JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-19, No.-5, May (2024) pp 46-72 ISSN (Print) 0973-8975

A REVIEW ON OPTIMAL PLACEMENT AND SIZING METHODS OF DISTRIBUTION GENERATION SOURCES

Smrutirekha Mahanta[1], Manoj Kumar Moharana[2]

[1]School of Electrical Engineering, KIIT Deemed to be University Bhubaneswar, Odisha, India.

[2] School of Electrical Engineering, KIIT Deemed to be University Bhubaneswar, Odisha, India.

Email : [1]m.smrutirekha88@gmail.com, [2]mkmfel@kiit.ac.in

Corresponding Author: **Smrutirekha Mahanta**

https://doi.org/10.26782/jmcms.2024.05.00004

(Received: March 21, 2024; Revised: April 23, 2024; Accepted: May 06, 2024)

Abstract

This manuscript outlines various work carried out in the field of Distributed Generation (DG). Increase in power consumption and shortage in transmission capabilities are addressed by DGs. In order to maximize the potential benefits, it is imperative to place the DGs at optimal locations and the DGs should have optimal size pertaining to that location. There are several research works that are carried out on the placement and sizing of DGs. Nonetheless, the methodical principle for this issue is still unsettled. Various optimization strategies can be used to obtain the appropriate placement and sizing of distributed generation (DG) in grids. This study provides a comprehensive overview of several DG placement approaches, including stochastic fractal search algorithms, particle swarm optimization, symbiotic search algorithms, opposition-based tuneable chaotic differential evaluation, and more. The benefits and potential uses of each method are briefly covered in this study. The study sheds light on the efforts made to determine the best location and size of DGs.

Keywords: Distributed Generation, DG Placement Techniques. Optimal Locations, Optimal Size,

I. Introduction

Reconstruction of electrical networks was apparently due to lessening reserves of perishable resources. The result of this reconstruction is grid integration of renewable energy sources. DGs over the years had evolved as one of the front-runners in the, modern power crunch society. It has also evolved as an alternative to fossil fuel-based power generations. Many of the western countries are on a process of either migrating or completely migrated to renewable based energy generation. The globe dockers made efficient hardware implementation of research works that made this transition possible, DG is a technique where power plants are located near load centers [I]. These DGs are integrated with the modern grid structure for efficient utilization of modern energy reserves. However, there are many problems like power loss, voltage profiling, sizing of DGs, reliability etc [II]. This problem can be overcome by utilizing suitable optimization methods to place and size DGs. The advantages of having DGs integrated into the conventional grids are categorized into environmental benefits, economic benefits and technical benefits. The environmental benefits include decline in emission of greenhouse gases, decline in sound effluence and decline in carbon footprints. The economic benefits include decline in operating cost of transmission and distribution network, savings of fossil fuels and decrease in price [III]. There is massive technical importance of using DGs in modern grids. The benefits include overall improvement in efficiency, reinforcement of grids, reduction in power loss of grids, improvement in reliability of power systems, jettisoning or differing upgrades in power systems that are long overdue, improving load power factors and it aids in voltage profiling. This is highlighted in Table 1.

Table 1: Merits of DG placement and sizing

Environmental benefits	• decline in emission of greenhouse gases, • decline in sound effluence and • decline in carbon footprints.
Economic benefits	• decline in operating cost of transmission and distribution network, • savings of fossil fuels and • decrease in price
Technical benefits	• overall improvement in efficiency, • reinforcement of grids, • reduction in power loss of grids, • improvement in reliability of power systems, • jettisoning or differing upgrades in power systems that are long overdue, • improving load power factors and • it also aids in voltage profiling

The ability to lower investments in power system operations and development is the most crucial part of DG positioning study for operators. It helps strengthen transmission and distribution networks, increase dependability, and decrease investments in extra control equipment [IV]. It helps operators enhance efficiency and reduce power transmission loss. Several issues with DG placement and sizing have been identified based on the data. Numerous methodologies are employed by researchers, including numerical, metaheuristic, analytical, and hybrid approaches. Numerous studies on DG location and sizing are compared in this publication. Test system type, DG count, load model, design variable, and optimization method for objective functions are all part of the comparison criteria [V-X]. Niknam et al.

