Research Article

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Hybrid optimization for optimal positioning and sizing of distributed generators in unbalanced distribution networks

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Abstract: The goal of this work is to reduce power loss and improve voltage profile by formulating the optimal DG placement problem as a restricted nonlinear optimisation problem. As a novelty, the proposed hybrid algorithm, referred to as Multifactor Update-based Hybrid Model (MUHM) is constructed by merging the concepts of Lion Algorithm (LA) & Sea Lion Algorithm (Sea Lion Optimization Algorithm (SLnO). The Forward-Backward Sweep (FBSM) Model is used to calculate the power loss. Three test cases are examined for the voltage profile & loss minimization in the feeder team with DGs: “case 1(DG supplying real power alone (*P*), case 2 (DG supplying reactive power alone (*Q*) and Case 3 (DG supplying both real and reactive power)”. Application of the suggested method to various IEEE test systems, including IEEE 33, IEEE 123, and IEEE 69, respectively, is used to assess its efficacy. According, the results show that the presented work at loading percentage = 0 is 12, 15, 135, 4.65, and 8 superior to SFF, BBO, BAT, LA and SLnO, respectively.

Keywords: multi-objective decision-making system; optimization algorithm; unbalanced distribution networks: distributed generations: power loss minimization; voltage profile enhancement.

Introduction

Over the decades, the entire globe is trying to rapidly penetrate its roots towards green technology due to the growing “demand of electrical energy, limited availability of fossil fuels” and the desire to concern our global planet. So the need for renewable-based generation in the DNet is alarming with the rapid penetration of DG (Arkadan and El Hariri 2016; Mota, Mota, and Galiana 2011; Rigatos, Siano, and Zervos 2014). However, a huge count of factors is still motivating the distribution system planners to determine the most favourable expansion strategies to serve the load growth and endow their customers with trustworthy and reasonable services. In the power sector, deregulation incentivizes the distribution system planners to look out for more economic and technical feasibility with the new energy supply alternatives similar to DGs (Manickavasagam 2015; Sun et al. 2015; Zhu et al. 2018). Moreover, the recent advancement in the generation’s techniques and hybrid power sources makes the distributed network more feasible and attractive for the planner. At the same time, they are making the current power system more complex than in the past) (Ji et al. 2019; Sudabattula and Kowsalya 2016; Vyas, Kumar, and Kavasseri 2017).

The DG is gaining a huge focus nowadays as they are capable of using the both “non-renewable and renewable sources of energy” to generate electricity (Zema et al. 2017). DG depictes by“electric power generation within distribution networks or on the customer side of the network” (Quattrini et al. 2021). In plenty of other words, “small sizes, between several kW and a few MW” are described as the range of generating units that are connected by DGs (Zubo 2017). The traditional non-renewable sources like gas or the renewable sources like wind, sun, hydro, and biomass are the principal and primary sources of energy for these generators, respectively (Sujatha and Umarani 2012). The major technical, as well as and economic issue, arises in the electrical environment when DG’s are interconnected with the electric grid (Othman et al. 2016; Shrivastava et al. 2017; Trovato et al. 2019). The quality of power, network stability, protection chaos, and voltage fluctuations fall under the technical issues. Further, in the case of renewable generators like solar panels, wind turbines, there are fluctuations in output power production rate since they are

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highly dependent on the natural forces (availability of renewable resource) (Biswas et al. 2017; Jamil and Anees 2016; Ji et al. 2018). The power system operating at the non-optimal places installed with DG units with non-optimal sizing tends to cause higher power losses, problems in power quality, system instability, and escalating operational costs.

Numerous works have been undergone in DGs to diminish the "power loss and enhance the stability" as well as the feasibility of the network in the electrical internet (Rajeshkumar 2019; Ravikumar, Vennila, and Deepak 2019; Srinivasa Rao, Tulasi Ram, and Subrahmanyam 2019). Further, maximum benefits can be gained from DGs using exploiting them in optimal position because of the improper placement or sizing 10 to generate undesirable effects. However, these DGs are implemented either in the "transmission or distribution sections", the utmost benefits can be realized during the insertion of the generators in distribution systems (Wang et al. 2019) (Yu et al. 2018). Further, to reap more benefits in terms of stability, power loss, and enhanced gain, the DG units should have the proper size and be placed appropriately (Ravindran and Victoire 2018). "The search space of optimal location and capacity of DGs is roomy. Different optimization methods have been used to solve different DG optimization problems (Gayathri Devi 2019; Shareef and Srinivasa Rao, 2018; Malhotra and Bakal 2018; Mistry and Roy 2014; Mohana and Mary 2017; Mohana, Sahaaya, and Mary 2016; Zahuruddin and Rukmini 2018)". The most interesting among them are discussed in the literature section.

The following are some of this research's contributions:

- To investigate a decision-making method to choose the most advantageous DG size and location relative to balanced/unbalanced distribution feeders in order to minimise power/energy loss while remaining within system limits.
- The anticipated decision-making strategy is based on MUHM, a novel multi-objective optimisation algorithm that conceptually combines SLnO with LA.

The remaining portion of this study is structured as follows: The literature studies conducted in DG optimum placement are covered in "Literature review". "Proposed optimal localization of distributed generations (DGs): an overview" display the proposed optimal localization of distributed generations (DGs): an overview. "Modelling of Distributed Generations and Load Flow Study" discusses Modelling of Distributed Generations and Load Flow Study, and "Objective function and proposed multi-objective optimization approach" portrays the objective function and suggested multi-objective optimization scheme. Discussion of the findings from the work provided is in "Results and discussion". Finally, "Conclusions" provides a compelling summary of this research.

Literature review

Related works

In 2016, Sudabattula and Kowsalya (Sudabattula and Kowsalya 2016) proposed an effective model in the DNet for the most favorable allocation of the solar-based DG with the aid of the BA. This research's major objective focused on minimising the "power loss of radial distribution system". Further, to achieve this objective, the authors have considered various operating constraints that were related to the DNet. Based on the suitable probability distribution function, they model the stochastic character of solar irradiance. Eventually, the planned model resulted in a notable reduction in power loss and a higher level of PV array penetration when built on the "IEEE 33 bus test system.".

In 2016, Othman et al. (Othman et al. 2016) have developed a novel and faster converging optimization algorithm in "balanced/unbalanced distribution systems for efficient sizing and siting of voltage-controlled DG". This investigation's main goal was to reduce active power loss or everyday energy loss. They implied a supervised FA method with an orientation table to reach the aim and restrict it from fall into local min positions. Further, the ideal location and the distributed generator's voltage capacity were identified for effective power loss mitigation. Finally, they employed their projected work on to the "balanced and unbalanced distribution feeders" and implemented them on the "IEEE 37 nodes feeder and IEEE 123-nodes feeder".

In 2018, Ravindran and Victoire (Ravindran and Victoire 2018) formulated a bio-geography-based optimization approach in electric distribution systems to enhance the system voltage profiles and decrease the system loss for the most favourable assignment and sizing of the multiple DG. They have reduced the total system losses by enhancing the system power factor by generating source installation on the surrounding area of the loads. Then, the power factor was preset with the proposed power factor model for each of the individual power systems having the distributed generator located at different locations. They have introduced the bio-geography optimization algorithm as a learning model for dealing with the issues related to high dimensionality and complex constraints.

Furthermore a suggested plan was implemented in “IEEE 33-bus and IEEE 69-bus systems”.

In 2018, Rastgou et al. (Rastgou, Moshtagh, and Bahramara 2018) investigated the DNet expansion problem in the distributed network with DGs. The proposed model considers practical aspects like the “pollution, investment and operation costs of DGs, purchased power from the main grid, dynamic planning, and uncertainties of load demand and electricity prices”. This research’s main objective was to model how much pollution DGs emit. They have utilized the probability distribution function to model the uncertainties in the system and have inserted the modelled uncertainties into the planning problem with the aid of the Monte-Carlo simulation. In addition, they have introduced the improved harmony search approach for solving ashortcomings of using numerous variables and constraints.

In 2018, Rodriguez et al. (Ruiz-Rodriguez, Jurado, and Gomez-Gonzalez 2014) had proposed a novel hybrid method in distribution systems by means of merging the P-3Phase LF and JFPSO for unbalanced voltages with photovoltaic generators. Further, based on the MCS, the new P-3Phase was introduced by them. The proposed model had considered the uncertainties related to the “active and reactive loads and the solar radiation”. In order to verify the effectiveness of the suggested model, they also deployed it on the IEEE-13 node testing feeder system.

In 2014, Yang et al. (Yang et al. 2019) had developed a novel PFOSMC of SCES system with renewable energy penetration in the microgrid with DGs. The inherent physical characteristics of SCES were investigated by constructing a stronger function in the passivity theory. Further, they have the FOSMC framework helped to increase the closed-loop system’s robustness. In the FOSMC framework, a more flexible control performance was gained by employing the fractional-order PDα sliding surface and the energy reshaping mechanism.

In 2019, Nguyen et al. (Nguyen, Tung The Tran, and Vo 2018) have projected a novel CSFS method in distribution systems for decisive the most favourable “sitting, sizing, and the number of DG units”. Subsequently, the "EEE 33-bus" has been used to test the proposed paradigm, 69-bus, and 118-bus radial distribution systems” & resultant of evaluation have demonstrated the enhancement in the proposed model by solving the issues related to the most favourable placement of DG units.

In 2018, Reddy and Prasad (Chandrashekhar Reddy and Prasad 2012) computed the most favourable position of DG units in the distributed power system using the GA and NN methods. Initially, the authors have employed the GA to localize the position of the active and reactive power constraints. Then, they have implied NN to get hold of the most excellent spot of DGs at the smallest amount of power loss. Then, the evaluation of the production capacities of DGs took place. The developed framework was then tested using the IEEE 30 bus system, and the results showed that it was superior in terms of the overall power loss across two DGs plus buses.

