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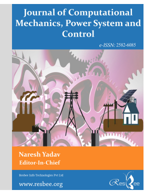

Optimal Positioning and Sizing of Distributed Generators Using Hybrid MFO-WC Algorithm

Rajeshkumar G
Kudankulam Nuclear Power Project
Tirunelveli, Tamil Nadu, India
kumargrajesh96@gmail.com

Sujatha Therese P
Noorul Islam University
Kumarakovil, Tamil Nadu, India

Abstract: The need for smart electrical systems containing low technical loss and environmental impact, which provides impulsion to go for Distributed Generations (DGs) that might present numerous other benefits like minimized transmission, increased reliability, and distribution system resources, enhanced power quality, and so forth. Nevertheless, depending on the system configuration and management, these benefits might not be accurate. In this paper, a hybridization of Moth Flame Optimization- Water Cycle Algorithm (MFO-WCA) is presented for the optimal sizing and placement of multiple DG to minimize the system loss and to enhance system voltage profiles in electric distribution systems. In the environs of the load, DG covers the technique for deploying generating sources, in order to enhance the power system factor, and thus considerably minimizing losses of the total system. In a distribution system, an effectual model of the power factor is developed to pre-set each distributed generator power factor placed at several positions. In the system, for the positioning of the distributed generators, a sensitivity factor method is developed to minimize the search space. Finally, the simulations results for both the proposed and conventional methods are performed in the IEEE 33 and 69 bus systems.

Keywords: Distributed Generators; Power System; Radial Distribution System; Optimal Sizing; IEEE Bus System

Nomenclature

Abbreviations	Descriptions
GA	Genetic Algorithm
APF	Active Power Filter
BFO	Bacterial Foraging Optimization
DG	Distributed Generators
NLPCI	Nonlinear Load Position based APF Current Injection
PSO	Particle Swarm Optimization
BCBV	Branch Current to Bus Voltage
ABC	Artificial Bee Colony
DE	Differential Evolution
BSO	Backtracking Search Optimization
RDS	Radial Distribution System
BIBC	Bus Current Injection to Branch Current matrix
TLBO	Teaching–Learning-Based Optimization
IDSA	Improved Differential Search Algorithm
QOTLBO	Quasi-Oppositional TLBO
GWO	Grey Wolf Optimizer
DS	Distribution System
CSOS	Chaotic Symbiotic Organisms Search
ACO	Ant Colony Optimization

1.Introduction

In electricity grids, the incorporation of DG resources is rising gradually. There are numerous motivations that persuade the operators to use DGs like limitations on the construction and development of transmission lines and distribution network, transition of conventional power systems to restructured electricity markets, the competitive circumstances in wholesale and retail markets, the insinuation of economic and environmental problems in the production of electrical energy, rising the system reliability and customer pleasing level. The reliability enhancement ability of power systems by exploitation of

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these units has attracted the interest of many electrical engineering experts and power system planners and operators.

Distributed Generators (DG) are exploited beside the network topology reconfiguration in the novel idea of the power system. Generally, DG represents a miniature decentralized generating units that deployed close to customer property. During the reconfiguration, the network switch states will change without unsettling network radiality. For the minimization of loss, the network topology reconfiguration is considered as the general economic approaches, which exploited in the distribution system [19]. Moreover, the reconfiguration assists the voltage enhancement balancing amid the equipment of the system other than the line losses. Diffusion of DG to reconfigured network tends to high line losses minimizations, enhancement of voltage profile and current drawn minimization from the substation.

The capacity of the distributed generator and optimal positioning plays an essential regulation in the attainment of obtaining the huge advantages from distributed generators [20]. Conversely, inappropriate sizing or positioning distributed generators might cause detrimental effects. The capacity and optimal positioning of distributed generators search space are spacious; various optimization algorithms were exploited to resolve different distributed generators optimization issues. Here, the optimization algorithms can be classified as numerical, analytical as well as heuristic [22] [23]. Moreover, the objective models such as reduction of power loss, reduction of cost, an increment of profit, investment of distribution system delay and reduction of environmental emission.

