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OPTIMAL DISTRIBUTED GENERATION FOR LOSS MINIMIZATION USING SAND CAT SWARM OPTIMIZATION

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ABSTRACT

Integration of Distributed Generation (DG) into the transmission system is the current paradigm for creating unique transmission grids. Grid line loss and voltage quality may suffer from unreasonably configured DG. The aim of this paper is to rationally allocate distributed generators (DGs) in the transmission network to reduce power losses and guarantee a safe and reliable power supply to the loads. The works suggests an optimal distributed generation using Sand Cat Swarm Optimization (SCSO) for loss minimization to reduce power loss while enhancing voltage stability. The proposed algorithm was simulated and evaluated using the Matrices Laboratory (MATLAB) script programming language and has been implemented on IEEE 14-bus transmission system. The results exhibit that the SCSO method is able to determine the optimal DG size and reducing total losses by 40.77 percent for DG type 1 as compared with Particle Swarm Optimization (PSO) algorithm, 38.98% at bus 10. It can be revealed that SCSO can be used by power system planners to choose the best sizing and location.

Keywords: *Distributed Generation, Sand Cat Swarm Optimization, DG Sizing, Transmission System*

1. INTRODUCTION

Nowadays, the number of consumers and energy demand are increasing and the fossil fuels are depleting [1]. Thus, it is very important for integrating renewable sources such as Photo-Voltaic (PV) and Wind Turbine (WT) into the existing of distribution, sub-transmission and transmission network. Distributed Generation (DG) are becoming important backup sources to the existing electrical system due to reasons such as increasing power demand and advances in technology. DG can be defined as a small electrical generation that reduces real power and reactive power losses, improves voltage profile, for system security and reliability.

Several issues for example energy efficiency and security of the supply are the major concerns due to encouraging usage of renewable energy. As a result, the insertion of DG into electricity network can increase and affect the system. An increase of load demand also will increase power loss, decreasing the voltage magnitude and voltage regulation in a system. Therefore, installing of DG into electrical system is an effective way to reduce power losses and improve voltage profile. However, the selection of DG location is very essential because the unsuitable location and sizing of DG units may cause increase of power losses as well as decreasing the reliability levels. It is worth to mention that the problem of determining the optimal sizing and location of DG has catch the attention of many researchers due to its different concerns and challenges.

Over the years, several planning, operation, and control issues involving power systems have been addressed using mathematical optimization techniques. A mathematical model for resolving system optimization has been developed utilizing some assumptions from the real world. However, given the supposition that has been made, it is difficult to optimize the power system because it has a huge, intricate, and geographically dispersed structure. Simply put, mathematical methods cannot be used to solve the power system problem that is connected to large and complicated grid systems. It only works well for solving local optimization problems.

Nowadays, meta-heuristic algorithms are built using experience or intuition. The optimization problem has a workable solution when it is addressed in a reasonable amount of time or computer space. It is impossible to forecast this workable answer in advance. Numerous engineering optimization issues frequently require the best solution in the vast and complicated search area. The search for effective optimization algorithms has grown to be a significant area of research due to the complexity, nonlinearity, limitations, and modelling challenges of real-world engineering issues. Hence, to obtain the optimal value of DG, it is necessary to develop a meta-heuristic algorithm that can effectively address the complexity, non-linearities, limitations, and modelling difficulties encountered when employing conventional methods. Nature Inspired Metaheuristic Algorithm (NIMA) such as Genetic Algorithm (GA), Evolutionary Programme (EP), Firefly Algorithm (FA), Ant Lion Optimizer (ALO), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are just a few of the methods that can be used to improve to power distribution system [1]-[7].

