ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
*Volume 13, Issue 1, March 2024*

# PARALLEL HYBRID PARTICLE SWARM-GREY WOLF ALGORITHMS FOR OPTIMAL LOAD-SHEDDING IN AN ISOLATED NETWORK

Sujono[1], Ardyono Priyadi[2], Margo Pujiantara[3], Mauridhi Hery Purnomo[4]

[1,2,3] Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember
[4] Department of Computer Engineering, Institut Teknologi Sepuluh Nopember
[1] Departemen of Electrical Engineering, Universitas Budi Luhur

email: 7022201016@student.its.ac.id[1], ardyono@its.ac.id[2], margo@ee.its.ac.id[3], hery@ee.its.ac.id[4]

**Abstract**

In distribution networks integrated with distributed generation (DG), disconnection from the main grid reduces the power supply significantly. The power imbalance between DG generation and load degrades network stability. This paper proposes a hybrid parallel Particle Swarm Optimization - Grey Wolf Optimizer (PSGWO) algorithm for load shedding optimization. This optimization aims to reduce the DG power not absorbed by the remaining loads and maintain the voltage within the specified limits. The performance of PSGWO is tested on an IEEE 33 bus radial distribution system, considering loading levels of 80% to 140% of the baseload. At a 100% loading level, PSGWO showed the best performance, with a load shedding of 2.2297 MW and a voltage deviation of 0.0049. These values are the smallest compared to the results of the standard PSO and GWO algorithms. The PSGWO algorithm remains superior and converges faster than standard PSO and GWO at all loading levels.

**Keywords :** load shedding, islanding, distribution network, particles swarm, grey wolf

**Received:** 01-03-2024 | **Revised:** 16-03-2024 | **Accepted:** 18-03-2024
DOI: https://doi.org/10.23887/janapati.v13i1.76093

## INTRODUCTION

Distributed generation (DG) is a low-capacity power generation system integrated in the distribution network close to the load center [1]. DG is generally sourced from renewable energy with small power capacity and geographically dispersed locations [2]. The application of DG in modern power systems is currently increasing because it is sourced from renewable energy that is environmentally friendly and has various advantages. DG integration can improve network performance, especially in loss reduction and maintaining bus voltage [3].

DG integration allows the distribution network to operate in two modes [4]. The first mode is grid-connected. In grid-connected mode, the distribution network meets the power demand of the load by utilizing the main grid and DG as a source. The power composition of both sources must be properly regulated to produce optimal power flow conditions. Ultimately, optimal power flow impacts the losses, bus voltage quality, and loading of the distribution lines. The second mode is isolated. This mode occurs when the distribution network's connection to the main grid is intentionally disconnected for maintenance or forced to be disconnected due to a fault on the network. In isolated mode, the distribution network must supply power to the load by relying on DG power generation. The DG generation capacity is deficient compared to the load power, causing a power imbalance. These conditions can significantly degrade the grid's stability, even cause blackouts, and stop all power supply to loads [4].

Operational strategies on isolated distribution networks can be done in several ways. The first is network reconfiguration by utilizing sectional tie switches that modify the network topology [5],[6]. In this way, the distribution line loading can be reorganized. The second is to divide into multiple independent pico-grids based on the presence of DGs [7]. The DG acts as a power source for the loads in each pico-grid. Network reconfiguration optimization using Grey Wolf Optimizer (GWO) is presented in [8], and a similar study was discussed in [9] by applying Geometric Mean Optimization (GMO) to improve voltage stability and minimize losses in isolated distribution networks. However, in some cases, isolated distribution networks cause huge power deficits between DG capacity and load. This situation makes the strategy of reconfiguring the network and dividing the network into multiple pico-grids inapplicable.

The power balance of an isolated DG-integrated network can be realized by releasing some of the loads connected to each bus. In the shedding process, the presence of priority loads that cannot tolerate the absence of a power supply must be considered. In addition, the composition of the remaining load at each bus after load shedding determines the balance and flow of power in the network, losses, bus voltage, and line loading in the distribution network. For this reason, an appropriate and optimal load-shedding strategy is required.

Various studies on load-shedding strategies in isolated networks have been conducted. Paper [10] presents load shedding and restoration strategies in isolated DG-integrated distribution networks using mixed-integer quadratic constraint programming (MIQCP). A load-shedding strategy to maintain energy supply to priority loads by applying time-continuous load flow is presented in [11]. Similar studies applying stochastic programming formulations and Markov decision processes to maximize network economic performance are discussed in [12]. The paper [13] discusses the distributed coordination approach using a sub-gradient algorithm on isolated networks to achieve practical and optimal load shedding. A data-driven load-shedding strategy using Duel deep Q-learning to maximize frequency recovery speed is presented in [14]. Optimal load planning taking into account topology and DG capacity in isolated networks has been presented in [15]. A distributed load shedding strategy based on network analysis for voltage collapse prevention is presented in [16]. The utilization of artificial intelligence-based algorithms in optimal load shedding planning has been widely studied. In [17], the application of Backtracking Search Algorithm (BSA) on load shedding planning to maintain power balance in isolated networks is presented. A similar study by applying the hybrid firefly-PSO algorithm is presented in [18].

Early detection of grid isolation by applying artificial neural networks and load-shedding techniques using BSA are discussed in [19]. Paper [20] discusses a hybrid method of genetics (GA) and neural networks (NN) on optimizing load shedding and maintaining voltage stability. The selection of priority buses and loads that must be released using the GA-PSO hybrid algorithm is discussed in [21], while in [22], using a hybrid of PSO-ABC. The load-shedding strategy in overcoming power deficit with the PSO algorithm to reduce the released load is presented in [23].