explains radial distribution networks using Volt/Var control, which takes DG performance into account. By strategically deploying DGs and using their appropriate controllers, network volt/var control and system losses can be significantly improved. Acharya et al. state that in order to reduce overall power losses in primary distribution networks, it is possible to analytically determine the optimal scale and location for DG deployment [XI-XV]. The findings of this methodology are compared to exhaustive load flows and loss sensitivity approaches to see if the strategy based on loss sensitivity factors finds the best spot to cut losses. The distribution feeder reconfiguration (DFR) problem, as it relates to the integration of RESs like solar, fuel cell, and wind turbines into the distribution network, may now be examined using an algorithm that was created by Niknam et al. When applied to the DFR problem, the results show that the suggested approach works and is believable. Although the study also showed that the cost objective function behaved differently from the other objective functions, it did find that voltage deviation and total emission behaved similarly [XVI-XX]. Niknam et al. explains radial distribution networks using Volt/Var control, which takes DG performance into account. By strategically deploying DGs and using their appropriate controllers, network volt/var control and system losses can be significantly improved. Hung et al. provided an approach for integrating dispatchable and non-dispatchable DG units to minimize yearly energy losses. There is a significant reduction in annual energy losses when using dispatchable DG units, or a combination of dispatchable and non-dispatchable DG units, compared to not using them. The results also show that the maximum reduction in annual energy losses is achieved for all scenarios proposed with DG operation at optimal power factor. With the right allocation and size of DG, the overall power loss is reduced, and the voltage profile is improved. This was demonstrated by Devi et al. in their work. Using the Bacterial Foraging Optimization (BFO) method with modification, the results gained pave the way for new and exciting study areas that will have faster convergence times and better results from using the BFO algorithm. As part of this research, Devi et al. introduced a technique called Particle Swarm Optimization that seeks to reduce total power loss while also improving the voltage profile of a Radial Distribution System using distribution static compensator (DSTATCOM). This study reveals that the ideal placement and size of DG and DSTATCOM in Radial Distribution System improves the voltage profile while reducing the system's overall power losses. The results were analyzed using Loss Sensitivity Factor. Prasad and colleagues published their findings in a paper. The best dispersed generation size is calculated using an algorithm inspired by elephant herding in the wild. It is modelled on elephant herding behaviour in the wild, therefore it is really effective. As well as being compared to other recently presented strategies, the results obtained by the elephant herding optimization algorithm were also superior in all scenarios. Yuvaraj et al. employed the nature-inspired Bat Algorithm (BA) to address the optimal placement and scale of DGs in distribution networks. In addition, two distinct types of DGs were taken into account in this research. The main objective of the current research is to reduce the actual power loss in the network. Additionally, the outcomes of the bat optimization algorithm have been compared to those of other recently presented methods, with the proposed method coming out on top in all of them. There have been several research on DG allocation, but this one published the results and examined them in context of the optimization algorithms and targets used by Ahmed et al. Despite extensive research into powerful and efficient metaheuristic optimization algorithms for DG allocation, there is still space for improvement and the development of more effective algorithms with strong capabilities in discovering global optimums is warranted. Findings from the study by Bikash et al. suggest that two separate RDNs (e.g., 33-bus and 69-bus distribution networks) can have their ideal DG sizes and locations identified. A number of additional optimization approaches are compared to their results, including particle swarm, teaching learning, cuckoo search, artificial bee colony, gravitational search, and stochastic fractal search. According to Sajjan et.al, a new opposition-based tuned-chaotic differential evolution (OTCDE) technique was developed to help optimize the size and location of numerous DG units in IEEE 33-bus, 69-bus, and 118-bus RDSs. The results show that OTCDE can handle a larger system, such the IEEE 118-bus system, with more decision variables and still have strong convergence characteristics. It has also been shown that OTCDE's results are superior to those of other recently developed methods, and this is true regardless of the circumstance. Usharani and colleagues Distributed generator (DG) optimal insertion in radial distribution systems has been achieved using an adaptive non-dominated sorting genetic algorithm (ANSGA II). According to this study's findings, the proposed algorithm outperforms the existing competitive algorithms such as Harmony Search Algorithm (HSA) and Fireworks Algorithm (FWA) but falls short of Genetic algorithm (GA) and Refined Genetic Algorithm (RGA). In the context of distributed generations, Tran et al. implemented the stochastic fractal search (SFS) algorithm to address the DNR problem in DGs. This strategy produced superior solutions than other methods when compared to those found in the literature, and the results proved it. As a result, SFS may be an excellent solution to the reconfiguration issue, especially if DGs are included in distribution networks. An enhanced variant of the first SOS algorithm, the Quasi-Oppositional Chaotic Symbiotic Organisms Search (QOCSOS) algorithm was put out by Truong et al. For a more powerful worldwide search, QOCSOS combines SOS with QOBL and CLS techniques [XXI-XXV]. All things considered, the proposed QOCSOS method produced superior results compared to the alternatives. Accordingly, the Optimal DG Allocation (ODGA) problem and other such complicated and large-scale systems may be amenable to QOCSOS. The stochastic fractal search (SFS) algorithm was used by Tran et al. to solve the DNR problem in distributed generation (DG) systems. The outcomes demonstrated that this approach outperformed competing strategies as reported in the literature. Consequently, SFS could be a great way to fix the reconfiguration problem, particularly if distribution networks incorporate DGs. Quasi-Oppositional Chaotic Symbiotic Organisms Search (QOCSOS), an improved version of the original SOS algorithm, was published by Truong et al. By integrating SOS, QOBL, and CLS, QOCSOS creates a more robust global search. In comparison to the other options, the suggested QOCSOS approach yielded better outcomes. Hence, QOCSOS might be able to solve the Optimal DG Allocation (ODGA) problem and similar complex, large-scale systems. For their study on radial distribution systems (RDSs) and optimal allocation of distributed generators (OADG), Nguyen et al. employed a new stochastic fractal search method (SFSA). Taking cues from the way in which plants and animals grow, meta-heuristic algorithms like the SFSA method apply a mathematical notion called fractals to optimize problems. Among the many advantages of the SFSA approach are its few control parameters and its relative simplicity of implementation. By improving the positioning and sizing of numerous DGs at once, the suggested method decreases power loss. To find the exact position and volume of DG, Ali et al. proposed an innovative approach. It was discovered that the size and location of the DG had a significant impact on system losses. Finding and sizing DG-based renewable energy sources in distributed systems is made easier with the help of the Ant Lion Optimization Algorithm (ALOA), according to this study. The suggested method optimized the location and sizing of numerous DGs at the same time as it decreased power loss. The ideal size and deployment of multiple DGs at once can be achieved, according to Aman et al., by increasing the system's load capacity without violating its constraints. Factors limiting the system's performance include DG penetration, transmission line length, and voltage magnitude. One other choice is HPSO, or hybrid particle swarm optimization. Power loss was decreased and the positioning and sizing of multi-DG were optimized efficiently using the suggested method. Using a multi-objective approach, as suggested by Prabha et al., it is possible to find the optimal distribution network for several distributed generation units with different load models. The loss sensitivity factor (LSF) is used to find out where the DGs should be placed. An effective optimization of system constraints and a substantial reduction in power loss were achieved using the invasive weed optimization technique. With several goals to balance, Prakash et al. proposed a new way to apply the Whale Optimization Algorithm (WOA) to choose where and how big to put DGs. The many goals of lowering operational expenses, optimizing the voltage profile, and decreasing power loss necessitate a fine balancing act between equality and disparity. To put the proposed method to the test, radial distribution test systems with 33-bus and 69-bus connectivity were employed. The proposed approaches' superior computational accuracy and DG placement strategies were revealed upon detailed examination. Siahbalaee et al. detailed an improved shuffled-frog-leaping method that was used to modify the size and placement of DGs. The results showed that more complex networks had greater performance and were more practical for analysis and DG deployment. This research provided by Usharani et al. presents an enhanced Elitist-Jaya algorithm for power distribution network reconfiguration and DG allocation. When compared to other solutions, the Elitist-Jaya algorithm produced more accurate results. Teimourzadeh et al. presented the concept of distributed generation planning and distribution network reconfiguration happening simultaneously. The problem is specified using an optimization model that includes three types of variables: the positions of the DGs as integers, the operating points of the DGs as continuous variables, and the open/close statuses of the switches as binary variables. Locations of DGs are subsequently optimized. A novel approach called the three-dimensional group search optimization (3D-GSO) method has been created to tackle this problem. Better optimization and more accurate findings were among the many advantages of the new method. The major contributions of some of the researchers are listed out in Table-2 [XXVI].

Table 2: Major contributions of some of the researchers

Reference	Work	YEAR
Truong et. al.	Overall, the suggested QOCSOS method outperformed existing approaches, especially for large-scale, complicated systems. This suggests that QOCSOS can be used to solve ODGA problems, particularly those involving huge systems.	2019
Tran et.al.	This strategy produced superior solutions than other methods when compared to those found in the literature, and the results proved it. In light of the involvement of DGs in distribution networks, SFS may prove to be a very beneficial solution for resolving the reconfiguration issue.	2019
Usharani et.al.	Comparing the results with those of competitor algorithms already published in literature, such as HSA, FWA, GA, and RGA, we can prove that the suggested algorithm is effective.	2019
Sajjan et.al.	For a bigger system like the IEEE 118-bus, the results show that OTCDE can handle more decision variables while still maintaining strong convergence characteristics. Additionally, the outcomes of OTCDE have been compared to those of other recently presented strategies, with the proposed technique coming out on top in all scenarios.	2019
Nguyen et.al.	When comparing the test system results to those of other approaches, it appears that the suggested method is capable of producing better solutions for the scenarios covered by the test systems.	2018
Bikash et.al.	They then compare their findings to those of other optimization methods, such as particle swarm, teaching learning, cuckoo search and artificial bee colony as well as gravitational search and stochastic fractal search.	2016