From the literature reviewed, it can be observed that GA is computationally time-consuming [8], EP might converge on local optimum missing the global optimum solution which means it will be not consistent across several runs [9]. It can be noted that FA are slow in terms of convergence speed and likely of being stuck in local optima. Furthermore, FA does not retain or memorize any past instances of better circumstances for any individual firefly [10]. As a result, they migrate independent of past instances of better circumstances, perhaps missing their own situation. For ALO, the drawbacks are it having a long run time due to the random walking process [11]. Some of the researchers also proposed ACO for optimal sizing and location of DGs. However, ACO's performance is sensitive to the appropriate tuning of its parameters. The choice of parameters, such as the pheromone evaporation rate and exploration-exploitation trade-off, can significantly impact the algorithm's convergence speed and solution quickly [12]. Although, ACO is able to adjust to changing conditions, abrupt or significant changes could provide difficulties. Meanwhile, PSO are the most NIMA applied to solve many optimization problems but according to author in [13], PSO tend to fall into local optimum in high-dimensional space and has low convergence rate in iterative process.

Prior to these drawbacks from GA, EP, FA, ALO, ACO and PSO, a novel meta-heuristic optimization method known as Sand Cat Swarm Optimization (SCSO) was proposed in 2020 [1],[14]. The fundamental basis of this SCSO lies in the concept of the swarm algorithm that emulates the sand cat's hunting behaviors. The impact of sound frequency varies among individual sand cats. The sand cat's decision to engage in predatory behavior or search for prey is contingent upon the frequency of the potential prey's sound. Sand cats employ a hunting strategy that involves maintaining proximity to their victim. Consequently, the sand cat will inevitably reach a state of local optimum, thereby diminishing the algorithm's capacity for optimization. Sand cats utilize the concept of trigonometric function computation to determine their subsequent position by using a Roulette Wheel selection method to calculate the distance between them and their prey.

This work proposes SCSO method that may be more suited for solving the optimal sizing and location of DG for loss minimization. The SCSO is implemented on the IEEE-14 bus system, and the findings are compared to those obtained without the penetration of DG. The results display the validation, applicability, and effectiveness of the SCSO for optimal sizing and location problems.

2. SAND CAT SWARM OPTIMIZATION (SCSO)

An overview of the sand cats that served as the initial inspiration is presented in this section. The suggested method is then described together with its mathematical model and operational mechanism.

2.1 Sand Cats in Nature as Inspiration

The Felis family of mammals includes a variety of creatures, including the sand cats (Felis Margarita). The sand cat inhabits stony and sandy

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desserts such as those in the Arabian Peninsula, Central Asia Sahara, and Africa. Small, agile, and modest, sands cat has unique hunting and dwelling habits. Despite having a similar appearance to a domestic cat, sands cats behave differently from domestic cats in their lives. Like many felines, sand cats do not live in colonies. Sand to light grey fur is more densely covered on the palms and soles of the feet of the sand cat. The fur on a person's foot soles protects the pads of their feet from the extreme heat and cold of the desert. In addition, the sand cat's hair qualities make detection and tracking challenging. The body length of a sand cat is between 45 and 57 cm. The length of its tail (28-35cm) is roughly half that of its head and body, and it has short legs next to its short, sharply bent frontier claws. The sand cats back claws are longer and slightly curved when facing. An adult sand cats' weights between 1 and 3.5 kilograms. The sides of the head ear's measure 5-7cm in length. The sand cat's ears play a significant role in foraging. This cat is unique since it lives underground, at night, and in secrecy [1,14].

It is difficult for any animal to find nourishment in a hostile environment. Even though the sand cats struggle to obtain food in the desert, they are helped by the chilly night. They typically try to hunt at night and rest in the subsurface during the day. Most of the time, they spend in their burrows, but when they lie down, they release heat from within by lying on their backs. Aside from that, they get water from meals to quench their thirst. They can consume more than usual but typically ingest roughly 10 % of their body weight. The average night time distance travelled by male and female sand cats is 5.5 km and 3.2 km respectively. The average value of walking during winter is lower than it is in the summer.

2.2 Mathematical Model and Sand Cats Algorithm

The natural sand cat swarm behavior was applied to construct the Sand Cat Swarm Optimization (SCSO) algorithm method. Basically, the main behaviors of the sand cat are prey and attacking. The method was inspired by its' unique capability to recognize low-frequency disturbances. The sand cat's amazing ability to trace prey for both conditions, below and above ground is a benefit. This essential characteristic enables it to quickly locate its prey. In addition, it also captures its prey.

