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Optimal Sizing of Various Types of Microgrids - A Review

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Abstract

In the future decades emphasizing the rapid-rise in energy demand, non-conventional energy will be a major source of energy rather than conventional sources of energy. The importance of renewable energy sources has increased due to the day-by-day decline in the availability of coal and petroleum products along with the occurrence of pollution by the same. The power generated from the different renewable energy sources (Photo Voltaic System, Wind Farm, Fuel Cell, Micro-hydro plants) will be integrated into a single microgrid (MG) for powering a small village (isolated or non-isolated) or for transmitting to a Low Voltage (LV) distribution system. Imminent MG technology is the most innovative energy balancing technology, which had diverted to the power distribution network recently. This paper focuses on a deep review of various optimization techniques along with the different types of MG and economic analysis reported in the domain of MG component sizing. Hence an effectively sized microgrid with a well achieved Energy Management System (EMS) that is necessary for the specific applications can be identified.

Keywords: Microgrid Sizing;Cost Analysis;Optimization Technique;Energy Management Systems;Different types of Microgrid

1 Introduction

One of the key backbones for the current economy is electricity, which is also a dominant share in the energy sector [1]. According to 2019 Energy Outlook Data, 90% of global electricity is consumed by buildings and industries, whereas only 2% is consumed by transport. Even in developing countries like India, many rural places have no proper chances of accessing electricity. The International Energy Agency (IEA) released a keynote about world unelectrified rural villages which is 16% [2,3]. The rising population and urban development have significantly increased the energy demand which becomes an another cause for raise in CO_2 pollution in the year 2018 [4],[5]. Even the non-emission technologies are encouraged to supply the electricity to reduce CO_2 emission and to intensify the usage of green energy.

The worldwide achievement in the advancement of Renewable Energy Technologies (RET) is a remarkable one. Even though there is a remarkable rise in the development of RET, the shortage of electricity that is needed for the day to day life for the rural people remains the same [6]. The World Energy Outlook 2019 has pointed out that energy demand will be increased by 1.0 % in every year from 2019 to 2040[1]. Around 2,378 GW of power has been raised globally in renewable energy power capacity in 2018 [7]. While looking through Renewable Energy (RE) power generation data published in Our World In Data - 2020, around 4,193.10 TWh, 1269.95 TWh, 584.63 TWh, 625.81 TWh are the total renewable energy power which is generated worldwide through Hydro, Wind, Solar, and from other sources respectively. Whereas India's contribution is of 139.67TWh from hydropower, 60.31 TWh from wind power, 30.73 TWh from solar and 30.46 TWh from all other sources. In 2017, approximately 79.7% of energy was generated through fossil fuel, 10.6% from renewable energy and the remaining 9.7% from other sources [8]. By 2040, renewable energy will be able to supply two-third of the energy demand worldwide. Solar and wind together will be able to supply 40%, and the remaining 25% will be of hydro and bioenergy [1]. In India, around 300 days can be considered as clear sky days for capturing maximum solar radiation. From India's total land area, Around five thousand trillion kilowatt-hours (kWh) solar energy can be generated [2,9]. In the year 2019, electricity generated from the conventional sources was about 112.831 (BU) whereas 13.575(BU) generated from renewable energy. While comparing the preceding year (2018) 5.84% growth was achieved in renewable energy generation [10]. RE sources are the best sources of energy by many advantages such as lifetime availability as a source, lesser maintenance, health benefits, etc... It also possesses some disadvantages such as high initial capital cost, intermittency, storage difficulty, and geographical, seasonal and climatic limitations. Storing the generated energy is one of the challenging tasks in the RE sector.

By means of Energy Storage System (ESS), it can provide a reliable power supply for various applications by storing the generated energy for later usages [11]. To enhance and promote RE, a better energy storage system can be adopted. Some genuine data shows that in 2011, around 2.2% of RE was able to be stored for later usage by various applications. In the same data, pumped storage systems account for the majority share [12]. For short- and long-term energy-storing: capacitors, hydrogen storage, pumped hydro storage, compressed air, superconducting magnetic storage, supercapacitors, batteries, flywheel, etc... are used based on their application needs, whereas battery is most widely used for storing electric power [13–15]. The initial development in the domain of the battery energy storage system was placed forward by Lee and Chen For two Taiwan Power Company

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System (TPCS) consumers [16]. Each and every storage system possesses its limits based on its properties such as capacity, charging and discharging limits, etc... An MG possesses trending features while integrating ESS such as, Peak shaving, price arbitrage, power quality improvement, spinning reserve, ancillary services, and load frequency control [17]. In [17] the overall running cost of the Drop Controlled Islanded Microgrid (DCIMG) is minimized by the means of Battery-ESS, whereas fuel and the Battery-ESS costs are the objective functions. A well-mapped idea about various energy storage applications in the area of the microgrid is categorized in [18]. Optimal switching between charging and discharging of an ESS is also an essential task for achieving higher efficiency with maximum storage and maximum life cycle [19]. Effective sizing of battery has been carried out by many pieces of literature. In [20], Particle Swarm Optimization (PSO) is used for optimal battery sizing and in [21], Genetic Algorithm (GA) is used. All-natural energy sources and ESS can be grouped in a closed-loop together with grid-connected mode or in standalone mode to form a microgrid. A typical microgrid network with various DG sources and loads can be seen in Fig. *1* below.

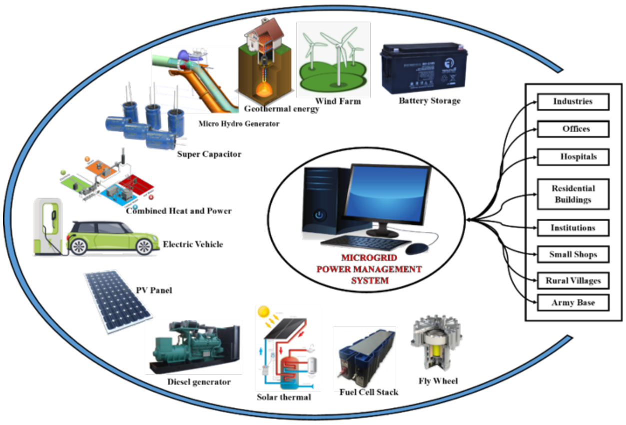

Fig. 1. Microgrid System

A microgrid is a novel distribution network that holds the overall potential of Distribution Energy Resources (DER) by integrating different Distribution Generators (DG) such as solar photovoltaics system, micro-generators, micro-turbine, wind-generator, fuel cell, storage devices such as flywheels, energy capacitors and batteries in a closed-loop [22–24], [25]. MG is also known as the future backbone for the emerging smart grid technologies[26]. The main objective of promoting MG is for assuring clean energy with economic benefits and security[27]. A microgrid is configured based on its functional control capabilities and can be run either in grid-connected mode (one end of MG would be connected to the transmission network) or in autonomous mode. While MG is connected in the grid-connected mode it should not try to alter the frequency due to the addition of DG sources. In that case, the grid should be much stronger in order to regulate the frequency and junction voltage at the Point of Common Coupling (PCC) [17]. The main advantage in the MG system is the isolated operation of MG when a severe problem occurs in the grid network which is known as islanded microgrid [17,23]. Many challenges can occur in a microgrid during the conversion of DC power to AC power such as reactive power compensation, voltage regulation, power quality, power loss, etc… This issue can be mitigated by incorporating Flexible AC Transmission System (FACTS) devices like SVC, DSTATCOM, UPSC, and IPFC [28]. While praising the advantages of MG a few pieces of literature focus on the disadvantages that occur in MG and suggest how they are overcome. The exigent task is between switching of MG from on-grid to off-grid which will be affected by the protection components incorporated along with the system. Shutting down of the system can also generate fault current, whereas the presence of limiters can able to withstand up to maximum extent [29]. Effective power flow management within microgrid is also a challenging task while designing the system.

