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Optimal Operation of Droop Control in Microgrids Using Different Techniques Optimization: Review

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Abstract: Microgrids are small power systems and can operate in two modes: island mode and grid-connected. Switching between these two modes may cause a change in the load, which causes disturbances that affect the operation of the microgrid (MG), as the load change leads to a change in the voltage and frequency of the system so the operating control problem main issue for the microgrids that is need addressed during operation. A control system is required for accurate synchronization, system protection, and load reduction in an imbalance scenario, as well as to achieve system stability while supplying robust and efficient electricity to the microgrids. Droop control is one of the common methods used in the microgrid (MG) to adjust the real power and reactive power and control the system voltage and frequency. However, the traditional droop control suffers from problems in the accuracy of load distribution, line impedance mismatch, and slow dynamic response, as a result, parameter values must be carefully chosen. To address these issues, many techniques have been used, one of which is the optimization techniques. This paper reviews five different optimization techniques based on metaheuristic optimization algorithms applied to microgrids that address some of the drawbacks of droop control by optimizing droop control parameters for optimal flexible microgrid (MG) operation. These techniques include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimization (GWO), Grasshopper Optimization Algorithm (GOA), and Salp Swarm Algorithm (SSA).

Keywords: Microgrid; Droop Control; Optimization Algorithms; Load Change; Voltage and Frequency Stability.

1. Introduction

A microgrid (MG) is a small-scale distribution network that is low voltage consisting of various distributed generation (DG) units whether it is renewable (wind turbines, microturbines, fuel cells, photovoltaic, etc.) conventional (gas microturbines, biomass boilers, etc.), or a combination of the two, and electrical loads that are either connected to the utility grid at the point of common coupling (PCC) or separated so Interconnecting power systems is important for maintaining an efficient power flow supply and improving the system's reliability. where renewable energy has become a significant source of power systems replacing conventional sources[1][2][3]. In recent decades, the use of distributed generation (DG) has increased dramatically, and the demand for electrical energy has risen as it has become a profitable supplementary service in our lifestyle[4]. DG units provide the following advantages over conventional centralized power generation: higher energy efficiency, less pollution, lower power transmission losses, and a more flexible installation site[5]. A microgrid can operate in two modes grid-connected mode and islanded mode. In the grid-connected mode, a controller's primary function is to manage energy. The microgrid connects to the utility grid via a bus bar known as the Point

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Common Coupling (PCC). In this mode of operation, the utility grid provides stability to the microgrid. In islanded mode, the controller maintains voltage and frequency stability while fulfilling local energy demands. The microgrid regulates this stability via the instrumentation of the electronic converters that connect the parallel generators[6][7]. One of the most distinguishing advantages of microgrids is their capability to operate in a decentralized way without the supervision of the utility main grid. Microgrids are essential for deploying renewable energy resources due to their distinct features[1]. To get high-quality voltage and power output from a parallel inverter, a control technique aimed at reducing certain performance parameters is required. To ensure microgrid stability, all DGs must share reactive and active power from the load at the same time. Electrical variables such as frequency and voltage will need to be regulated to safeguard the stability of the microgrid[8]. So there are several methods for controlling micro-grid contain; the master-slave technique, the current power-sharing technique, and the droop control[9]. Droop control is one of the common inverter control techniques in which the alteration in real and reactive power is tackled by changing the magnitude of supply voltage and supply frequency, identical to that of the governor running the alternator[10]. Droop control is typically employed in microgrid island operations. The two primary control objectives are proper load sharing and reliable power supply. To accomplish these, droop control, which simulates the behavior of a synchronous generator in the system of power by decreasing the voltage and frequency magnitude, is extensively employed for coordinating parallel inverters[11][12]. The main benefit of the droop control method is no communication lines between parallel-connected inverters. The non-existence of communication links between parallel-connected inverters offers substantial flexibility and good reliability. In previous literature, many methods have been presented to optimize droop control such as, In[13], the Aquila Optimizer Algorithm is used to improve the capability of droop control on a DC microgrid. In[14], the author combined droop control with ant colony optimization (ACO).Based on a real-time self-tuning mechanism to conventional PI regulators for accurate power sharing across parallel linked inverters in an AC MG standalone mode. In[15], Harris Hawks Optimization (HHO) was used on a microgrid to calculate droop control scheme coefficients and PI controller gains. In [16], using a new optimization technique called sine-cosine based monarch butterfly (SCMBO), an optimal energy management solution is found, and droop control. In[17], a new evolutionary technique named cuckoo search is used to coordinate the power management of distributed generators in an online droop tuning system. In[18], used (DE-NGM) is a new variant of Differential Evolution (DE) to compute islanded MGs' power flow solution. This paper presents a review of five different optimization techniques to optimize droop control coefficients, four of which are swarm intelligence behavior tracking (Particle swarm optimization, Grey wolf optimizer, Grasshopper optimization algorithm, Salp swarm algorithm) and one is evolutionary behavior tracking(Genetic algorithm), which aims to improve droop control when the droop control isn’t optimal, in case the deviations that occur as a result of switching between grid-connected mode and island mode for microgrids are not minimized.

The paper is arranged as follows: Section 2 presents the concept of droop control, Section 3 presents the concept of optimization in general, followed by the presentation of the classification of optimization algorithms, Section 4 presents the optimization in droop control and presentation of the methods that used in optimize the droop control, While Section 5 discussed the optimization algorithms in detail and explain the scientific literature review for droop control when the authors used these algorithms and Finally, Section 5 indicates the conclusion of this paper.

2. Concept of Droop Control

The basic droop control is the initial stage of the inverter control approach. Droop control utilizes inverse droop control or conventional by utilizing a relationship between the grid's frequency and voltage and the power generated by the inverters with no need for communication among inverters The droop controller regulates frequency and voltage according to the current loading conditions. To create voltage and frequency, it mainly relies on computing the active and reactive power and inserts the coefficient of droop can be expressed as the equations below, and Fig.1 shows droop characteristics. In a microgrid, power generation is indicated by the voltage and frequency levels. The droop uses this information to adjust the power that the inverters deliver by adjusting the reactive and active power set points. This method allows for grid expansion to handle additional distributed loads and DERs. It is also permitted for DERs and loads to be disconnected. Furthermore, droop control doesn't require high-speed communication, which results in significant cost savings and exceptional dependability[19]. Fig.2 Shows the droop line for the VF and PQ control.

$$f = f_n - m(P - P^*) \quad (1)$$
$$v = v_n - n(Q - Q^*) \quad (2)$$

Where f: is the reference frequency, V: is the reference voltage, f_n: refers to the frequency characteristics' constant coefficients, V_n: refers to the voltage characteristics' constant, and n and m: denote the droop coefficients.

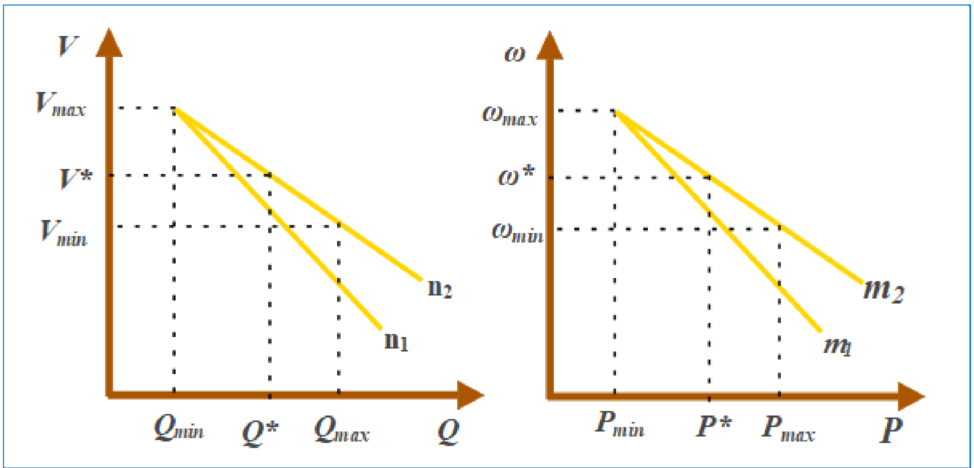

Fig. 1. The droop characteristic of conventional [20].

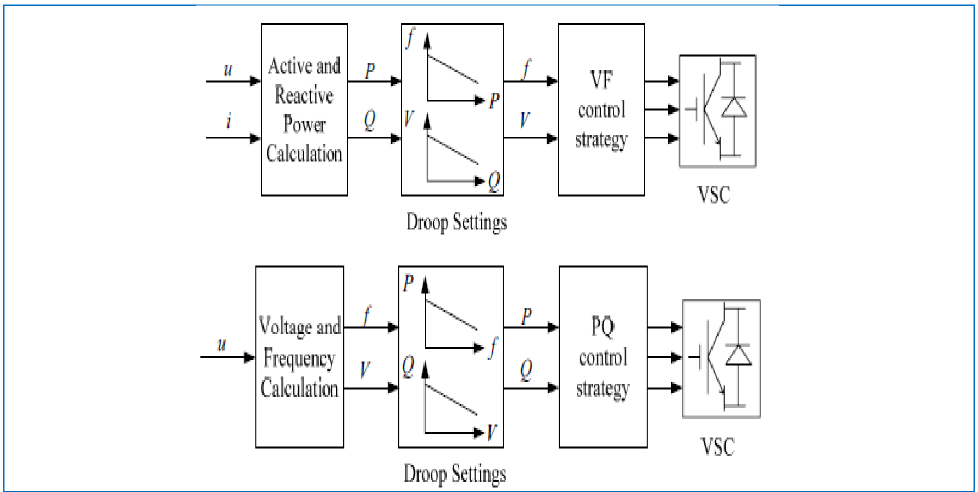

Fig. 2. Line of droop for the(VF and PQ) control strategy [21].

3. *Concept of optimization*

Optimization in general is determining the best values for a given problem's variables to minimize or maximize an objective function. Optimization challenges exist in a variety of domains of study. To address an optimization problem, several steps are required. First, the problem of the parameters must be determined. The Problems can be classed as continuous or discrete depending on their parameters.

Second, the constraints applied to the parameters must be identified, Constraints divide optimization issues into two categories: constrained and unconstrained. Based on the parameters' nature, an FF or objective function (OF) is produced, which must be maximized or minimized to obtain the optimal set of parameters. Third, investigate and consider the problem's objectives. In this scenario, optimization issues are divided into single-objective problems and multi-objective problems, and finally, according to the specified categories of parameters, restrictions, and number of targets, an appropriate optimizer must be selected and used to address the problem[22][23]. So any mathematical optimization problem, either minimizing or maximizing a certain objective function, typically contains four major components: objective functions, decision variables, equality and non-equality constraints, and the optimization algorithm used[1]. A metaheuristic optimization algorithm could demonstrate very promising results when addressing a specific type of optimization issue, yet the same algorithm may demonstrate poor performance on other optimization problems [24]. Mathematical optimization mostly depends on the gradient-based construction of the associated function to get the optimum solution. Mathematical optimization has some drawbacks such as: Mathematical optimization methods ridden from local optima trap. This means an algorithm that assumes the local solution to be the global solution. This fails to achieve the global optima. They are frequently useless for issues with expensive computational derivations that the unknown[22].

3.1. Classification of optimization algorithms

The range of computing problems that exist and the quantity of algorithms that have been devised to tackle them are tough to imagine[25]. So, the algorithm can be classified into many types as the Fig.3 The majority of real-world optimization problems face various challenges, including, non-linear constraints, high computational cost, dynamic/noisy objective functions, non-convex search landscape, and huge solution space. These issues are the primary criteria for selecting whether to use an accurate or approximation algorithm to address complex problems[26]. Metaheuristic optimization algorithms (MAs) have gained popularity in recent decades due to their reduced requirements computation capacity, simplicity, high performance, derivation-free mechanism, flexibility, and local optima avoidance compared to deterministic algorithms for optimization issues[27][28].

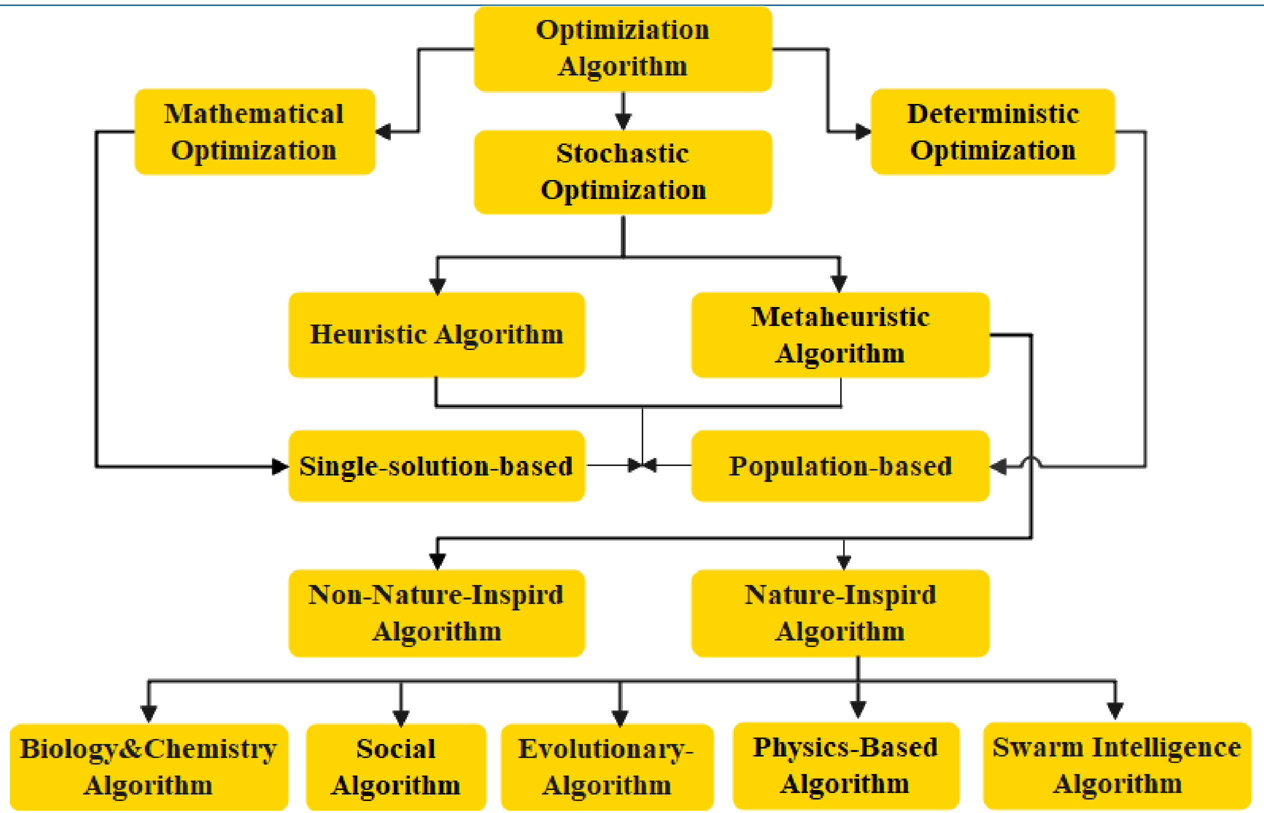

Fig. 3. Classification of Optimization Algorithms.

3.1.1. Swarm intelligence (SI)

Swarm intelligence (SI) refers to the collective behavior of decentralized, self-regulating systems. Typically, SI systems are composed of a population of simple factors that interact individually with their environment and one another Additionally, the SI can be characterized as a branch of artificial intelligence that is employed to mimic the collective behavior of natural social swarms, such as ant colonies, animal herding, fish schooling, bacterial growth, animal herding, and bird flocking[29][23]. to create swarm intelligent life systems having cooperative behavior using computers. There are five fundamental principles of swarm intelligence [30][31]. proximity principle: The swarm must be capable of performing the basic space and time calculations, Quality principle: The swarm must have the ability to respond to environmental quality factors, Stability principle: The swarm should maintain the same behavior mode regardless of environmental changes, Diverse response: The swarm should not confine its resources to a narrow scope, Adaptability: The swarm should change its behavior mode when it is appropriate.

4. Optimization in droop control

The traditional droop method has several disadvantages, such as an inherent trade-off between load sharing and voltage regulation, slow transient response, line impedance mismatch among parallel-connected inverters that affects reactive and active power sharing, weak harmonic load sharing among parallel-connected inverters in situations with non-linear loads, and poor performance via renewable energy resources. Therefore, the values of the droop control coefficients must be chosen carefully[32]. Significant attempts were made to improve the droop control strategy and droop gain optimization[33]. Optimization techniques are an important topic for researchers to improve droop control parameters. where various computational and optimization algorithm techniques are to address the problem in microgrid and optimization droop control such as in In[13], the Aquila Optimizer Algorithm is used to improve the capability of droop control on a DC microgrid. In[14], the author combined droop control with ant colony optimization (ACO).Based on a real-time self-tuning mechanism to conventional PI regulators for accurate power sharing across parallel linked inverters in an AC MG standalone mode. In[15], Harris Hawks Optimization (HHO) was used on a microgrid to calculate droop control scheme coefficients and PI controller gains. The authors in[34] used a new optimization technique called Moth-Flame Optimized(MFO) adaptive droop control to optimize power and current sharing while minimizing voltage variance between the DC-DC converters in microgrids the suggested technique adjusts droop gains in response to changes in dynamic voltage and load current, outperforming traditional droop control techniques which struggle for robustness under such situations. In [16]An optimal energy management solution and droop control are found using a new optimization technique called sine-cosine-based monarch butterfly (SCMBO).

