**FACTA UNIVERSITATIS**
Series: **Electronics and Energetics** Vol. 37, Nº 3, September 2024, pp. 541 – 560
https://doi.org/10.2298/FUEE2403541G

**Original scientific paper**

# THE SYNERGY OF MPJSA: A NOVEL META-HEURISTIC APPROACH FOR OPTIMIZING DISTRIBUTION SYSTEMS WITH DGS

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**Abstract**. *This article uses an innovative approach to illustrate optimal distribution systems planning, incorporating DG systems. It intends to decrease energy losses while enhancing voltage profiles and the net profit, crucially influenced by reactive and active power injections. The recommended approach combines the Marine Predator Algorithm (MPrA) and Jellyfish Search Algorithm (JSA) into a hybrid meta-heuristic optimization technique named MPrJSA. The hybrid MPrA and JSA draws inspiration from the efficient hunting behavior of marine predators like sharks and the collective movement patterns of jellyfish. By combining these strategies, it aims to enhance optimization algorithms exploration, exploitation, adaptability, and robustness in solving complex problems. Motivated by the societal conduct of marine predators and jellyfish, this hybrid algorithm is employed to assess the consequences of installing DG in radial distribution systems, considering techno-economic benefits. Multiple DGs are evaluated to achieve optimization goals. The MPrJSA effectiveness is illustrated using the IEEE 33-bus system, showing significant reductions in energy and power losses and upgraded voltage profiles with total net profit. Comparative analysis with other nature-inspired approaches highlights the excellence of the proposed method.*

**Key words**: *Distributed Generation, Hybrid Optimization, Marine Predator Algorithm, Jellyfish Search, Radial Distribution System*

## 1. INTRODUCTION

Today, there is widespread agreement that using distributed generators (DGs) made of renewable energy sources is essential for meeting the world growing electricity demand, the difficulty and cost of using conventional power sources, the eventual depletion of

Received February 06, 2024; revised July 02, 2024; accepted July 04, 2024
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those resources, environmental concerns and lowering its overall carbon footprint [1]. As demand rises, it is one of the most effective and practical planning techniques for boosting the network performance.

### 1.1. Background

The distribution and transmission system are two primary parts of the electricity system [2]. At the distribution level, the word DG refers to small, dispersed generation units that are installed close to load center to meet the local energy demand. The introduction of DG into distribution system (DS) involves multiple benefits like improved power quality, cost savings, decrement in losses, improvement in the bus voltages and lower environmental contamination in terms of greenhouse emissions and therefore promotes sustainability. Additionally, it aims to boost the security, stability, and dependability of the system. These days, decentralized microgrids, which include many kinds of DGs, are a hot issue because of their simplicity and efficacy [3]. Due to these socio-economic benefits, the proportion of DG resources in the DS has significantly expanded. DG might have negative consequences on the system's stability, overheating and excessive power losses if not allocated optimally.

### 1.2. Literature Review

The DGs are placed in the optimum configuration to minimize energy losses and maximize benefits. There have been some previous investigations that have allocated DGs. Surveys like those in [4] and [5] have brought attention to how important this issue is. Many researchers have been involved, employing a range of techniques that can be grouped into classical, analytical, metaheuristic, heuristic, and hybrid approaches. The most recent publications in each of these categories are discussed in this section to analyze the research undertaken and identify novel areas of further research. The Kalman Filter Algorithm [6] and the use of dynamic programming and bifurcation analysis in [7] are examples of traditional methods for tackling the DG Allocation Problem.

An analytical technique, which is claimed to be faster and easier than conventional approaches, is provided in [8] and [9] by developing an analytical expression. A dual index technique, an improved interval arithmetic method, and an analytical expression are all suggested in [10-12]. Sensitivity approaches for resolving the DG allocation problem are included in other studies that make use of the analytical methodology [13] and [14]. The analytical method with optimal power flow methodology are used by authors [15] and [16]. The analytical approach is straightforward to use but it can only be used to consider one DG and one objective at a time.

In [17], a non-linear Programming was used to arrange DG sources in the optimum locations. To minimize energy loss, the authors use a wind-based DG allocation strategy using a probabilistic approach [18]. The method suggested in [19] is modified to try to determine the loss sensitivity factors deficiency and to determine where the DGs will ultimately be placed. In order to improve microgrid flexibility and lower operating costs, [20], a unified two-stage stochastic optimisation framework, highlights the usage of flexibility resources like generators with quick starts and quick responses to needs. The study in [21-23] offers a solid mixed integer linear programming (MILP) model for various objectives in microgrid operation like uncertainty, reliability etc. that successfully integrates for various DG operations and models.

The next category of studies are those that used the meta-heuristics algorithms such as swarm intelligence, evolutionary, and physics-based algorithms [24]. Numerous evolutionary algorithms have been used to address DG integration challenges, including the ant lion optimization technique [25], improved moth algorithm [26] and genetic algorithm [27]. Ref [28] design a new voltage stability index for optimal DG allocation using particle swarm optimization (PSO). An optimisation strategy utilising a quadratic transfer function in a particular variation of PSO is suggested [29]. PSO is used because it can effectively tackle intricate, multi-dimensional optimisation issues. In [30] authors make use of bacterial foraging algorithm to identify the ideal sizes and placements for DGs to simultaneously improve voltage stability and minimize operating expenses. The ideal size and place for PV-DG is found using a weighted-sum approach and PSO algorithm, respectively in [31]. The other methods for optimal DG allocation include the curve-fitted technique [32], modified honeybee mating [33]. The grey wolf optimization (GWO) explained in [34] is used to compute power system parameters and for the analysis of the impact of the various factors. In reference [35], the authors elucidate on the GWO approach for determining optimal locations for DG installations. Modified metaheuristic approaches like modified whale optimization algorithm (MWOA) [36] show promise for real-world optimization problems, competing well with contemporary methods. The sensitivity-based approach [37] has shown to be effective in locating DGs optimally close to any load centers.

