Artificial Intelligence Application using Nutcracker Optimization Algorithm to Enhance Efficiency & Reliability of Power Systems via Optimal Setting and Sizing of Renewable Energy Sources as Distributed Generations in Radial Distribution Systems

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Abstract
People have been using more energy in the last years. Several research studies were conducted to develop sustainable energy sources that can produce clean energy to fulfill our energy requirements. Using renewable energy sources helps to decrease the harm to the environment caused by conventional power plants. Choosing the right location and capacity for DG-RESs can greatly impact the performance of Radial Distribution Systems. It is beneficial to have a good and stable electrical power supply with low energy waste and high effectiveness because it improves the performance and reliability of the system. This research investigates the ideal location and size for solar and wind power systems, which are popular methods for producing clean electricity. A new artificial intelligent algorithm called Nutcracker Optimization Algorithm (NOA) is used to find the best solution in two common electrical systems named IEEE 33 and 69 bus systems to examine the improvement in the efficiency & reliability of power system network by reducing power losses, making voltage deviation smaller, and improving voltage stability. Finally, the NOA method is compared with another method called PSO and developed Hybrid Algorithm (NOA+PSO) to validate the proposed algorithm effectiveness and enhancement of both efficiency and reliability aspects.
Keywords:
Artificial intelligence algorithms, efficiency, reliability, renewable energy sources, nutcracker optimization algorithm, distributed generation, radial distribution systems.

1. Introduction

Radial distributed systems (RDSs) are commonly utilized in areas with minimal population due to their affordability and ease of construction. In these systems, one power source gives electricity to lots of customers. However, they have some problems [1].

One problem is that if the power goes out or the power line gets broken, all the energy will be lost and cannot come back until it is fixed. Another negative aspect is that power losses are increasing, which would make efficiency lower and harm the economy [2].

Compensators serve as a key solution for addressing these problems [1-4]. RDSs employ numerous devices to enhance voltage and power quality, minimize power loss, and increase generation reserve [3,4]. The way these compensators work is by helping to keep the reactive power of the system balanced. Adding some smaller power generation sources, particularly those that use renewable energy sources, is another crucial method. DGs are technologies that can be placed close to where the power is needed. They are flexible and can be easily adjusted to meet different requirements. They make the power transmitted through the transmission lines, so there is less power lost and the system becomes more efficient. One of the main advantages of using DG-RESs is that it gives customers reliable, affordable, and environmentally friendly electricity [5]. Renewable energy's inclusion in the power grid is seen as an important solution for the rising need for electricity and to address environmental issues. Many renewable energy sources, such as solar panels, wind turbines, and fuel cells, were added to the electrical grid [6].

There are three primary advantages to the electricity system when renewable energy sources are utilized as distributed generators: environmental preservation, financial savings, and enhanced technical aspects [7,8]. Furthermore, installing Renewable Energy Sources (RESs) in the right location with enough capacity can improve the quality of distribution power systems. This can enhance the voltage profile and decrease power losses in the network [8–11]. Studies have shown that the placement of DGs in incorrect locations and at appropriate capacities has been shown to result in power flowing back towards the distribution substation. The system might get overloaded, which could make the system lose more power [12]. Different research studies in this filed have recently focused on finding out an optimal DG location and size in distribution systems via different methods of implantation methods, for example, solving multi-objective functions, most sensitive buses, novel power stability indexes, and lowest voltage buses [13-16]. Many of these works used optimization methods to make finding the best place and size for DGs easier. There are several artificial intelligent algorithms for optimization that scientists use to solve problems. Some of these algorithms include Particle Swarm Optimization, Genetic Algorithm, Gray Wolf Optimization,

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Hybrid Big Bang–Big Crunch Approach, Bat Approach, Modified Bacterial Foraging Optimization, Invasive Weed Optimization, Water Cycle Algorithm, Ant Colony Algorithm, Chaotic Symbiotic Organisms Search Algorithm, Modified Teaching–Learning based Optimization Algorithm, Cuckoo Search Algorithm, Marine Predators Optimizer, and Heuristic Methods [17–34] were proposed to handle the process of placing DG. In this work, we are using two common radial systems, IEEE 33 [35–51], and 69 [52–61], the objective of these studies was to find out the optimal location and size of distributed generators in the radial distribution systems, considering the requirements for voltage stability and minimal power losses. These studies were able to figure out the best position and size, while considering the power losses and voltage levels. You can still try to solve this problem using newer optimization methods instead of the ones mentioned in [35–61].

This work presents a new way to find the best placement and size of DGs in RDSs. The goal is to reduce power losses and improve voltage levels to enhance both the system efficiency and reliability, while considering all the needs and restrictions for the task of optimization. This new optimization technique is called Nutcracker Optimization Algorithm (NOA) [62] which has many advantages such as:

- Easy to implement.
- Able to avoid falling into local optima for several optimization problems with various characteristics.
- Having a high convergence speed

We still don't believe that RESs can be optimized using NOA. This encourages us to support NOA in managing this task. It is used to find the best ways to assign and utilize DG in Standard RDSs. The NOA findings are being compared with different method PSO to see if it is good at finding the best ways to allocate resources and manage DGs. This helps decrease power loss and improve voltage levels in addition to improving reliability. Developed hybrid (NOA+PSO) has been presented to furnish the improvement and effectiveness of the performance and system.

This article provides the following contributions:

• NOA as a successful optimization tool to handle the issue of the optimum position and size of PV and WT in RDSs is adopted to reduce power losses and reinforce the system voltage profile.