2.2.1 Initial Population

The relevant variables' values must be specified according to how the present problem is resolved while solving an optimization problem. A sand cat can be defined as a 1-dimensional array in a 2-dimensional optimization problem. In this study, the variable values $(x1, x2, \ldots., xd)$ is set as DG sizing where must be placed in between the lower boundaries and upper boundaries $(\nabla xi \in [lower, upper])$. Next, a candidate matrix is generated together with the population of the sand cat. The corresponds to the problem size (N_{pop} x N_d), (pop=1,….,n) to initiate the SCSO algorithm. Additionally, each sand cat's fitness cost is calculated by analyzing a specific fitness function. The relevant parameter problems are identified by fitness function. Thus, the SCSO will choose the optimal variable values. The associated function will receive a value from each sand cat. After the iteration is completed, the best solution is chosen, and subsequent iterations involve the other sand cats attempting to move in the route of this best-selected cat. Considering that, the optimal response in every iterations identifies that closest to its prey. If the subsequent iterations do not yield a better solution, the iteration's solution is not kept in memory to ensure memory efficiency [1,14]. In this study, total loss is used as a fitness function.

2.2.2 Searching The Prey

Each sand cat's location is presented by the word Pos_i. The sand cat's ability to hear low-frequency signal is advantageous to the SCSO algorithm. The low frequency below 2 kHz can be detected by every sand cat. As a result, the sensitivity range is from 2 to 0 kHz. Furthermore, the SCSO algorithm exploration as well as exploitation capability are controlled, and the parameter R is derived using formula (2). In the sensitivity range aspect, each sand cat will at random select a new site to look for prey. In this environment, algorithms can be explored and used more effectively. Sensitivity range (r) for each sand cat is unique to prevent slipping into the local optimal. This is based on formula (3).

$$rG = Sm - \left(\frac{Sm \times t}{T}\right) \quad (1)$$

$$R = 2 \times rG \times rand(0,1) - rG \quad (2)$$

Where T is the maximum iteration number, t is the current iteration number and Sm is 2.

$$r = rG \times rand(0,1) \quad (3)$$

Where rG is the guidance parameter for r.

Each sand cat will explore for its prey's location based on the best candidate position (Pos_{bc}), current position (Psoc(t)), and sensitivity range (r). The precise formula is displayed in (4).

$$Pos(t+1) = r \times (Posbc(t) - rand(0,1) \times Posc(t)) \quad (4)$$

2.2.3 Attack Prey (Exploitation)

Formula (5) states the distance (Pos_{rnd}) between the sand cat and the prey. The sand cat's sensitivity range is assumed to be circle, and the movement of its direction is determined by the Roulette Wheel election mechanism. The direction of movement can be selected by a random angle (α). The value of the randomly chosen angle, which ranges from -1 to 1, is between 0^o and 360^o. As seen in Figure 1, the direction movement for is in a different circumferential inside the search area. The prey is then attacked using a formula (6). The dune cat may get closer to its hunting position faster in this approach.

$$Posrnd = |rand(0,1) \times Posb(t) - Posc(t)| \quad (5)$$

$$Pos\ (t+1) = Pos_b(t) - r \times Pos_{rnd} \times \cos(\alpha) \quad (6)$$

2.2.4 SCSO Algorithm Implementation

The SCSO algorithm controls algorithmic exploitation as well as exploration by adjusting the adaptive parameters *rG* and *R*. Equation (1) demonstrates that *rG* is decreased linearly during iteration from 2 to 0. As a result, the random value [-4,4] is assigned to the parameter *R*. If *R* is not more than or equal to 1, the sand cat will attack its prey. In any other case, as indicated by formula (7), the sand cat will hunt prey.

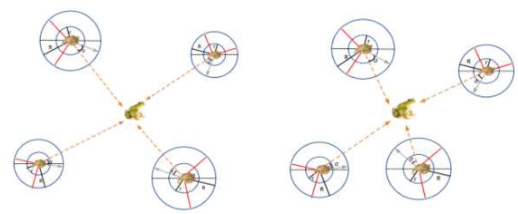

Figure 1: The SCSO Algorithm's Mechanism for Location Update a) The Sand Cat Group's Position for Iteration; b) The Sand Cat Group's Position for iteration t+1

$$Pos\ (t+1) \begin{cases} r \times (Pos_{bc}(t) - rand\ (0,1) \times Pos_c(t) & |R| > 1; Exploration \\ Pos_b(t) - Pos_{rnd} \times \cos(\alpha) \times r & |R| \leq 1; Exploitation \end{cases} \quad (7)$$

Equation (7) exhibits the location updates for each sand cat during the exploitation and exploration phases. The sand cat will attack its prey if *R≤1*. Else, the sand cat's job is to hunt for fresh prey across the global search area.

