

Dingo Optimization Algorithm for Sizing and Allocation of Wind Energy Systems in Radial Distribution System

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Abstract: - Many studies have investigated Distributed Generation (DG) using Renewable Energy Sources (RESs) to treat the rising global energy demand. These renewable sources also help reduce the environmental impacts associated with conventional power plants. Proper sizing and placement of DGs based on RESs are essential for improving the reliability, power quality, and bus voltage profile, power quality, and in Radial Distribution Systems (RDSs), especially about active losses. This work focuses on the use of DG represented by wind power systems in RDS. Therefore, in this study, wind turbines (WT), which is one of the most commonly utilized RES, are selected to give the optimized placing and volume. This optimization, which was carried out using the Dingo Optimization Algorithm (DOA), aims to improve system reliability by reducing active losses and improving the profile and quality of the voltage. The IEEE 69-bus system is used to test the performance of the developed method. Results indicate that the proposed DOA method not only correctly located the optimal size and placement of the WT as well, but also improved the voltage profile, and reduced active losses over existing methods. In addition, the developed DOA is proven to be effective for various types of loading constraints.

Key-Words: - Dingo Optimization Algorithm, Power Loss, Wind Systems, Radial Distribution System, Load Variations, VSI.

Received: April 13, 2024. Revised: September 15, 2024. Accepted: February 2, 2025. Published: April 1, 2025.

1 Introduction

Radial Distribution Systems (RDSs) are commonly used in sparsely populated areas due to cheaper and simpler construction. But a major disadvantage of RDSs is that they are susceptible to power failures, short circuits, and damaged conductors that can interrupt the electricity supply to the consumers. These problems must be addressed to reinstate the integrity of the power system [1] and [2]. In the case of Renewable Energy Sources (RES), Distributed Generations (DGs) provide a solution that enhances power supply proximity to the demand which in return increases efficiency. DGs are defined as load-centered, adjustable systems with decentralized power generation. They improve efficiency by decreasing the dependence on long transmission lines, thus reducing the power and

current losses. DG-RESs afford consumers dependable, inexpensive, and green energy [3] and [4]. In addition, they reduce feeder congestion improve network reliability and security, improve profile and voltage stability, and minimize power losses [5] and [6].

Integrating wind energy into power networks diversifies electricity generation sources, reducing reliance on conventional fossil fuels and strengthening the resilience of the grid [6], and [7]. As a clean, renewable source, wind power enhances energy security by providing a local supply while lowering greenhouse gas emissions and carbon dioxide, helping in climate alter mitigation. The scalability of wind energy allows flexible incorporation into power systems, tailored to domestic needs and sources availability, [8].

Additionally, the wind energy sector stimulates industries in manufacturing, installation, and maintenance, promoting economic growth in areas where wind farms are developed. Ongoing advancements in Wind Turbine (WT) technology have increased energy capture and cost-efficiency, while progress in storage technology has further improved wind energy reliability [9] and [10].

In recent years, numerous surveys have been conducted to determine the optimum placement of DG for minimizing the previously mentioned objectives, employing a range of optimization techniques, such as the Artificial Bee Colony Approach [11], Particle Swarm Optimization [12], Genetic Approach [13], Cuckoo Search [14], Sine Cosine Approach [15], Modified Teaching–Learning based Optimization Approach [16], Improved Harris Hawks Optimizer [17], Heuristic Methods [18], Ant Colony Approach [19], and Shark Optimization Approach [20].

The previously mentioned approaches have several limitations, including a tendency to get stuck in local optima and the requirement for significant computational sources along simulations. These challenges encouraged the development of a pioneer, slight, efficient, and fast population based optimized method for determining the optimal position of DG in the form of wind systems as in RDS. Furthermore, the use of the Dingo Optimization Algorithm (DOA) for identifying the optimum allocation and sizing of wind systems in RDSs has not been analyzed before.

2 Problem Formulation

The cost charge function could be resolved using the integration of three targets, namely F_1 , F_2 , and F_3 , pioneering the finest site selection of wind systems and their related potentials, [3]. Voltage profile, active losses, and Voltage Stability Index (VSI) are associated with F_1 , F_2 , and F_3 , successively. These three targets are cumulated to provide the objective function.

$$F_1 = \frac{\sum_{n=1}^k P_{loss(n)_{with\ WT}}}{\sum_{n=1}^k P_{loss(n)_{without\ WT}}} \quad (1)$$

F_2 may be chosen to allow for voltage profile improvement.

$$F_2 = \frac{\sum_{n=1}^N |V_i - V_{i,ref}|_{with\ WT}}{\sum_{i=1}^N |V_i - V_{i,ref}|_{without\ WT}} \quad (2)$$