The Energy Management System (EMS) is a robust technique that needs to be considered when constructing a microgrid [30]. The key function of EMS is to sustain the power flow throughout the various components which are associated with a microgrid. Battery degradation and utilizing the maximum renewable energy resources with minimal fuel consumption are the main objectives of EMS [31]. In literature [6], the author used EMS for a hybrid microgrid system with PV/WT/DG/BT as sources. In [32], the author developed both rule-based and optimization-based EMS system for a Standalone Multi-Carrier Microgrid (SMCMG). The author used optimization algorithms for reducing complexity while incorporating many sources into the microgrid. In [33] EMS with three cases namely energy loss, CO_2 emission, and main grid energy were considered as the objective functions for a GA based optimization technique. In literature [34], the author optimally sized PV with BES and concludes that the generation of power from oil-based thermal power stations can be reduced and will be able to supply clean energy without any interruption. A fuzzy export system with EMS is been used for cost optimization in [35].

Having a well-sized microgrid will capture maximum free and clean energy from all the DG sources. The most challenging task is to optimally size the microgrid by considering cost-effective methods and harvesting natural resources to generate power. There is no point in producing extra power or less power than the needed energy for the load profile [36]. Generating extra power will lead to higher capital and operational cost which is not economical. Moreover, generating less power will not be able to satisfy the load profile thereby needing to seek yet another source [37]. In the literature [11] the author designed a PV based isolated Hybrid Microgrid System (HMS) and illustrated a generic sizing procedure using design procedure and pinch analysis. The author also implemented a unique methodology for sizing a microgrid with DG, PV, and Hybrid Storage System (HSS) based on the demand and availability of resources. To avoid complex modelling, an MG system optimization algorithm was used for effective and easy modelling.

The process which finds the best fit value for a specific problem by maximizing or minimizing its objective function is known as optimization [38]. In the recent era, optimization is widespread in all research areas [39]. In the past, optimization for microgrid had been done by using different software applications such as PVSYST, HOMER Pro, HYBRID, SOMES, HOGA, INSEL, PV-DESIGN PRO, RSHAP, ORIENTE, SOLSIM, RAPSIM, and HYBRIDS [40][41] GAMS, MINLP [42]. Even though all these software applications were able to optimize the microgrid to some extent, but it was also having some demerits[43]. To overcome these demerits, new computational techniques have been studied and applied. Many new bio-inspired optimization methods have been studied and tried based on the optimization objective in microgrid and the best method was chosen [6,43]. A specific optimization problem solving by not generalizing or not applicable to any similar problems are known as heuristic algorithms. If an optimization problem is guided by its design it is known as metaheuristic optimization [44]. A particular algorithm is selected based on its application[45]. Some heuristic applications are the neural network, data mining, etc. On the other hand, high-level metaheuristic optimization algorithms such as particle swarm intelligence, a flock of birds, colonies of ants and bees etc…, is been used in different applications [46]. The objective function is the core function in optimization used to maximize or minimize a particular function in a system. Considering multiple objectives simultaneously in a single process is known as multi-objective optimization [47]. Constraints are nothing but the limits which are assigned to the objective function. The two types of constraints are soft and hard constraints. Soft constraints are considered to be in higher preference over other whereas hard constraints inevitably satisfy [48]. The objective function can be of either single objective function or with multiple objective functions to maximize and minimize simultaneously. In [49] the author considers six multi-objective minimization functions for the Distributed Energy Resources (DER). Incorporating all above mentioned microgrid features a few key areas where microgrid applications got established are discussed in the upcoming section.

This review article is systemized based on the following sections. In previous Section-0 a detailed introduction about optimal sizing of MG is illustrated. Section-2 will be giving a brief idea about different types of microgrid. Optimal sizing of a microgrid will be structured in section-3using different optimization methodologies. Cost-based analysis in the MG system is pointed out in Section- 4. Section-5 will give an outline of detailed comparison in different sizing components followed by challenges faced in different sizing techniques. In the last section 6 concludes this review paper.

2 Types of microgrid

A microgrid is a common junction, which interconnects different renewable energy resources along with consumers and other energy-storing backups. Microgrid can be isolated from a central grid known as islanded microgrid (off-grid) or it can operate with support from the utility grid (on-grid) [50]. The system sizing methods can be classified in many ways such as the simulation-based, analytical methods, iterative method, graphical method and based on heuristic or metaheuristic optimization algorithms [31]. Few commonly used microgrid configurations are discussed below and illustrated in Fig. 2.

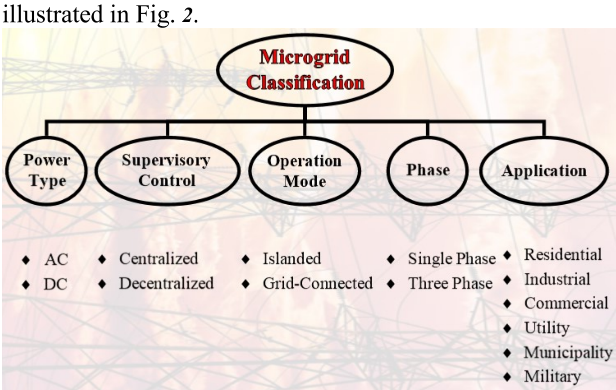

Fig. 2. Microgrid Classification

2.1 Hybrid microgrid

Hybrid-RES (HRES) is one of the trending resources which economically feasible energy resource for rural areas [48]. A Hybrid Microgrid System (HMS) is the parallel interconnection of many distribution resources with electronically balanced operation [51]. HMS can be operated either in a grid interconnected mode of operation or in off-grid mode.

In [52], the author considered a standalone HRES with PV, WT and DG with BSS optimally sized the RE component based on the reliability. The author in [6] selected PV, WT, DG as the sources along with the battery bank for formulating a hybrid microgrid. In [31], they designed a Hybrid autonomous microgrid with PV/ WT/ BSS and DG with an effective rule-based EMS. Apart from commonly used RE resources for bonding a hybrid microgrid system, in [53] the author combined WT with BSS. The author modelled the sources for satisfying the daily load demand (with a lower and higher peak from morning and evening). In [54] author considered a HMG system consisting of PV/ WT/ FC with a hydrogen storage system based on three case studies in Iran and the author used PSO concludes:

- The reliability of the system is dependent on cost.
- Optimum rating of wind/ Storage system/ PV

In [51] PV/WT/BT/DG and BT are considered as sources for an islanded HMGS in Sundarban a place in India to increase the access the energy through RE.

2.2 Islanded microgrid / Stand-alone Microgrid (SMG)

Even though our world developed so far in technologies and infrastructures, there are 1 billion people lacking the facility of electrification in their households [55]. In which 14% of the global population is covered [56]. The key reason for the dearth of electricity in rural areas is because of lesser efficiency in transmitting power from the central grid to such a long distance. In such rural areas, constructing an islanded microgrid with available RE sources will be more appropriate. Recently, short and long-time power failures have occurred due to many natural calamities. Even in such circumstances islanded microgrid with distributed generator connected to priority loads will be more helpful [37]. Multiple energy sources need to be added to the microgrid for a better reliable power generation. There are many pieces of literature based on islanded microgrid for powering rural areas.