In the distribution networks, optimal sizing, positioning, and planning of DG units are carefully considered in numerous articles. In the existing state-of-the-art, different approach reasons are calculated for the best possible planning issue of DG units similar to decrease losses of the power system [24] [25], control reactive power, enhancement of voltage profile, enhancement for the security of the system and progress of consistency, and weaken the potential of the DG diffusion [22].

In the field of soft computing method, with the up to date developments, various stochastic optimization techniques were effectively applied to resolve the sizing and positioning issue of DGs in RDS. In [7], a hybrid GA-PSO technique was presented to discover the optimal sizing and positioning of Distributed Generations, on the basis of the objective of network power loss reduction. In [8], BFO approach was used to discover the tactical sizes and positions of multiple Distributed Generations with a concurrent reduction in a power loss of the network and costs for the operational with enhancement instability of voltage. In [9], Tabu search-based technique was developed for the optimal positioning of DGs. DE algorithm was exploited in [10] for optimal positioning of DGs in IEEE 69-bus RDS taking into consideration of minimization of real power loss as well as augmentation of voltage profile. In [14] [13] and [11], ACO, ABC and BSO were exploited to resolve DGs positioning and allocation issue. In [12], TLBO technique and QOTLBO was applied in order to solve the sizing and siting issue of Distributed Generators in the RDS.

The objective of this paper is to propose the hybridization of MFO-WC algorithm in order to solve the optimal sizing and positioning of the Distributed Generators. Moreover, the proposed technique is used to reduce the power loss and enhancement of the system voltage profile.

2.Literature Review

In 2019, Faheem Ud Din et al.[1], presented a Genetic Algorithm that was exploited as a resolving tool. Moreover, this technique was exploited to discover the optimal sizing of DGs and optimal network reconfiguration in a deviating environment load. The positioning of buses in DGs was established by the network sensitivity examination. In accordance with the network topology, on BIBC matrix and BCBV matrix, forward/backward sweep and analysis of speedy harmonic load flow techniques based were elaborated.

In 2016, M.M. Othman et al. [2], worked on a competent and rapid converging optimization technique on the basis of an adaptive conventional firefly technique. The proposed technique was utilized in unbalanced/balanced DSs for the optimal siting and positioning of voltage-controlled DGs. The presented method adapts the conventional firefly algorithm in order to pact with the sensibly constrained optimization issues. Moreover, the formulas were developed to tune the method parameters and equations updating. The proposed technique was simulated in IEEE 123-nodes feeder to decrease the loss of power loss for the system by means of vigorously revealing of the optimal positioning and sizing of the DGs without infringes the constraints of the system.

In 2016, Satish Kumar Injeti [3] worked on choosing the optimal sizing and positioning of DG in RDS. Hence, they have proposed IDSA to resolve the optimization issue through Pareto optimal technique by taking into consideration of both the financial and technical advantages of Distributed Generators as objectives. Moreover, this method was exploited to decrease losses, improve voltage profile and decrease the cost of operating.

In 2019, Ashokkumar Lakum and Vasundhara Mahajan [4] discussed the effect of Distributed Generators diffusion on the optimal sizing and positioning of APF. Also, the novel NLPCI approach was presented to place the possible buses for the position of APF in the occurrence of nonlinear load merely and DG. Moreover, the GWO was exploited to identify the optimal sizing of APF.

In 2016, Subhodip Saha and Vivekananda Mukherjee [5], presented a new CSOS technique to discover the optimal sizing and positioning of real power Distributed Generators in an RDS taking into consideration of constant load models. This DG sizing, as well as siting issue, was related to the minimization real loss of power loss and enhancement of voltage stability objectives.

