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WHALE OPTIMIZATION ALGORITHM FOR OPTIMAL LOCATION AND SIZING OF RENEWABLE DISTRIBUTED GENERATION.

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ABSTRACT

Renewable generation is a viable source of clean and smart energy in a modern distribution network. Thus, the synergy between photovoltaic and small-hydropower yields a complementary and uninterruptible power output. However, location and sizing mostly affect operational output. This paper presents a combined Voltage Stability Index estimation (VSI) and Whale Optimization Algorithm (WOA) for the optimal allocation of renewable-based energy sources. The nodes voltage stability index is ranked to signal the whale optimization selection of candidate solution agents at each algorithm iterations. Thereby turning the Distributed Generation (DG) node selection into non-random mode to improve simulation time and performance. The WOA technique is modeled using the hunting activities of whales and analysed on IEEE 33 bus systems. The results confirm the algorithm's improved performance of 89% voltage improvement and 48.50 power loss reduction for single PV integration. The technique ensures efficient network resource management for improved output.

Keywords: Whale optimization algorithm, voltage stability index, distribution network, distributed generation, voltage improvement, power loss reduction.

INTRODUCTION

Modern distribution network (DN) is tending toward automation, accuracy, cleanliness and improved system efficiency. DN power losses of the total generation capacity are 15.5% (Dinakara et al, 2018). Therefore, the network must be strategically managed to ensure that the voltage and losses are within the statutory limit of the power system operation. DGs are embedded in DN to perform a significant role in tackling the rapidly increasing network demand. It has served as a more economical option to traditional solutions like network reconfiguration, transmission expansion and system upgrade. It improves the system voltage profile and provides ancillary services like reactive power compensation, frequency control, and improvement of power qualities (Muttaqi et al, 2014). Agglomeration of different power generation using mixed or renewable energy is called a renewable hybrid system (Hatefi et al, 2017). Prominent among renewable energy sources (RES) are solar photovoltaic (PV) and small-hydropower (SHP). In (Margeta & Glasnovic, 2010), the authors affirm the complementary of PVSHP to provide sustainable energy and continuous power production. However, wrong location and poorly sized grid-connected RESs units lead to reverse power flow, excessive losses, increased network operating costs/network capital, demand-supply imbalance, the decline in power quality and consequently feeder overload (Atwa et al, 2010, Georgilakis & Hatziargyriou, 2013).

The challenges are solved using various techniques. In (Almabsout, 2020), the author proposed an improved genetic algorithm (GA) for optimal sizing of DG and shunt capacitor, combining local search schemes to achieve less computation time for best placement on DN. However, GA is challenged with substantial computation time and the possibility of trapping at local optima. An improved grey wolf (GWO) optimization technique was presented in (Li et al, 2020) for the optimization of reactive power injection in the active distribution network (ADN). However, GWO possesses slow convergence and low precision. A hybrid of particle swarm optimization and WOA was developed in conjunction with the loss sensitivity factor in (Adetunji et al, 2020) for optimal allocation of DG. However, there is a need for analysis on a standard network. A multi-objective function was applied in DG optimization using simulated annealing (Gandomkar, 2005); the results revealed the efficient DG location and sizing within a lesser time than the genetic algorithm.

However, the method is not proficient as the network gets larger.
A hybrid of harmony search and simulated annealing optimization algorithm was investigated in (Guangqian et al, 2018), for optimal allocation of standalone hybrid PV/wind power generation. The strength of each metaheuristic was combined for improving network performance. In (Bechouat et al., 2017), the authors investigated the backstepping controller for PV/wind hybrid system using particle swarm optimization (PSO). The current flow and zero reactive power control were achieved through a grid-connected three-phase inverter. The simulation yields improved results with slight harmonic distortion in the current injection mode despite climate change in the wind speed and the irradiation. However, the percentage improvement of selected objective functions was not quantified.
The author in (Dinakara et al., 2018) presented optimal renewable energy placement in the distribution system (DS) by combining power loss index and WOA. The results show improved network performance. The WOA is versatile and efficient in handling complex optimization problems. However, its exploration and exploitation properties can be further enhanced through a combination of other methods. The study's main contribution is the combination of VSI on the distribution network with the WOA (VSIWOA). The VSI signals the selection of solution nodes/buses to reduce the search space at each iteration and improve the optimization algorithm convergence to yield an optimum solution.