In[35][36], the Hybrid Big Bang-Big Crunch (BB-BC) algorithms regulate frequency and voltage and enhance power control by optimizing the PI controller gains in real-time. In[17]A new evolutionary technique, cuckoo search, coordinates the power management of distributed generators in an online droop tuning system. In[37], Turbulent Flow Water-Based Optimization (TFWO) to determine the ideal size for a hybrid standalone microgrid generation. In [38], This work offers an optimal droop control approach for the distributed inverters in a microgrid in standalone mode using real-coded differential evolution (DE). In[18], used (DE-NGM) is a new variant of Differential Evolution (DE) to compute islanded MGs' power flow solution. Also the researchers in[39] This study uses an adaptable Differential Evolution (ADE) method to improve the droop control virtual resistances for dispatchable units' grid-connected converters, allowing power flow to be managed and minimize costs connected with utility networks, renewable energy sources (RES), fuel cells, energy storage systems (ESS), and distribution power losses and reduce the operational costs of DC microgrids using real-time pricing. In [40] a new optimized droop control method is proposed that employs a metaheuristic multi-objectives evolution algorithm known as the Centering Force-Gravity Search Algorithm (CF-GSA) to enhance frequency and voltage stability, power sharing, and power quality in microgrid systems.[41] This work presents a new optimization algorithm a Modified Osprey Optimization Algorithm (MOOA) to improve the droop control method in DC microgrids that combines the L'evy flying method and the Osprey Optimization Algorithm (OOA).

In addition, many algorithms rely on swarm intelligence that has been used to solve many problems small networks suffer from. The droop controller was developed using Henry Gas Solubility Optimization (HGSO) to optimally select PI controller gains and droop control parameters to achieve a better microgrid output responsiveness during islanding[42]. This study provides a new methodology for improving the control of islanded microgrids (MGs) with the Coot Bird Metaheuristic Optimization (CBMO). The study's goal is to determine the optimum gains for a PI inside a multi-objective optimization structure[43]. In[44]This paper proposed developing an optimal droop controller for microgrids during islanding utilizing the artificial fish swarm algorithm (AFSA) to reduce the frequency deviation that happens when the microgrid transits islanded mode or when the loads fluctuate or vary. In addition, many algorithms rely on swarm intelligence that has been used to solve many problems small networks suffer from. Fig. 4 illustrates a flowchart of the optimization process when using algorithms to improve droop control for microgrid systems.

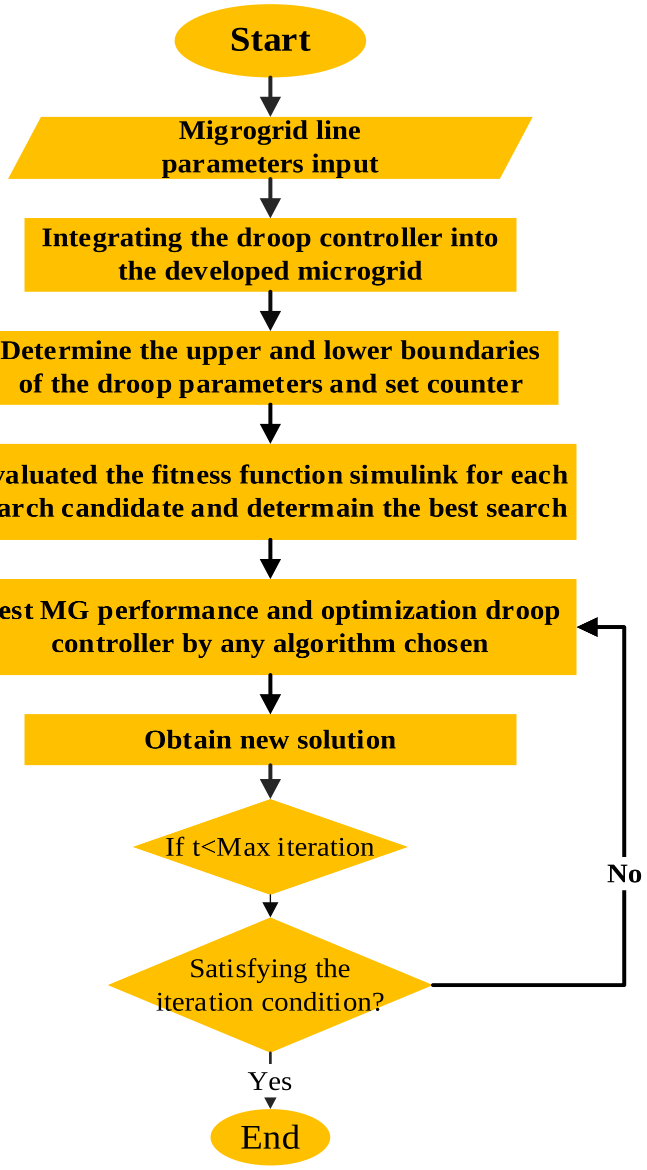

Fig. 4. Flowchart used in the optimization of the droop control for microgrid.

Because it is difficult to cover all of the optimization methods utilized in droop control for MG applications, this article is limited to "swarm intelligence" based optimization strategies for four algorithms (PSO, GWO, GOA, SSA) and one of the evolutionary algorithms (GA). These algorithms are the most common in the subject of droop control. The following is a review of these algorithms along with a previous review of studies that have used these techniques to optimize droop control parameters in microgrids.

5. Optimization techniques

5.1. Particle Swarm Optimization Algorithm (PSO)

Particle swarm optimization (PSO) is a population-based stochastic optimization method that mimics the intelligent social behavior of animals including schools of fish, flocks of birds, and herds, which was proposed by[45]. These swarms follow a cooperative food-finding strategy, with each member modifying the search behavior depending on themselves and other members' experiences of learning. PSO allows particles to adjust their velocities and location in response to environmental changes, meeting quality and proximity requirements. Particles in PSO keep stable mobility in the seeking space while adapting to environmental changes[30]. The PSO algorithm design is based on two research studies: One is an evolutionary algorithm, similar to an evolutionary algorithm; PSO also employs a swarm mode, allowing it to simultaneously search a vast region in the solution space of the optimized objective function, The other is artificial life, which is the study of artificial systems that exhibit lifelike features[30]. Particle swarm optimization (PSO) may address numerous problems, such as the problem of constructing reliability-specified optimum microgrid structures[46].

5.1.1. mathematical model of the particle swarm optimization (PSO)

5.1.1.1. Parameter of PSO

There are various significant parameters in the PSO algorithm. They are as follows:

- ***Inertia weight:*** Inertia weight balances local and global searches. A larger inertia weight tends toward global searches, while a lower inertia weight tends toward local searches. As a result, the value of inertia weight decreases over time.
- ***Learning factors c_1 and c_2:*** The learning factors c_1 and c_2 denote the weights of the stochastic accelerating terms that pull each particle into the g_{Best} (or n_{Best}) and p_{Best}. In many situations, c1 and c2 are set to 2.0, causing the search to include the region centered on g_{Best} and p_{Best}. Another popular value is 1.49445, which ensures the convergence of the PSO algorithm.
- ***Speed limits V_{max}:*** The particles' speed was restricted by a maximum speed V_{max}, which can be utilized as a restraint to control the particle swarm's global search capability.
- ***Position limits X_{max}:*** The particle locations may be restricted by a maximum location Xmax to prevent particles from flying outside of the actual solution space.
- ***Population size:*** The population size selection is associated with the issues to be addressed, although it isn't susceptible.
- ***Initialization of the population:*** Initialization of the population is also a critical problem Generally; the starting population is produced at random.

5.1.1.2. Basic of PSO

The original particle operated according to the mathematical model of velocity and position

$$v_i^{k+1} = v_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 \left(g_{\text{best}} - x_i^k\right) \tag{3}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4}$$

where: k: number of iterations, i: particle index, v_i^k: the velocity of particle i at iteration k, p_i^k: local best position, g_{best} : global best position, x_i^k: location of particle i at iteration k, c_1 and c_2: coefficients which are usually between [0 2], r_1 and r_2: Random values are created for each velocity update.

$$v_i^{k+1} = w(t) * v_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 \left(g_{\text{best}} - x_i^k\right) \tag{5}$$

$$w(t) = w_{max} - \left((w_{max} - w_{min}) * 1/k\right) \tag{6}$$

Where, $w(t)$: inertia constant it is often in the range [0 1]

5.1.1.3. PSO with inertia

The velocity update is as follows:

$$v_i^{k+1} = \chi\left(v_i^k + \phi_1 * r_1 * \left(p_i^k - x_i^k\right) + \phi_2 * r_2 * \left(g_{best} - x_i^k\right)\right) \tag{7}$$

Regarding the bird's analogy, Birds fly to find food. The position of food is equivalent to the best solution to the problem. The birds' goal is to converge or narrow down the position of the food. The final site where the birds settle is the optimum option discovered by the solution process, three elements determine particle motion. They are as follows [46].

- ***Inertia:*** particles tend to travel in the same direction that they were initially moving.
- ***Personal Best:*** Every particle recalls particularly the site that provided the best estimate of the objective function. This position (or solution) is referred to as the particle's personal best.
- ***Group Best:*** every particle gravitates toward the group that performs best. The group's best position is the swarm's best solution at any given time step. Fig.5 explains the steps of optimization of PSO to optimize the droop control.

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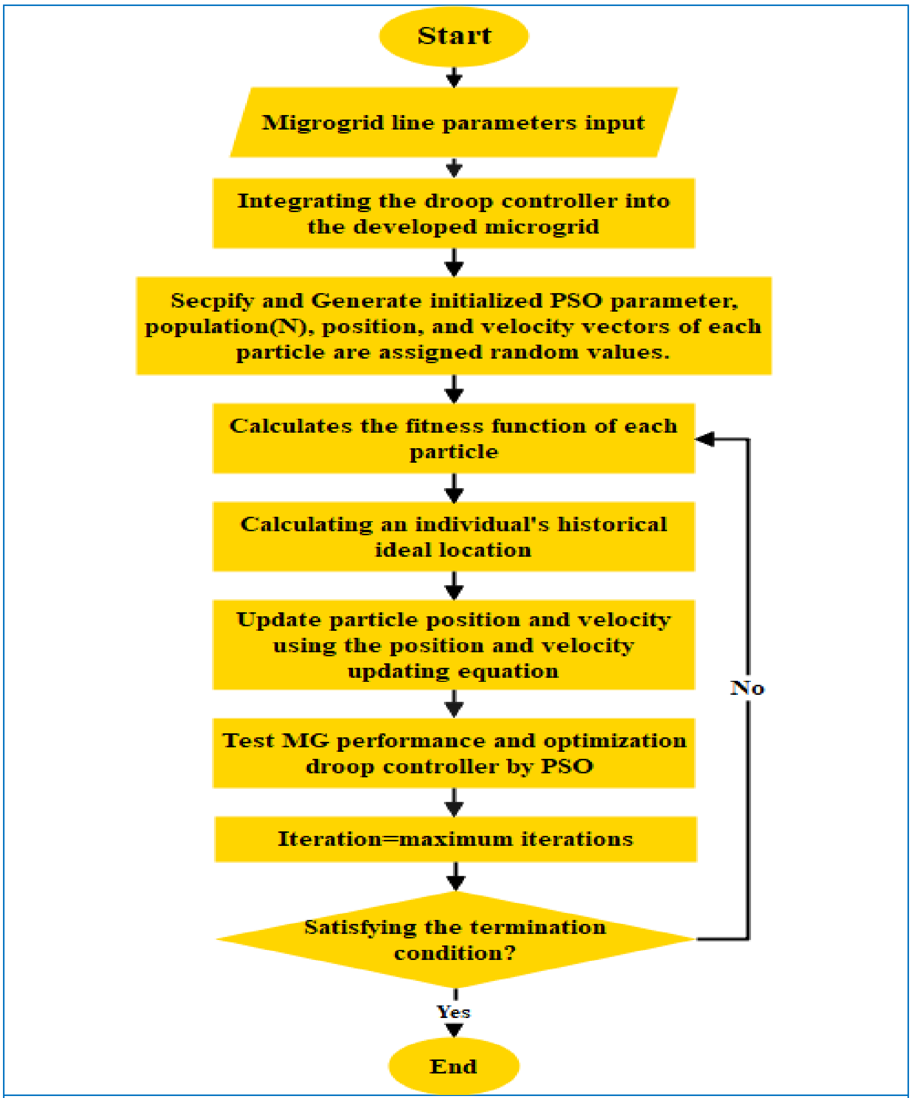

Fig. 5. Flowchart using particle swarm optimization to optimize droop control.

The following is a review of literature using the PSO to optimize droop control

The authors in [47], have been improving particle swarm optimization algorithms in standalone microgrids (MG) with several distributed generations (DG) paralleled to get optimal conventional droop control in real-time and analyze for small signal stability. Proposed the method by utilizing the basic particle swarm optimization (PSO) algorithm. First, an analysis is conducted of the microgrid structure and the impact of line characteristics on the conventional droop control approach. Then the fuzzy inference system is proposed to dynamically modify the particle swarm optimization parameters as well. The precision and convergence speed are improved and effectively improve the ability to search locally and globally of the original algorithm by using the fitness function in the equation (8). The research author used this method, to study the microgrid with several DGs where used only the case of two equivalent DGs in parallel, taking into account the output characteristics of different DGs and improving the algorithm to better the effectiveness of the suggested control approach in more intricate experimental scenarios, where the capacity ratio between DG1 and DG2 is 2:1 and the thresholds for setting the voltage deviation $\Delta U(\%)$ are 10% and the frequency deviation f (Hz) is 0.3 Hz. This way many scenarios such as unbalanced conditions with constant power load in scenario show the case at $t = 1.3$ s, reactive load rises by 2 kvar, and the active load increases by 5 kW. At $t = 1.6$ s, the reactive load is decreased by 2 kvar, and the active load is decreased by 2 kW. And shows the highest frequency variation is 0.2 Hz, which stabilizes after 0.2 s of oscillation. the voltage drop reaches up to 3 V but may be recovered after 0.05 s to the rated voltage, it can reduce voltage variation and enhance power allocation accuracy. unbalanced condition with the motor, in this scenario, uses the motor load to show the highest frequency variation is 0.25 Hz, which stabilizes after 0.2 s of oscillation The voltage drop is up to 7 V, and the value can be recovered to 220 V after 0.1 s. subsequently, improves system stability compared with the conventional methods. Mutation of line parameters, this case shows the situation in which the system line parameters change suddenly. Under the conventional droop control, the deviation in reactive and active power between two DGs is more noticeable when the system parameters of the line change abruptly. plug-and-play functionality in this scenario, When DG2 switching occurs, the control approach can more correctly allocate system power than conventional droop control. The suggested control system ensures accurate allocation of reactive and active power based on DG-rated power, even in the event of a failure. In the last scenario communication link failure, the show although the power allocation precision is reduced Despite the communication system collapse, the error is still significantly lower than conventional droop control. As a result, the suggested algorithm can effectively respond to a momentary disruption of the communication system. Finally, Simulation and experimental results prove that the control technique can significantly enhance reactive power allocation accuracy while keeping system frequency stability and bus voltage, as well as achieve undeferential adjustment of power and voltage under different operating conditions, thereby improving the system's dynamic performance and transient stability.

$$F_i = \Delta P_i + \Delta Q_i + \Delta U_i + \Delta f_i \quad (8)$$

Where: ΔP_i represent the active power deviation, ΔQ_i: represent the active power deviation, ΔU_i: represents the voltage deviation, Δf_i : represent the frequency deviation

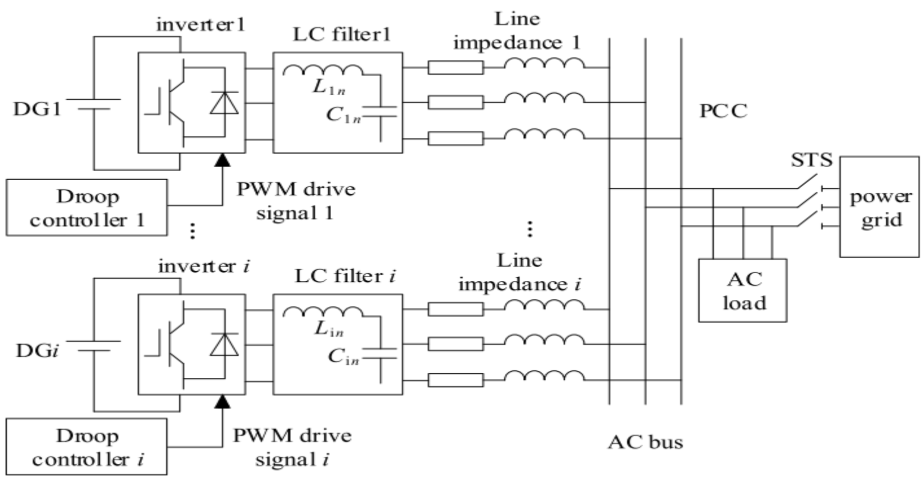

Fig. 6. Topological schematic of a multi-source microgrid [47].

In reference [48], the author uses the particle swarm optimization algorithm as an optimization technique to Optimize the Microgrid controller's parameters in standalone mode for controlling distributed generation. This is done by minimizing the errors in the voltage and current controllers. The research author used this method, to study the microgrid with two DG under the maximum voltage deviation (ΔV) is set to 5% and maximum frequency deviation (Δf) is set to 0.5 Hz. The findings from the simulation demonstrate the efficient operation of the suggested optimal approach. Where these results showed the frequency deviation is within the limit permissible range, The DGs are shown to follow rapidly to changes in load and to reduce overshoot, Power sharing is correctly distributed between DG units and It is evident that the system responds appropriately to transient responses. This paper sets the minimal limits for all coefficients to zero. the optimization problem can be expressed as equation (9). Finally, the microgrid has well responds and performs well when using the improved controller.

$$\text{Min}(\text{Error}) \tag{9}$$

The authors Yavuz et al. 2023,[49] present a novel method for solving the problem of optimal droop coefficient selection by incorporating a Newton-Raphson (NR) algorithm into a sequential sampling-based particle swarm optimization (PSO). The NR algorithm's adaptability and rapid quadratic convergence make it excellent for addressing power flow equations in standalone microgrids. PSO's capability to operate without making assumptions about the form of objective function or restrictions makes it a flexible choice for carrying out the process of optimization. The research describes a sequential sampling-based stochastic optimization approach for optimizing design variables inside a droop control mechanism to ensure the stability of a standalone microgrid while addressing system-level objectives in a stochastic setting. Also introduces the JA-MNR method to improve the MNR's convergence capabilities and incorporates the restricted PSO methodology into the proposed simulation optimization scheme. To validate the efficacy of the suggested strategy, two structurally distinct test cases were developed. Case 1: is a single microgrid, in this situation first tested the suggested technique in a 6-bus system to see how utilizing improved droop coefficients affected distribution losses and microgrid stability across the network. The technique is proven utilizing and 33-bus test and IEEE-30 networks, situation 2 consists of two interconnected six-bus systems. It is also established to validate the collaborative operations of two associated microgrids that can interchange conduct cooperative and electricity operations. In both instances 1 and 2, it is assumed that a failure occurs in the main grid, rendering it unable to supply electricity to the adjoining microgrid. Thus, the only electricity-generating sources in microgrids are RES with droop-controlled DGs and maximum power point tracking (MPPT). Simulation results demonstrate that the suggested strategy improves a microgrid's stability while decreasing active and reactive distribution losses across the network. The results also show substantial enhancement in the voltage bus profiles while keeping a steady frequency throughout the standalone mode of operation within the investigated microgrids as compared to their traditional equivalents. Finally, the results demonstrate that the suggested approach can improve the coefficients of droop of the dispatchable droop-controlled DGs while capturing the randomness in the system with great accuracy.