3.Mathematical Formulation

3.1 Objective Model

In general, distributed positioning and sizing represents an NP-hard problem, and it is represented as a multi-objective optimization issue. Here, the objective of this paper is to optimize the positioning and sizing of distributed generator units, which needs to be deployed. Moreover, an effectual power factor is considered in order to assure the minimization of loss of power as well as an enhancement of voltage profile. In the distribution system, a direct procedure for stating the number of reactive and real power loss is contemplated. In each branch, the losses occurred are calculated and summed to compute the total real power loss of the systems. The objective model formulation is stated in eq. (1). In eq. (1), δ_1 represents the contributory factor, U_i indicates the voltage magnitude at the bus i, N_1 indicates the number of the branch in the network, R_i indicates the apparent power at the bus i, γ_1 and γ_2 indicates the penalty factor coefficient, R_i^{max} indicates the utmost apparent power at the bus i, N_a indicates the number of buses.

$$O_f = \min(f_1 + \delta_1 f_2) + \gamma_1 \sum_{i=1}^{N_a} \max\left(U_i - U_i^{max}, 0\right) + \max\left(U_i^{min} - U_i, 0\right) + \gamma_2 \sum_{i=1}^{N_h} \max\left(\left|R_i\right| - \left|R_i^{max}\right|, 0\right) \tag{1}$$

In eq. (2), M_{loss} represents the total power loss, U_{PE} represents the voltage profile enhancement value in eq. (3).

$$f_1 = M_{loss} \tag{2}$$

$$f_2 = U_{PE} \tag{3}$$

In eq. (4) and (5), i represents sending node, j represents receiving node, Δ represents the phase angle, N_{k_i} represents the reactive power supplied from bus i, ϕ_{ij} represents load angle between bus i and j, M_{c_i} represents the real power demand connected at bus i, X_{ij} represents the reactance between the bus i and j, M_{k_i} represents the real power generation available at bus i, M_{c_i} reactive power demand at bus i.

$$M_{loss} = \sum_{\substack{i=2 \\ j=2}}^{n_a} \left(M_{k_i} - M_{c_i} - U_i U_j X_{ij} \cos\left(\Delta_i - \Delta_j + \phi_{ij}\right)\right) \tag{4}$$

$$N_{loss} = \sum_{\substack{i=2 \\ j=2}}^{n_a} \left(N_{k_i} - N_{c_i} - U_i U_j X_{ij} \sin\left(\Delta_i - \Delta_j + \phi_{ij}\right)\right) \tag{5}$$

Eq. (6) states the enhancement of voltage profile, U_{PE} represents the voltage profile enhancement value, U_i represents the voltage bus magnitude at the bus i, $U_{i,ref}$ represents the rated bus voltage.

$$U_{PE} = \min\left\{\sum_{i=1}^{N_a} \left|U_i - U_{i,ref}\right|^2\right\} \tag{6}$$

3.2 Constraints

In this section, the constraints that need to be fulfilled for optimal sizing and positioning of Distributed Generators are represented.

(i) Equality constraint:

At several positions, while installing the Distributed Generators in the system, the below stated power-flow eq. (7) and (8) must be fulfilled.

$$\sum_{i=2}^{n_a} M_{k_i} - M_{c_i} - U_i \sum_{j=1}^{N_a} U_j X_{ij} \cos(\Delta_i - \Delta_j - \phi_{ij}) = 0 \tag{7}$$

$$\sum_{i=2}^{n_a} N_{k_i} - N_{c_i} - U_i \sum_{j=1}^{N_a} U_j X_{ij} \sin(\Delta_i - \Delta_j - \phi_{ij}) = 0 \tag{8}$$

In order to solve eq. (7) and (8), the forward/backward sweep technique is exploited for U_{PE} and M_{loss} to identify the objective model value.