In 2016, Muthukumar and Jayalalitha (Muthukumar and Jayalalitha 2016) presented the HSA approach to diminish power losses in radial distribution networks and improve bus voltage profile. Finally, the experimental outcome shows its effectiveness in the placement of DG as well as shunt capacitors in distribution networks.

In 2020 Montoya (Montoya, Gil-González, and Orozco-Henao 2020) have employed the CBGA to solve the master stage, and the OPF method by the VSA was presented to solve the slave stage. The experimental outcomes show the effectiveness of the employed algorithms under power loss reduction compared to other existing methods.

Review

Few of the most exciting study undergone on this subject are discussed, along with the features and challenges in Table 1. Among them, in (Sudabattula and Kowsalya 2016), the BAT algorithm is efficient in diminishing the power loss, and here the penetration level of optimal PV arrays is high. Apart from these advantages, they suffered from the drawbacks like lower convergence and higher cost, and the decrease of real power loss remains a difficulty. Further, in the supervised firefly algorithm (Othman et al. 2016), the robustness and convergence speed are high. But, it suffered from higher computational complexity and had no consideration for the uncertainties of the realistic output. In bio-geography-optimization (Ravindran and Victoire 2018), the dimensionality is reduced, and the voltage profiles are improved. Both the speed and quality of the results from this technique must improve.The proposed model’s major advantage was that the voltage profile and pollutant emission were alleviated in an improved harmony search algorithm (Rastgou, Moshtagh, and Bahramara 2018). This technique also suffers from the drawbacks like lower sensitivity and has no consideration for maintaining the power factor. Then, JFPSO in (Ruiz-Rodriguez, Jurado, and Gomez-Gonzalez 2014) was embedded with the pros like quicker convergence and Lower computational cost. The active and reactive loads can be improved further to produce better power loss minimizations. PFOSMC in (Yang et al. 2019) had lower tracking error, and the overall control costs are lower. Here, renewable energy penetration was lower here, and the flexibility needs to be enhanced further. The Power loss reduction was improved along with the voltage profile in CSFS (Nguyen, Tran, and Vo 2018). As a controversy to these advantages, the effective cost model needs to be further enhanced to make the model more effective and flexible. Further, GA + NN in (Chandrashekhar Reddy and Prasad 2012) have the advantages like minimum power loss, and here, the voltage profile of the buses remained stable within tolerable limits. But, the buses are in a thirst for more stability, and here, the uncertainties of the real and reactive power system aren't considered.

Numerous works have been focused on optimal DG placement. But still, there exist common problems like low convergence, high cost, utilization of more parameters, low sensitivity, voltage unbalance, no consideration of the power factor and energy losses. In order to address the aforementioned problems, this research suggests a hybrid metaheuristic method for distributed generator placement and size optimisation in imbalanced distribution networks. The suggested model aids in reducing power loss and improving voltage profiles.

Proposed optimal localization of distributed generations (DGs): an overview

Distributed generations: a short description

The electric utility system is typically categorized into 3 sub-systems: "generation, transmission, and distribution". Among all of these, distribution is essential since the effectiveness of it directly impacts customers (Soumya and Amudha 2013). Therefore, it is vital to properly plan the distribution system to enhance its efficiency and overall performance. Further, there is a day-by-day increase in the

Table 1: Features and Challenges of Existing Works on optimal DG placement.

Author [Citation]	Methodology	Features	Challenges
Sudabattula and Kowsalya (2016)	BAT algorithm	– Efficient in minimizing the power loss – The highest penetration level of optimal PV arrays	– Need to reduce the real power losses further – High cost – Lower convergence
Othman et al. (2016)	SFF algorithm	– High speed of convergence – Highly robust – Enhanced active power loss minimization	– Considers huge count of parameters – No consideration on the uncertainties of the realistic output
Ravindran and Victoire (2018)	BBO	– High dimensionality reduction – Reduces total system losses – The power factor is close to unity	– Need to generate superior results in terms of speediness and excellence – Instable for unbalanced systems
Rastgou, Moshtagh, and Bahramara (2018)	The improved harmony search algorithm	– Enhances the voltage profile – Reduces pollutant emission – Reduces the costs of planning	– Low sensitivity – No consideration on the power factor
Ruiz-Rodriguez, Jurado, and Gomez-Gonzalez (2014)	JFPSO	– Quicker convergence – Low computational cost – Considers the probability of unbalance nodes	– Need further improvement in the active and reactive loads – Need to address the voltage unbalance
Yang et al. (2019)	PFOSMC	– Improves the dynamic response – Lower tracking error	– Need to enhance the flexibility – Lower renewable energy penetration
Nguyen, Tung The Tran, and Vo (2018)	CSFS	– Higher power loss reduction – Higher speeds – Improvement in the voltage profile	– Needs effective cost model – Energy losses need to be considered
Chandrashekhar Reddy and Prasad (2012)	GA + NN	– Optimal location of buses – Improves power quality and reliability	– Need to make the bus system more stable – No consideration on the uncertainties of real and reactive power

load demand, and hence to gratify the desires of the customers, the alive power ought to be expanded. In other words, expansion said to be "transformer up-gradation, substation up-gradation, feeder reconfiguration, etc.". Actually, all of this couldnt economical and complex too. But, as a promising solution to the problem of distribution expansion planning comes the DGs. The DG is said to be small-scale generation ranging from a few kWs to 50 MW and it is defined as "the generating plants that serve a customer on -site or provide support to the distribution network, connect to the grid at the distribution-level voltage", by International Energy Agency (IEA). A one-line diagram of DG installed in a two-PQ bus system was displayed in Figure 1. Here, the power generated in any bus is $P_c + jQ_c$ and the load is $P_L + jQ_c$.

The integration of DG with the distribution system offers quite a few technological and cost-effective profits to utilities and consumers (Mahesh, Nallagownden, and Elamvazuthi 2016). However, the meagre enclosure of DGs may not promise enhancement in system performance. Further, the major advantageous effect of distributed generations depends mainly on its localization and size. Therefore, based on the DGs' location, size, and diffusion level on the distribution network, the system might negatively influence it. Additionally, to reduce the power loss in power systems, it is merely significant to "define the size and location of distributed generation to be placed".

In before the improvement of a novel multi-objective based decision-making system for optimal placement of DGs, it is crucial to explore answers to certain critical questions:.

- What are the constraints taken into consideration for the optimal placement of DGs?
- During the placement of DGs into the balanced/unbalanced distribution feeders, the power loss automatically increases, and how can it be suppressed?

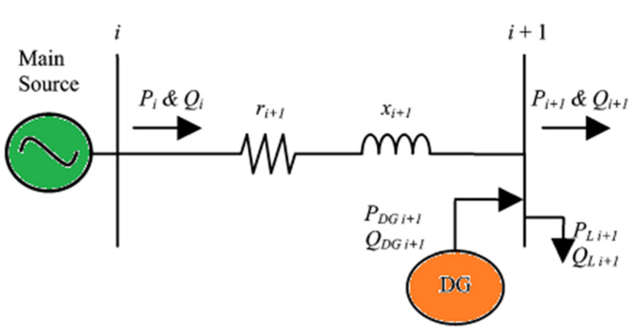

Figure 1: One-line diagram of DG installed in two bus system.

- How the system voltage profile enhanced and what is done to retain the voltage of each bus within a permissible range?
- Is it possible to diminish the genuine power loss of the system without going against the system limitations, and how is it possible?
- As a solution to all these questions, this research work intends to develop a novel multi-objective-based optimization approach.

Proposed solution for optimal placement of DGs

A successful technique is introduced here for "optimal allocation (positioning) and sizing of voltage-controlled DGs using a novel hybrid algorithm". The main objective of the suggested model is to reduce power loss while increasing the reliability and efficiency of voltage-controlled DGs in unbalanced distribution networks. The suggested multi-objective optimisation method is innovative in that it is created by integrating the LA and SLnO. In proposed multi-objective optimization, the DG is modelled as a "voltage controlled (PV) node with the flexibility to be converted to constant power (PQ) node in case of reactive power limit violation". Figure 2 shows the schematic diagram of the model that is being given.

Modelling of distributed generations and load flow study

Modelling of DGs

In a distribution system, the count of DG allocation highly depends on the load demand of the system and the maximum allowable size of DG (Ramamoorthy and Ramachandran 2016). "The maximum allowable size of DG is up to 25–30% of the total load". Here, the IEEE-123 feeder system is taken into consideration. It is proposed to select a maximum of 5 DGs and a minimum of 2 DGs. The most favorable dimension of DG to be located at each one bus is established out using the proposed multi-objective optimization algorithm. In general, DG is categorized into 2 piece, from the energy source to the point of view. "One is non-renewable energy including cogeneration, fuel cells and microturbine systems and the other is renewable energy including photovoltaic, wind, geothermal, biomass and so on".