• The efficiency factors for the system are examined to find the power losses after placing the DGs in the standard IEEE 33, and 69 Bus systems. Moreover, the voltage stability index (VSI) and is inspected for all RDSs.

• The reliability factors for the system are examined to find EENS, LOLE, SAIDI and CAIDI after placing the DGs in the standard IEEE 33 and 69 Bus systems.

This article is arranged as follows: the suggested NOA and Hybrid (NOA+PSO) are discussed in Section 2; then, the developed objective function is addressed in Section 3; the outcomes and discussion are illustrated in Section 4, and finally, Section 5 presents the conclusion.

2. Nutcracker Optimization Algorithm

In this research, we started by surveying the different existing teaching strategies. This survey looked at different ways and mainly focused on traditional and virtual teaching strategies.

2.1 Inspiration of Nutcracker in Nature

The Nutcracker optimization algorithm (NOA) is a nature-inspired algorithm that simulates the distinct behavior of a nutcracker bird that occurs in two separate periods. Nutcrackers are intelligent birds with a strong spatial memory.

Nutcrackers are medium-sized birds with long, sharp bills as shown in Fig. 1. Pine seeds represent the primary food source of these birds. In the summer and fall seasons, the nutcracker searches for seeds and stores them in appropriate caches. Later in the winter and spring seasons, the nutcracker uses its powerful memory to recover previously stored seeds.

Fig. 1. Nutcracker Bird

2.2 Foraging and Storage Strategy

Nutcracker employs the first strategy, represented by the foraging and storage. It implements the first strategy in the summer and fall seasons and searches for good seeds and stores them, in suitable areas, away from the collection area as shown in Fig. 2.

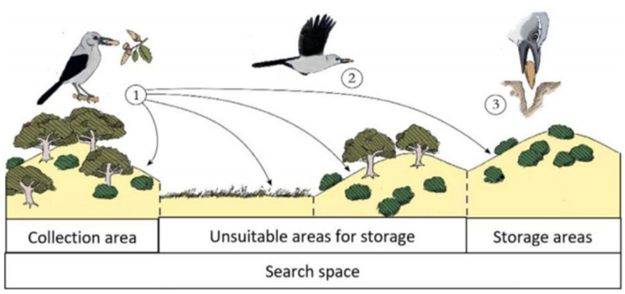

Fig. 2. Search Space in NOA

2.3 Cache-Search and Recovery Strategy

Nutcracker employs the second strategy, represented by cache-search and recovery. It implements the second strategy in the winter and spring seasons. Also, nutcracker uses more than one object or marks reference points (RPs) that help it remember storage locations as shown in Fig. 3.

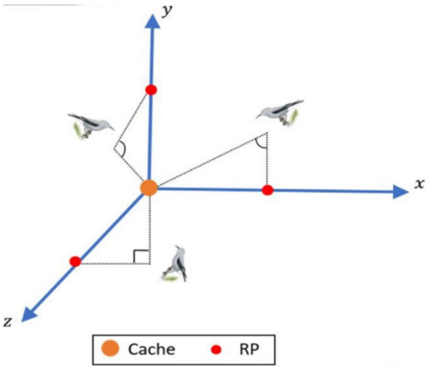

Fig. 3. Three different locations for the nutcracker in 3-D space, with three different locations of ***RP*** for one cache

2.4 Reference Memory

Nutcracker uses the spatial memory strategy to search for the hidden caches marked at different angles using various RPs as represented in Fig. 4.

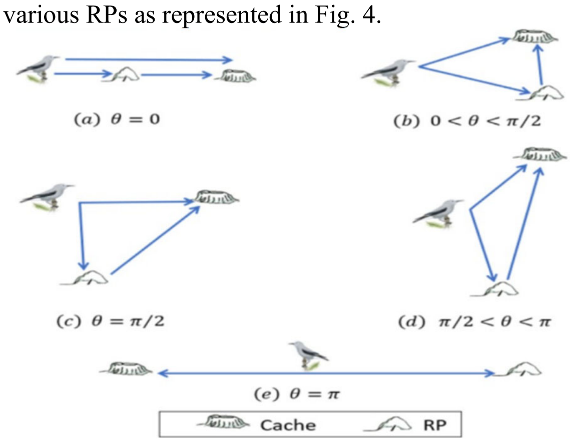

Fig. 4. Different viewing angles of the nutcracker for both cache and ***RP***

In Fig. 5, flowchart has been illustrated the framework of NOA in information sharing mechanism among two strategies.

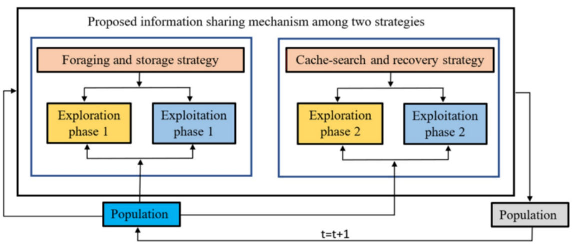

Fig. 5. Framework of NOA

2.5 Exploration Phase 1 (Foraging Stage)

At this stage, the nutcracker starts foraging for good seeds in the collection area (the search space). If the nutcracker cannot find good seeds, then it will seek another cone in another position within pine trees or other trees. This behavior can be mathematically modelled using the position update strategy as follows:

$$\vec{X}_i^{t+1} = \begin{cases} X_{i,j}^t & if\ \tau_1 < \tau_2 \\ X_{m,j}^t + \gamma.\left(X_{A,j}^t - X_{B,j}^t\right) + \mu.\left(r^2.U_j - L_j\right), & if\ t \le T_{max}/2.0 \\ X_{C,j}^t + \mu.\left(X_{A,j}^t - X_{B,j}^t\right) + \mu.\left(r_1 < \delta\right).\left(r^2.U_j - L_j\right), & Otherwise \end{cases} \quad (1)$$