3. METHODOLOGY

The technique was simulated using MATLAB on a PC, Intel Core i5 5200 U 2.20 processor with 8 GB RAM. The simulated parameters are listed in Table 1. The worldwide optimum value is f_{min}. There are 30 separate runs for each algorithm used for the average value of each objective function, along with the maximum iteration number and population size to compare the execution of the SCSO algorithm with the other methods. Figure 2 shows the SCSO algorithm flowchart while Figure 3 shows the IEEE 14-bus system.

3.1 Problem Formulation for Loss Minimization

In this study, the primary objective function is to reduce the overall amount of power losses as much as possible as stated in (8). The problematic has different constraints due to the voltage limits as in (9) and the DG size is set to a maximum 100MW. The voltage magnitude is supposed to vary between 0.95 p.u for V_{min} and 1.05 p.u for V_{max} respectively.

$$fobj = \min(Ploss) \quad (8)$$

$$Vmin \leq V \leq Vmax \quad (9)$$

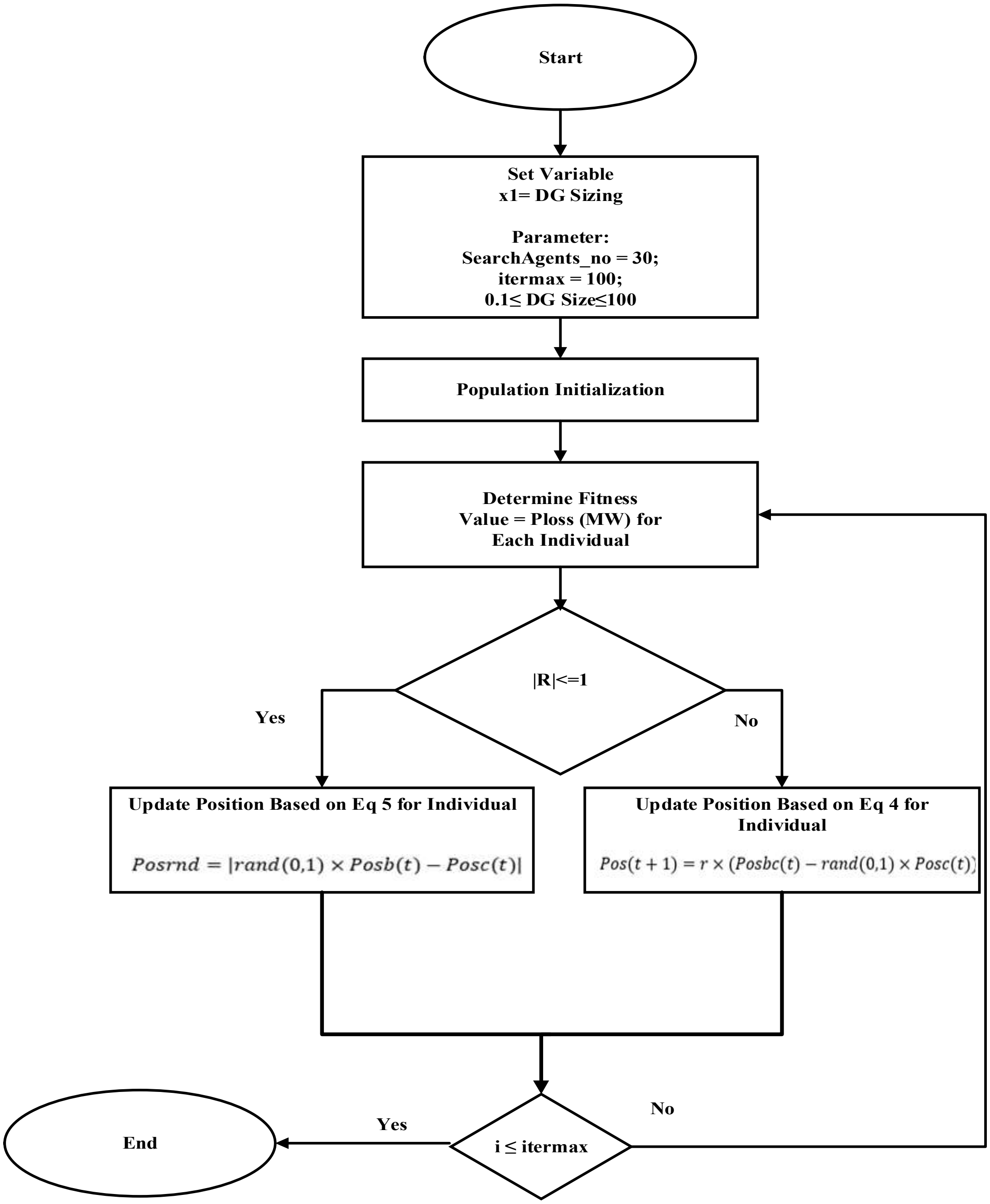

Figure 2: The Sand Cat Swarm Optimization Algorithm Flowchart

The procedure to obtain the optimal location and sizing of DG requires load flow to be run iteratively. The procedure is stopped after obtaining the best location and sizing and then the results will be recorded. The following procedures were implemented as in Figure 2 to determine the optimal sizing scheme.