Devi et. Al.	For optimized voltage profile and reduced system losses, the best location and sizing of DSTATCOM in Radial Distribution System uses Loss Sensitivity Factor analysis.	2014
Devi et. Al.	Using the BFO method with modification, the results gained pave the way for new and exciting study areas that will have faster convergence times and better results from using the BFO algorithm.	2014
Hung et.al.	When compared to not using dispatchable DG units—or a mix of dispatchable and non-dispatchable DG units—there is a considerable decrease in annual energy losses. All of the suggested scenarios also illustrate that operating DG at optimal power factor reduces annual energy losses to their maximum.	2013
Hung et.al.	69-bus distribution test results show that the proposed methodologies can be appropriate for DG unit location, size, and power factor determination to minimize energy losses.	2012
Niknam et. Al.	The results suggest that the proposed strategy works well and is credible when applied to the MDFR issue. A similarity in behaviour was found between voltage deviation and total emission, although the cost objective function had a different behaviour from the other objective functions, as was also revealed in this study	2011
Naresh et.al.	This methodology's results are evaluated against exhaustive load flows and loss sensitivity methods to determine whether or not the loss sensitivity factor-based approach leads to the ideal location for loss reduction	2006
Nikram et.al.	Volt/Var control in the network can be greatly improved while system losses can be reduced by properly placing DGs and utilising the suitable controllers for them.	2003

II. Approaches For Placement and Sizing of DGs

In order to place the DGs at optimal locations with optimal size it is imperative to formulate a system structure. Table-3 lists out a few of DG placement techniques. Table-4 lists out a few of DG sizing techniques [XXVII].

Table 3: DG placement techniques analysis

Reference	Test System	No.of DGs	Load Model	Design Variable	Objective Function	Optimization Technique
Kaushal et.al.	IEEE-33	Multi	Constant Power	Location	Real and reactive power loss minimization	Local Search Optimization
Afroz et.al.	IEEE-33/69	Multi	Constant Power	Location	Power loss minimization and voltage profile improvement	Teaching Learning Combined with Harmony Search
Fandi et.al	IEEE-33	Multi	Constant Power	Location	Power loss minimization and voltage profile improvement	Analytical Approach
Angalaeswari et. al.	IEEE-33/69/118	Multi	Constant Power	Location	Power Loss Minimization	Parameter Improved Particle Swarm Optimization
Zongo et.al.	IEEE-14	Multi	Constant Power	Location	Power loss minimization and voltage profile improvement	Particle Swarm Optimization and Newton Rapson Power Flow

The system structure should necessarily indicate the choice of number of DGs, IEEE test system, design variables. After the formulation of system, the objective function or cost function is to be determined.

Table 4: DG sizing ANALYSIS

Reference	Test System	No. of DGs	Load Model	Design Variable	Objective Function	Optimization Technique
Reddy et.al.	IEEE-15/33/69/85	Multi	Constant Power	sizing	power loss minimization	Whale optimization algorithm
Adel et. al	IEEE-33/69	Multi	Constant Power	sizing	Real and reactive power loss minimization	Water Cycle Algorithm
Partha et.al	IEEE-33/69/83/119	Multi	Constant Power	sizing	Real power loss minimization and voltage profile improvement	Decomposition Algorithm,
Veera et.al.	IEEE-15/33/69/85	Multi	Constant Power	sizing	power loss minimization	Ant Lion Optimization
Sirine et.al.	IEEE-33	Multi	Constant Power	sizing	power loss minimization	Analytical Approach

Depending upon the design variable and objective function the choice of weather it is a minimization type optimization function or maximization type optimization is made. Then the approaches are compared with other techniques using the same optimization techniques to prove superiority of the chosen approach. When deciding where to put a DG, factors including location, size, type, and the number of DGs must be taken into account, as well as load variables like constant power and changing power based on bus voltage magnitude, probabilistic, and fuzzy. Based on the problem at hand the choice of DG placement technique is made. The techniques may be categorized into the following groups.

a. Numerical Methods based DG placement

b. Analytical Methods based DG placement

c. Metaheuristic approach based DG placement

d. Hybrid Approaches

Numerical Methods based DG placement- The numerical method utilization for optimal placement and optimal sizing of DGs are one of the oldest techniques. In this technique extensive numerical analysis is carried out but the efficacy of these methods are less which is due to ever increasing complexity of the systems under study. This is the reason why these methods are not utilized now. The Loss Sensitivity Factor (LSF) forms the basis of analytical methods that are used for DG placement. To solve the optimal DG placement challenge, LSF relies on injecting equal current. Its inapplicability to the uniform distributed load model is a drawback of this method. For the simple reason that it adheres to the precise loss formula. The magnitude of DGs is provided via the Sensitivity Factor equation. A combination of the sensitivity index, the exact loss formula, and the voltage sensitivity coefficient is used to minimize power loss and improve voltage profiling. Metaheuristic approach-based DG placement- This is accomplished by using various optimization algorithms. It is one of the highly efficient approaches to solve the complex network of grids. In this approach, an optimization is carried out for either maximization of power flow or minimization of power loss. In grid-connected networks, the latter is often chosen as it tends to better results. Recently researchers are adopting this technique owing to its reduced complexity and enhanced accuracy. Some of the optimization techniques are explained below. Stochastic fractal search algorithm is a metaheuristic algorithm. It is inspired by natural phenomena of growth based on mathematical approach called fractal. There are two processes in this algorithm. They are diffusing process and updating process. In diffusing process, each particle diffuses in its local space so as to escape from being trapped in local minima. In updating process as a part of information exchange, ach particle updates its position in the global space. Technique for tuning chaotic differential evaluation on the basis of opposition- It has four phases, which is standard for differential evolution methods. Initialization, mutation, crossover, and selection are all steps in the procedure. To obtain updated parent vectors, the initialization stage is modified using an opposition-based learning technique. It is done this way to prevent convergence from slowing down. During the stages of mutation and cross-pollination, a trial vector is created by exchanging mutant vector components for parental vector components in this process. It is only made for the member that competes with the parent vector in order to reduce computing time that a mutant vector is generated. You can pick any number in this range for the crossover ratio CR and the mutation factor (0, 1). Increasing the CR value enhances mutation likelihood, which aids the solution in expanding its scope of application. Similarly, a smaller CR value aids in faster convergence of the solutions. Because of this, with each generation development, the value of CR drops linearly from 0.95 to 0.75, in order to achieve a healthy balance between exploration and exploitation. Selecting which parent vector or trial vector will make it to the next generation is done during the selection stage [XXVII].