PSO and GWO are commonly used algorithms in optimization. PSO has simplicity in mathematical modeling, is easy to implement, and has low memory requirements [24]. PSO has a fast global search capability but not so in local search. PSO has early convergence, so it is easily trapped in local optima [25] and provides low-quality solutions [26][27]. GWO is an optimization method focusing on the three most optimal individual [28]. GWO has a slightly more complex mathematical model than PSO. In local search, selecting the three best solutions to be used in the solution update at each iteration can accelerate the convergence of GWO [29] [30]. Combining the advantages of the two algorithms allows an algorithm that can converge quickly and have better solution quality.

This paper proposes a hybrid parallel Particle Swarm-Grey Wolf Optimizer (PSGWO) algorithm for load-shedding optimization. This optimization aims to reduce the DG power not absorbed by the remaining loads in the network and maintain the load bus voltage within the specified limits. The proposed algorithm is to hybridize in parallel to get the best solution between PSO and GWO at each iteration, which is used in the next iteration to converge faster and get a globally optimal solution.

The contributions of the paper include the following:

- Proposed parallel hybrid of PSO-GWO algorithm to improve the optimization performance which converges faster and produces global optimal solution.
- Optimization of load shedding strategies in isolated DG integrated distribution networks to maximize the remaining load in the network.
- Optimization considering priority load and network loading level.
- Load shedding strategy to maximize the utilization of DG generation in maintaining the continuity of power supply to the load.
- Optimal composition of load retained after load shedding so that power losses in the network are minimized.

## METHOD

The load-shedding strategy aims to realize the power balance between the maximum capacity of the DG generation and the demand for the load. The load that is released must be determined appropriately so as to obtain a power equilibrium with an optimal composition of the remaining load on the network. The optimal composition of the remaining load at each bus determines the power flow in the network so that it can reduce losses and voltage deviations in the network. Some important parameters are

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
*Volume 13, Issue 1, March 2024*

used in optimizing load shedding, which are discussed in the following subsections.

**Distribution Line Power Loss**

Figure 1 shows part of the distribution line connecting bus-$i$ and bus-$j$. Power proportional to the line current ($I$) flows from bus-$i$ to bus-$j$ through a line with impedance ($R_{i,j} + X_{i,j}$). The powers at bus-$i$ and bus-$j$ are $P_i$, $Q_i$, $P_j$, and $Q_j$, respectively. The load power at bus-$i$ and bus-$j$ are $PL_i$, $QL_i$, $PL_j$, and $QL_j$, respectively.

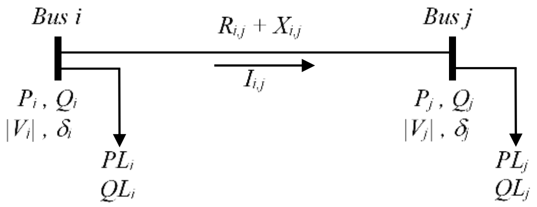



Figure 1. Two bus network

The line loss ($P_{loss-i,j}$ and $Q_{loss-i,j}$) are expressed in equations (1) and (2) below [31]:

$$P_{loss-i,j} = R_{i,j} \cdot \left|I_{i,j}\right|^2 \quad (1)$$

$$Q_{loss-i,j} = X_{i,j} \cdot \left|I_{i,j}\right|^2 \quad (2)$$

Total line losses are the accumulation of all line losses expressed in equations (3) and (4).

$$P_{loss-total} = \sum_{k=1}^{NL} R_k \cdot |I_k|^2 \quad (3)$$

$$Q_{loss-total} = \sum_{k=1}^{NL} X_k \cdot |I_k|^2 \quad (4)$$

k is the line number, NL is the number of lines, R is the line resistance, X is the line reactance, and I is the line current.

**Voltage Deviation Index**

The length of the line from the generating bus to the load bus causes a voltage drop proportional to the total impedance and line current. The voltage difference between the load bus and the generating bus is known as voltage deviation. The voltage deviation index ($TDV$) is the accumulation of the square of the absolute value of the voltage deviation for all buses in the distribution network [32]. Mathematically, the $TDV$ value can be expressed as in equation (5).

$$TDV = \sum_{i=2}^{NB} |V_s - V_i|^2 \quad (5)$$

$NB$ is the number of buses, $V_s$ and $V_i$ are the source and actual voltages at bus-$i$, respectively.

**Load Power Remains**

The relationship between the total load on the network before and after load shedding and the total load shed from the network is expressed mathematically as equation (6).

$$P_{remain} = P_{load-total} - P_{shed} \quad (6)$$

$P_{load-total}$ is the total load before the shedding process, $P_{shed}$ is the load released from the network, and $P_{remain}$ is the total load remaining in the network after the load-shedding process.

**Formulation of Objective Function**

Load-shedding optimization aims to maximize the amount of load remaining in the network after the shedding process, as expressed in equation (7).

$$f_{obj} = max(P_{remain}) \quad (7)$$

To maintain power balance in isolated networks, $P_{remain}$ should not exceed the generation capacity of the DG as a power source. The difference between the total DG generation capacity ($P_{DG}$) and the remaining load ($P_{remain}$) is used as a power reserve ($P_{reserve}$) expressed in equation (8).

$$P_{reserve} = P_{DG} - P_{remain} \quad (8)$$

The objective function to maximize $P_{remain}$ in equation (7) can be expressed as (9) to minimize $P_{reserve}$.

$$f_{obj} = min(P_{reserve}) \quad (9)$$

**Constraints**

The balance and imbalance constraints that must be met in load shedding optimization include the following:

- *Power balance*
  The power balance between DG generation, remaining load, and losses in the network after the load shedding process is expressed in equations (10) and (11).

$$\sum_{i=1}^{N_{DG}} P_{DG,i} = \sum_{j=1}^{N_b} P_{remain,j} + P_{loss-afterLS} \quad (10)$$

$$\sum_{i=1}^{N_{DG}} Q_{DG,i} = \sum_{j=1}^{N_b} Q_{remain,j} + Q_{loss-afterLS} \quad (11)$$

  $P_{DG,i}$ and $Q_{DG,i}$ are the active and reactive power generation by DG-$i$, respectively, $N_{DG}$ is the number of DGs in the network, $P_{remain,j}$ and $Q_{remain,j}$ are the active and reactive power of the remaining load at bus-$j$, $P_{loss-after\ LS}$ and $Q_{loss-after\ LS}$ are the total active and reactive power losses in the network, respectively.