MATERIALS AND METHOD

Voltage Stability Index Evaluation

The significance of VSI is to ascertain the vulnerable buses/branches on the power system network (Amrane et al, 2015). It indicates the value of the index closer to the critical point. As the value tends to the extreme, the corresponding node and bus are weaker, signifying the point of voltage instability with eventual system failure. Therefore, this study employs the voltage stability index method to evaluate and determine the potential location for the allocation of DG. For N number of buses on DN, the source node with voltage $V_i<\theta_i$ and P_i+jQ_i, is the input power on node j. The bus output voltage is $V_j<\theta_j$ and the input power of P_j+jQ_j. The line impedance is $R+jX$, by ignoring admittance. The voltage stability index estimation is expressed as (Tu et al, 2018):

$$VSI = \frac{4Q_j\left(R^2+X^2\right)}{XV_i^2} \leq 1 \tag{1}$$

The critical operating value is indicated as the VSI gets closer to 1, while better stability value is ensured with smaller values. Considering the effect of the embedded DG on DN, Figure 1 presents the schematic DN with embedded DG. After the DG integration at the receiving end node, the real and reactive power load referring to the source is:

$$P'_{load} = P_{load} - P_{DG} \tag{2}$$

$$Q'_{load} = Q_{load} - Q_{DG} \tag{3}$$

where λ represents the proportion of variation in busload, P_{load} and Q_{load} are the real and reactive load power, P'_{load} and Q'_{load} are the real and reactive load power after the DG integration.

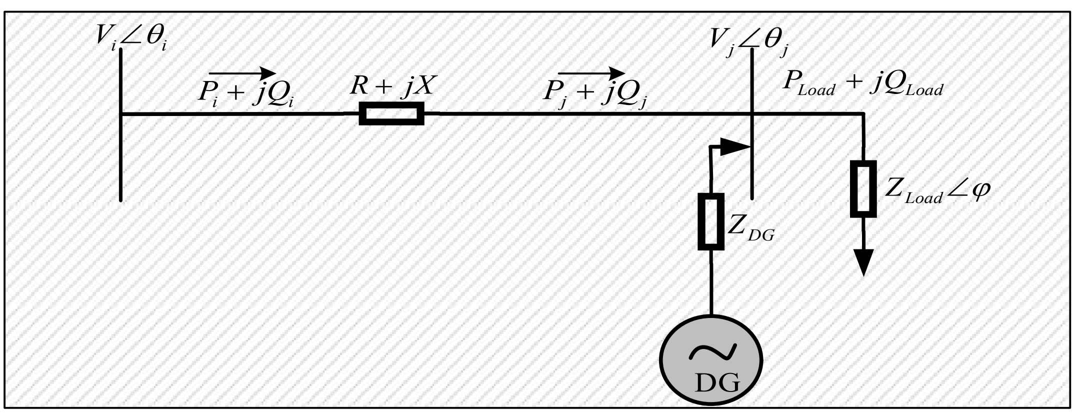

Figure 1: Schematic of DN with DG.

The current through the network is:

$$I = \frac{E}{\sqrt{\left(Z\cos\theta + Z_{load}\cos\varphi\right)^2 + \left(Z\sin\theta + Z_{load}\sin\varphi\right)^2}} \tag{4}$$

Where E is the terminal voltage, Z is the impedance, θ is the phase angle and φ is the load angle. Though type I and type III DGs are considered in this work, different types of DGs are categorized as: Type I (which can inject real power only, the PV generation falls in this category), Type II (which can inject reactive power only), Type III (which can inject both real and reactive power, the small hydro falls in this category), Type IV (which can inject real power but absorbing reactive power).