Where: $\vec{X}_i^{t+1}$ is the new position of the ith nutcracker in the current generation t; $\vec{X}_{i,j}^t$ is the jth position of the ith nutcracker in the current generation; $\vec{X}_{m,j}^t$ is the mean of the jth dimensions of all solutions of the current population in the iteration t; Uj and Lj are vectors, including the upper and lower bound of the jth dimension in the optimization problem; γ is a random number generated according to the levy flight; $\tau 1, \tau 2, r$, and $r1$ are random real numbers in the range of [0,1]; A, C, and B are three different indices randomly selected from the population; and μ is a number generated based on the normal distribution.

2.6 Exploitation Phase 1 (Storage Stage)

At this stage, the nutcrackers begin by transporting the food to a storage area, where they exploit pine seed crops and store them. Such behavior can be mathematically expressed as follows:

$$\vec{X}_i^{t+1(new)} = \begin{cases} \vec{X}_i^t + \mu.\left(\vec{X}_{best}^t - \vec{X}_i^t\right).|\lambda| + r_1.\left(\vec{X}_A^t - \vec{X}_B^t\right) & if\ \tau_1 < \tau_2 \\ \vec{X}_{best}^t + \mu.\left(\vec{X}_A^t - \vec{X}_B^t\right) & if\ \tau_1 < \tau_3 \\ \vec{X}_{best}^t.l & Otherwise \end{cases} \quad (2)$$

Where: $\vec{X}_i^{t+1(new)}$ is a new position in the storage area of the nutcrackers in current iteration t; $\vec{X}_{best}^t$ is the best position/cache in iteration t, λ is a number generated according to the levy flight, and $\tau 3$ is a random number between 0 and 1; and l is a factor that linearly decreased from 1 to 0 to diversify in the exploitation behavior of NOA. This variety in the exploitation operator of NOA will help in accelerating its convergence speed, in addition to avoiding stuck into local minima that might occur when searching in one direction.

2.7 Balance between Exploration Phase-1 and Exploitation Phase-1

In the NOA, in order to maintain the balance between exploration phase 1 and exploitation phase 1 as shown in Fig. 6, the following formula is proposed:

$$\vec{X}_i^{t+1} = \begin{cases} Eq.(1), & if\ \varphi < P_{a1} \\ Eq.(2), & Otherwise \end{cases} \quad (3)$$

Where: φ is a random number between zero and one, and P_{a1} represents a probability value that is linearly decreased from one to zero based on the current generation.

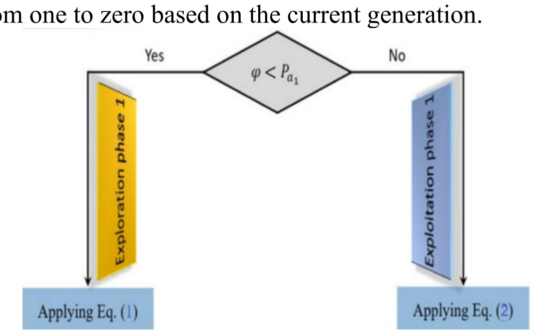

Fig. 6. Flowchart of the exploration and exploitation process in the foraging and storage strategy

2.8 Exploration Phase 2 (Cache-Search Stage)

At this stage, the Nutcrackers begin to search and explore their caches. They use a spatial memory strategy to locate their caches and use multiple objects as signals for a single cache. For simplicity, we will assume that each cache has only two objects. In NOA, two RPs of each cache/nutcracker of the population can be defined using the following matrix:

$$\text{RPs} = \begin{bmatrix} \overrightarrow{RP}^t_{1,1} & \overrightarrow{RP}^t_{1,2} \\ \vdots & \vdots \\ \overrightarrow{RP}^t_{i,1} & \overrightarrow{RP}^t_{i,2} \\ \vdots & \vdots \\ \overrightarrow{RP}^t_{N,1} & \overrightarrow{RP}^t_{N,1} \\ \vdots & \vdots \end{bmatrix}$$

Where: represent $RP\{_1$ and $RP\{_2$ (objects) of cache position Xf of ith nutcracker in the current generation t.

The first and second RPs are generated by updating the current position within the neighbouring regions to find hidden caches around the nutcrackers. The mathematical formula for generating the first and second RPs are as follows:

$$\overrightarrow{RP}^t_{i,1} = \begin{cases} \vec{X}^t_i + \alpha.\cos(\theta).(\vec{X}^t_A - \vec{X}^t_B) + \alpha.RP, & if\ \theta = \pi/2 \\ \vec{X}^t_i + \alpha.\cos(\theta).(\vec{X}^t_A - \vec{X}^t_B), & Otherwise \end{cases} \quad (4)$$

$$\overrightarrow{RP}^t_{i,2} = \begin{cases} \vec{X}^t_i + (\alpha.cos(\theta).((\vec{U} - \vec{L}).\tau_3 + \vec{L}) + \alpha.RP).\vec{U}_2, & if\ \theta = \pi/2 \\ \vec{X}^t_i + \alpha.cos(\theta).((\vec{U} - \vec{L}).\tau_3 + \vec{L}).\vec{U}_2, & Otherwise \end{cases} \quad (5)$$

Where: $RP\{_1$ and $RP\{_2$ represent the first and the second RP of the cache position $\vec{X}^t_i$ of the ith nutcracker in the current iteration t; $\vec{r}_2$ is a vector that includes values randomly generated in the range [0, 1]; $\vec{X}^t_A$, $\vec{X}^t_B$ t are the cache positions of the Ath and Bth nutcrackers, respectively, in the iteration t; RP is a random position; θ is a random in the range [0 , π]; and $\vec{U}_2$ is a random number equal to 1 if $\vec{r}_2 < P_{rp}$, otherwise equal to zero, P_{rp} is a probability employed to determine the percentage of globally exploring other regions within the search space.

