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Moth Flame Algorithm to Optimize the Size and Location of Energy Storage Units in a Radial Distribution Network to mitigate Power Loss

Abstract: -The ideal placements and capacities for Battery Energy Storage Systems (BESS) sources in a distributed generation (DG) environment have an impact on power losses in the distribution network. Therefore, engineers are quite concerned with DG and BESS. The output from DG is, however, typically unpredictable and inconsistent. The secure and stable functioning of the power system will be impacted to varying degrees when it is connected to various sites, capabilities, and power grids. To provide a safer, more stable, more dependable, as well as more effective power grid operation, power grid planners must take the impact of capacity, type, and location into account while choosing the best BESS accessibility method. The objective is to choose bus stops with the right potential and minimal loss. This study demonstrates how to use a Moth Flame Optimization Algorithm (MFOA) to establish the appropriate battery energy storage system (BESS) sizing in a hybrid solar and wind energy conversion system (WECS) generation integrated in a radial distribution network. This research investigates the optimal capacities and allotment of the BESSs within a 33-bus and 69-bus radial network of distribution for the maximum power dissipation reduction. This research also provides a framework for carrying out conservation voltage reduction (CVR) when distributed energy resources like solar photovoltaic (PV) systems, WECS, and energy storage systems (ESSs) are connected into distribution networks. The simulation has been conducted using Matlab code and the suggested method's output is compared with Firefly Algorithm (FA), Genetic Algorithm (GA) and Ant Colony Algorithms (ACA) and evaluated against other results.

Keywords: X band, split ring resonators, radiation pattern, gain, voltage standing wave ratio, HFSS.

I. INTRODUCTION

Due to limitations on fossil fuel reserves and environmental emission regulations, renewable energy sources (RES) with ESS will soon become the main source of energy generation. With the need for energy in the world steadily rising, microgrids are becoming more and more popular. The best design considers both the system's cost and the effectiveness of its energy management. A micro-grid (MG) is made up of several micro-sources, loads, and energy storage technologies. It has two modes of operation: connected to the grid and islanded mode. The main grid regulates the MG frequency in the grid-connected mode. Due to its low overall inertia, MG is susceptible to unbalanced load generation when it is abruptly disconnected from the utility grid, and as a result, it may experience more frequency variations than a bulk power system. A shortage of reserve power may cause a blackout in an MG. Therefore, having a sufficient and quick-reacting reserve power source is essential for frequency control [1]-[2].

Due to their delayed response, DG units like solid oxide fuel cells, diesel generators and micro-turbines cannot take part in frequency control. However, the BESS responds in a matter of milliseconds, which is far faster. The BESS is used in an MG for a number of purposes, including frequency regulation, regulating energy, power quality conditioners, and other things. Distribution networks typically contain radial strictures with high R/X values, which results in greater power losses than transmission systems with low R/X values. High power losses are the main issue in electrical power distribution systems, as a result wherein 13% of generated power is lost in distribution networks[3]. There is an open research topic with the goal of developing new approaches to address this issue. In order to reduce active electrical energy losses of distribution networks, this research suggests a MFOA algorithm approach that determines the best placement and size of the BESS units. The system's active power losses can be minimized by placing BESS in the best possible positions [4].

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To discover the ideal location and size of BESS units so that distribution companies will benefit from the integration of DG units into the distribution system, numerous research that are currently available in the literature have presented various optimization techniques and objective functions [5]. This research problem was tackled in [5] as a weighted multiobjective optimization problem with the objectives of the voltage profile, line loading, active and reactive power losses of the system, and voltage stability [6]. The improved raven roosting optimization (IRRO) technique was utilized by the authors to install DG in RDS in the best possible way. Regarding the ideal sizing of PV-battery systems, there are a number of restrictions in the present research [7]-[8]. Typically, studies concentrate on a specific goal, such as boosting self-consumption, lowering demand peaks, or maximizing economic gains. The single objective optimization approach is unable to offer insightful information about the trade-offs between these objectives because the targets are mutually exclusive. A complex multi-objective problem is inevitably simplified into a weighted single objective problem, yet this intrinsic simplification leaves out underlying patterns. The proposed methodology was put into practice on the PG & E 69 and IEEE-33 bus systems. In order to position DG units and capacitors in RDS in the best possible way, an enhanced genetic algorithm was created in [9].

The PV & WECS are frequently unregulated and highly dependent on local wind and sunlight [10]. The amount of electricity generated increases or decreases depending on the quantity of solar energy currently available, despite the load demand at a particular time [11]. When the load requirement surpasses the DG's output capacity, voltage fluctuation issues result. Customers may be forced to pay for unintended damages brought on by abrupt voltage increases or decreases in the network [12]-[13]. The result is that a few remedies to the voltage fluctuation issue have been put out in the literature. BESS are a good strategy for reducing the voltage increase problem. However, installing a BESS on every bus in the network is expensive. Therefore, it is crucial to place BESS in the ideal location for the system. Because the price of a BESS rises with its capacity, choosing the optimum BESS size is essential. With the aid of ideal BESS sizing, the system can attain a proper BESS size for sustaining voltage regulation.

In a radial distribution network (RDN) with DG and Conservation Voltage Reduction (CVR), a new intelligence approach that utilizes the Moth Flame Optimization Algorithm (MFOA) to select the ideal BESS unit's size and position is offered in order to lower the overall system power losses. BESS size and position can be determined simultaneously using MFOA. In order to reduce power loss and compare the efficiency of the FA technique, the appropriate positions and sizes for BESS modules from identified buses will be investigated in this study utilizing few additional random search-based optimization algorithms, GA, FA and ACA [14]. A thorough examination of an IEEE 33 & 69 bus Radial Distribution Network is conducted to show the value of the suggested approach [15]. A wide range of situations are taken into account, and the algorithms' usefulness is demonstrated by the results. The simulation results, which compare the performance of the suggested approaches to that of GA, FA and ACA using power loss as a performance metric, are used to contrast them [16]. The findings show that the suggested MFOA approach outperforms expectations for a variety of factors.

