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Research Article

Optimal Sizing and Placement of the Renewable Energy Source in a Microgrid using Butterfly Optimization Algorithm

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ABSTRACT

An essential consideration for a microgrid's cost-effectiveness is the size of its renewable energy sources. A collection of RES, a storage system, converters, and loads make up the grid-connected hybrid renewable energy system. The operating area needed by the type of DG technology is one variable used in this article to determine the DG sizing, while all potential candidate buses in the various AC/DC micro-grid system zones are another variable, taking into account the HPC losses in the system. A hybrid AC/DC MG system is created to optimize the size and designing using different renewable energy sources. To evaluate the proposed approach, Butterfly Optimization Algorithm is implemented on aforementioned micro-grid systems and the obtained results are verified with other Particle swarm optimization in the paper. The results proved that the proposed approach is better than the other approaches in technical aspects.

Keywords: Butterfly Optimization, Cost Minimization, Microgrid, Particle Swarm Optimization, Sizing

INTRODUCTION

Hybrid renewable energy systems (HRES) is a new way to generate low carbon emissions by moving away from conventional energy networks and they are expanding recognition in remote areas to be connected worldwide. Recently, renewable energy RE has been used for isolated households in various countries with the aim of controlling the flow of HRES electricity, particularly, a combination of solar and wind energy. The problem created by the conventional electricity has been resolved by the combination of renewable energy resources and storage devices in an optimal way [1]. The connection of multiple renewable energy sources plays a vital role and proper storage can substantially enhance the reliability and efficiency of HRES. It is reported that due to the unstable nature of electricity generated by RES, it is important to incorporate storage devices in remote locations. The photovoltaic power changes, which are significantly influenced by weather conditions, bring the stability of MG regarding frequency regulation to its limits. The unpredictable nature of power demand can further contribute to this issue. As frequency deviation from the nominal value is seen as a direct indicator of power balance between generation and consumption, it can degrade the reliability of connected devices or even harm them. This is likely even when ESS is incorporated, owing to the rapid changes in insolation fluctuations relative to DG and ESS dynamics [2]. Integrated Renewable Energy Systems are an emerging approach in recent years for providing power generation services for stand-alone applications, especially in remote locations. This can be attributed to the inherent drawbacks of single technology-driven systems in separate mode, like high system cost and low reliability, as demand grows. Adaptive supervisory energy management systems, along with many other solutions have been proposed to overcome these challenges. The paper [3] outlines one such strategy that explores a hybrid renewable energy system comprising solar, wind, battery, and fuel cell technologies to satisfy the energy needs of remote locations. In this regard, the authors present an adaptive energy management for a supervisory system that adopts the adaptive Pontryagin's minimum principle to optimize the performance of hybrid fuel cell/energy storage system. The approach has shown an effective system performance monitoring, control and optimization in various simulation and experimental scenarios with system load profiles. A hierarchical energy management strategy is proposed [4] for an island PV/fuel cell/battery hybrid DC microgrid. The proposed strategy consists of a local control layer to control the natural running characteristics of the components comprising the system and a system control layer to determine the power distribution between the battery and fuel cell minimizing hydrogen consumption. This is a difficult challenge to tackle in the context of microgrids especially when there is no central energy management system in place and no direct communication between the different units. A viable solution to this problem is offered by decentralized control strategies, which provide energy management in a continuous manner between generation units and loads connected without the need for complex communication infrastructure [5].

The result of combining Ant Colony Optimization (ACO) and Artificial Bee Colony Optimization (ABCO) can lead to a stronger and more productive optimization algorithm that uses the best parts of both methods. This mixed approach tries to blend the exploring skills of ACO with the exploiting abilities of ABCO. This mix has the potential to find better answers to optimization problems [6]. The combination of Krill Herd Optimization (KHO) with Ant Lion Optimization (ALO) is one powerful algorithm with enhanced search capabilities. This combination exhibit improved convergence speed, better solution quality, and robustness in supervision complex optimization problems compared to using either algorithm individually. Additionally, the hybridization can control the harmonizing strengths of both techniques to achieve a balanced exploration-exploitation trade-off, resulting to potentially superior performance in solving optimization problems [7]. Cuckoo Search is a nature-inspired optimization algorithm that is based on the brood parasitism of some cuckoo species. The algorithm is known for its simplicity and efficiency in finding optimal solutions to optimization problems. The consequence of using Cuckoo Search includes fast convergence to high-quality solutions, robustness in handling various types of optimization problems, improved management of grid-connected and islanded modes for enhanced resilience, improved energy efficiency, and cost savings [8,9].The Firefly Algorithm rooted in how fireflies blink often gets used to crack optimization challenges. When FA is implemented into microgrid optimization, this algorithm comes up with answers that fit the special needs of microgrid set-ups. It provides balancing power generation and demand with efficient optimization of microgrid. It better deals in dynamic scheduling to minimize costs and enhance reliability [10]. The "Flower Pollination Algorithm" (FPA), is a nature inspired optimization technique, that mimics the pollination behavior of flowering plants. When applied to microgrid optimization, some potential results can be observed such as efficient management of power flow to meet the demand, enhanced grid stability, reliability by balancing supply and demand, dynamic adaptation to changing grid conditions, enhanced utilization of energy storage systems for peak shaving and backup power [11]."Particle Swarm Optimization" (PSO) is a metaheuristic algorithm implemented after how birds or fishes move in groups. When PSO is used to make microgrids better, it gives better outcomes that leads to making exact plans with low costs, reliable systems, use storage at peak times, real-time adaptation to changing grid conditions and demand profiles, optimal coordination of storage systems [12]. Multimodal Delayed Particle Swarm Optimization (MDPSO) is a superior version of Particle Swarm Optimization (PSO) designed to control multimodal functions by maintaining variety and avoiding impulsive convergence. In the perspective of microgrid optimization, MDPSO can be used for optimal energy management, helps in optimal scheduling of generators, reducing fuel costs and emissions, stability and reliability enhancement, helps in determining the best locations and sizes of DERs to minimize losses and improve grid efficiency, enables effective participation of consumers in demand-side management programs [13]. Hybrid Simulated Annealing - Particle Swarm Optimization (SA-PSO) combines the global search capabilities of Simulated Annealing (SA) with the fast convergence of Particle Swarm Optimization (PSO). This hybrid approach enriches exploration (diversity) and exploitation (convergence) in optimization problems, making it appropriate for microgrid applications [14].

