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RESEARCH ARTICLE

Load-Shedding Optimization Using Hybrid Grey Wolf - Whale Algorithm to Improve The Isolated Distribution Networks

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Abstract: The integration of distributed generation allows the distribution network to operate in either on-grid or off-grid mode. In off-grid mode, the power supply from the main grid is interrupted, and distributed generation becomes the main source of power to meet the load's power demand. The absence of power supply from the main grid reduces the grid's ability to meet load power demand. The load power demand is larger than the distributed generation capacity, causing a power deficit in the network. This paper studies strategies for restoring power balance through optimal load shedding, taking into account the presence of priority loads that require power demand to be maintained and met. The optimization objective is to maximize the remaining load with an optimal composition so that the power loss is minimal. The load-shedding optimization uses a hybrid Grey Wolf Algorithm and Whale Optimization Algorithm (GW-WOA). The performance of GW-WOA is tested by load shedding optimization on a 118-bus IEEE radial distribution system integrated with 12 units of DG. The network loading factor variation consists of 80%, 100%, and 140% of the base load. Regarding all loading factors, the GW-WOA hybrid algorithm is superior to the standard GWO and WOA. The GW-WOA hybrid algorithm can converge faster to obtain the global optimal solution to realize power balance, overcome power deficit, maximize remaining load, and minimize power loss in the network. The GW-WOA hybrid algorithm has improved the performance of load-shedding optimization in isolated distribution networks with global optimal results and shorter iterations.

Keywords: grey wolf, hybrid algorithm, isolated network,load shedding, whale optimization

1 Introduction

Distributed generation (DG) is a generation system installed dispersed in the distribution network to shorten power delivery to the load and reduce power losses [1]. DG generally utilizes environmentally friendly renewable energy such as wind and solar [2]. DG integration can improve bus voltage regulation and allow distribution networks to operate on or off-grid [3]. Off-grid mode occurs when the distribution network is disconnected and isolated from the main grid. When isolated, DG is the primary source for meeting the power demand of all network loads. The presence of DG allows the distribution network to continue supplying electricity to loads, especially priority loads. DG capacity far below the load power causes a power imbalance, which will degrade the network's voltage and frequency stability. The worst conditions that can occur are a power outage and the cessation of the power supply to the entire load in the network [4] [5].

Network reconfiguration is one of the alternatives to overcome isolated distribution networks [6]. The operation of the sectional tie switch changes the configuration and power flow in the network, allowing the loading of each line to be rearranged [7]. Reconfiguration can also be done by dividing a large network into several smaller networks (pico-grid) according to the location of DG installation in the network [8]. Each pico-grid utilizes DG as a source to meet load power demand [9]. To improve the resilience of isolated networks, reconfiguration of isolated networks should be followed up with distributed generation scheduling [10]. However, in some cases, the isolation of the distribution network causes a huge power difference between DG generation and load. Network reconfiguration cannot solve the power deficit in the network [11]. Partial load shedding must be performed to solve the power deficit problem and realize power balance in the network [12]. When performing load shedding, priority loads must be maintained in the network so that their power demand can be met. The composition of the remaining load affects the power flow and power losses on each line [13]. Optimization is very crucial in load shedding.

Load shedding optimization has been an interesting research topic. An analytical approach to dynamically plan the optimal load coverage limit on an isolated system considering the availability of generation capacity is presented in [14]. Load shedding planning for balancing power on isolated networks using the Firefly-PSO (FAPSO) algorithm is discussed in [13], the Backtracking Search Algorithm (BSA) is studied in [15], and hybrid PSO-GWO is presented in [16]. Paper [17] presents network analysis for load shedding planning to prevent voltage collapse.

GWO and WOA algorithms have been widely implemented in optimization problems. Both algorithms have advantages and disadvantages. WOA has a simpler mathematical model than GWO. GWO has better local search capabilities, while WOA has better global search. Hybridization of algorithms opens up opportunities to get algorithms that converge faster and can provide globally optimal solutions [18].

This paper examines the hybrid Grey Wolf and Whale Optimization Algorithm (GWWOA) applied to load shedding. Both algorithms are combined in parallel to get the best population at each iteration. The best population is used for calculations in the next iteration so that it converges faster in obtaining the global optimal solution. The objective of this optimization is maximizing the remaining load by considering the priority load in the network. This paper has the following contributions:

1. Improved algorithm performance by combining the Grey Wolf and Whale Optimization Algorithms in parallel.

2. Improve the reliability of isolated distribution networks in ensuring power supply to loads, especially priority loads.
3. Load shedding to realize power equilibrium so that load power fulfilment is maintained, especially for priority loads.
4. Obtain the optimal composition of the remaining load to reduce network power losses.

2 Research Method

Load shedding can realize power equilibrium between generating capacity and load power demand on the network. Load shedding must be done appropriately to obtain the optimal composition of the remaining load and minimize power losses in the network.