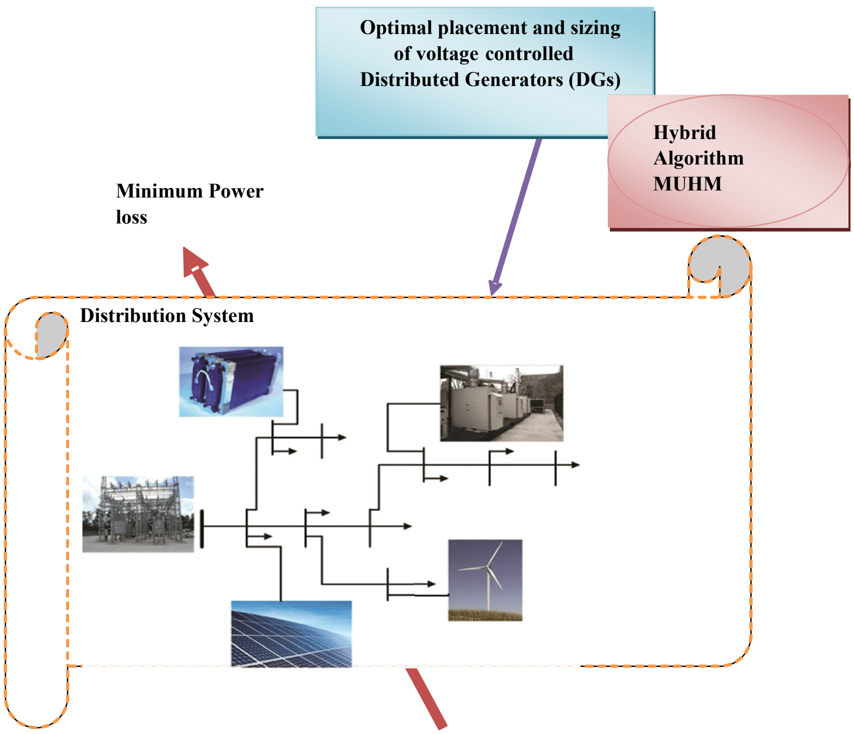

Figure 2: Block diagram of the proposed model.

Similar to the central generation, the DG source is also an active power constraint and it is formulated as per Eq. (1).

$$P_{g_i}^{\min} \le P_{g_i} \le P_{g_i}^{\max} \tag{1}$$

$P_{gi} \rightarrow$ Real power production accessible at i^{th} bus.

Because the energy source at any given site intrinsically limits DG capacity, the DG capacity limitation must be calculated between the min and max generation in accordance with Eq. (2).

$$P_{\text{DG}i}^{\min} \le P_{\text{DG}i} \le P_{\text{DG}i}^{\max} \tag{2}$$

Moreover, the reactive power output is also important, and it is also taken into consideration as per Eq. (3).

$$Q_{g_i}^{\min} \le Q_{g_i} \le Q_{g_i}^{\max} \tag{3}$$

$Q_{gi} \rightarrow$ Reactive power supplied from i^{th} bus.

Further, to improve the voltage profile as well as voltage at every one bus is obliged to be maintained inside the restrictions as per Eq. (4).

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{4}$$

Where, $V_i^{\min} \rightarrow$ Greatest permissible in-service voltage at i^{th} bus, $V_i^{\max} \rightarrow$ Least permissible in-service voltage at i^{th} bus.

In the current research work, the voltage limit is set as $V_i^{\min} = 0.97 \le V_i \le V_i^{\max} = 1.05$. When the voltage goes beyond the limit, a penalty factor is added, which is also taken as the objective function.

Three types of DGs for two DG models are discussed below:

Case 1: These types of DGs generate only real power (e.g. Photovoltaic). A bus *i*, the best possible size of DG, is found by adjusting its generated real power within the maximal $P_{g_i}^{\min}$ and minimal limits $P_{g_i}^{\max}$ of 0 to 250 kw. Real power adjustment in two DG system is shown in Figure 3.

Case 2: "The synchronous condenser DG generates only the reactive power" and it is adjusted to get better the voltage profile. A reactive power is adjusted within limits within the maximal $Q_{g_i}^{\min}$ and minimal limits $Q_{g_i}^{\max}$ of 0 to 2500 kw. Reactive power adjustment in two DG system is shown in Figure 4.

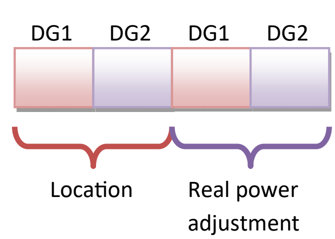

Figure 3: Case 1: Real power adjustment in two DG system (type 1).

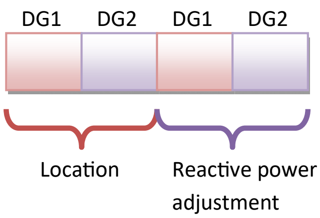

Figure 4: Case 2: Reactive power adjustment in two DG system (type 2). The voltage profile enhancement V_{PE} is given as per Eq. (5).

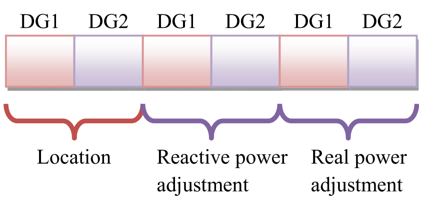

Figure 5: Case 3: Real and reactive power adjustment in two DG system (type 3).

$$V_{\mathrm{PE}} = \min \sum_{i=1}^{N_b} \left| V_i - V_{i,\mathrm{ref}} \right|^2 \tag{5}$$

Where, $V_{i,\mathrm{ref}} \rightarrow$ Rated Voltage at bus i.

Case 3: This type of DG supplies "real power and in turn consume the reactive power". When it comes to wind turbines, the real power is generated by induction generators and the reactive power will be obsessive here. Therefore, the adjustment is made in both the real and reactive power. Real and reactive power adjustment in two DG system (Type 3) is shown in Figure 5.

Then, to again establish the most advantageous placement of DG with a minimum loss, the load flow analysis is computed. The connection between the bus system and DGs is modelled using the load flow analysis that is based on the backward, forward sweep method.

Load flow study

The active and reactive power in an ac power system typically flows from the generating station to the load via diverse bus networks and branches (Rajeshkumar and Sujatha 2019). "The flow of active and reactive power is called power flow or load flow". The load-flow study's main goal is to provide information on:
- Phase angle & voltage magnitude at every bus.
- A flow of "Real and Reactive power" in every element.

Calculating the "real and reactive power" flow passing through each line is significantly simpler once the voltage phase angle have been determined. Further, concerning a power flow difference between the sending and the receiving ends, the line losses can be calculated at each of the lines. This helps determine the most favourable position and the most advantageous ability of the presented generating station substation and new lines. The following "power-flow formulae" are used when putting the DGs into the system at various locations expressed in Eq. (6) and Eq. (7) should be satisfied.

$$\sum_{i=2}^{N_b} \left[P_{g_i} - P_{d_i} - V_i \sum_{j=1}^{N_b} V_j Y_{ij} \cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \tag{6}$$

$$\sum_{i=2}^{N_b} \left[Q_{g_i} - Q_{d_i} - V_i \sum_{j=1}^{N_b} V_j Y_{ij} \cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \tag{7}$$

Where, $P_{d_i} \rightarrow$ Demand of Real power connected at i^{th} bus, $V_i \rightarrow$ Magnitude of Voltage at i^{th} bus, $Y_{ij} \rightarrow$ Admittance amid i^{th} bus and j^{th} bus, $\delta_i \rightarrow$ Phase angle at i^{th} bus, $\theta_{ij} \rightarrow$ Load angle amid i^{th} bus and j^{th} bus, $Q_{g_i} \rightarrow$ Reactive power supplied from i^{th} bus and $Q_{d_i} \rightarrow$ Reactive Power demand at i^{th} bus.

The "backward forward sweep method" is picked for power flow development in the current research work. This approach involves no matrix inversions with limited matrix operations. The two major steps of backward, forward sweep method are:.

Step 1: "backward sweep step→ the branch current" here is computed using KCL depending on node currents.

Step 2: "forward sweep step→ at every nodes", the updated voltages are computed using KVL.

Realization of DG-based DG placement

The decision-making process in the most favourable assignment of DGs is based on the proposed multi-objective optimization algorithm. The overall steps are shown below:

Step 1: Initially, the DG is placed at a location, and its reactive, real, or real + reactive power is adjusted within the minimal and maximal limits.

Step 2: Then, the power loss P_{loss} is computed using the power flow analysis.

Step 3: The voltage limit and power loss P_{loss} is verified to be minimal, which is the objective function. A penalty function is added if the voltage goes beyond or below the limit.

Step 4: This penalty function and P_{loss} is fed as input to suggested plan for minimization. This helps in the optimal placement of DGs.

Objective function and proposed multi-objective optimization approach

Objective function and solution encoding

The multi-objective optimisation method MUHM that has been devised serves as the foundation for the decision-making process for the best placement of DGs. Here, the power loss as well as the penalty function are quite important. Minimizing "the quantity of real power loss inside the distribution system in addition to the penalty function" is the main goal of the current study activity. The objective function Obj is expressed mathematically as per Eq. (8)

$$\mathrm{Obj} = \min\left(P_{\mathrm{loss}} + \mathrm{Penalty}\right) \tag{8}$$

"The losses associated with each branch are computed and summed to calculate the system's total real power loss". The equation for total real power loss P_{loss} is depicted in Eq. (9).

$$P_{\mathrm{loss}} = \sum_{i=2,j=2}^{N_b} \left[P_{g_i} - P_{d_i} - V_i V_j Y_{ij} \cos\left(\delta_i - \delta_j + \theta_{ij}\right)\right] \tag{9}$$

Where, N_b indicates the number of bus. To achieve this objective, the penalty and P_{loss} are fed as the solution to the proposed MUHM algorithm as illustrated in Figure 6.

Proposed MUHM optimization algorithm

The aforementioned optimisation problem is addressed in this work by the development of the innovative algorithm known as MUHM, an enhanced version of the LA model, and the SLnO model. The most intelligent animals, sea lions, provided the raw inspiration that led to the development of the classic SLnO. While LA is based on the "lion's unique characteristics such as territorial defense and territorial take over" (George and Rajakumar 2013; Rajakumar 2013; Swamy, Rajakumar, and Valarmathi 2013).