Combining the operators of different metaheuristic algorithms is one type of hybridization and having superior performance in various terms like solution quality, convergence speed etc. [38,39]. In [40], authors provide a fuzzy-based multi-objective hybrid GA to identify the best location and DG sizes in the RDS for various load scenarios. Clone selection algorithm was used with Fuzzy set theory in two stages by the authors of [41] to determine the ideal placement for the DG and the size of the DG. For the effective DG planning of radial distribution systems, an enhanced wild horse optimization technique is available [42]. A new hybrid genetic PSO is put forth to discover the best distribution of DG with multi-objective system in [43]. A hybrid Teaching-Learning based GFO [44] is suggested for single and multi-objective functions. The study [45,46] implements mixed binary continuous PSO and IoT enabled hierarchical framework to manage fully competitive electricity market problems while integrating renewable energy sources effectively. In [47], compare DG allocation methods based on sensitivity approach. In [48] authors redevelop the MPrA and JFA individually and algorithms were then hybridized to get rid of their individual flaws.

### 1.3. Research Contribution

This article considers multiple DGs for the best siting and rated power values under a variety of operational conditions. Three case studies have been presented without and with DG. It has been found after a thorough analysis of the literature that the Marine Predator Algorithm (MPrA) and Jellyfish Search Algorithm (JSA) algorithms have not been applied yet in case of DG allocation. The MPrA and the JSA are lightened to shorten execution time while maintaining their advantages. The major highlights of this study are:

a) A goal-oriented framework has been created by concurrently considering the three goals of reduce energy loss, enhance the voltage profile and save annual energy loss (AELS).
b) Techno-economic benefits has been analysed on the best combination of DGs in RDS.

c) A novel optimization technique (hybridized MPr-JSA), has been developed to pick the optimal solution with regard to all objectives.
d) On an IEEE-33 distribution feeder, the suggested methodology superiority over alternative approaches has been evaluated.

## 2. MODELLING

### 2.1. Line Modelling

A one-line diagram of Fig. 1 is shown in Fig. 2. The complex power injection at the $u^{th}$ bus is given as,

$$S_u = P_u + jQ_u \tag{1}$$

Where, $P_u$ and $Q_u$ is real and reactive power load at the $u^{th}$ bus, respectively.

The current injected at the $u^{th}$ bus ($I_u$) is given by

$$I_u = \frac{P_u - jQ_u}{V_u^*} \tag{2}$$

Where, $V_u$ is the voltage at $u^{th}$ bus.

The real power loss in a branch connecting node $u$ and $v$ is given by (3)

$$P_{loss}(u,v) = \left(\frac{P_u^2 + Q_u^2}{V_u^2}\right) R \tag{3}$$

### 2.2. Load modelling

The load model chosen is constant complex power load.

$$P_u = P_0 V^0 \tag{4}$$

$$Q_u = Q_0 V^0 \tag{5}$$

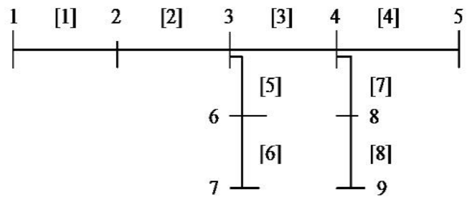


**Fig. 1** Sample distribution network

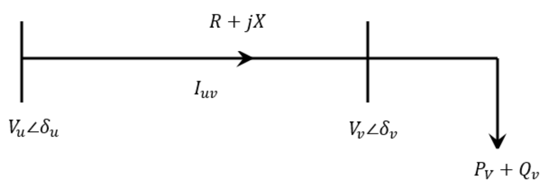


**Fig. 2** Single-line diagram

### 2.3. DG modelling

A DG of small rating is operated as constant negative PQ load. The load at a DG installed node is given by (6) and (7).

$$P_u = P_{load,u} - P_{DG,u} \quad (6)$$

$$Q_u = Q_{load,u} - Q_{DG,u} \quad (7)$$

$$cos\emptyset_{max} = P_{DG,u} \times \tan(\emptyset) \quad (8)$$

Where $P_{load,u}$ and $Q_{load,u}$ is real and reactive power load connected at $u^{th}$ node, respectively. $P_{DG,u}$is generated real and $Q_{DG,u}$is the reactive power of DG at $u^{th}$ node. $cos\emptyset_{max}$ is the maximum power factor.

## 3. Problem Formulation

### 3.1. Objective Function

The presented work is mainly aimed to maximize the benefits of optimal planning of the integration of the DG in RDS. Hence, minimizing the total power loss ($F_1$), voltage deviation ($F_2$) and annual cost of energy loss (ACEL) and DG cost are formulated independently.