Proposed Technique Based on Whale Optimization Algorithm

The optimal allocation problem of the DG is formulated as a constrained optimization model. The paper combines the voltage stability index evaluation technique with a whale optimization algorithm to allocate the best site for DG capacity. The problem to solve has two parts. The first part is to solve for the best location of renewable generation and secondly the best sizing. Results from the first are non-zero positive integers, which are buses along the network feeder. The first bus is the source bus and assumes not to access the integration of DG. The rest buses from the second to the end bus are potential candidate solutions. However, most candidate buses for installing a DG are introduced using the voltage stability index evaluation. The VSI is lumped into WOA to determine the most suitable candidate buses at each iteration time. The buses with high VSI, which have their voltage level toward voltage instability, are selected as a possible candidate solution. The suggested bus (i) at the current iteration (it) is mathematically expressed as:

$$Bus_i^{it} = \begin{Bmatrix} 1, & if \quad Index_i^{it} > \quad 0.1 \\ 0, & Otherwise \end{Bmatrix} \tag{5}$$

1 signifies that the *ith* bus is active for selection and inactive to accommodate DG when the value is 0. The 0.1 stands for 10% of the highest threshold of the VSI. The WOA is then updated at each iteration to finally return the optimal sizing and location of renewable DG sources. WOA has a fast convergence property, which makes it attractive for large and time-consuming optimization problems. The algorithm moves from its exploration mode to exploitation mode to yield an optimal solution as it covers the whale movement from the point of sighting the prey to its eventual arrival at prey location. The stages are mathematically modeled as follows (Mirjalili & Lewis, 2016):

Encircling Prey

The behaviour is mathematically represented as:

$$\vec{D} = \left| \vec{C}\vec{X}^*(t) - \vec{X}(t) \right| \tag{6}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}\vec{D} \tag{7}$$

Where t is the present iteration, $\vec{A}$ and $\vec{C}$ are both coefficient vector, $\vec{X}^*$ is the current position vector of the optimal solution so far, $\vec{X}$ represent the positional vector, $|\,|$ is the modulus of the value consisting of elements product. The position $\vec{X}^*$ is updated at each iteration when a better value is obtained. $\vec{A}$ and $\vec{C}$ are computed as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{8}$$

$$\vec{C} = 2.\vec{r} \tag{9}$$

Bubble-Net Attacking Method

A spiral equation is then developed between the position of the whale and prey to replicate the helix-shaped navigation of the humpback whales as:

$$\vec{X}(t+1) = \vec{D}'.e^{bl}\cos(2\pi l) + \vec{X}^*(t) \tag{10}$$

Where $\vec{D}' = \left| \vec{X}^*(t) - \vec{X}(t) \right|$ and stands for the distance between an agent whale to the prey. b is a constant of the logarithmic spiral shape, l takes a random number in [-1,1]. The humpback whales navigate the search space for prey within the shrinking circle and spiral-shaped route concurrently. The concurrent behaviour is modeled by assuming a probability of 0.5 swings between the shrinking encircling and the spiral updating model. This is mathematically defined as:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}\vec{D} & if \quad p < 0.5 \\ \vec{D}' \; e^{bl}.\cos(2\pi l) + \vec{X}^*(t) & if \quad p \geq 0.5 \end{cases} \tag{11}$$

Where p denotes the random number in [0,1].

Search for Prey

The search for prey takes the exploration phase of the algorithm and vector $\vec{A}$ is also adapted for modification towards reaching the prey. The humpback randomly search based on the position of each other while vector $\vec{A}$ spans between greater than 1 or less than -1 to boost the search agent exploration far away from the referenced whale. The search agent position is updated based on randomly chosen agents instead of the best agent searched so far. The modulus of $\vec{A}$ greater than 1 emphasizes the exploration and enhance algorithm for global search. The model is mathematically outlined as follows:

$$\vec{D} = \left| \vec{C}.\vec{X}_{rand} - \vec{X} \right| \tag{12}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{13}$$

Where $\vec{X}_{rand}$ represents the random position vector selected from the population at the current iteration.

Problem Formulation

The technique in this study aims at optimizing the performance indexes of the DN by minimizing the power losses and voltage deviation. And the decision variables are the DG location and DG sizing. The photovoltaic DG is modeled as unity power factor and the small hydro is configured to inject both real and reactive power.