The design and optimization of microgrids has been the focus of broad research in recent years. One of the key challenges in microgrid design is the optimal sizing and placement of renewable energy sources, such as solar photovoltaic systems and wind turbines. There are various optimization techniques that have been proposed to discuss this problem, including linear and non-linear programming methods, dynamic programming, rule-based methods, and metaheuristic approaches [15]. Among the metaheuristic approaches, the Butterfly Optimization Algorithm has gained significant attention due to its ability to effectively solve complex optimization problems. The Butterfly Optimization Algorithm is a nature-inspired optimization algorithm that mimics the searching behavior of butterflies. The algorithm has been successfully applied to various optimization problems in the field of electrical power systems, including the optimal placement and sizing of distributed energy resources, the optimal operation of microgrids, and the design of power management systems [16]. In the context of microgrid optimization, the Butterfly Optimization Algorithm can be applied to find the optimal size and location of renewable energy sources, to minimize the complete cost of the microgrid while ensuring reliable and efficient operation [17]. For example,It has been

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demonstrated in [18] that a mixed-integer linear programming-based methodology for the optimal design of a microgrid, incorporating the sizing of the battery energy storage systems. The other example [19] describes a control methodology for an isolated microgrid system, where the battery energy storage systems are used as grid-forming units to maximize the exploitation of renewable energy sources. The proposed research paper aims to build upon these previous techniques by proposing a novel approach for the optimization of microgrid design using the Butterfly Optimization Algorithm.

PROPOSED SYSTEM CONFIGURATION AND MODELLING

In this research paper, we propose the use of the Butterfly Optimization Algorithm to address the problem of optimal sizing and placement of renewable energy sources in a microgrid. The Butterfly Optimization Algorithm is a nature-inspired metaheuristic algorithm that has been successfully applied to various optimization problems in the field of power systems. The proposed methodology for optimizing the sizing and placement of renewable energy sources in a microgrid using the Butterfly Optimization Algorithm consists of the following steps: Firstly, the microgrid system and its components, including renewable energy sources, energy storage systems, and loads, are modeled mathematically. The objective function for the optimization problem is then defined, which typically includes the minimization of the total cost of the microgrid, including capital, operating, and maintenance costs, as well as the maximization of the utilization of renewable energy resources. Next, the Butterfly Optimization Algorithm is applied to the optimization problem, where the algorithm iteratively adjusts the size and location of the renewable energy sources to find the optimal solution. The algorithm's performance is evaluated using various metrics, such as the convergence rate, solution quality, and computational efficiency. The following assumptions are made in this analysis in order to determine the suitable resource mix:

(i) The existing load scenario is used to calculate the optimal resource combination.
(ii) Only discrete sizes of the candidate units are provided.
(iii) It is assumed that the lifespan of generating units is equal to the number of planning years.
(iv) It is expected that the initial costs increase in proportion to the size.
(v) Only generators and battery storage are liable for operating and maintenance costs.
(vi) It is assumed that converters and battery storage have no salvage value.

Both DC and PFAC buses are present in the hybrid system. All DC energy sources (solar) are connected to the DC bus in this architecture via appropriate interface circuits. DC/DC converters are used to directly service DC loads via DC buses, if necessary. The PFAC bus provides electricity to AC loads. PFAC energy sources can be directly connected in this control scheme without the need for any auxiliary circuits. Consequently, compared to DC coupled and AC coupled schemes, the hybrid DC–AC coupled setup is more cost-effective and energy-efficient. The control and energy management of the hybrid scheme, however, are very complicated.