*3.1.1. Real power loss Minimization*

The objective function is defined as

$$\text{F1} = \text{minimize } (P_{loss}) = \left(\frac{{P_u}^2 + {Q_u}^2}{{V_u}^2}\right) R \quad (9)$$

*3.1.2 .Voltage deviation minimization*

For voltage profile improvement, the voltage deviation has to be minimised which is defined as

$$F_2 = \text{minimize}\,(V_D) = 1/\textstyle\sum_{u=1}^{N}(V_u - V_{rated})^2 \quad (10)$$

*3.1.3 Annual cost of energy loss and DG cost minimization*

The total net profit (TNP) is the difference between ACEL without DG and ACEL with DG. This can be maximised by minimizing the ACEL [28] due to introduction of DG

$$ACEL = (P_{loss} \times E_C \times T)\ \$ \quad (11)$$

where the energy rate $E_C$ is 0.06\$/kWh and annual time duration $T$ is 8760 h (24 h throughout 365 days).

DG's real power cost characteristics [47] is expressed as

$$C(P_{DG}) = a \times P_{DG}^2 + b \times P_{DG} + c\ \$/\text{h} \quad (12)$$

Where cost coefficients are [27]: $a = 0, b = 20\ and\ c = 0.25$

### 3.2. Constraints

The objective functions are subject to constraints. The power balance equations are given as:

$$P_{Gu} = P_{loss,u} + P_{L,u} \tag{13}$$

$$Q_{Gu} = Q_{loss,u} + Q_{L,u} \tag{14}$$

where $P_{Gu}$ and $Q_{Gu}$ are generated active and reactive powers at the $u^{th}$ bus, respectively. Similarly, the inequality constraints are required to be restricted within upper and lower bounds and are given as in [28]:

$$\text{Bus voltage limit, } 0.95\ pu \leq V_u \leq 1.05\ pu \tag{15}$$

$$\text{Thermal Constraint, } i_u \leq i_u^{Max} \text{ line current at node u} \tag{16}$$

$$\text{Reactive limit, } Q_{Gu}^{Min} \leq Q_{Gu} \leq Q_{Gu}^{Max} \tag{17}$$

$$\text{Real limit, } P_{Gu}^{Min} \leq P_{Gu} \leq P_{Gu}^{Max} \tag{18}$$

$$\text{DG real power generation, } 0 \leq P_{DG,u} \leq P_{DG,u}^{Max} \tag{19}$$

$$\text{DG reactive power generation, } 0 \leq Q_{DG,u} \leq Q_{DG,u}^{Max} \tag{20}$$

## 4. MARINE PREDATORS-JELLYFISH SEARCH OPTIMIZATION ALGORITHM

### 4.1. Marine Predators Algorithm

A contemporary algorithm such as MPrA was inspired by the interactions between the ocean predators and their prey as well as the Levy and Brownian movement techniques [49].

#### *4.1.1. Initialization*

MPrA derives its initial solutions at random using (21).

$$Prey_j^k = lb^k + rand(0,1) \times (ub^k - lb^k) \tag{21}$$

Where $Prey_j^k$ and rand (0,1) are the $k^{th}$ dimension of the $j^{th}$ prey's position and a random number between (0,1), respectively. $ub^k$ and $lb^k$ are the upper and lower bounds on the $k^{th}$ dimension, respectively

#### *4.1.2. Optimization*

The algorithm is divided into three phases which simulate predator tactics use to capture a prey. Each of the three primary stages of the MPrA takes into account a different velocity ratio. A specified number of iterations are assigned for each phase.
*Phase 1* (*Exploration stage*): Prey is quicker (higher velocity) than the predator
Phase 1 is selected while $It < 1/3\ Max_{iter}$. The solutions are updated using (22).

$$Prey_j = Prey_j + P.R \times stepsize_j \tag{22}$$

$$stepsize_j = R_{Bj}(Elite - R_{Bj} \times PRE_i) \tag{23}$$

$$R_{Bj} = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{24}$$

Where $R_{Bj}$ and R, a matrix of numbers generated by the Brownian movement and matrix of random numbers within (0,1), respectively and are of size 1 × dim. Coefficient P is 0.5,. Elite is the best solution found till date.

*Phase 2* (*Exploration and Exploitation stage*): In terms of unit velocity ratios, the prey and the predator travel almost simultaneously.

The solutions are equally divided for exploitation and exploration. The Predator oversees exploring, and the prey is being exploited. The prey's displacement and the predator movement is dictated by the Levy function and the Brownian motion, respectively. The following equations are updated for the one-half of the population.

$$stepsize_j = R_{Lj}(Elite - R_{Lj} \times PRE_i) \tag{25}$$

$R_{Lj}$ is a matrix of the same size that of R that contains random walk data generated by the Levy function which is given as

$$L(Prey_j) \approx |\omega|^{1-a} \tag{26}$$

where the $\omega$ is the flight length and a is in the range (1, 2) that controls the scale, taken as 1.5. The following integral shows the probability distribution associated with Levy function:

$$f_L(\omega; a, \gamma) \approx \frac{1}{\pi} \int_0^{\infty} \exp(-\gamma q^a) \cos(q\omega)\, dq \tag{27}$$

which reduces further for colossal value of $\omega$:

$$f_L(\omega; a, \gamma) \approx \frac{\gamma \Gamma(1+a) \sin\left(\frac{\pi a}{2}\right)}{\pi \omega^{(1+a)}} \omega \longrightarrow \infty \tag{28}$$

Where Γ is a Gamma function.

The latter segment of the population involved in exploration is governed by equations (29-31).

$$Prey_j = Prey_j + P.CF \times stepsize_j \tag{29}$$

$$stepsize_j = R_{Bj}(Elite \times R_{Bj} - Prey_j) \tag{30}$$

$$CF = \left(1 - \frac{IT}{Max_{Itre}}\right)^{\left(2 \times \frac{IT}{Max_{Itre}}\right)} \tag{31}$$

where CF controls the step size.