In this research[50], Particle swarm optimization is used to find the ideal values for the optimized parameters in each microgrid operator mode. In addition, nonlinear time-domain-based and eigenvalue-based objective functions are developed to reduce measurement error and improve damping characteristics. Many issues were presented in the research as optimization problems, such as Microgrid models that operate in various modes, both linear and nonlinear, controller parameters and Power-sharing factors optimized in islanded mode, the optimal design of an LC filter and in the grid-connected mode dampening resistance is carried out. Linear and nonlinear models were created using MATLAB code to investigate the stability of an inverter-based microgrid operating in both stand-alone and grid-connected modes. In the case of grid-connected mode, the DG unit is made up of a DC voltage source, coupling inductance Lc, a series LC filter, and a VSI. The test inverter-based DG has a rating of 10 kVA. The inverter is controlled to inject the actual and reactive power needed by the utility. To assess the performance of the proposed controller in this mode, a nonlinear time-domain simulation was performed. To show how effective the suggested controllers and design strategy are, an eigenvalue analysis has been done. This method proposed PSO-based design approach has been implemented and is used to shift the eigenvalues to the left in the s plane to maintain the stability of the system. In the standalone mode, three inverter-based DGs (10 kVA) are coupled to two loads via a series LC filter, lines, and coupling inductance Lc.in these modes nonlinear time-domain simulations were performed at two various disturbances to investigate the effectiveness of the most optimal settings of the proposed controllers and power-sharing coefficients. Finally, the findings indicate significant improvement in damping characteristics and system performance, including reduced overshoots and settling time.

M. A. Ebrahim et al.in 2018,[51], use the particle swarm optimization algorithm to optimize the secondary control level by compensating for any voltage and frequency variations produced by the primary level To obtain a steady state and good dynamic performance for microgrid frequency and voltage. The modeling, analysis, and control techniques for a VSI-based standalone microgrid are created. An integrative control system for a standalone microgrid is carried out, with two levels of control, the primary control, and the secondary control. The primary control level includes the voltage and current inner control loops, droop control loops, and virtual inductor loops. This control level is required to adjust frequency and voltage, as well as to ensure accurate power sharing across paralleled distributed generators (DGs). The secondary control level is used to remove the angular frequency and voltage magnitude variations caused by the primary control level. Tests have been conducted on two microgrid structures that are modeled and simulated in MATLAB The first scheme contains only one DG unit. The second structure consists of four DG units. All structure is evaluated without and with a secondary level of control under changes in load to demonstrate the control system's robustness. When a microgrid consists of only one DG unit, in the case without secondary control can be observed there are numerous variations from the set-points of voltage and frequency magnitude. And in the case of existence the of secondary control, the output reactive and real powers are noticeably higher than in the case without secondary control. The transient oscillations in frequency and voltage magnitude are highly damped compared to the conventional controller. Furthermore, this method reduces steady-state time for frequency and voltage responsiveness compared to the conventional controller. moreover, the responses of reactive and real powers for conventional and optimized secondary controllers are nearly identical. When a microgrid contains four DGs, it can be seen that the frequencies of DG units increment at the time 1 second by activating the conventional secondary control from 49.78 Hz to 50 Hz. Furthermore, it can be seen the increase in the voltage and real output power under the load variation The voltage amplitude under the load fluctuation at the time of 3 s remains constant at 311.2 V for DG1, climbed from 306.8 V to 309.5 V for DG2, increased from 309.6 V to 311.2 V for DG3, and increased from 308 V to 310 V for DG4 and the power at 3 s, the power of DG1 and DG3 increases from 16.1 KW to 18.3 KW, and DG2 and DG4 increase from 12.2 KW to 13.7 KW. The results demonstrate the efficiency performance of the suggested optimal strategy. From these results can be concluded: that (i) the droop control enabled optimum power sharing among the independent paralleled DGs. (ii) the intended values of voltage and frequency magnitude were recovered without any variations under load change by activating the secondary control. (iii) In addition, the PSO technique was used to choose an accurate secondary controller parameter. Finally, the use of optimized secondary controllers improves the voltage and frequency responses of all DGs.

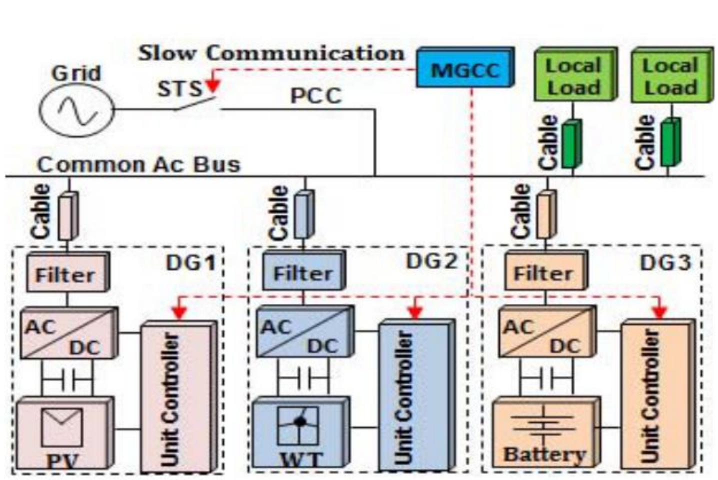

Fig. 7. The basic structure of microgrids used in this paper [51].

This work,[52] provides a method for determining the optimum droop parameters of dispatchable distributed generation (DG) units in autonomous droop-controlled DC microgrids. The main objectives for this work are to reduce fuel costs, improve small signal system stability, increase system damping, and shift the dominating eigenvalue off the imaginary axis to the left of the s-plane. The author used a particle swarm optimization algorithm (PSO), and using a fuzzy max-min method to solve the bi-objective optimization problem. To validate the proposed method simulations, a bus droop-controlled DC microgrid test system is used. This method studied many scenarios such as: (i) Optimizing droop constants for minimum fuel cost by using equation (10) (ii) Optimizing droop constants for maximum small signal stability by using equation (11) (iii) Optimizing droop constants for minimum maximum small signal stability and minimum fuel cost. The dominant eigenvalues are nearer to the imaginary axis for scenario (i). So, for scenario (ii), the dominating Eigenvalues are located on the left side of the s-plane, the furthest from the imaginary axis. for scenario (iii), the dominant Eigenvalues are located in between those for scenarios (i) and (ii). It is noted that the system stays stable under varying loads in all three scenarios (S1, S2, and S3). On the other hand, scenario (ii) has the maximum degree of small signal stability, whereas scenario (i) has the lowest. The level of stability for scenario (iii) lies halfway between scenario (i) and (ii) scenarios. when the scenario loads at buses 2 and 3 don't change. In this situation as well, scenario (ii) produces the highest level of stability, whereas scenario (iii) produces the lowest level of stability. Scenario (i) level of stability falls between that of scenario (ii) and (iii). Moreover, time-domain simulations were run to verify the outcomes. Additionally, a controlled elitist genetic algorithm to optimize the droop value for the simultaneous saving of fuel costs and improvement of small signal stability. Finally, the proposed method's outcome has been verified through comparison with the controlled elitist genetic algorithm's outcome.

$$\text{Minimize: } OF_1 = \left(\max_{\forall k \in K}(\text{Real}\{\lambda_k\})\right) + \sum_{k \in K} (1 - \xi_k) \tag{10}$$

$$\text{Minimize : } OF_2 = \sum_{i=1}^{NDG} \left(a_i + b_i Pg_i + c_i Pg_i^2\right) \tag{11}$$

Where: ξ_k: represents the damping ratio for the k_{th} eigenvalue, k: represents the set of each eigenvalue, a_i, b_i, c_i:represents the fuel cost coefficients, NDG represents the number of DG units dispatchable in the DCMG, and Pg_i : represents the power generation DG unit dispatchable.

In this paper [53], proposes a method to optimize droop-controlled islanded microgrids (DCIMG). The main objectives of this work are (i) to reduce the emissions in a droop-controlled islanded microgrid yet achieve all operational requirements. (ii) Reduce the operational cost. The problem of multi-objective optimization is tackled by utilizing fuzzified particle swarm optimization (PSO). The suggested formulation considers electricity demand, renewable power uncertainties, load uncertainties, and heat demand in the microgrid. A set of operational constraints of a DCIMG were used such as:(i) All the line currents were within limits (ii) all node voltages were within the permitted limits. (iv) DGs outputs of reactive and active power within their rated capacity. To verify the suggested method for the problem of total operation cost (TOC) and emission minimization by using equations (12,13). The suggested algorithm's performance was evaluated using a 33-bus DCIMG test system without regard for BESS. The system has a peak reactive power load of 2.290 MVAr and a peak active power load of 3.715 MW with A nominal voltage level is 12.66 kV. To test the system are considered two case studies tacked into account as (i) 33 Bus DCIMG system with no batteries, in case 1, when DG units had capacity-based droop settings, in this case, the result shows the natural gas turbine (NGT) is the biggest dispatchable DG unit and droop constants are the lowest also show Biomass and natural gas fuel cell (NGFC) DG units have identical ratings. In case 2, when only total operation cost (TOC) minimization in this case, the result shows, that the Biomass DG unit operates in droop mode, and NGFC and NGT DG units operate in PQ mode. NGFC and NGT units have higher power efficiency than biomass DG units, and their fuel costs (natural gas) are substantially lower than those of biomass units. To minimize TOC, natural gas-based DG units (NGT and NGFC) provide as much inexpensive power as feasible, whereas biomass DG units generate only enough power to meet the balance power need. In case 3, only emission reduction in this situation, the biomass DG unit operation in PQ mode, NGFC and NGT and NGFC operation in droop mode, to reduce emissions, it generates as much clean power as possible and NGT units produce greater power than NGFC units. In case 4, when Bi-objective optimization, in this scenario, the aim is to reduce both TOC and total emissions concurrently. Test system 2, 33-bus DCIMG battery-operated system, in this case, it is presumed that a 500 kWh and 150 kW battery is linked to bus number 6. The minimum and maximum energy permitted in the battery are 500 kWh and 100 kWh (equivalent to a State of Charge (SOC) of 0.2). Finally, the suggested algorithm for tackling the multi-objective optimization issue is significantly easier to code than prior GA-based multi-objective solutions.

$$\min f_1 = \sum_{s=1}^{NS} \pi_s^{norm} \cdot f_{1s} \quad (12)$$

$$min f_2 = \sum_{s=1}^{Ns} \pi_s^{\text{norm}} \cdot f_{2s} \quad (13)$$

In this work,[54], The nonlinear model's optimal controller design for a standalone inverter-based microgrid has been utilized. An individual inverter's nonlinear model consists of the controllers, coupling inductors, and output filter. Particle swarm optimization (PSO) was used to obtain the optimal controller parameters for the proposed method and to optimize the proposed nonlinear current and voltage controllers. The main objective of this work is to investigate the stability of the system for the selected values of droop gains. The test system comprises of three inverter-based microgrids that link with two loads via coupling inductances and series LC filter. The system was tested under two types of disturbance (i)The first disturbance: fault occurs at the first load. (ii) The second disturbance is a step change in the real power of 3.8-Kw. In the first disturbance, It can be noted that DG1 took the majority of the transient response, whilst DG2 and DG3 responded more slowly based on the effective impedance visible from the load point because DG1 is closer to the altered load and the system is steady after a perturbation. In the second disturbance, to investigate the low-frequency mode response under severe test load conditions, a test involving a step change of load 1 was conducted. In this test, there was first no load connected to the system, but later a load of 3.8 kW at bus 1 was switched on. the test Shows the reactive and active power responses of the inverters during such a load transient. It is also possible to conclude that reactive power sharing is unsatisfactory in this scenario. Increasing reactive power droop increases can boost performance, but may result in poor bus voltage regulation. Finally, based on the results, we can conclude that the PSO technique is highly effective for managing the PI controllers to obtain sufficient system stability following disturbances.

Chung et al. in 2010,[55], suggests using particle swarm optimization (PSO) to optimize inverter-output controllers and droop controllers for inverter-interfaced distributed generators. To address persistent frequency and voltage fluctuations in a microgrid, an L1 resilient control theory based on the double-layer PSO algorithm was suggested. The double-layer PSO method determines the narrowest bound of the L1 system operator norm, ensuring that the closed-loop system is resistant to external disturbances like frequency and bus-voltage fluctuations and the system's nonlinearity is accommodated by taking into account different power system conditions of operation. The microgrid system model includes three-level PWM voltage source inverters and two inverter-interfaced DGs. Two solutions can be used to achieve good performance under a variety of operating circumstances, one method is to adaptively adjust the control gains. and the other method is to discover optimal gains to ensure that the controller is robust to changes in operating conditions. This work depends on the second solution, which is to identify a reliable set of control parameters that are adjusted for various operating situations. The microgrid's optimal control parameters are verified through simulation. The simulation time is set from 0 to 1.2s, it is divided into periods: (0 - 0.3s) simulation initialization,0.3s the DG1 and DG2 power inverters begin producing reactive and actual powers of up to 1.0 MVar and1.5 MW, respectively (in grid-connected),0.6s The intertie breaker separates the microgrid from the grid, causing it to operate in island mode,0.9s The load reference signals are provided to the DGs' droop controllers to restore nominal frequency and voltage and 1.2s The local loads abruptly drop (load fluctuation in island mode). Finally, in the grid-connected mode, the system frequency and bus voltage remain close to their nominal levels of 60HZ and 1.0 p.u, respectively. In the standalone mode, they change based on power mismatch and droop control features. The simulation results show the effective performance of the proposed optimal approach.

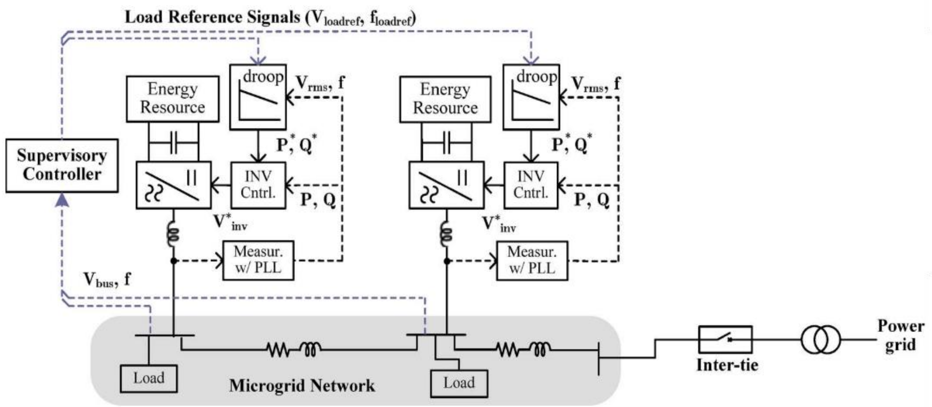

Fig. 8. Concept controlling several DGs with droop controllers in a microgrid, using in this paper [55].

This work [56], provides an effective optimal control parameter-tuning methodology based on the particle swarm optimization (PSO) algorithm. And describes control strategies for coordinating multiple microgrid generators, particularly using a voltage source inverter type interface, in both grid-connected and standalone modes. In this work, the author relied on the following ideas to simulate the model and PSO algorithm. first, six control parameters are specified as (6) for optimization, presuming that the configuration of three DGs has the same configuration, ratings, and PI controllers and that they can all function with identical PI gains (K_{pi}, T_{ii}, K_{pp}, and T_{ip}) for simplicity and used PSCAD/EMTDC to create a microgrid power system model with three-level voltage source inverter models, and they integrated the optimization algorithm into the model utilizing c-interface functions. the cost function (J) in the form of the integral of time-weighted absolute error (ITAE) can be defined as equation (14). The simulation results show: (i) the cost has been reduced to 19.54 in 600 iterations. (ii) The three DGs, the outputs of which are determined by the droop controllers, can securely sustain power. (iii) maintained of voltage and frequency value (±0.1p.u. and ±0.016 p.u (1.0Hz) from the nominal values. Finally, the optimization solution presented in this study is more precise and practical than that of small-signal models that have been simplified and linearized around a particular operating state.

$$J = \sum_{k=k_s}^{T_c} (k - k_o) \cdot W \cdot E_{abs}(k) + \sum_{i=1,2} c_i \cdot \gamma_i \quad (14)$$

Where: k: represents the current sample time, ko: represents the starting time of load change in autonomous operation, Tc represents the ending time of load change in autonomous operation,

As mentioned earlier in this article, the particle algorithm can be combined with search techniques to improve local search ability and solve many problems: In a study presented by (Liang and Zou 2022),[57], The adaptive particle swarm optimization (ASAPSO) algorithm based on simulated annealing is utilized in this work this enhances the particle swarm's convergence accuracy and speed to improve droop control, increase system stability, and improve power quality. This method is considered an enhanced droop control approach according to the optimal compensation technique. The author is validating the effectiveness of the technique to enhance the droop control by creating a simulation model of the microgrid in Matlab 2018b. The simulation model is made up of two DGs that run in parallel to the power of supply to linear loads. The microgrid simulation process is as follows: (i) ST1 and ST2 are closed at 0.00-0.15 s (through simulation initialization); (ii) the frequency and voltage control modules are engaged; and (iii) 0.3 s to shut the circuit breaker and connect the load2. The results show: (i) at 0-0.3s, the improved droop control can prevent substantial changes in reactive and active power by adaptively modifying particle swarm (PSO) velocity. (ii) The load power is evenly split among two inverters connected in parallel. (iii) The system's oscillation is minimized, while its steadiness and speed are improved. Finally, from these results may be inferred the algorithm-optimized droop control may achieve the coordination of numerous DGs in the microgrid system, it improves the precision of reactive and active power distribution, and the accuracy of this power is higher than that of the conventional resistive droop control, allowing the microgrid to be stabilized quickly and the power supply system is stable under various operating conditions, and the power quality is increased. Furthermore, the improved control technique decreases system power loss and the difference in power between the two inverters.