The structure of the paper is as follows. Section III explains the MFOA concept. The mechanism under consideration is thoroughly explained in Section III. The case study and discussion are offered in Section IV. The conclusion is presented in Section V.

II. MFOA ALGORITHM

Moths are classified as members of the phylum Arthropoda, a group of insects. Like all insects, they have a head, a pair of antennae, one thorax, a set of six legs, plus an abdomen. They also have two sets of large wings covered in small scales [17]. Moths are closely related to the of butterflies and are classified as insects in the order Lepidoptera. Moths come in a variety of varieties, although the majority of these creatures are nocturnal as well phototropic.

Researchers studying metaheuristics are interested in the moths because of their distinctive navigational strategies [18]. The moth actually has a navigational system, so "moth to the fire" isn't a suicide behavior, according to researchers. Moths possess compound eyes, but their vision is weak. Because they are unable to see the roadway clearly at night, they can only calculate their current location and the direction in which they will fly by comparing it to the location of the light source, which is typically the moon [19]. Transverse Orientation is the name of this Orientation technique. Moths are often nocturnal explorers who use the moonlight as a guide. The transverse alignment mechanism can be used to mimic the moths' directional pattern. The flight pattern is set up to maintain a crosswise inclination while maintaining a straight path by maintaining a consistent angle with the moon [20], [21].

Moth and flame are the two most significant elements of MFOA. The difference between the two solutions is that the moths in the main component of the real search algorithms of spiral flight and the flame have been moths in search of the best position so far [22]. It is therefore preferable to search within moths to a flame position, as this will mark the fire and of the neighborhood spiral movement. Three requirements must be met for a moth to spiral around a flame: the moth must be in its current location at the beginning of the flight, the flame must be in its current location at the end of the flight, and the spiral flight must follow a logarithmic spiral curve.

The location of a moth in space is the variable that needs to be solved in the MFOA method, where the moth is taken as a potential candidate solution. Moths are able to fly in one, two, three, as well as higher dimensions by altering their position vectors. Given that the MFOA method is effectively a swarm intelligence optimization technique, the moth population could be expressed as decision variables as trails in the matrix:

$$M = [M_1\ M_2\ \vdots\ M_N] = [m_{1,1}\ m_{1,2}\ m_{2,1}\ \ddots\ \cdots\ m_{1,n-1}\ m_{1,n}\ \ldots\ m_{2,n}\ \vdots\ddots\vdots\ m_{N-1,1}\ \ldots\ m_{N,1}\ m_{N,2}\ \cdots\ \ddots\ m_{N-1,n}\ m_{N,n-1}\ m_{N,n}\ ] \quad (1)$$

The problem's dimension is represented by the number n, where N is the number of moths. An individual moth's fitness is represented as the vector below:

$$Fit[M] = [Fit[M_1]\ Fit[M_2]\ \vdots\ Fit[M_N]\ ] \quad (2)$$

Below is a representation of the flame matrix. Since every moth circles a flame, the size must match that of the moth matrix previously described.

$$F = [F_1\ F_2\ \vdots\ F_N\ ] = [f_{1,1}\ f_{1,2}\ f_{2,1}\ \ddots\ \cdots\ f_{1,n-1}\ f_{1,n}\ \ldots\ f_{2,n}\ \vdots\ddots\vdots\ f_{N-1,1}\ \ldots\ f_{N,1}\ f_{N,2}\ \cdots\ \ddots\ f_{N-1,n}\ f_{N,n-1}\ f_{N,n}\ ] \quad (3)$$

The flame matrix's equivalent fitness is provided below in equation (4).

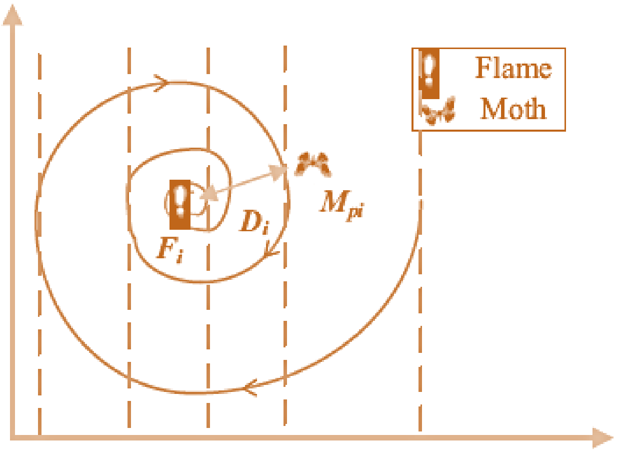
$$Fit[F] = [Fit[F_1]\ Fit[F_2]\ \vdots\ Fit[F_N]\ ] \quad (4)$$