*Phase 3 (Exploitation stage):* Relative to the prey, the predator has a higher velocity.

Predators are kept up to date during this phase. Eq. (32-33) formulated this behavior mathematically.

$$Prey_j = Elite + P.CF \times stepsize_j \tag{32}$$

$$stepsize_j = R_{Lj}(Elite \times R_{Lj} - Prey_j) \tag{33}$$

**Input:** Number of predators ($N_{pred}$), maximum iteration ($Max_{iter}$), FADs, problem's specifications and parameters
**Output:** *Elite*
% Initialization
Create initial predators within the problem space randomly by equation 21
Calculate Predators' fitness and select Elite

for *It* = *1*: $Max_{iter}$
    % Optimization
    if $It < \frac{1}{3}\ Max_{iter}$
        Update Predators by equation 22
    else if $It > \frac{1}{3}\ Max_{iter}$ $\&\&It < \frac{2}{3}\ MaxIt$
        Update first half of the Predators by equation 24
        Update second half of the Predators by equation 29
    else if $It > \frac{2}{3}\ Max_{iter}$
        Update Predators by equation 32
    end if
    Calculate Predators' fitness and update Elite

    % Marine memory
    Apply greedy selection mechanism

    % Eddy formation
    Update Predators by equation considering the FADs
    Calculate Predators' fitness and update Elite

    % Marine memory
    Apply greedy selection mechanism
end for
Return *Elite*

**Fig. 3** Pseudocode for MPrA

*4.1.3 Eddy formation*

This phase emulates Fish Aggregating Devices (FAD), leading to a behavioural shift in predators, mathematically formulated as follows:

$$Prey_j = \begin{cases} Prey_j + CF \times [lb + R \times (ub - lb)] \times U & r \leq FADs \\ Prey_j + [FADs \times (1-r) + r](X_{r1} - X_{r2}) & otherwise \end{cases} \tag{34}$$

$$U = rand(1, dim) < FADs \tag{35}$$

Where U is a binary vector, the FADs is 0.2, Xr1 and Xr2 are two random solutions selected among the population.

*4.1.4 Predator memory*

Marine predators have an excellent memory for places where they have been successful in finding food and returns to those locations after successful foraging [49]. By preserving memories in MPrA, this capacity is emulated. The solutions in each iteration is compared with its previous solution to determine the better solution. The pseudo-code is shown below.

### 4.2. Artificial Jellyfish Search Algorithm

*4.2.1. Inspiration*

The artificial JFSA [50] mimics the jellyfish movement in either swarm or on their route to the ocean current in search of food.

*4.2.2. Initialization*

Jellyfish population is initialized randomly. This might lead to slow convergence and a risk of getting stuck in local optima due to poor population diversity. Logistic chaotic map given in Eq. (36) offers a reduced probability of early convergence and more varied initial populations than random initialization.

$$JS_{i+1} = \eta JS_i(1 - JS_i), 0 \leq JS_0 \leq 1 \tag{36}$$

where, $JS_i$ is the logistic chaotic value; $JS_0$ is varied to generate initial jellyfish population, $JS_0 \notin \{0, .25, .5, .75, 1\}$, and 4 is the value for the parameter $\eta$.

*4.2.3. Ocean current*

The average of the vectors from every jellyfish to the one in the best location at any given time is used to determine the direction of the ocean current. and is provided with (37).

$$\overrightarrow{Direction} = \frac{1}{N_{JSP}} \sum (JS^* - e_c JS_i) \tag{37}$$

where, $N_{JSP}$ represents number of jellyfishes in swarm and $JS^*$ represents the best jellyfish while attraction govern factor is represented by $e_c$.

$$\overrightarrow{Direction} = JS^* - e_c \frac{\sum JS_i}{N_{JSP}} = JS^* - e_c \mu_{JS} \tag{38}$$

Where $\mu_{JS}$ shows the mean position of all the jellyfishes in an ocean

$$e_c = \beta_{JS} \times rand(0,1) \tag{39}$$

Where $\beta_{JS}$ is distribution coefficient whose value is taken as 3.
The new jellyfish position is defined as:

$$JS_i(t+1) = JS_i(t) + rand(0,1) \times \overrightarrow{Direction} \tag{40}$$

Substituting (38) and (39) in (40) gives

$$JS_i(t+1) = JS_i(t) + rand(0,1) \ [JS^* - (\beta_{JS} \times \mu_{JS} \times rand(0,1))] \tag{41}$$

*4.2.4. Jellyfish swarm*

The majority of jellyfishes exhibit passive motion (type A) at first around their initial sites, as the jellyfish swarm is still forming. They start to move more actively (type B) as time progresses.

$$JS_i(t+1) = JS_i(t) + \gamma_{js} \times rand(0,1) \times (ub - lb) \tag{42}$$

Where $\gamma_{js}$ represents the motion coefficient and its value is taken as $0.1$.