In evolutionary algorithms, the Genetic Algorithm is a metaheuristic method of natural selection inspired by natural selection. Biochemical operators including mutation, crossover and selection are used by T in order to get high-quality solutions to optimization and search issues. A genetic algorithm necessitates the creation of a genetic representation of the solution and a fitness function specific to the solution domain in order to function. To implement a genetic algorithm, you will need the following materials. Each of these functions has a representation and initialization component. Genetic operators, which are stochastic transitional rules, are used to create a better population. Introduction strategies for crossovers can take many forms. Crossover ensures that the search area is intensified while mutations are in charge of diversification. The controller parameters were adjusted using a genetic algorithm in this investigation. An optimization technique known as the PSO algorithm is an evolutionary computing technique. A specified quantity is used to iteratively improve or better the solution. There are no or few assumptions about the problem being optimized; hence, PSO is meta-heuristic in that it searches enormous spaces. Other methods necessitate a differentiable optimization problem for them to work. PSO, on the other hand, does not ensure the best outcome. They move around in the search space, guided by their known positions in the search space as well as all the swarms' best-known solutions. The particles or swarms. The cycle is repeated until the problem is solved. The problem, on the other hand, is that the answer might not be ideal. PSO's control parameters include the problem's size, the number of particles, the acceleration coefficients, the inertia weights, the size of the neighbourhood, and the number of iterations. The Jaya algorithm is always working to improve its chances of success while minimizing the likelihood of failure. It makes an effort to come closer to the ideal solution while avoiding local minima and maxima along the way. Jaya algorithm's benefits include it uses just two common parameters: population size and the number of iterations. JAYA, an intelligent population-based algorithm, is a simple but effective optimization algorithm for approximating optimal solutions. While other optimization algorithms require adjustment of their parameters to work well, Jaya is unique in that it does not. Jaya may be used to tackle problems involving constraint and unconstraint optimization. The number of design variables, the size of the population, and the termination criteria are all JA variables (iterations). The equation serves as the foundation for the entire JAYA algorithm. Depending on our optimization criteria, the objective function must be either minimized or maximized. The use of nature-inspired optimization techniques such as symbiotic search algorithms is becoming increasingly popular. The term "symbiosis" refers to two organisms coexisting harmoniously. It means the coexistence of two organisms in a mutually beneficial relationship. When it comes to symbiotic relationships in nature, mutualism, commensalism, and parasitism are the most prevalent sorts to notice. Both species gain from mutualism. During this stage, one species may gain an advantage over the other. Biology defines commensalism as an arrangement in which individuals from different species benefit from each other's food or resources without causing harm to either of them. In the parasitism phase, there is a mutually beneficial connection between two species in which one is damaged and the other benefits. This relationship benefits one creature while harming another. The parasite gains from the interaction while the host suffers. This algorithm makes advantage of nature-inspired processes to maximize benefits while minimizing resource consumption. An adaptive genetic algorithm that is not dominated by any one gene this algorithm employs a number of different goals. Based on the evolution approach, the individuals in this algorithm progress towards an end goal. Fast non-dominated sorting procedure to determine each individual's non-dominated level can be inferred as the population evolutionary approach. The whale optimization algorithm (WOA) and similar swarm-inspired algorithms are relatively recent developments. In order to find the optimal solution, it imitates the way humpback whales hunt. Humpback whales are thought to have the ability to track down and encircle their prey. Due to the lack of prior knowledge regarding the location of the ideal design in the search space, the WOA technique operates under the assumption that the closest or target solution is the best candidate solution at the present time. The remaining search agents will try to get closer to the best search agent once it has been discovered. The most optimal choice is thus identified. The manuscripts that are currently being reviewed have their similarities and differences listed in Table 5 [XXVIII].

Table 5: similarities and dissimilarities between the manuscripts under review

Reference	**Test System**	**No. of DGs**	**Load Model**	**Design Variable**	**Objective Function**	**Optimization Technique**
Niknam et. al	IEEE-34 bus	Multiple	Constant Power	Location and size	Power Loss	Genetic Algorithm
Usharani et. al.	IEEE-33 bus	Multiple	Constant Power	Location and size	Multi objective	Adaptive non dominating sorting Genetic Algorithm
Tran et.al.	IEEE-33/69/84/119/136 bus	Multiple	Constant Power	Location and size	Power Loss	Stochastic Fractal Search
Truong et.al.	IEEE-33/69/118	Multiple	Constant Power	Location and size	Multi objective	Quasi oppositional chaotic symbiotic organism search optimization
Naresh et. aL.	IEEE-33/69 bus	Multiple	Constant Power	Location and size	Power loss	Analytical Approach

Bikash et. al.	IEEE-33/69 bus	Multiple	Constant Power	Location and size	Multi Objective	Symbiotic Organism Search
Devi et.al	IEEE-11/33/68 bus	Multiple	Constant Power	Location and size	Power loss	Modified Bacterial Forging
Devi et.al	IEEE-11/33/69 bus	Multiple	Constant Power	Location and size	Multi Objective	PSO
Hung et. al	IEEE-69 bus	Multiple	Constant Power	Location and size	Power Loss	Analytical Approach
Hung et.al	IEEE-69 bus	Multiple	Constant Power	Multiple	Multi Objective	Dispatchable and non dispatchable
Sajan et.al.	IEEE-33/69/118	Multiple	Constant Power	Multiple	Multi Objective	Opposition based Chaotic Differential Evolution
Nguyen et. al	IEEE-33/69/118 bus	Multiple	Constant Power	Location and size	Multi Objective	Stochastic Fractal Search
Prabha et.al.	IEEE-33/69 bus	Multiple	Constant Power	Location and size	Multi Objective	Invasive Weed Optimization
Prakash et.al	IEEE-33/69 bus	Multiple	Constant Power	Location and size	Multi Objective	Whale Optimization Algorithm
Yuvaraj et.al	IEEE-33 bus	Multiple	Constant Power	Location and size	Power Loss	Bat Optimization Algorithm
Aman et.al	IEEE-16/33/69 bus	Multiple	Constant Power	Location and size	Multi Objective	HPSO
Ali et.al	IEEE-33/69	Multiple	Constant Power	Location and size	Multi Objective	Ant Lion Optimization
Hari Prasad et.al	IEEE-15/33/69	Multiple	Constant Power	Location and size	Multi Objective	Elephant Herding Algorithm

III. CMAESAO

When deciding where to put a DG, factors including location, size, type, and the number of DGs must be taken into account, as well as load variables like constant power and changing power based on bus voltage magnitude, probabilistic, and fuzzy. The problem in hand is addressed by using hybridizing two optimization techniques. The two optimization techniques are CMAES and AO. An evolutionary algorithm is the category to which CMAES belongs. An evolutionary strategy that derives from the idea of self-adaptation is CMAES. In order to speed up the algorithm's convergence, the correlation between parameters is utilized. The CMAES method generates a new population by sampling a probability distribution function. The advantages of CMAES include a high convergence rate for nonlinear fitness functions, the fact that searching in CMAES is performed independently of the coordinate system, and its versatility over a wide range of fitness functions. While searching, the method updates the covariance matrix, which causes it to evolve. The creation of additional offspring from a normal distribution is represented by Eq. (1).