- *Allowable bus voltage magnitude*
  The overall voltage magnitude of the buses in the network must be within the allowable limits.

$$V_{min} \le V_i \le V_{max} \ \ , i = 1,2,3,\ldots.,Nb \quad (12)$$

  $V_i$ is the voltage magnitude at bus-i, $V_{min}$ is the minimum voltage limit ($V_{min}$= 0.95 p.u), and $V_{max}$ is the maximum voltage limit ($V_{max}$= 1.05 p.u).

- *Minimum remaining load power at each bus in the network*
  The remaining load power is equal to or greater than the priority load for each bus in the network.

$$P_{priority,i} \le P_{remain,i} \quad (13)$$

$$Q_{priority,i} \le Q_{remain,i} \quad (14)$$

  $P_{priority,i}$ and $Q_{priority,i}$ are the powers of the priority load at bus-$i$, respectively. $P_{remain,i}$ and $Q_{remain,i}$ are the powers of the remaining load at bus-$i$ after load shedding.

- *DG Generation*
  DG generation is set at the maximum limit to maximize DG's utilization in maintaining the continuity of power supply to the load.

$$P_{DG} = P_{DG}^{max} \quad (15)$$

  $P_{DG}$ is the DG generation, and $P_{DG}^{max}$ is the maximum DG generation limit.

**Particle Swarm Optimization Algorithm**

PSO is a metaheuristic algorithm inspired by the behavior of a flock of birds when finding food. The simplicity of the mathematical model has made PSO widely applied in various optimization problems. In a flock of $N_p$ birds, each individual has its position $(x_1^t, x_2^t, x_3^t, \ldots, x_{Np}^t)$ and velocity $(v_1^t, v_2^t, v_3^t, \ldots, v_{Np}^t)$. An individual's fitness represents the suitability of their position to the food location. The individual's position is updated based on the individual fitness and repeated until all individuals find the food source in the exact location [24].

Individual positions are updated based on individual fitness and repeated until all individuals find the food source in the right location

$X_{best}$ is the individual's position with the best fitness in each iteration, while $X_{gbest}$ is the position with the best fitness in all iterations that have been performed. Updates to velocity and position are performed using equations (16) and (17).

$$v_i^{t+1} = k.v_i^{t+1} + c_1.r_1\,(X_{best} - x_i^t) + c_2.r_2\,(X_{gbest} - x_i^t) \quad (16)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (17)$$

where, $x_i^t$ and $x_i^{t+1}$ are the position of individual $i$ at iteration $t$ and $t+1$, $v_i^t$ and $v_i^{t+1}$ are the velocity of individu $i$ at iteration $t$ and $t+1$, $k$, $c_1$ and $c_2$ are weight factors, $r_1$ and $r_2$ are random values between 0 and 1, and $i = 1,2,\ldots,Np$.
Velocity and position updates are performed until the maximum iteration or termination criteria have been met.

**Grey Wolf Optimizer**

The GWO algorithm is inspired by the leadership hierarchy in hunting prey of a pack of gray wolves. Alpha (α) is considered the most dominant wolf, followed by Beta (β) and Delta (δ). Omega (ω) is considered the least dominant individual and is only allowed to eat at the last moment [29].

In searching for prey, wolves surround their prey, which can be expressed as equations (18) and (19).

$$D = \left|C.X_p(t) - X(t)\right| \quad (18)$$

$$X(t+1) = X_p(t) - A.D \quad (19)$$

$X_p$ is the prey position, $X$ is the grey wolf position, and $t$ indicates the iteration. $A$ and $C$ are coefficients calculated using equations (20) and (21) below:

$$A = 2.a.r_1 - a \quad (20)$$

$$C = 2.r_2 \quad (21)$$

where $r_1$ and $r_2$ are a random values in [0,1], and the component $a$ is determined by equation (22).

$$a = 2\left(1 - \frac{t}{t_{max}}\right) \quad (22)$$

where, $t_{max}$ is maximum iterations.
Alpha, beta, and delta are the three individuals with the best fitness. All other individuals update their positions based on the positions of the three best individuals with equations (23), (24), and (25).

$$D_\alpha = |C_1.X_\alpha(t) - X| \quad (23)$$

$$D_\beta = \left|C_2.X_\beta(t) - X\right| \quad (24)$$

$$D_\delta = |C_3.X_\delta(t) - X| \quad (25)$$

Adjustment of individual positions to alpha, beta, and delta positions using equations (26), (27), and (28).