The mathematical process of the developed optimization concept is depicted below:

Step 1: Total population Pop of result P_{loss} as well as penalty was initialized as t = 1:Pop. Also along with terrestrial lion (both male X^{Ma} and female X^{Fe}), a nomadic lions were initialized. Additionally, the SLnO model represents the separation in between target prey as well as the sea as $\overrightarrow{\mathrm{Dis}}$, & vector position $\vec{S}(t)$ as well as target prey $\vec{M}(t)$ group in location update were initialized.

Step 2: For the current iteration t, if $t \le$ Pop/5, then solution location is updated using the female update of LA revealed in Eq. (10), Eq. (11), and Eq. (12), respectively. X^{Fe} endure update $X^{\mathrm{Fe+}}$ as per Eq. (11).

$$x_l^{\mathrm{Fe+}} = \begin{cases} x_u^{\mathrm{Fe+}}\ ; \text{if } l = u \\ x_l^{\mathrm{Fe}}\ ; \text{otherwise} \end{cases} \tag{10}$$

$$x_l^{\mathrm{Fe+}} = \min\left[x_u^{\max}, \max\left(x_u^{\min}, \nabla_u\right)\right] \tag{11}$$

$$\nabla_u = \left\lfloor x_u^{\mathrm{Fe}} + (0.1r_2 - 0.05)\left(x_u^{\mathrm{Ma}} - r_1 x_u^{\mathrm{Fe}}\right)\right\rfloor \tag{12}$$

Equation for x_l^{Fe+} and x_u^{Fe+} related to l^{th} and u^{th} vector elements were signified in Eq. (11) and Eq. (12), accordingly. A female update function (∇) was manifested Eq. (12). And, r_2 and r_1 were integers.

The resultant of the female update $x_l^{\mathrm{Fe+}}$ is stored in $\overrightarrow{S_{\mathrm{rnd}}}(t)$ and $\vec{S}(t) = \overrightarrow{S_{\mathrm{rnd}}}(t)$.

Step 3: If $t > \mathrm{Pop}/5$ & $t <= 2\mathrm{Pop}/5$, update search agent location with tracking stage of SLnO. Eq. (13) is a mathematical representation of this occurrence. A present step was represented utilizing term t as well as random vector $\vec{G}$ lies between [0, 1] is squared by 2 to increase search space also to attain near-optimal solution. This behaviour of approaching the nearest prey is quantitatively represented by Eq. (14).

$$\overrightarrow{\mathrm{Dis}} = \left|2\vec{G}.\vec{M}(t) - \vec{S}(t)\right| \tag{13}$$

$$\vec{S}(t+1) = \vec{M}(t) - \overrightarrow{\mathrm{Dis}}.\vec{H} \tag{14}$$

The very next step represented as (t + 1) and here, the value of $\vec{H}$ is lessened in a gradual manner from 2 to 0 over the course of iterations.

Step 4: If $t > 2\mathrm{Pop}/5$ & $t <= 3\mathrm{Pop}/5$, then position update was done by exploration phase of standard SLnO.

(a) **Dwindling encircling approach:** $\vec{F}$ value was key term for this scheme. In this $\vec{F}$ value range from 2 to 0 over iteration step. $\vec{F}$ value reduction serves sea lion director in shifting towards a prey as well as surrounding them.

Circle updating position: This mechanism of the sea lions is modeled mathematically as per Eq. (15). Here, the detachment in flanked by the excited solution (target prey) and the search agent (sea lion) is

Figure 6: Solution encoding.

symbolized as $\left|\vec{M}(t) - \vec{S}(t)\right|$. in the interval [−1, 1] the ransomed term is symbolized as l. The sea lions chase these bait balls in a circular motion and $\cos(2\pi l)$ depicts this mechanism.

$$\vec{S}(t+1) = \left|\vec{M}(t) - \vec{S}(t).\cos(2\pi l)\right| + \vec{M}(t) \tag{15}$$

The resultant acquired in the exploration phase is stored in $\overrightarrow{S_{\mathrm{rnd}}}(t)$.

Step 5: The leftover solutions are updated by SLnO exploitation phase. This process is expressed mathematically in Eq. (16) and Eq. (17), respectively.

$$\overrightarrow{\mathrm{Dis}} = \left|2\vec{B}.\overrightarrow{S_{\mathrm{rnd}}}(t) - \vec{S}(t)\right| \tag{16}$$

$$\vec{S}(t+1) = \overrightarrow{S_{\mathrm{rnd}}}(t) - \overrightarrow{\mathrm{Dis}}.\vec{H} \tag{17}$$

A pseudo-code of proposed model is shown in Algorithm 1.

Algorithm 1: Pseudo-code of the proposed model
The overall population Pop of the solution P_{loss} and penalty is initialized
For $t = 1 : Pop$
If 1 $t \le Pop/5$
Update the position of the solution with the female update of LA using Eq. (10), Eq. (11) and Eq. (12)
Else If 2 $t > Pop/5$ $\&\, t <= 2Pop/5$
Update the position of the search agent using Eq. (13)
Else If 3 $t > 2Pop/5$ $\&\, t <= 3Pop/5$
Update the position of the solution with the exploration phase of standard SLnO using Eq.(15)
Else
Update the position of the solution with the exploitation phase of Eq. (16) and Eq. (17)
End if3
End if 2
End if 1
end

The flow chart of the proposed model is shown in Figure 7.

Results and discussion

Simulation procedure

MATLAB was used to develop the suggested hybrid optimisation techniques for the best location and sizing of voltage-controlled generating units in unbalanced distribution networks. On an IEEE bus test system, the created

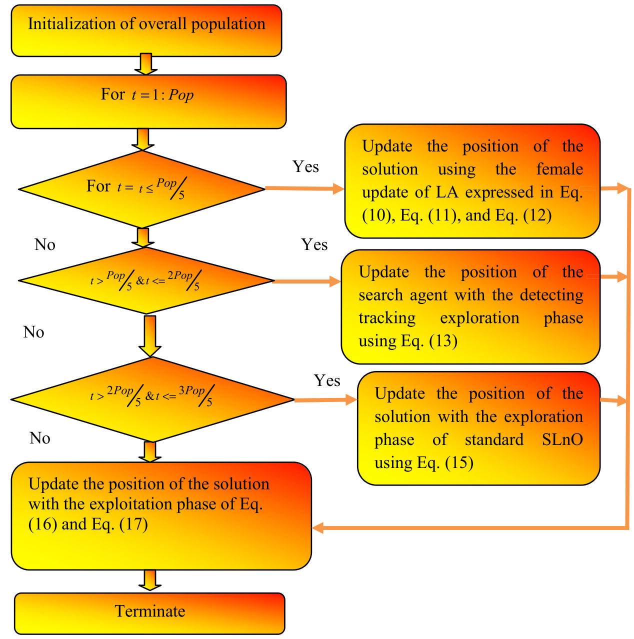

Figure 7: Flow chart of proposed MUHM model.

method MUHM is put to the test. Additionally, a contrast of the suggested method with well-known optimisation methods as SFF, BBO, BAT, LA, and SLnO shows that it effectively reduces power losses. Application of the suggested method to various IEEE test systems, including IEEE 33, IEEE 123, and IEEE 69, respectively, is used to assess its efficacy. The evaluation is completed for DG = 1, DG = 2, and DG = 3 in case of Power loss. The highest count of DG is fixed at 3. Since, three different types of DG are modelled here, the evaluation is done under each case. The evaluation is carried out for each scenario because there are three different forms of DG modelled here. The simulation's inputs are displayed in Table 2.

Power loss evaluation for case 1, case2 and case 3: DG count Versus power loss

The real power is changed and the power loss is assessed for several IEEE test systems, including IEEE 33, IEEE 123, and IEEE 69, in the event of DG type 1. The acquired results are represented visually in Figure 8. The submitted approach, with DG = 1, achieves the lowest power loss in Figure 8(a), which corresponds to the IEEE 33 bus system. Overall, the power loss for the suggested model, MUHM, is reduced when compared to the current model, demonstrating its effectiveness. On observing Figure 8(b), the lowest power is achieved by the presented work and at

Table 2: Simulation parameter.

Algorithm	Parameters
FireFly	Alpha = 0.5; $beta_{min}$ = 0.2; gamma = 1
BBO	KeepRate = 0.2
	Alpha = 0.9
	pMutation = 0.1
BAT	A = 0.5 r = 0.5
	Q_{min} = 0
	Q_{max} = 2
LA	Mature_age = 3 maxium strength = 3
	Gmax = 10
	mutation_rate = 0.15
	Maxium age = 3
	Male rate = 0.15
	Female rate = 0.15
SLnO	θ = 45°
	φ = 45°
Proposed	θ = 45°
	φ = 45°

DG = 2, the presented work MUHM is 2, 3, 2.3, 4 and 4.2% better than SFF, BBO, BAT, LA and SLnO, respectively. In Figure 8(c), the presented work achieved the lowest power loss in the case of the varying count of DGs. The lowest power loss is achieved by the presented work at DG = 2.

Figure 9 exhibits the evaluation of suggested plan over the existing work for type 2 DGs (case 2). On observing Figure 9(b), the presented work has achieved the lowest power loss, and at DG = 1, the presented work is 5, 4.8, 9, 6 and 5% better than existing SFF, BBO, BAT, LA and SLnO, respectively. Then, on observing Figure 9(b) and Figure 9(c) corresponding to IEEE 123 and IEEE 69, the presented work achieves the lowest power loss.