A stand-alone microgrid [32] consisting of six sources such as PV/ WT/ MT/ EES/ TES/ and Gas Boilers (GB) proves the significance of the Photovoltaic Thermal (PVT) panel in SMCMG since it is able to reduce the cost by 35.68% and 5% increment in the energy dump. The emission of 404 tons of CO_2 can be reduced by encouraging the same system. In the literature [21] includes Hydrogen Storage System (HSS) along with PV/ BSS, which is used to size a standalone microgrid. The author used EA and UC for the better technical and economic sized standalone microgrid. In the literature [37], the author considered nine microgrid system components such as PV, solar heating system, HSS, heating boilers, AC, electric, thermal, cooling and hydrogen loads. In [57] the author states about a relevant microgrid system which includes energy storage for temporary back supply along with PV and WT as power generating sources. In [11] the author considered an off-grid microgrid system with different profiles such as a rural village, a telecom tower, welding shop, lift load and different storage systems for sizing methods.

Standalone microgrid [58] for Dongfushan, a rural area in China, considered for optimal component sizing and better cost reduction. A Pumped Hydro Storage(PHS)/ BSS/ PV/ WT systems was developed to form an islanded microgrid for a small village by [59].

The impression highlighted in the public eye about various microgrid applications as claimed by its easy concept and higher feasibility is a remarkable one. The following are the classifications of MG focusing on its applications published in some older studies:

2.3 Industrial MG

Widespread application of MG is also reached in industrial sectors. A high range of electric power can be generated from the industry sector through RE. In [24] the author concludes that, the mathematically modelled energy demand for the considered industry can be fully satisfied by means of generated renewable energy power from the same industry. In [60] author concludes that remarkable amount of CO_2 emission is reduced by the means of industrial MG implementation.

2.4 Military

The global demand required for electrical energy in military applications is inevitable. During war periods, relying on the main grid power will not be feasible always. The main grid can be destroyed by enemies and power interruption can occur. Also transporting fuel to the power plant is a risky task since it is explosive. Constructing one feasible MG with readily available DG sources in a closed-loop can solve these problems. A few papers regarding microgrid in the domain of military applications are discussed in [61–68].

2.5 Residential

A small microgrid system can be implemented in residential buildings. The microgrid can acquire power from the installed residential solar power, the power generated from the residential diesel generator and from other small residential power generating sources. Many kinds of literature report a detailed idea in the area of microgrid and residential application such as:

- Effective MG using V2G (Vehicle 2 Grid) for better EMS[69–72],[73]
- Optimal control for a residential microgrid [74]
- Smart residential microgrid [75][76]
- Based on household appliance [77]
- Residential MG and energy storing system [78]
- Residential DC microgrid [79]
- Home to the grid [80].

In [81] author considered a residential microgrid with PV and battery as the primary sources. The excess generated power from MG is feed forwarded to the main grid.

2.6 Electric Vehicles

In the present era, EV is widespread for both short and long-distance travel, hence the requirement of EV charging point and advanced energy storing system are high. The important powering sources in EV are from the BSS. In the application related to MG and EV, both systems are mutually benefitted. The excess generated power from the MG can be stored in EV batteries without diverting to any dump load, and also it can be used for ancillary services, clipping the peak rise in the demand and valley filling [82,83]. In [84] deals about energy storing capability by EVs from non-residential building for valley filling and peak clipping. In [83], the author frames an advanced extension of study from literature [85,86]. Initially, the author in [85] optimally reduced the overall operating cost by incorporating EVs to an MG. From advancement from the previous study, author innovate much more in the literature [86] by optimally sizing the charging location with multiple binaries. At the latest, the author succeeds by integrating both in location finding and with level two V2G parking facilities in the MG closed-loop [83]. Bidirectional charge transfer of EV based system with DCMG consisting of PV and ESS in [87]. The author explains a methodology for the economic sizing of DCMG considering EV necessity based on various scenarios.

2.7 Rural village

Electricity distribution to rural villages had become a worldwide challenge. Most rural villages are located far away from the national grid such as in the fields, terrains, mountains and in the thick jungle, forests, etc… Laying transmission line or fuel transport towards such places will lead to high cost in the country economy. Developing an efficient MG in such locations will provide a better solution and this will be able to power up single-phase load to higher-rated 3-phase loads (based on the MG sizing) which can also support a small house load from 5 KW. While considering a common home located in Indian rural village will consume 8.9kWh [10]. In [2] the author designed a microgrid system with PV and valve controlled based storage devices for a rural village. The author carried out the Optimal PV and battery sizing by using HOMER software. A standalone MG with optimum component sizing for the rural area (tested in actual MG of Dongfushan, China) with ESS/ PV/ WT/ DG is processed with GA in the literature [58]. Two unelectrified rural areas Dhakla and Tangier, located in Moroco have been electrified by using PV/WT/ DG and BT as the prime sources [88]. The author used Multi-objective Particle Swarm Optimization (MOPSO) for effective sizing of HMG to rise the reliability of the system and to lowering the emission reduction benefit cost in [89]

2.8 Communication Network

Uninterrupted availability of mobile networks is a mandatory requirement in everyone's day to day life. Digital India Campaign (DIC-2015) conducted in 2015 forwarded the vision for implementing and strengthening of internet facilities in rural India by implementing around 1,00,000 networking towers. Uninterrupted and unavailability of electric power was one of the major issues faced while starting the installation project. The working researchers in the same area stated that around 40% was receiving interrupted power supply whereas 22% are off-grid towers [90,91]. In [92] proposed an optimal DC microgrid by using NSGA-II with PV and WT for telecommunication towers for the supply of economical, clean and eco-friendly power. The author was also able to minimize Cost of Energy (COE) with a markable reduction of 13%, EE and a 20% rise in Loss of Power Supply Probability (LPSP). There are many works of literature stating effective work placed in rural villages providing clean and reliable energy at minimal cost such as in [93–95]. In [96] the author proposes a minimal cost-wise analysis for various household loads in a rural village. A Solid Oxide Fuel Cell (SOFC) with Gas Turbine (GT) was effectively sized for a rural MG which also is an advancement in the PQ and grid stability [97].

3 Optimal sizing of Microgrid

Observing, exploring and learning from nature is the best solution for any arduous problem. Even before mankind evolved on this planet, nature has overcome the exacting problem by the means of evolution [39]. A novel idea for solving the optimization problem through computer simulation was developed by Holland by the evolutionary concept [98].

Previous sections exposed a detailed overview of different types of microgrid used in microgrid applications. Different types of sizing optimization used in the domain of MG are discussed in this section such as GOA, FA, PSO, GWO, EA, GA, ACO, BA, ISA, SO.

3.1 Grasshopper Optimization Algorithm (GOA)

GOA is a metaheuristic nature-inspired algorithm introduced by Seyedali Mirjalili, a professor from Torrens University, Australia. Grasshoppers are usually known as the farmer's enemy since they damage crops by forming a big group. Fig. *3* exemplifies the growth cycle of the grasshopper [99] .

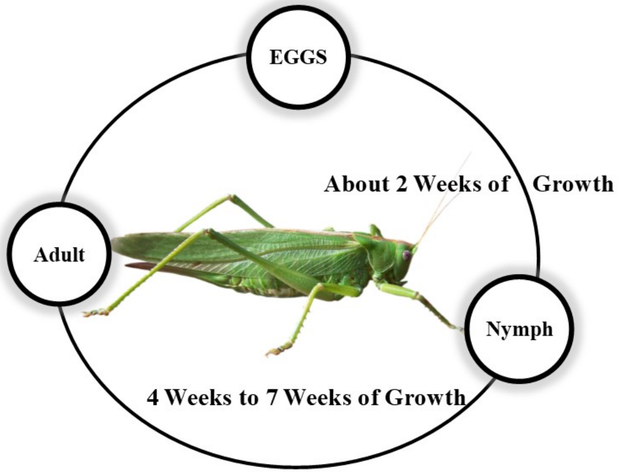

Fig. 3. life cycle of a grasshopper [99]

Swarming is seen in both nymphs and adult stages of the grasshopper [38,39]. The locomotion of nymph grasshopper is much slower than adulthood, due to the absence of wings. But the nymph will take that as an advantage and will grasp more vegetation. The presence of wings in adult grasshopper will help them to swarm in a larger radius, with more speed. Coordinate point of any individual grasshopper in a swarm is determined based on three forces such as [100–102].