The moth along with the flame are the two main characters of MFO. For the moth to achieve the desired effects, it must pass through the flame. The following equation defines the logarithmic spiral function, which is used to simulate the moth's spiral motion:

$$M_i^{j+1} = \begin{cases} d_i * e^{st} * \cos(2\pi t) + F_i(j), & i \le N\cdot F \\ d_i * e^{st} * \cos(2\pi t) + F_{N,F}(j), & i \ge N\cdot F \end{cases}$$

$$M_i^{j+1} = \{d_i * e^{st} * cos\ cos\ (2\pi t) + F_i(j), \quad i \le N\cdot F\ d_i * e^{st} * cos\ cos\ (2\pi t) + F_{N,F}(j), \quad i \ge N\cdot F\ \ M_i^{j+1} = \{d_i * e^{st} * cos\ cos\ (2\pi t) + F_i(j), i \le N\cdot F\ d_i * e^{st} * cos\ cos\ (2\pi t) + F_{N,F}(j), i \ge N\cdot F \quad (5)$$

$$Fit[M] = [Fit[M_1]\ Fit[M_2]\ \vdots\ Fit[M_N]\ ]$$



$Fit[M] = [Fit[M_1]\ Fit[M_2]\ \vdots\ Fit[M_N]\ ]$Fig. 1 Track for individual optimization

Where ‘d’ represents the distance between a moth at point Mi and its matching flame Fi. According to b and t (a chance number between -1 and 1), which specify how near the moth is to its flame in Fig. 1, the spiral flight search is determined. Fig. 2 depicts a moth flying in a spiral pattern towards a similar flame. Over the course of the iterations, the value of t decreases, balancing the exploration and utilization at the start and finish of the iterations.

Every iteration, the flame location for the previous and current iterations is gathered and sorted based on the local and global search fitness values. The finest and worst fitness levels are the first and last flames, respectively.

The moths then arrived in the identical order to snare each flame individually. Over the course of the number of iterations, the same- and lower-ordered moths will always catch the last flame.

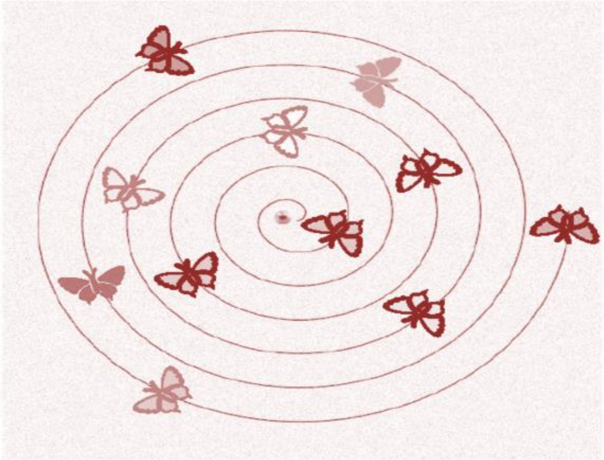


Fig. 2 Moth flying in a spiral pattern around the flame

The flow diagram of the proposed algorithm is depicted in the figure 3.

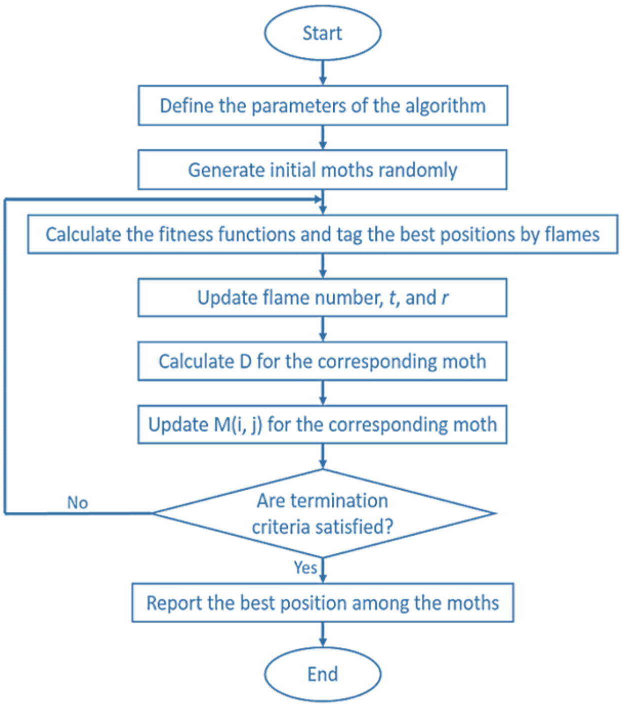


Fig.3 Flow diagram

III. OVERVIEW OF THE SYSTEM CONSIDERED

3.1 Proposed Bus Configurations

The appropriate network losses computation method should be used according to the characteristics associated with the distribution network's expected load in order to determine the active power losses for the distribution network during distribution system BESS placement planning. Power losses across the distribution system will be impacted by the inclusion of DG depending on the size and location of the BESS's link to the grid. Figures 4 and 5 each display a single-line representation for the IEEE standard 33-bus & 69-bus radial network (RN) under discussion.