Then, the suggested scheme contrasting with existing work for type 3 DGs (case 3). Here, the lowest power loss is recorded in Figure 10(a) when DG = 1. In situation of IEEE 123 bus system, the presented work achieves the lowest power loss when DG = 2 and it is 2, 1.3, 2.3, 4 and 6% better

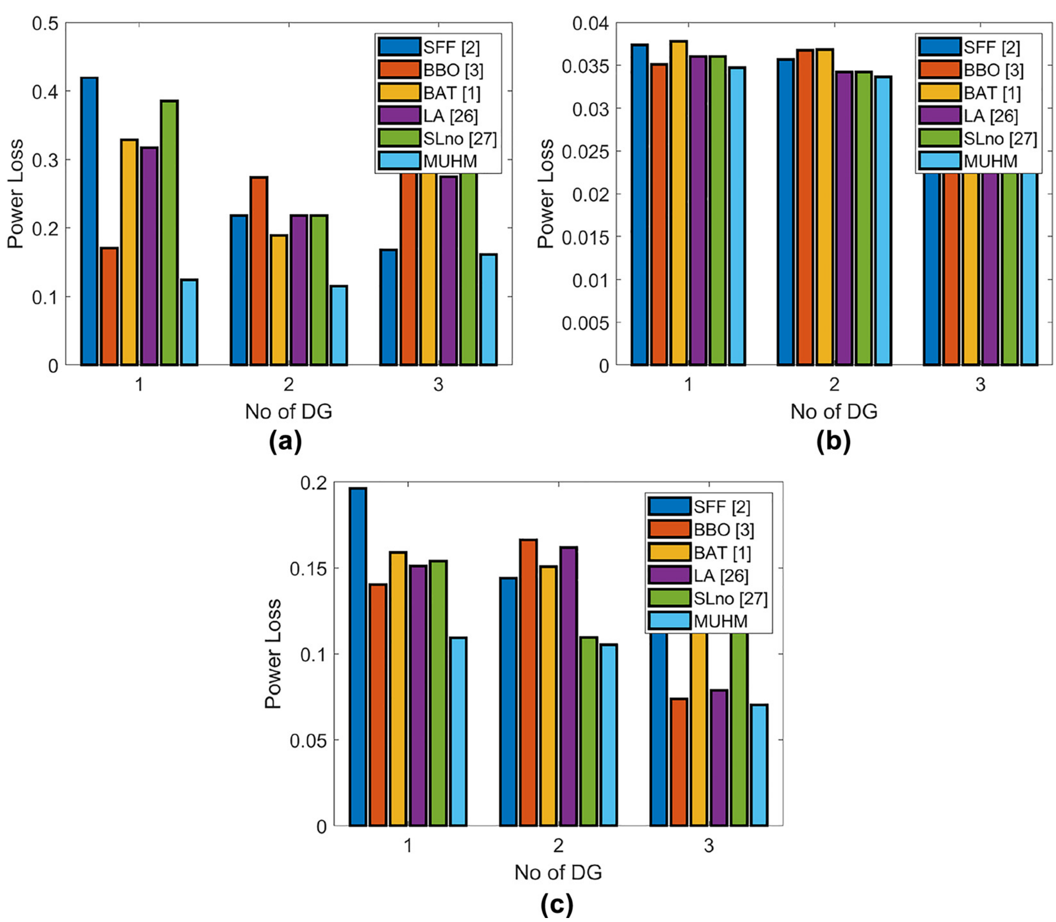

Figure 8: Power loss versus DG count evaluation for type 1 DG (case 1) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

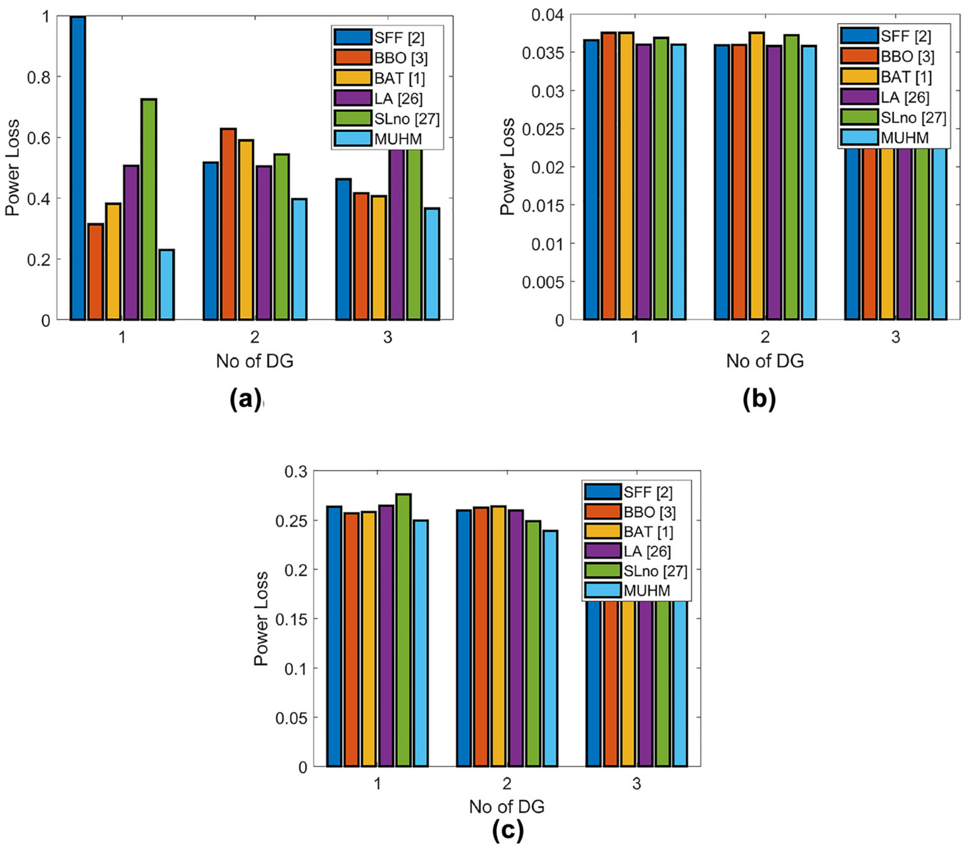

Figure 9: Power loss versus DG count evaluation for type 2 DG (case 2) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

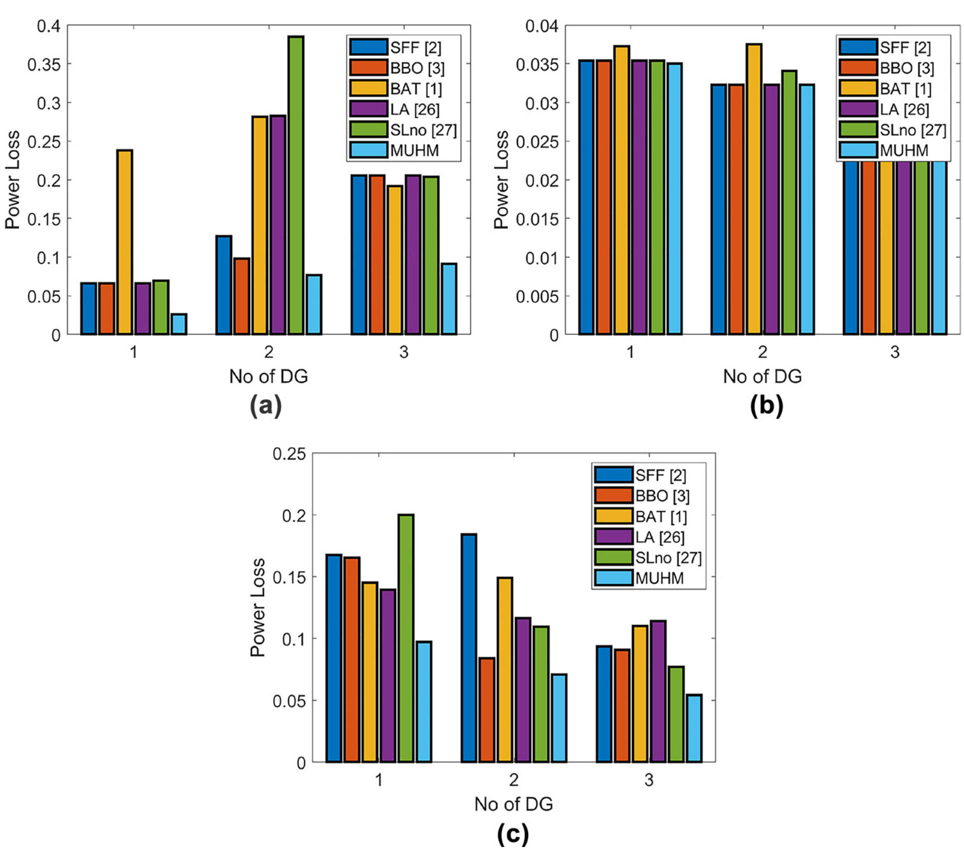

Figure 10: Power loss versus DG count evaluation for type 3 DG (case 3) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

than SFF, BBO, BAT, LA and SLnO, respectively. In Figure 10(c), the lowest power loss is recorded by the presented work when DG = 3. It is clear from the overall assessment that the work presented has produced the least amount of power loss.

Power loss evaluation for case 1, case 2 and case 3: loading versus power loss

Figure 11 shows the loading versus power loss for suggested scheme over the traditional job for different IEEE test systems like IEEE 33, IEEE 123 and IEEE 69, respectively, for type 1 DG (case 1). The loading percentage (LP) is varied from 0 to 40. In Figure 11(a) and Figure 11(b), the lowest power is achieved in IEEE 33 and IEEE 123 bus networks in all variations in the loading percentage. Then, in the case of Figure 12(a), the lowest power loss is recorded at LP = 0 and it is 5, 8.6, 4, 5.6 and 9% better than traditional SFF, BBO, BAT, LA and SLnO, respectively. Then, in the case of Figure 12(b) corresponding to type 2 DG (Case 2), the presented work achieves the lowest power loss in case of all the variations in the loading percentage. Similar to this, the presented work achieves the lowest power loss in IEEE 69 bus network in the case of each variation in the loading percentage. Figure 13 shows the power loss evaluation for variation in the loading percentage for case 3 DGs. In Figure 13(a), the lowest power is achieved by the presented work at loading percentage = 0 and it is 12%, 15%, 135, 4.65%, and 8% better than SFF, BBO, BAT, LA and SLnO, respectively. Similar to this, the suggested plan achieves the lowest power loss for every variance in the loading percentage in IEEE 123 and IEEE 69, respectively.