$$x_k^{(g+1)} \sim m^{(g)} + \sigma^{(g)} N\left(0, C^{(g)}\right) \quad \forall \begin{matrix} k = 1,2,3\cdots\lambda \\ g = 1,2,3\cdots \end{matrix} \tag{1}$$

where, λ, g, $N\left(0, C^{(g)}\right)$, C^g, σ^g, m^g, and $x_k^{(g+1)}$ represents population size, number of generations, multivariate normal distribution function with zero mean, covariance matrix, step size at g^{th} generation, mean value of the search distribution of g^{th} generation and k^{th} offspring of the $g+1$ generation respectively. The fitness function is examined using a subset of members from the normal distribution. The normal distribution is moved into the problem space to produce better members if the analysis is not satisfactory. Therefore, the determination of $C^{(g+1)}$, $\sigma^{(g+1)}$ and $m^{(g+1)}$ is crucial to generate a new population. The mean of the next generation ($m^{(g+1)}$) specifies sampling zone of the normal distribution. Based on the data from the past, this is decided the mean ought to be shifted into that region. The mean is thus calculated as the weighted average of the better fitness functions. $m^{(g+1)}$ is expressed mathematically by Eq. (2).

$$m^{(g+1)} = \sum_{i=1}^{\mu} \left(\sum_{i=1}^{\mu} \omega_i \right) x_{i:\lambda}^{(g+1)} \tag{2}$$

where, μ represents best individuals of present and previous generations, ω_i represents positive weighted average of better fitness functions, $x_{i:\lambda}^{(g+1)}$ represents the i^{th} best offspring out of $x_1^{(g+1)}, x_2^{(g+1)}, x_3^{(g+1)} \cdots x_\lambda^{(g+1)}$. Based on the values of their fitness function, the offspring are sorted. The probability of selection is displayed by the covariance matrix. In evolutionary techniques, the value of the fitness function decreases as the number of generations begins to rise. The covariance matrix of a previous generation can be utilized to generate the covariance matrix of the next generation ($C^{(g+1)}$).Mathematically, $C^{(g+1)}$ is expressed by Eq. (3).

$$C^{(g+1)} = \frac{1}{g+1} \sum_{i=0}^{g} \frac{1}{\sigma^{(i)^2}} \sum_{i=1}^{\mu} \omega_i \left(x_{i:\lambda}^{(g+1)} - m^{(g)} \right) \left(x_{i:\lambda}^{(g+1)} - m^{(g)} \right)^T \tag{3}$$

where, $\sigma^{(i)^2}$ represents the square of the step size at i^{th} generation. The length of the path under random selection is compared to its anticipated length. If the evolutionary path is longer than anticipated, the value of is increased; if it is shorter than anticipated, the value is decreased. The path's length is equal to what is anticipated under ideal circumstances. The previous generation's step size can be used to express the step size of the upcoming generation. Mathematically, $\sigma^{(g+1)}$ is expressed by Eq. (4).

$$\sigma^{(g+1)} = \sigma^{(g)} \exp\left(\frac{C_\sigma}{d_\sigma} \left(\left\| P_\sigma^{(g+1)} \right\| \times E \left\| N(0,1) \right\|^{-1} \right) - 1 \right) \tag{4}$$

where, damping parameter, learning rate of the conjugate evolution path, the normalization constant and the rescaling of the coordinates is represented symbolically by d_σ, $\sigma^{(g)}$, C_σ, $\sqrt{C_\sigma (2 - C_\sigma) \mu_{eff}}$, $C(g)^{-0.5}$. $E\left\| N(0,1) \right\|$ is the expected length to update $\sigma^{(g)}$ and $P_\sigma^{(g+1)}$ is the conjugate evolution path which is expressed mathematically by Eq. (5) .

$$P_\sigma^{(g+1)} = (1 - C_\sigma) P_\sigma^{(g)} + \sqrt{C_\sigma (2 - C_\sigma) \mu_{eff}}\, C(g)^{-\frac{1}{2}} \frac{m(g+1) - m(g)}{\sigma^{(g)}} \tag{5}$$

Eq. (4) determines the ideal step size, which improves the search capability and convergence speed. Figure 1 depicts the CMAES flow diagram. In order to avoid premature convergence, CMAES estimates the distribution parameter. It searches in an exploratory manner. An ideal step size improves both the search capabilities and the convergence speed. Instead of estimating the CMAES parameters, they should be updated for faster convergence. When it comes to nonlinear functions, CMAES has a very high convergence rate. The remarkable performance of CMAES under conditions of discontinuities, noise, randomness, and time variance led to its selection [XXIX].

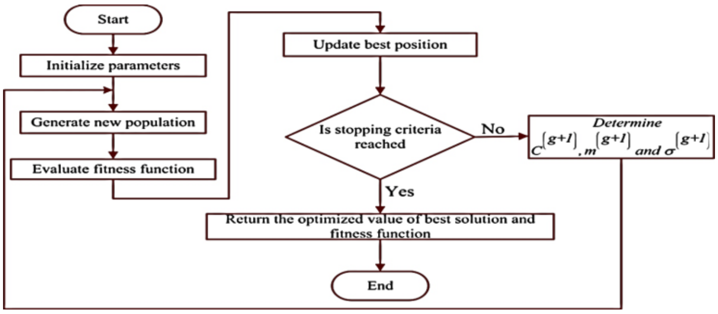

Fig. 1. Flowchart for CMAES technique

IV. Aquila Optimization (AO)

AO draws its inspiration from the hunting behavior of Aquila. In AO the total number of candidates (N) and the dimension (D) is used to create an array (X) of potential solutions. The array has a dimension of $N \times D$. The selection of each candidate is governed by Eq. (6).

$$X_{ij} = rand \times \left(UB_j - LB_j\right) + LB_j \quad where, \begin{matrix} i = 1 \cdots N \\ j = 1 \cdots D \end{matrix} \tag{6}$$

where, X_{ij}, $rand$, UB_j, LB_j, i and j represents candidate of i^{th} row and j^{th} column in X, a random number between 0 and 1, upper bound for j^{th} dimension, lower bound for j^{th} dimension respectively. Broadly the hunting procedure of is divided into four modes. They are high soar and vertical stoop or expanded exploration, contour flight with short glide or narrowed exploration, low flight with short decent or expanded exploitation and walking and grabbing prey or narrowed exploitation. During high soar and vertical stoop stage the Aquila flies high to explore the hunting area. This is mathematically termed as expanded exploration. This stage is symbolically represented as X_1. Expanded exploration stage is expressed mathematically by Eq. (7).

$$X_1(t+1) = X_{best}(t) \times \left(1 - \frac{t}{T}\right) + \left(X_M(t) - X_{best}(t) \times rand\right) \tag{7}$$

where, the total number of iterations is represented by T, current iteration is represented by t, the solution of the next iteration is represented by $X_1(t+1)$, the location of prey or the best solution is represented by $X_{best}(t)$ and $X_M(t)$ represents mean location of the current iteration. In the second mode the Aquila starts to corner the prey and begin hounding. This stage is known as contour flight with short glide or narrowed exploration. Narrowed exploration is symbolically represented as X_2. Narrowed exploration stage is expressed mathematically by Eq. (8).