5.2. Genetic algorithm optimization (GA)

The GA is a population-based stochastic algorithm inspired by the Darwinian theory of evolution proposed by [58], as a heuristic method. based on the principle of genetic selection. It is similar to biology for chromosomal formation, with factors such as selection, crossover, and mutation representing genetic processes that would be applied to a random population at the beginning[59].GA uses a fitness objective function to assess each individual of the population's level of fitness. The best solutions are selected at random using a selection mechanism (such as a roulette wheel) to improve poor solutions. This operator is more probable to select the best solutions because the probability is proportional to fitness (objective value). Avoiding local optima increases the likelihood of selecting suboptimal solutions[60]. Genetic algorithms (GAs) have emerged as a strong tool for handling search and optimization problems. Also, GA is a prominent optimization approach for solving nonlinear microgrid system equations and identifying control parameters through the natural selection process[61]. Genetic algorithms have been used to solve many engineering problems and have also been used in microgrids to perform some tasks.

5.2.1. Operation performed in GA

GA, like other evolutionary algorithms, relies on selection, crossover, and mutation as its core operators[60].

- ***Selection:*** A chromosome contains information specific to the solution it represents. Every chromosome can be represented by a binary string. Each bit in the string is accountable for containing specific aspects or standards of the solution[59].
- ***Crossover:*** After choosing individuals utilizing a selection operator, they have to be utilized to produce the new generation. In nature, the chromosomes of a male and female are united to form a new one. This is emulated by integrating two solutions (parent solutions) chosen by the roulette wheel to create two new solutions (children's solutions) using the GA algorithm[60].
- ***Mutation:*** mutation involves modifying one or more genes after creating children's solutions. In GA, a low mutation rate is used due to the high mutation rates convert GA to random search The mutation operator keeps population variety by introducing an additional level of randomization. This operator prevents solutions from becoming too like and increases the likelihood of preventing local solutions in the GA algorithm[60]. Fig.9 illustrates the cycle of GA and Fig.10 explains the steps of optimization of GA to optimize the droop control.

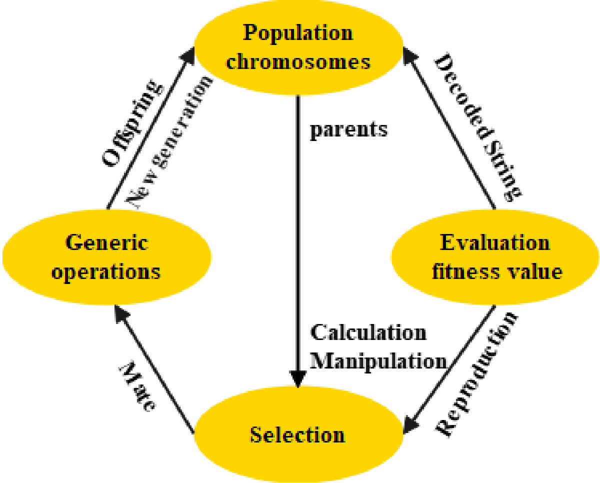

Fig. 9. GA cycle [62].

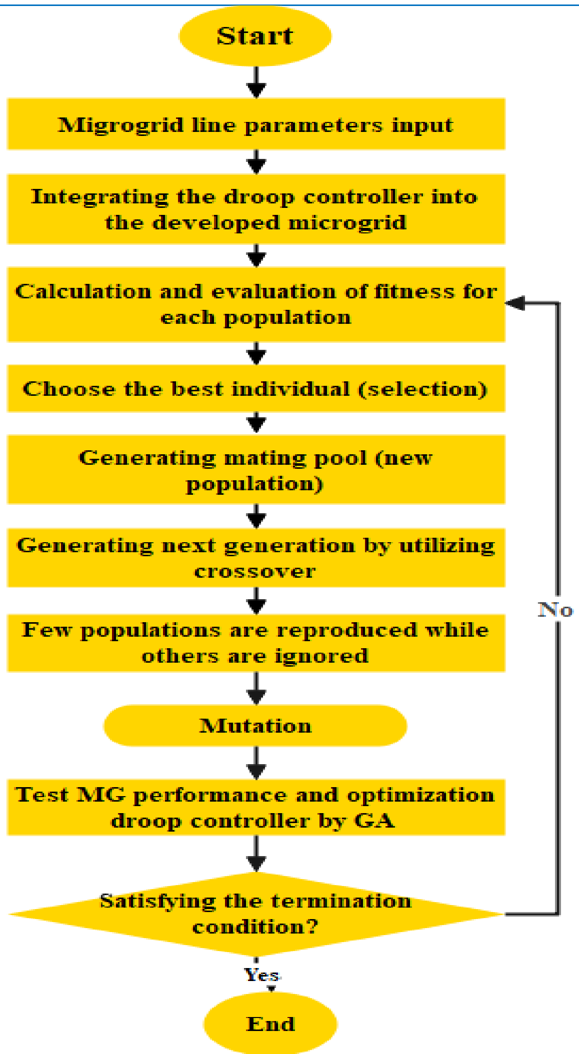

Fig. 10. Flowchart using Genetic optimization algorithm to optimize droop control.

The following is a review of literature using the GA to optimize droop control

In this work [63], the genetic algorithm is employed to optimize the microgrid droop controller, and the drooping parameters can be collected over time based on the load feedback scenario. This strategy employs a new control mechanism that runs in parallel mode with inverters that don't need bus connections, and voltage and frequency control can be performed without any common communication or control circuit between the inverters. The author is validating the effectiveness of the strategy to improve the droop control by creating a simulation model of the microgrid in Matlab using the model containing three distributed generations (DGs) and three loads P1 = 60 kW, $Q1$ = 10 kVAR, $P2$ = 70 kW, $Q2$ = 5 kVAR, $P3$ = 80 kW, $Q3$ = 0 kVAR. From the simulation result When the load is uneven, the optimal droop control parameter can be achieved by adjusting itself. at the time 0–0.5 s The system runs normally, with a frequency of 50 Hz and a voltage of 311 V. Various DG active powers are distributed in an 8:7:6 ratio, while reactive power is allocated equally. After 0.5 seconds, separates from load 2, under the assumption that the droop controller is optimized, and the frequency and voltage fluctuate but keep stability. Finally, the optimization utilizing the genetic algorithm has resulted in stable reactive and active power control performance. It can also ensure that the power supply system operates normally in the event of a sudden load change and improves the system's anti-interference capacity.

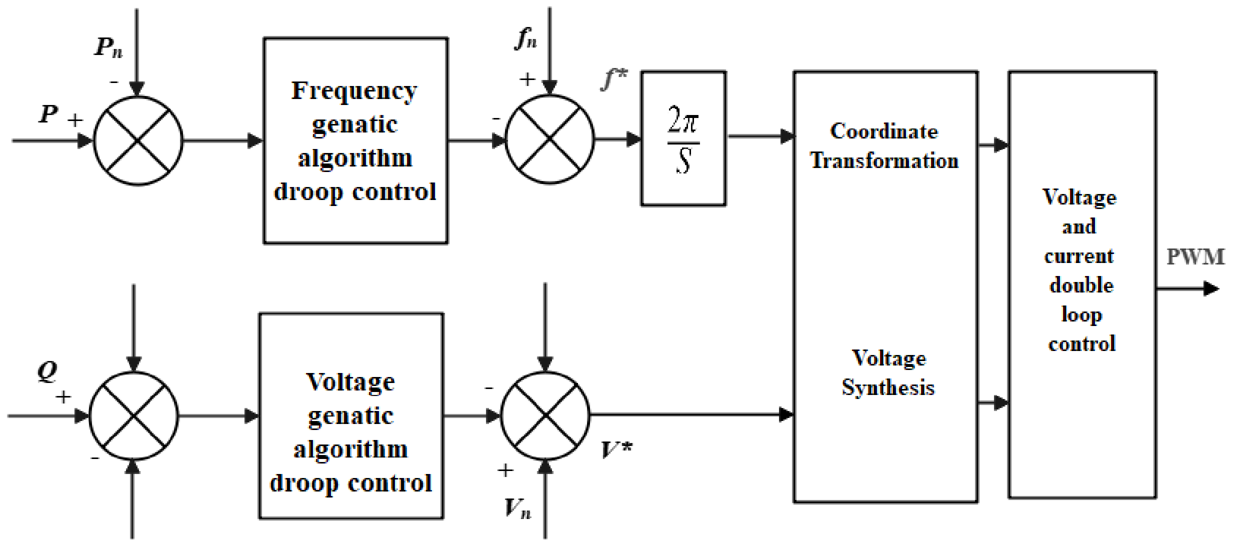

Fig. 11. Block schematic of the GA droop control system [63].

Goodarzi and Kazemi in 2017 [64], introduces a novel hybrid algorithm, Imperialist Competitive Algorithm-Genetic Algorithm (ICA-GA), to address the multi-objective optimization problem such as finding and selecting the optimum operation mode and DG site of an islanded MG. The operation is optimized by identifying and utilizing the optimal DG droop gain parameters. A multi-objective optimization problem is used to formulate three key factors and use membership functions as equation (15). These factors include improving voltage variations and stability, and decreasing fuel consumption costs while taking into account operational and security constraints. For the operation of the suggested method, a novel load flow formulation based on droop control is used, with the system's steady state frequency, frequency reference, reference voltage, and DG droop parameters as optimization variables. The proposed method provides the Pareto front of non-dominated results, followed by the best result of non-dominated outcomes by utilizing a fuzzy approach. To solve the multi-objective problem: firstly, The ICA algorithm is operated to determine the optimal droop parameters, location, and production of DGs by calculating the cost of colonies and imperialists in each empire. Secondly, The GA method is utilized to produce a new set of colonies in all search spaces at a better cost than the imperialist by employing operators such as mutation and crossover. To demonstrate the usefulness of the suggested technology, it is implemented on 33 buses in Matlab a test system of 2.30 Mvar and 3.715 MW total load is examined for two scenarios. In the first scenario, four DGs were placed on buses 9, 22, 25, and 26. It is assumed that the positions of DG units are predetermined, and only the optimal droop parameters of DG units are obtained. from the result of this scenario can be seen that (i) the suggested approach delivers the best values for objective functions, while PD provides the worst values. (ii) The suggested technique produces the lowest reactive and active energy losses. (iii) The voltage profile is enhanced compared to predetermine optimization at all nodes in every approach. additionally, demonstrates that the best VSI is attained by ICA-GA and the worst by PD. In the second scenario, the optimum production and droop parameters placed for three DGs were obtained. Finally, the proposed ICA-GA algorithm improves power system optimization by combining the benefits of ICA and GA approaches, resulting in better results than other commonly used methods. It can be concluded that the suggested technique algorithm is an effective tool for discovering the optimal place and operating a standalone MG at the same time.

$$\mu_{f_i} = \begin{cases} 1, f_i \le f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}}, f_i^{\min} \le f_i \le f_i^{\max} \; i = 1,2,3 \\ 0, f_i \ge f_i^{\max} \end{cases} \tag{15}$$

Where: μ_{f_i}: represents the fuzzy subordination of the optimal objective.

The author in 2013,[61], to reduce voltage and frequency disturbances in island microgrid mode, a new control approach is developed that employs two optimization algorithms genetic algorithm (GA) and imperialist competitive algorithm (ICA). The purpose of using two algorithms is to compare and debate based on the outputs of the applied methods and select the most fitness analysis. In addition, a new idea of traditional droop control in the form of a fast droop controller (FDC) is developed to ensure the reliability of the microgrid system in conjunction with a modern frequency controller this approach is a flexible control system with adjustable parameters allows for faster injection of required power. The microgrid system is simulated utilizing MATLAB's control block diagram and power electronic equipment and has two DGs capable of meeting the local demand. The objective of this study examine the controllability and dependability of microgrid systems in various modes. The entire system is placed in island mode, and there are 8 operating modes with load changes for determining the performance of control parameters. In the first standalone mode, the local load is steady at 0 - 0.2, and the control parameters can regulate the system frequency to 50 HZ. In the 0.2, the local load abruptly increases, causing frequency to drop. This disruption is quickly eliminated, and frequency returns to its nominal value. The frequency variations based on ICA are a significant symptom of an unstable system. In scenario voltage regulation the overload reduces the voltage, and as the load drops, the bus voltage rises, all of which are validated by losses. The resulting bus voltage from ICA demonstrates the incorrect performance of control parameters. Results showed: (i) The ICA algorithm optimizes control parameters equally with the GA algorithm. Countries in ICA share the same role of chromosomes in GA. (ii) The minimum cost of ICA is higher than that of GA. The value for ICA is 4.38. ICA performs well when two values are near in primitive iterations. (iii) The ICA method failed to achieve the control target within the simulation time limit. (iv) The results revealed that the GA algorithm had better performance. Finally, the main constraint with this concept is the range of droop-rated powers. To address this problem, an additional frequency controller is added to the inverter control circuit to quickly set the system frequency to the nominal value. Furthermore, the main concern with this design is the coordination of controllers.

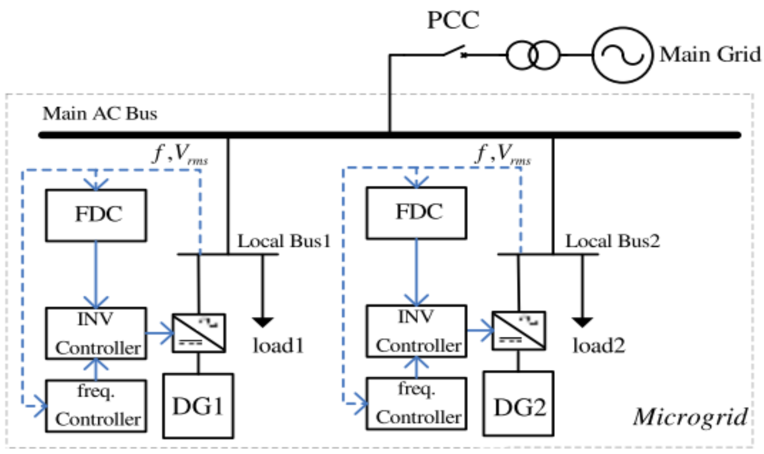

Fig. 12. Diagram of a controllable microgrid network [61].

In this work,[65], a new hybrid optimization approach for solving the power flow problem in an islanded MG is developed based on an imperialist competitive algorithm (ICA) and genetic algorithm (GA). is represented without a slack bus by including the steady-state frequency as a power flow issue variable. The main objective of this method is to model various control modes of DGs, such as droop, PV, PQ, and droop in an islanded MG, to reduce total reactive and active power mismatch in a standalone MG. The power flow issue requires redefined without slack bus consideration. To achieve this, a new droop controller, called droop bus, must be introduced to power flow equations alongside PQ and PV buses. In this proposed method, First, the ICA method is utilized to obtain the system's local voltage and frequency at every bus of the DG unit by the droop controller by computing the cost value of colonies and imperialists in every Empire. Then, the GA approach uses crossover and mutation operators to generate a new set of colonies in the total search spaces that an objective function values toward the imperialist. ICGA Algorithm: The suggested ICGA methodology contains excellent features of both ICA and GA techniques, such as comprehensive searching of solution space, Lack of rapid convergence in a local minimum, better outcomes in phase errors and magnitude average compared to ICA and Newton-trust approaches, as well as the conversion of the receiving end bus from droop control mode to PQ mode. To address the power flow issue, an algorithm is constructed in two loops: the main loop and the inner loop. The main loop determines the optimal solution for the objective function. the inner loop is for determines the load flow. The suggested algorithm's performance was evaluated using 6-bus and 33-bus MG systems and three case studies (test systems) were used to validate the suggested power flow approach. In the first case, the first system consists of a 6-bus system with a rated voltage of 127. This system operates in an autonomous mode and it contains three comparable droop control DGs installed on busses 4, 5, and 6. The result in this case shows ICGA has lower phase and magnitude errors compared to ICA, which has the highest, The ICGA has an average phase error of 0.115% and magnitude error of 0.039% when compared to time domain simulations, These findings show that the suggested load flow algorithm for MG operating in the islanded mode using droop control performs well, The proposed approach produced a steady-state frequency of 0.9992 p.u. A slight frequency deviation is caused by active power sharing across different DGs. In the second case, the second system is an MG with 33 buses and a rated voltage of 12.66 KV. Four DGs were installed on busses 26, 22, 25, and 9. The proposed approach yields a steady-state frequency of 0.998846 p.u. In the third case, the third system consists of a 69-bus distribution system with a combined reactive and active load of 3.772 MW and 2.694 Mvar, respectively. On buses, the following five DGs were set: 50, 27, 35, 46, and 65. Two scenarios were studied to evaluate the influence of the PV bus voltage on reactive power sharing. In the first scenario, the voltage on bus 26 was assumed to be 1 p.u. In the second scenario, the voltage was totaled to be 1.02 p.u. In both situations, the reactive power outputs of droop control DGs remained within their permissible ranges. The results found that during 1 p.u, other DGs go from droop to PQ mode, achieve their permissible ranges, and function within those ranges for 1.02 p.u. When the PV bus voltage was lower than 1 p.u, under-voltage was noted at most network buses. These findings demonstrate that a proper PV bus voltage setting promotes effective reactive power sharing across drooping distributed generators and mandates maintaining PV bus voltage within specified bounds. Although the ICA method solutions converge faster than the ICGA method, they aren't truly global solutions. Due to the minor local voltage and frequency interval fluctuation of droop DG units. When compared to ICA, the suggested method has a lower objective function value. Finally, the suggested algorithm performs well, according to the results. Additionally, the GA, Newton-trust, and time domain approaches were used to compare the corresponding findings of the 6-bus MG system. This suggests that ICGA can produce convergence outcomes that are more uniform while requiring less computation time.