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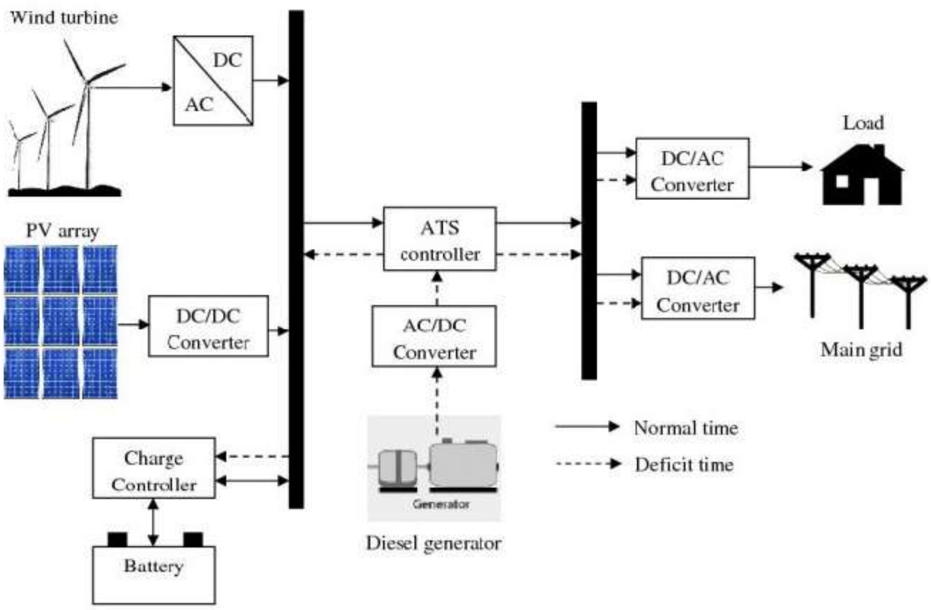

Fig 1: Integrated Hybrid Microgrid System consisting of PV, WT, DG, BS

2.1 PV Modeling

Photovoltaic modules are devices that generate power from direct sunlight. The annual energy consumption of a PV module at a specific location with known solar radiation and temperature can be modelled by the energy production per year E_{PV} and the time duration (in hours) of the sun's operation on the PV with the output power P(T,G) of PV module at solar radiation G and temperature T computed using eq.(1);

$$E_{PV} = T_{hr} \sum_{G_{min},T_{min}}^{G_{max},T_{max}} P(T,G) \quad (1)$$

The output power P(T,G) is determined by equation (2);

$$\mathrm{P(T,G)} = P_{ST}\frac{G_{IN}}{G_{ST}}(1 + k(T_{cell} - T_{ref})) \quad (2)$$

where P_{ST} represents the maximum power for the PV module at standard test scenarios, G_{IN} is the dropped irradiation, G_{ST} represents the irradiation at STC (1000 W/m^2), k is the power temperature coefficient of power, T_{cell} is the cell temperature and T_{ref} is the reference temperature.

2.2 Wind Turbine (WT) Modeling

Wind turbines (WTs) generate mechanical energy from kinetic energy (derived from wind speed), which is subsequently used to produce electrical energy. The height of a WT and site weather data can be used to determine the electrical energy it produces. The equation (3) can be used to model the energy available from wind for a known or given speed profile.

$$E_{WT} = T_{hr} \sum_{Vmin}^{Vmax} P_0\, f(v,k,c) \quad (3)$$

Here, E_{WT} and T_{hr} denotes the energy output from wind turbine in kWh at a given location and the time duration (hours) respectively. P_o denotes the power output of wind turbine (kW), (V_{min},V_{max}) denotes the minimum and

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maximum speeds of wind, and *f (v,k,c)* denotes the Weibull function for a specified site wind speed (v) at a designed modeling coefficient *k* and scaling coefficient *c*.

2.3 Diesel Generator (DG) Modeling

Conventional diesel generators have been operated for standby power and peak shaving. Fuel efficiency and consumption are characteristics of the electricity produced by DGs. For more efficient use, DGs run between 80 and 100 percent of their nominal power. A DG's potential energy output is calculated using equation (4);

$$E_{DG}(t) = \eta_{DG} T_{hr} P_{DG}(t) \tag{4}$$

Here T_{hr} denotes DG operating hours, P_{DG} denotes DG rated power, E_{DG} is the DG annual energy (KWh) and η_{DG} is the DG efficiency

2.4 Battery Bank Modeling

An electrochemical device called a battery is used to store electrical energy from AC or DC MG units for future use. In an MG system, the battery's state of charge (SOC) is continuously fluctuating in accordance with the random behavior of the renewable sources' (WT and PV) output. The formula for calculating the necessary battery bank capacity for an MG system is represented by equation (5)

$$B_{req} = \frac{L_{Ah/day} N_c}{M_{DD} D_f} \tag{5}$$

where B_{Req} is the necessary battery bank capacity in Ampere-hour (Ah), $L_{Ah/day}$ is the Ah load consumption per day, M_{DD} is the maximum discharge depth, D_f is the discharging factor and N_c represents the independent day's number. In order to supply the Ah required by the MG system, the number of parallel linked (N_P) batteries is calculated using equation (6)

$$N_P = \frac{B_{req}}{B_c} \tag{6}$$

while the number of series connected (N_s) batteries for the specified V_N is finalized using equation (7)

$$N_s = \frac{V_N}{V_B} \tag{7}$$

where B_c is the chosen battery capacity in Ah , V_N is the MG system voltage and V_B is the voltage of battery. The N_{BT}, or total number of batteries, is determined as

$$N_{BT} = N_P N_S \tag{8}$$

2.5 Inverter Modeling

The interface that connects energy between MG components and the load is typically an inverter. The maximum energy that AC loads may predict must be controlled by the inverter that is being used. Stand-alone, grid-tied battery-less, and grid-tied with battery backup inverters are the three primary categories into which the inverters are divided. The equation (8) can be used to model and count the number of inverters required for a given load demand.

$$N_{inv} = \frac{P_{g\_max}}{P_{inv\_max}} \tag{8}$$

Where, N_{inv} is the number of inverters, P_{g_max} is the maximum power generated by the MG, and P_{inv_max} is the maximum power that the inverter can deliver.

