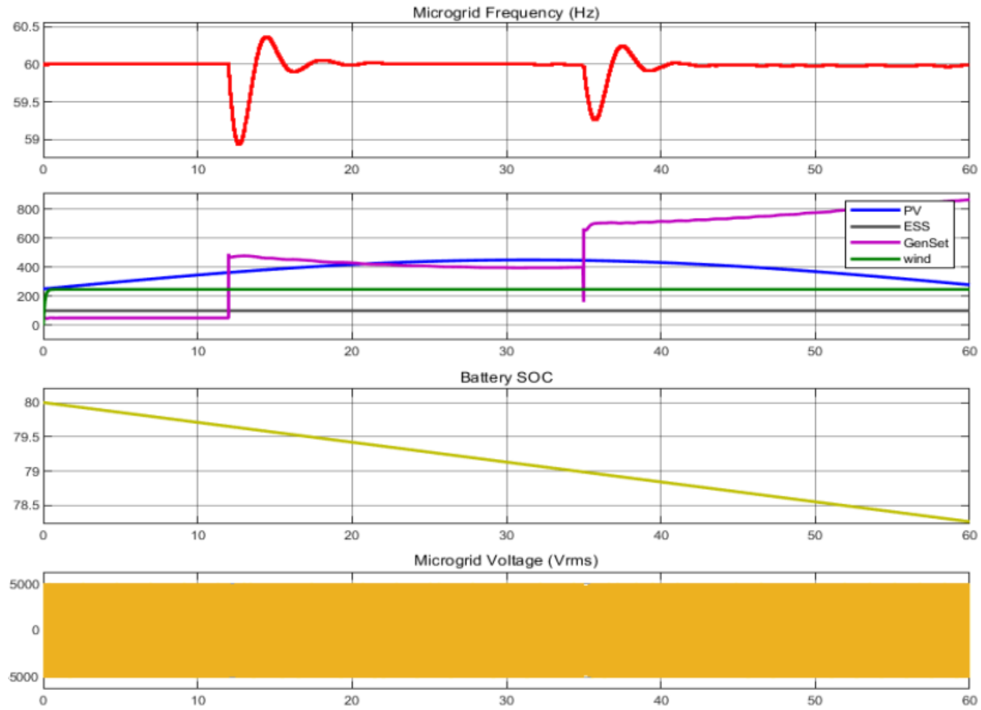


Fig 4. Hybrid system frequency and power.

## 4.2 Radial Distribution Network Integrated DG Units: Static Analysis

In this section, a radial distribution network is analyzed in presence of a hybrid multi-sources microgrid. The IEEE 16 bus network shown in Fig. 5 (Civanlar et al., 1988) is simulated for load flow analysis including MG at bus 15 to show the impact of integrating renewable energies on the voltage profile.

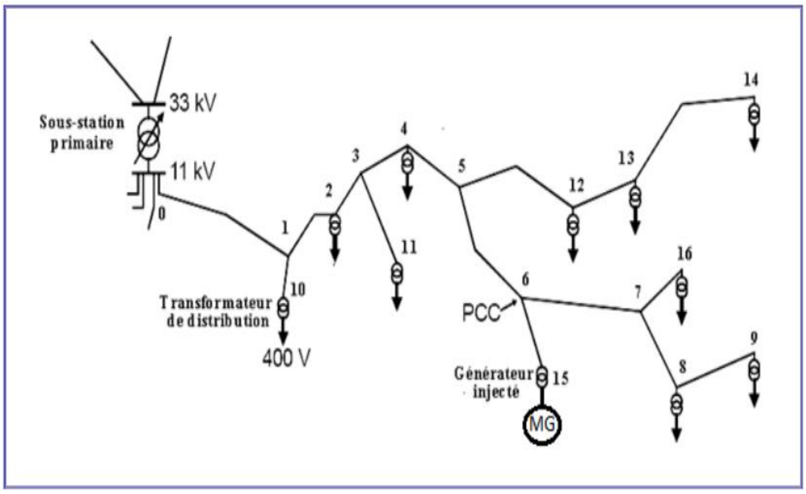


Fig 5. One-Line Diagram of the IEEE 16 bus Distribution Network.