This work [66], introduces a novel hybrid algorithm (HS-GA) based on genetic algorithm (GA) and harmony search(HS) to solve multi-objective optimization problems such as: Solving the reliability and technical issues of microgrids (MGs) by building several self-sufficient standalone sub-MGs using MG clustering thinking, reliability enhancement, and voltage profile enhancement are regarded as objective functions and power losses reduction. The proposed approach is regarded as the optimal method for finding cut set lines to convert an MG to several sub-MGs to safeguard the MG from any failure, hence increasing the robustness of the MG. Two case studies 69-bus and 33-bus according to islands MG and three scenarios were evaluated to demonstrate the effectiveness of the suggested strategy and test system. In the first case, it was used 69-bus. The system consists of 68 lines with maximum reactive and active loads of 2.69 MVar and 3.8 MW, respectively, and a nominal voltage of 12.66 kV. And This case considers three scenarios. In the first scenario, MGs use only droop controllers and, in this situation, 7 DGs operate using a droop controller. Compared with a predetermine method when droop parameters are constant (without tuning) The scenario shows the power determined by the suggested technique is lower than that of the PD method. In the second scenario when using MGs with PQ Buses and droop controllers, in this scenario used five DGs that utilize a droop controller, and three DGs according to PQ operation are tested to show the scenario raising the number of sub-MGs, the values of the objective function rise and when a fault occurs in the MG, systems created using Scenario 2 are more reliable than those planned using Scenario 1. In the third scenario, when using MGs equipped with droop controllers, capacitance, and PQ buses, in this scenario, The MG arrangement is similar to Scenario 2, with the exception that three capacitances that total 120 kVar are added to the system this shows that using capacitances in sub-MGs improves the operation of MGs. In the second case, the system Includes 32 lines, four DGs with 3 capacitances with 80kVar used, a maximum reactive and active load of 2.30 MVar and 3.715 MW, and the MG nominal voltage of 12.66 kV. The findings demonstrate that HS-GA may successfully handle relations interconnected among decision variables. The results also suggest that using DGs based on droop controllers and PQ, as well as capacitances, increases the performance of MGs.

In this work [67], an optimal droop control strategy for a DC/DC Boost power converter is utilized to control a standalone operation of a test microgrid developed based on the Genetic Algorithm (GA). The main objects of this work are (i) voltage bus regulation and equal power sharing in the shortest amount of time when the load changes abruptly. (ii) Used GA, to identify the optimal parameters for PI controllers to reduce the related cost function. The advantages of this proposed method are: The suggested technique only requires local output information; therefore, the advantages of conventional droop control are preserved, and it is less dependent on the network's mathematical model. The suggested controller's benefits are demonstrated by modeling a 600 V and 100 kW (±5%) DC microgrid in MATLAB software and the system consists of a Battery Energy Storage System (BESS) block and three DG units with 3 μ-sources and maximum power generation, 30 kW, 30 kW, and 40 kW, respectively. when the loads are changed among the maximum and minimum values abruptly by contemplating the worst–case scenario in changing load values which is the step changing that is utilized in this situation. In this scenario for stability study analyzed the Microgrid performance in two crucial worst cases, first the maximum in the period [0.6 - 1.2] and the second the lowest in the time interval [1.9 - 2.5] load levels. In these cases, if a system is BIBO stable If a system is BIBO stable, the output will be bounded for all bounded input values. DC bus voltage errors are a reliable measure of microgrid stability, falling within the 600 ±5% range and the voltage errors are outside the range at t=0.6 s and t=1.2 s. voltage error can be obtained in range and access to equal power sharing among the DGs less than 0.5 s when the disturbance is injected into the Microgrid within the time range [0.6 - 1.2] the simulation results demonstrated the effectiveness of the proposed methodology when compared to other conventional methods in various scenarios. Finally, from this result, It has been verified that the proposed controller performs well when the load varies between minimum and maximum levels.

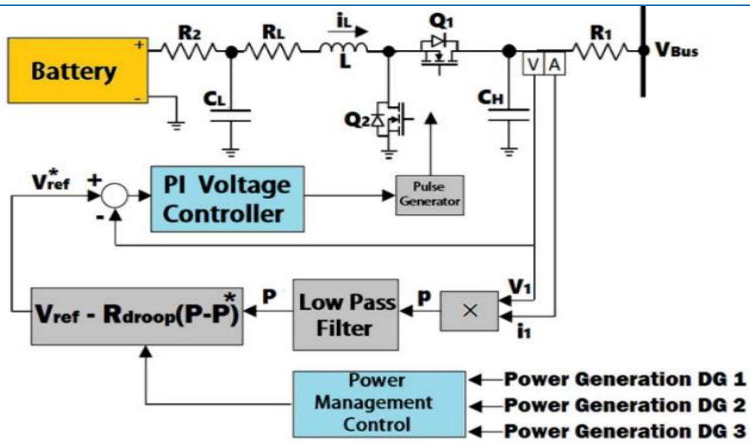

Fig. 13. Source structure (BESS) used in this paper.

Where Yu et al. in 2016[68] provided a detailed and precise small-signal state-space model of a microgrid based on a droop control technique, which consisted of load, network, and inverter dynamics, and then integrated it with a common reference frame to create the final model. Then used genetic algorithm to optimize the microgrid's operational characteristics under time-domain simulation in MATLAB/Simulink. To test the performance of the suggested control optimization strategy the microgrid model is used for both rapid load changes and mode transitions in many cases: (i) at 0-0.8 s, the system works in grid-connected mode. (ii) at 0.8–1.5 s breaking the PCC causes the microgrid to go into standalone mode. (iii) at 1.5–2 s abruptly shuts off the public load, with the maximum generation is 100, the initial crossover chance is 0.7, the initial population size is 40, and the mutation probability is 0.01. Simulation results show that when the system changes to autonomous mode after t=0.8, the DG's output power increases and then decreases once the load is turned off. the system frequency variations after optimization which are well maintained around the nominal values. This Simulation validates demonstrated the usefulness of the proposed small-signal dynamic model and optimization algorithm the genetic algorithm (GA), as well as improved the microgrid's dynamic performance, making it a useful reference for parameter design of droop control in low-voltage microgrids. The results also verify four parameters (integral current parameter Kic voltage parameter Kpu and power droop gain mp, nq) from small-signal analysis have a significant impact on microgrid dynamic and stability performance during load disturbances. and validate the effectiveness of the suggested GA technique in improving the dynamic performance of microgrids. Consequently, the suggested control optimization plan makes a substantial contribution to maintaining microgrid stability and low-voltage network parameter selection. Finally, according to the results, the minimum power damping through the switch between different operator's modes and the minimal oscillation during steady-state operation has been accomplished, implying that the suggested control optimization approach nearly matches the small-signal analysis while improving system dynamic and stability performance.

As presented by M.Abedini in 2016[69], a new algorithm for load flow analysis in an Autonomous microgrid is presented. The load flow problem was modeled without any slack bus by including the steady state frequency as a load flow variable. A novel formula for load flow equations is provided to simulate several DG control modes, like droop, PQ, and PV, in an autonomous microgrid. Based on a hybrid optimization algorithm (ICGA), genetic algorithm (GA), and imperialist competitive algorithm (ICA). the main idea of this approach was to address the issue of traditional load flow analysis, which isn't able to deal with isolated microgrid situations. To address the proposed load flow problem formulation, an optimization problem is established. The aim is to reduce the absolute mismatch between reactive and active power by using equation (9). For this objective, a droop control mode for DG operation is initially considered. Then, different DG operation modes are used. The local voltage and system frequency for every bus of DGs are then determined using a droop controller. This is followed by estimating the reactive and active power produced by DGs to match the reality of decentralized droop control using an Autonomous microgrid. At last, the angles and voltages of the other buses in the Autonomous microgrid are determined using an iterative approach to reduce the total reactive and active power mismatch. The suggested algorithm's performance was evaluated using 6-bus and 33-bus MG systems and two case studies (test systems) were used to validate the suggested load flow approach. In the first study, the system has 6- buses with a rated voltage of 127V. This system runs in Autonomous mode and consists of 3- similar droop control DGs located on busses 4, 5, and 6. From the result this case demonstrates that ICGA has the smallest phase and magnitude errors, while ICA has the highest and lowest errors compared with GA and Newton-trust and the steady state frequency was 0.9992 p.u. A small fluctuation in frequency is caused by active power sharing among various. In the second study, the system has a 33-bus microgrid with a rated voltage of 12.66 KV. Four DGs were installed on buses 26, 22, 25, and 9. From the result, this case demonstrates the sensitivity of power flow to voltage settings on a PV bus. The voltage of a PV bus was considered in 3-values: lower than 1 p.u., 1 p.u., and 1.02 p.u. when the voltage of the PV bus is lower than 1 p.u., Under-voltage occurs at the majority of buses of the network. Furthermore, the results demonstrate that for 1 p.u., other DGs convert from droop mode to PQ mode while reaching their permissible ranges for 1 p.u. and operating in the allowed ranges for 1.02 p.u. Finally, ICGA was capable of minimizing the mismatch between total reactive and active power.

5.3. Gray wolf optimizer (GWO)

The gray wolf is a new type of swarm intelligence (SI) metaheuristic algorithm proposed by [28]and is inspired by mimics of the social leadership hierarchy and hunting behavior of (GWO) in nature. Grey wolves, often known as timber or western wolves, typically dwell in packs of 5-12 individuals of a wolf. To hunt the prey while maintaining discipline the gray wolf algorithm (GWO) has a very rigid social dominant hierarchy that is divided into four categories called (alpha (α), beta (β), delta (δ), and omega (ω)) as shown in Fig.14. The first group (α),the leaders are female and male. The alpha is responsible for the pack's key choices. Alpha is also known as dominant. The second type of wolf called beta is the submissive wolf, who relays the alpha wolf's messages to other wolves and assists the leader wolf in making decisions such as hunting and location selection also, a beta can be male or female. the last category of the pack is omega these wolves who have authorization to eat food are included in the end. These wolves are an important part of the pack because, without them, the pack may experience internal conflict issues. If the wolves aren't an α, β, ω) are categorized as subordinate or delta wolves. sentinels Scouts, hunters, elders, and caretakers fall under this category. Sentinels protect and ensure the security of the pack. Scouts are liable for observing the boundaries of the area and informing the pack in the event of any threat. Hunters assist the alphas and betas by pursuing prey and providing food for the pack. Elders are skilled wolves who serve as alpha or beta. In addition to the leadership hierarchy, there is another behavior of gray wolves called hunting, Group hunting is an important part of the pack. Their hunting process includes three steps. main phases of the grey wolf hunting process involve three steps: -

- Monitoring, chasing, and approaching prey.
- Follow, encircle, and harass the prey.

- Attack the prey

The gray wolf optimization algorithm is used by many researchers to solve different problems in engineering.

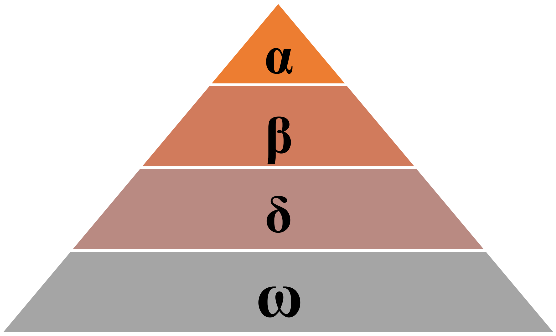

Fig. 14. Hierarchy of (GWO) [28].

5.3.1. Mathematical model of (GWO)

- ***Social hierarchy: -*** Analyzing social behavior in wolf packs identifies the fittest candidate as the alpha wolf (α) or solution. consequently, with second and third-best fitness are referred to as "Beta wolves (β) ", "delta wolves (δ) ", and "Omega wolves (ω)".
- ***Encircling prey: -*** The mathematical model for wolves' encircling approach around prey is proposed as follows the equations:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \quad (16)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (17)$$

Where: the t is the current iteration, $\vec{X}_p$ is the position vector of prey, $\vec{X}(t)$ is the position vector of the wolf $\vec{X}(t+1)$ is the position of the wolf at (t+1)th, $\vec{A}$ & $\vec{C}$ are coefficient vectors can calculated as the following:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (18)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \quad (19)$$

- ***Hunting: -*** Grey wolves recognize the position of prey and encircle them. To mathematically recreate grey wolf hunt behavior, consider the alpha (optimal candidate solution), beta, and delta to better understand possible prey locations. Consequently, keep the first three best solutions acquired thus far, and require the remaining search agents (including the omegas) to update their positions based on the positions of the best search agents. By using this approximation, each wolf can update its position by:

$$\overrightarrow{D_a} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_a} - \vec{X}\right| \text{ , } \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right| \text{ , } \overrightarrow{D_g} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \quad (20)$$

Where $\overrightarrow{X_a}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ are position vectors (α, β, δ), The final location vectors of the present individuals are determined as follows:

$$\overrightarrow{X_1} = \overrightarrow{X_a} - \overrightarrow{A_1} \cdot \left(\overrightarrow{D_a}\right) \text{ , } \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta}\right) \text{ , } \overrightarrow{X_3} = \overrightarrow{X_6} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_s}\right) \quad (21)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (22)$$

A_1, A_2, A_3 the random vector

- ***exploitation (attacking prey): -*** when the prey stops moving, the grey wolves end their hunt by attacking them, to represent approaching the prey, they reduce the value of $\vec{a}$. The fluctuation ranges of $\vec{A}$ decrease by $\vec{a}$, $\vec{A}$ is a random value in the interval [-2a, 2a], where a decreases from 2 to 0 over repetitions. When random values of $\vec{A}$ are in [1, 1], the search agent's position in the future can be anywhere between its current location and the prey's position. The exploration happens when $\vec{A}$ is either larger than or less than -1. When C exceeds 1, it fosters exploration.
- ***exploitation (search for prey): -*** Grey wolves search mostly based on the alpha, beta, and delta positions. They split in search of prey and then unite to attack it. To mathematically describe divergence, we use $\vec{A}$ with random values higher than 1 or less than -1 to force the search agent to diverge from its prey. in addition, exploitation is greater when $|A| < 1$ and $C < 1$. During optimization, $\vec{A}$ decreases linearly to highlight exploitation as the iteration counter climbs. C is created randomly during optimization to encourage exploration and exploitation at all stages, which helps resolve local optima entrapment[70]. Fig.15 explains the steps of optimization of GWO to optimize the droop control.

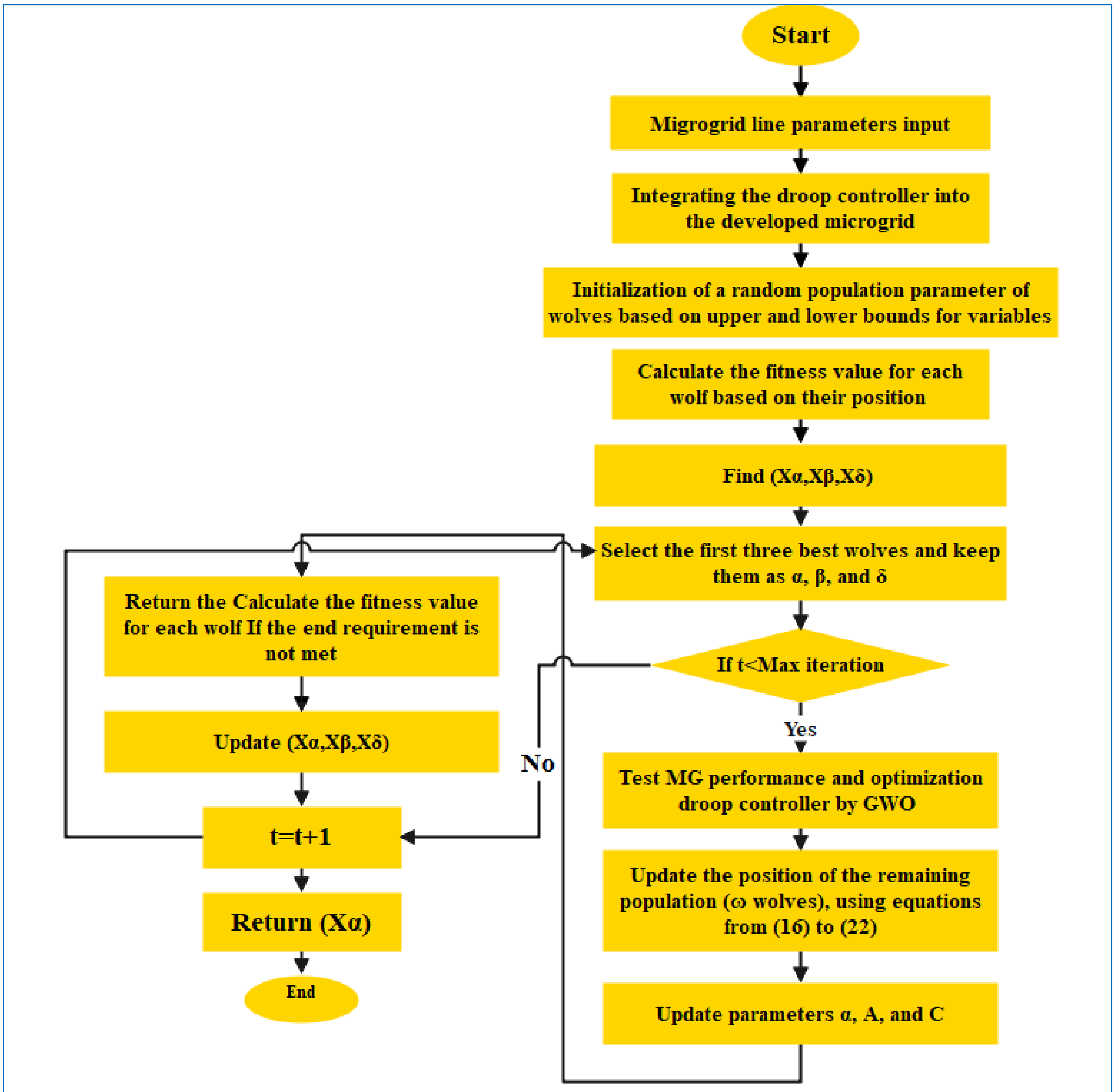

Fig. 15. Flowchart using Grey Wolf Algorithm to optimize droop control.