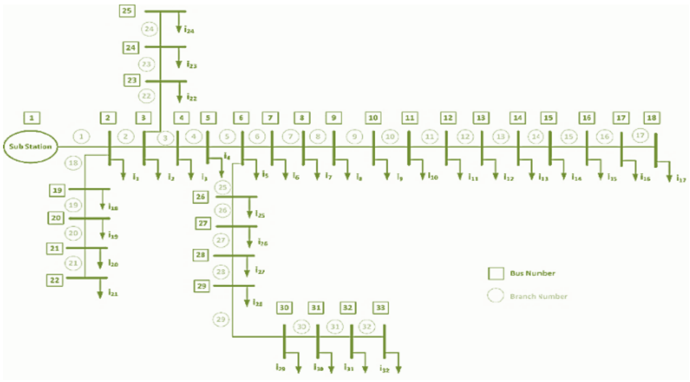


Fig. 4 33-bus Radial Distribution Network

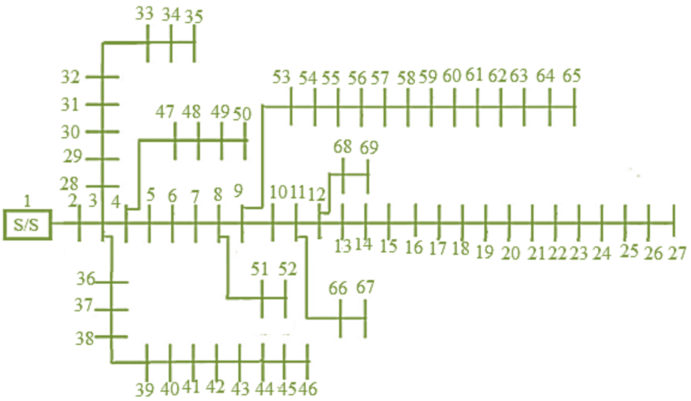


Fig. 5 69-bus Radial Distribution Network

In this study, solar power networks, WECS, battery energy storage systems, and loads are the four primary elements which are integrated with the distribution system. The unpredictability of solar photovoltaic (PV) with WECS systems is one of their main issues, which has a direct impact on the system's ability to balance electricity generated and consumed [23]. The majority of experts concur that a viable approach in these circumstances is to use BESS to provide or store electrical energy as needed. By placing DG units and BESSs near demand centers, the network's current flow is decreased, resulting in a reduction in energy losses [24]. However, distributed system power losses could be further, significantly reduced with the correct BESS distribution into the network. Figure 6 depicts a more simplified configuration for the PV and WECS systems combined with the BESS-equipped distribution system.

3.2 Development of the Objective Function

In this section, it is recommended that FA choose the appropriate size and position for DG systems within the distribution system in order to lower overall system loss. Reducing the loss is expected to enhance the voltage characteristic at each bus. The parameters of the best DG deployment are indicated as follows:

$$a = [(a_{1l}, a_{1b}), \ldots\ldots (a_{nl}, a_{nb})] \tag{6}$$

where the number of BESS elements is denoted as ‘n’, that need to be installed in the system, ‘l’ indicates the BESS’s location and ‘b’ represents the BESS’s size. While those parameters are included in the data set for the load flow, the proposed technique is then used to calculate the system's total loss. In order to obtain the best BESS allocation, the algorithm must be run numerous times [25]. Once the ideal BESS position and size are simultaneously achieved, the process is finished. The objective function, f(a), which represents the system's the entire loss, P_{loss}, which need to be minimized, is as follows:

$$f(a) = min(\sum_{i=1}^{m} \quad P_{loss}) \tag{7}$$

where 'm' stands for the number of transmission lines in the distribution system.

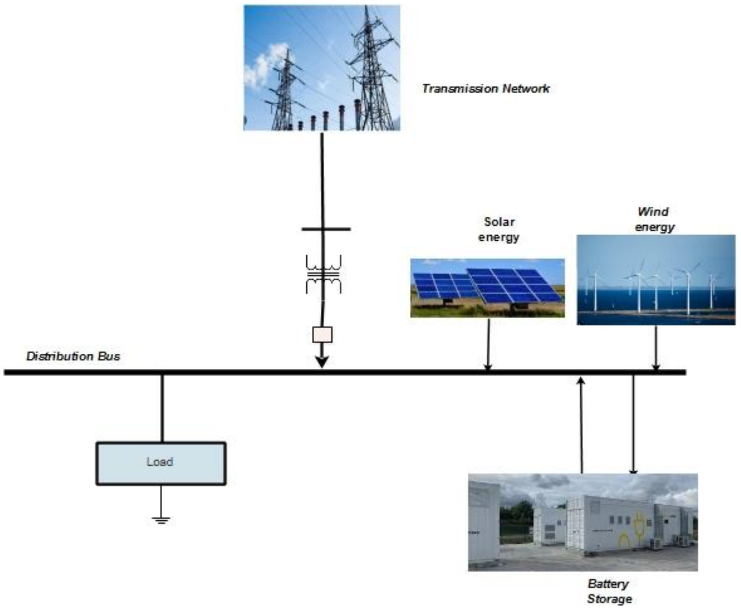


Fig. 6 Basic block diagram of the distribution network connected with the PV, WECS, and BESS systems

3.2 Principle of CVR

To decrease voltage without directly harming consumers in order to conserve energy and improve dynamic stability, the CVR strategy is based on the demand mitigation and peak trimming principles. It is put into practice by lowering grid voltage, which lowers energy usage relative to load voltage sensitivity. It immediately equalizes energy use on a dynamic time scale as a result, improving grid stability.

CVR is given by the following equation (8).

$$CVR^{f} = \frac{\Delta E\%}{\Delta v\%} \tag{8}$$

Where ΔE and ΔV represent the percentage of overall energy saved as a result of the feeder's reduced voltage. The load configuration changes periodically. Consequently, the fixed load example may not adequately assess the suggested CVR approach. Due to the fact that residential and business customers depend more on voltage than industrial loads do, adopting a contingent load configuration results in greater energy savings for these customers. As a result, the CVR factor is determined by categorizing clients into several groups as follows:

$$CVR_f = R \cdot CVR_{fR} + I \cdot CVR_{fI} + C \cdot CVR_{fC} \tag{9}$$

where $R \cdot CVR_{fR}$, $I \cdot CVR_{fI}$, and $C \cdot CVR_{fC}$ are the CVR factor coefficients, which represent the load proportions of the residential, industrial, and commercial client classes, respectively.

$$P_{li} = P_{ni} \left(\frac{v_i}{v_n}\right)^{k_p} \tag{10}$$

$$Q_{li} = Q_{ni} \left(\frac{v_i}{v_n}\right)^{k_q} \tag{11}$$

where P_{li}, P_{ni} are the ith bus's active power and active load; Q_{li}, Q_{ni} are the ith bus's reactive power and reactive load; v_i and v_n are the system's rated voltage and bus voltage, respectively; The variables k_p and k_q indicate exponential parameters.