MIROGRID OPTIMIZATION

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Optimization is the process of selecting variables while keeping limitations in mind in order to determine a function's least or maximum value. The fitness or objective function, which is the optimization function, is usually computed with the aid of simulation tools. The best answer is not always found using an optimization technique. This may not always be realized because of the nature of the problem. Based on the category of cost function that needs to be solved, an optimization strategy is chosen. Certain methods cannot handle non-convex and non-smooth optimization. These methods struggle to deal with inequality limitations. PSO is a reliable optimization method that is used in many MG applications. Both discrete and continuous optimization issues can be resolved by it. In this paper, Butterfly Optimization Algorithm is implemented to get the optimal solution for the placement and designing of a microgrid.

3.1. Butterfly Optimization Algorithm

A population-based, naturally inspired algorithm is the central concept of the Butterfly Optimization Algorithm. The BOA imitates the social and foraging behaviors of butterflies [12]. The following is a description of the biological and natural behavior. Butterflies are Lepidopteran insects. The five senses they possess are smell, sight, taste, touch, and hearing. They employ their three senses to locate food, find a mate, migrate, and flee from adversaries. Even though butterflies have many senses, their ability to smell is thought to be the most crucial one for locating food. The male butterfly uses the female's pheromone to identify her during mating.

Butterflies emit a strong scent that spreads over distances as they travel from one place to another. The intensity of the butterfly's aroma attracts the other butterflies, who are able to detect it. A butterfly will approach the best butterfly when it detects its scent. This procedure is known as global search. In local search, it randomly shifts to a different location in the search space whenever it is unable to detect the scent of any butterflies.

When a butterfly moves, it releases a strong smell. Based on the intensity of the smell, the other butterflies were drawn to the butterfly. Each butterfly's smell can be described using the formula shown in equation (9)

$$pf_i = cI^a \tag{9}$$

where c and I stand for the sensor modality and scent intensity, respectively, and pf_i for the perceived magnitude of reference. The power exponent, or parameter a, indicates the extent of smell absorption.

3.2 Movement of butterflies (Global Search)

Butterfly movements are based on the following three phases:

1. Global search phase: When a butterfly travels, it releases a smell, and other butterflies are drawn to it based on how strong the smell is. This procedure, known as a global search, is described in equation (10)

$$x_i^{t+1} = x_i^t + (r^2 g^* - x_i^t) f_i \tag{10}$$

where g is the overall optimal solution, r is a random number in [0,1], f_i is the i^{th} butterfly's fragrance, and x_i^t is a vector that represents the butterfly (solution) at iteration t.

2. Local search phase: The butterfly moves erratically throughout the search area when it is unable to detect the scent of the other butterflies. This procedure is known as local search and is described by equation (11)

$$x_i^{t+1} = x_i^t + (r^2 x_j^t - x_k^t) f_i \tag{11}$$

where two vectors, x_i^t, x_j^t, represent two distinct butterflies within the similar population.

3. Analysis of the Solution: The butterfly's objective function is represented by the strength of its smell. Based on the intensity of its smell, the butterfly draws in other butterflies.

3.3 Objective functions

Single objective function

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Single-objective optimization involves maximizing or minimizing a function. The objective functions that are commonly used in MG optimization are summed up in the following sections:

(i) Minimize- The single objective function minimizes the Costs of life cycle [24], Emissions of gases, including CO2, NOx, SO2, PM2.5, and PM2.5-10, Power outages (both reactive and active), Degradation throughout the years

(ii) (ii) Maximize- The single objective function maximizes the profits or advantages, power generation, load ability, net present value, unmet load (UL), loss of load hours (LLH), loss of load risk (LOLR), loss of power supply probability (LPSP), loss of load probability (LLP/LOLP), and level of autonomy (LA) are all factors that affect reliability.

Multi-objective function

Single-objective-function optimization is the term used to describe optimization problems where there is only one criterion to be maximized. In other situations, multiple criteria need to be optimized at the same time; this type of optimization problem is known as a multi-objective optimization problem. Multiple goals that need to be accomplished at the same time contribute to multi-objective optimization problems. The process of resolving conflicting objective functions is known as multi-objective optimization.

Constraints

Constraint for energy equilibrium:

In the microgrid, the amount of power generated and consumed should always be balanced. As a result, the objective function should adhere to the constraints listed below in order to preserve the power balance and the physical boundaries of the generating systems.

$$P_{load} = P_{PV} + P_{WT} + P_{DG} + P_{Batt} \tag{12}$$

where photovoltaic system output power is equal to P_{PV}. P_{WT} is the output power of the wind system. P_{load} is equal to load demand. P_{Batt} is the battery's output power (positive while discharging, negative when charging). P_{DG} is the output power of diesel generators.

Constraint for photovoltaic (PV) system:

The constraint for photovoltaic system can be written as

$$0 \leq P_{PV} \leq P_{PV,max} \tag{13}$$

where $P_{PV,\,max}$ is the maximum output power of the PV system.

Constraint for wind turbine (WT) system:

The constraint for the wind turbine system can be written as

$$0 \leq P_{WT} \leq P_{WT,max} \tag{14}$$

Where $P_{WT,\,max}$ is the maximum output power of the wind turbine system.