The direction of the motion of the jellyfish in search of its food and its updated location in the search space are simulated by (43) and (44), respectively.

$$\overrightarrow{Dir} = \begin{cases} JS_j(t) - JS_i(t) & if\ f(JS_i) \geq f(JS_j) \\ JS_i(t) - JS_j(t) & if\ f(JS_i) < f(JS_j) \end{cases} \tag{43}$$

Where, $f(JS_i) and\ JS_i$ represents the objective function and jellyfish location.

$$JS_i(t+1) = JS_i(t) + \overrightarrow{step} \tag{44}$$

where

$$\overrightarrow{step} = rand(0,1) \times \overrightarrow{Dir} \tag{45}$$

*4.2.5. The control mechanism*

The time control function ($C(t)$) [0,1] helps in determining the type of jellyfish motion and its switch from one swarm to another over time. The jellyfish float with the ocean current if its value surpasses $C_0$ and remain as part of the swarm when it is < $C_0$.

$$C(t) = \left|\left(1 - \frac{1}{Max_{Iter}}\right) * (2\, rand(0,1) - 1)\right| \tag{46}$$

where, $Max_{iter}$ represents maximum number of iterations.

*4.2.6. Boundary conditions*

A jellyfish that ventures outside the search area's bounds will eventually return back. This reintegration process is depicted by

$$\begin{cases} JS'_{i,d} = (JS_{i,d} - U_{b,d}) + L_b(d) & if\ JS_{i,d} > U_{b,d} \\ JS'_{i,d} = (JS_{i,d} - L_{b,d}) + U_b(d) & if\ JS_{i,d} < L_{b,d} \end{cases} \tag{47}$$

Where the $i^{th}$ jellyfish location in $d^{th}$ dimension is represented by $JS_{i,d}$ and its lower and upper bounds in food search space is given by $L_{b,d}$ and, $U_{b,d}$ respectively . $JS'_{i,d}$ is the updated position of the ith jellyfish.

The extended learning vector in Learning automata (LA) is given by the following equation:

$$P_r = \{P_1, P_2, \dots \dots, P_{nm}\} \tag{48}$$

$$P_r = \begin{bmatrix} P_{1JS1} & \cdots & P_{nmJS1} \\ \vdots & \ddots & \vdots \\ P_{1JSNoJS} & \cdots & P_{nmJSNoJS} \end{bmatrix} \tag{49}$$

The optimal motions are more likely to be chosen since they have more likely values. Non-optimal solution movements, on the other hand, have lower probability values and, thus, a lesser likelihood of being chosen.

$$Action\_index = find\left(rand(0,1) \le \frac{p_i}{\sum_{i=1}^{nm} p_i}, 1'first'\right) \tag{50}$$

where *find* is a searching function and $p_i$ represents the probability of $i^{th}$ motion. The pseudocode for the proposed JSA is illustrated in Fig. 4.

```
Input: No. of jellyfish (NoJS), parameters value, maximum iteration, problem's
specifications
Output: JS*

% Initialization
Initialize jellyfishes using Logistic chaotic map using equation no. 47
Calculate JS's fitness and select JS*

For It = 1: Max_Iter
        for i = 1: NoJS
                Calculate time control parameter using equation 46
                if C(It) ≥ C_0
                        % Ocean current Movements
                        Update ith jellyfish using equation 40
                else
                        % inside swarm movement
                        if rand(0,1) ≥ 1 − C(It)
                                % Passive Motion
                                Update ith jellyfish using equation 42
                        else
                                % Active motion
                                Update ith jellyfish using equation 44
                        end if
                end if
                Check ith jellyfish feasibility and apply greedy selection mechanism
                Calculate fitness of the ith jellyfish and update JS*
        end for
end for

Return JS*
```

**Fig. 4** Pseudocode for JSA

### 4.3. LA-based Hybridization

The limitations of the individual metaheuristic algorithms such as insufficient movements of jellyfish, scattering of jellyfishes in the search space and MPrA complexity, slow or premature convergence locking in local optima and sluggish search is overcome by the proposed hybridization of the LA-based MAJSA which will improve the reliability of the algorithms. Fig. 5 shows the MAJSA flowchart.