- ♦ Social interaction (Si)
- ♦ Gravity force (Gi)
- ♦ Wind advection (Ai)

The numerical simulation of GOA is based on Eq. 3.1 to Eq. 3.5 [101]

$$X_i = S_i + G_i + A_{i,} \quad (1)$$

$$S_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s(d_{ij})\widehat{d_{ij}} \quad (2)$$

The difference in the driving ride from the i[th] to the j[th] grasshopper is d_{ij}. s denotes the power of the grasshoppers ' social power.

$$s(r) = fe^{-\frac{r}{l}} - e^{-r} \quad (3)$$

Strength of the mutual attraction between the grasshopper and duration scale is demonstrated as f and l respectively.

$$Gi = -g\hat{e}_g \quad (4)$$

The upright movement in the air is demonstrated by A_i.

$$A_i = u\hat{e}_g \quad (5)$$

Many pieces of literature explained GOA in much detail for different optimization problem statement [39]. [31] has used GOA for microgrid sizing design problems and obtained 14% achievement in capital cost while comparing with CS and PSO. The author designed a microgrid with PV, W T, BSS and Diesel generator (DG) to satisfy ED problems focusing on the Deficiency of Power Supply Probability (DPSP) and COE for five residential houses in Yobe State in Nigeria, an off-grid community. The author compared GOA results with existing results from literature [38] and GOA can achieve more in convergence and local optima avoidance.

3.2 Firefly Algorithm (FA)

FA is a well know metaheuristic algorithm framed by Yang in 2008 [103],[104]. The basic concept behind firefly algorithm is based on observing its nature of movement and fire glowing character which is considered as the objective function. Since fireflies are unisex, they will be attracted to each other despite seeing their own sex. Highly shining fly will be most near to the best fit solution or else the lesser glowing one will move towards brighter firefly. If a brighter firefly is not available then the fly will travel randomly by searching for a brighter one in the search space. Many literature papers have clearly explained about the firefly algorithm for various optimization applications [105].

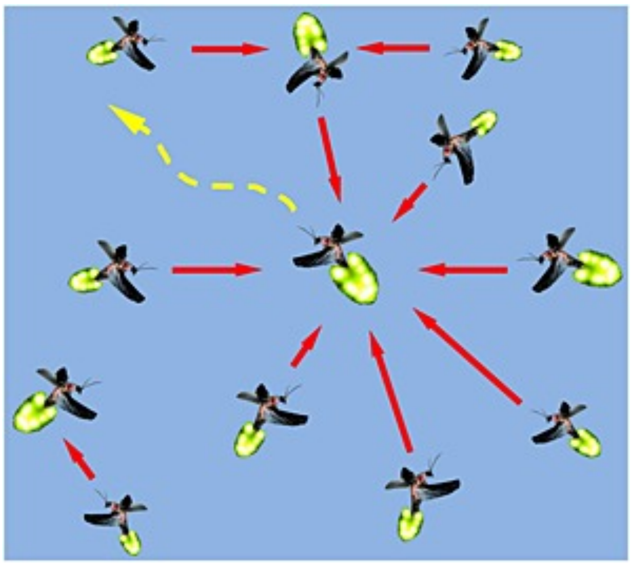

Fig. 4. Firefly Algorithm[106]

By observing Fig. *4* it will give a clear picture of FA. Following key points can be summarised in general for FA such as:

- ♦ Mating partners will be attracted
- ♦ Less glowing flies will attract towards brighter fireflies

- ♦ Random search for a brighter fly if no brighter flies has been seen in the search space

The intensity level of light can be mathematically represent based on inverse square law Eq. (6) [107]

$$1 \propto \left[\frac{1}{r^2}\right] \tag{6}$$

The light intensity from the source can be obtained from the Eq. (7). Where I_0 is the intensity level of light in the source point.

$$I = I_0\, e^{-\gamma r^2} \tag{7}$$

The brighter firefly can be found by obtaining β value from Eq. (8)

$$\beta = \beta_0\, e^{-\gamma r^2} \tag{8}$$

The low glowing firefly will move towards the brighter fly by using the updating formula from Eq. (9)

$$x_i := x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha(\varepsilon(\,) - 0.5\,) \tag{9}$$

The attractiveness in the position r=0 of the second firefly x_j is represented as β_0. Whereas α and $\varepsilon(\,)$ represents the step length and random movement vector ranges from 0 and 1 respectively. The brighter fly x_b can find out from Eq. (10)

$$x_b := x_b + \alpha(\varepsilon(\,) - 0.5\,) \tag{10}$$

FA is used by the author for optimal sizing of the battery which will eliminate the over deep discharging of the energy storing device [108]. Renewable power supply sources such as DG, WT, and PV incorporating with battery energy storage system used and compared the results with ABC, PSO and HAS algorithms from [109,110] and concluded that

- FA runs with a lesser operating cost of 0% LPSP
- PSO and HAS could not meet the targeted load and leads to load shedding.
- Optimum battery size is necessary to reduce battery costs which will also reduce overall MG system cost.

3.3 Grey Wolf Optimisation (GWO)

A modern metaheuristic algorithm that replicates the character of a grey wolf that belongs to the Canidae family is proposed by Seyedali Mirjalili [111] in 2014. Both male and female wolf can be leaders and the remaining pack will be following the same. Alphas in the top order who decides about the plan such as hunting plan, snooze and rouse time. As part of showing respect while gathering, the entire pack of wolfs will bow down their tails. The hierarchical order of the Grey wolf is shown in

Table *1*. Followed by alpha they have their subordinate for assisting them while decision making and helping in activities know as a beta. This subordinate can be either male or female and need to be responsible for behalf of alfa meanwhile without losing respect to alfa. All scouts (who used to make boundary secure), sentinels (protects and guarantee the full pack), elders (well experienced wolfs), hunters (one who find food for the pack) and caretakers (nurse the injured wolf) belongs to the third category called Delta. The last ordered wolf is known as omega [112].

Table *1* gives a detailed idea about the Hierarchal model of grey wolfs [111]

Table 1. Grey Wolf Hierarchal model [113]

ALPHA	1. The Dominant Wolf 2. Best in managing the pack
BETA	1. Subordinate wolves 2. Advisor to the alpha 3. Discipliner for the pack
DELTA	1. Not an alpha, beta, or omega 2. Submit to alphas and betas
OMEGA	1. The lowest ranking wolfs 2. Plays the role of scapegoat

The cyclic behaviour of GWO is mathematically illustrated by three variables such as $\overrightarrow{A}, \overrightarrow{C}, \overrightarrow{D}$.[114,115].

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}(\mathrm{t})| \tag{11}$$

$$\overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}(\mathrm{t})| \tag{12}$$

$$\overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}(\mathrm{t})| \tag{13}$$

't' represents the iteration number. Below *Table 2* represents the positions vectors of different wolves and their mathamarical representation. The $\overrightarrow{D_\alpha}$, $\overrightarrow{D_\beta}$, $\overrightarrow{D_\delta}$ vectors can be obtained from Eq. (11),(12),(13) respectively.