In this scenario, bus 15 was selected to be the integration node of the connected MG. During the simulation, different power rates of penetration have been applied in the first case, and then the type of distributed generation sources have also changed from wind, PV and wind-PV-Storage. In order to find the optimal capacity and sizing of the distributed generation units to be integrated into the radial network a comparative study was performed as presented in Table 1 and Fig. 6.

Table 1. DG units variation type and penetration ratio.

| | MG | P(KW) | Q(KVAR) |
|---|---|---|---|
| 1st Case | PV | 1117 | 556 |
| 2nd Case | Wind turbine | 1117 | 556 |
| 3rd Case | PV-WT- Storage | 1117 | 556 |

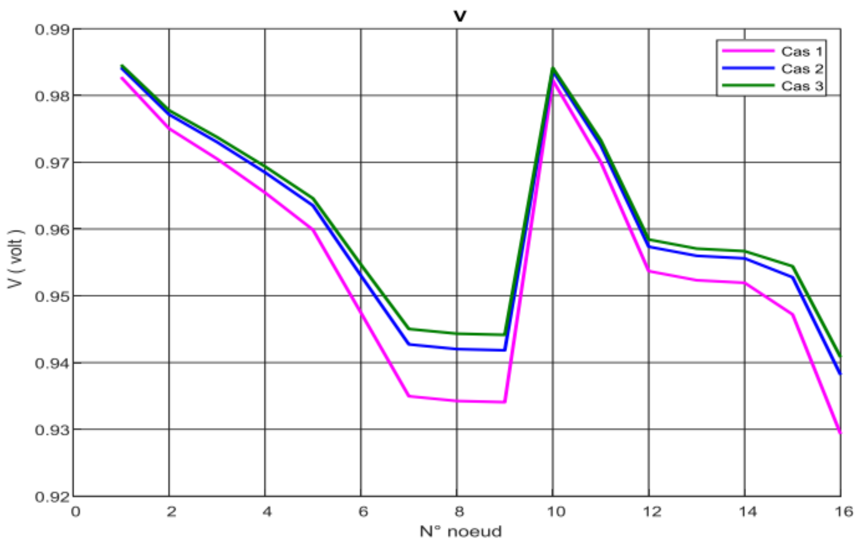


Fig 6. Voltage profile at bus 15.

In this scenario the integration placement was fixed and bus 15 was used as integration bus. Three different rates of DG unit capacity including wind and PV generator have been simulated as given in

Table 1, where the voltage profile of each bus in the IEEE 16 bus was analyzed to show the contribution of renewable energies to enhance power system static performances. As presented in Figure 6. it can be observed that the integration of DG can enhance the voltage profile, while the insertion of a hybrid wind-PV system including storage system can improve the voltage values the most effectively.

### 4.3 Radial Distribution Network Connected Microgrid: Dynamic Analysis

In this scenario, we propose the transition from a static analysis to a dynamic analysis in the presence of distributed production units via the connection of the IEEE 16 bus with the hybrid multi-source micro-grid already studied previously in case 4.1. The micro-grid was connected at bus 15, where, two scenarios have been considered:

- Scenario 1: The Microgrid was connected to the radial system without fault as shown in Fig. 7.
- Scenario 2: The Microgrid was connected to the radial system in presence of short circuit fault as shown in Fig. 8.

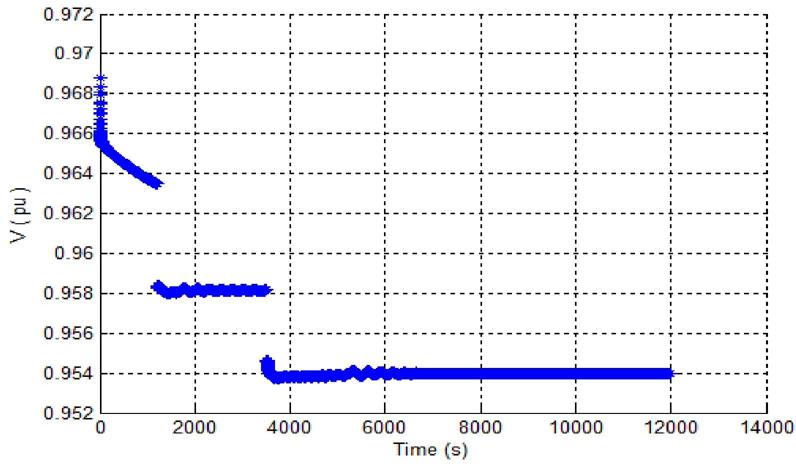


Fig 7. Voltage profile at bus 15 after MG connection.