This work scans the refinements done by the VSI, [21], as showed:

$$F_3 = \frac{1}{VSI_{with\ WT}} \quad (3)$$

The target objective of this work is the minimization of F_t , that is expressed as the aggregation of the three distinct targets timed by their own weighting operators α_1 , α_2 and α_3 each separately:

$$F_t = \alpha_1 F_1 + \alpha_2 F_2 + \alpha_3 F_3 \quad (4)$$

The best values of 3 weighted constants were evaluated and analyzed across various layouts. It was concluded that α_1 should have a greater value contrasted to the two distinct constants, α_2 and α_3 . Accordingly, the values were adjusted to 0.5, 0.25, and 0.25, respectively, as stated and documented in [20].

The targeted function presented in (4) is optimized, ensuring that the optimization satisfies the following inequality and equality constraints [22] and [23]:

- The whole active and reactive power flows of input and output through the RDS can be expressed as:

$$P_S + \sum_{i=1}^{NDG} P_{DG}(i) = \sum_{i=1}^L P_{L_{loss}}(i) + \sum_{q=1}^N PL(q) \quad (5)$$

$$Q_S + \sum_{i=1}^{NDG} Q_{DG}(i) = \sum_{i=1}^L Q_{L_{loss}}(i) + \sum_{q=1}^N QL(q) \quad (6)$$

- The voltage at each node must fall within the standard satisfactory boundaries as follows:

$$V_{min} \leq |V_i| \leq V_{max} \quad (7)$$

To prevent reverse power flow, the mounted capability of the DG in the system has been ranged to ensure it is not overcome the supplied power from the substation, [3].

This work presents the employing of DOA as the finest procedure to minimize the targeted function. Achieving this target needs addressing several constraints, such as harmonizing the generated power with the load requirements, assuring voltage remains within acceptable boundaries, and adhering to wind rating limitations.

3 Dingo Optimization Algorithm

Nature has always been the greatest teacher, guiding the survival of every species on earth through unique mechanisms. One of these mechanisms is the dynamic nature of social relationships. Animal social behavior can be categorized into distinct segments. The first category is shaped by environmental factors, such as resource availability and threats posed by other species. The second one

is determined by the personal actions or characteristics of an individual. In this light, the dingo serves as inspiration for this work, for deeply ingrained in it is an intricate social structure. The dingo is a species of wild canine called *Canis lupus*, a remarkably intelligent social animal. Dingoes are pack animals and expert hunters, living in groups of 12 to 15 animals. Their social structure is highly organized, with an alpha at the peak of the hierarchy who can be a female or male. The leader, or the most powerful, is in charge of the whole pack and chooses where to sleep, decides where to go hunting, and protects the pack. So, it demonstrates the need for discipline and organization in society more than raw power. The rest of the pack agrees with the alpha's order and the rest of the pack lowers their tails as a sign of acceptance. Primary to the alpha in command is the beta, which plays an important role as a 'middle' dingo among the rest of the pack and the alpha. The beta plays a pivotal role as the alpha's adviser and enforces the pack's orders. This enables the alpha to focus on more important matters. If the alpha is no longer able to lead, the beta takes over the leadership role. Pack members who are neither alpha nor beta are considered subordinates, and they follow the directives of the higher-ranking members. Scouts are responsible for patrolling the pack's territory and alerting the group to potential threats, while hunters assist the betas and alphas in capturing chase and supplying food for the herd. Research shows that dingoes possess a refined ability to communicate with each other, using variations in sound intensities to exchange information. As a dingo moves into a new area, the strength of its communication signals changes, allowing for effective coordination within the group. Group hunting is a particularly fascinating aspect of dingo social behavior, further showcasing their complex social interactions. The chasing scheme is systematized in their stages namely attacking, grouping, and scavenging [24] and [25].

3.1 Team Attacking

Chasers possess strong hunting talents. The dingo is specifically adept at categorizing prey during hunts. When the prey is small, dingoes hunt alone, but they chase in teams when the prey is large. Like wolves, dingoes have an instinctive capability to allocate prey and encircle it, [26]. Team attack can be modeled in (8).

$$\vec{a}_i(t+1) = \beta_1 \sum_{k=1}^m \frac{\left(\vec{\varphi}_k(t) - \vec{a}_l(t) \right)}{m} - a_*(t) \quad (8)$$

Where the novel location of the search agent is symbolized by $\vec{a}_i(t+1)$, m is a haphazard number. The subgroup of search agents is symbolized by $\vec{\varphi}_k(t)$. The ongoing search agent is symbolized by $\vec{a}_l(t)$. The supreme search agent merged from the prior iteration is symbolized by $\vec{a}_*(t)$. β_1 is a homogeneously generated haphazard value between $[-2, 2]$.