Table 2. Mathematical equations for different type of wolves in GWO [116]

Vector	Wolf Type	Mathematical Equation	Eq. No
$\vec{X}(\mathrm{t})$	Grey Wolf	$\vec{X}(\mathrm{t}) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3}$	*Eq. (3.14)*
$\overrightarrow{X_1}$	Alpha	$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}$	*Eq. (3.15)*
$\overrightarrow{X_2}$	Beta	$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}$	*Eq. (3.16)*
$\overrightarrow{X_3}$	Delta	$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta}$	*Eq. (3.17)*

GWO has widespread in many optimizations and also introduced in new designs with certain modifications in [118] and [119]. The author [117] used GWO for optimal sizing BES system which operates at the least cost. The following system was designed with following RE components along with following minimum and maximum power such as MT 6-30 (KW), FC 3-30 (KW), PV 0-25 (KW), WT 0-15 (KW), Li-ion battery-Ve 30to30 (KW) energy storage system and utility with -Ve 30to30 (KW). The obtained GWO is considered with three different cases for minimum MG operating cost and then compared with previous research results published by [118] using GA, PSO, BA, IBA, TS, DE, BBO and TLBO.

3.4 Particle Swarm Optimization (PSO)

PSO is the most commonly used metaheuristic optimization technique formulated by Kennedy and Eberhart [119,120]. It can be said as a flock of birds searching for food in a vector space. The global optimum position of the bird can be concluded by observing the personal best and the global best simultaneously. The optimal solution will be the global best position of the swarm[32,121]. PSO can be summed up in the following Eq. (14) & (15).

$$v_j^{t+1} = v_j^t + \alpha R_1.[g^* - x_j^t] + \beta R_2.[x_j^* - x_j^t] \quad (14)$$

R1&R2 are two Random Vectors which lies between 0 and 1. The particle will try to converge towards global best (g^*) than from personal best $x_j^*\ if\ \alpha > \beta$. Whereas α & β are learning vector constants and the Initial velocity is assumed as 0. The new position is determined by the below equation (15).

$$x_j^{t+1} = x_j^t + V_j^{t+1} \quad (15)$$

A clear view of Fig. *5* below gives a detailed overview of PSO.

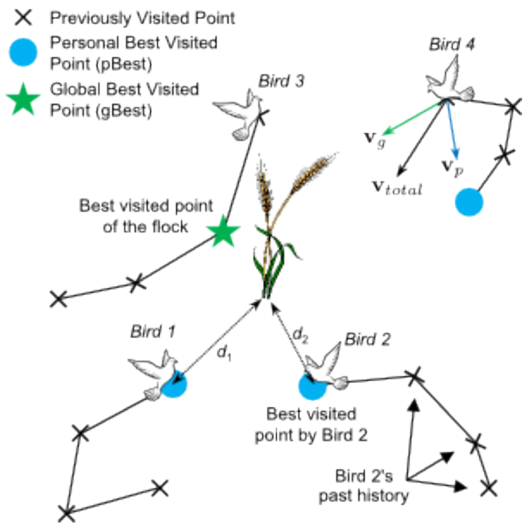

Fig. 5. Particle swarm optimization pictorial representation

To be general PSO optimizes the objective function based on the following three steps:

- Fitness evaluation of the particle
- Updating global fitness and positioning
- Particle velocity updating (Exploration, learning factor, momentum weight) [110][122]

Battery sizing for ED problems in a grid-tied MG is solved by using PSO in [20]. In [123] the author has used a new particle swarm optimization (NPSO) algorithm for solving economic dispatch (ED) problems. Multi-objective Adaptive Modified Particle Swarm Optimization (MOAMPSO) is used by [124] for minimizing emission and system running cost. For solving multiple operation management problems author [122] introduces a fuzzy Self Adaptive PSO (FSAPSO). FASPSO optimization is stopped either in maximum iteration level or by on minimal error else if the entire population will be replaced by a new set of population and the cycle is repeated till achieving the Global best (G-best) from the last iteration. The proposed FASPSO is used to optimize power generation cost, unit starting and shutting down cost, and pollution reduction. The author used a new algorithm known as natural selection particle swarm optimization (NS-PSO) in [125] consisting of PV/WT/BT in a hybrid power system. By including comprehensive observation, the overall system execution can be improved. In [126]used PSO for optimal capacity sizing for an MG with PV, TE, CCHO, ESS, and other auxiliary systems. In the literature [32] the author developed a new enhanced evolutionary PSO (E-PSO) for defining the EMS problem, and for finding TAC and LPSP for an SMC-microgrid. The author concludes that he obtained better TAC while comparing it with other algorithms. In [127], PSO is used in a standalone unit that contains the PV and WT units for minimizing the cost by considering full demand for a period of 20 years. The author compared the results with GA and observed 73.7 seconds advanced in PSO computational time. In [128] the author used PSO for reducing the annual cost and to promote majority usage in energy from renewable energy sources such as PV/WT (Battery is used for storing excess energy) which is operated in standalone hybrid mode. In [129] the author considered PSO for optimal power flow problem within 2 MG systems with 10MW and 2MW respectively. In [59] the author used PSO for sizing an islanded microgrid with PV/WT/ BSS and pumped hydro as the main source. A smart microgrid with PV and battery as a primary source is optimally sized by using PSO in [81]. In the literature [130] PSO is used for minimizing the cost and to determine the LPSP of a PV and WT based microgrid system. PSO is used by the author in [51] for effective sizing of an islanded HMGS with effective cost management and with better system reliability.

3.5 Multi-Objective Particle Swarm Optimization (MOPSO)

Multi-Objective optimization is simply the ability to consider many objective functions simultaneously. MOPSO can mathematically represent based on Eq. (16) & Eq. (17). [131–133]

$$\text{Minimize: } F(X) = f_1(X), f_2(X) \dots \dots \dots f_G(X) \quad (16)$$

$$Subject\ to:\ R_i^{lower} \le x_i \le R_i^{upper} \quad (17)$$

Where $i = 1,2, \dots \dots \dots, d$. G represents the total number of objectives and total number of variables is represented by d. The $[R_i^{lower}, R_i^{upper}]$ are the i[th] vector boundary variables.

Here in MOPSO both inequality constraints and equality constraints are obtained[134]. In [134] author used MOPSO to develop an optimal cost management system for reducing operating cost and emission that occurred due to pollution in a microgrid with WT, PV, BS system. The author compared the optimized result obtained from MOPSO with NSGA -II and it achieved better performance in MOPSO by optimal operational cost and emission due to pollution.

Table 3. Better efficiency obtained by MOPSO in three cases from [134]

Scenario	Operation Cost €ct	Emission (Kg)	Time (Sec)
Case 1	27.8	7.8	25.2
Case 2	0.2	38.9	23.3
Case 3	3.8	4.7	30.1

Table *3* shows the improvement obtained from MOPSO in operation cost, emission and simulation time [134]. An HMS consisting of PV/WT/BT/DG described in [135] used MOPSO for selecting optimal HMG combination. Real-time EMS for an islanded MG is explained in [136] by using MOPSO. In [137] Based on a modified PSO energy storage system is designed in a distribution system. In [88] author used MOPSO to increase the reliability and minimize the NPC for a microgrid with PV/WT/DG and BT as sources.

3.6 Multi-Objective self-adaptive differential evolution algorithm (MOSaDE)

In 1995, the differential evolution algorithm (DEA) was developed by Price and Storn while solving the Chebyshev polynomial fitting problem. DEA follows three stages named as mutation, crossover and selection. SaDE is based on considering the previous best fit individuals obtained [138][6].