Power Losses
Considering a distribution line between ‘i’ and ‘k’ buses, as shown in Figure 2. The power losses in the system are calculated and computed as follows:

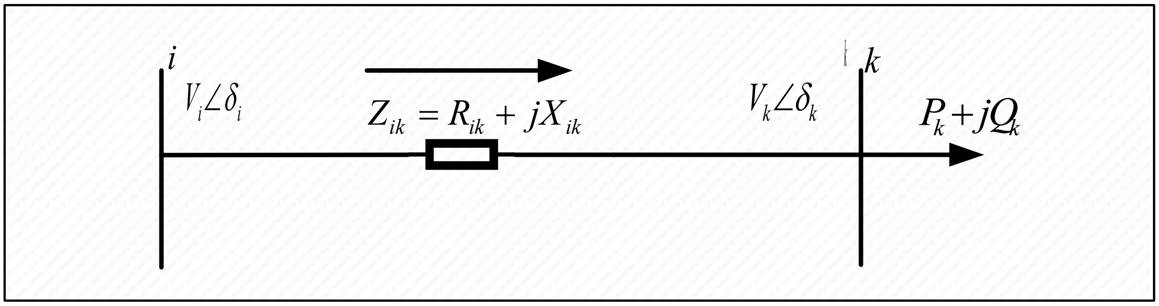

Figure 2: A branch flow of radial distribution system

$$P_{ik\_loss} = \frac{R_{ik}\left(P_k^2 + Q_k^2\right)}{\left(V\right)^2} \tag{14}$$

Where R_{ik} is the line resistance between bus *i* and *k,* P_k and Q_k are the real and reactive power flow and V is the terminal voltage.

Voltage Profile
The objective function to minimize the voltage deviation is:

$$V_{ik\Delta} = \sum_{i=1}^{k}\left(V_{ref} - V_k\right) \tag{15}$$

Where V_{ref} is the reference voltage and $V_{ik\Delta}$ is the deviated voltage between bus *i* and *k*.

Constraint
The constraints considered are load balance constraint, voltage limits, renewable generation constraints, thermal and other limits. The power balance equations should be fulfilled as follows:

$$\begin{aligned} &P_{Gni} - P_{Dni} - V\sum_{j=1}^{N} V_{nj}Y_{nj}\cos\left(\delta_{ni} - \delta_{nj} - \theta_{nj}\right) \\ &Q_{Gni} - Q_{Dni} - V\sum_{j=1}^{N} V_{nj}Y_{nj}\cos\left(\delta_{ni} - \delta_{nj} - \theta_{nj}\right. \end{aligned} \tag{16}$$

Where $n_i = 1,2,\ldots,n_n$.

The generator voltage and the load/bus voltage maintain the same level in connection with power flow along the line. The voltage rise is proportional to power flow. Therefore, the increase in power flow significantly affects voltage level. Hence, the voltage has to be maintained within the statutory limit at each bus:

$$V_{ni}^{\min} < V_{ni} < V_{ni}^{\max} \tag{17}$$

For the distribution network, the value adopted for this work ranges from 0.95 to 1.05.
The DG size is inherently limited due to available energy resources in a selected location. Hence, the need to maintain the capacity between the minimum and maximum values.

$$P_{Gni}^{\min} \le P_{Gni} \le P_{Gni}^{\max} \tag{18}$$

The thermal limit of the DN must be kept within the limit:

$$\left|S_{ni}\right| \le \left|S_{ni}^{\max}\right| \quad i = 1,\ldots,N \tag{19}$$

Implementation Algorithm
The detailed algorithm for the proposed methodology is as follows:

VSIWOA implementation for DG sizing and location

1. **Read**: load data and line data of the distribution system
2. **Store:** the agent number, MaxCycle and set matric format for final solution

   MaxCycle is the maximum cycle or iteration (500), Agent population = 100.

3. **Set:** DG and system constraints
4. **Initialization:** population is randomly generated: 100 agents at random

   The decision variables are the location and sizing of DG.

$$X_i = \left(\left(upperbound - lowerbound\right).*rand\left(1,dim\right) + lowerbound\right),$$

$$X_i = \left(X_i^1, \ldots X_i^{dim}, \ldots X_i^n\right),\ for\ \ i = 1,2\ldots N$$

Where $X_i^{\dim}$ denotes the position of *ith* agent in the *dimth* dimension, *n* is the

5. **Set:** Zero the counter
6. **Calculate:** power flow analysis for DG connected power network
7. **Compute:** feeder voltage stability index for each bus using Equation (1)
8. **Evaluate:** objective functions using Equation (14) and (15)
9. **Update:** fitness function for the minimization of voltage deviation and loss reduction
10. **Update:** velocity and position using Equation (6),(7),(10),(11),(12) and (13)
11. **Calculate:** the new bus voltage stability index using Equation (5)

12: **Generate:** the updated population for the next iteration

13: Cycle = 1

14: **Repeat:** step 6 to 12

15: **Store:** the best solution so far

16: **Cycle** = Cycle + 1

17: Until, Cycle = MaxCycle

18: **Print:** Final solution

Figure 3 presents the flowchart for the VSI/WOA algorithm.