3.2 Molestation

When dingoes chase small victims, they hunt them until each one is caught separately. Molestation can be represented in (9).

$$\vec{a}_i(t+1) = \vec{a}_*(t) + \beta_1 \cdot e^{\beta_2} \cdot (\vec{a}_{ri}(t) - \vec{a}_i(t)) \quad (9)$$

Where β_2 is a homogeneously haphazard value originated between $[-1, 1]$, ri is the haphazard value originating from 1 to the peak size of search agents, and $\vec{a}_{ri}(t)$ is the ri -th search agent, as $i \neq ri$, [27].

3.3 Scavenger

Scavenging is the attitude exhibited by a dingo when it comes over remains to consume while wandering aimlessly within its zone, [28]. This may occur in (10).

$$\vec{a}_i(t+1) = 0.5 \cdot [e^{\beta_2} \cdot \vec{a}_{ri}(t) - (-1)^\sigma \cdot \vec{a}_i(t)] \quad (10)$$

Where σ is a binary value originated at random, $\sigma \in \{0, 1\}$.

4 Results and Discussions

This work assesses the superiority of the DOA scheme in determining the optimum placement and capabilities of DG units represented in wind energy systems. The analysis is performed using the IEEE 69 RDS, with the IEEE 69 bus system depicted in Figure 1. The technique is developed using MATLAB software.

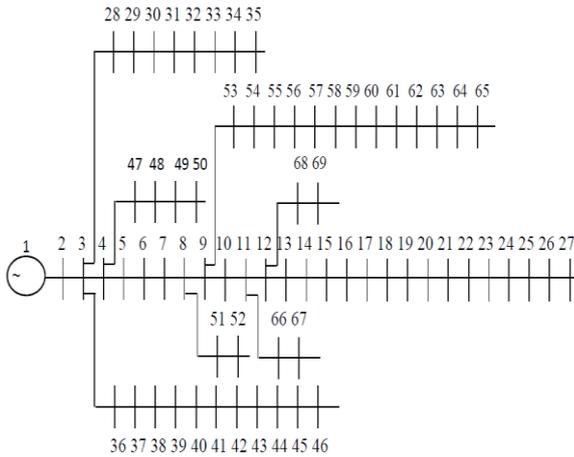


Fig. 1: IEEE 69 bus system

4.1 Single WT location

The optimal location and sizing for a single WT installation are determined using DOA as shown in Table 1. Bus number 61 is identified as the finest location for WT installation with a capacity of 2230 kVA with a power factor of 0.81 lagging. With the WT type, active losses are lessened to 23.1524 kW, representing an 89.7073% reduction. The proposed DOA results in annual energy savings of \$106,059.56. The lowest voltage is raised to 0.9716 p.u. Additionally, the proposed algorithm outperforms CSA, SGA, PSO, BB-BC, GA, and ALOA in lessening losses and hence enhancing savings, as demonstrated in Table 1 and Table 2.

Table 1. 69 bus system results

Items	Without DG	With DG (kVA/P. F)	
		One WT	Two WT
Total losses (kW)	224.940	23.1524	20.9028
Loss reduction (%)	-	89.7073	90.7071
Minimum voltage	0.9102	0.9716@ 27	0.9745 @65
WT	-	2230/0.81 @61	700/0.82 @17 1500/0.82 @61
VSI	61.2379	65.3431	66.1348
Cost of losses (\$)	118228.46	12168.9	10986.5
Saving (\$/year)	-	106059.56	107241.96

Table 2. Results for one WT installation.

Technique	DG installation		Power loss (kW)	
	Size (kVA/P.F)	Bus	Value	%
Without	-	-	224.94	-
GA [29]	2155.6/NR	61	38.458	82.9
CSA [30]	2300 /NR	61	52.6	76.6
SGA [30]	2600/NR	61	64.4	71.37
PSO [30]	2300/NR	61	52.6	76.6
BBBC [31]	2223/0.81	61	23.1737	89.697
ALOA [3]	2227.9/0.82	61	23.1622	89.703
DOA	2230/0.81	61	23.1524	89.707

NR: Not Reported

4.2 Two WT sites

To confirm the impact of DOA in determining the best site and adjusted size of WT, it is applied to two potential WT sites. Buses 17 and 61 are identified as the finest sites for mounting, with capacities of 700 kVA and 1500 kVA, with 0.82 lagging power factor. Active losses are reduced to 20.903 kW, achieving a 90.71% decline in overall losses.