α ensures that the NOA converges on a regular basis, allowing the nutcracker to improve its RP selection in the next generations. a can be calculated according to the following equation:

$$\alpha = \begin{cases} \left(1 - \frac{t}{T_{max}}\right)^{2.\frac{t}{T_{max}}}, & if\ r_1 > r_2 \\ \left(\frac{t}{T_{max}}\right)^{\frac{2}{t}}, & Otherwise \end{cases} \quad (6)$$

Where: t and T_{max} indicate the current and maximum generations, respectively. The first state in Eq. (6) linearly decreases with the iteration to improve the convergence speed of the NOA. Meanwhile, the second state linearly increases to avoid being stuck into local minima, which might occur because of the first state.

In NOA, all nutcrackers will apply the exploration mechanism to search for the most promising areas that might contain a near-optimal solution. With each generation passed, the algorithm will explore and exploit areas around caches with appropriate RPs to avoid getting stuck in local minima. The new position of a nutcracker can be updated using the following equation:

$$\vec{X}^{t+1}_i = \begin{cases} \vec{X}^t_i, & if\ f(\vec{X}^t_i) < if(\overrightarrow{RP}^t_{i,1}) \\ \overrightarrow{RP}^t_{i,1}, & Otherwise \end{cases} \quad (7)$$

2.9 Exploitation Phase 2 (Recovery Stage)

At this stage, the Nutcracker tries to recover its cache. The following scheme (recovery scheme) depicts the possibilities that a Nutcracker might encounter when searching for its cache as shown in Fig. 7:

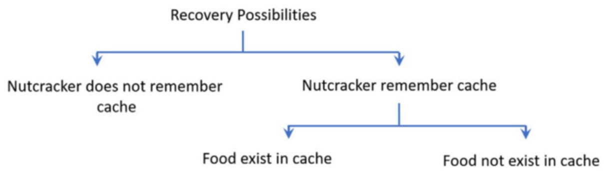

Fig. 7. Probable options for the Nutcracker to recover its recover its cache

The following equation simulates the first possibility (Nutcracker remember cache)

$$X^{t+1}_{i,j} = \begin{cases} X^t_{i,j}, & if\ \tau_3 < \tau_4 \\ X^t_{i,j} + r_1.(X^t_{best,j} - X^t_{i,j}) + r_2.(\overrightarrow{RP}^t_{i,1} - X^t_{C,j}), & Otherwise \end{cases} \quad (8)$$

However, the following equation simulates the second possibility (Nutcracker does not remember cache):

$$\vec{X}^{t+1}_i = \begin{cases} \vec{X}^t_i, & if\ \ f(\vec{X}^t_i) < if(\overrightarrow{RP}^t_{i,2}) \\ \overrightarrow{RP}^t_{i,2}, & Otherwise \end{cases} \quad (9)$$

Eq. (9) offers an opportunity for the NOA to explore new regions around the second RP and exploit promising areas where a potential solution could be found. In NOA, a nutcracker is assumed to find its cache using the second RP, so Eq. (8) is updated based on the second RP using the following equation:

$$X_{ij}^{t+1} = \begin{cases} X_{ij}^{t}, & if\ \tau_5 < \tau_6 \\ X_{ij}^{t} + r_1.(X_{best,j}^{t} - X_{ij}^{t}) + r_2.(\overrightarrow{RP}_{i,2}^{t} - X_{Cj}^{t}), & Otherwise \end{cases} \quad (10)$$

Where: r_1, r_2, τ_4 and τ_5 are a random number between 0 and 1.

In summary, the simulation of the recovery behavior (recovery scheme) can be summarized in the following:

$$\vec{X}_i^{t+1} = \begin{cases} Eq.(13), & if\ \tau_7 < \tau_8 \\ Eq.(15), & Otherwise \end{cases} \quad (11)$$

Where: τ_7 and τ_8 are a random number between 0 and 1. The following equation is proposed to achieve the trade-off between exploration behaviors about the first and second RPs:

$$\vec{X}_i^{t+1} = \begin{cases} Eq.(7), & if\ f(Eq.(7)) < f(Eq.(9)) \\ Eq.(9), & Otherwise \end{cases} \quad (12)$$

2.10 Balance between Exploration Phase-2 and Exploitation Phase-2

In the NOA, to maintain the balance between exploration phase 2 and exploitation phase 2, the following formula is proposed:

$$\vec{X}_i^{t+1} = \begin{cases} Eq.(11), & if\ \emptyset < P_{a2} \\ Eq.(12), & Otherwise \end{cases} \quad (13)$$

$\emptyset$ is a random number between zero and one, and P_{a2} represents a probability value that is equal to 0.2.

The flowchart of NOA is represented to explain the algorithm process steps as illustrated in Fig. 8 in Annexure.