2.1 Grey Wolf Optimizer (GWO)

GWO is an algorithm that adopts the mechanism of wolves in hunting prey. α, β, and δ are the wolves with the highest priority, while ω is the wolf with the lowest priority that gets the last chance to eat the prey caught [19]. Wolves set traps by encircling prey. Eq. (1) and (2) express the wolf's distance to the prey D_{GWO} and the wolf's position update $X_{\text{GWO}}(t+1)$ to be performed.

$$D_{\text{GWO}} = |C \cdot X_p(t) - X_{\text{GWO}}(t)| \tag{1}$$

$$X_{\text{GWO}}(t+1) = X_p(t) - A \cdot D_{\text{GWO}} \tag{2}$$

X_p is the position of the targeted prey, X_{GWO} is the current position of the wolf, and t is the current iteration. A and C are obtained from Eq. (3) and (4).

$$A = 2 \cdot a \cdot r_1 - a \tag{3}$$

$$C = 2 \cdot r_2 \tag{4}$$

r_1 and r_2 are random numbers from 0 to 1. The value of a is obtained using Eq. (5).

$$a = 2\left(1 - \frac{t}{t_{\text{max}}}\right) \tag{5}$$

t_{max} is maximum iterations.

The next phase is the α-guided hunt. The prioritized wolf positions are X_α, X_β, and X_δ which are closest to the prey. The other wolves must update their position towards these three wolves. The distances of wolf X_{GWO} to the three prioritized wolves (D_α, D_β, and D_δ) are expressed in Eq. (6), (7), and (8).

$$D_\alpha = |C \cdot X_\alpha(t) - X_{\text{GWO}}| \tag{6}$$

$$D_\beta = |C \cdot X_\beta(t) - X_{\text{GWO}}| \tag{7}$$

$$D_\delta = |C \cdot X_\delta(t) - X_{\text{GWO}}| \tag{8}$$

The movement of wolf X_{GWO} towards X_α, X_β, and X_δ is determined using Eq. (9), (10), and (11).

$$X_{\text{GWO}-\alpha} = X_\alpha - A \cdot D_\alpha \tag{9}$$

$$X_{\text{GWO}-\beta} = X_\beta - A \cdot D_\beta \tag{10}$$

$$X_{\text{GWO}-\delta} = X_\delta - A \cdot D_\delta \tag{11}$$

Update the position of wolf X_{GWO} at iteration $(t+1)$ following Eq. (12).

$$X_{\text{GWO}}(t+1) = \frac{X_{\text{GWO}-\alpha} + X_{\text{GWO}-\beta} + X_{\text{GWO}-\delta}}{3} \tag{12}$$

The process is repeated until all wolves are in the prey position.

2.2 Whale Optimization Algorithm (WOA)

WOA is an algorithm that adopts the techniques used by whales to trap and ambush prey. Whales dive while making traps from air bubbles and then ambush the trapped prey [20]. Eq. (13) expresses the distance of the whale X_{WOA} to the prey position X^*. The position update of whale X_{WOA} towards the prey is expressed in Eq. (14).

$$D_{\text{WOA}} = |C \cdot X^*(t) - X_{\text{WOA}}(t)| \tag{13}$$

$$X_{\text{WOA}}(t+1) = X^*(t) - A \cdot D_{\text{WOA}} \tag{14}$$

t denotes the current iteration. The calculation of A and C uses the same formula as in the GWO algorithm using Eq. (3), (4), and (5).

Whales circle their prey, following a shrinking spiral path with a 50% probability, which is mathematically represented by Eq. (15).

$$X_{\text{WOA}}(t+1) = \begin{cases} X_{\text{WOA}}(t) - A \cdot D_{\text{WOA}}, & \text{if } p < 0.5 \\ D_{\text{WOA}} \cdot e^{bL} \cdot \cos(2\pi l) + X^*(t), & \text{if } p \geq 0.5 \end{cases} \tag{15}$$

p is a random value between 0 and 1, b is a spiral-shaped constant, and L is a random value between -1 and 1.

Whale X_{WOA} also moves towards another randomly selected whale (X_{rand}). Eq. (16) states the calculation of the distance (D_{rand}) from X_{WOA} to X_{rand}, while Eq. (17) is used to calculate the movement of X_{WOA} towards X_{rand}.

$$D_{\text{rand}} = |C \cdot X_{\text{rand}} - X_{\text{WOA}}| \tag{16}$$

$$X_{\text{WOA}}(t+1) = X_{\text{rand}} - A \cdot D_{\text{rand}} \tag{17}$$

3 Problem Formulation

3.1 Power Losses on The Line

Figure 1 shows the network between bus i and j connected by the line impedance $R_{i,j} + X_{i,j} \cdot I_{i,j}$ the line current. The power at bus i is P_i and Q_i, while that at bus j is P_j and Q_j. The load on bus i is PL_i and QL_i, while on bus j is PL_j and QL_j.

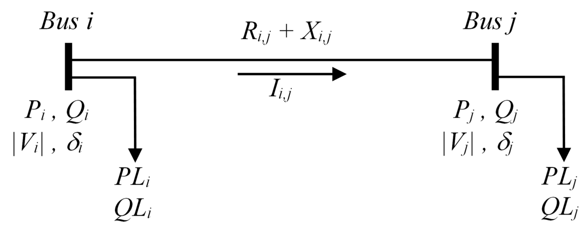

Figure 1: Two bus network.