$$X_2(t+1) = X_{best}(t) \times L(D) + X_R(t) + (y - x) \times rand \quad (8)$$

where, solution of the next iteration as generated by the second mode is $X_2(t+1)$, $L(D)$ represents the levy distribution for D, $X_R(t)$ represents the random solution for i^{th} iteration, y and x defines the spiral shape of decent of Aquila. In the third mode the AO enters its exploitation stage. In this phase the Aquila enters Low flight with short decent or expanded exploitation mode. In this mode, Aquila observes the behavior of prey. This stage is symbolically represented as X_3. Expanded exploration stage is expressed mathematically by Eq. (9).

$$X_3(t+1) = \alpha \times X_{best}(t) - \alpha \times X_R(t) - rand + \delta \times rand \times (UB - LB) + \delta \times LB \quad (9)$$

where, solution of the next iteration as generated by the second mode is $X_3(t+1)$, α and δ represents the exploitation stage adjustment parameters. In the last mode landing of Aquila while taking down the prey is mimicked. This stage is known as walking and grabbing prey or narrowed exploitation. This stage is symbolically represented as X_4. Expanded exploration stage is expressed mathematically by Eq. (10).

$$X_4(t+1) = QF \times X_{best}(t) - G_1 \times X(t) \times rand - G_2(t) \times L + rand \times G_1 \quad (10)$$

where, QF and $X_4(t+1)$ represents the quality function used to balance out the search strategies and the solution at next iteration. G_1 and G_2 represents the movement made by Aquila during the hunting process. the solution at i^{th} iteration is represented by $X(t)$. Where, the solution of the next iteration as generated by the second mode is. Fig. 2 depicts the flowchart for the AO [XXX].

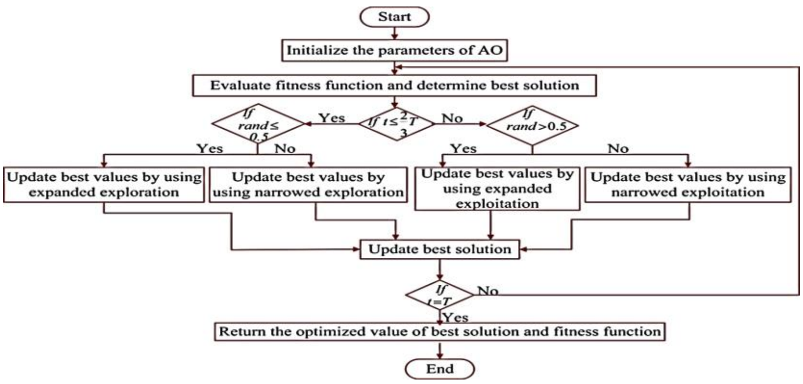

Fig. 2. Flowchart for AO

V. CMAESAO

By combining the best features of the AO and CMAES optimization algorithms, the new AOCMAES algorithm is born. Although AO has been around for a while, it does have a few drawbacks, such as a slower convergence rate, longer run times, and a tendency to get stuck at local optima [XXXI]. Among CMAES's many strengths as a local search optimization method are its ability to avoid local minima, shorten runtime, and increase convergence time. Hence, to aid AO in more rapid optimization, the hybrid technique is suggested. Better global search capabilities, a more even distribution of effort between exploration and exploitation, and a faster convergence rate are all benefits of the innovative hybrid approach that has been suggested. In Figure 3, we can see the AOCMAES algorithm's flowchart. Figure 3 shows the established flow of the AOCMAES optimization method. Every optimization process starts with setting the variables and iteration counter to 1. Then, after deciding on the optimal values for the fitness function, the optimization method AO is started [XXXII]. We input the y algorithm the optimal values that the AO optimization approach has found. Next, we compare the best values found by the two optimization techniques and choose and store the overall best values. Next, one is added to the iterative counter. The procedure is carried out until the maximum iteration criterion is satisfied. To increase performance, the suggested optimization method strikes a better balance between the optimization process's exploration and exploitation phases. In order to get ideal values quickly, the optimization parameters are defined in a certain way. Table 6 displays the optimization parameters [XXIV].

Table 6: CMAESAO technique optimization parameters

Optimization technique Metric	Value
Maximum iteration	1000
Alpha (α)	[0.1,0.9]
Delta(δ)	[0.1,0.9]
Dimension	4
Number of Aquila`	100

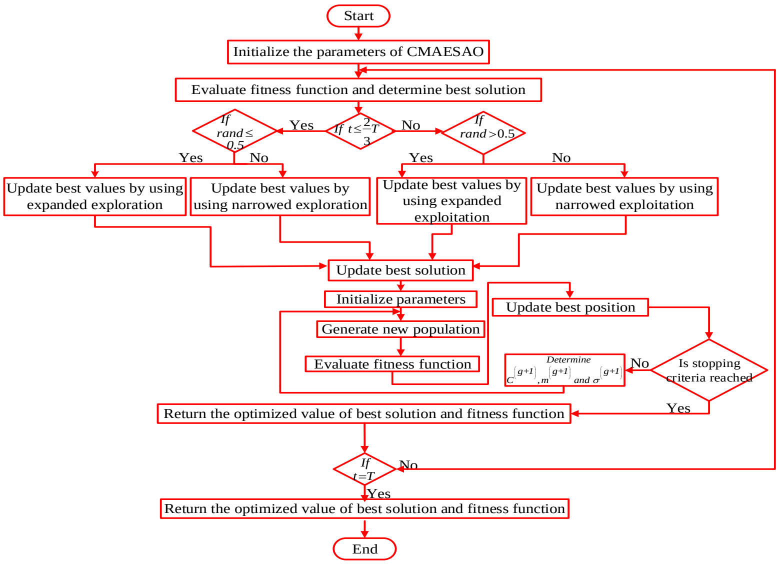

Fig. 3. Flowchart for CMAESAO technique

The bench mark functions are placed in Table 7. The performance analysis of the CMAESAO is tested using well established benchmark functions as listed in Table 8. This proposed work uses 23 benchmark functions to establish the superiority of the CMAESAO's performance evaluation [XIII].