(ii) Voltage Limits:

Within the limits, the voltage should be maintained at each bus. In eq. (9), U_i^{min} and U_i^{max} represents the least and highest permitted operating voltage at the bus i.

$$U_i^{min} \le U_i \le U_i^{max} \tag{9}$$

(iii) Thermal Limits

In order to operate the distribution network lines are preserved in the thermal limits:

$$|R_i| \le |R_i^{max}| i = 1,......, N_h \tag{10}$$

(iv) Constraint of Distributor Generator Capacity

By the energy resources, the capacity of the Distributor Generator is intrinsically limited at any given position. Consequently, it is essential to limit the capacity of Distributor Generator within the minimum and maximum generation limits:

$$M_{dgi}^{min} \le M_{dgi} \le M_{dgi}^{max} \tag{11}$$

(v) Loss Sensitivity Factor (LSF)

At each bus, the LSF is computed in order to find the most sensitive bus for the positioning of a Distributed Generator. Initially, this phrase was exploited for the capacitor position problem and in a while for Distributor Generator position [15]. In eq. (12), S_{ij} represents the resistance among bus i and j.

$$LSF = \frac{2N_{j,eff} * S_{ij}}{(U_j)^2} \tag{12}$$

Around the initial state, the eq. (12) is linearized for the reactive power phrase and loss.

(vi) Efficient Power Factor:

For the computation of LSF, at each bus, the effectual load of the distribution system is computed, and after that, the efficient power factor for each bus is computed using eq. (13). $M_{i,epf}$ and $N_{i,epf}^2$ represents an effective reactive and real power load linked at the bus i.

$$ePF_i = \frac{M_{i,epf}}{\sqrt{M_{i,epf}^2 + N_{i,epf}^2}} \tag{13}$$

The effectual bus power factor is supposed to be the power factor compensated by the Distributed Generator at that specific bus [16]. In eq. (14), ePF_i indicates the effectual power factor at the bus i, and $PF_{DG,i}$ indicates the power factor of the DG linked at the bus i.

$$PF_{DG,i} = ePF_i \tag{14}$$

4. A Proposed Method for Optimal Positioning and Sizing of Distributed Generators

4.1 Conventional Water Cycle Algorithm

In [17], WCA is a new metaheuristic algorithm that imitates the water cycle in nature to resolve the optimization issues. On the basis of the conceptual bases, the WCA facilitate the techniques to resolve the optimization issues, powerfully.

Generally, the WCA exploits an array named stream to illustrate the decision variables for an optimization issue.

$$R_d = [y_1, y_2, ... y_n] \tag{15}$$

In eq. (15), n indicates the number of decision variables and $y_1, y_2, ... y_n$ represents the decision variables of the problem. The conventional WCA technique represents a set of streams that must be generated at the creation as eq. (16).

$$R_d = \begin{bmatrix} y_1 & y_2 & .. & y_n \\ y_1 & y_2 & .. & y_n \\ \vdots & \vdots & \vdots & \vdots \\ y_1 & y_2 & \cdots & y_n \end{bmatrix} \tag{16}$$

In the initial population, the number of streams is equal to the number of rows that is an input parameter of the algorithm. Subsequently, this method computes the value of the objective model for each stream in the initial population after that classes the streams concerning their consequent value of the objective model value from the optimal to the worst as well as sets the optimal stream as the sea. Next to $(M_{sr} - 1)^{th}$ streams are represented as rivers. The residual $(M_{pop} - M_{sr})^{th}$ is contemplated as streams.

In nature to imitate the flow of the rivers as well as streams to the sea, WCA exploits the eq. (17) to update the position of the stream towards the rivers.

$$y_{stream}^{i+1} = y_i^{stream} + r \times c_n \times \left(y_i^{river} - y_i^{stream}\right) \tag{17}$$

where r represents a random number among 0 and 1 produced by means of uniform distribution, and c_n represents a continuous number among 1 and 2. While each stream updates its position to its subsequent river, if the stream objective model in its new position is enhanced its consequent river, the algorithm changes the position of the river and stream.

On the basis of the flow intensity, the WCA allocates streams to the sea and rivers that are decided using eq. (18).

$$MS_n = \text{round}\left\{\left|\frac{Cost_n}{\sum_{i=1}^{M_{sr}} Cost_i}\right| \times M_{RD}\right\} \tag{18}$$

In conventional WCA method, to evade trapping in local optima as well as to maximize the randomization, the raining and evaporations circumstances are contemplated. While the distance between a sea and the river are minimum than f_{max}^{i}, the raining and Evaporation happen; also this process happens while the distance among any stream and the sea is minimum than f_{max}^{i}.