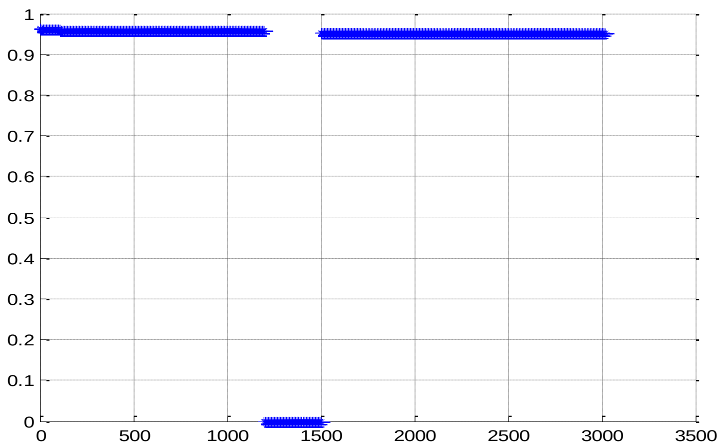


Fig 8. Voltage profile at bus 15 after MG connection and short-circuit fault.

According to the obtained simulation results, the integration of DG units into the radial distribution network contributes to the change of voltage profile, moreover major faults such as three phases short-circuit fault can affect the dynamic performances and influence the transient stability of the distribution system. In this context, in the next simulation, the study was extended to apply optimization algorithm to find the best allocation and sizing of MG including DGs in the aim to enhance voltage stability.

### 4.4 Optimal Sizing and Allocation Using PSO

In this part, an optimal solution using the PSO algorithm was employed to find the best bus placement for integrating the microgrid with optimal DG units capacity. As shown in Fig. 9, the single-line diagram of the IEEE 33 bus radial distribution network was used as test system (Kaushal & Tomar 2017). During the simulation the estimated base power is fixed at 10 MVA and the base voltage at 12.66 kV. The PSO optimization algorithm was employed and tested using IEEE 33 bus network based multi-objective fitness function. during the optimization process the PSO algorithm was used to find the best allocation and capacity of the MG according including DG units. The obtained results are shown in Table 2, where, Fig. 10 depicts the curve of the voltage profile at each bus in the radial distribution network. Finally, Fig. 11 shows the convergence characteristic of the PSO algorithm.

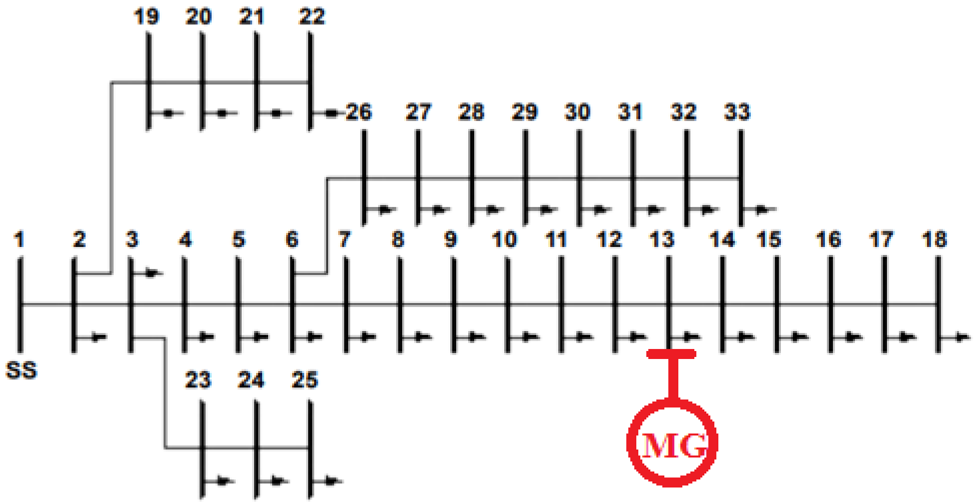


Fig 9. Single-line diagram of IEEE 33 bus radial distribution test system.