$$X_1 = X_\alpha - A_1.D_\alpha \quad (26)$$

$$X_2 = X_\beta - A_2.D_\beta \quad (27)$$

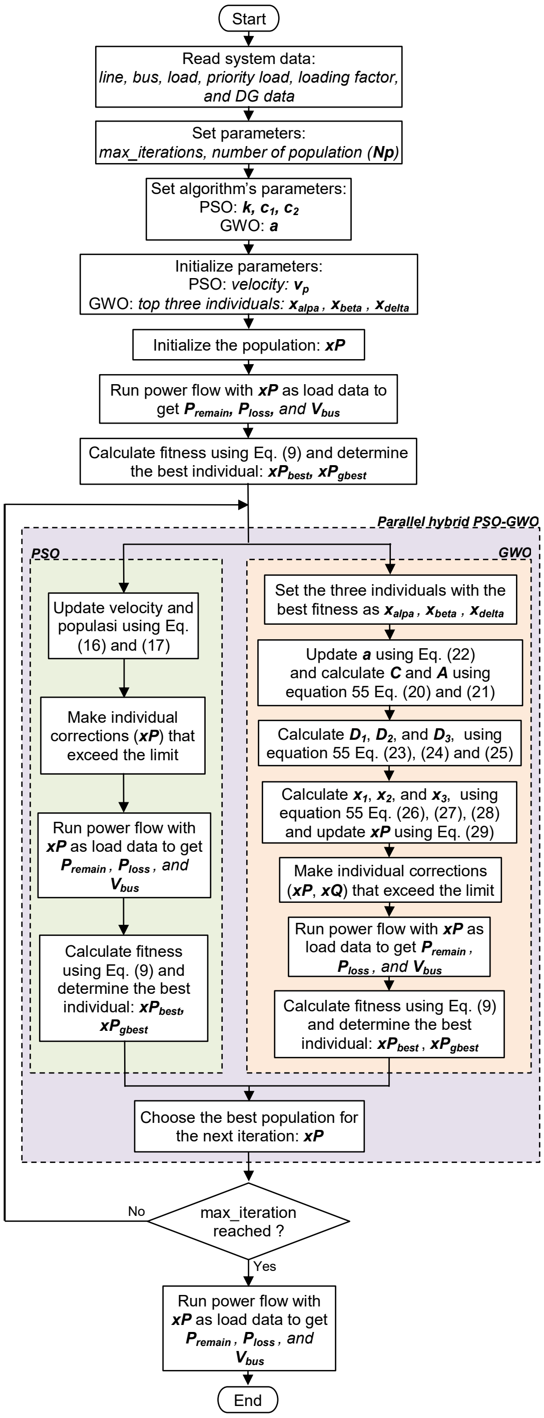
$$X_3 = X_\delta - A_3.D_\delta \quad (28)$$

The final position of an individual at iteration $t+1$ is determined by equation (29). The calculation is repeated until the maximum iteration or stopping criteria is reached.

$$X(t+1) = \frac{X_1+X_2+X_3}{3} \quad (29)$$

**Load shedding optimization procedure using PSGWO algorithm**

The PSGWO algorithm is a parallel hybrid of the PSO and GWO algorithms. At each iteration, both algorithms are applied simultaneously. The best position and fitness at each iteration are selected and used as the basis for calculations in the next iteration. This combination can accelerate convergence and obtain a globally optimal solution. Figure 2 describes the flow chart of load-shedding optimization using the PSGWO algorithm.



ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
*Volume 13, Issue 1, March 2024*

Figure 2. Flowchart of load shedding optimization using PSGWO

## RESULT AND DISCUSSION

The test system used in this study is an IEEE 33-bus radial distribution network (RDN) integrated with three DG units, as shown in Figure 3. The number of buses and lines in the test system are 33 and 32, respectively. The total power of the base load used is 3.715 MW and 2.29 MVAR. Table 1 presents the data of the three DGs integrated into the RDN.

Detailed load data including active and reactive power, power factor, and priority load at each bus in the network is presented in Table 2.

Table 1. Location, type, power capacity, and power factor of DGs

| DG | Bus | Type | Max $P_{out}$ (MW) | Power factor |
|---|---|---|---|---|
| 1 | 8 | PQ-DG | 700 | 0.8 |
| 2 | 25 | PQ-DG | 300 | 0.8 |
| 3 | 30 | PQ-DG | 500 | 0.8 |

Table 2. Baseload data

| *Bus* | $P_{load}$ (kW) | $Q_{load}$ (kVAR) | *power factor* | % *Load priority* |
|---|---|---|---|---|
| 1 | 0 | 0 | - | 0 |
| 2 | 100 | 60 | 0.86 | 33 |
| 3 | 90 | 40 | 0.91 | 24 |
| 4 | 120 | 80 | 0.83 | 20 |
| 5 | 60 | 30 | 0.89 | 17 |
| 6 | 60 | 20 | 0.95 | 24 |
| 7 | 200 | 100 | 0.89 | 36 |
| 8 | 200 | 100 | 0.89 | 22 |
| 9 | 60 | 20 | 0.95 | 7 |
| 10 | 60 | 20 | 0.95 | 20 |
| 11 | 45 | 30 | 0.83 | 0 |
| 12 | 60 | 35 | 0.86 | 33 |
| 13 | 60 | 35 | 0.86 | 10 |
| 14 | 120 | 80 | 0.83 | 28 |
| 15 | 60 | 10 | 0.99 | 12 |
| 16 | 60 | 20 | 0.95 | 45 |
| 17 | 60 | 20 | 0.95 | 38 |
| 18 | 90 | 40 | 0.91 | 33 |
| 19 | 90 | 40 | 0.91 | 15 |
| 20 | 90 | 40 | 0.91 | 48 |
| 21 | 90 | 40 | 0.91 | 21 |
| 22 | 90 | 40 | 0.91 | 29 |
| 23 | 90 | 50 | 0.87 | 5 |
| 24 | 420 | 200 | 0.90 | 17 |
| 25 | 420 | 200 | 0.90 | 11 |
| 26 | 60 | 25 | 0.92 | 36 |
| 27 | 60 | 25 | 0.92 | 21 |
| 28 | 60 | 20 | 0.95 | 25 |
| 29 | 120 | 70 | 0.86 | 16 |
| 30 | 200 | 60 | 0.96 | 35 |
| 31 | 150 | 70 | 0.91 | 23 |
| 32 | 210 | 100 | 0.90 | 32 |
| 33 | 60 | 40 | 0.83 | 4 |