In the literature [6], MOSaDE for optimizing an HMS in Yanbu, a city located in Saudi Arabia, was studied. This HMS was comprised of PV/WT/DG along with battery storage. MOSaDE is used to analyse LPSP, COE, and the Renewable Factor (RF) where LPSP and COE are the objective functions for optimization. The Author compared HMS with multi-objective function by splitting into three case studies based on different houses as data set and compared with valuable results obtained in [110] and selected the optimal HMS system.

3.7 Evolution Algorithm (EA)

Evolutionary algorithms are based on the learning process in natural evolution[139,140]. Steps followed by EA can be easily understood by observing the below Fig. *6* [141] .

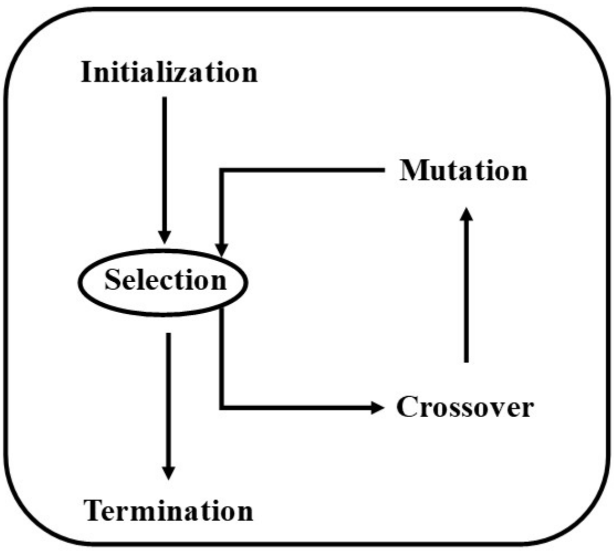

Fig. 6. Stages in an Evolutionary Algorithm (EA)

Different populations of DE algorithm are solved by using Eq. (18)[6,142,143]

$$X_{ij} = l_j + rand() \cdot (U_j - l_j) \tag{18}$$

Below

Table *4* represents the different parameters used in EA

Table 4. Parameters in in EA

X_{ij}	Dimension of *j* in the individual *i*
l_j	Minimum limit
$rand()$	Random value [0,1]
U_j	Maximum limit

In [144] author used a two-step process with an adaptive nesting evolutionary algorithm for optimally size MG with the best operation schedule. Three variable steps of the iteration are performed. The iteration stops randomly while achieving the best individual triggering the first step of EA. In IInd step of EA stops, after reaching to its saturation. In [21] optimal sizing of standalone MG by using EA and MILP for scheduling is developed. The author achieved in EMS and decision anticipating which is compared with classical rule-based strategy. In [41] the author used EA based multi objective optimization for a hybrid PV/ WT/DG/BT which reduced the NPC and CO2 Emission .

3.8 Genetic Algorithm (GA)

From the outset, the complex optimization problem evolved in many applications was able to solve by using GA [145]. The basic idea followed by GA is by the mimic process of a gene such as selection, recombination, and mutation which inspired Darwin's theory. In GA optimization problem develop some random solution variable (individuals) as the initial process. All individual variables are considered to be as gene and a set of variables resembles a chromosome. The entire solution obtained is known as the population of the GA and the best chromosome is nominated for the next population [39]. Below Fig. *7* represents the flow diagram for GA.

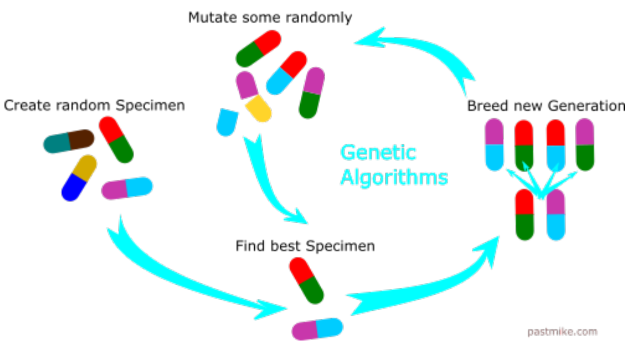

Fig. 7. Genetic Algorithm [141]

In the reference [21] used GA for succeeding in a cost-effective PV, BSS, electrolyser and FC elements considered as a leader program for a tabulated time period. The author compared the results with traditional rule-based approaches with an advanced EMS which have a tolerable capacity and able to anticipate the results. GA is considered as the apt algorithm for optimizing the energy management system by considering its easiness for solving large variables [33]. In a hybrid Mg system with PV / FC/ BES author [146] used GA to obtain power and the outlay of the MG. GA is used by the author [58] for a standalone MG system for optimal component sizing of PV/WT/ DG with BSS, and minimizing the LCC and pollution.

Few literatures have used non-dominated sorting genetic algorithm (NSGA -II) for attaining better performance in MG. In [147] used NSGA-II for cost reduction and reducing the overall emissions. There are other few pieces of literature which has used NSGA-II [148] in the same domain. The author in [149] used multi objective self-adaptive GA and triangular model for optimize and promote the maximum use of RE and also to increase the reliability of Combined Heat and Power (CHP) microgrid.

3.9 Ant Colony Optimization (ACO)

In 1990 Marco Dorigo along with his offsider proposed a novel optimisation technique by observing colonies made by ants[150,151]. A particular path will be used by ants while collecting food which is marked by the means of pheromone which will help them to follows the same path while returning back[152] to the colony. The path which is having higher pheromone scent will be used by many ants and weaker scent path will be avoided [153,154]. The accumulation of pheromones correlated for each possible route is modified for a better result based on below Eq.(19) [155,156].

$$T_{ij}(t) = PT_{ij}(t-1) + \Delta_{T_{ij}} \tag{19}$$

T	Iteration No. / Generation Cycle
$T_{ij}(t)$	Revised concentration
$T_{ij}(t-1)$	Concentration of previous iteration
$\Delta_{T_{ij}}$	Change in pheromone concentration
P	Pheromone evaporation rate (0-1)

After achieving a better understanding in Ant colony optimization [157] ACO is used for optimal design for HES in [43]. In [158] the author used ACO for implementing a power management controller for an alternative energy distribution generation system to optimise the economical emission and total operating cost. A stand-alone hybrid system is optimally sized by using ACO in [159]. The author needs to consider more classic data's which will able to increase the accuracy. However, with the selected data, the author is able to reduce the yearly system costs with higher reliability. In [160], ACO is used for optimising the total system cost of WT/ PV/BT based off-grid system. In [161], the author considered three different places in Egypt such as Kharga, Saint Katheina, Qussair for modelling a hybrid microgrid system with solar , wind , battery, fuel cell and other distribution generation sources. The author used ACO for bring down the cost of electricity and to reduce the CO2 emission. The obtained results are compared with PSO, GA and HOMER for validating ACO as the best for the particular data set.

3.10 Bat Algorithm (BA)

Yet another well-known population and iterative based optimization algorithm offered by Yang 2010 is known as Bat Algorithm (BA) [162]. The unique ability in bats helps them to identify its prey/food and echolocation detects the distance [163]. The variations in their loudness (wavelength) determines their target. x_0, v_0, f_i is generated as inceptive population of BA. New population is obtained from Eq. (20) and Eq. (21) [164].

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{20}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x^*)f_i \tag{21}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{22}$$

Through local search procedure, the best solution from each iteration is streamlined.

$$A_i^{t-1} = \alpha A_i^{(t)} \tag{23}$$

$$r_i^{(t)} = r_i^{(0)}[1 - \exp(-\gamma \in) \tag{24}$$

α and γ are the constants in Eq. (23) and Eq. (24). The obtained new population is examined and the best solution is taken. The new population acquired is judged based on the objective functions and a best solution is decided. Fig. *8* provides the pictorial description of BA.