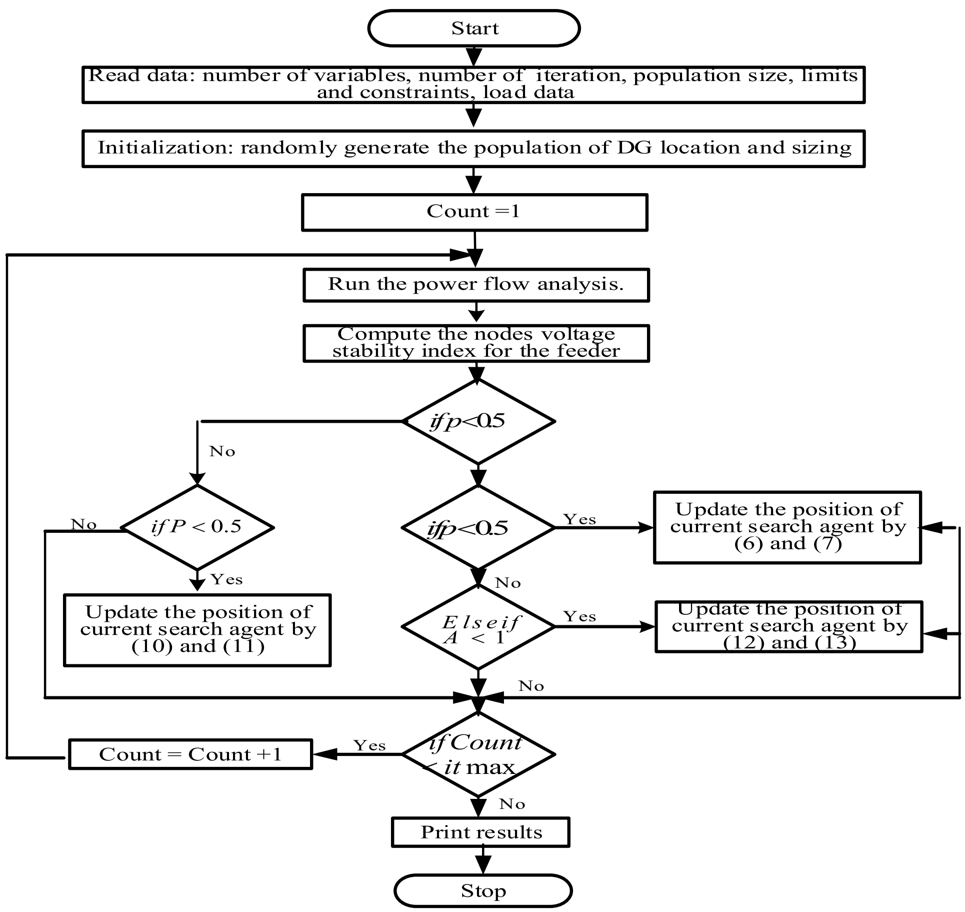

Figure 3: Flowchart of the proposed algorithm

RESULTS AND DISCUSSION

The proposed combined voltage stability index evaluation/whale optimization algorithm is tested on DN feeders. The performance analysis on IEEE 33 is presented as follows:

3.1 IEEE 33-Bus Test Network

The effectiveness of the VSIWOA optimization technique for the allocation of renewable-based DG is verified using a standard IEEE 33 bus system. Figure 4 presents the thirty-three bus system. It has the main feeder with three laterals connected on thirty-two branches.