The proposed DOA results in an annual energy savings of \$107,241.96. The minimum voltage increases to 0.9745 p.u as mentioned in Table 1. Also, the algorithm outperforms CSA, SGA, PSO, and ALOA in minimizing losses and improving savings as introduced in Table 3. Furthermore, the impact of adding different numbers of WTs on voltage profiles and VSI is illustrated in Figure 2 and Figure 3. The reactive power capability of WTs significantly contributes to enhancing voltage profiles and lessening power losses.

Table 3. Results of two WT installations

Algorithm	With DG		Loss (kW)	
	Size (kVA/P. F)	Bus	Value	%
Without	---	---	224.940	---
CSA [30]	800 /NR	18	39.9	82.26
	2000/NR	61		
SGA [30]	600/NR	18	44	80.4
	2300/NR	62		
PSO [30]	900/NR	18	42.4	81.15
	1900/NR	62		
ALOA [3]	726.62/0.83	17	20.9342	90.69
	1500/0.8	61		
DOA	700/0.82	17	20.9028	90.7071
	1500/0.82	61		

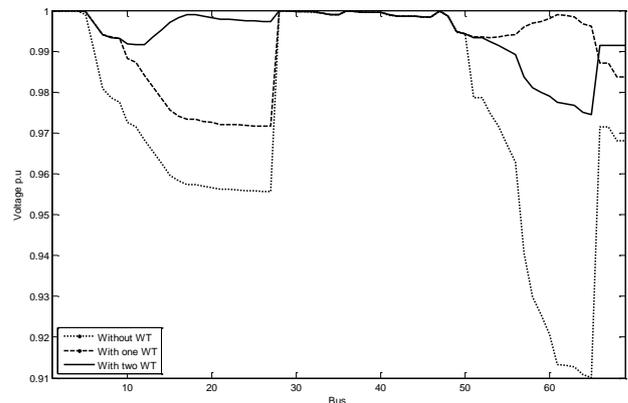


Fig. 2: Effect of WT on voltage profiles

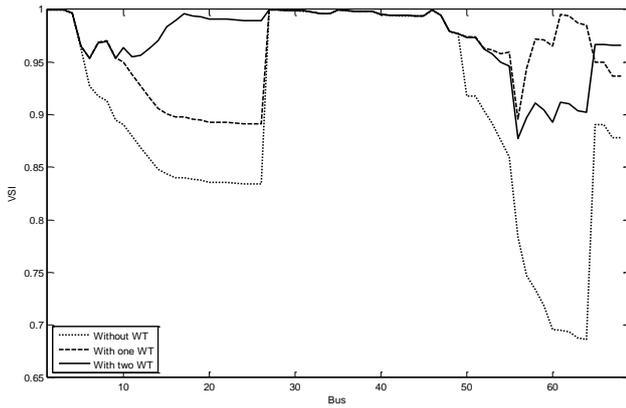


Fig. 3: Effect of WT on VSI values

4.3 Effect of Load Variations

A fixed load throughout the year represents a hypothetical circumstance, as the load configuration is impacted by seasonal and time-based fluctuations. To imitate this influence, the yearly load is modeled as an integration of three load stages with variant durations, as shown in Table 4. The DOA decides the finest sizes of WT for each load stage. Table 5 presents the values of active losses and mounted WT capabilities for the 69-bus system under changeable loads. It is obvious that losses diminish through different load stages as the number of installation locations expands.

Table 4. Time span of load variations

Load levels	L ₁	L ₂ (Base case)	L ₃
Level	0.625	1.0	1.25
time (hours)	1000	6760	1000

Table 5. Optimal positioned at various loadings

No of units	Load level	Size of WT/P.F		Losses (kW)
		61	17	
One	L ₁	1400/0.81	-	8.9149
	L ₂	2230/0.81	-	23.1524
	L ₃	2550/0.81	-	38.77
Two	L ₁	1250/0.82	400/0.82	3.0245
	L ₂	1500/0.82	700/0.82	20.9028
	L ₃	1800/0.82	900/0.82	37.3731

5 Conclusions

This paper highlights the successful application of DOA in selecting optimal position and deciding wind system ratings as a DG unit throughout the IEEE 69-bus RDS. The suggested process is constructed as an optimization issue, incorporating power loss calculations, voltage profiles, and VSI. The results attained through the DOA approach are assessed against those from various other

techniques. The analysis shows that the suggested method significantly enhances bus voltage profiles, reduces power losses, and lowers annual costs. DOA effectively identifies the prime capability and position of the wind system, achieving a loss reduction of 89.7073% with one WT installation and 90.7071% with two WT installations, outperforming other methods. Finally, the suggested DOA is reliable, and it can be deployed for variant loads requirements.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.

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