The following is a review of the literature using the GWA to optimize droop control.

The Yuan and Li in 2023,[71], use the gray wolf algorithm to optimize the microgrid parameters, such as the Droop control parameters that enable switching of the microgrid from grid-connected mode to islanded mode, due to the switching process and Load changes affecting both dynamic and grid behavior. Also, this study created an accurate small signal space state model of a microgrid using a droop management technique, which included inverter dynamics, grid dynamics, and load. Finally, the findings indicate that the optimal control can protect the microgrid against frequency variations induced by load changes and fluctuations. The findings suggest that the optimal control strategy described in this article may protect the microgrid against frequency changes induced by load changes and fluctuations of up to 10 Amp for load current. The parameters and coefficients of the controllers for the intended control method in this article have been tuned to maximize performance. Furthermore, by utilizing this control technique, undesired harmonics were greatly decreased. Furthermore, the suggested control system's design assures that DG units operate properly microgrids.

Then J. Zhang, Wang, and Ma in 2019, [72], due to the power management approaches that take into account economic concerns, they are limited by the fixed structure of microgrid (MG) and mathematical model. In this article the researcher presented the Gray Wolf optimizer, taking into account the economic dispatching problem, and an additional secondary controller known as virtual rated power (VRP) is built this increases MG control flexibility and reliability. In this manner, we gain active and reactive power sharing, real-time online cost coefficient adjustment is done by using the nature of multi-agent consensus theory. the study two cases to verify the effectiveness of the proposed control when load3 disconnected and connected under (i) fixed communication topology and (ii) switch topology fixed topology The cost of the load 3 disconnected case is reduced by 14.5%, while the cost of the load 3 connected case is reduced by 9.2% under GWO. When the switch topology GWO reduces costs by 2.5% for load 3 unconnected cases and 8.9% for load 3 connected cases Finally, the findings from the simulation demonstrate the efficient operation of the suggested optimal approach which can achieve the active and reactive power sharing. The researcher couldn't able to confirm the effectiveness of the method through the experiments because of the constraints in conditions.

As presented Saeed et al. in 2023[73], To address the drawbacks of the voltage droop control technique this study introduces an adaptive control technique that can simultaneously share current and adjust the voltage by load conditions. When the load in the microgrid is low, the output current is less than the maximum limit, making it easy to share the current. When the load rises and the output current oversteps the maximum limit, current sharing becomes critical. This solution addresses the problem by incrementing the total droop gains. In other words, the total droop gains are adjusted depending on the load current by using a gray-wolf algorithm (GWO) to optimize the droop gains. The objective of this work is to reduce the cost function. By reducing the cost function, the system responds swiftly to changes in nominal power, and this power is stabilized without any overshoot during switching moments by using the objective function as follows in equation (23). To evaluate the efficacy of the proposed adaptive control system, a DC microgrid with three distributed generation units was simulated using the MATLAB Simulink software. Each distributed generation source has a separate nominal current of 10, 10, and 5 amps Each of these sources contains a DC-to-DC buck converter with an external voltage controller internal and current controller. of these sources contains a DC-to-DC buck converter with an external voltage controller internal and current controller. A 4 Ω resistor is utilized to provide a light load for the system. To imitate larger loads, another size 4 resistor is added to the load after 0.25 s. To demonstrate the efficaciousness of the adaptive approach in comparison to the primary way, droop gains sets of 2, 2, and 4 were taken into consideration for greater gains. From the result finding the issue is that the dispersed production units' current exceeds its maximum value and reaches the entire load current due to an error in dividing the output-current. Distributed generation sources' output voltage nevertheless exceeded its normal range. Furthermore, the suggested adaptive technique features an acceptable voltage regulation. Simulation results demonstrate that, for low load currents, distributed generation units' output currents differ from the maximum standard value. Thus, sharing the current is not a difficult problem. When the load increments, the output currents in distributed generating sources tend to peak within the standard range. As a result, in loads with huge currents, high-precision current sharing becomes critical. Finally, the suggested adaptive approach increases overall gain adaptively in response to rising load, enabling more accurate current sharing.

$$inJ = \sum_{i=1}^{M} \left\{ \int_{t=t_0^i}^{t_f^i} \left(t - t_0^i\right)[P(t) P^*(t))^2 + (Q(t) - Q^*(t))^2] dt \right. \tag{23}$$

This paper [74], offers to develop local control levels for the DC MG using the hybrid particle swarm optimization/grey wolf optimizer (HPSO-GWO) algorithm. To solve DC issues MG's local control layer is under numerous power-production variations and load interruptions, including incorrect power-sharing between sources and uncontrolled DC-bus voltage of the microgrids, together with a significant ripple of battery current. The basic objective of this hybridization is to improve the ability of exploitation in PSO with the power of exploration in GWO and it is distinguished by its simplicity and ease of utilization as a tool to be employed in effective execution, and competitive performance, in comparison to those other optimization algorithms. The main objective of this work is to solve the problem: of proper power sharing, proper voltage regulation, low settling time, fewer power losses, regular and transmission maintenance expenditures, and power outage grid shutdowns. To test the performance of the suggested control optimization strategy the microgrid model is used, a typical MG contains many types of distributed energy resources, like wind turbine generators (WTG), fuel cells, and photovoltaics (PV), accompanied by ESSs to deal with the intermittent nature of such sources and the droop control strategy is used to maintain the stability of the DC-bus voltage and the battery's automatic charge and discharge operation. to optimize the PI controllers' parameters that are used at the local control level of the examined MG based on the objective function in Equation (24). As a result, accurate power transfer and appropriate voltage control are achievable, potentially improving the simulated MG's performance. This approach was evaluated under different load and PV-generation situations. To test the efficiency of the proposed technique in increasing the performance of the local control layer different situations were applied consisting of PV-generation variations and load changes and the suggested method's durability was assessed utilizing the rate of overshooting and undershooting in MG voltage, battery current tracking, power sharing, and system responsiveness. In this scenario, load changes by 50%, 38%, and 32%, with solar irradiance fluctuations occurring at 2 s, 3.5 s, and 4 s, respectively. The quantity of PV-generated power stays at 470 W until 2 s, therefore there is no surplus power that may be used to charge the battery during that time interval (1 s-2 s), due to the demand of the load rising to 500 W. Thus, the DC-link voltage drops dramatically at 1 s, it may also be observed that PV generation increases to 580 W at 2 s, resulting in an increase in DC-connected voltage up to 50.25 V. Load demand rises at different rates at 1 s, 3 s, and 4 s, causing the bus voltage to deviate significantly from the statutory limit of 5% at certain times. From this result can be observed this method is ineffective when dealing with crucial operating situations like load-generation uncertainty. It is also worth mentioning that, while the battery current is strictly monitored in its reference value, certain undesired ripples remain. By using GWO, the voltage of the simulation MG increases from 43.66 V to 47.016 V, with a 50% increase in load demand at 1 s as well as a voltage-overshoot drop from 50.25 V to 48.7 V at 2 s, the simulation results show keeping the bus voltage at the suitable level (1.67%), optimal battery current tracking and optimal power sharing with its reference value are accomplished, In compared to the conventional control strategy utilized in the DC microgrid's local control layer, the suggested control method produces less overshoots and undershoots in the DC bus voltage, less current and voltage ripples, and a shorter settling time, increasing the microgrid's reliability. Finally, the System response is effectively improved to withstand any disturbance that may occur without producing any power dissipation. The suggested method enables fast voltage restore with low settling time, rising time, and undershoot/overshoot, making system operation more dependable and stable under critical operating situations, ensuring the robustness of this control technique.

$$\mathrm{ITAE} = \frac{\sum_{\mathrm{Er}}^{N} \int_0^{\infty} t|\mathrm{Er}(t)|dt}{N} \tag{24}$$

Where: N: represents the number of errors acquired from PI controllers and $\mathrm{Er(t)}$: represents the disparity between the beginning point and the variable to be controlled.

Moazami and Kazemi in 2018[75], identify the optimal clustering of standalone microgrids by considering variables like distributed generation (DG) droop characteristics, renewable energy sources, the position and capacity of DG units, capacitors, and power line transmission and increased planning accuracy. This study presents a novel multi-objective optimization strategy called the chaotic grey wolf optimizer (CGWO) algorithm. CGWO was utilized to increase converging and improve optimal solutions. The approach's effectiveness is examined across three different scenarios using a 69-bus MG. In scenario one when using DG units with a droop controller, can be seen that optimized droop parameters significantly reduce active and reactive power losses in MGs. In scenario 2 when DG units are based on a droop controller and PQ, can be seen PQ concurrently increases the robustness of MGs against unexpected interruptions or failures, and in scenario 3 when using DG units with droop controllers, PQ, and capacitors it can be shown that employing capacitors in MGs reduces the values of the objective functions. Furthermore, the reactive power imbalance in MGs is mitigated when compared to the other situations. Finally, the findings showed that using distributed generation (DG) units based on droop controllers, capacitors and variable power increased the performance of MGs when compared to using just droop controller DGs.

From the results of the previous studies discussed, it can be said that the Gray Wolf Algorithm (GWO) outperformed the Particle's Swarm Algorithm (PSO)in improving the droop control parameters and reducing the deviations that occur in the system during the transition to the isolated mode or during the sudden change in the load.

5.4. Grasshopper Optimization Algorithm (GOA)

The Grasshopper Optimization Technique (GOA) is considered a nature-inspired optimization methodology that mimics inspiration from the swarming behaviors and social interaction observed among grasshoppers (Abdulwahab et al., 2021) [9] The life cycle of (GOA) consists of three stages: egg, nymph, and adult, as shown in Fig.16. This algorithm has many advantages such as the grasshoppers' slow motion and short steps are the swarm's distinguishing feature during the larval phase. In contrast, long-range and sudden movement is the swarm's distinguishing attribute in adulthood. Another significant characteristic of grasshopper swarming is their search for food sources [76][22]. the proposed (GOA) has been used and compared to traditional methods for solving engineering challenges[77], Nature-inspired algorithms have been widely used in science and industry because of their simplicity, gradient-free mechanism, high local optima avoidance, and consideration of issues as black boxes.

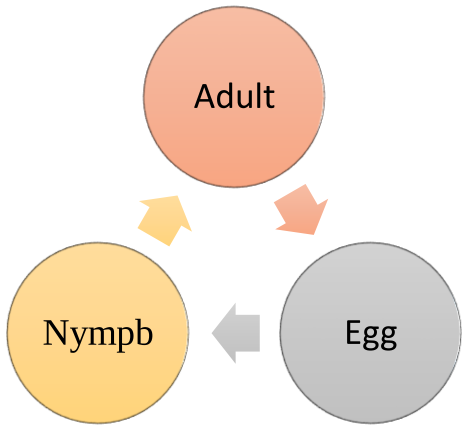

Fig. 16. Life cycle of GOA [22].

5.4.1. Mathematical model of GOA

The performance (GOA) is divided into two tendencies: exploration and exploitation process during the searching process like all nature-inspired algorithms [77]. The mathematical model employed in (GOA) is the equation (25)

$$X_i = S_i + G_i + A_i \quad (25)$$

Where: X_i & S_i & G_i & A_i represent the position of the i_{th} grasshopper, the social interaction of the grasshopper, the gravitational force on the i_{th} grasshopper, and the wind advection. to create some randomness in the behavior of (GOA)and modify, the equation (25) becomes as follows:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (26)$$

Where r_1, r_2, and r_3 are defined as random in the domain [0,1]

$$s_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\widehat{d_{ij}} \tag{27}$$

Where d_{ij} represents the distance between the i_{th} and the j_{th} grasshopper

$$d_{ij} = |x_j - x_i| \tag{28}$$

Where: N: represents the total number of grasshoppers, d_{ij} is a unit vector from the i_{th} grasshopper to the j_{th} grasshopper and S: is a function that defines the strength of social forces and is determined using an equation (29)

$$S(r) = fe^{-\frac{r}{l}} - e^{-r} \tag{29}$$

Where: l represents the attractive length scale, and f is the strength of attraction, The G_i component in equation (30)

$$G_i = -g\hat{e}_g \tag{30}$$

where g represents the gravitational constant and ˆ eg denotes a unit vector, the component A is calculated as in equation (31)

$$A_i = u\widehat{e_w} \tag{31}$$

By substituting the value of S_i, G_i and A_i in Equation (1), a new equation is given;

$$X_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} S(|X_j - X_i|)\frac{X_j - X_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \tag{32}$$

This mathematical model cannot be utilized to address optimization problems directly, mostly because the grasshoppers quickly reach their comfort zone and the swarm does not converge to a specific point. A modified version of this equation is proposed below to tackle optimization problems [22].

$$X_i = c\left(\sum_{\substack{j=1 \\ j \neq i}}^{N} c\,\frac{u_1 b_d - lb_d}{2} s\left(|x_j^d - x_i^d|\right)\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \tag{33}$$

where l_{bd} is the lower bound, and is the upper bound in the D_{th} dimension, k: is the value of particles for the current iteration, ˆTd: represents the value of the D_{th} dimension in the target. To balance exploitation and exploration properties, lower the coefficient c proportionally to the number of iterations. As the number of iterations increases, the coefficient c decreases the comfort zone correspondingly, as calculated below[77].

$$c = c_{max} - k\,\frac{c_{max} - c_{min}}{K_{max}} \tag{34}$$

Where: c_{min} : is the minimum value, c_{max} : is the maximum value,k: represents the current iteration, and K_{max}: represents a maximum number of iterations.

The following is a review of the literature using the GOA to optimize droop control.

Where (Abdulwahab et al. 2021)**,**[9] presented this method to improve the droop controller parameters (k_p, k_{pv}, k_{iv}, $k_{pi,}$ and k_{ii}) , and ensure equal power sharing between the DG_S, when the switch is done between mode microgrid (islanded mode and grid–connected) the frequency and voltage deviate from their nominal values, this method is included so that deviations during islanding and load changes are as low as possible. To optimize the droop controller, a grasshopper optimization algorithm is embedded in the controller parameters to maintain stability during disturbances (islanding and rapid increases in load), This study's system includes DGs, a voltage-source inverter (VSI), a power controller, coupling inductors, and LC filters. Simulations results obtained from the developed scheme when the load equal 6kw it is observed the largest frequency deviation after islanding was 0.0018 Hz, Moreover, it was found that the frequency deviation registered when the load was increasing from 6 kW to 10 kW resulted in 0.0004 Hz. A comparison was made between the results obtained from the devised scheme and those acquired when the Genetic Algorithm (GA) was utilized to optimize the controller. The aforementioned comparison showed that the grasshopper Optimization Algorithm (GOA) outperformed the Genetic Algorithm (GA) by 0.2104% and 0.0092% in terms of the recorded frequencies immediately after islanding and during the load increase, respectively. Ultimately, it can be determined that the GOA-optimized droop controller effectively minimized the deviation experienced when the micro-grid transitioned into Island mode and when a rapid change in load occurred.

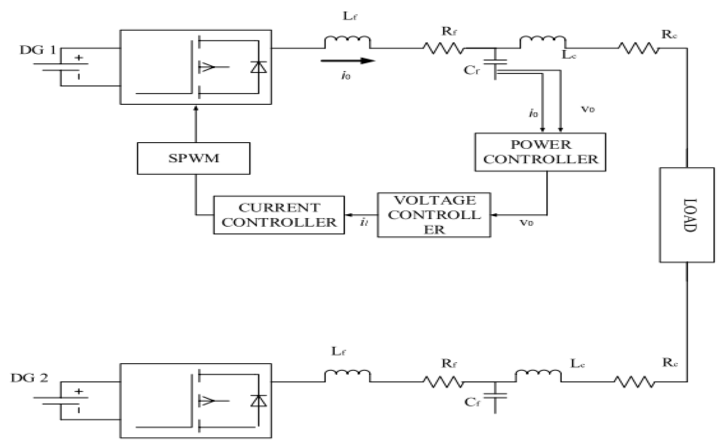

Fig. 17. Structure of MGs.