Constraint for battery storage (BS) system Battery storage system constraints include the nominal charging or discharging rates, the SOC limits, and the battery's maximum power under charging or discharging conditions. The limitations of the battery storage system can be expressed as

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{15}$$

$$-P_{batt,max} \leq P_{batt}(t) \leq P_{batt,max} \tag{16}$$

$$-\frac{P_{Batt\_nom}}{V_{Batt}} \leq I_{Batt} \leq \frac{P_{Batt\_nom}}{V_{Batt}} \tag{17}$$

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where, V_{batt} is the usual voltage SOC_{min} represents the lower limit of SOC, SOC_{max} represents the upper limit of SOC, P_{Batt_nom} represents the battery's rated power, and $P_{Batt,max}$ represents the battery's maximum power under both charging and discharging conditions.

Optimization constraints

Equality constraint:

Power balance is when the total power produced equals the demand for the load. The load power P_{load} is calculated using the power output P_i with the i_{th} generating unit and t is the time. The total number of generating units is represented by N equation (18)

$$P_{load,t} = \sum_{i}^{N} P_{i,t} \tag{18}$$

Inequality constraints:

Power output from each producing unit must fall between the minimum (P_{min}) and maximum (P_{max}) limitations of the rate power unit.

$$P_{i,min} \leq P_{i,t} \leq P_{i,max} \tag{19}$$

3.4 Particle Swarm Optimization

It is believed that HMGS optimization is a multi-objective issue. A multi-objective function is converted into a single-objective function using the linear scalarization method, and the objectives may be constraints or a linear function [17]. It is characterized by limitations that are specified as, and an objective function (fitness).

$$f(x) = min\left\{\sum_{i=1}^{k} w_i \frac{f_i(x)}{f_i^m}\right\} \; with \; w_i \geq 0 \; and \; \sum_{i=1}^{k} w_i = 1 \tag{20}$$

The PSO process is as follows:

1) Establish the goal function and its limitations, which include the number of dwellings [1,15], the renewable factor [> 0.01], PV [5,50], autonomous days [0,5], and wind turbines [0,5].
2) Initialize the Population Array, Global Best, location, particle velocity, and population members.
3) Choose the particle's position and velocity at random, create the starting population, and determine the swarm's optimal fitness value.
4) Achieve your own best. As a worldwide best and update iteration, the lowest POE and LPSP have been chosen.
5) Revise your worldwide and personal top positions. Put a stop condition in place.

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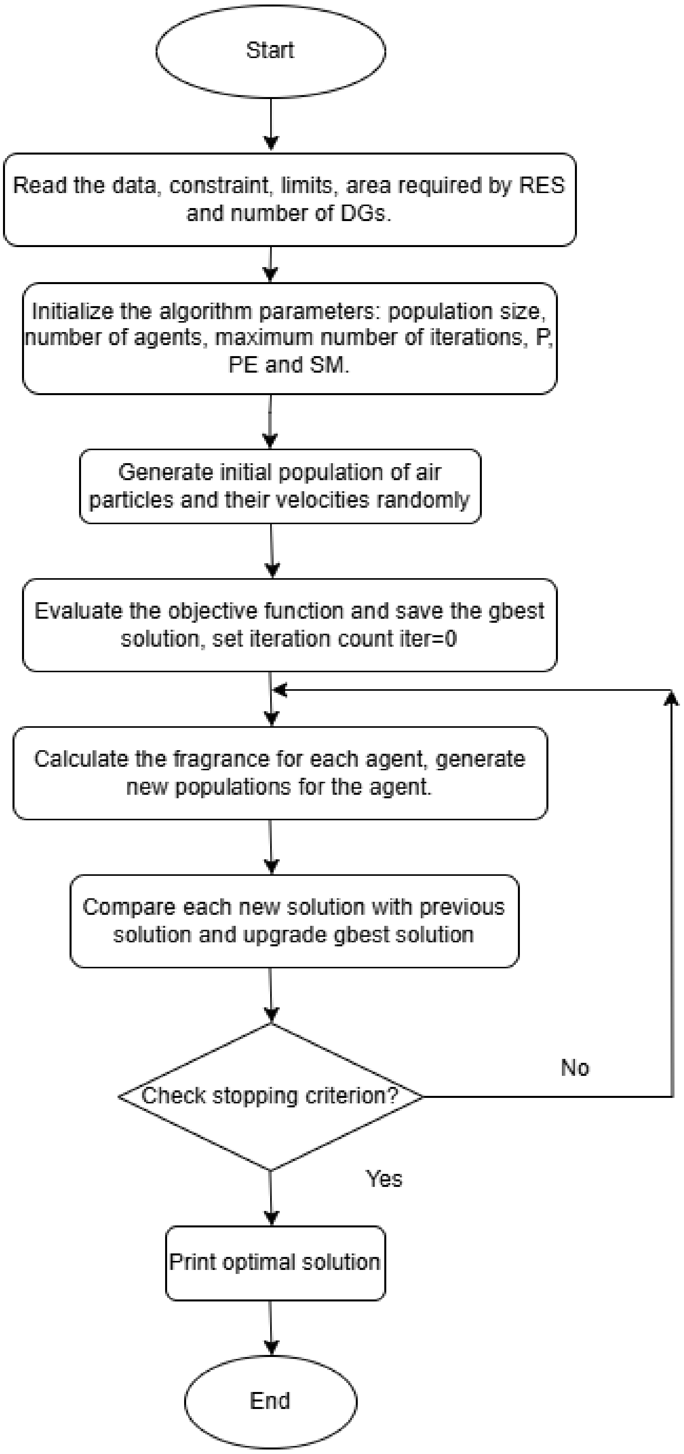

Fig 3: Flowchart for Butterfly optimization

PERFORMANCE COMPARISON OF VARIOUS OPTIMIZATION TECHNIQUES

The cost-benefit analysis of an MG might not be justified in the absence of optimization methodologies. The goal of optimization is to determine which of a collection of given solutions is the most cost-effective or has the best achievable performance provided the given restrictions. In situations where traditional optimization techniques fail to yield an optimal solution, a variety of methods are available to handle optimization challenges. One approach to cost optimization that shows potential is artificial intelligence (AI). The primary benefit of artificial intelligence is its capacity to integrate many approaches, initially identifying the optimal primary answer and then identifying an

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improved one. The optimization strategies utilized to find the most practical solution to the cost reduction problem in MGs are listed in the table 1.