IV. RESULTS AND DISCUSSON

The described methods have been implemented with the IEEE 33 bus as well as 69 bus distribution test system shown in figures 4 and 5 to organize BESS modules in the MATLAB environment. The six DG units are chosen as 4 solar panels along with 2 wind systems, all of them having a capacity of 100 kW. They are placed at random across the distribution system on the buses 3, 9, 16, and 25 (PV Modules) and the buses 7 and 13 (Wind Systems) respectively. The results are presented and validated. The GA [26], MFOA [27], ACA [28], and FA [29] [30] algorithms identify the best position and dimension for BESS units.

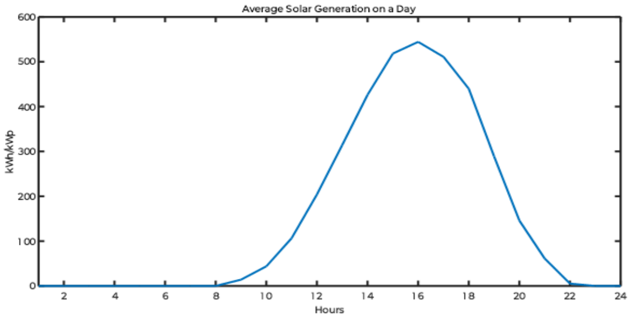


Fig. 7 Curve of solar energy production during a single day

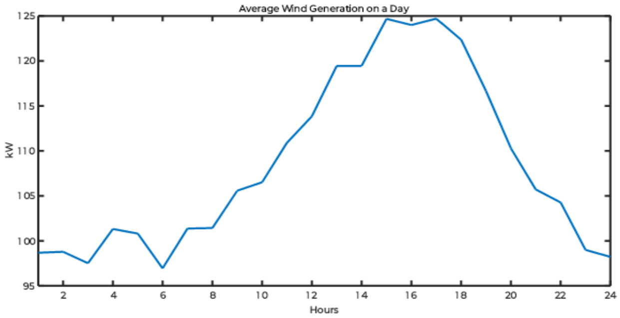


Fig. 8 Curve of wind power production during a single day

The hourly production of solar and wind energy is shown in Figures 7 and 8.

4.1 33-Bus System's Simulation Results

The proposed algorithms are implemented using the IEEE-33 bus system. The performance measures are shown in figures 9 through 17. The optimum cost function is determined using BESS after a predetermined number of iterations, as shown in the flowchart in figure 3. The proposed MFOA is clearly considerably cheaper than the other three approaches, as shown in Figure 9. The measured voltage in the graph 10 is shown both prior to and after a BESS installation using all four methods. Figures 11 and 12 displays the real and reactive power losses for the 33-bus system. Figures 11 and 12 depicts the power losses for the MFOA, FA, ACA and GA approaches both before and after BESS installation.

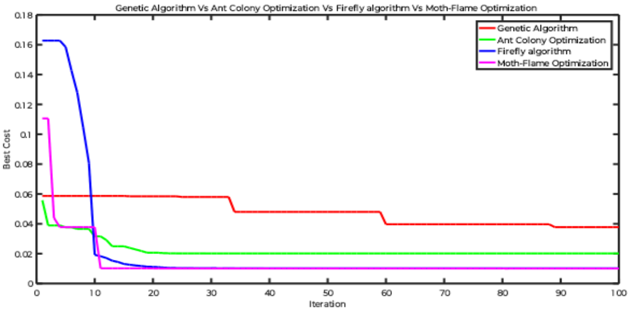


Fig. 9 Comparison of Cost Function values for the proposed methods

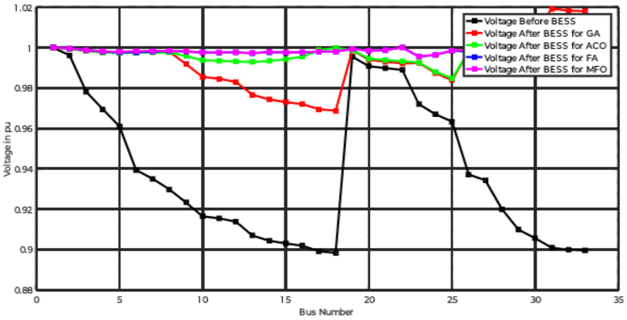


Fig. 10 Comparison of p.u. Voltage with and without BESS for the proposed methods