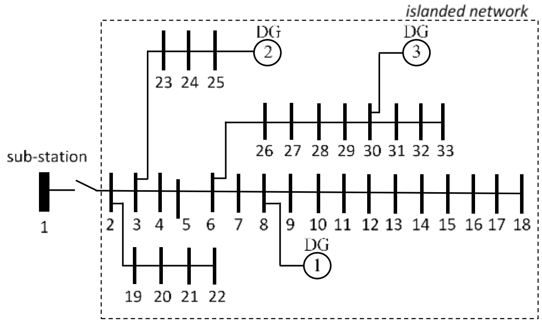



Figure 3. IEEE 33-bus RDN integrated with three DG units

Table 3. Case study on Load Shedding Optimization

| Case study | DGs and location | Max power (MW) | Loading factor (% base load) |
|---|---|---|---|
| 1 | DG 1 (bus 8)<br>DG 2 (bus 25)<br>DG 3 (bus 30) | 700<br>300<br>500 | 80 |
| 2 | DG 1 (bus 8)<br>DG 2 (bus 25)<br>DG 3 (bus 30) | 700<br>300<br>500 | 100 |
| 3 | DG 1 (bus 8)<br>DG 2 (bus 25)<br>DG 3 (bus 30) | 700<br>300<br>500 | 140 |

Table 4. PSO, GWO, and PSGWO algorithm parameters

| Parameter | PSO | GWO | PSGWO |
|---|---|---|---|
| Population (Np) | 30 | 30 | 30 |
| Max Iterations | 100 | 100 | 100 |
| Parameters | kP = 0.25<br>$C_1$ = 2.5<br>$C_2$ = 2 | a = 2 | kP = 0.25<br>$C_1$ = 2.5<br>$C_2$ = 2<br>a = 2 |

The load shedding simulation includes 3 case studies as shown in Table 3.

Load shedding optimization is performed by applying the PSGWO algorithm and compared with standard PSO and GWO algorithms. Table 4 presents the parameters used for each algorithm. The performance of the PSGWO algorithm is measured based on the results of load shedding optimization, which includes the fitness of the desired objective, convergence speed, power loss in the network, and bus voltage profile after load shedding.

***Case-1: Load shedding in IEEE 33-bus integrated three DG with a loading factor of 80% of baseload***

When the distribution network is loaded at 80% of baseload, the total active and reactive

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
*Volume 13, Issue 1, March 2024*

power of the load in the network is 2.9720 MW and 1.4080 MVAR, respectively. The maximum power generation of the three DG units is 1.500 MW and 1.2000 MVAR, with a power factor of 0.8. The isolated network had a deficit of generation and load power of 1.4720 MW. Partial load shedding is required to obtain a power balance between DG generation and load.

A summary of the optimization results, including the total load power of 80% of the baseload ($P_{load}$), total load shed ($P_{shed}$), total load power remaining in the network ($P_{remain}$), power loss in the network ($P_{loss-afterLS}$), and voltage deviation ($VD$) after load shedding optimized with the proposed PSGWO algorithm, PSO and GWO for comparison is shown in Table 5.

From Table 5, it can be observed that the PSGWO algorithm can show its superiority over the PSO and GWO algorithms. The PSGWO algorithm produces the highest value of load remaining in the network ($P_{remain}$) of 1.4875 MW, and the load released from the network ($P_{shed}$) is the lowest value of 1.4845 MW compared to the results of the PSO and GWO algorithms. These results show that PSGWO can provide the most optimal results to maximize the load remaining in the network or minimize the load released from the network.

Table 5. Summary of load shedding optimization results for a loading factor of 80% of baseload

| Parameter | PSGWO | PSO | GWO |
|---|---|---|---|
| $P_{load}$ (MW) | 2.9720 | 2.9720 | 2.9720 |
| $P_{shed}$ (MW) | 1.4845 | 1.4890 | 1.4854 |
| $P_{remain}$ (MW) | 1.4875 | 1.4830 | 1.4866 |
| $P_{loss-afterLS}$ (MW) | 0.0137 | 0.0173 | 0.0133 |
| $VD$ | 0.0055 | 0.0067 | 0.0058 |

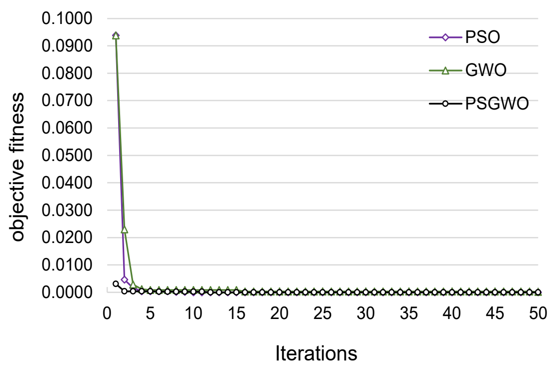



Figure 4. Convergence characteristics for a loading factor of 80% of baseload.


Figure 5. Bus voltage profile after load shedding for a loading factor of 80% of baseload

The power loss in the network after load shedding ($P_{loss-afterLS}$) optimized with PSGWO is 0.0137 MW. This value is far below the result obtained by the PSO algorithm of 0.0173 MW. In this case, GWO provides the lowest power loss of 0.0133 MW.

The convergence characteristics in Figure 4 show the performance comparison of the three algorithms in load-shedding optimization. All the algorithms can provide globally optimal results. The figure shows that PSGWO, as the proposed algorithm, has the best performance compared to PSO and GWO. PSGWO converges the fastest.

The bus voltage profile after load shedding optimized with the three algorithms is shown in Figure 5. From figure 5 it can be observed that the voltages at all buses in the network are within the allowable values, between 0.95 p.u and 1.05 p.u. The bus voltage deviation after load shedding with PSGWO, PSO, and GWO algorithms are 0.0055, 0.0067, and 0.0058, respectively, as shown in Table 5. This value indicates that the bus voltage profile after load shedding optimized by the PSGWO algorithm is the best because it is generally higher with the lowest voltage deviation compared to the results of PSO and GWO algorithms.