Line power loss can be expressed in Eq. (18) and (19) below [21]:

$$P_{\text{loss}-i,j} = R_{i,j} \cdot |I_{i,j}|^2 \tag{18}$$

$$Q_{\text{loss}-i,j} = X_{i,j} \cdot |I_{i,j}|^2 \tag{19}$$

In the networks with NL lines, total power loss is the accumulation of each line's power loss, which is mathematically expressed in Eq. (20) and (21).

$$P_{\text{loss-total}} = \sum_{k=1}^{NL} R_k \cdot |I_k|^2 \tag{20}$$

$$Q_{\text{loss-total}} = \sum_{k=1}^{NL} X_k \cdot |I_k|^2 \tag{21}$$

k indicates the line number, R_k is the resistance of line-k, X_k is the reactance of k-line, and I_k is the current on line-k.

3.2 Objective of Optimization

The load that is kept connected to the network (P_{rem}) is equal to the total load before load shedding ($P_{\text{load-total}}$) minus the load shed from the network (P_{shed}) and can be mathematically expressed by Eq. (22).

$$P_{\text{rem}} = P_{\text{load-total}} - P_{\text{shed}} \tag{22}$$

The optimization objective is to maximize the remaining load (P_{rem}) expressed in Eq. (23).

$$f_{\text{obj}} = \max(P_{\text{rem}}) \tag{23}$$

P_{rem} must be less than the maximum of DG generation for power balance to be realized.

3.3 Constraints

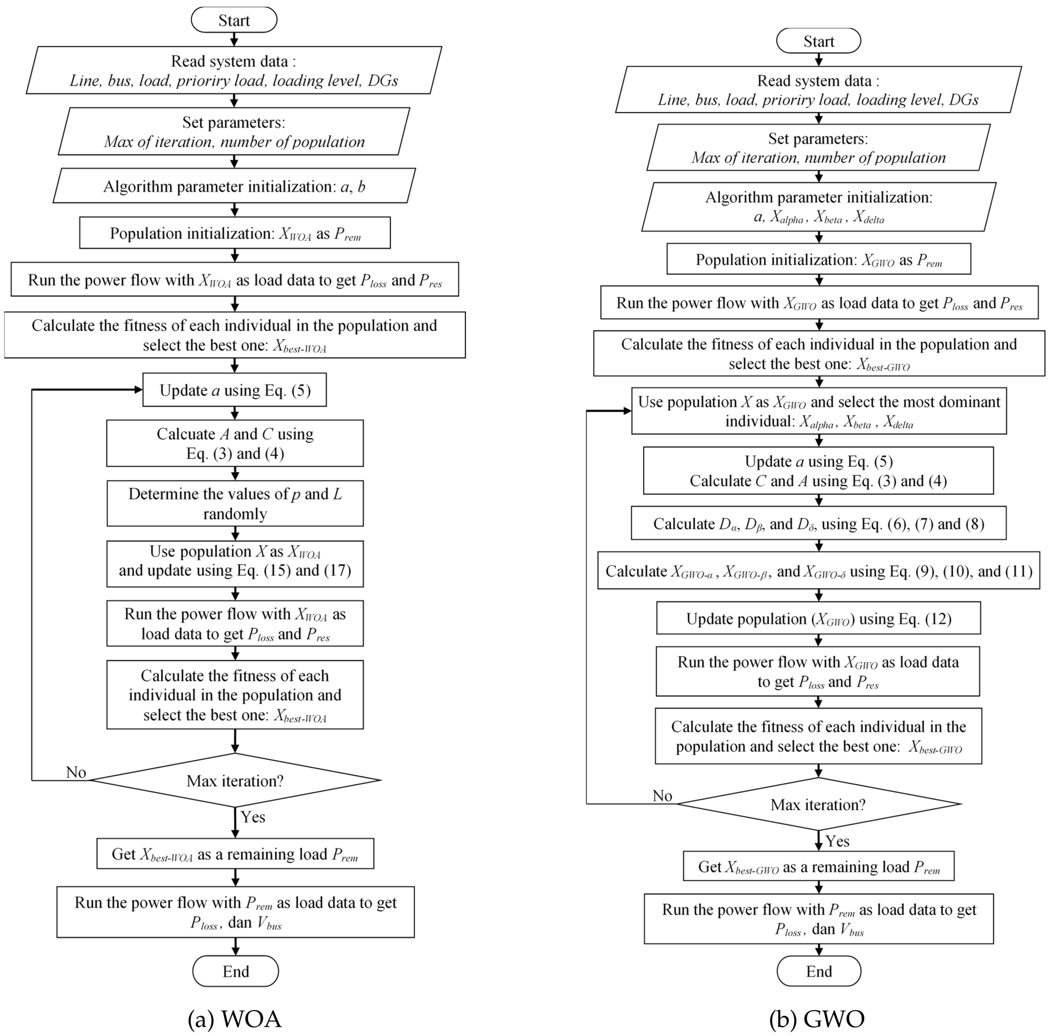

Figure 2: Flowchart of load shedding optimization using.