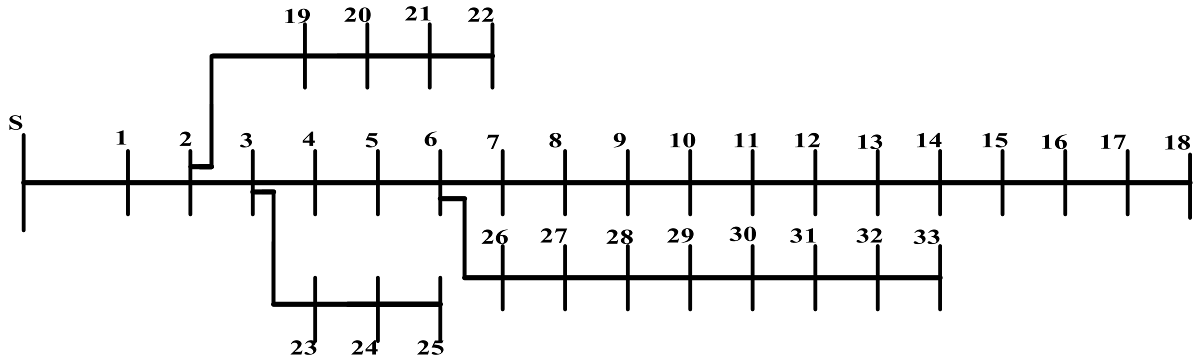

Figure 4: IEEE 33-bus system feeder

The real and reactive load demands are 3.72 MW and 2.3MVAr respectively. 12.66kV is the substation voltage at the base power of 100MWA (Wang et al., 2018). The system data are referenced as (Das et al, 1995). The VSI estimation for all the busses without the addition of DG is given in Figure 5.

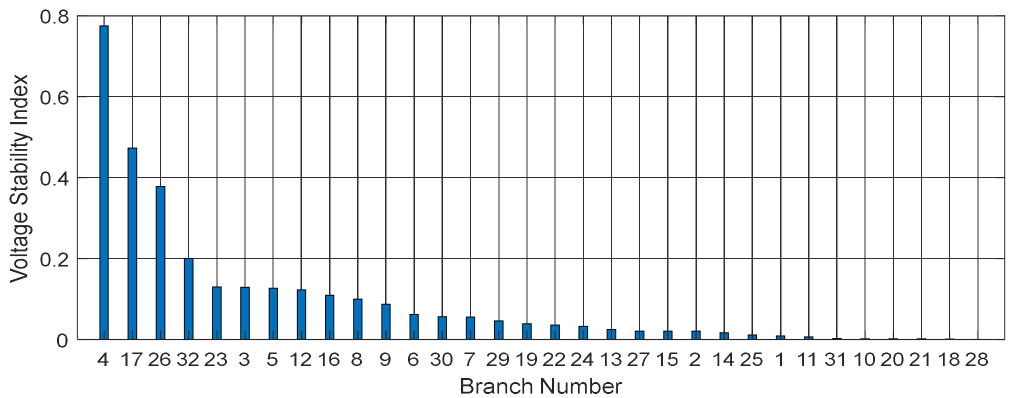

Figure 5: IEEE 33 – bus distribution system voltage stability index

It is observed that the 4th branch is the highest index branch. Therefore, the 5th bus next to the branch with the highest index is selected for one DG integration. The selection of buses keeps changing and updated at the end of each iteration. However, the whole voltage stability index is shown in Table 1.

Table1: Results for voltage stability index in the IEEE 33 – bus distribution system

Branch	Index	Branch	Index	Branch	Index	Branch	Index
4	0.7747	16	0.1096	22	0.0358	1	0.0088
17	0.4729	8	0.0998	24	0.0326	11	0.0063
26	0.3777	9	0.0871	13	0.0249	31	0.0029
32	0.2005	6	0.0618	27	0.0211	10	0.0019
23	0.1300	30	0.0566	15	0.0210	20	0.0017
3	0.1292	7	0.0554	2	0.0206	21	0.0015
5	0.1265	29	0.0457	14	0.0172	18	0.0009
12	0.1225	19	0.0386	25	0.0114	28	0.0003

The performance analysis of the proposed VSIWOA is verified by comparing it with the results obtained from standalone WOA. Table 2 shows the network performance indicators in terms of voltage deviation and power loss due to the installation of PV and SHP renewable sources. With one location of DG, the optimal capacity and location obtained are shown in Table 2. The best site for installing the PV generation is bus 6, and its capacity evaluated is 2499kW. A decrement in power losses from 243.60kW to 125.45kW resulted in 48.50 power loss reduction. The lowest voltage at bus 18 improved from 0.9131 p.u. to 0.9500 p.u.