Table 6. Summary of load shedding optimization results for a loading factor of 100% of baseload

| Parameter | PSGWO | PSO | GWO |
|---|---|---|---|
| $P_{load}$ (MW) | 3.7150 | 3.7150 | 3.7150 |
| $P_{shed}$ (MW) | 2.2297 | 2.2308 | 2.2305 |
| $P_{remain}$ (MW) | 1.4853 | 1.4842 | 1.4845 |

ISSN 2089-8673 (Print) | ISSN 2548-4265 (Online)
*Volume 13, Issue 1, March 2024*

| | | | |
|---|---|---|---|
| $P_{loss-afterLS}$ (MW) | 0.0147 | 0.0158 | 0.0155 |
| $VD$ | 0.0049 | 0.0062 | 0.0058 |

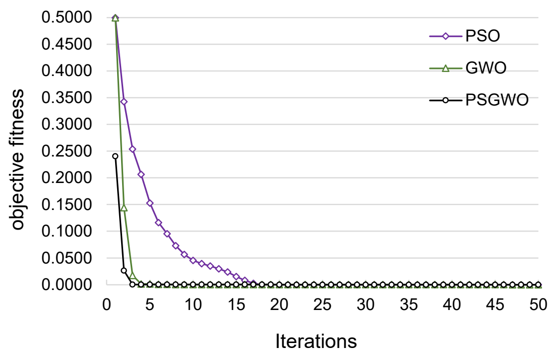



Figure 6. Convergence characteristics for a loading factor of 100% of baseload.

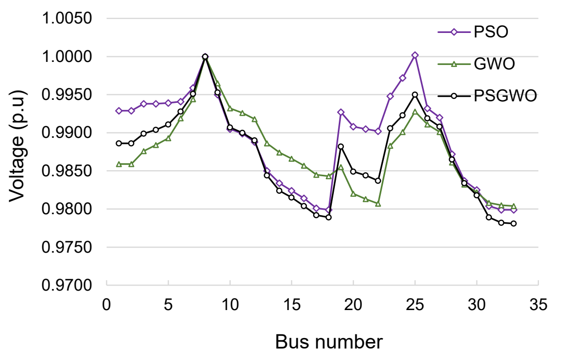



Figure 7. Bus voltage profile after load shedding for a loading factor of 100% of baseload

***Case-2: Load shedding in IEEE 33-bus integrated three DG with a loading factor of 100% of baseload***

For a loading factor of 100% of the baseload, the total active and reactive power of the load in the network is 3,175 MW and 1,760 MVAR. With a maximum DG generation of 1,500 MW, the isolated network has a generation and load power deficit of 1,675 MW. Table 6 summarises the load-shedding optimization results for the PSGWO algorithm compared to the PSO and GWO algorithms.The convergence characteristics in Figure 6 show the performance comparison of the three algorithms in load-shedding optimization. All algorithms are still able to converge and provide global optimal results. From the figure, it can be observed that PSGWO is still superior to PSO and GWO. At 100% baseload loading factor, the difference in convergence of PSGWO against PSO and GWO is more significant than at 80% baseload.

The bus voltage profile after load shedding optimization using the three algorithms is shown in Figure 7. Table 6 shows the bus voltage deviation after load-shedding with PSGWO, PSO, and GWO algorithms at 0.0049, 0.0062, and 0.0058, respectively. This value proves that the PSGWO algorithm can produce the most optimal load-shedding optimization with the best bus voltage profile and the lowest voltage deviation compared to the PSO and GWO algorithms.

***Case-3: Load shedding in IEEE 33-bus integrated three DG with a loading factor of 140% of baseload***

When the network is at a loading factor of 140% of baseload, the total active and reactive power of the load in the network is 5.2010 MW and 2.4640 MVAR. With the maximum DG generation of 1,500 MW, the power deficit in the network reaches a significant value of 3.7010 MW. Table 7 summarizes the load-shedding optimization results for the PSGWO algorithm compared to the PSO and GWO algorithms.

The PSO algorithm cannot converge in load-shedding optimization, while PSGWO still shows superiority over the GWO algorithm. Figure 8 shows the convergence characteristics of PSGWO and GWO algorithms. The superiority of PSGWO is more evident at a loading factor of 140% of the baseload. PSGWO converges much faster than GWO.

Table 7. Summary of load shedding optimization results for a loading factor of 140% of baseload

| Parameter | PSGWO | PSO | GWO |
|---|---|---|---|
| $P_{load}$ (MW) | 5.2010 | 5.2010 | 5.2010 |
| $P_{shed}$ (MW) | 3.7150 | NAN | 3.7151 |
| $P_{remain}$ (MW) | 1.4860 | NAN | 1.4859 |
| $P_{loss-afterLS}$ (MW) | 0.0140 | NAN | 0.0152 |
| $VD$ | 0.0047 | NAN | 0.0054 |

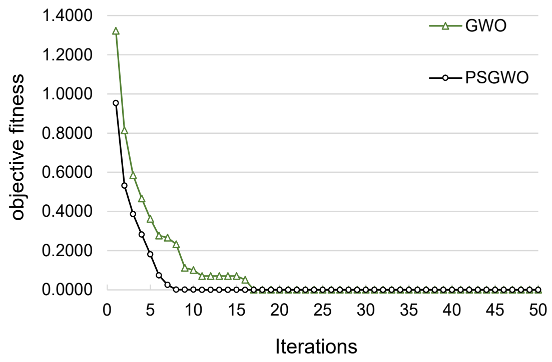



Figure 8. Convergence characteristics for a loading factor of 140% of baseload.