Load shedding optimization is subject to the following constraints:

1. Power equilibrium The remaining load power and power losses do not exceed the DG generation power, which can be mathematically expressed in Eq. (24) and (25).

$$\sum_{i=1}^{N_{\text{DG}}} P_{\text{DG},i} = \sum_{j=1}^{N_b} P_{\text{rem},j} + P_{\text{loss-after LS}} \tag{24}$$

$$\sum_{i=1}^{N_{\text{DG}}} Q_{\text{DG},i} = \sum_{j=1}^{N_b} Q_{\text{rem},j} + Q_{\text{loss-after LS}} \tag{25}$$

$P_{\text{DG},i}$ and $Q_{\text{DG},i}$ are the power generation of DG-i. N_{DG} is the number of DGs. $P_{\text{rem},j}$ and $Q_{\text{rem},j}$ are the power of the load that is kept connected at bus-j. N_b is the number of buses. $P_{\text{loss-after LS}}$ and $Q_{\text{loss-after LS}}$ are the power losses in the network.

2. Remaining load
   All priority loads must be kept connected to the network.

$$P_{\text{prior},i} \leq P_{\text{rem},i} \tag{26}$$

$$Q_{\text{prior},i} \leq Q_{\text{rem},i} \tag{27}$$

   $P_{\text{prior},i}$ and $Q_{\text{prior},i}$ are the priority load at bus-i. $P_{\text{rem},i}$ and $Q_{\text{rem},i}$ are the remaining loads on bus-i.
3. Power generation of DG The power generation from DG is set at the maximum limit.

$$P_{\text{DG}} = P_{\text{DG}}^{\text{max}} \tag{28}$$

   P_{DG} is power generation of DG and $P_{\text{DG}}^{\text{max}}$ is maximum power limit of DG.

3.4 Hybrid GW-WOA Algorithm for Load Shedding Optimization

The hybrid Grey Wolf and Whale Optimization Algorithm (GW-WOA) is a parallel combination. The parallel combination is done by applying population update calculations from both GWO and WOA algorithms. The two resulting populations are then compared, and the best one is selected based on its fitness value to be used as a candidate population for the next iteration. In this way, it is expected to accelerate the convergence of iterations to obtain a globally optimal solution. Figure 2a and 2b show the flowcharts of WOA and GWO, respectively. In this paper, the proposed GW-WOA hybrid algorithm in load-shedding optimization is shown in Figure 3.

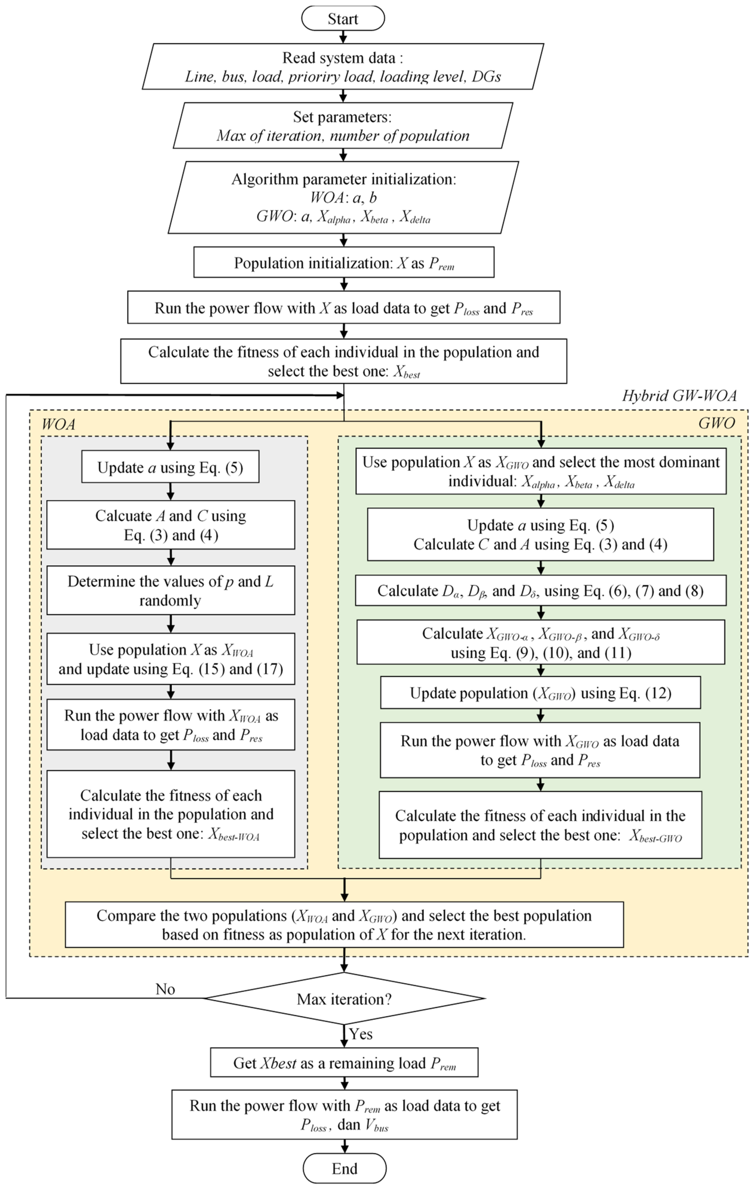

Figure 3: Flowchart of hybrid GW-WOA for load shedding optimization.