The process was conducted by generating control variables using random number generation, *Xi* which represents DG sizing. The minimum and maximum DG sizing is 0.1 and 100 respectively. The population size depends on the number of individuals.

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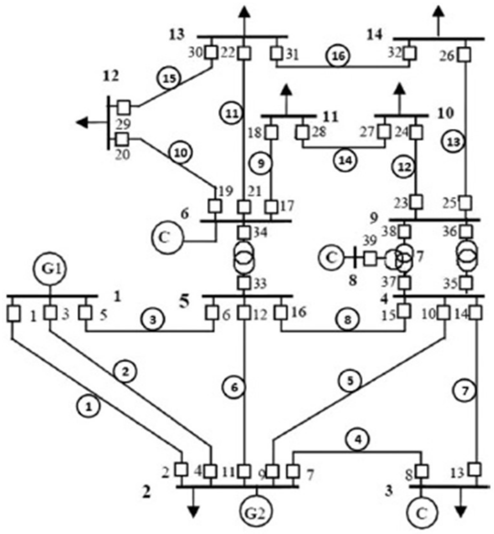


Figure 3: The Schematic of the IEEE-14 Bus System.

Table 1 indicates the case studies addressed in this paper. The installation of DG type 1(injected active power) for Case II and DG type 2 (injected reactive power) for Case III are studied to acquire the best DG installation. DG is located on buses 10 to 14 with a single DG unit. The percentage of improvement for Case II and Case III are computed by comparing the loss reduction with respect to the best-case scenario. The process frameworks for modelling DG types are illustrated in Figure 4.

The result of implementing the SCSO algorithm to the DG planning problem to determine DG size is presented in this section. The implementation of DG into the system yields the results summarized in Table 2. The effects of

***Table 1:** Case study using the SCSO algorithm for the optimal size of the DG.*

CASE	Bus Location	DG SIZE	
		Type 1 (MW)	Type 2 (MVAR)
I	Without DG	-	-
II	Bus 10 to 14	√	
III	Bus 10 to 14		√

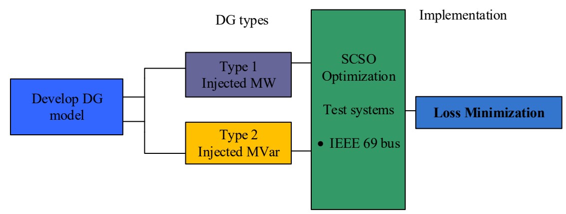


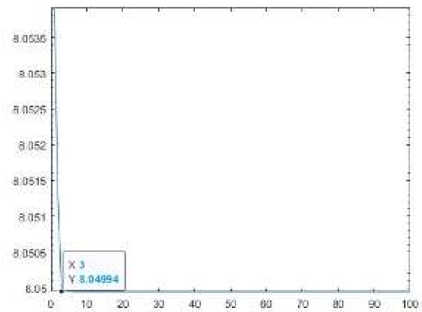
Figure 4: Implementation of DG types modeling process frameworks