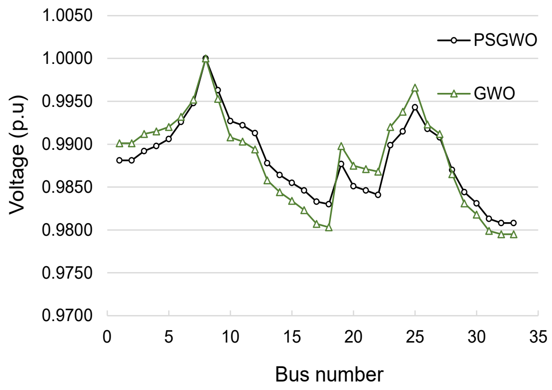



Figure 9. Bus voltage profile after load shedding for a loading factor of 140% of baseload

## CONCLUSION

This paper discusses a hybrid parallel PSGWO algorithm for optimal load-shedding strategies in isolated distribution networks. The proposed method is suitable for solving load-shedding optimization using PSO and GWO advantages. Load shedding optimization using PSGWO has been studied to maximize the remaining load in the network by considering priority load and variation of loading factor. The conditions of voltage profile, power loss, and voltage deviation are also used to evaluate the optimization results. The results of load-shedding optimization with the proposed PSGWO algorithm are compared with the standard PSO and GWO algorithms. The performance of the PSGWO algorithm can outperform the standard PSO and GWO algorithms, as shown by the achievement of optimization objectives and convergence speed.

In practice, the increasing integration of DG into the distribution network can open up opportunities to maintain the continuity of power supply to the load, especially when isolated from the main network. The isolation of the distribution network from the main grid causes a power deficit due to DG generation being far below the power of the load connected to the network. An optimal load-shedding strategy is required to realize the new power balance.

For future studies, the study can be developed to optimize simultaneous load shedding and reconfiguration in isolated distribution networks to improve reliability.

## ACKNOWLEDGMENT

The research was supported by a research grant from the Ministry of Research, Technology and Higher Education.

## REFERENCES

[1] A. S. A. Awad, T. H. M. El-Fouly, and M. M. A. Salama, “Optimal distributed generation allocation and load shedding for improving distribution system reliability,” *Electr. Power Components Syst.*, vol. 42, no. 6, pp. 576–584, 2014, doi: 10.1080/15325008.2014.880962.

[2] S. Sepasi, C. Talichet, and A. S. Pramanik, “Power Quality in Microgrids: A Critical Review of Fundamentals, Standards, and Case Studies,” *IEEE Access*, vol. 11, no. October, pp. 108493–108531, 2023, doi: 10.1109/ACCESS.2023.3321301.

[3] Y. Ma, P. Yang, Z. Zhao, and Y. Wang, “Optimal Economic Operation of Islanded Microgrid by Using a Modified PSO Algorithm,” *Math. Probl. Eng.*, vol. 2015, pp. 1–10, 2015, doi: 10.1155/2015/379250.

[4] M. Dreidy, H. Mokhlis, and S. Mekhilef, “Application of meta-heuristic techniques for optimal load shedding in islanded distribution network with high penetration of solar PV generation,” *Energies*, vol. 10, no. 2, pp. 1–24, 2017, doi: 10.3390/en10020150.

[5] V. V. V. S. N. Murty and A. Kumar, “Optimal DG integration and network reconfiguration in microgrid system with realistic time varying load model using hybrid optimisation,” *IET Smart Grid*, vol. 2, no. 2, pp. 192–202, 2019, doi: 10.1049/iet-stg.2018.0146.

[6] L. A. Alnabi, A. K. Dhaher, and M. B. Essa, “Optimal Allocation of Distributed Generation with Reconfiguration by Genetic Algorithm Using Both Newton Raphson and Gauss Seidel Methods for Power Losses Minimizing,” *Int. J. Intell. Eng. Syst.*, vol. 15, no. 1, pp. 464–476, 2022, doi: 10.22266/IJIES2022.0228.42.

[7] K. Narayanan, S. A. Siddiqui, and M. Fozdar, “Optimal placement of distributed generators in radial distribution system for reducing the effect of islanding,” *J. Electr. Eng. Technol.*, vol. 11, no. 3, pp. 551–559, 2016, doi: 10.5370/JEET.2016.11.3.551.

[8] A. K. Barnwal, L. K. Yadav, and M. K. Verma, “A Multi-Objective Approach for Voltage Stability Enhancement and Loss Reduction under PQV and P Buses Through Reconfiguration and Distributed Generation Allocation,” *IEEE Access*, vol. 10, pp. 16609–16623, 2022, doi: 10.1109/ACCESS.2022.3146333.

[9] S. Kamel, M. Khasanov, F. Jurado, A. Kurbanov, H. M. Zawbaa, and M. A. Alathbah, “Simultaneously Distributed Generation Allocation and Network Reconfiguration in Distribution Network Considering Different Loading Levels,” *IEEE Access*, vol. 11, no. August, pp. 105916–105934, 2023, doi: 10.1109/ACCESS.2023.3319456.

[10] J. Xu *et al.*, “Load Shedding and Restoration for Intentional Island with Renewable Distributed Generation,” *J. Mod. Power Syst. Clean Energy*, vol. 9, no. 3, pp. 612–624, 2021, doi: 10.35833/MPCE.2019.000062.

[11] B. De Nadai Nascimento, A. C. Z. De Souza, J. G. De Carvalho Costa, and M. Castilla, “Load shedding scheme with under-frequency and undervoltage corrective actions to supply high priority loads in islanded microgrids,” *IET Renew. Power Gener.*, vol. 13, no. 11, pp. 1981–1989, 2019, doi: 10.1049/iet-rpg.2018.6229.