4 Results and Discussion

The load-shedding optimization uses the IEEE 118-bus radial distribution network test system shown in Figure 4 [22]. The test system has 117 lines and 118 buses. The total base load power is 22,709.72 kW and 17,041.068 kVAR. Several DGs with capacities and locations, as shown in Table 1, were integrated into the network.

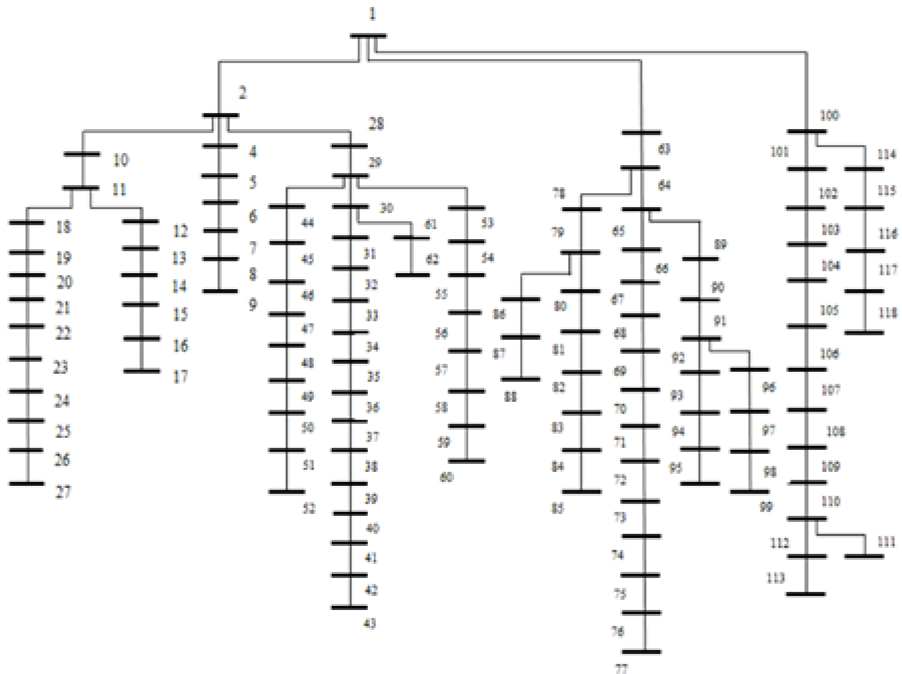

Figure 4: IEEE 118-bus radial distribution network.

Table 1: DG location and capacity

DG	Bus GD	$P_{\text{out-max}}$ (MW)
1	77	500
2	76	700
3	75	700
4	74	300
5	73	500
6	43	500
7	27	300
8	42	500
9	52	700
10	72	500
11	26	300
12	51	500
Total DG Capacity		**6000**

The load shedding optimization includes 3 case studies with loading levels of 80%, 100%, and 140% of base load. Based on the optimization results of conformity to the optimization objective, network loss, and convergence speed, the performance of GW-WOA is compared with that of GWO and WOA.

4.1 Case-1: Load shedding optimization at 80% of baseload

At 80% of the baseload, the total load power is 18,167.20 kW and 13,632.70 kVAR. With the maximum generation of DGs being 6,000 kW, the power deficit in the network is 12,167.20 kW. Proper load shedding can realize the power balance of the remaining load against the DG generation capability. Optimization is performed by applying GW-WOA, GWO, and WOA algorithms. Table 2 summarizes the results of optimization using GW-WOA, GWO, and WOA algorithms up to 500 iterations.

Table 2 shows that in 500 iterations, the GWO algorithm has not been able to provide optimal load shedding. P_{rem} = 6,545.30 kW exceeds the maximum power that can be generated by DG, which is 6,000 kW. The balance of load power and DG generation power has not been achieved. Even if the value of losses on the network of P_{loss} = 1,560.60 kW is taken into account, it will increase the power deficit.

Table 2: The results of load shedding optimization at 80% of the baseload

Parameter	Algorithm		
	GW-WOA	WOA	GWO
P_{load} (kW)	18,167.20	18,167.20	18,167.20
P_{shed} (kW)	12,937.40	12,961.20	11,622.10
P_{rem} (kW)	5,230.90	5,205.70	6,545.30
P_{loss} (kW)	468.30	472.90	1,560.60
$P_{\text{rem}} + P_{\text{loss}}$ (kW)	5,699.20	5,678.60	8,105.90

The GW-WOA algorithm releases load from the network of P_{shed} = 12,937.40 kW, while the WOA algorithm results in P_{shed} = 12,961.20 kW. The GW-WOA algorithm can provide more optimal to minimize the load released from the network.

The GWO-WOA and WOA algorithms provide a remaining load (P_{rem}) of 5,230.90 kW and 5,204.70 kW, respectively. The power loss (P_{loss}) after load shedding for both algorithms is 468.30 kW and 472.90 kW, respectively. The power deficit in the network can be overcome where the total remaining load power and power loss are still below the maximum power generation by DG. DG generation capacity can be maximally utilized to continue power supply to the remaining loads during network isolation.