A high amount of f_{max}^{i} must be represented, to concentrate more on exploration. For exploitation, a little value for f_{max}^{i} is better. Consequently, the value of the f_{max}^{i} must be high to concentrate more on exploration in the first iterations, as well as in the final iterations must be less to use the solution space, the value of the f_{max}^{i} represented to modify against the course of the iteration. Hence, eq. (19) is exploited to minimize the f_{max}^{i} value linearly against the course of the iteration.

$$f_{max}^{i+1} = f_{max}^{i} - \frac{f_{max}^{i}}{Max_{it}} \tag{19}$$

In eq. (19) Max_{it} demonstrates the maximum amount of iterations. The raining procedure happens while the distance among a stream or river as well as the sea is minimum than f_{max}^{i} to make new streams to flow to sea and rivers. This procedure happens iteratively to until reaching the stopping state.

4.2 Conventional Moth Flame Optimization Algorithm

Moths are considered as an insects group, which is same as the butterflies. The unique navigation method is known as the most attractive moth's behavior. Moth flies in a fixed angle regarding the moon to move long distances in a straight path and this efficient method is known as transverse orientation [18]. The efficiency of the transverse inclination robustly based on the light source distance.

As, the flying moth's path is spiral in the region of their equivalent flame; so, a logarithmic spiral model is described to place a spiral fly path for the moths.

$$M_{o_i}^{Y+1} = \left|M_{o_i}^{Y} - f_{li}\right| \cdot e^{at} \cdot \cos(2\pi t) + f_{li} \tag{20}$$

The parameter t is an arbitrary uniform number among -1 as well as 1 that describes the nearness of the subsequent position of the moth to its equivalent flame. In the first iterations, to search the solution space efficiently as well as in last iterations exploitation of the solution space, an adaptive process is presented to minimize the values of the parameter for the t against the iterations.

$$b = -1 + \text{current}_{it}\left(\frac{-1}{\max_{it}}\right) \tag{21}$$

$$t = (b-1)\times r + 1 \tag{22}$$

Where $\max_{it}$ represents the utmost number of iterations described as a convergence constant that minimizes linearly from −1 to −2 against the course of the iteration. In the MFO technique, this assures both exploitation and exploration. The number of flames is minimized against the iteration of the MFO method to attain the final solution, which is represented in eq. (23).

$$f_l = \text{round}\left(A_{fl} - l\,\frac{A_{fl}-1}{\max_{it}}\right) \tag{23}$$

In eq. (11), f_l indicates the number of flames in the current iteration, $\max_{it}$ indicates the utmost number of iterations A_{fl} indicates the number of flames in the final iteration as well as l indicates the current iteration.

4.3 Proposed Hybrid MFO-WC Algorithm

The conventional WCA possess the enormous capability for exploring the solution space of the issue. In conventional WCA, rivers, and streams update their position in the direction of the sea, and this process aids the search agents to update their position regarding the optimal solution. On the other hand, the WCA undergoes the requirement of a competent operator to achieve exploitation.

Conversely, the conventional MFO exploits the spiral movement capability in order to execute the exploitation other than searching the solution space economically. This happens since each moth updates its position in the direction of its equivalent flame. As a result, the optimal solution information attained hitherto using the MFO is not disclosed among the search agents. The proposed method is the hybridization of the MFO and WCA that has the compensation of both techniques. In the proposed Hybrid MFO-WC technique, the WCA is represented as the fundamental technique.

In the WCA, the initial enhancement is done by the spiral movement of the moths. It is used to position updating of the rivers and the streams. In conventional WCA, the updating process consists of the space among the river and a stream while the position of a stream updating.

Conversely, then the stream position should be in the space among the stream as well as its equivalent river. On the other hand, the updating process of the MFO technique permits the moths to update their position wherever in the region of their equivalent flame. By exploiting the movement of the spiral of the moths, allows the rivers and streams to update their position, considerably maximizes the exploitation capability of the proposed Hybrid MFO-WC.