As presented by Jumani et al. 2018,[77] proposed a Grasshopper Optimization Algorithm (GOA))-based controller to improve PI controller parameters by minimizing the error associated with integrating the (FF) for optimal dynamic response of an islanded MG. And to create an optimal control technique for frequency and voltage regulation of PV-based MG systems in autonomous mode. The GOA uses its intelligence to optimize PI controller parameters. This improves the power quality and dynamic response of the tested MG system under load change and DG insertion situations. In addition to voltage and current control loops, the control architecture includes a droop control for power-sharing purposes. The system contains two DG_s each on connected point common coupling, a DC-DC boost converter, two solar PV, three-phase VSI, RLC filter, the Droop controller produces reference voltage and frequency signals for the voltage controller, which then generates reference current signals for the current controller. To evaluate the proposed controller's efficacy, its performance in reaching the rated frequency and voltage values, thereby ensuring high-power quality, is compared to that of Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) based controllers under the same controller configurations and operating conditions. Simulation results show that GOA outperforms PSO and WOA, resulting in lower voltage and frequency overshoot, output current, settling time for both DG insertion and load change conditions, Total Harmonic Distortion, minimal settling time and overshoot during DG insertion and load shift situations. The GOA-based controller demonstrates 23.81% and 33.33% faster convergence than previous WOA and PSO controllers, respectively. The FF demonstrates a higher minimum final optimized value (0.496) than WOA (0.87) and PSO (1.00), resulting in a high-quality solution to the optimization problem. The power quality analysis shows that the GOA-based controller has the lowest THD (0.08%) compared to WOA (0.15%) and PSO (0.18%). The main objective was to reduce the FF.

$$F.F = \text{Min}\{\int_0^\infty t * |e_p| dt + \int_0^\infty t * |e_q| dt\} \tag{35}$$

Then Swastika Tarafdar in 2019[78], a method is proposed for optimizing the droop constants of an islanded DC microgrid while also taking into account fuel efficiency and tiny signal stability. System Eigenvalues are computed to determine the initial objective function for tiny signal stability. The second objective function, which represents fuel cost, is determined using unit cost constants and power generation. This optimization problem is then solved using the Multi-Objective Grasshopper optimization algorithm, which takes into account these two objectives. The results achieved are compared to those of the multiobjective genetic algorithm. A time domain voltage response is also recorded to demonstrate the stability. in the research, the author used two objective functions for improving small signal stability and reducing fuel costs:

$$Ob_1 = w_1 \times \max_{\forall k \in K}(\text{Real}\{\lambda_k\}) + w_2 \times \sum_{k \in K} (1 - \varepsilon_k) \quad (36)$$

$$Ob_2 = \& \sum_{i=1}^{Ng} \left(a_i + b_i P_{gi} + c_i P_{gi}^2\right) \quad (37)$$

In This study [24], the proposed algorithm is employed in an independent microgrid system to ascertain the optimal configuration of the system that will efficiently meet the energy demand, taking into consideration the probability of power supply deficiency (DPSP) and the cost of energy (COE) duo to the algorithm GOA optimizes faster, reducing computing time and resource utilization while producing better results than its equivalent. . propose a rule-based energy management scheme (EMS) to coordinate power flow among microgrid components. The proposed microgrid consists of photovoltaic modules, a wind turbine, battery storage, and a diesel generator. The suggested GOA is compared to particle swarm optimization (PSO) and cuckoo search (CS) algorithms to evaluate its effectiveness in optimizing the problem. This method has proven its effectiveness through simulation results these results show that GOA outperforms CS and PSO in terms of optimal system sizing. This results in a 14% and 19.3% reduction in system capital costs. The GOA approach can produce global optimums with a low processing requirement and fast computational convergence.

Jumani, Mustafa, Rasid, Mirjat, et al. introduce a study in 2019[79], The objective of this study is to create an intelligent and robust optimal power flow controller that uses a grasshopper optimization algorithm (GOA) to maximize the grid-connected MG's power quality and dynamic response while distributing the desired quantity of power to the grid. The main objective of this investigation was to exchange reactive and active power between MG and the utility grid at the increased DG penetration level (100 kW, 70 kVAR) with the least amount of settling time, overshoot, and overall harmonic distortion by reducing the error associated with the fitness function (FF) It guarantees the optimum set of optimized PI parameters and, as a result, produces the optimized transient response of the grid-connected MG studied. Additionally, the fast Fourier transform (FFT) is used to analyze the harmonics of the system's output current waveform to assess the power quality analysis of the power system studied. The research author used this method, to study the microgrid with, the DC-DC boost converter circuit, two solar PV modules, the coupling inductor, the six-pulse, three-phase VSI, the RLC low pass filter, and the three-phase delta linked load make up the power circuit The following three scenarios have been used to assess the efficacy of the suggested GOA-based controller: Reactive and Active Power Control for MG Injection and Rapid Load Change, in this scenario, results show a better dynamic response when adjusting DG's reactive and active power than the previously employed PSO where the percentage overrun in DG's active power produced by the DG injection is 180%, which is accomplished as 94.40% and The percentage overrun for a step load shift and the active load power curve through MG injection is 2.63%, and 12.96% respectively this is also considerably better for PSO-based controllers, where the values are 108.50% and 81.81%, respectively in this study. Case when Power Quality Analysis, in this situation, the FFT analysis of the inverter output current waveform has been done. According to the FFT analysis, the current harmonic contents after MG insertion (0.07%) and load change (0.09%) are much below 5% and%, respectively. THD was measured at 1.06% and 3.93%, better than PSO-based MG controllers. When comparing of Proposed GOA with the PSO-Based Controller in this scenario, FF reduction is necessary to obtain the optimal dynamic response of the analyzed system. To demonstrate the effectiveness of the suggested GOA-based controller, its performance in obtaining the desired power-sharing ratio while maintaining optimum power quality and dynamic response is compared to that of its predecessor particle swarm optimization (PSO), which is based on the most optimum choice of PI parameters that gives the optimum transient response of the examined grid-connected MG system and -based controller under MG injection and sudden load change conditions. in comparison to the PSO-based controller, the proposed controller obtains a better transient response in terms of settling time and overshoot since The GOA achieves a greater rate of convergence and enhanced quality for the minimizing of a similar fitness function. Finally, The findings demonstrate that under various operating scenarios, such as MG injection and sudden load fluctuations, the suggested controller outperforms the alternative in terms of extracting and retaining the predetermined ratio of power from the MG and provides better transient response over PSO-based power flow controllers previously used, the suggested controller offers exceptional dynamic response for the system while minimizing current harmonic distortion, even at higher degrees of DG penetration. the main objective was to reduce the FF.

$$F.F = \mathrm{Min}\left\{\int_0^\infty t * \left|e_p\right| dt + \int_0^\infty t * \left|e_q\right| dt\right\} \quad (38)$$

From the results of the previous studies discussed, it can be said that the Grasshopper Optimization Algorithm (GOA) outperformed the Particle's Swarm Algorithm (PSO) and Genetic Algorithm (GA) in improving the droop control parameters and reducing the deviations that occur in the system during the transition to the islanded mode for microgrid system or during the sudden change in the load.

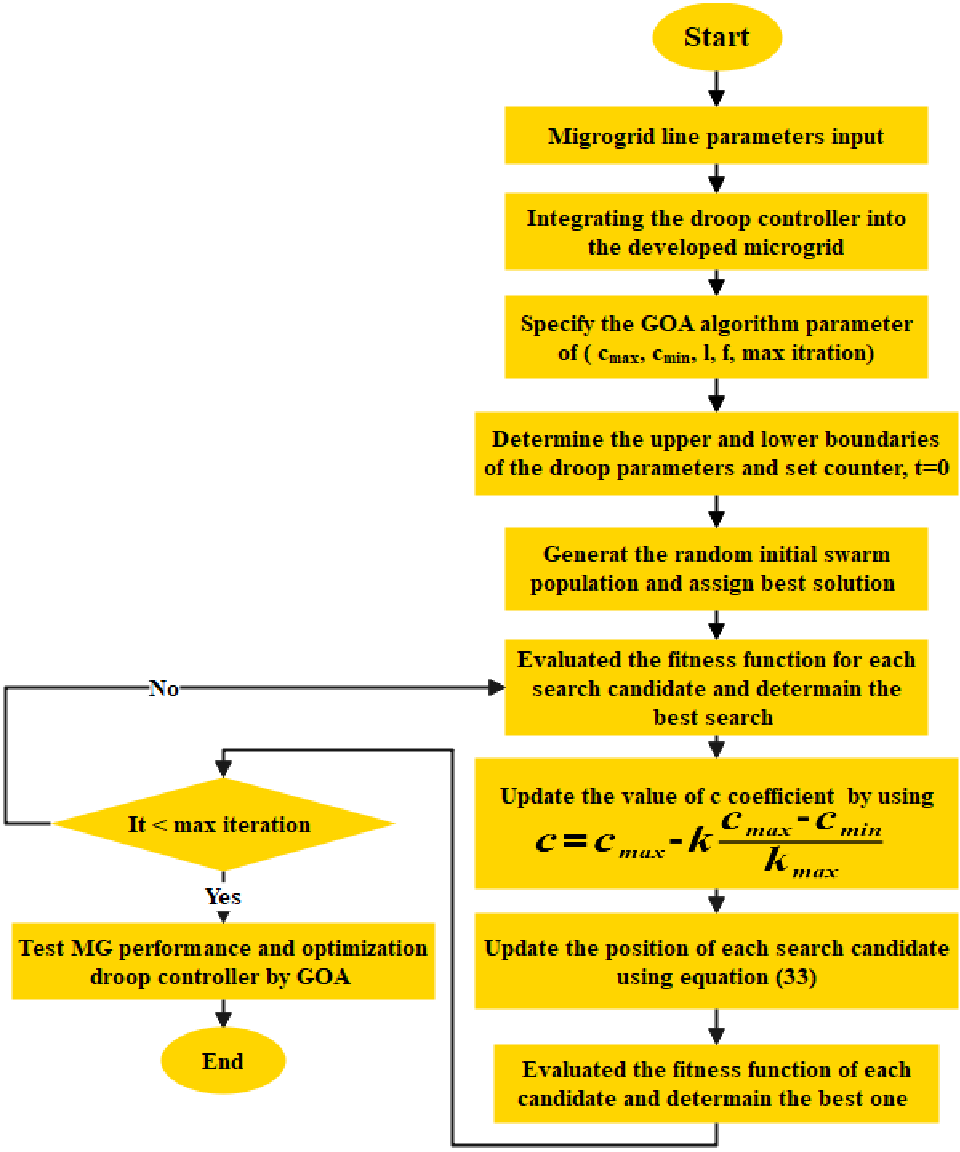

Fig. 18. Flowchart using GOA optimization to optimize droop control.

5.5. Salp swarm-inspired algorithm (SSIA)

The Salp swarm algorithm (SSA) is a new swarm intelligence technique recently proposed by a meta-heuristic algorithm optimizer by Mirjalili *et al.*, 2017 [80] to efficiently solve optimization issues. Salps belong to the Salpidae family. Salps have a barrel-shaped, translucent body. Salps are quite jellyfish-like. The salp ecosystem is difficult to access and maintain in the laboratory, making preservation challenging[81]. SSA mimics the swarming behavior of salps foraging in the oceans. Salps typically form a swarm in the heavy ocean known as a salp chain [82]. The Salp chain is divided into two group leaders and followers. The SSA is triggered by the swarming activity of salp fishes in oceans, which build salp chains. Salpfish is transparent and move by pumping water through their body[82]. The SSA algorithm has been used in many types of research in the field of microgrids[83] The salp swarm algorithm can be utilized to solve numerous.

5.5.1. a mathematical model for moving the salp chain

To mathematically model the salp chain divided into two groups leaders and followers as shown the Figure. 13 the leader is the salp at the front of the chain, while the following is referred to as the remainder of the salp. Similarly, to other swarm-based strategies, salps' positions are specified in an n-dimensional search space, where n represents the number of variables in a particular problem. As a result, the positions of all salps are kept in a two-dimensional matrix denoted x. It is also assumed that a food source known as F exists in the search space and serves as the swarm's target.[80] So, to update the location of the leader can use the equation:

$$x_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 \geq 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 < 0 \end{cases} \quad (39)$$

Where; $x^1{}_j$: first Salp (leader) position in the j_{th} dimension, F_j: food source position of the j_{th} dimension, u_{bj}: upper bound of j_{th} dimension, l_{bj}: lower bound of j_{th} dimension,l: current iteration, L: maximum number of iterations, c_1, c_2, and c_3: random numbers uniformly generated in the interval of [0,1].

Salp chains can help SSA reduce inertia towards local optima, However, SSA may struggle to strike an appropriate balance between exploration and exploitation[84]. So, to make a balance between exploration and exploitation use the parameter c_1 the following equation is used to determine the c_1

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (40)$$

The followers' positions will be updated using Newton's law of motion, as seen below:

$$x_j^l = \frac{1}{2}ct^2 + v_0 t \quad (41)$$

were $i \geq 2$, x^i_j shows the position of i_{th} follower salp in j_{th} dimension, t: is time, v_0 : is the initial speed, and $a = \frac{v_{\text{final}}}{v_0}$, $v = \frac{x-x_0}{t}$

In iterative optimization, the difference among iterations is equal to 1, and considering $v_o = 0$, the equation as follows: This equation considers the modification of the above equation.

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right) \quad (42)$$

The following is a review of the literature using the GWA to optimize droop control.

The A. Ebrahim et al. in 2022, [81], Optimal Droop Control Design based Salp Swarm Optimization with Self-Adaptive Mechanism. The work aimed to develop an optimized controller to enable parallel-connected inverters to share microgrid load. SSIA-enabled controllers on microgrid test equipment ensure power-sharing between several sources and regulate voltage and frequency. Optimize the controller that will be utilized to determine the PI controller gains and the droop control system coefficients. The cost function takes four forms: IAE, ISE, ITAE, and ITSE. The ideal way is to implement ITAE as an objective function. To check the performance of the proposed method takes into account two types of loads: constant and continuous change, as well as RER variability (changing irradiance, temperature). when fixed cyclic load variations the SSIA-based droop control technique effectively addressed RER variability, as evidenced by the findings. When continuous cyclic load variations, SSA results demonstrate that the frequency response significantly impacts the rate of power change, whereas the voltage is very marginally affected. So, the simulation findings demonstrate the efficient operation of the suggested optimal approach. The frequency variation is acceptable, and the DGs respond well to load changes.

In 2020 [85], this work developed a real-time implementation and optimum design of the microgrid droop controller-based self-adaptive salp swarm optimization with updated particle swarm optimization (PSO) characteristics. The main aim of the work was to address real-world microgrid droop control uncertainties such as controller gain inaccuracy, system parameter deterioration, multi-source energy sharing difficulty, and system dynamics. The hybrid SSIA-PSO also includes a self-adaptive mechanism, which eliminates the need to refine the algorithm parameters for each optimization problem. This method was used because the hybrid approach has the advantage of combining the best aspects of both PSO and SSIA to determine the ideal global efficiency for solving intricate optimization issues, including the microgrid's optimum operation as well as the hybrid SSIA-PSO improves the ease of exploitation in PSO with the ability to explore in SSIA. The proposed optimal method-based control approach is empirically validated in a real-time setting where the simulation results show that the hybrid SSIA-PSO algorithms outperform the other strategies provided. It was done in this way to handle one of the most common microgrid technical difficulties presented in the optimal design for the parameters of the PI controller and the parameters of the droop control to maintain fair power sharing between diverse sources. Despite the benefits of the suggested method, it requires more experiments on large-scale systems with several parameters that must be optimized under various uncertainties. In this regard, the authors propose using the provided approach to solve various multi-objective engineering challenges.

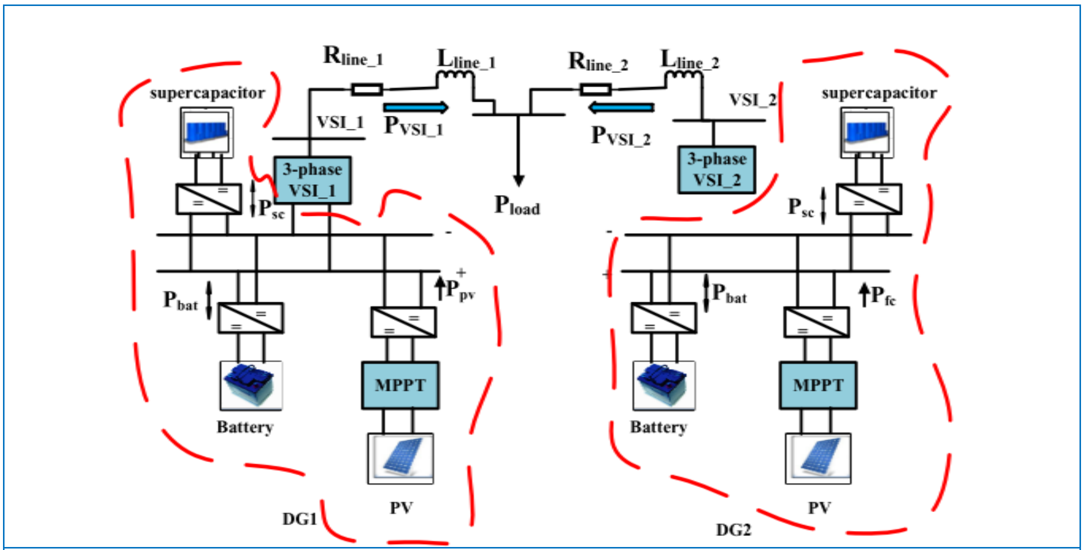

Fig. 19. Test system diagram [85].

In this article [86], developed Power Quality and Dynamic Response Enhancement of an Islanded Microgrid based Slap Swarm Optimization Algorithm. The main aim of the work was to (i) optimize MG control parameters (ii) improve transient response under different operation conditions for islanded MG (iii)voltage and frequency regulation. to achieve these control objectives efficiently, and choose the optimal combination of the PI gains (kp and ki) as well as DC side capacitance (C) the suggested controller uses droop control and back-to-back proportional plus integral (PI) regulator-based voltage and current controllers. To assess the effectiveness of the proposed control technique its outcomes are compared with the partical swarm optimization(PSO) , grasshopper optimization algorithm (GOA) and The model is then assessed for all three case, in first case when study frequency and voltage regulation during Load Change and DG Insertion that achieving a steady rated frequency and voltage during DG introduction and sudden load changes with little overshoot and settling time necessitates fine-tuning of system parameters, to reduce overshoot and settle time after a disruption in the MGs system The SSA searched for the best combination of PI gains and capacitance to minimize FF and obtain excellent dynamic responsiveness with minimal overshoot and settling time At the end of the simulation, optimum values for four PI gains as well as the capacitance value were acquired, resulting in the least error while integrating the FF value, ensuring the optimum dynamic behavior of the constructed MG model To ensure a fair comparison of the three optimum parameter selection methods, namely GOA, PSO, and SSA, the DG rating and other system characteristics were kept constant for each three scenarios. During the simulation, a load of 40 kW and 20 kVAR was applied at 0.25 s, causing a dip in system voltage. In the case two analysis the Performance Evaluation of Studied Optimization Algorithms in this case GOA, PSO, and SSA were tested to reduce the fitness function under similar operating conditions and system characteristics. by using an identical number of iterations (50 iterations) In the 17th iteration, the SSA had the lowest fitness function value (0.5840618), while the PSO and GOA had the lowest magnitudes at 0.9211586 and 0.8748774 in the 21st and 25th iterations, respectively. As a result, the SSA converges faster and produces higher-quality solutions than its competitors. In the third case study power quality analysis When analyzing the harmonic contents contained in the acquired current waveform, the Fast Fourier Transform (FFT) analysis It is obvious from the FFT analysis of the examined power system that the SSA-based controller suitably meets the power quality and the suggested controller converts the solar PV dc output current to a nearly pure sine wave with minimal distortion. Finally, the results show The SSA optimization method outperforms GOA and PSO in terms of overshoot and settling time for all three tested circumstances.