2.11 Developed Hybrid Algorithm (NOA+PSO)

A hybrid algorithm is a method that uses multiple algorithms to solve a problem. It can either use one algorithm based on the data or switch between them during the process. This is usually done to put together the best parts of each, so that the whole algorithm is better than each one alone.

A "Hybrid Algorithm" is not just about mixing different algorithms to solve a new problem. Many algorithms are already made up of smaller parts. Hybrid algorithms are specifically about combining different algorithms that solve the same problem but have different performance.

In this article, the proposed NOA has been utilized to create hybrid algorithm using one of previous famous optimization algorithm that called Particle swarm optimization (PSO) which create the hybrid algorithm (NOA+PSO) as presented in flow chart in Fig. 9 in Annexure.

3. Objective Charge Function

The developed objective charge function has been used to decrease the amount of power losses and to enhance the voltage profiles and voltage stability index (VSIs). The optimal DG location and size can be determined by solving the objective charge function (14):

$$F_t = w_1.of_1 + w_2.of_2 + w_3.of_3 + w_4.of_4 + w_5.of_5 + w_6.of_6 + w_7.of_7 \quad (14)$$

where of_1 represents the real losses minimization as shown in equation (15):

$$of_1 = \frac{\sum_{i=1}^{L}(P_{Lineloss}(i))_{after\ DG}}{\sum_{i=1}^{L}(P_{Lineloss}(i))_{before\ DG}} \quad (15)$$

of_2 displays the improvement of the VDI according to the following equation:

$$of_2 = \frac{VDI(k)_{before\ DG}}{VDI(k)_{after\ DG}} \quad (16)$$

of_3 refer to the VSI improvement which can be calculated through equation (17):

$$of_3 = \frac{VSI(k)_{before\ DG}}{VSI(k)_{after\ DG}} \quad (17)$$

of_4 shows the reduction in expected Energy Not Supplied ENS as follows in equation (19):

$$of_4 = \frac{ENS(k)_{after\ DG}}{ENS(k)_{before\ DG}} \quad (19)$$

of_5 offers the reduction in expected Energy Not Supplied ENS as representing in equation (20):

$$of_5 = \frac{LOLE(k)_{after\ DG}}{LOLE(k)_{before\ DG}} \quad (20)$$

Where LOLE means the loss of load expected in percentage (%).

of_6 shows the enhancement in the System average Interruption Duration Index (SAIDI) as per equation (21):

$$of_6 = \frac{SAIDI(k)_{after\ DG}}{SAIDI(k)_{before\ DG}} \quad (21)$$

of_7 appears the enhancement in the Customer Average Interruption Duration Index (CAIDI) according to equation (23):

$$of_7 = \frac{CAIDI(k)_{after\ DG}}{CAIDI(k)_{before\ DG}} \quad (23)$$

$w1$, $w2$, $w3$, $w4$, $w5$, $w6$, and $w7$ are weighting factors. The sum of the weights is one that can be observed in the equation (25):

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 = 1 \quad (25)$$

The weighting factors assumption used are as follows:

$$w1 = 0.2,\ w2 = 0.05,\ w3 = 0.05,\ w4 = 0.15,\ w5 = 0.15,\ w6 = 0.2 \text{ and } w7 = 0.2$$

4. Outcomes and Discussion

The newly developed NOA and hybrid (NOA+PSO) were studied for different RDSs. The results of RDSs IEEE 33 bus and IEEE 69 bus are furnished in detail. The new techniques were examined using MATLAB.

4.1. Simulation Results for the IEEE-33 Bus RDS

The first case study done using NOA involved a system with 33 nodes. Figure 10 shows a simple drawing of the system that has main feeders' line and three branches. This net standard demand of the system is 3720 kW and 2300 kVar at a voltage scale of 12.66 kV. The developed NOA has proved its effectiveness to determine the optimal allocation and sizing of PV (solar panels), and WT (wind turbines) individually and combined with comparison to another algorithm like PSO (Particle Swarm Optimization). Tables 1, 2, and 3 in Annexure illustrate the influences of establishing various scenarios of DGs installation either individually or combined on the system behaviors.

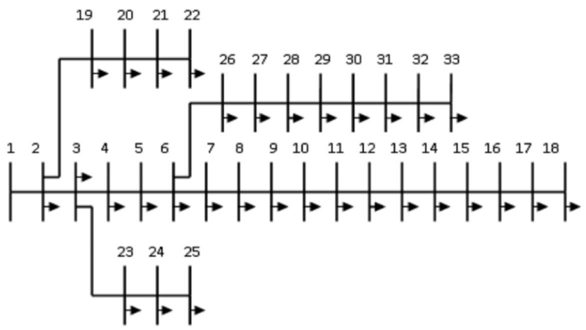

Figure 10. IEEE-33 Bus Radial Distribution System

4.1.1. PV as a DG-RES in IEEE 33-bus system:

In this case, only the PV system has been added as a DG-RES for the IEEE-33 bus system. The optimal placement for the PV system was determined to be at bus 26, 6, 26, with the rating of 1715 kW using NOA, PSO, and Hybrid (NOA+PSO) methods, respectively.

This improvement was achieved by using the NOA algorithm, which facilitated the identification of the most suitable position and size for deploying a single DG-PV unit inside the IEEE 33 Bus RDS as summarized in Table 1 in Annexure.

The voltage profile was improved by using NOA and Hybrid (NOA+PSO) approach, resulting in a minimum value of 0.963202 p.u at bus 18 as shown in Fig. 11 which reflect better result than PSO 0.963196 p.u. at bus 18.