Table 7. The details of the benchmark functions used in performance analysis of CMAESAO

Function Name	**Function Definition**	**Dimension (D)**	**Range**	F_{min}
$F_1(x)$	$F_1(x)=\sum_{i=1}^{D} x_i^2$	30	[-100,100	0
$F_2(x)$	$F_2(x)=\sum_{i=0}^{D} \lvert x_i \rvert+\prod_{i=0}^{D} \lvert x_i \rvert$	30	[-10,10]	0
$F_3(x)$	$F_3(x)=\sum_{i=1}^{D}\left(\sum_{j=1}^{i}(x_j)\right)^2$	30	[-100,100	0
$F_4(x)$	$F_4(x)=\max_i\left\{\lvert x_i \rvert,(1\le i\le n)\right\}$	30	[-100,100	0
$F_5(x)$	$F_5(x)=\sum_{i=1}^{D}\left[100\left(x_i^2-x_{i+1}\right)^2+(1-x_i)^2\right]$	30	[-30,30]	0
$F_6(x)$	$F_6(x)=\sum_{i=1}^{D}\left(\left[x_i+0.5\right]^2\right)$	30	[-100,100	0

$F_7(x)$	$F_7(x)=\sum_{i=1}^{D}\left(i\times x_i^4+random[0,1)\right)$	30	[-128,128	0
$F_8(x)$	$F_8(x)=\sum_{i=1}^{D}\left(-x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)\right)$	30	[-500,500	0
$F_9(x)$	$F_9(x)=\sum_{i=1}^{D}\left(x_i^2-10\cos(2\pi x_i)+10\right)$	30	[-5.12, 5.12]	$-418.9829 \times D$
$F_{10}(x)$	$F_{10}(x)=-20\times\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x$	30	[-32,32]	0
$F_{11}(x)$	$F_{11}(x)=1+\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)$	30	[-600,600	0
$F_{12}(x)$	$F_{12}(x)=\frac{\pi}{n}\{10\sin(\pi y_i)\}$ $+\sum_{i=1}^{D-1}(y_i-1)\left[1+10\sin^2(\pi y_{i+1})\right)+\sum_{i=1}^{D}u(x_i,10,1$ where, $u(x_i,a,k,m)=\begin{cases}K(x_i-a)^m & if \quad x_i>a\\ 0 & -a £ x_i>a \quad ;\\ K(-x_i-a)^m & -a £ x_i\end{cases}$ $y_i=1+\frac{1+x_i}{4};$	30	[-50,50]	0
$F_{13}(x)$	$F_{13}(x)=0.1\sin^2(3\pi x_1)+\sum_{i=1}^{D}(x_i-1)^2\left[1+\sin^2(3\pi x_i+1)\right.$ $+\sin^2(2\pi x_D)+\sum_{i=1}^{d}u(x_i,5,100,4)$	30	[-50,50]	0
$F_{14}(x)$	$F_{14}(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}}(x_i-a_{ij})\right)^{-1}$	2	[-65,65]	0
$F_{15}(x)$	$F_{15}(x)=\sum_{i=1}^{11}\left[a_i-\frac{x_1(b_i^2+b_ix_2)}{(b_i^2+b_ix_3+x_4)}\right]^2$	4	[-5,5]	0
$F_{16}(x)$	$F_{16}(x)=4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$	2	[-5,5]	0
$F_{17}(x)$	$F_{17}(x)=\left(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6\right)^2+10\left(1-\frac{1}{8\pi}\right)\cos x_1$	2	[-5,5]	0

$F_{18}(x)$	$F_{18}(x)=\left[1+(x_1+x_2+1)^2(19-14x_1+3x_2\ 1-14x_2+6x_1x_2\right.$ $\left[30+(2x_1-3x_2)^2\times(18-32x_i+12x_1^2+48x_2-3\right.$	2	[-2,2]	0
$F_{19}(x)$	$F_{19}(x)=-\sum_{i=1}^{4}c_i exp\left(-\sum_{j=1}^{3}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	3	[-1,2]	0
$F_{20}(x)$	$F_{20}(x)=-\sum_{i=1}^{4}c_i exp\left(-\sum_{j=1}^{6}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	6	[0,1]	0
$F_{21}(x)$	$F_{21}(x)=-\sum_{i=1}^{5}\left[(X-a_i)(X-a_i)T+c_i\right]^{-1}$	4	[0,1]	0
$F_{22}(x)$	$F_{22}(x)=-\sum_{i=1}^{7}\left[(X-a_i)(X-a_i)T+c_i\right]^{-1}$	4	[0,1]	0
$F_{23}(x)$	$F_{23}(x)=-\sum_{i=1}^{10}\left[(X-a_i)(X-a_i)T+c_i\right]^{-1}$	4	0,1]	0

Outperforming algorithms such as grasshopper, equilibrium, particle swarm, dragonfly, ant lion, grey wolf, marine predator, salp swarm, sine cosine, whale, and slime mold in terms of fundamental statistical metrics, the AO has emerged as the clear winner. Table 8 compares the statistical metrics of AO with CMAESAO, taking into consideration the prior comparison. When looking at the numbers in Table 8, it's clear that CMAESAO does a better job of finding the best solutions on a worldwide scale [XXIII].

Table 8: Benchmark function performance evaluation of CMAESAO and AO

Function Name	Metrics	AO	CMAESAO	Function Name	Metrics	AO	CMAESAO
$F_2(x)$	Mean	$9.4973e^{-218}$	$6.23e^{-266}$	$F_{14}(x)$	Mean	$2.3207e^{0}$	0.0068
	Standard Deviation	$0.00e^{000}$	$0.00e^{000}$		Standard Deviation	$1.0246e^{0}$	$9.3403e^{-13}$
	Best	$6.5477e^{-225}$	$1.2406e^{-268}$		Best	9.9800e1	$1.565e^{-04}$
	Worst	$3.214e^{-217}$	$6.2425e^{-265}$		Worst	2.9821e0	0.0274
$F_4(x)$	Mean	$9.9112e^{-218}$	$8.8368e^{-251}$	$F_{15}(x)$	Mean	5.5089e-4	$1.2106e^{-58}$
	Standard Deviation	$0.00e^{000}$	$0.00e^{000}$		Standard Deviation	1.9027e-4	$3.7682e^{-58}$
	Best	$2.322e^{-211}$	$3.5950e^{-247}$		Best	4.0581e-4	$7.6985e^{-62}$
	Worst	$3.4546e^{-217}$	$1.7427e^{-245}$		Worst	8.4575e-4	$9.6548e^{-58}$
$F_5(x)$	Mean	$1.8851e^{-3}$	$0.00e^{000}$	$F_{16}(x)$	Mean	-1.0316	$-3.7895e^{-03}$
	Standard Deviation	$2.5151e^{-3}$	$0.00e^{000}$		Standard Deviation	6.5206e-8	$1.1659e^{-18}$
	Best	$5.8588e^{-5}$	$0.00e^{000}$		Best	-1.0316	$-3.7895e^{-03}$