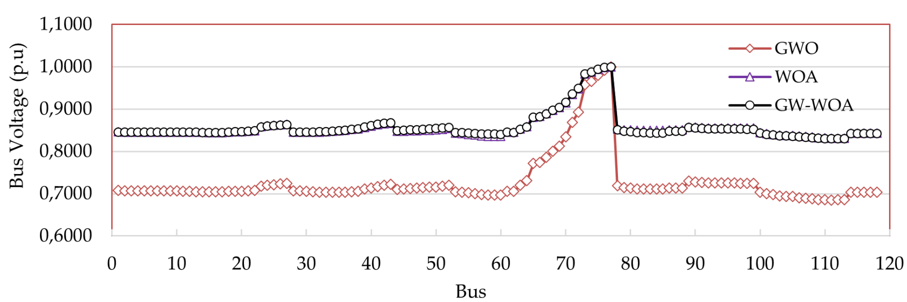

Figure 5: Bus voltage profile in a network loaded with 80% of baseload after load shedding optimization using GW-WOA, WOA, and GWO algorithms.

Figure 5 presents the voltage profile after load shedding optimization. The figure shows that after load shedding optimization with the GW-WOA algorithm, the bus voltage in the network is also better than the results given by the standard WOA algorithm. The GW-WOA algorithm provides relatively higher bus voltages than the WOA algorithm.

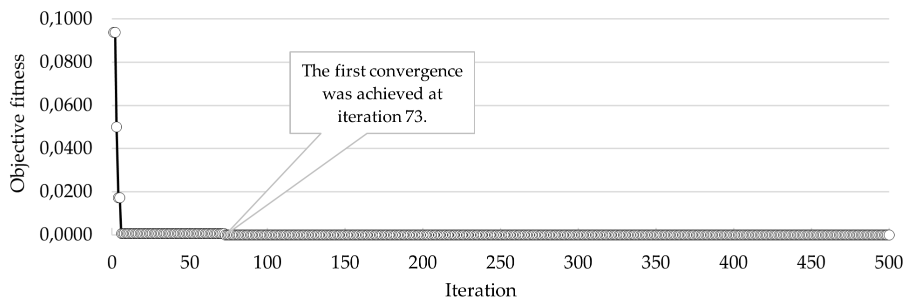

Figure 6: Convergence of hybrid GW-WOA in load shedding optimization on the networks with 80% of baseload.

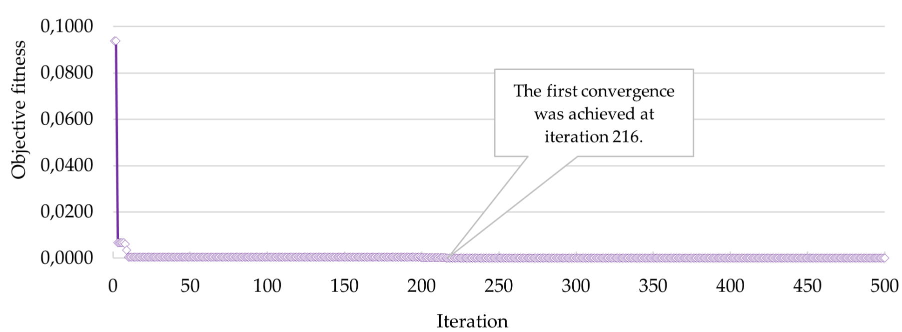

Figure 7: Convergence of WOA in load shedding optimization on the networks with 80% of baseload.

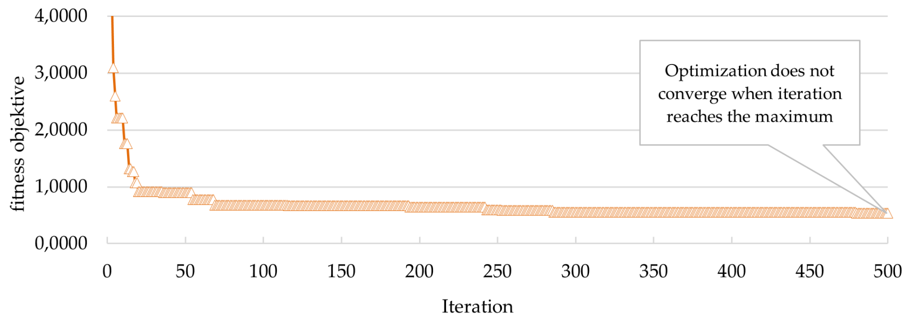

Figure 8: Convergence of GWO in load shedding optimization on the networks with 80% of baseload.

Figure 6, 7, and 8 show the convergence of each algorithm. Until the maximum iteration limit, the GWO algorithm has not converged. Meanwhile, the GW-WOA and WOA algorithms have reached the convergence point before the maximum iteration limit. The GW-WOA algorithm provided optimal results at iteration 73, while the WOA algorithm provided optimal results at iteration 216. The hybridization of GWO and WOA algorithms to form the GW-WOA hybrid algorithm has improved performance significantly compared to the GWO and WOA algorithms. The GW-WOA algorithm converges faster than GWO and WOA.