3. RESULTS AND DISCUSSION

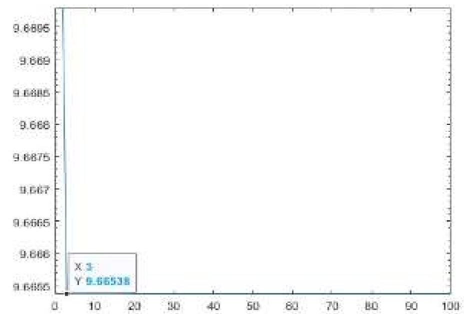
distributed generation (DG) on reducing power loss in a power distribution system are discussed. There are four columns in this table represented as Case, DG Location, DG Size (MW) and Ploss (MW).

Table 2. Simulation Results Using SCSO Algorithm For The Application Of The DG Placement.

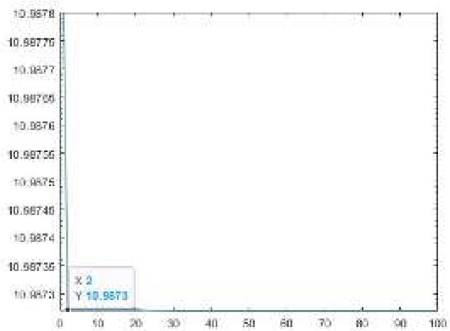
Case	DG Location	DG Size (MW)	DG Size (MVAR)	Ploss (MW)
I	-	-	-	13.59
II	10	98.4265	-	8.0499
	11	73.4605	-	9.6654
	12	47.4881	-	10.9873
	13	77.6250	-	9.0784
	14	64.6993	-	9.2587
III	10	-	16.4011	13.4371
	11	-	8.3166	13.5118
	12	-	3.2478	13.5835
	13	-	11.1279	13.4911
	14	-	10.4367	13.4483