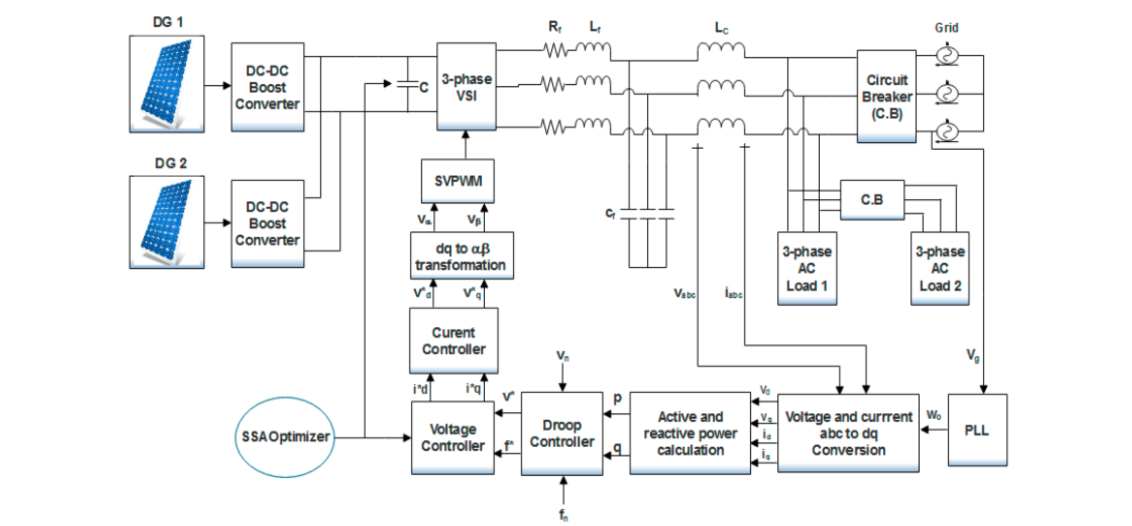

Fig. 20. Structure of islanded microgrid with droop control [86].

Ferahtia et al.in 2022[87]**,** The purpose of this paper is to introduce an optimized load-sharing approach based on a droop control strategy for parallel batteries operating in a DC microgrid and control algorithm utilization to prevent non-matching conditions when including the real battery capacity which its lifecycle can influence, Consequently, power-sharing will be proportionate to the real capacity. so the lifecycle of the batteries will be extended and power-sharing will be optimized. The actual battery capacity is identified using a metaheuristic optimization algorithm known as the Salp Swarm Algorithm (SSA) to achieve this. The operating principle and limitations are elucidated and examined. In numerous operating scenarios, including batteries with similar and dissimilar capacities, as well as a sudden disconnection of a battery, all battery's output is regulated by bidirectional DC/DC converters to ensure the charging and discharging process. The simulation demonstrates the capability of the proposed control strategy to effectively manage these situations. Fig.21 explains the steps of optimization of SSA to optimize the droop control.

From the results of the previous studies discussed, it can be said that the Salp Swarm optimization (SSA) outperformed the Particle's Swarm Algorithm (PSO) Grasshopper Optimization Algorithm (GOA) in improving the droop control parameters and reducing the deviations that occur in the system during the transition to the islanded mode for microgrid system or during the sudden change in the load.

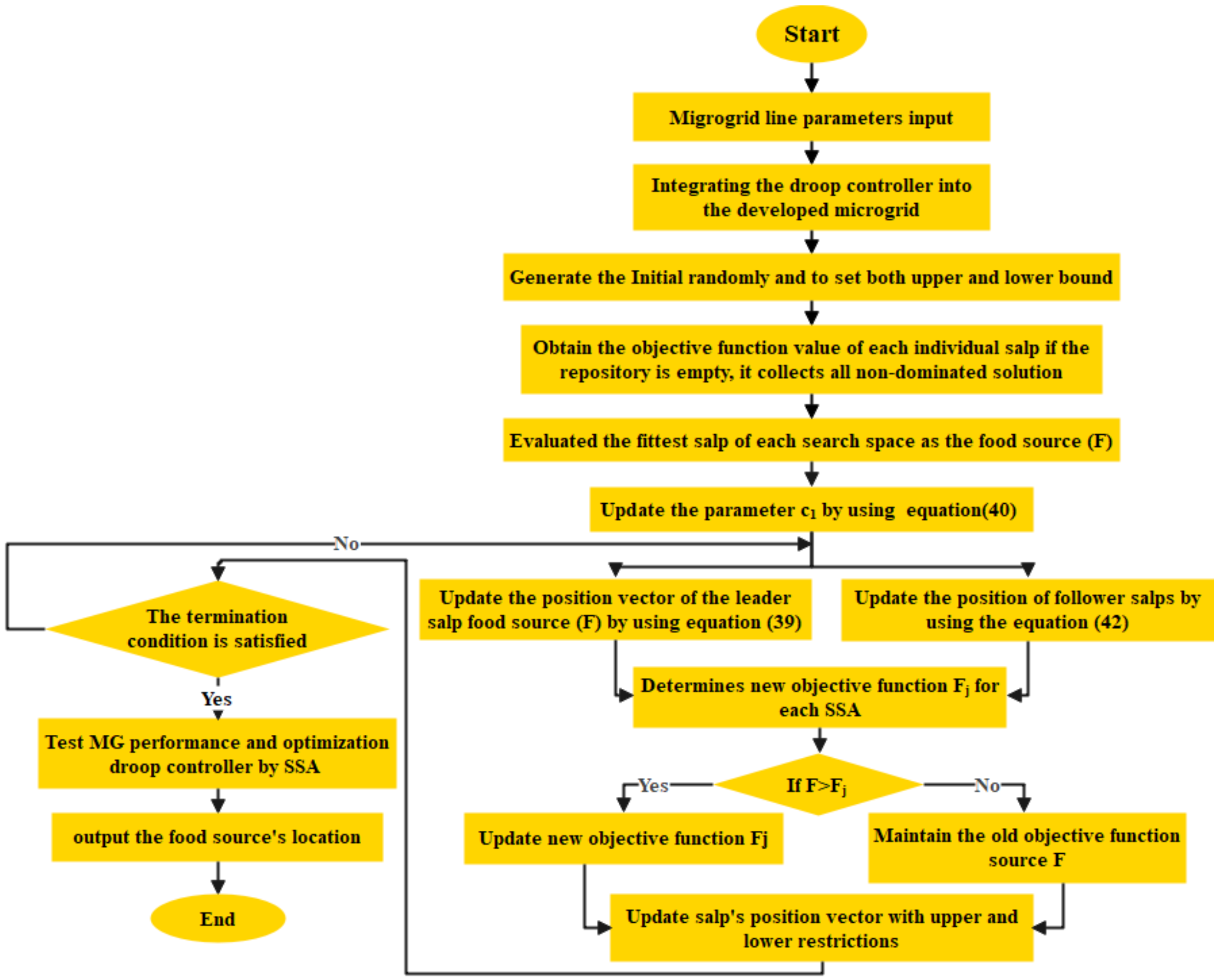

Fig. 21. Flowchart using Salp swarm Algorithm to optimize droop control.

Table 1. Summary of Advantages and Disadvantages of the optimization methods in droop control.

NO	Methods	Advantages	Disadvantages
		• The algorithm is easy and simple to implement using programming with fewer parameters for tuning, It doesn't	• Standard PSO suffers from a significant increase in search difficulty as the dimension of the

1	Particle Swarm Optimization (PSO)	need optimized functions such as derivative, differentia, and continuous [30] • The PSO is an intelligent method that gives the optimal control parameters to release qualifying reference current vectors [88]. and has a quick convergence rate [23]. PSO offers the capacity to reposition particles in a multi-dimensional search space[85] • The PSO method is based on artificial intelligence, hence it may be employed in both engineering applications and scientific research[89] • It is more robust and flexible than traditional approaches (traditional droop control) because it employs probabilistic transition principles and the quality of the proposed approach's solutions is independent of the starting population[50]	search space increases[89] • PSO requires additional time to obtain the global optimal value in the search space[88]. • The PSO algorithm fails to deliver satisfying results due to an absence of collaboration from effective search strategies. The cause for this is that the PSO method does not fully utilize the information gathered during the computing stage. Instead, throughout each iteration, only the individual and swarm optimization information is used, Although the PSO algorithm permits global seek, it does not guarantee convergence with the global optimum [30].
2	Genetic Algorithm Optimization (GA)	• A decent answer can be found quickly. • Genetic algorithms constantly consider a population of solutions. Keeping many solutions in memory at each iteration has numerous benefits. • The algorithm may integrate multiple answers to create better ones, allowing it to take advantage of an assortment.	• The convergence advances towards the local answer rather than the global solution since only excellent genetic information may be transferred. • In particular optimization issues and computation time, simple optimization methods may offer better results than GA, it is hard to operate with sets of dynamic data.
3	Grey Wolf Optimization (GWO)	• Simplicity, ability to find local optimum, high search precision, fast seeking speed, easy to realize, a highly effective algorithm.	• limited population variety. • Imbalanced exploitation and exploration and premature convergence • The GWO's position update equation is useful for exploitation but does not sufficiently an acceptable solution to find the droop control coefficients

Table 2. Summary of Advantages and Disadvantages of the optimization methods in droop control (Cont).

NO	Methods	Advantages	Disadvantages
		• long-range and sudden movement is the	• The performance of GOA is

4	Grasshopper Optimization Algorithm (GOA)	swarm's distinguishing attribute to capture the optimal solution for the droop control coefficient's	dependent on the careful adjustment of its parameters. SO finding the optimal set of droop control coefficients can be difficult and may necessitate significant experimentation.
5	Salp Swarm Algorithm (SSA)	• SSIA offers several benefits, including accelerated convergence, an expedited approach to providing superior solutions Looking for a globally effective method, Compatibility with a variety of optimization issues, A few settings for adjustment, simplicity of implementation, low parameters, and high performance.	• the negatives stem from the potential of being caught in local minima, early convergence, and delayed searching.

Table 3. Comparative Literature Survey.

Ref.No	Optimizer	Controller	Control Area	Source	Comparative Study
[13]	AOA	Droop control, PI	DC microgrids	PV, Battery	PSO, conventional methods
[14]	ACA	Droop control, PI	AC microgrid islanded mode	DG (VSI)	real-time self-tuning method
[15]	HHO	Doop control, PI	Microgrid	(SPVA), (SC), two battery stations (BSs), fuel cell system (FC)	SSA, PSO, ABC
[16]	SC-MBO	Droop control	Stand-alone DC microgrid	PV, BSS, Diesel generator	MBO, PSO
[17]	CS	Droop control	Microgrid	Multi -DG	EA
[18]	DE-NGM	Droop control	Islanded DC microgrid	PV	ICGA, GPSO-GM
[34]	MFO	Droop control	DC microgrid	PV	Traditional droop control
[35]	HBB-BC	Droop control, PI	Autonomous microgrids	DG	PSO, BB-BC
[36]	MOHBB-BC	Droop control, PI	Microgrid	PV, FC	MOPSO
[37]	TFWO	Droop control	Hybrid isolated microgrid	PV, WT, BES	HHO, WOA, JSO
[38]	DE	Droop control	Microgrid	DG	GA, PSO

Table 4. Comparative Literature Survey (Cont).

Ref.No	Optimizer	Controller	Control Area	Source	Comparative Study

Ref.No	Optimizer	Controller	Control Area	Source	Comparative Study
[39]	ADE	Droop control	DC microgrids	RES, ESS	GA
[40]	CF-GSA	Droop control	AC microgrid	DG	Traditional droop control
[41]	OOA	Droop control, PI	DC Microgrids	PV, DCG	AO, WOA, MPA, GJO, RSA
[42]	HGSO	Droop control, PI	Microgrid	PV,Battery, supercapacitor	PSO, ALO
[43]	CBA	Droop control, PI	Islanded microgrids	Multi-DG	PSO, SFO, Ziegler-Nichols
[44]	AFSA	Droop control, PI	Microgrid	DG	Traditional droop control
[47]	PSO	Droop control	Islanded microgrid	DG	Traditional droop control
[48]	PSO	Droop control, PI	Islanded microgrid	CDG	Traditional droop control
[49]	PSO-NR	Droop control	Microgrid	RES	ABC, PSO-EA PSO-OCBA
[51]	PSO	Droop control, PI	Hybrid Microgrids (TWO MG)	PV, WT, Battery	Traditional and optimized secondary controllers
[52]	PSO	Droop control	DC Microgrid	DG	controlled elitist genetic algorithm.
[53]	Fuzzified-PSO	Droop control	DC Islanded Microgrid	BES, WT	---
[55] [56] [57]	PSO	Droop control, PI	Microgrid	RES	---
[63]	GA	Droop control	Microgrid	PV, WT, Battery	---
[64]	ICA-GA	Droop control, PD	Autonomous Microgrid	DG	GA, ICA, PSO, HTS
[61] [65] [69]	GA&ICA	Droop control, PI	Islanded Microgrid	DERs PV	--- GA, Newton-trust, and time domain method
[66]	HS-GA	Droop control	Microgrid	DG	---
[67]	GA	Droop control,PI	DC Microgrids	BESS	Traditional droop method

Table 5. Comparative Literature Survey (Cont).

[68]	GA	Droop control,PI	Microgrid Based on Small-Signal Dynamic Model	DG	---
[71] [73]	GWO	Droop control,PI	Microgrid	DG	---
[75]	CGWO	Droop control	Microgrid	DG	Traditional droop control
[9]	GOA	Droop control	Microgrid	DG	GA
[77]	GOA	Droop control, PI	Islanded Microgrid	DG	PSO, WOA
[81]	SSA	Droop control, PI	Microgrid	PV, Battery, supercapacitor	---
[85]	SSA-PSO	Droop control, PI	Microgrid	PV, Battery, supercapacitor	PSO, SCA, ALO, DA, ABC, GWO-PSO

6. Conclusion

This paper discussed the review of five techniques of optimization algorithms including the swarm intelligence algorithm, Particle Swarm Optimization algorithm (PSO), Grey Wolf Optimization Algorithm (GWO), Grasshopper Optimization Algorithm (GOA), Salp Swarm Algorithm (SSA), and one evolutionary algorithm Genetic Algorithm (GA). This review included a literature review on these techniques by a group of researchers to improve droop control for microgrids to solve some of the problems that the droop control parameters suffer from, to reduce the variation that occurs in frequency and voltage, or the problem of power-sharing. At the beginning of this paper, a review of the algorithms were reviewed to understand their nature of work, and then some of the research that used these methods was summarized to know their effect on the droop control coefficients. Therefore, the ultimate objective of these algorithms is to improve the droop parameters, as was done they are used in PI gain voltage, current, and frequency controllers to ensure optimal operation of microgrids as well as improve controller behavior. Finally, From the reviewed literature review, it was found that these algorithms have some advantages and disadvantages when used to optimize the droop control parameters, based on these studies, it can be said that the Salp Swarm Algorithm (SSA) and Grasshopper Optimization Algorithm (GOA) were the best.

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List of Abbreviations used in this paper.

Abbreviation	Full From	Abbreviation	Full From
MGs	Microgrid System	AFSA	Artificial Fish Swarm Algorithm
DG	Distributed Generation	PSO	Particle Swarm Optimization
PCC	Point Common Coupling	GWO	Grey Wolf Optimizer

AO	Aquila Optimizer	GOA	Grasshopper Optimization Algorithm
HHO	Harris Hawks Optimization	SSA	Salp Swarm Algorithm
SCMBO	Sine-Cosine- Monarch butterfly optimization	GA	Genetic Algorithm
HBB-BC	Hybrid Big Bang-Big Crunch	OF	Objective Function
TFWO	Turbulent Flow Water-Based Optimization	SI	Swarm intelligence
DE	Differential Evolution	MO-OPF	Multi-Objective Optimal Power flow
HGSO	Henry Gas Solubility Optimization	NR	Newton-Raphson
CBA	Coot Bird Algorithms	RES	Renewable Energy Source
DER	Distributed Energy Resources	MPPT	Maximum Power Point Tracking
TOC	Total Operation Cost	BESS	Battery Energy Storage System
PV	Photovoltaic	SOC	State of Charge
ITAE	Integral Time Absolute Error	APSO	Adaptive Particle swarm optimization
ICA	Imperialist Competitive Algorithm	FDC	Fast Droop Controller
BIBO	Bounded-Input, Bounded-Output	VRP	Virtual Rated Power
WTG	Wind Turbine Generators	CGWO	Chaotic Grey Wolf Optimizer
WOA	Whale Optimization Algorithm	HS	Harmony Search
CS	Cuckoo Search	DPSP	Deficiency Power Supply Probability
EMS	Energy Management Scheme	COE	Cost Of Energy
FFT	Fast Fourier Transform	AVR	Automatic Voltage Regulator
DR	Demand Response	RTP	Real-Time Price
IAE	Integral Absolute Error	ISE	Integral Square Error
ITSE	Integral Time Square Error	MFO	Mothe Flame Optimization
OOA	Osprey Optimization Algorithm	GSA	Gravity Search Algorithm
ABC	Ant Bee Colony	MBO	Monarch Butterfly optimization
EA	Evolutionary Algorithms	ICGA	Imperialist comparative algorithm genetic algorithm
NGM	Newton-Gauss- based mutation	GPSO-GM	Guaranteed convergence Particle Swarm Optimization with Gaussian Mutation
JSO	Jellyfish Search Optimizer	MPA	Marine Predator Algorithm
GJO	Golden Jackal Optimization	RSA	Reptile Search Algorithm
ALO	Ant Lion Optimizer	SFO	Sun Flower Optimization
OCBA	Optimal Computing Budget Algorithm	HTS	Heat Transfer Search
SPVA	Solar PV Array System	SC	Supercapacitor

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