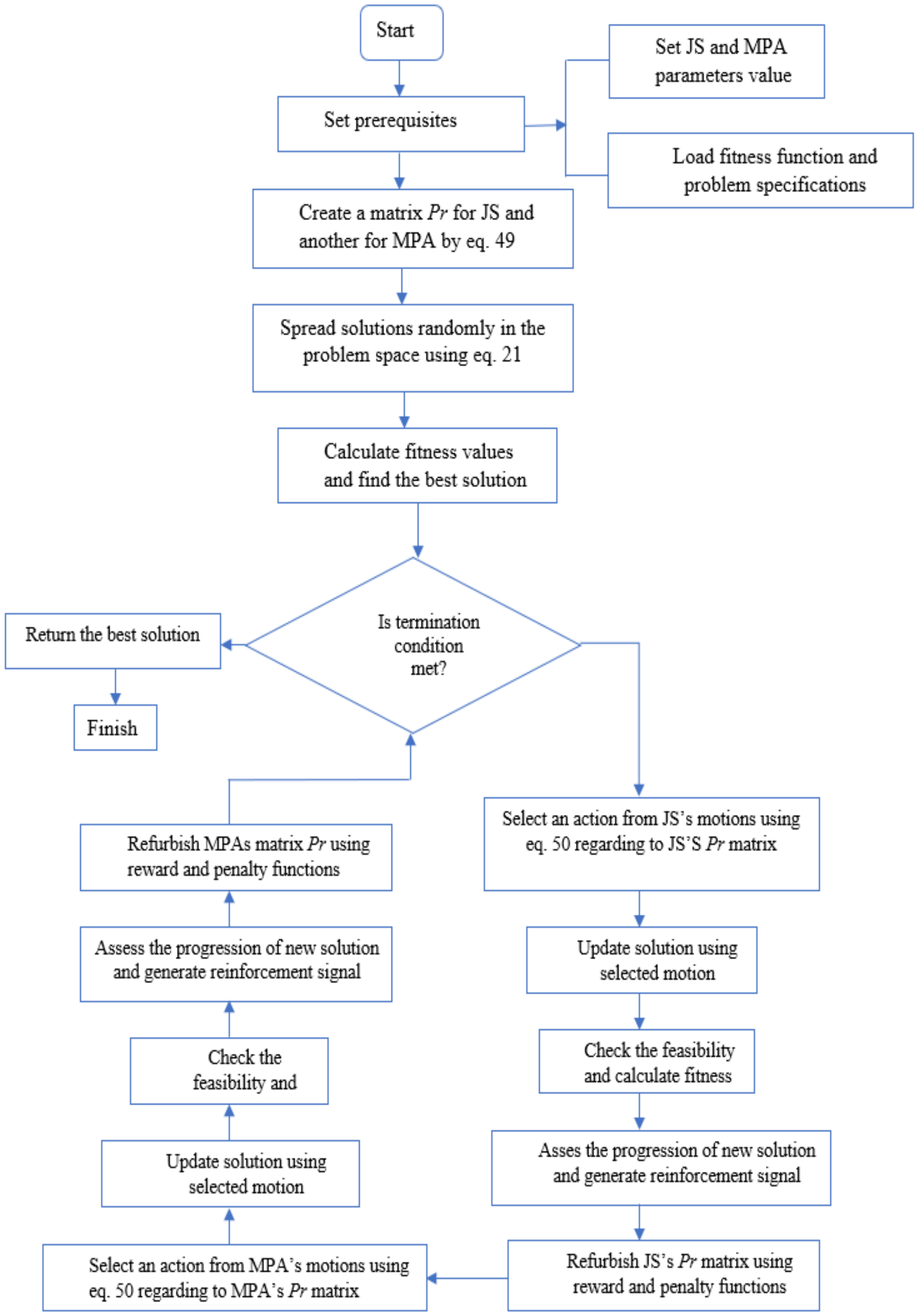


**Fig. 5** Flow chart for hybrid MPrJSA

## 5. Simulation Results and Analysis

The IEEE 33 bus RDS [51] has (3.72+j2.3) MVA of power load demand. The base values are 12.66 kVA and 100 MVA. It is used to illustrate and evaluate the feasibility of the suggested technique in installation of DG units in using hybrid MPJSA. The DG size cannot exceed 2 MW. The three case studies considered are

1. Base case scenario (no DG)
2. Second scenario (2 DG units' installation)
3. Third scenario (3 DG units' installation)

The load flow calculations provide the bus voltages and power losses. The ACEL and energy loss reductions are calculated. The performance of hybrid MPJSA is compared to PSO, Differential Evolution (DE), JSA and MPrA algorithms available in the literature and is presented in Table 1.

In all the scenarios, the performance from the hybrid MPJSA outweighs others in terms of losses and (min) voltage. Applying the suggested methodology yields the best DG integration for both the cases under consideration.

**Table 1** Performance evaluation of different algorithms for 33-bus RDS at unit power factor

| No. of DG | Algorithm | DG location | $V_{min}$ pu. @ bus (% improvement) | RPL (kW) | RPLR in kW (%) | REPL (kVAr) | $C(P_{DG})$ ($/h) | ACEL ($) | TNP/AELS ($) |
|---|---|---|---|---|---|---|---|---|---|
| Base Case | _ | - | 0.9131@ 18 | 210.0704 | - | 142.4372 | - | 110,413.0 | - |
| Two DG | PSO | 14, 33 | 0.9595 (5.08%) | 79.6471 | 130.4233 (62.08) | 52.3366 | 6.855 | 41,862.51 | 68,550.49 |
| | DE | 15, 33 | 0.9595 (5.08%) | 79.6172 | 130.4532 (62.09) | 52.3103 | 6.856 | 41,846.80 | 68,556.2 |
| | JSA | 15, 32 | 0.9619 (5.35%) | 79.2253 | 130.8451 (62.28) | 51.5741 | 6.877 | 41,640.81 | 68,772.19 |
| | MPrA | 15, 31 | 0.9620 (5.36%) | 79.0780 | 130.9924 (62.35) | 51.5115 | 6.885 | 41,563.39 | 68,849.61 |
| | Proposed MPrJSA | 15, 32 | 0.9622 (5.37%) | 79.0077 | 131.0627 (62.38) | 51.4336 | 6.888 | 41,526.44 | 68,886.56 |
| Three DG | PSO | 15, 31, 33 | 0.9714 (5.84%) | 51.4309 | 158.6395 (75.51) | 35.2859 | 8.338 | 27,032.08 | 83,380.92 |
| | DE | 16, 30, 33 | 0.9715 (5.84%) | 49.0461 | 161.0243 (76.65) | 32.9086 | 8.463 | 25,778.63 | 84,634.92 |
| | JSA | 15, 30, 33 | 0.9748 (6.75%) | 48.7440 | 161.3264 (76.79) | 32.6901 | 8.479 | 25,619.84 | 84,793.16 |
| | MPrA | 13, 30, 33 | 0.9660 (5.79%) | 49.4146 | 160.6558 (76.47) | 33.5292 | 8.444 | 25,972.31 | 84,440.69 |
| | Proposed MPrJSA | 15, 30, 32 | 0.9716 (6.40%) | 48.1950 | 161.8754 (77.057) | 31.8756 | 8.508 | 25,331.29 | 85,081.71 |

### 5.1. DG impact on Power Losses

Table 1 makes it evident that the real power loss (RPL) and reactive power loss (REPL) without DG placement was found to be 210.0740 kW and 142.4372 kVAr. After the 2-DG and 3-DG unit installation the losses got reduced to 79.0077 kW and 48.195 kVAr with a real power loss mitigation (RPLR) of 62.38% and 77.057%, respectively. This will result in the release of the 131.0627 kW in real power demand.