Table 2: The network results for 33 bus system

Items	**Base**	**One DG**		**Hybrid**
		PV	**SHP**	**PVSHP**
Total losses (kW)	243.60	125.45	80.843	78.32
Loss reduction (%)	…	48.50	66.81	67.85
Min. voltage	0.9131	0.9500	0.9468	0.9470
Max. voltage	0.9965	1.0511	1.0697	1.0511
Bus no		6	30	30
Power Factor		unity	0.8	0.6
Size(kW)		2499		
Size(kVA)			1792	1799
Feeder voltage deviation (pu)	1.7009	0.1845	0.2660	0.2650
Voltage Improvement. (%)		89.15	84.36	84.42

The small hydro generator operates at 0.8 power factor to yield a better loss reduction due to the generation of reactive power compared to PV operation at unity power factor. However, PV has the highest impact in terms of voltage improvement. The combination of PV/SHP in hybrid configuration results in a slight improvement in loss reduction. Besides, a comparison of the proposed technique in terms of voltage deviation and power loss reduction with standalone WOA simulated under the same condition is shown in Table 3.

Table 3: Comparison of the proposed method with other techniques

DG.	Method	DG installed Size (kVA/PF)	Bus	% Loss reduction	Minimum voltage	Maximum voltage	% Voltage improvement
PV	WOA	2489/1	9	48.25	0.9635	1.0021	86.67
	Proposed	**2499/1**	**6**	**48.50**	**0.9686**	**1.0110**	**89.15**
SHP	WOA	1789/0.8	31	65.42	0.9646	1.0064	84.20
	Proposed	**1792/0.8**	**30**	**66.81**	**0.9720**	**1.0217**	**84.36**

The convergence property using the proposed VSIWOA and standalone WOA optimization technique is illustrated in Figure 7. The figure establishes the capability of the proposed method in yielding efficient results with improved convergence compared to WOA. It is observed that the convergence in VSIWOA is achieved earlier before that of WOA in less than 50 iterations with a lesser simulation time of 252.65s as against 259.50s in WOA.

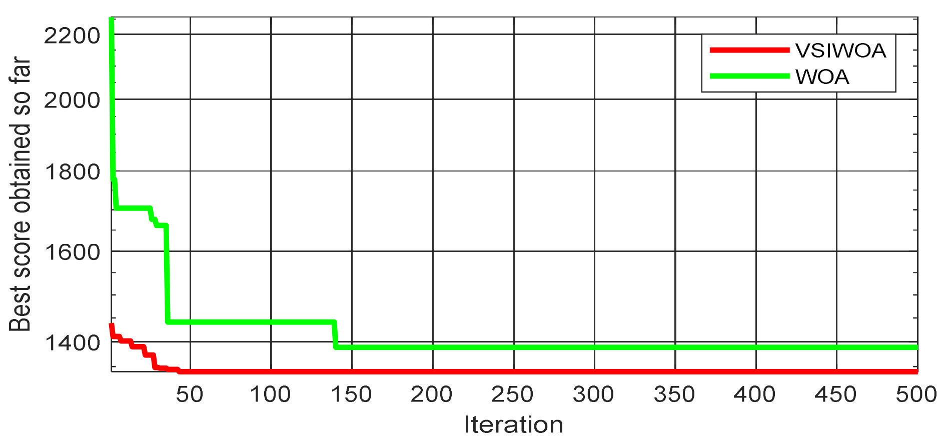

Figure 7: Convergence property of VSIWOA technique

CONCLUSION

This study implements a combined VSEWOA for the optimal location and sizing of renewable energy sources, particularly PV and SHP. The voltage stability index of the network is assessed at each algorithm iteration to suggest the vulnerable nodes of the feeder for the improved capability of the WOA within the shortest period. The effectiveness of the proposed algorithm is clarified using IEEE 33 bus system. The simulation results are computed and compared with what is obtainable in standalone WOA algorithms. The comparison shows that the present study provides notable network performance in terms of power loss reduction and voltage improvement.

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