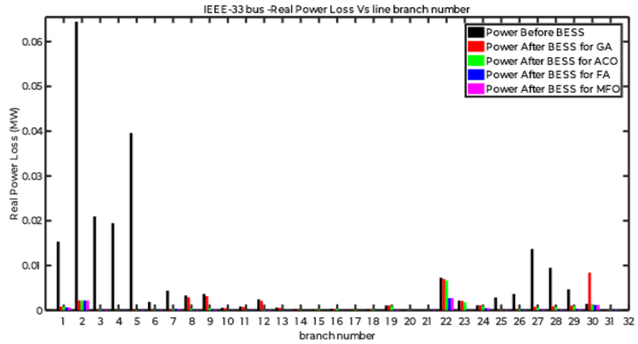


Fig. 11 Real Loss Comparison for the proposed methods with and without BESS

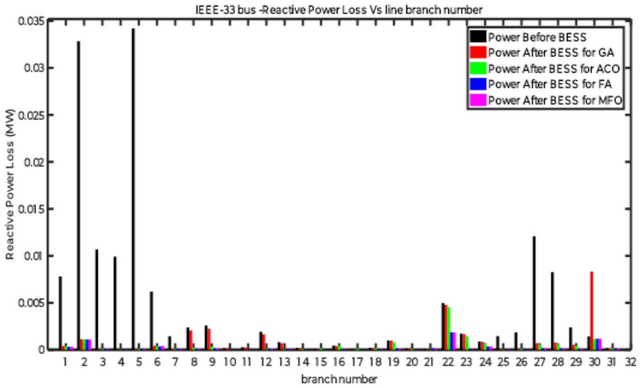


Fig. 12 Reactive Loss Comparison for the proposed methods with and without BESS

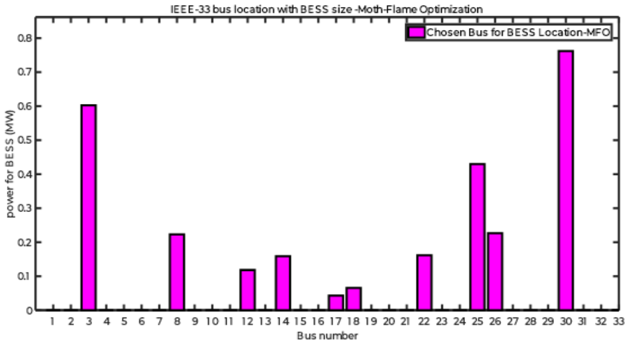


Fig. 13 BESS's Position and Power for the Proposed MFOA Technique

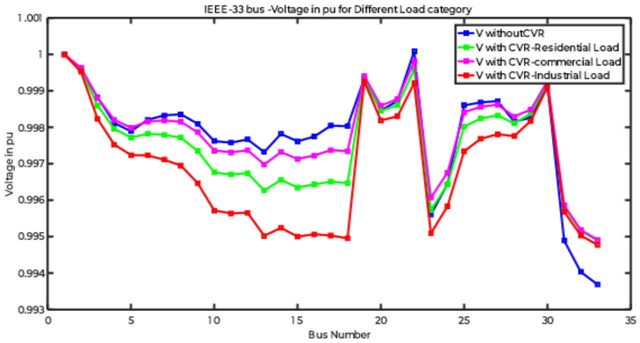


Fig. 14 Load voltage profiles with and without CVR

The model is simulated both including and without including CVR installation in order to accurately measure the CVR impact for comparison. Figures 14–16 display the voltage and actual and reactive power loss both with and without CVR. As seen in Figure 14, it is evident that each of the distribution feeder's voltage profiles decline to some degree. For the 33-bus system taken into consideration in this study, figures 15 and 16 highlight and illustrate the actual and reactive power losses both with and without CVR.

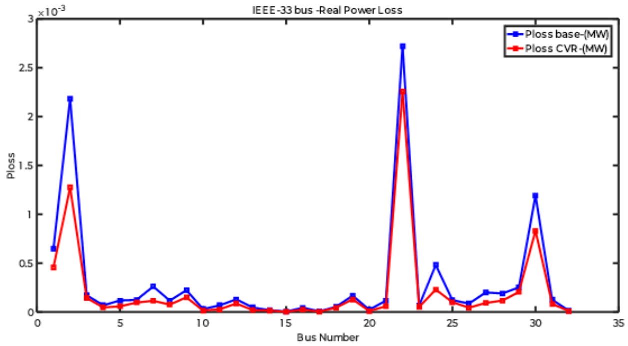


Fig. 15 Real power loss using MFOA Algorithm with and without CVR

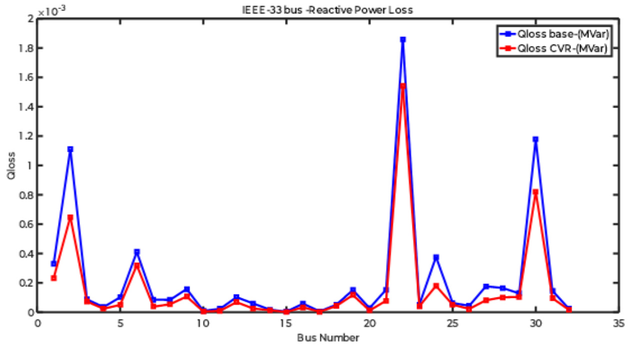


Fig. 16 Reactive power loss using MFOA Algorithm with and without VR

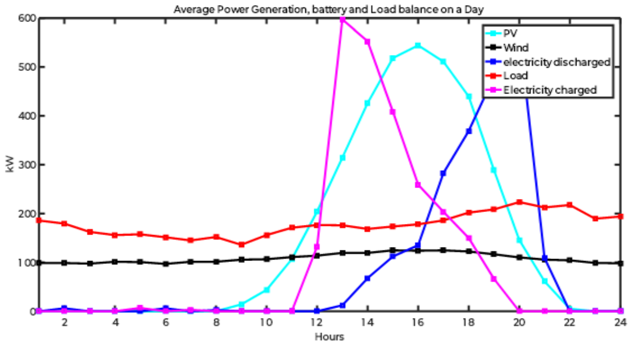


Fig. 17 Profile of Energy Management for the System Under Examination

The average power output during an entire day, including solar, wind, and BESS battery charging and discharging, is shown in Figure 17.

4.2 69-Bus System's Simulation Results

The suggested approach is also tested on a 69 bus system, as illustrated in figure number 5, in a manner similar to the aforementioned procedure. The 69 bus system's performance characteristics are shown in figures 18 to 27.