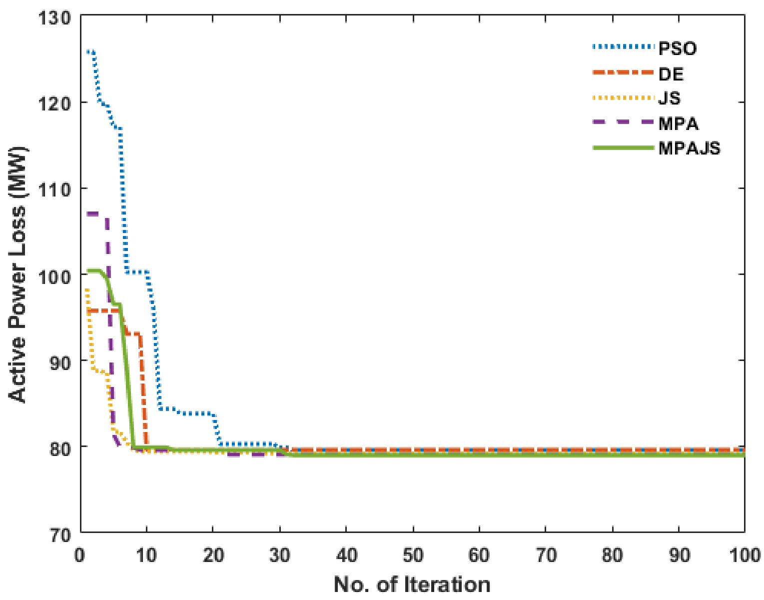


**Fig. 6** Convergence curve with 2 DG units

For scenario 2, the corresponding percentages of power loss reduction are 62.08, 62.09, 62.28, 62.35 and 62.38 for techniques PSO, DE, JSA MPrA and hybrid MPrJSA respectively. For scenarios 3, the corresponding percentages of power loss reduction are 75.51, 76.65, 76.79, 76.47 and 77.057 for techniques PSO, DE, JSA MPrA and hybrid MPrJSA respectively. This will result in the release of the 161.8754 kW in real power demand. Comparing the convergence curves shown in Fig 6 and 7, it is observed that the suggested method achieved faster convergence than the other techniques.

### 5.2. DG impact on Voltage Profile

Table 1 shows that each scenario significantly improves the system's min voltage magnitude. In the base case, the min voltage is enhanced from 0.9131 pu to 0.9622 and 0.9716 pu at 18$^{th}$ bus for case 2 and case 3 with a voltage improvement of 5.37% and 6.40% respectively. Fig. 8 and 9 compare and display the voltage profiles for two scenarios which have greatly improved following integration of DG.

### 5.3. DG impact on Annual Energy Loss Savings

The strategic placement of the DG units improves net profit by mitigating the ACEL from 110,413.00$ to 41,526.44$ and 25,331.29$ for 2-DG and 3-DG units, respectively. The TNP for the two cases are 68,886.56$ and 85,081.71$, respectively from Table 1.