Real power evaluation for case1, case 2, and case 3

A presented work acquired the optimal values over existing works for optimal localization of DG at various locations. Table 3 shows the optimal resultant for type 1 DGs corresponding to IEEE bus 69. The resultant real power (P) acquired at each location is shown. When, DG = 2, the real power 0.12 is acquired by the presented work at the

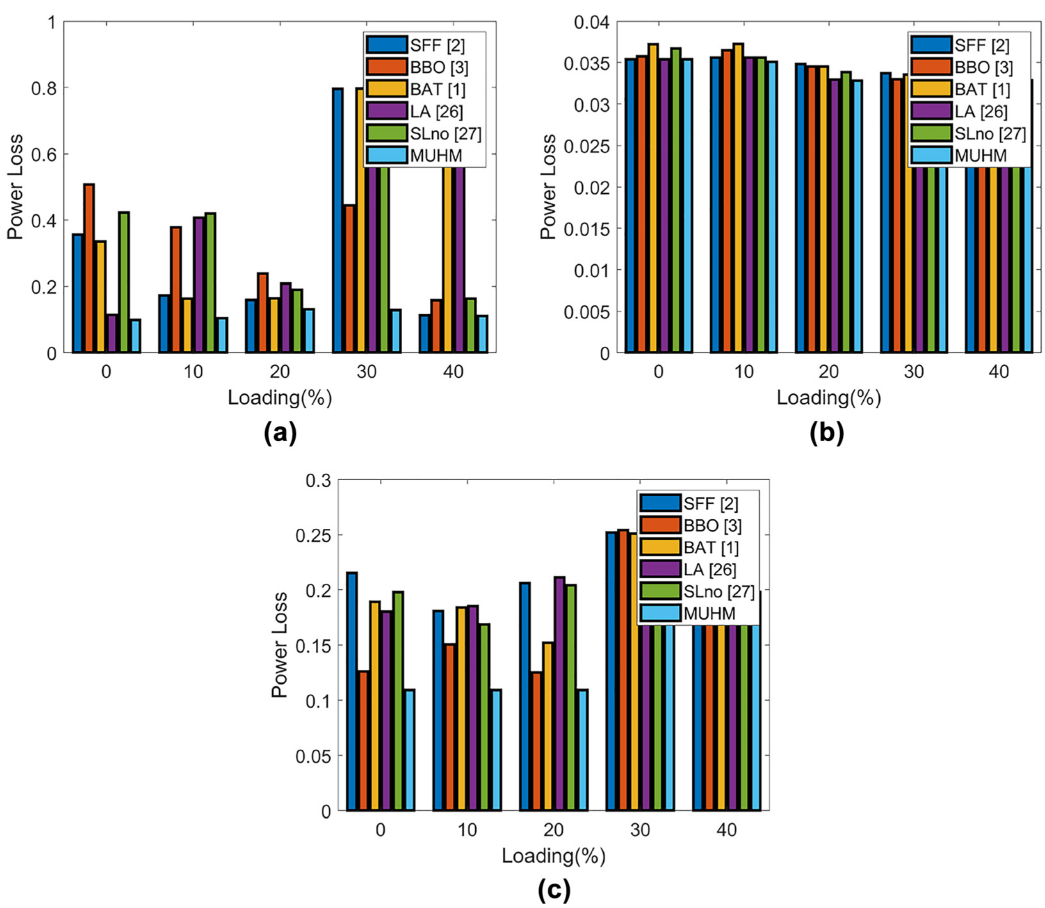

Figure 11: Power loss versus loading factor evaluation for type 1 DG (case 1) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

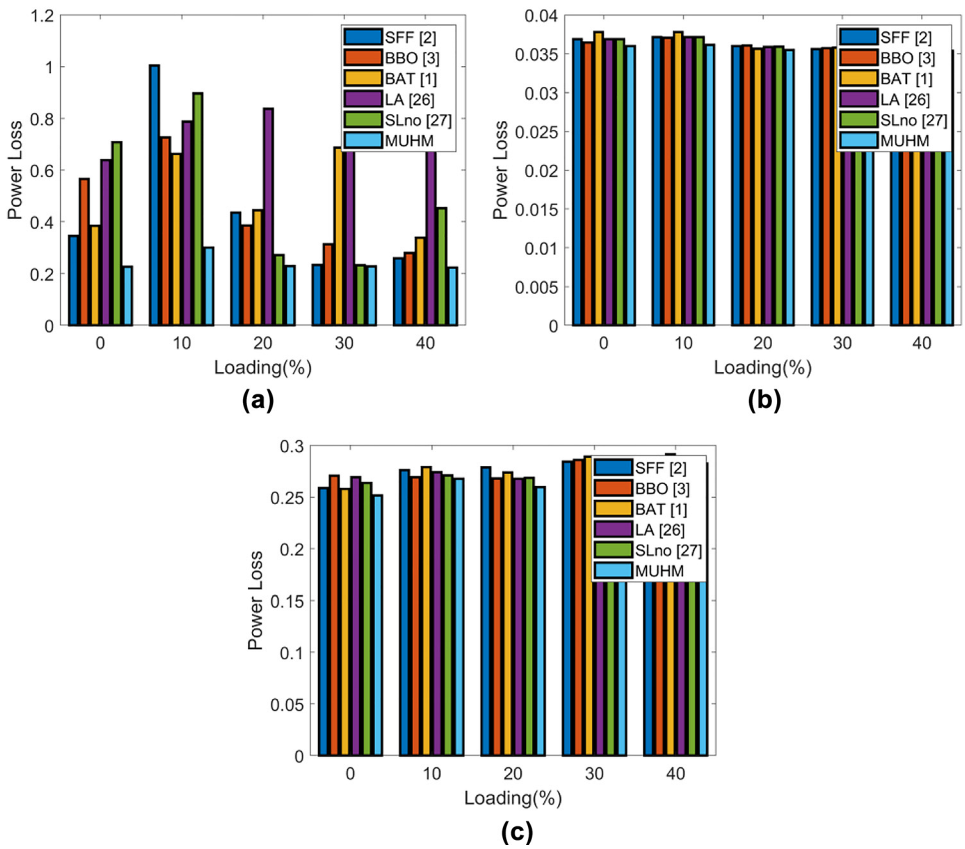

Figure 12: Power loss versus loading factor evaluation for type 2 DG (case 2) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

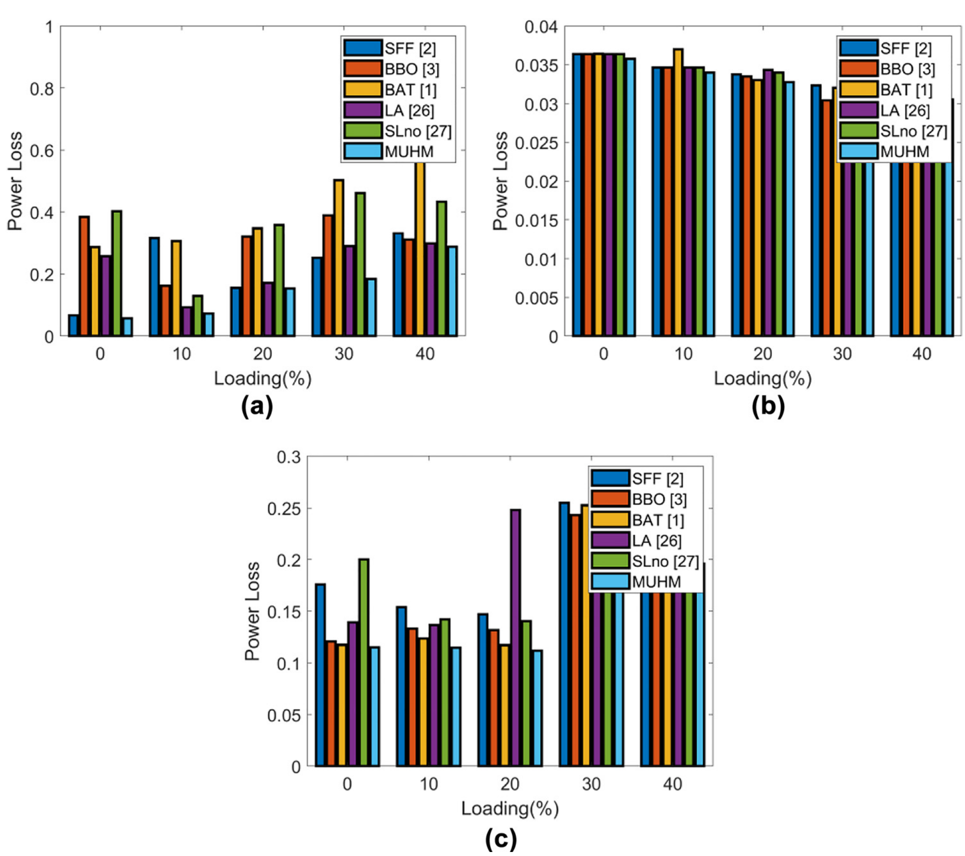

Figure 13: Power loss versus loading factor evaluation for type 3 DG (case 3) for (a) IEEE 33, (b) IEEE 123 and (c) IEEE 69.

Table 3: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type 1 and Type II for IEEE-69 bus system.