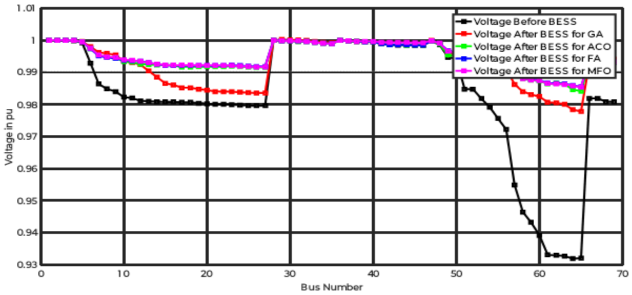


Fig. 18 Comparison of Cost Function values for the proposed methods

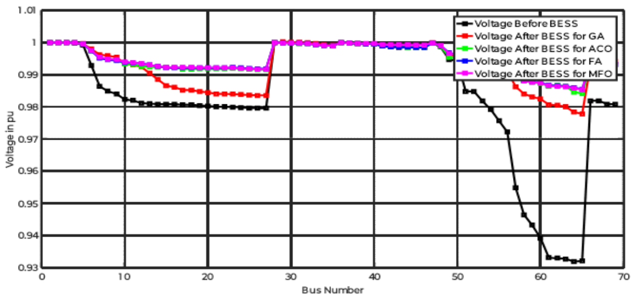


Fig. 19 Comparison of p.u. Voltage with and without BESS for the proposed methods

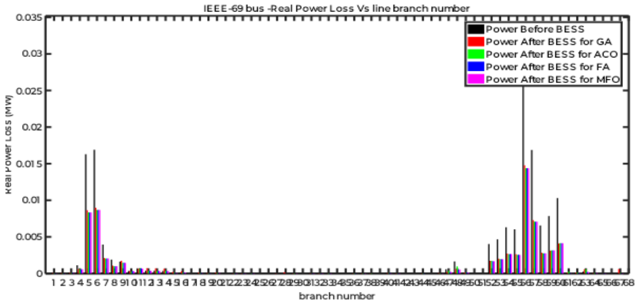


Fig. 20 Real Loss Comparison for the proposed methods with and without BESS

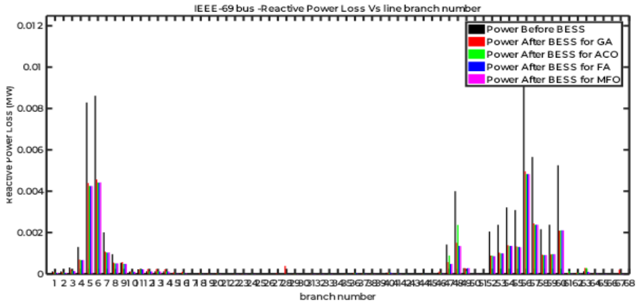


Fig. 21 Reactive Loss Comparison for the proposed methods with and without BESS

According to the flowchart in figure 3, using BESS, the ideal cost function for a 69-bus system is found after a set number of iterations. According to Figure 18, the proposed MFOA is unquestionably less expensive than the other three strategies. Figure 19 depicts the p.u. voltage in each of the all the methods both before and after the BESS installation. The 69-bus system's actual and reactive power losses are shown in Figures 20 and 21 respectively. The power losses for the MFOA, FA, ACA, and GA approaches are shown in Figure 20 both before and after the BESS installation.

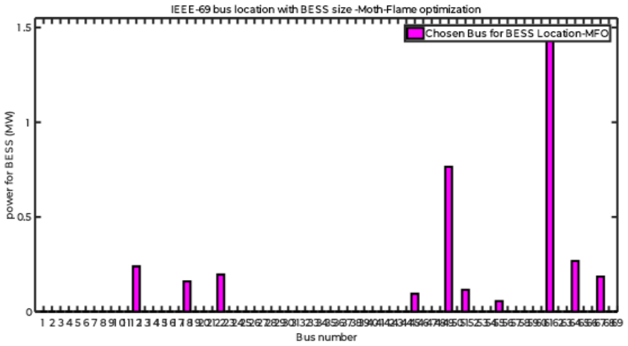


Fig. 22 BESS's Position and Power for the Proposed MFOA Technique

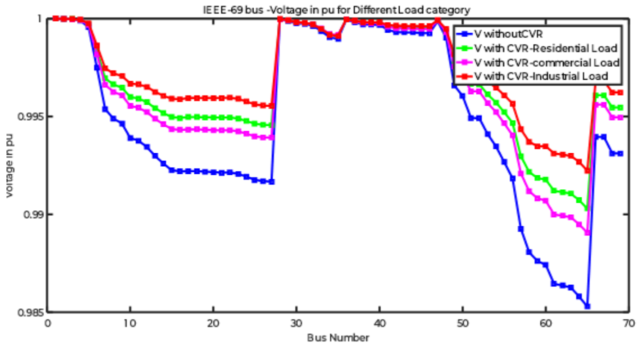


Fig. 23 Load voltage profiles with and without CVR

There is no doubt that the recommended MFOA algorithm has lesser losses than the competing methods. The figure 20, for example, makes this very obvious to see. The ideal BESS size and position for the intended MFOA approach are shown in Figure 22 in their finest forms.