4.2 Case-2: Load shedding Optimization at 100% of Baseload

When the network load is 100% of the baseload, the total load power is 22,709.70 kW and 17,041.20 kVAR. With the maximum power generation of DG being 6,000 kW, the power deficit in the network is 16,709.70 kW. Table 3 summarizes the results of optimization using GW-WOA, GWO, and WOA algorithms up to 500 iterations. GWO algorithm has not been able to provide optimal results in load shedding. Up to the maximum iteration, the values of P_{rem} = 6,557.80 kW and P_{loss} = 1,571.20 kW indicate that there is still a power deficit of 2,129.00 kW.

Table 3: The results of load shedding optimization at 100% of the baseload

Parameter	Algorithm		
	GW-WOA	WOA	GWO
P_{load} (kW)	22,709.70	22,709.70	22,709.70
P_{shed} (kW)	17,492.200	17,537.30	16,152.10
P_{rem} (kW)	5,217.60	5,172.10	6,557.80
P_{loss} (kW)	459.00	510.60	1,571.20
$P_{\text{rem}} + P_{\text{loss}}$ (kW)	5,676.60	5,682.70	8,129.00

The GW-WOA and WOA algorithms have provided optimal results before the maximum iteration limit. Load shedding optimization using GW-WOA leaves the load in the network P_{rem} = 5,217.60 kW and power loss P_{loss} = 459.00 kW, while WOA results in P_{rem} = 5,172.10 kW and P_{loss} = 472.90 kW. The GW-WOA algorithm provides more optimal load shedding, where the load that can be maintained in the network reaches the maximum with minimal power loss.

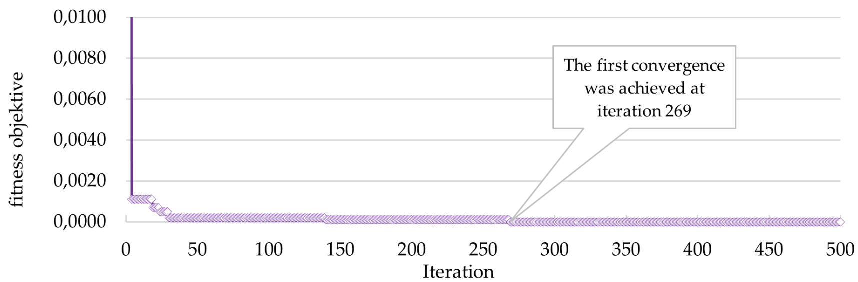

Figure 9: Convergence of hybrid GW-WOA in load shedding optimization on the networks with 100% of baseload.

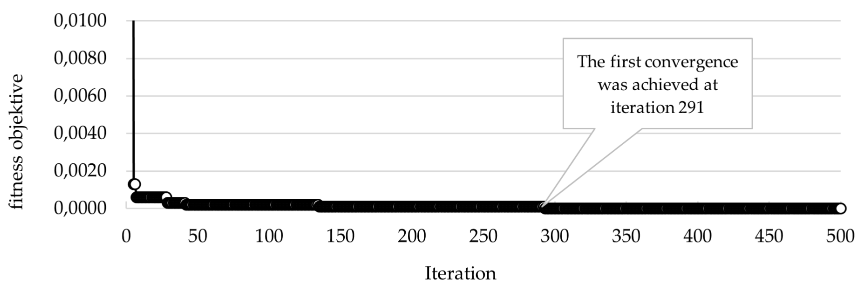

Figure 10: Convergence of hybrid WOA in load shedding optimization on the networks with 100% of baseload.

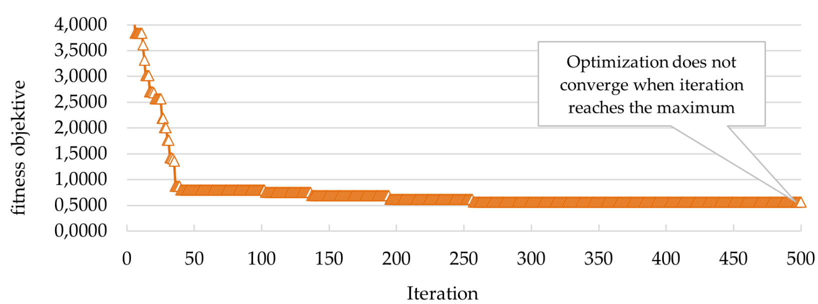

Figure 11: Convergence of hybrid GWO in load shedding optimization on the networks with 100% of baseload.

Figure 9 and 10 show that the GW-WOA algorithm converges in 269 iterations, while the WOA algorithm converges in 291 iterations. Figure 11 shows that the GWO algorithm does not converge when the iterations reach the maximum limit. The GW-WOA algorithm is superior to the GWO and WOA algorithms.

4.3 Case-3: Load shedding Optimization at 140% of Baseload

When the loading level is 140% of the base load, the total power of the network loads is 31,793.20 kW and 23,857.20 kVAR, respectively. With the maximum total power generation from 12 DG units of 6,000 kW, the grid power deficit is 25,932.20 kW.