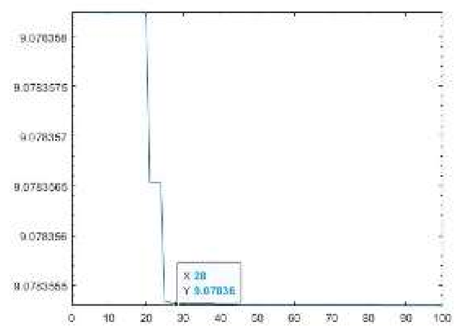
(a) Case II: DG at Bus 10



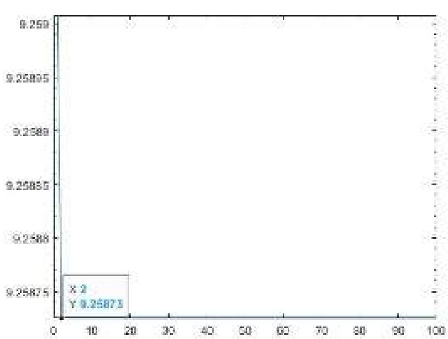
(b) Case II: DG at Bus 11



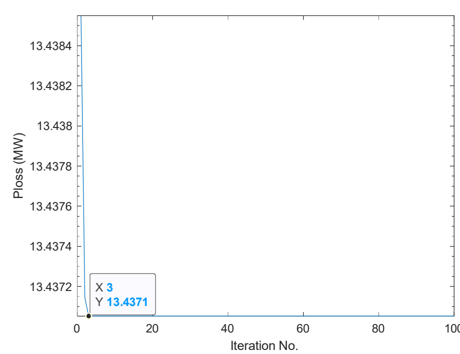
(c) Case II: DG at Bus 12



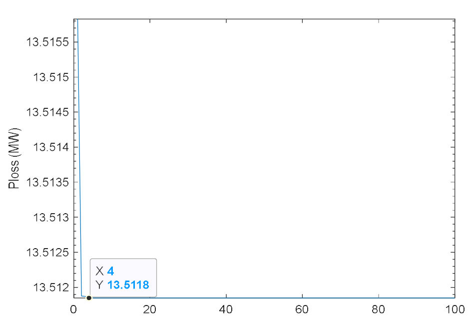
(d) Case II: DG at Bus 13



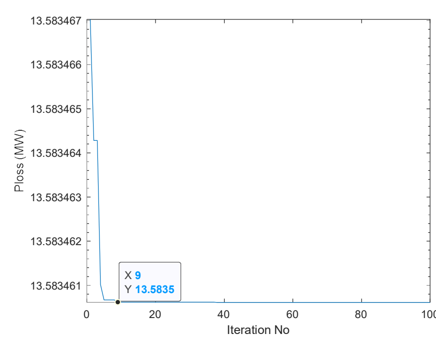
(e) Case II: DG at Bus 14



(f) Case III: DG at Bus 10



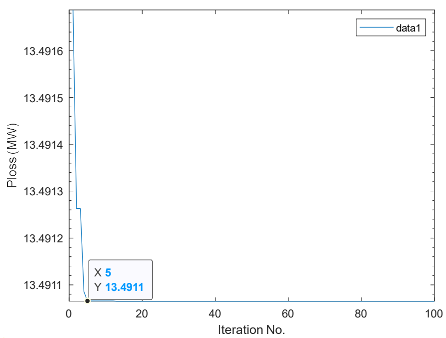
(g) Case III: DG at Bus 11



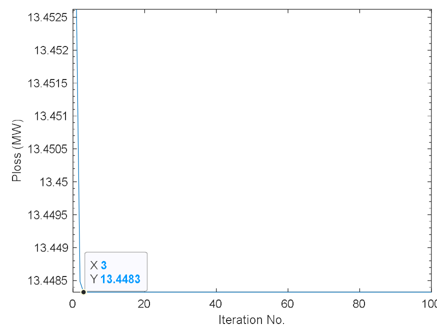
(h) Case III: DG at Bus 12

Table 3. Simulation results using PSO algorithm for the application of the DG placement.

Case	DG Location	DG Size (MW)	DG Size (MVAR)	Ploss (MW)
I	-	-	-	13.5869
II	10	93.7883	-	8.7608
	11	68.4258	-	10.4315
	12	43.9134	-	11.6734
	13	86.1558	-	9.8052
	14	60.9695	-	9.9044
III	10	-	16.4230	13.4728
	11	-	8.3246	13.5478
	12	-	3.2395	13.5775
	13	-	11.1378	13.5270
	14	-	10.4461	13.4842



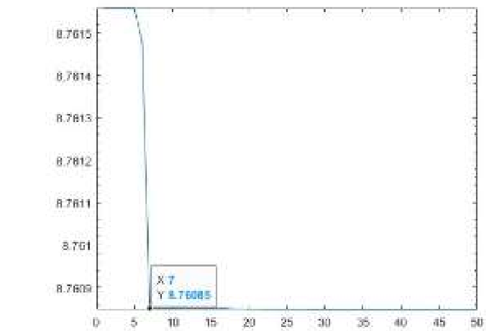
(i) Case III: DG at Bus 13



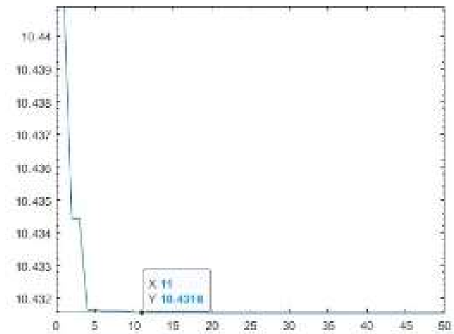
(j) Case III: DG at Bus 14

Figure 4. Convergence characteristic using SCSO for case II and III.