In the conventional WCA algorithm, the second enhancement is enhancing the raining procedure. In the meta-heuristic technique, aforesaid, randomization approach plays a foremost task. In the hybrid MFO-WC technique, to maximize the randomization, two procedures are contemplated. In the conventional WCA, the initial approach is raining procedure. While the distance among a stream or river and the sea is minimum than f^{i}_{max}, the hybrid MFO-WC executes raining procedure to produce new solutions. By an arbitrary walk (Levy flight) the next approach is allowing the streams to flow arbitrarily in the solution space. If the streams update their positions and cannot discover the enhanced solution by considering an iteration of the WCA, hence the position of the sea and the rivers could not be changed until the next iteration. In the hybrid MFO-WC, by eq. (24) to augment the randomness, streams are permitted to update their position using Levy flight.

$$y_{i+1} = y_i + \text{levy}(\text{dim}) \otimes y_i \tag{24}$$

where y_i is the current position of the stream, y_{i+1} is the subsequent position of the stream, and dim represents the dimension of the issue. Eq. (25) is used to calculate the levy flight.

$$\text{levy}(y) = \frac{0.01 \times \eta \times r_1}{|r_2|^{1/\delta}} \tag{25}$$

Where, r_1 and r_2 are randomly produced numbers among 0 and 1. Eq. (26) is used to calculate the parameter η.

$$\eta = \left(\frac{\Gamma(1+\delta) \times \sin\left(\frac{\pi\delta}{2}\right)}{\Gamma\left(\frac{1+\delta}{2}\right) \times \delta \times 2\left(\frac{\delta-1}{2}\right)} \right)^{1/\delta} \tag{26}$$

5.Results and Discussions

5.1 Experimental Procedure

This section examines the proposed Hybrid MFO-WC method on IEEE 69-bus and 33-bus radial RDSs. Here, the number of Distributed Generation units to be positioned in the system is pre-set and assumed, as well as the power produced by the Distributed Generation is set as constant. Moreover, the proposed technique was compared with four existing techniques like PSO [7], GA [13], FF [2] and ACO [11] and the resulted were stated in below sub-sections.

5.2 IEEE 33 Bus system

Fig 1 depicts the diagrammatic representation of a single line for IEEE 33 bus system. Table 1 states the comparative analysis of the proposed and existing technique in IEEE 33 Bus system. Here, the proposed technique is calculated for minimization of loss, Ploss and Power factor. The power factor of the proposed technique is 22% better than the PSO, 23% better than GA, 25% better than the FF and 24.23% better than the ACO algorithms. Hence, the overall analysis states that the proposed technique is better than the conventional techniques in IEEE 33 Bus system.

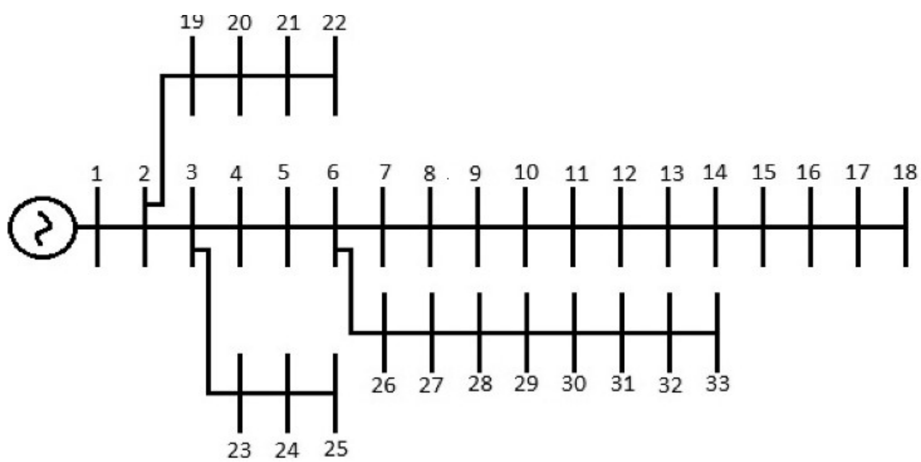

Fig. 1. *Diagrammatic representation of a single line for IEEE 33 Bus system*

Table 1. *Performance analysis of the proposed technique with existing approaches In IEEE 33 Bus system*