Table 4 summarizes the load shedding optimization results using the three algorithms. The GWO and WOA algorithms cannot provide optimal results when the iteration reaches the maximum limit, as shown by the P_{rem} of 6,672.50 kW and 7,232.60 kW, respectively. These values still exceed the maximum power generated by DG $P_{\text{max DG}}$ = 6,000 kW, which causes a power deficit in the grid.

Table 4: The results of load shedding optimization at 140% of the baseload

Parameter	Algorithm		
	GW-WOA	WOA	GWO
P_{load} (kW)	31,792.20	31,792.20	31,792.20
P_{shed} (kW)	26,587.20	25,121.10	24,561.00
P_{rem} (kW)	5,206.70	6,672.50	7,232.60
P_{loss} (kW)	769.30	1,683.80	3.020.20
$P_{\text{rem}} + P_{\text{loss}}$ (kW)	5,976.00	8,356.30	10,252.80

The GW-WOA algorithm results in the load released from the network P_{shed} = 26,587.20 kW, the remaining load in the network P_{rem} = 5,206.70 kW, and the power loss P_{loss} = 769.30 kW. The sum of P_{rem} and P_{loss} is 5,976.00 kW and can be met from DG generation. These results show that the GW-WOA algorithm provides optimal results for realizing power balance in the network.

Based on Figure 12, the GW-WOA algorithm shows superior performance, with the first convergence achieved at iteration 205. The GWO and WOA algorithms have not converged when the iteration reaches the maximum limit, as shown in Figure 13 and 14.

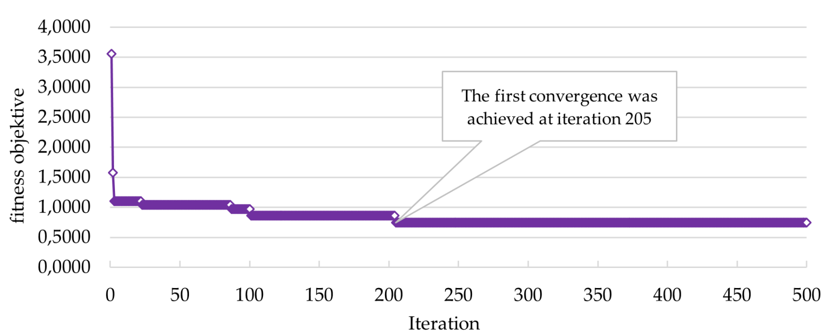

Figure 12: Convergence of hybrid GW-WOA in load shedding optimization on the networks with 140% of baseload.

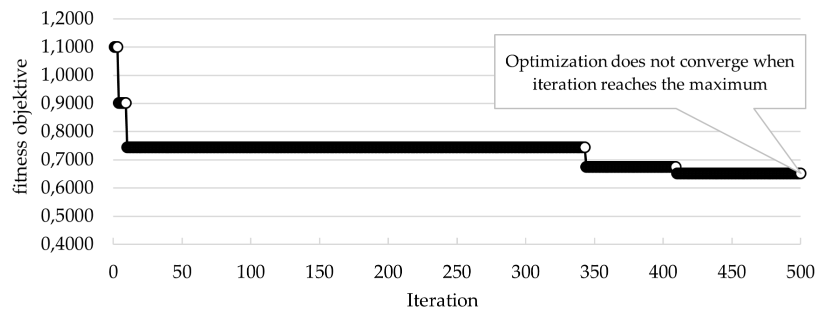

Figure 13: Convergence of hybrid WOA in load shedding optimization on the networks with 140% of baseload.

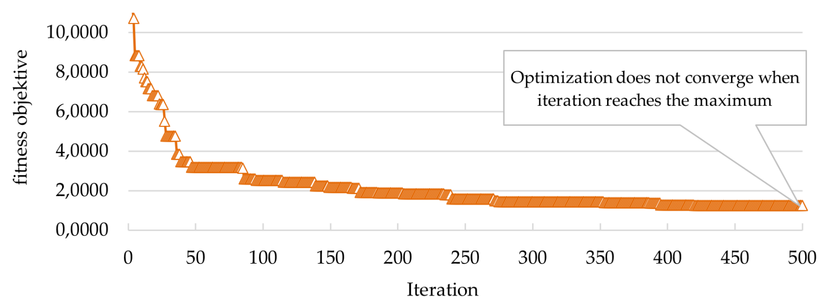

Figure 14: Convergence of hybrid GWO in load shedding optimization on the networks with 140% of baseload.

5 Conclusion

Integration of DG allows the network to continue service even when isolated from the main network. However, DG's generation limitations cannot meet the power demand of the entire load in an isolated network. This paper discusses optimization in load shedding to realize power equilibrium in distribution networks that are isolated from the main network. Load shedding is optimized using a hybrid GW-WOA algorithm, which considers the priority of loads that must be maintained in the network. The objective of optimization is to maximize the load that is kept connected to the network so that the DG generation capacity can be used as much as possible to continue providing services to customers. The GW-WOA algorithm's performance is compared with that of the GWO and WOA algorithms. The GW-WOA algorithm outperforms the GWO and WOA algorithms, which is indicated by more optimal results and faster convergence. Hybridization can improve an algorithm's performance. Future research is a combination of simultaneous load shedding and reconfiguration to improve the reliability of isolated distribution networks.

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