Table 1: Summary of studies of unit sizing based on different algorithms used

Algorithm used	Resources used	Objective Function	Outcome
Hybrid of Ant Colony and Artificial Bee Colony optimization [26k]	Gas turbine, Fuel Cell, Wind energy	Voltage stability index, minimization of cost, emission and power losses	faster convergence to optimal solutions
Krill herd and ant lion optimization [18]	PV, wind turbine, fuel cell, microturbine, battery, grid	Total operational cost, pollutant emissions, minimization of cost and emissions	achieve a balanced exploration-exploitation trade-off
Cuckoo search [8]	Wind turbine, PV, DG and batteries	Minimizing total investment cost, emissions and their costs	Minimization of peak load demand through intelligent scheduling and control strategies.
Firefly Algorithm[27]	Diesel generator, wind turbine and fuel cell	Power output, cost	Enhanced grid stability and resilience through intelligent optimization techniques
Flower Pollination Algorithm [3]	Microturbine, PV, Fuel cell, wind power and batteries	DG price, start-up and shutdown prices in generation, storage price, and prices due to power interchange between the main grid and price in the demand response program	Dynamic adaptation to changing grid conditions and load profiles, Improved utilization of energy storage systems for peak shaving and backup power.
Particle Swarm optimization[16]	Fuel cell, wind turbine, electrolyzers, a reformer, an anaerobic reactor and some hydrogen tanks.	Total net present cost	Enhanced resilience and reliability of the microgrid, Efficient optimization of microgrid operation by balancing generation and demand.
Multimodal delayed PSO [4]	WT, PV, DG and battery storage system	minimum levelized cost of energy (LCOE), the lowest loss of power supply probability (LPSP), and the maximum renewable factor (REF)	Prevents premature convergence to local optima, ensuring more stable microgrid operation.
Hybrid simulated annealing PSO	Wind turbine, PV, DG and battery	LCOE, total benefit	PSO accelerates solution discovery, while SA refines it, Ensures optimal scheduling and dispatch even under uncertain conditions.
Whale optimization[14]	DG, FC, microturbine, WT, PV and battery	Operation cost, emission cost	Balances exploration and exploitation for better optimization results.
Butterfly optimization	PV, WT, DG and battery	Operating cost	Improved stability performance, optimal sizing and operation

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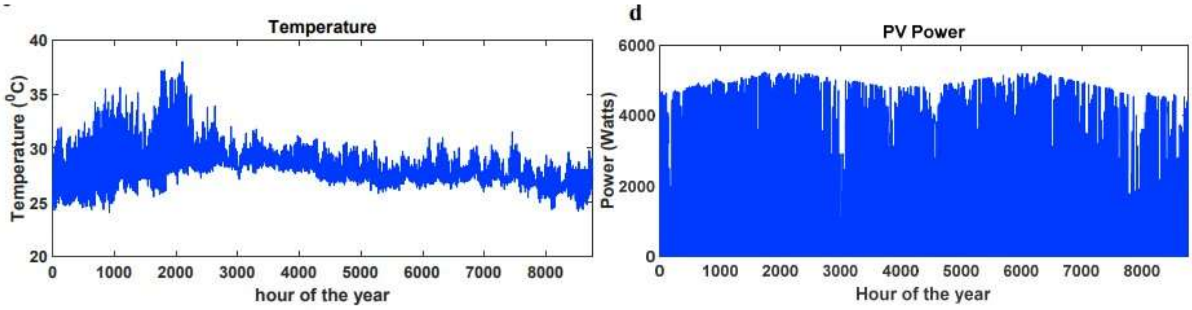
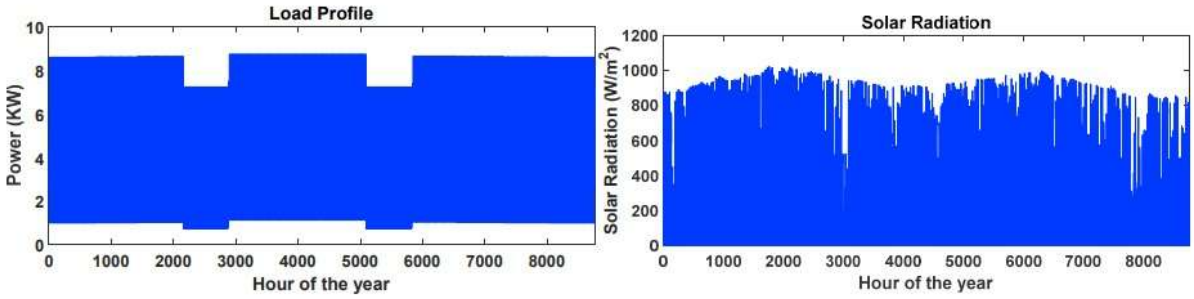
RESULT & DISCUSSIONS