[12] H. Gao, Y. Chen, Y. Xu, and C. C. Liu, “Dynamic load shedding for an islanded microgrid with limited generation resources,” *IET Gener. Transm. Distrib.*, vol. 10, no. 12, pp. 2953–2961, 2016, doi: 10.1049/iet-gtd.2015.1452.

[13] X. Wu, S. Feng, and P. Jiang, “Distributed Coordination Load Shedding of Islanded Microgrids Based on Sub-Gradient Algorithm,” *IEEE Access*, vol. 5, pp. 27879–27886, 2017, doi: 10.1109/ACCESS.2017.2725901.

[14] C. Wang, H. Yu, L. Chai, H. Liu, and B. Zhu, “Emergency Load Shedding Strategy for Microgrids Based on Dueling Deep Q-Learning,” *IEEE Access*, vol. 9, pp. 19707–19715, 2021, doi: 10.1109/ACCESS.2021.3055401.

[15] H. E. Brown, S. Suryanarayanan, S. A. Natarajan, and S. Rajopadhye, “Improving reliability of islanded distribution systems with distributed renewable energy resources,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2028–2038, 2012, doi: 10.1109/TSG.2012.2200703.

[16] A. Tian and X. Mou, “A Network Analysis-Based Distributed Load Shedding Strategy for Voltage Collapse Prevention,” *IEEE Access*, vol. 7, pp. 161375–161384, 2019, doi: 10.1109/ACCESS.2019.2950628.

[17] A. Khamis, H. Shareef, A. Mohamed, and Z. Y. Dong, “A load shedding scheme for DG integrated islanded power system utilizing backtracking search algorithm,” *Ain Shams Eng. J.*, vol. 9, no. 1, pp. 161–172, 2018, doi: 10.1016/j.asej.2015.10.001.

[18] J. Jallad, S. Mekhilef, H. Mokhlis, J. Laghari, and O. Badran, “Application of hybrid meta-heuristic techniques for optimal load shedding planning and operation in an islanded distribution network integrated with distributed generation,” *Energies*, vol. 11, no. 5, 2018, doi: 10.3390/en11051134.

[19] A. Khamis, H. Shareef, and A. Mohamed, “Islanding detection and load shedding scheme for radial distribution systems integrated with dispersed generations,” *IET Gener. Transm. Distrib.*, vol. 9, no. 15, pp. 2261–2275, 2015, doi: 10.1049/iet-gtd.2015.0263.

[20] V. Tamilselvan and T. Jayabarathi, “A hybrid method for optimal load shedding and improving voltage stability,” *Ain Shams Eng. J.*, vol. 7, no. 1, pp. 223–232, 2016, doi: 10.1016/j.asej.2015.11.003.

[21] R. M. Larik, M. W. Mustafa, M. N. Aman, T. A. Jumani, S. Sajid, and M. K. Panjwani, “An improved algorithm for optimal load shedding in power systems,” *Energies*, vol. 11, no. 7, pp. 1–16, 2018, doi: 10.3390/en11071808.

[22] V. Tamilselvan, “A hybrid PSO-ABC algorithm for optimal load shedding and improving voltage stability,” *Int. J. Manuf. Technol. Manag.*, vol. 34, no. 6, pp. 577–597, 2020, doi: 10.1504/IJMTM.2020.109999.

[23] L. M. Cruz, D. L. Alvarez, A. S. Al-Sumaiti, and S. Rivera, “Load curtailment optimization using the PSO algorithm for enhancing the reliability of distribution networks,” *Energies*, vol. 13, no. 12, 2020, doi: 10.3390/en13123236.

[24] A. G. Gad, *Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review*, vol. 29, no. 5. Springer Netherlands, 2022. doi: 10.1007/s11831-021-09694-4.

[25] M. Li, W. Du, and F. Nian, “An adaptive particle swarm optimization algorithm

based on directed weighted complex network," *Math. Probl. Eng.*, vol. 2014, 2014, doi: 10.1155/2014/434972.

[26] D. E. Gbenga and E. I. Ramlan, "Understanding the limitations of particle swarm algorithm for dynamic optimization tasks: A survey towards the singularity of PSO for swarm robotic applications," *ACM Comput. Surv.*, vol. 49, no. 1, 2016, doi: 10.1145/2906150.

[27] I. Rahman, P. M. Vasant, B. S. M. Singh, and M. Abdullah-Al-Wadud, "On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles," *Alexandria Eng. J.*, vol. 55, no. 1, pp. 419–426, 2016, doi: 10.1016/j.aej.2015.11.002.

[28] P. Niu, S. Niu, N. liu, and L. Chang, "The defect of the Grey Wolf optimization algorithm and its verification method," *Knowledge-Based Syst.*, vol. 171, pp. 37–43, 2019, doi: 10.1016/j.knosys.2019.01.018.

[29] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[30] S. K. Mosavi, E. Jalalian, and F. S. Gharahchopog, "a Comprehensive Survey of Grey Wolf Optimizer Algorithm and Its Application," *Int. J. Adv. Robot. Expert Syst.*, vol. 1, no. 6, pp. 23–45, 2021.

[31] T. H. B. Huy, D. N. Vo, K. H. Truong, and T. Van Tran, "Optimal Distributed Generation Placement in Radial Distribution Networks Using Enhanced Search Group Algorithm," *IEEE Access*, vol. 11, no. September, pp. 103288–103305, 2023, doi: 10.1109/ACCESS.2023.3316725.

[32] D. V. Bhatt, Y. H. Bhatt, and V. H. Pakka, "Loss Sensitivity and Voltage Deviation Index Based Intelligent Technique for Optimal Placement and Operation of Distributed Generators," *2018 IEEE 7th Int. Conf. Power Energy, PECon 2018*, pp. 310–315, 2018, doi: 10.1109/PECON.2018.8684177.