Type 1																			
Methods	**DG = 2**				**DG = 3**						**DG = 4**								
	Loc	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***	**Loc**	***P***
SFF (Othman et al. 2016)	27	0.047	65	0.091	63	0.061	65	0.09	12	0.0724	16	0.076	64	0.103	14	0.013	21	0.107
BBO (Ravindran and Victoire 2018)	64	0.12	65	0.0641	64	0.113	65	0.0949	63	0.117	24	0.120	21	0.112	64	0.112	18	0.11
BAT (Sudabattula and Kowsalya 2016)	64	0.12	65	0.064	64	0.113	65	0.095	63	0.117	24	0.12	21	0.112	64	0.12	18	0.11
LA (Boothalingam 2018)	64	0.12	20	0.073	1	0.017	13	0.12	65	0.12	64	0.12	29	0.12	69	0.002	69	0.12
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	69	0.12	65	0.12	65	0.11557	27	0.10391	69	0.12	65	0.086868	56	0.12	69	0.12	69	0.12
MUHM	65	0.103	56	0.114	13	0.045	19	0.033	65	0.12	64	0.089	57	0.12	69	0.057	65	0.12

Type 2																			
Methods	**DG = 2**				**DG = 3**						**DG = 4**								
	Loc	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***	**Loc**	***Q***
SFF (Othman et al. 2016)	56	0.083	20	0.071	55	0.111	56	0.030	54	0.045	46	0.061	56	0.100	25	0.090	27	0.085
BBO (Ravindran and Victoire 2018)	27	0.120	64	0.110	26	0.114	27	0.108	17	0.114	27	0.109	56	0.071	26	0.113	21	0.101
BAT (Sudabattula and Kowsalya 2016)	64	0.120	69	0.120	13	0.120	36	0.018	27	0.120	69	0.118	56	0.088	24	0.12	68	0.051
LA (Boothalingam 2018)	69	0.069	64	0.120	26	0.112	65	0.082	39	0.120	21	0.12	27	0.12	26	0.12	56	0.118
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	27	0.111	32	0.032	63	0.119	68	0.115	16	0.091	69	0.12	64	0.090	27	0.12	69	0.059
MUHM	56	0.120	27	0.120	27	0.12	56	0.120	26	0.120	123	0.12	38	0.12	16	0.12	68	0.12

location (loc) = 64. Then, When DG = 3, the real power is acquired as 0.078719, 0.067731, and 0.11689 at locations 64, and 62.

In Table 4, the real power (*P*) and reactive power (*Q*) for the IEEE-69 bus system's Type III for DG = 2 are displayed. When DG = 2, location 65's actual and reactive power, respectively, are 0.12 and 0.10961. The actual and reactive power of the activity that is being provided at site 24 is then 0.06284 and 0.082147, accordingly, when DG = 3. Then, at optimal location 61, the real power is 0.091612 and the reactive power is 0.084255. Table 5 displays the real power (*P*) and reactive power (*Q*) for the best localisation of the DG under Type III for the IEEE-69 bus system for DG = 3.

The real power and reactive power for optimal localization of DG under Type III for IEEE-69 bus system for DG = 4 is shown in Table 6. When DG = 4, the real and the reactive power of the presented work is 0.092624 and 0.06572 at optimal location 33.

In Tables 7 and 8, the Real Power (*P*) & Reactive Power (*Q*) for DG = 2, DG = 3, and DG = 4 optimal localisation within Type I and Type II for IEEE-33 bus system are shown. On noticing Table 8, at location 24, for DG = 1 belonging to

Table 4: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type III for IEEE-69 bus system for DG = 2.

Methods	DG = 2					
	Location	P	Q	Location	P	Q
SFF (Othman et al. 2016)	65	0.072481	0.084928	25	0.070414	0.047011
BBO (Ravindran and Victoire 2018)	65	0.11591	0.088017	7	0.072972	0.021979
BAT (Sudabattula and Kowsalya 2016)	69	0.052181	0.12	61	0.12	0.12
LA (Boothalingam 2018)	64	0.12	0.12	65	0.12	0.12
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	69	0.029481	0.12	26	0.084681	0.1015
MUHM	65	0.12	0.10961	24	0.0843	0.09549

Table 5: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type III for IEEE-69 bus system for DG = 3.

Methods	DG = 3								
	Location	P	Q	Location	P	Q	Location	P	Q
SFF (Othman et al. 2016)	22	0.056568	0.077265	21	0.049068	0.032575	26	0.071566	0.032664
BBO (Ravindran and Victoire 2018)	21	0.079832	0.081072	20	0.11987	0.076709	64	0.076723	0.02357
BAT (Sudabattula and Kowsalya 2016)	1	0.11994	0.12	7	0.12	0.05785	65	0.12	0.061165
LA (Boothalingam 2018)	65	0.11531	0.11492	11	0.11395	0.09025	63	0.11348	0.059721
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	26	0.074117	0.10754	22	0.057936	0.060953	65	0.093483	0.078027
MUHM	24	0.06284	0.082147	61	0.091612	0.084255	65	0.066121	0.10513

Table 6: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type III for IEEE-69 bus system for DG = 4.

Methods	DG = 4											
	Location	P	Q	Location	P	Q	Location	P	Q	Location	P	Q
SFF (Othman et al. 2016)	43	0.032	0.023	13	0.087	0.102	64	0.054	0.076	65	0.099	0.082
BBO (Ravindran and Victoire 2018)	27	0.052	0.045	56	0.100	0.107	65	0.038	0.079	64	0.047	0.054
BAT (Sudabattula and Kowsalya 2016)	1	0.086	0.006	1	0.120	0.120	69	0.017	0.093	61	0.120	0.047
LA (Boothalingam 2018)	22	0.010	0.024	4	0.091	0.106	65	0.043	0.071	64	0.111	0.086
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	22	0.017	0.027	18	0.095	0.107	65	0.053	0.072	63	0.116	0.091
MUHM	33	0.093	0.066	26	0.075	0.096	62	0.119	0.092	64	0.006	0.057

Table 7: Real Power (*P*) for optimal localization of DG under Type I for IEEE-33 bus system for DG = 2, DG = 3 and DG = 4.

Methods	DG = 2				DG = 3						DG = 4							
	Loc	P	Loc	P	Loc	P	Loc	P	Loc	P	Loc	P	Loc	P	Loc	P	Loc	P
SFF (Othman et al. 2016)	33	0.102	33	0.12	12	0.100	20	0.083	7	0.077	27	0.023	14	0.097	18	0.0703	12	0.12
BBO (Ravindran and Victoire 2018)	20	0.048	12	0.105	12	0.050	16	0.045	13	0.010	7	0.017	9	0	4	0.0312	10	0.093
BAT (Sudabattula and Kowsalya 2016)	20	0.120	33	0.085	12	0.111	20	0.049	9	0.094	1	0.000	20	0.108	33	0.0959	33	0.100
LA (Boothalingam 2018)	33	0.082	20	0.119	12	0.100	20	0.083	7	0.077	51	0.088	20	0.107	11	0.0907	33	0.074
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	20	0.068	33	0.113	12	0.100	20	0.083	7	0.077	44	0.072	20	0.080	26	0.0609	33	0.12
MUHM	12	0.097	18	0.076	7	0.082	17	0.065	12	0.088	51	0.059	25	0.039	9	0.0656	12	0.082

Table 8: Reactive Power (*Q*) for optimal localization of DG under Type II for IEEE-33 bus system for DG = 2, DG = 3 and DG = 4.

Methods	DG = 2				DG = 3						DG = 4							
	Loc	Q	Loc	Q	Loc	Q	Loc	Q	Loc	Q	Loc	Q	Loc	Q	Loc	Q	Loc	Q
SFF (Othman et al. 2016)	13	0.021	5	0.015	2	0.112	11	0.042	13	0.015	39	0.066	20	0.112	12	0.080	14	0.1178
BBO (Ravindran and Victoire 2018)	33	0.049	12	0.073	13	0.017	30	0.065	16	0.069	39	0.091	25	0.028	12	0.085	8	0.0147
BAT (Sudabattula and Kowsalya 2016)	33	0.058	12	0.085	5	0.117	2	0.117	13	0.016	56	0.088	20	0.002	12	0.118	33	0.0248
LA (Boothalingam 2018)	33	0.091	12	0.075	4	0.109	21	0.044	13	0.015	39	0.113	16	0.005	20	0.110	32	0.0086
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	1	0	13	0.018	4	0.110	2	0.011	13	0.015	54	0.119	26	0.015	27	0.119	33	0.0938
MUHM	24	0.069	12	0.0624	12	0.094	25	0.103	22	0.033	39	0.113	18	0.007	12	0.116	32	0.0378

type I, the proposed model consumes the reactive power of 0.069497 at location 24. Table 9 shows the actual power (*P*) & reactive power (*Q*) for the best localisation of the DG under Type III for the IEEE-33 bus system for DG = 2, and DG = 3.

The real power (*P*) and reactive power (*Q*) for optimal localization of DG under Type III for IEEE-33 bus system for DG = 4 is illustrated in Table 10.

The real power (*P*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 2, DG = 3 and DG = 4 is depicted in Table 11. The reactive power (*Q*) for optimal localization of DG under Type I for the IEEE-123 bus system for DG = 2, DG = 3, and DG = 4 is shown in Table 12.

The real Power (*P*) and reactive power (*Q*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 2, and DG = 3 is illustrated in Table 13. The real Power (*P*) and reactive power (*Q*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 4 is depicted in Table 14.

Convergence analysis

Figure 14 shows the convergence evaluation of the proposed MUHM paradigm over the traditional models. On observing Figure 14, when the iteration increases, the proposed MUHM method accomplishes minimum value when compared with other traditional approaches. From Figure 14, at the 40th iteration, the proposed method is 8.158, 6.559, 8.830, 6.927 and 6.582%, superior to SFF, BBO, BAT, LA and SLnO. As a result, the suggested MUHM algorithm's effectiveness is established.