As considering around all optimal design algorithms will be pulled down with its own demerits. In BA, chances for getting held up in local optima are more.

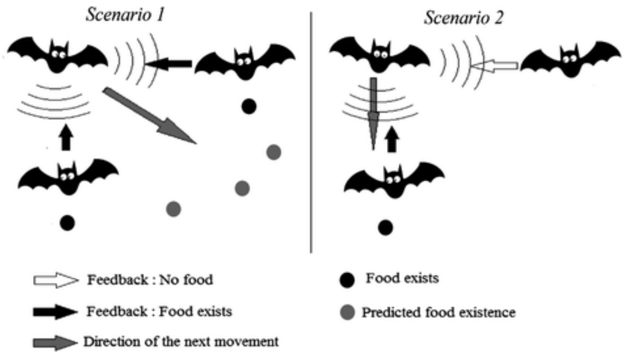

Fig. 8. Bat Algorithm [165]

In order to overcome this drawback, a slight modification is enhanced by [118] named as an improved version of BA (IBA). Placing of FCL in optimally sized location is also a difficult task so the author used BA and CS for the same in [29].

3.11 Based on Optimizing Tools

Hybrid Optimization Model for Electric Renewables (HOMER) was intended by United States – National Renewable Energy Laboratory (US-NREEL). By using HOMER, a typical physic model of a power system for total cost analysis such as installation cost, operational cost, life cycle cost, for a period of life spam can be analysing [166]. The input data can be provided and the model possesses PV and WT data. [40,167]. The author used HOMER for selecting a combination with the lesser discharge of CO2 along with the less budget [168]. Five different combinations such as PV/DG, DG alone, WT/DG, PV/WT, and PV/WT/DG are the different respective cases. The author concluded that Case four was not having emission (0% emission) whereas the fifth case was with less emission along with the lesser cost.

In [169] author considered a campus MG system with PV/WT/ES installed in Aligarh Muslim University (AMU) designed using HOMER. A case study with 3.4MWh/day which is considered as mandatory load and a deferrable load of 3.3MWh/day is considered in [167]. The system successfully to attained 0.092$/kWh Levelized Cost (LC) which also minimizes 38.3% CO2 emission along with 6.18% annual cost.

4 Cost analysis in microgrid sizing

While designing a system, cost analysis is an important criterion. There are many works of literature that analysed and sized the microgrid which in an economically feasible manner. Utilization cost, the lifespan of the system, the return of investment, maintenance of system, system replacement cost, investment cost, degradation cost and additional fuel supply are some of the key terms considered by different authors while analysing the cost for microgrid sizing. In the domain of microgrid COE (unit electricity cost), Life Cycle Cost (LCC), TNPC (all cost needed for the system such as present cost, operating cost along with the maintenance cost) are the most considered cost analysis [110].

In the literature [32], the author has considered Total Annual Cost (TAC) as his main objective function for analysing optimally size techno-economical energy and cost-efficient SMCMG.

The MG system supplied with 44% from PV, 14% from WT, 26%, from BSS and 16% from DG was able to cut short 0.365$/ KWh in COE while compared with CS and PSO [31].

In [37], different utilization components have been accessed for proper minimizing of operational cost. In [53] the operational cost has been analysed with a linear model for all dispatch costs. The system comprises a WT and BSS. In order to overcome the slow start-up of the system, it requires start-up, shutdown along with the setup cost. Variable cost will be linearly increased according to the production amount, whereas in the fast start generator only linearly variable cost is considered which has high expensive unit production cost.

In literature [117], the author able to minimize the overall cost needed to be spared in MG. the author considered the system with three different cases and concluded that an effectively sized MG with Effective BES will reduce the overall cost. The result obtained from GWO was then compared with a different optimization method which was used in [118]. The author [48] presented a detailed cost analysis about the considered three phases of his study. The excess generated energy is supplied to the utility grid by two-time scales for a day which varies from 22.00 hrs to 18.00hrs and 18.00hrs and 22.00 hrs with respective tariffs (One-two). For the first time, $0.054 per kWh and scale $0.14 per kWh is charged for drawn grid current and Rs.0.030 per kWh and 0.068 per kWh is charged for grid injection. [2] optimized the cost for PV and BT system by different stages and concluded DSS is best with a reduction of 8.26%. The reduced percentage of 48.3% of battery size pockets the overall $2000 savings. In [170] based on iterative simulation the author optimally sized PV/WT/BT/DG with lesser cost and higher demand availability for a building load located in Sohar, a place in Oman. [118] quotes avoiding storing device will reduce 40% of daily applicable charges. GA is used by the author [146] for maximizing the net present worth of the entire system. A notable reduction of 0.010 $/kWh is able to achieve in the hybrid electricity market while comparing with the pool market. In [20] MM-EMS is considered for the best operation of MG with lesser cost by using LP(linear Programming) and MILP considering three different action plans. NSGA-II is proposed for NPC minimization and escalate basic savings in energy[171]. 27% of O&M cost and 30% of emission cost was able to be reduced by considering TE based MG [126].

5 Comparison

In previous sections a detailed idea about various microgrid configurations and different types of microgrid has been explained. An effective sized microgrid will be much reliable to the society. Many pieces of literature used different optimization algorithms in the domain of microgrid sizing. By analysing below *Table 5* it's much easier to understand about different optimal sizing algorithms used in the domain of microgrid sizing. Different optimization algorithms are used for solving objective functions such as

- Cost Minimization
- Emission Minimization
- Reliable Power Supply
- Operational Loss Minimization
- Reliable Component Sizing
- Energy Consumption
- System Stability

Table 5. Detailed comparison based on different optimization algorithm with different sets of components and different types of MG

Sl. No	Algorithm / Tool used	DG – SOURCE									Type of MG	Objective Function	Results Compared With	Inference	Ref
		PV	WT	BT	DG	MT	TES	GB	HSS	FC					
1.	PSO	✓	✓						✓	✓	HMG	Reliable power supply in all weather conditions		• Cost directly depended on reliability.	[54]
2.	ABC	✓						✓			Hybrid stand alone and grid connected	Energy and annual cost Minimization	HOMER	• Reliable and affordable electricity to the rural village from the locally available RE Resources.	[172]
3.	BA	✓	✓	✓							Grid-Tied MG	Total Cost Minimization	GA, PSO	• From three cases it's understandable that the system has convergence speed, robustness, • cost reduction due to optimal battery size, • MG without BES will drop down 40% of the daily charge	[118]
4.	EA	✓	✓	✓							HMG	Cost Optimisation	Non nesting 2-step algorithm	• Best result is obtained in the IInd iteration of 20.04% improvement.	[144]
5.	EA	✓		✓					✓		Standalone MG	Cost optimisation	Rule based strategy	• Optimal sizing of standalone MG • Component sizing and total cost is dependent on operation strategy, initial condition and time resolution.	[21]
6.	MOEA	✓	✓	✓	✓				✓		Isolated Hybrid Microgrid	NPC, CO_2, Unmet Load		• Simultaneous reduction in pollution and cost of the system	[41]
7.	E-PSO	✓	✓	✓		✓	✓	✓			SMCMG	Optimal Cost less emission and optimal sizing	DE, PSO, GA, HAS	• Better solution with fast convergence • Less variance • Better energy efficiency,	[32]