The proposed study using the butterfly optimization algorithm has been applied to a a microgrid system, and the results have been examined. A number of renewable energy sources, including photovoltaic, wind, and battery energy storage systems, are included in the case study microgrid system. Additionally, there is the option to purchase electricity from the main utility grid. The cost of purchasing electricity from the grid, the cost of battery degradation, and the capital and operating costs of renewable energy sources are all taken into account when minimizing the objective function. The results indicate that the butterfly optimization method can identify the ideal locations and sizes for the microgrid's renewable energy sources, resulting in a considerable decrease in total system costs while preserving dependable operation. The results are compared with other optimization techniques, such particle swarm optimization, to demonstrate the effectiveness of the proposed approach. Fig. 4a and Fig. 4b depicts the temperature and PV power plots, respectively, for the PV Array of the 5kW PV system for the Microgrid case study at different solar irradiance levels. It is clear that with the two parallel strings created from 17 series connected modules, the PV array system of 5kW with a peak current of 8 A and voltage 465V was realized for irradiance of 1000W/m² at 25°C.



(a) (b)

Fig. 4. a) Temperature throughout the year b) PV Power output throughout the year



(a) (b)

Fig. 5. a) Load Profile throughout the year b) Solar Radiation throughout the year

Simulation results of the PMSG WTGS connected to a controller obtained to determine its performance. As shown in Fig. 6a and 6b, it has been shown that the WT, which is directly connected to the PMSG, extracts the most power when exposed to a wind speed of 9 m/s and a pitch angle of 0°.

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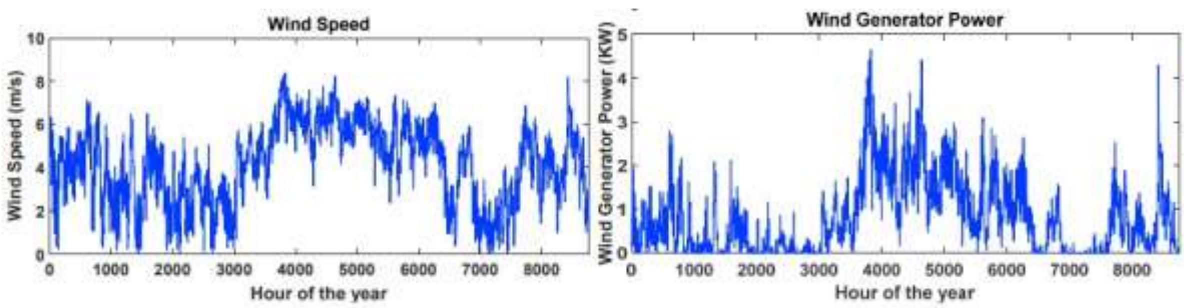

(a) (b)

Fig.6. a) Wind speed throughout the year b)Wind generator power throughout the year

The output voltage and current of the WECS is displayed in fig 7. At 0.6 seconds, the output voltage dips as the harmonics occurs for a short period of time. The output current also changes with the specific voltage conditions.

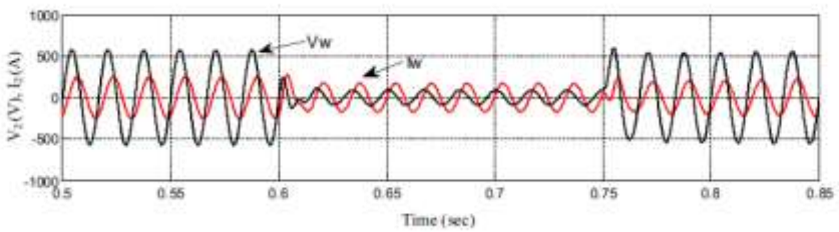

Fig.7. WECS output voltage and current under grid voltage dips.

The voltage, current and power of the grid side is shown in fig. 8 under the stable loads. As it can be seen that the power initially rises to above 100 kW and then further decreases after 0.1 second. Initially, high transient power can be seen but it quickly reaches to the steady state value. The voltage and current also has a minimal phase difference at the grid side.

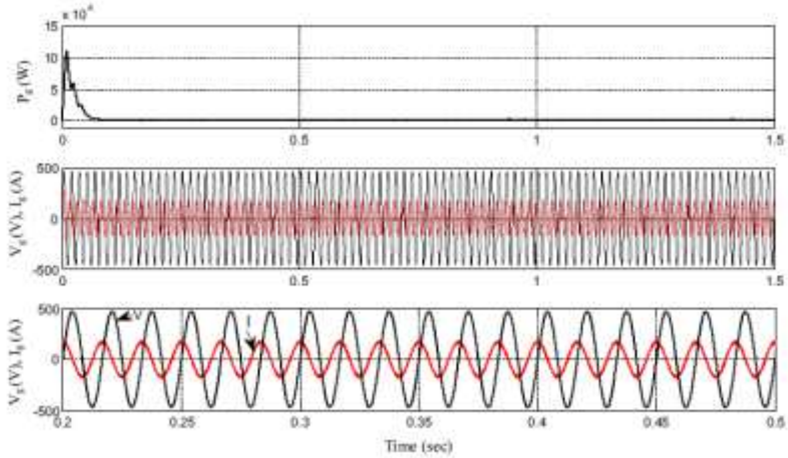

Fig.8. Grid side power, voltage and current under stable AC and DC loads.