Computational time

A computational complexity of presented MUHM algorithm over the other traditional algorithm is illustrated in Table 15. On observing Table 15, Conclusion: When compared to previous algorithms, the suggested hybrid MUHM method computes more quickly. A proposed

Table 9: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type III for IEEE-33 bus system for DG = 2, and DG = 3.

Methods	DG = 2						DG = 3								
	Loc	*P*	*Q*	Loc	*P*	*Q*	Loc	*P*	*Q*	Loc	*P*	*Q*	Loc	*P*	*Q*
SFF (Othman et al. 2016)	12	0.069	0.064	29	0.065	0.082	19	0.100	0.045	12	0.094	0.038	24	0.085	0.077
BBO (Ravindran and Victoire 2018)	12	0.069	0.064	29	0.065	0.082	23	0.114	0.037	26	0.101	0.068	12	0.117	0.077
BAT (Sudabattula and Kowsalya 2016)	12	0.029	0.033	29	0.110	0.088	16	0.120	0.120	20	0.120	0.120	10	0.120	0.120
LA (Boothalingam 2018)	12	0.069	0.064	29	0.065	0.082	1	0.114	0.095	9	0.066	0.047	33	0.116	0.071
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	12	0.088	0.071	32	0.067	0.100	20	0.120	0.087	25	0.114	0.087	14	0.120	0.120
MUHM	12	0.052	0.066	25	0.054	0.038	18	0.095	0.102	12	0.097	0.014	17	0.045	0.080

Table 10: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type III for IEEE-33 bus system for DG = 4.

Methods	DG = 4											
	Loc	*P*	*Q*	Loc	*P*	*Q*	Loc	*P*	*Q*	Loc	*P*	*Q*
SFF (Othman et al. 2016)	25	0.073	0.084	12	0.026	0.074	19	0.100	0.041	12	0.013	0.100
BBO (Ravindran and Victoire 2018)	25	0.073	0.084	12	0.026	0.074	19	0.100	0.041	12	0.013	0.100
BAT (Sudabattula and Kowsalya 2016)	25	0.070	0.083	11	0.025	0.074	18	0.095	0.037	12	0.008	0.100
LA (Boothalingam 2018)	25	0.073	0.084	12	0.026	0.074	19	0.100	0.041	12	0.013	0.100
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	25	0.072	0.084	11	0.026	0.074	19	0.099	0.040	12	0.011	0.100
MUHM	28	0.102	0.117	4	0.005	0.12	13	0.082	0.055	14	0.007	0.111

Table 11: Real Power (*P*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 2, DG = 3 and DG = 4.

Methods	DG = 2				DG = 3						DG = 4							
	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*	Loc	*P*
SFF (Othman et al. 2016)	43	0.025	4	0.036	33	0.0007	5	0.016	38	0.107	26	0.0002	21	0.062	2	0.088	22	0.078
BBO (Ravindran and Victoire 2018)	27	0.070	11	0.087	44	0.0204	53	0.029	2	0.053	49	0.114	40	0.096	12	0.006	45	0.088
BAT (Sudabattula and Kowsalya 2016)	1	0.118	1	0	56	0.12	56	0.119	1	0.120	56	0.12	56	0.12	56	0	56	0
LA (Boothalingam 2018)	22	0.071	8	0.024	53	0.0543	14	0.034	28	0.093	18	0.108	38	0.092	55	0.018	34	0.046
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	22	0.071	8	0.024	53	0.0543	14	0.034	28	0.093	12	0.101	34	0.037	8	0.046	27	0.064
MUHM	33	0.069	14	0.109	35	0.1024	53	0.099	51	0.023	18	0.108	38	0.092	55	0.018	34	0.046

Table 12: Reactive power (*Q*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 2, DG = 3, and DG = 4.

Methods	DG = 2				DG = 3						DG = 4							
	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*	Loc	*Q*
SFF (Othman et al. 2016)	28	0.089	3	0.077	18	0.094	11	0.029	44	0.098	27	0.087	30	0.023	9	0.087	52	0.040
BBO (Ravindran and Victoire 2018)	41	0.025	2	0.035	21	0.009	30	0.095	33	0.063	7	0.114	4	0.041	12	0.109	17	0.048
BAT (Sudabattula and Kowsalya 2016)	1	0.001	1	0.12	1	0	56	0.12	1	0	1	0.001	1	0.12	56	0.119	1	0.003
LA (Boothalingam 2018)	27	0.053	26	0.110	19	0.071	44	0.112	29	0.038	51	0.098	38	0.081	33	0.101	25	0.034
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	4	0.050	39	0.076	12	0.034	36	0.109	36	0.024	44	0.043	36	0.081	27	0.006	33	0.014
MUHM	27	0.053	26	0.110	19	0.071	44	0.112	29	0.038	51	0.098	38	0.081	33	0.101	25	0.034

Table 13: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 2, and DG = 3.

Methods	DG = 2						DG = 3								
	Loc	P	Q	Loc	P	Q	Loc	P	Q	Loc	P	Q	Loc	P	Q
SFF (Othman et al. 2016)	10	0.084	0.004	27	0.048	0.098	39	0.014	0.103	52	0.096	0.112	16	0.030	0.015
BBO (Ravindran and Victoire 2018)	10	0.084	0.004	27	0.048	0.098	39	0.014	0.103	52	0.096	0.112	16	0.030	0.015
BAT (Sudabattula and Kowsalya 2016)	56	0.120	0.120	56	0.000	0.000	56	0.000	0.000	1	0.000	0.120	5	0.000	0.000
LA (Boothalingam 2018)	10	0.084	0.004	27	0.048	0.098	39	0.014	0.103	52	0.096	0.112	16	0.030	0.015
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	10	0.084	0.004	27	0.048	0.098	54	0.001	0.058	54	0.104	0.067	35	0.049	0.004
MUHM	56	0.092	0.091	29	0.025	0.022	39	0.014	0.103	52	0.096	0.112	16	0.030	0.015

Table 14: Real Power (*P*) and Reactive power (*Q*) for optimal localization of DG under Type I for IEEE-123 bus system for DG = 4.

Methods	DG = 4											
	Loc	P	Q	Loc	P	Q	Loc	P	Q	Loc	P	Q
SFF (Othman et al. 2016)	47	0.047984	0.041297	49	0.094528	0.11368	10	0.088361	0.043325	9	0.094947	0.042932
BBO (Ravindran and Victoire 2018)	47	0.047984	0.041297	49	0.094528	0.11368	10	0.088361	0.043325	9	0.094947	0.042932
BAT (Sudabattula and Kowsalya 2016)	56	0	0	56	0.12	0.12	1	0.12	0.12	56	0	0
LA (Boothalingam 2018)	47	0.047984	0.041297	49	0.094528	0.11368	10	0.088361	0.043325	9	0.094947	0.042932
SLnO (Masadeh, Mahafzah, and Sharieh 2019)	49	0.097222	0	50	0.073605	0.028471	8	0.028341	0.06325	21	0.02761	0.070462
MUHM	47	0.047984	0.041297	49	0.094528	0.11368	10	0.088361	0.043325	9	0.094947	0.042932

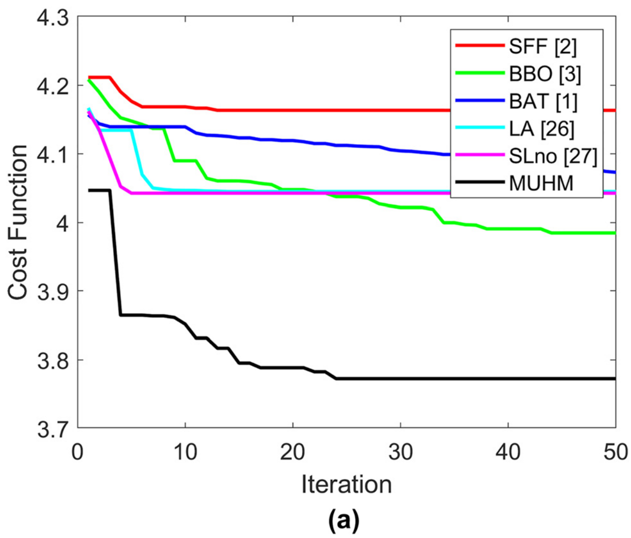

Figure 14: Convergence analysis of the proposed over the conventional models.

Table 15: Computational time of proposed over the conventional models.

S. No	Methods	Computational time (s)
1.	SFF (Othman et al. 2016)	120.09
2.	BBO (Ravindran and Victoire 2018)	126.13
3.	BAT (Sudabattula and Kowsalya 2016)	118.79
4.	LA (Boothalingam 2018)	390.96
5.	SLno (Masadeh, Mahafzah, and Sharieh 2019)	119.99
6.	MUHM	115.4

algorithm is 3.91, 8.51, 2.85, 70.48, and 3.82% better than the conventional SFF, BBO, BAT, LA, and SLnO algorithms.

Conclusions

In order to minimise power/energy loss while remaining within the bounds of the system, this research effort has developed a novel decision-making technique to identify the ideal sizing and localisation of DGs linked to balanced/unbalanced distribution feeders. The suggested method of generating decisions was based on MUHM, a novel multi-objective optimisation algorithm that combines SLnO with LA. Application to various IEEE test systems, including IEEE 33, IEEE 123, and IEEE 69, served as a gauge of the suggested method's effectiveness. By using the most modern machine learning algorithm to aid in the fault location, this work's future directions can be broadened. This suggested MUHM model can be used in the future to size infinite generators with changeable power factor constraints in radial test feeders, such as solar and wind generators. Additionally, a model of this kind will be modified to include capacitors & battery energy storage systems for islanded microgrid uses.

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