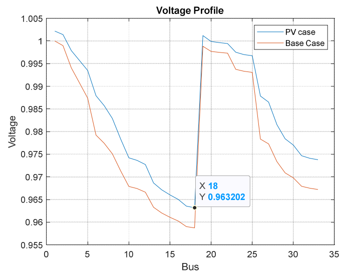

Fig. 11. Voltage Profile of IEEE-33 Bus in case of DG PV using NOA Algorithm

4.1.2. WT as a DG-RES in IEEE 33-bus system:

In this case, WT system has been adopted as a DG-RES for the IEEE-33 bus system. The optimal placement was determined to be at bus 18, with the rating of 3560 kW/712 KVar using NOA, PSO, and Hybrid (NOA+PSO) methods.

This improvement was achieved by using the NOA algorithm, which facilitated the identification of the most suitable position and size for deploying a single DG-PV unit inside the IEEE 33 Bus RDS as summarized in Table 2 in Annexure.

The voltage profile was improved by using NOA approach, resulting in a minimum value of 0.962 p.u at bus 18 as shown in Fig. 12.

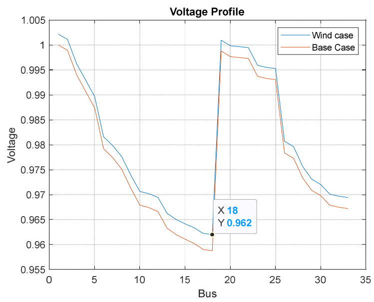

Fig. 12. Voltage Profile of IEEE-33 Bus in case of DG WT using NOA Algorithm

4.1.4. Combined PV and WT as a DG-RES in IEEE 33-bus system:

This combined PV and WT system will be used as a DG-RES for the IEEE-33 bus system. NOA, PSO, and Hybrid (NOA+PSO) were used to compute these optimum locations as per the results shown in Table 3 in Annexure, PV and WT should be installed on buses 18/21, 18/19, and 18/29, and PV system ratings, were 2500 kW, 2500 kW, and 2800 kW, whereas WT systems had ratings of 2283 kW/331 KVar, 2284 kW/57 KVar, and 2552 kW/-697 KVar, respectively.

The voltage profile improved using NOA technique to a minimum of 0.961855 p.u. at bus 18 as shown in Fig. 13, whereas the best result was obtained from Hybrid (NOA+PSO) to be 0.961868 p.u.

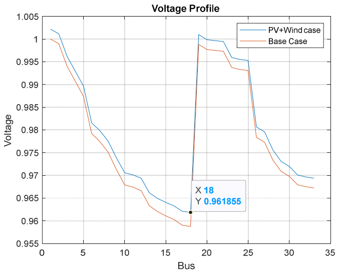

Fig. 13. Voltage Profile of IEEE-33 Bus in case of Combined DGs PV and WT using NOA Algorithm

4.2. Simulation Results for the IEEE-69 Bus RDS

The first case study done using NOA involved a system with 69 nodes. Figure 14 shows a simple drawing of the system that has main feeders' line and three branches. This net standard demand of the system is net standard demand of 3800 kW and 2690 kVar at a voltage scale of 12.66 kV. The developed NOA has proved its effectiveness to determine the optimal allocation and sizing of PV, and WT individually and combined with comparison to other algorithms such PSO (Particle Swarm Optimization). Tables 4, 5, and 6 in Annexure illustrate the influences of establishing various scenarios of DGs installation either individually or combined on the system behaviors.

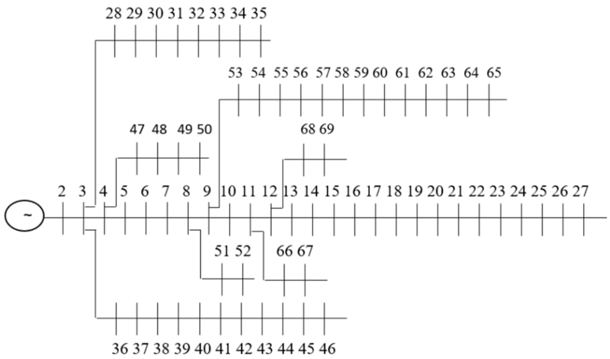

Figure 14. IEEE-69 Bus Radial Distribution System

4.2.1. PV as a DG-RES in IEEE 69-bus system:

In this scenario, only PV system has been utilized as a DG-RES for the IEEE-69 bus system. The optimal placement for the PV system was determined to be at bus 9, with the ratings of 6631 kW, 5596 kW and 6631 kW using NOA, PSO, and Hybrid (NOA+PSO) methods, respectively.

This improvement was obtained by using NOA algorithm, which facilitated the identification of the most suitable position and size for deploying a single DG-PV unit inside the IEEE 69 Bus RDS as summarized in Table 4 in Annexure.

The voltage profile was improved by using NOA and Hybrid (NOA+PSO) approach, resulting in a minimum value of 0.975814 p.u at bus 27 as shown in Fig. 15 which reflect better result than PSO 0.974951 p.u. at bus 27.

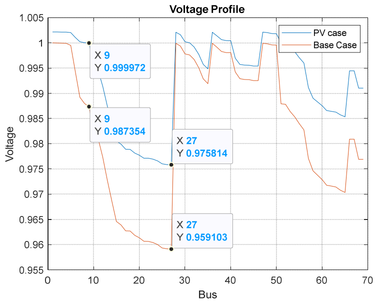

Fig. 15. Voltage Profile of IEEE-69 Bus in case of DG PV using NOA Algorithm

4.2.2. WT as a DG-RES in IEEE 69-bus system:

In this case, WT system has been incorporated as a DG-RES for the IEEE-69 bus system. The optimal placement was determined to be at bus 27, with the rating of 7120 kW/ 1424 KVar using NOA, PSO, and Hybrid (NOA+PSO) methods.