	Worst	2.5151e^{-3}	0.00e^{000}		Worst	-1.0316	-5.6879e^{-01}
$F_6(x)$	Mean	6.3114e^{-5}	1.2858e^{-05}	$F_{17}(x)$	Mean	3.9789e-1	0.4208e^{-3}
	Standard Deviation	2.9614e^{-5}	1.2809e^{-07}		Standard Deviation	4.7081e-7	1.0600e^{-15}
	Best	7.28e^{-8}	1.1399e^{-6}		Best	3.9789e-1	0.4208e^{-3}
	Worst	1.9689e^{-4}	2.4937e^{-5}		Worst	3.9789e-1	0.4208e^{-3}
$F_7(x)$	Mean	1.5929e^{-3}	7.9575e^{-05}	$F_{19}(x)$	Mean	-3.8624	-0.3926
	Standard Deviation	4.8479e^{-4}	6.9694e^{-04}		Standard Deviation	8.4657e-4	9.6523e^{-5}
	Best	6.6048e^{-5}	1.6114e^{-4}		Best	-3.8628	-0.3926
	Worst	1.5929e^{-3}	1.5365e^{-04}		Worst	-3.8607	-0.3926
$F_8(x)$	Mean	-2.2694e^{3}	-1.8025e^{3}	$F_{20}(x)$	Mean	-3.3014	-5.4250
	Standard Deviation	4.6187e^{2}	8.4242		Standard Deviation	4.9969e^{-2}	7.8695e^{-3}
	Best	-2.6958e^{3}	-1.80247e^{3}		Best	-3.3220	-5.7693
	Worst	1.4073e^{3}	-1.80247e^{3}		Worst	-3.1994	-5.7673
$F_{10}(x)$	Mean	8.8818e^{-16}	9.1595e^{-17}	$F_{21}(x)$	Mean	-10.149	-10.1413
	Standard Deviation	0.00e000	0.00e000		Standard Deviation	4.9969e^{-2}	4.8699e^{-2}
	Best	8.8818e^{-16}	1.6438e^{-16}		Best	-10.153	-10.1413
	Worst	8.8818e^{-16}	1.6438e^{-16}		Worst	-10.14	-10.1413
$F_{12}(x)$	Mean	2.9262e^{-5}	1.3676e^{-07}	$F_{22}(x)$	Mean	-10.401	-10.3801
	Standard Deviation	3.5700e^{-5}	1.4126e^{-07}		Standard Deviation	2.9768e^{-3}	2.8765e^{-3}
	Best	1.1309e^{-7}	5.7279e^{-09}		Best	-11.040	-10.3801
	Worst	1.0421e^{-4}	3.7378e^{-07}		Worst	-10.395	-10.3801
$F_{13}(x)$	Mean	9.5026e^{-5}	6.0499e^{-07}	$F_{23}(x)$	Mean	-10.536	-10.535
	Standard Deviation	1.0312e^{-4}	3.8953e^{-08}		Standard Deviation	2.756e-4	2.755e-4
	Best	2.7176e^{-6}	7.77564e^{-06}		Best	-10.536	-10.535
	Worst	2.7104e^{-4}	2.0815e^{-05}		Worst	-10.535	-10.534

VI. Simulink Results

Statistical Analysis of Performance Index

By comparing the two algorithms' results for the identical fitness function (), we can see that CMAESAO performs better. For the same set of optimization parameters, the optimization methods were tested. Figure 4 shows that CMAESAO is better than AO. Comparing CMAESAO to AO, it is clear that the former produces fewer outliers with a lower value of ITAE.

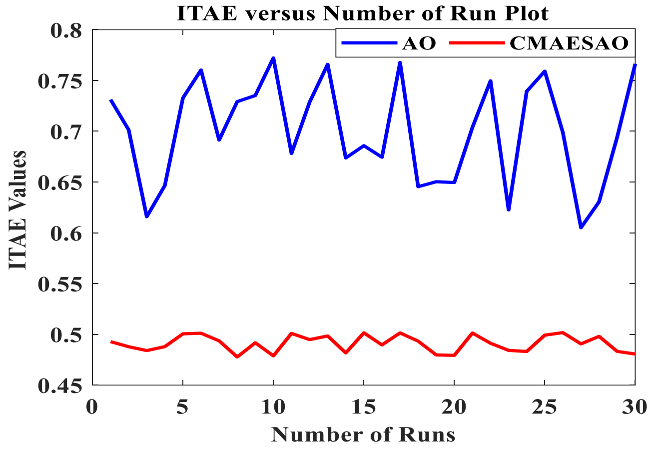

Fig. 4. ITAE versus no runs plot

A statistical analysis of CMAESAO is presented in Table 9. Because CMAESAO is so much better, even the lowest possible AO value is greater than the highest possible CMAESAO value. For AO, the range of values is 0.7762–0.505578, with a minimum of 0.693846 and a standard deviation of 0.056755578. Mean: 0.490154, standard deviation: 0.007902, maximum: 0.5021, minimum: 0.4777 for CMAESAO.

Table 9: Statistical comparison of AO and CMAESAO

Metrics	AO	CMAESAO
Maximum	0.7762	0.5021
Minimum	0.6007	0.4777
Mean	0.693846	0.490154
Standard Deviation	0.056755578	0.007902

Convergence Rate Analysis

Figure 5 displays the convergence plot for both CMAESAO and AO. From the figure, it is clear that CMAESAO outperforms AO. Figure 5 clearly shows that prior to CMAESAO, AO converges to a minimal value. As compared to CMAESAO's 0.4779, AO optimizes at about 0.7067. That CMAESAO converges to a better value than AO is evident from this.

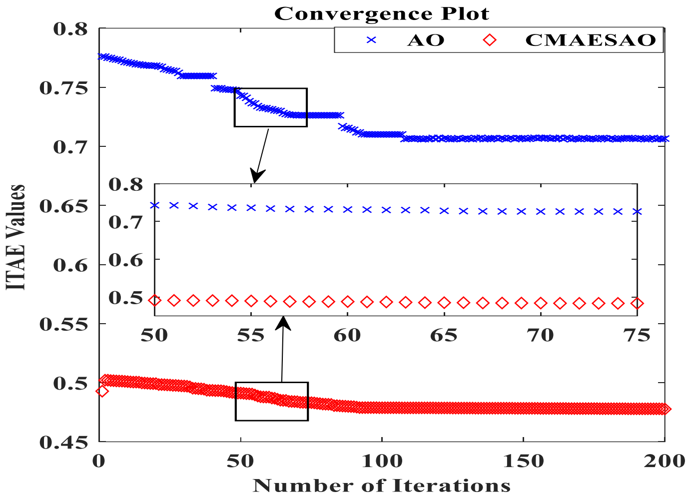

Fig. 5. Convergence plot for CMAESAO and AO

VII. Conclusion

This manuscript evaluates a brief review on the various methods and techniques used for placement of DGs in grid network. Through this review, it is concluded that the objective of most manuscripts was minimization of power loss. The load design model was a constant power-based model. It is also concluded that most manuscripts under this review used size and position of DGs as their design variables and most model went for multiple DG placements. There are many techniques used to evaluate optimal sizing and positioning of the DGs. Numerical methods proved to be far more complex with reduced accuracy. This problem was somehow reduced by the use of analytical methods but the complexity burden on the system is even more. Metaheuristic approaches provide better accuracy but the drawbacks of this system can be utilised for further analysis with new objective function like dynamic placing of DGs, stochastic optimization and behaviour under fault conditions.

Conflict of Interest:

The author declares that there was no conflict of interest regarding this paper.

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