The instantaneous grid power spikes sharply and indicates the high inrush and transient power at the starting. The grid power gradually decreases to the steady state value. The true power of AC load, wind and the grid side is shown in fig. 9. The contribution of the grid decreases as the wind energy supplies power to the load.

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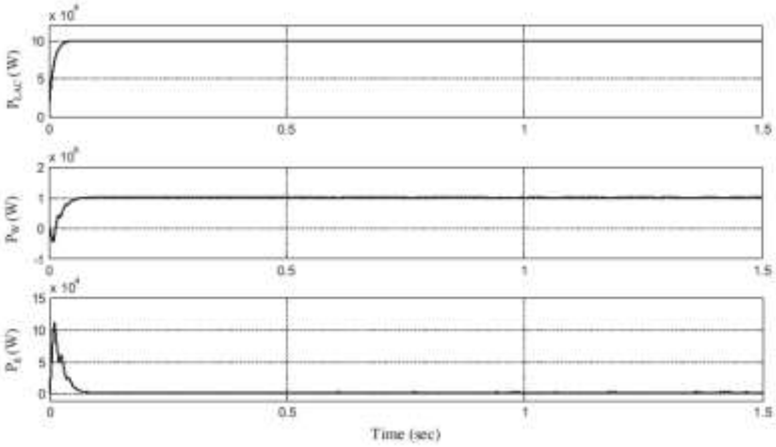

Fig. 9 Active power of AC load, wind and grid under stable AC and DC loads.

The DC load current quickly stables after a high transient at starting. The DC load power is consistent under fixed load conditions. The voltage ensures the proper system performance and regulation in the DC system. The DC current, power and voltage waveform is shown in fig. 10.

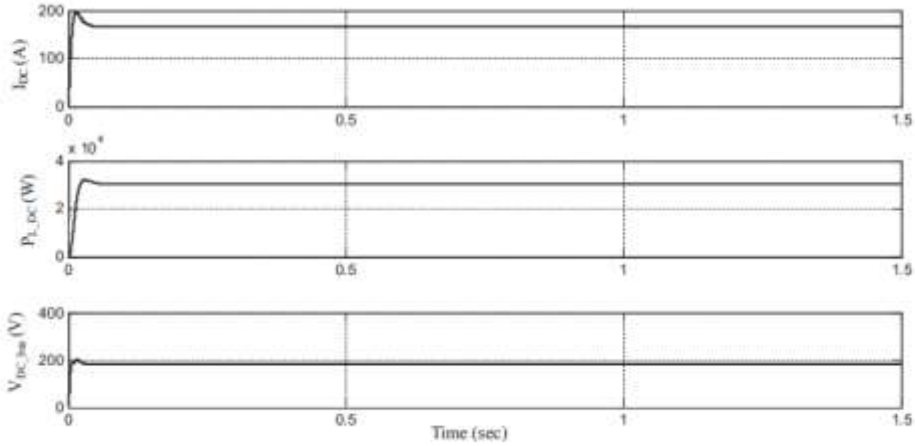

Fig. 10. DC load current, load power and load voltage.

When the AC load changes, the AC load power, wind power and the grid power also changes in the system. As the load is changing after 0.5 seconds, the grid side power has also some transients in the system that can be shown in fig 11. As the system gets stabilized, the grid power is no more active for it.

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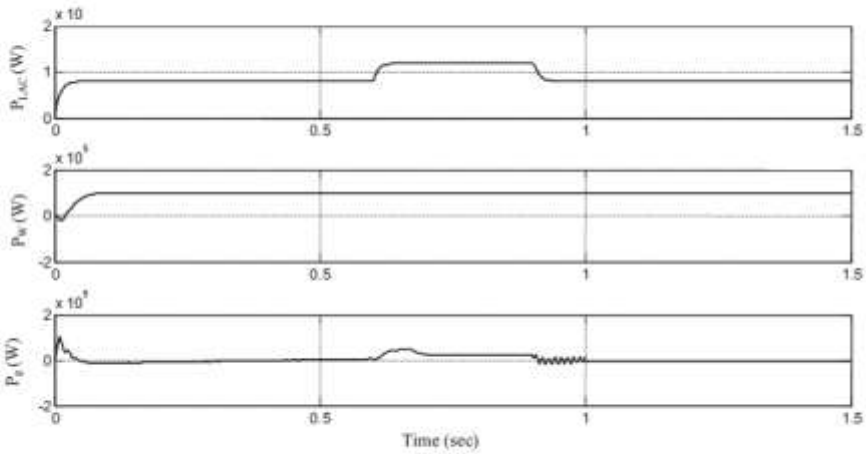

Fig. 11. AC load power, wind power and grid power with AC load change.

CONCLUSION

The optimal sizing of the microgrid with different renewable sources have been examined in the paper. The two different optimization techniques involved in the study. The butterfly optimization technique has fast convergence speed and provides better results for the current scenario. In conclusion, this research paper presented the use of the Butterfly Optimization Algorithm for the optimal sizing and placement of renewable energy sources in a microgrid. The results demonstrate the effectiveness of the proposed methodology in finding the optimal configuration of the microgrid, which minimizes the overall cost while ensuring reliable and efficient operation. The application of the Butterfly Optimization Algorithm to microgrid optimization represents a significant contribution to the field of power systems engineering and provides a valuable tool for the design and operation of sustainable and efficient energy systems.

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