Techniques	Minimization of loss (%)	Ploss	Power Factor
PSO	57.3	113.23	2234
GA	56.8	115.23	2265
FF	58.34	113.67	2287
ACO	57.64	119.23	2285
Proposed	59.34	121.32	2310

5.3 IEEE 69 Bus system

Fig 2 demonstrates the diagrammatic representation of a single line for the IEEE 69 bus system. Table 2 summarizes the performance analysis of the proposed and conventional approach in IEEE 69 Bus system. Here, the proposed technique is computed for minimization of loss, Ploss and Power factor. The minimization of loss of the proposed method is 12% better than the PSO, 15.22% superior to GA, 17% better than the FF and 18% superior to the ACO algorithms. Hence, overall analysis summarizes that the proposed method is superior to the conventional techniques in the IEEE 69 Bus system.

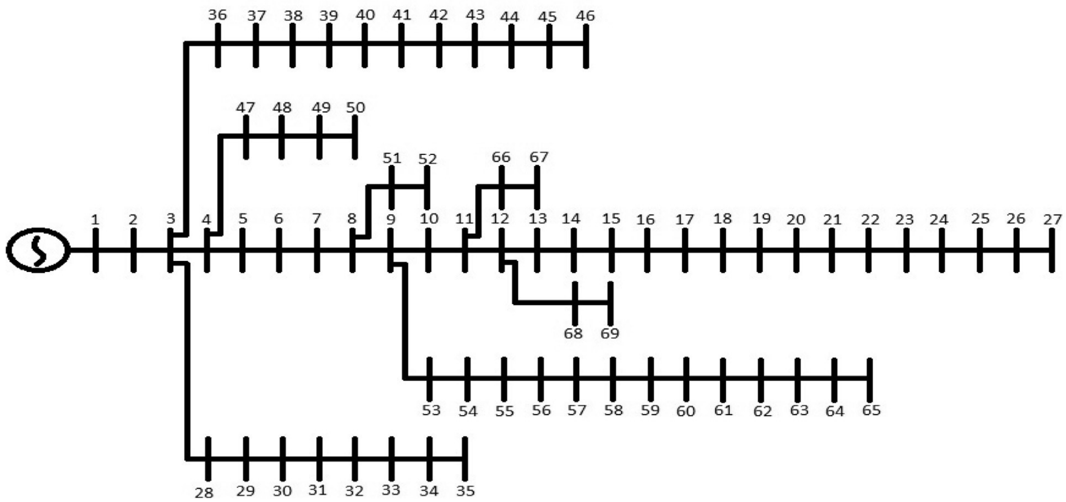

Fig. 2. *Diagrammatic representation of the single line for IEEE 69 Bus system*

Table 2. *Comparison of proposed technique with existing techniques for IEEE 69 Bus system*

Techniques	Minimization of loss (%)	Ploss	Power Factor
PSO	71.32	126.12	3216
GA	76.83	136.13	3156
FF	73.24	143.22	3213
ACO	72.32	142.62	3214
Proposed	79.12	148.12	3246

6. Conclusion

In this paper, the optimal sizing and positioning of the DGs are presented. Here, the DGs were placed appropriately to remunerate the factors of the power system on the basis of an effectual power factor model. In order to comprehend this, a novel approach was presented (i.e.) hybridization of both the MFO-WC algorithms. Moreover, the presented method was shown as an effectual approach in order to discover enhanced outcomes about the quality and speed of the solution produced. Here, the experimentation was done by exploiting two standard bus systems in order to show the performance of the proposed technique. Finally, outcomes exhibit the effectiveness of proposed method in order to attain the minimized losses of power, and enhanced voltage profiles. It was attained by the handling of the power capability for the system without additional expansion or compensation.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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