As summarized in Table 5 in Annexure, the improvement was achieved by using the NOA algorithm, which facilitated the identification of the most suitable position and size for deploying a single DG-PV unit inside the IEEE 69 Bus RDS

As shown in Fig. 16, it is observed the voltage profile improvement by using NOA approach, resulting in a minimum value of 0.974283 p.u at bus 27.

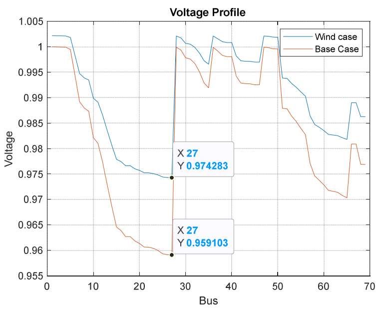

Fig. 16. Voltage Profile of IEEE-69 Bus in case of DG WT using NOA Algorithm

4.2.4. Combined PV and WT as a DG-RES in IEEE 69-bus system:

This combined PV and WT system will be incorporated as a DG-RES for the IEEE-69 bus system. As illustrated results in Table 6 in Annexure, NOA, PSO, and Hybrid (NOA+PSO) were utilized to compute the optimum locations for PV and WT which should be installed on buses 27/69, 27/26, and 27/69, and PV system rating, were 7120 kW, whereas WT systems had rating of 7120 kW/-892 KVar, 7120 kW/262 KVar, and 7120 kW/435 KVar, respectively.

The voltage profile improved using NOA technique to a minimum of 0.974183 p.u. at bus 18 as shown in Fig. 17.

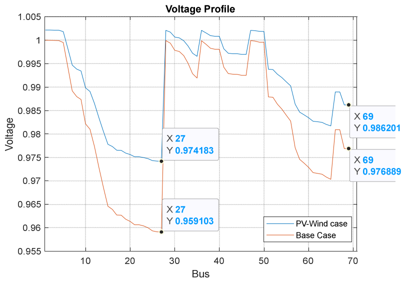

Fig. 17. Voltage Profile of IEEE-69 Bus in case of Combined DGs PV and WT using NOA Algorithm

5. Conclusions

This article used NOA and hybrid (NOA+PSO) to find the best location and size of energy distributed generators in common radial distribution system. This process was created to make the system more efficient and reliable by improving the system indices that related to power loss, voltage levels, VSI, VDI, ENS, LOLE, SAIDI, and CAIDI. The results compared with other famous methods. The most important findings of this paper were:

1. A multi-objective function was created with considering an assumption weighting factors to improve the electricity systems performance. It aims to reduce power losses, improve voltage levels, in addition to improve selected reliability indices of various RDSs such as ENS, LOLE, SAIDI and CAIDI.
2. The WT installation is more effective at reducing power loss compared to PV.
4. With the combination of PV, and WT which shows the results enhancement in the overall system performance in both efficiency and reliability aspects and provide the best fitness value with respect to the selected weighting factors for the objective function.
5. The importance of NOA was confirmed in relation to power losses reduction to be 2.81% in IEEE33 Bus system, and 55.83% in IEEE 69 Bus system. The future concern of this study is on implementing new approaches for large-scale renewable energy systems with other energy sources and utilizing battery energy storage systems (BESS).

Conflict of interest

The authors assert that no conflict of interest exists.

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Annexure

Fig. 8. Flowchart of NOA

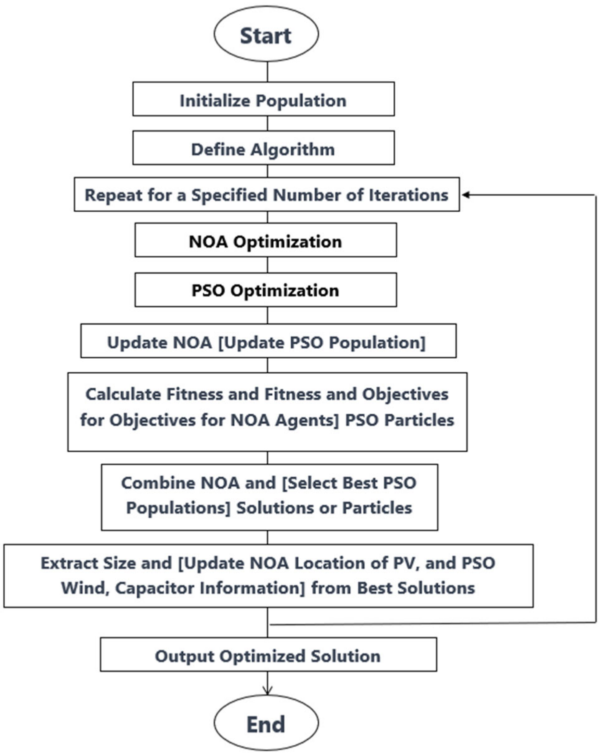

Fig. 9. Flowchart of Hybrid Algorithm (NOA+PSO)