														economical and reliable. • 404 tons of CO_2 can be reduced	
8.	**FA**	✓	✓		✓						Isolated Microgrid	Cost Minimisation	ABC, HAS, PSO	• BESS optimally discharges when insufficient power delivered from RES which reduces BT operating cost. • FA with 0% operating cost in LPSP	[108]
9.	**FASA**	✓		✓							SAPV	SAPV sizing	PSO, EP, GA	• FASA optimize much faster while comparing with ISA • FA is 1.9309 times faster than PSO, EP, GA	[105]
10.	**GA**	✓		✓							Grid connected Microgrid	Energy loss, energy cost, CO_2 emission		• Overall energy losses occurred in microgrid is reduced • Minimized the CO_2 emission and imported energy cost	[33]
11.	**GA**	✓		✓						✓	Hybrid electricity market	Net present worth (NPW)	Pool market Grid	• 0.010$/kWh achieved in Hybrid electricity market • Totally NPW decreased	[146]
12.	**GA**	✓	✓	✓	✓						Stand-alone MG	LCC minimization, maximization of RE injection and Reducing emission due to pollution		• Satisfied the Objective function. • Improve the production of energy from renewable energy sources	[58]
13.	**GOA**	✓	✓	✓	✓						Hybrid Autonomous MG	DPSP, COE	PSO, CS	• 14% and 19.3% reduction in overall system initial investment • Zero DPSP & minimized COE • Effective RE component Sizing	[31]
14.	**GWO**	✓	✓	✓		✓				✓	Hybrid MG	Total cost minimization	GA, TS, PSO, DE, BBO, TLBo. GWO	• Better performance and convergence speed.	[117]
15.	**Homer**	✓	✓	✓							Campus MG	Energy consumption, COE		• 75%of increase in COE and 35% energy consumption in the last 5 years. • PV+B mode is 64.2% higher with respect to the existing system and G+PV is 57.2% lower with respect to existing. • Mitigate CO2, SO2, NOX as 636*106 Kg, 1.578*104 Kg, 7.7*103 Kg respectively	[169]
16.	**MOAMPSO**			✓		✓				✓	Hybrid power source	Optimal Operation with minimum Cost and Emission	GA & PSO	• Analysing the environment, the best power dispatch plan can be selected.	[124]
17.	**MOPSO**	✓	✓						✓	✓	HMG	Annual Cost Minimisation and EMS	Single Objective algorithms	• Keep down the annual total cost and reliability indices • Effective energy management system	[173]
18.	**MOPSO**	✓	✓							✓	Hybrid Stand alone	Annualized cost, Expected loss of load and energy	SOA	• Cost directly dependent on reliability • Effective sizing for avoiding losses	[174]
19.	**MOPSO**	✓	✓	✓	✓					✓	HMG	Operating Cost, pollution emission cost	NSGA-II	• Infinite power exchange between LV and MV is the best case from three cases • Operating cost and pollution are minimized	[134]
20.	**MOPSO**	✓	✓	✓	✓						HMG	COE and LPSP		• RE sources promoted more rural electrification in Iran	[135]
21. `	**MOPSO**	✓	✓	✓	✓						HMG	NPC & ERBC		• Electrified unelectrified two rural areas in Morocco with minimized NPC and Emission Reduction and Beneficial Cost (ERBC)	[88]
22.	**MOSaDE**	✓	✓		✓						HMG	EMS, LPSP, COE, RF		• Optimal capacity sizing of the sources • Price reduction in RE prices	[6]

23.	NA	✓	✓	✓	✓			BISS	Minimizing cost and maximum availability	HOMER	• Cost minimization and demand maximization. • Better performance while comparing with Homer	[170]
24.	NSPSP	✓	✓	✓				Hybrid Power System			• Minimized energy wastage, voltage fluctuations, cost • Improved reliability of the system.	[125]
25.	PSO	✓	✓	✓				Standalone Hybrid	Cost Minimisation RE promoting		• Effective EMS is designed • Reduced the annual cost • Promoted the usage of RE sources	[128]
26.	PSO	✓	✓	✓				Standalone generation unit	Cost minimization	GA	• Better convergence, speed, and accuracy while comparing with GA.	[127]
27.	PSO	✓	✓	✓	✓			Islanded HMGS	Effective cost and System reliability		• Promoting RE in Sundarban/ India is economical to increase the energy access through RE	[51]
28.	Triangular aggregation and levy-harmony	✓	✓	✓				Islanded MG	Economy, RE technology, Pollution, Reliability	Standard harmony algorithm	• Developed triangular aggregation model and improved Leavy harmonics model • Three objectives can be placed in three axes of the triangle. • Data lose can be avoided	[57]
29.	MHBMO	✓	✓				✓	Standalone MG	Minimize electrical power loss,	Standard test system	• Used fuzzy decision maker for selecting non dominant optimal solution. • Results compared with two standard test system	[175]
30.	ACO	✓	✓	✓		✓		Standalone MG	Cost minimisation, Max reliability		• More standard data's to be consider for more accuracy • Ant count should be calculated • Minimal annual cost and more reliability in the present system data	[159]
31.	ACO	✓	✓	✓	✓		✓	HMG Islanded	Cost minimisation	GA, PSO, HOMER	• System developed in three different locations of Egypt • Energy cost is minimized • Reduced CO_2 emission	[161]

Based on the need different DG sources are used to form a microgrid. Below Fig. 9 shows the detailed graphical representation of different DG sources used in various microgrid applications.

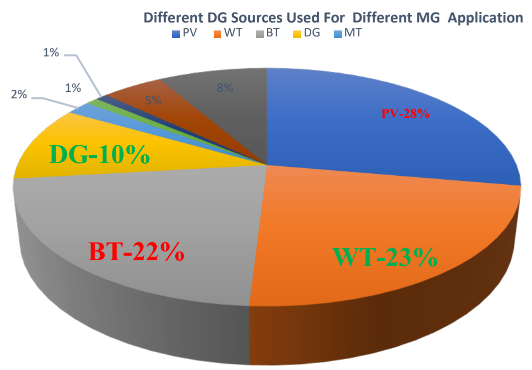

Fig. 9. Different DG sources used in Different MG application

It is clear that almost all combinations of PV/WT/BT are used. Around 10% used different diesel generating system for the backup supply of power.

For drafting this detailed review paper, different papers from peer-reviewed journals are selected. Below Fig. *10* gives an idea about, total number of papers collected from the year 1995 to 2020 to formulate this review paper

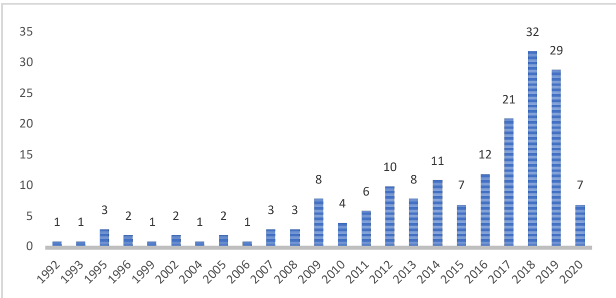

Fig. 10. Papers from the year 1993 to 2020

6 Conclusion

The initiation needed to encourage and promote renewable energy sources are becoming a mandatory task due to high rise in energy demand and reduction in the supply of non-renewable resources. This review paper offers a thorough examination of the optimal scale of the microgrid based on different applications. The value of productive magnification of MG can be inferred with greater economic significance. It is obvious that specific optimization algorithms are the best for various optimization problems, depending on the application needs or the role played by the algorithm. It is another difficult task to identify the best optimization method for a particular objective. Pictorial representation of mostly used optimization algorithm is given in this review paper for a better analysing the concept of optimization. A comparative study is done based on different algorithms and different DG sourced used for forming MG is been analysed. Year-wise literature collection will give a better idea about the advancement and increasing trend that occurred in the field of MG.

In order to encounter the global depletion in nonconventional sources of energy, this review paper will help to promote RE sources and to form an optimally sized microgrid.

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