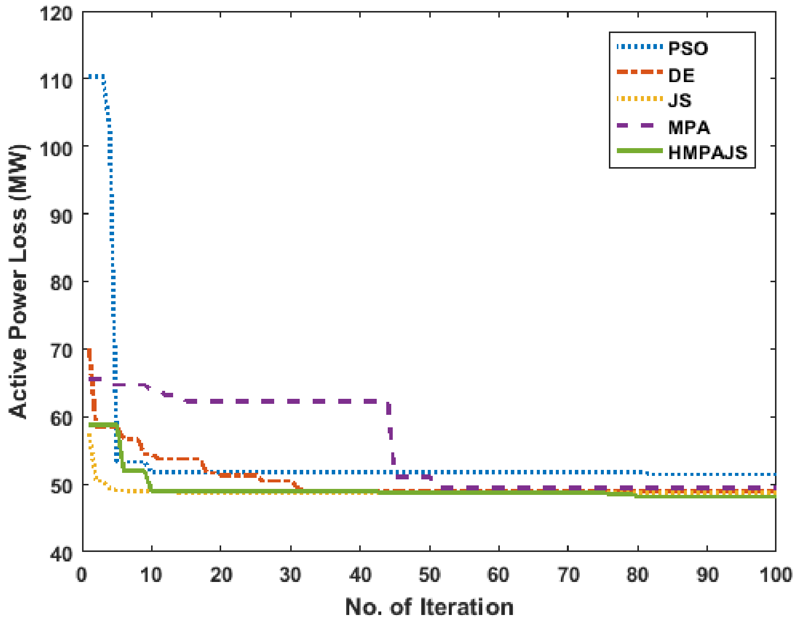


**Fig. 7** Convergence curve with 3 DG units

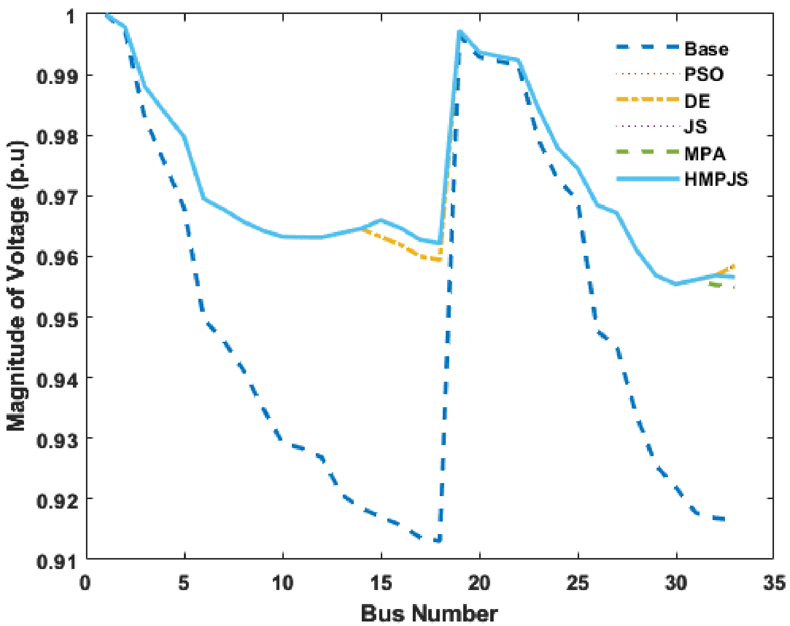


**Fig. 8** Voltage Profile for 2 DG installation

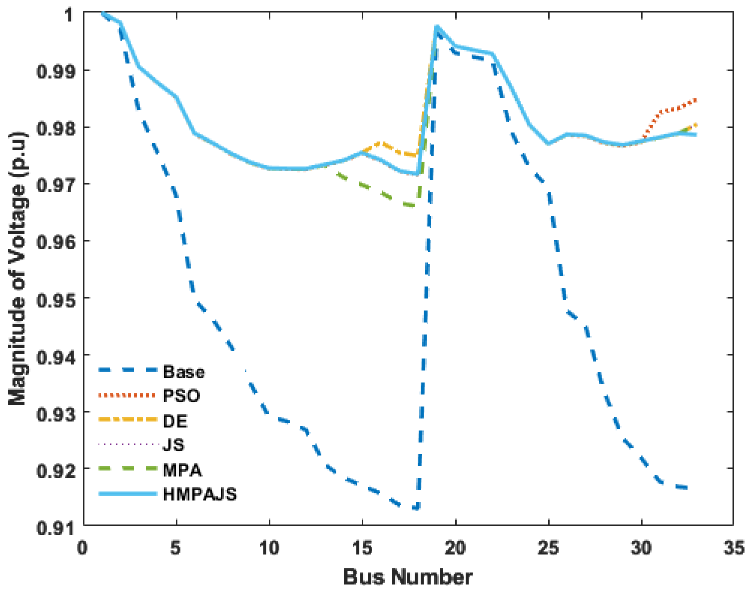


**Fig. 9** Voltage profile for 3 DG units installation

In Table 2, the outcomes of MPrJSA are contrasted with a number of previously established techniques from the literature. When compared to other approaches, MPrJSA is observed to provide the best result.

**Table 2** Comparison of outcomes with alternative algorithms for 33-bus RDS

| Method | Power loss without DG, kW | Two DGs | | Three DGs | |
|---|---|---|---|---|---|
| | | location | Power loss, kW | location | Power loss, kW |
| Fuzzy Clonal algorithm [40] | 203.27 | 30, 32 | 117.3946 | 30, 31, 32 | 117.358 |
| Backtracking Search [19] | 210.84 | 13, 31 | 89.34 | 13, 28, 31 | 89.05 |
| KHA [54] | 210.98 | 29, 13 | 87.426 | 14, 24, 30 | 73.2968 |
| SKHA [54] | 210.98 | 13, 30 | 87.1656 | 13, 24, 30 | 72.7853 |
| Proposed MPrJSA | 210.0704 | 15, 32 | 79.0077 | 15, 30, 32 | 48.1950 |

## 6. CONCLUSION

The hybrid MPJSA method has been effectively used in this study to address the DG integration in the distribution system. To demonstrate the superiority of the proposed approach in loss reduction and improved voltage magnitude due to 2 DG and 3 DG installation in IEEE 33 RDS is used to evaluate the suggested technique to provide notable performance in terms of appreciable rise in min voltage, reduction in ACEL and remarkable net profit savings. The percentage of RPLR and net savings are improved in the range of 62.08-77.057% with multiple DG penetration. The findings show that multiple DG installation is more efficient than single DG installation. The simulated outcomes are also compared with the other algorithms result reported in the literature.

According to the computational findings, the hybrid MPJSA performs more effectively than the others in most circumstances. The proposed solution methodology provides higher net savings.

Power and energy systems have undergone a revolution in the previous several decades. One potential future goal is to manage distributed energy resources (DERs) deployment, and microgrids (an array of dispersed energy supplies and loads that is often linked to the grid upstream) have emerged as a critical component of smart grids [52]. Studying algorithms in larger power systems with more buses and VAR compensators presents promising research avenues. This includes scalability assessment, power flow optimization, VAR compensator integration, network resilience, renewable energy management, cybersecurity, and real-time challenges. Risk management during energy exchange, owing to load demand and DG uncertainty in RDS were also future issues [53]. Researchers aim to advance algorithmic solutions for better power grid efficiency, reliability, and resilience.

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