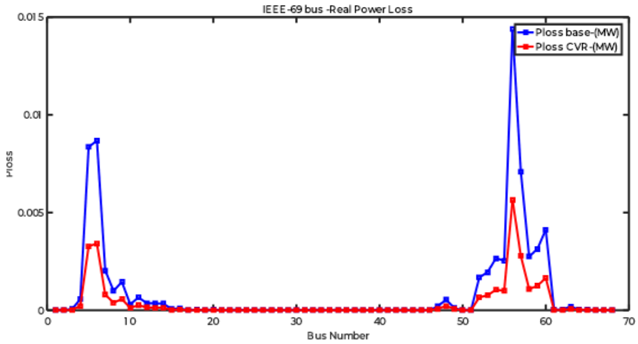


Fig. 24 Real power loss using MFOA Algorithm with and without CVR

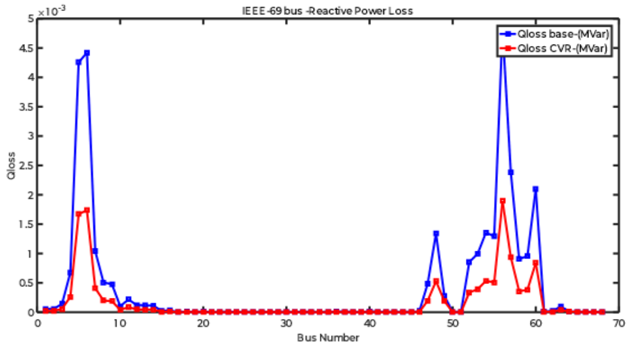


Fig. 25 Reactive power loss using MFOA Algorithm with and without CVR

To precisely measure the CVR effect for comparison, the 69-bus system is simulated both with and without CVR implementation. The voltage and actual and reactive power loss with and without CVR for a 69-bus system are shown in Figures 23–25. Evidently, all distribution feeder voltage profiles drop to some extent, as seen in Figure 23. Figures 24 and 25 note and plot the actual and reactive power losses for the 69-bus system that was taken into consideration for this study, both with and without CVR.

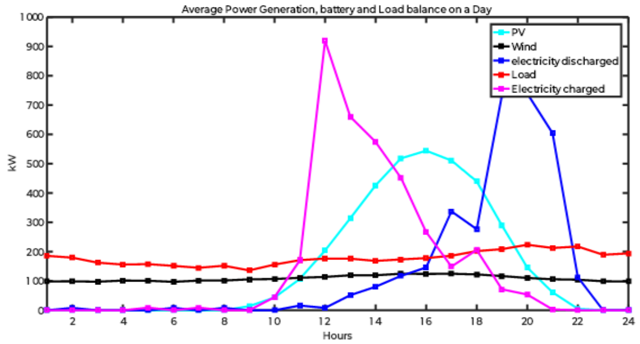


Fig. 26 Profile of Energy Management for the System Under Examination

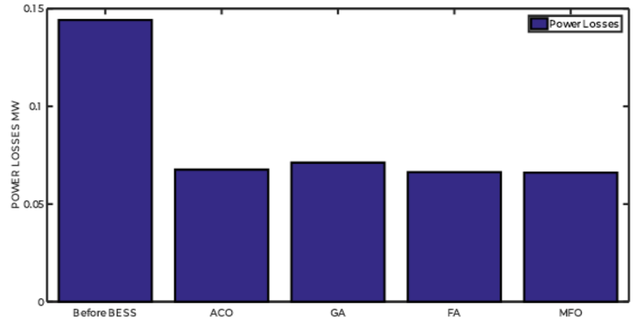


Fig. 27 Total Power Losses Comparison for all the Suggested Methods

The average power output of a 69-bus network over a 24-hour period, including BESS charging and discharging, is shown in Figure 26. The comparison of the total power losses with and without BESS utilizing all the suggested approaches is shown in Figure 27. It is evident that, when compared to other methodologies, the MFOA methodology obviously results in the fewest losses.

Table 1 Comparison of Results for the proposed methods of 33-bus system

Parameters	Using GA	Using ACA	Using FA	Using MFOA
Power Losses including PV, WECS & BESS (MW)	0.037773	0.020149	0.010201	0.010078
Average voltages of buses in p.u.	0.99318	0.99678	0.99777	0.99787
Reduction in real power loss (%)	83.3175	91.101	95.4948	95.5488

Table 2 Comparison of Results for the proposed methods of 69-bus system

Parameters	Using GA	Using ACA	Using FA	Using MFOA
Power Losses including PV, WECS & BESS (MW)	0.071194	0.067613	0.066292	0.066121
Average voltages of buses in p.u.	0.99263	0.9946	0.99479	0.99487
Reduction in real power loss (%)	50.6199	53.1035	54.0193	54.1382

Table 3 Operation results comparison – Power loss

Parameters	33-bus system	69-bus system
P_{loss} without CVR in MW	0.010078	0.066121
P_{loss} with CVR-Residential Load in MW	0.0067593	0.027158
P_{loss} with CVR-commercial Load in MW	0.0066055	0.033807
P_{loss} with CVR-Industrial Load in MW	0.0073865	0.018626

V. CONCLUSION

This study integrates the effects of CVR and BESS to plan for the ideal BESS size and location in the IEEE 33-bus and 69-bus system with a variable load configuration. The optimal BESS size and location in radial network electrical distribution networks are suggested by this study. The allocation BESS is categorised as a prospective optimisation problem by the various load settings models. By combining MFOA, FA, GA, and ACA optimisation approaches, these adjustments seek to reduce annual running costs for energy loss BESS installation. The observation and results show that combining CVR with BESS results in a sizable reduction in power. By combining CVR and batteries, the utility is able to address the problem of increasing load demand and achieve dynamic stability while saving more energy. The suggested techniques for choosing the right BESS size and placement along with loss minimization are successfully constructed in Matlab utilising m-file coding. This means that, with regard to of power losses using tables 1 and 2, the output resulting from the suggested methodology performed better than the GA, FA and ACA methods. It could be claimed that in order to find the overall optimum value for the test functions, MFOA is superior to the aforementioned optimisation strategies

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