Table 2. Optimal Placement and Sizing Results.

| Optimal Placement (bus) | Optimal Capacity (pu) | Qloss (pu) | Ploss (pu) |
|---|---|---|---|
| 13 | 2.1295 | 0.1703 | 0.2541 |

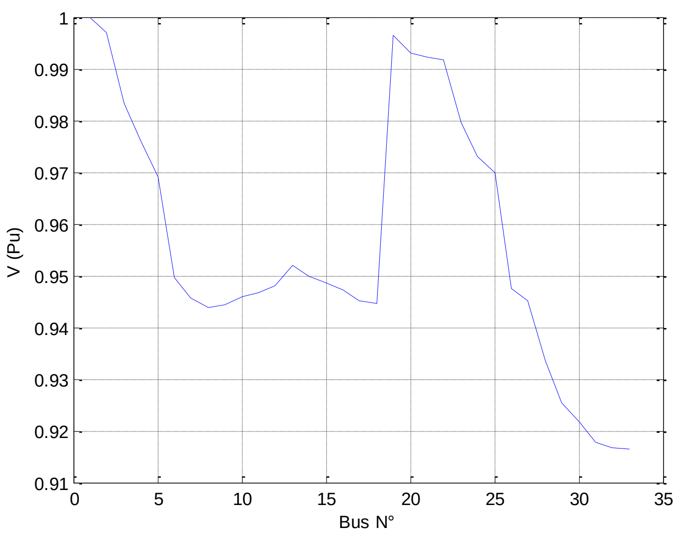


Fig 10. Voltage profile of the IEEE 33 bus Distribution Network.

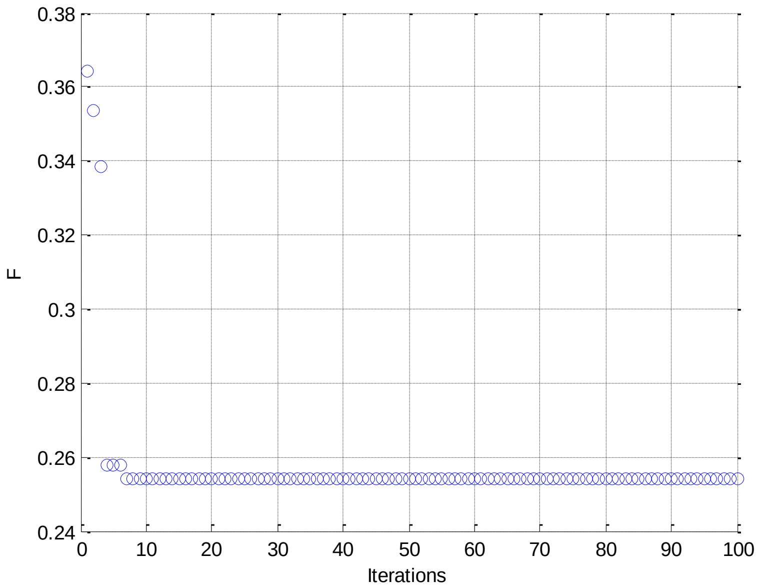


Fig 11. PSO Convergence Characteristic.

It is clear from the obtained results that there is an observable reduction in power losses with the optimal placement of the microgrid at bus 13. The reduction in power losses was observed using PSO algorithm. Also, the optimal capacity of the Dg unit integrated in the MG at bus 13 has shown a significant improvement in the voltage profile at neighbouring buses.

## 5. CONCLUSION

In this paper, a distributed generation models reported in the literature have been used for the connection of microgrids system integrated renewable sources into radial distribution power system. Furthermore, a review of the optimal placement of DGs was presented on the IEEE 16 bus distribution network. It was concluded that a proper allocation of MGs in the distribution system can reduce the power losses and enhance the voltage profile of the system. To find the best bus placement and the optimal capacity of the connected MGs, various objectives, namely a single objective and imposed constraints, are identified by the researchers. It is also identified that the most common objective is the minimization of total power loss and enhancement of the system voltage. Therefore, in this paper the optimization PSO based approach was employed for the placement of MGs to reduce the losses and improve the voltage profile. Proper sizing and optimal placement of microgrids in the network will significantly reduce the power losses in the system. The employed strategy shows high performances and capacity in reducing the losses and enhancing the voltage stability. As future works, this study will be extended to the Algerian isolated network named In Salah-Adrar-Timimoun (PIAT) in Presence of Renewable Energy Sources.

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