Table 1. Outcomes for the 33-node grid in case of DG PV

Item	Base Case Without DG	With DG PV		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	1387	1715	1715	1715
Net DG (kW)/bus	--	3546/26	3546/6	3546/26
Power Loss (kW)/(KVar)	34.47/23.55	35.87/25.72	35.99/25.79	35.87/25.72
Power Loss Index (PLI)	2.49	2.09	2.1	2.09
Lower Voltage (P.U)/bus	0.958763/18	0.963202/18	0.963196/18	0.963202/18
VSI	0.72	0.62	0.63	0.62
VDI	0.84	0.85	0.85	0.85
ENS (kWh)	422	94	94	94
Loss of load Expected (%)	23	5	5	5
SAIDI (Hours)	2044	454	454	454
CAIDI (Hours)	11	2	2	2
Fitness Value	1	0.46489	0.46501	0.46489

Table 2. Outcomes for the 33-node grid in case of DG WT

Item	Base Case Without DG	With DG WT		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	1387	1391	1391	1391
Net DG (kW)/(kVar)/bus	--	3560/712/18	3560/712/18	3560/712/18
Power Loss (kW)/(KVar)	34.47/23.55	33.57/22.9	33.57/22.9	33.57/22.9
Power Loss Index (PLI)	2.49	2.41	2.41	2.41
Lower Voltage (p.u)/bus	0.958763/18	0.962/18	0.962/18	0.962/18
VSI	0.72	0.71	0.71	0.71
VDI	0.84	0.85	0.85	0.85
ENS (kWh)	422	418	418	418
Loss of load Expected (%)	23	23	23	23
SAIDI (Hours)	2044	2025	2025	2025
CAIDI (Hours)	11	11	11	11
Fitness Value	1	0.99358	0.99358	0.99358

Table 3. Outcomes for the 33-node grid in case of combined PV and WT

Item	Base Case Without DG	With Combined DG PV and WT		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	1387	1392	1392	1393
Net DG PV (kW)/bus Net DG WT (kW)/(kVar)/bus	--	2500/18 2283/331/21	2500/18 2284/57/19	2800/18 2552/-697/29
Power Loss (kW)/(KVar)	34.47/23.55	33.72/23	33.72/23	33.73/23.01
Power Loss Index (PLI)	2.49	2.42	2.42	2.42
Lower Voltage (p.u)/bus	0.958763/18	0.961855/18	0.961855/18	0.961868/18
VSI	0.72	0.71	0.71	0.71
VDI	0.84	0.85	0.85	0.85
ENS (kWh)	422	115	115	106
Loss of load Expected (%)	23	6	6	6
SAIDI (Hours)	2044	557	557	513
CAIDI (Hours)	11	3	3	3
Fitness Value	1	0.48662	0.48662	0.47912

Table 4. Outcomes for the 69-node grid in case of DG PV

Item	Base Case Without DG	With DG PV		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	2671	3383	3354	3383
Net DG (kW)/bus	--	6631/9	5596/9	6631/9
Power Loss (kW)/(KVar)	64.1/31.88	42.54/21.4	38.7/19.36	42.54/21.4
Power Loss Index (PLI)	2.4	1.26	1.15	1.26
Lower Voltage (p.u)/bus	0.959103/27	0.975814/27	0.974951/27	0.975814/27
VSI	0.84	0.73	0.89	0.73
VDI	1.16	0.9	0.74	0.9
ENS (kWh)	1151	440	468	440
Loss of load Expected (%)	30	11	12	11
SAIDI (Hours)	2639	1007	1073	1007
CAIDI (Hours)	14	2	2	2
Fitness Value	1	0.7074	0.70779	0.7074

Table 5. Outcomes for the 69-node grid in case of DG WT

Item	Base Case Without DG	With DG WT		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	2671	2680	2680	2680
Net DG (kW)/(kVar)/bus	--	7120/1424/27	7120/1424/27	7120/1424/27
Power Loss (kW)/(KVar)	64.1/31.88	28.21/13.96	28.21/13.96	28.21/13.96
Power Loss Index (PLI)	2.4	1.05	1.05	1.05
Lower Voltage (p.u)/bus	0.959103/27	0.974283/27	0.974283/27	0.974283/27
VSI	0.84	0.89	0.89	0.89
VDI	1.16	0.8	0.8	0.8
ENS (kWh)	1151	1142	1142	1142
Loss of load Expected (%)	30	30	30	30
SAIDI (Hours)	2639	2617	2617	2617
CAIDI (Hours)	14	5	5	5
Fitness Value	1	1.2054	1.2054	1.2054

Table 6. Outcomes for 69-node grid in case of combined DGs PV & WT

Item	Base Case Without DG	With Combined DGs PV and WT		
		Proposed NOA	PSO	Hybrid (NOA+PSO)
Network Power (kW)	2671	2689	2689	2689
Net DG PV (kW)/(kVar)/bus **Net DG WT (kW)/(kVar)/bus**	--	7120/27 7120/-892/69	7120/27 7120/262/26	7120/27 7120/435/69
Power Loss (kW)/(KVar)	64.1/31.88	28.4/14.06	28.4/14.06	28.4/14.06
Power Loss Index (PLI)	2.4	1.06	1.06	1.06
Lower Voltage (p.u)/bus	0.959103/27	0.974183/27	0.974183/27	0.974183/27
VSI	0.84	0.89	0.89	0.89
VDI	1.16	0.8	0.8	0.8
ENS (kWh)	1151	425	425	425
Loss of load Expected (%)	30	11	11	11
SAIDI (Hours)	2639	974	974	974
CAIDI (Hours)	14	2	2	2
Fitness Value	1	0.61227	0.61227	0.61227