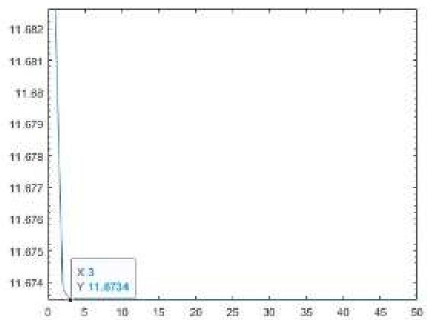
Table 2 tabulates the simulation results using SCSO algorithm with the implementation of DG for the IEEE 14 bus system. It can be observed that for case I is the base case in which no DG is implemented in the system. In this case, the power loss is 13.59 MW. Case II and III represent conditions in which DG is installed at various locations and sizes throughout the system. The percentage of improvement column displays the reduction in power loss relative to the base case. In this study, the DG location indicates where the DG is located within the system. The numbers 10,11,12,13 and 14 represent various buses where DG can be installed. The injected DG is 98.4256 MW and the loss is estimated to be 8.0499 MW. The simulation results for case III indicate a similar location to case II. The DG sizing is 16.4011 MVAR and the P_{loss} is 13.4371 MW. In terms of loss minimization, the implementation of DG type 1 (Case II) yields superior results than DG type 2 (Case III), which can reduce more losses. However, in case II, the DG size is larger than in case III. In terms of convergence characteristics, Figure 4 shows the results of SCSO for case study II and III as tabulated in Table 1. The simulation only considers the implementation of single unit of DG. The graph also indicates the iteration number at x-axis and the optimal value of the objective function, Ploss in MW at y-axis.



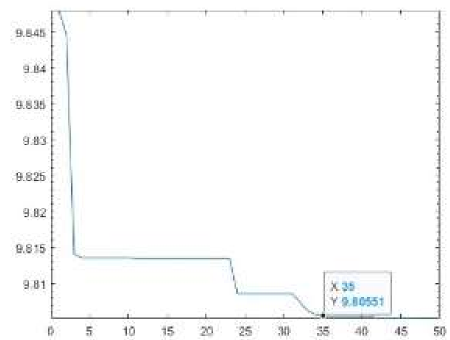
(a) Case II: DG at Bus 10



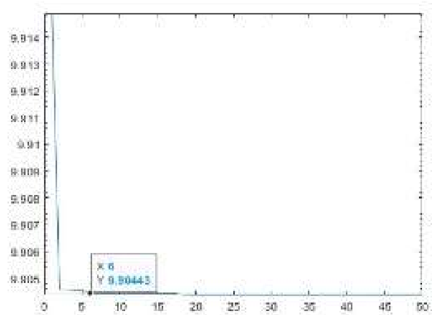
(b) Case II: DG at Bus 11



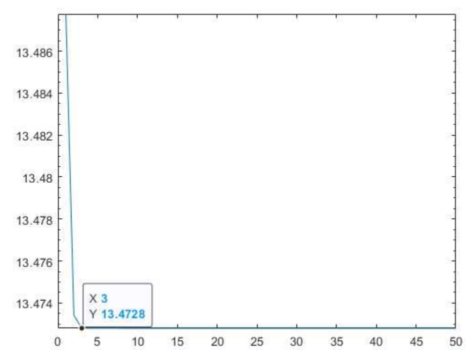
(c) Case II: DG at Bus 12



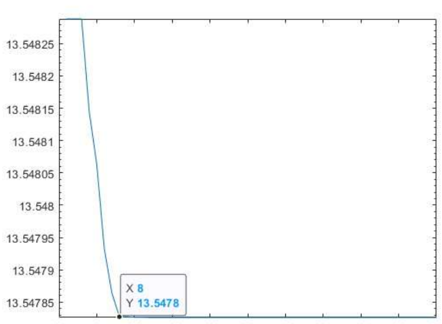
(d) Case II: DG at Bus 13



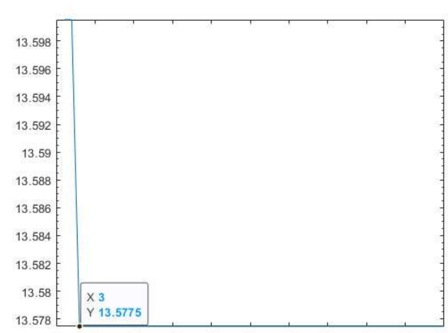
(e) Case II: DG at Bus 14



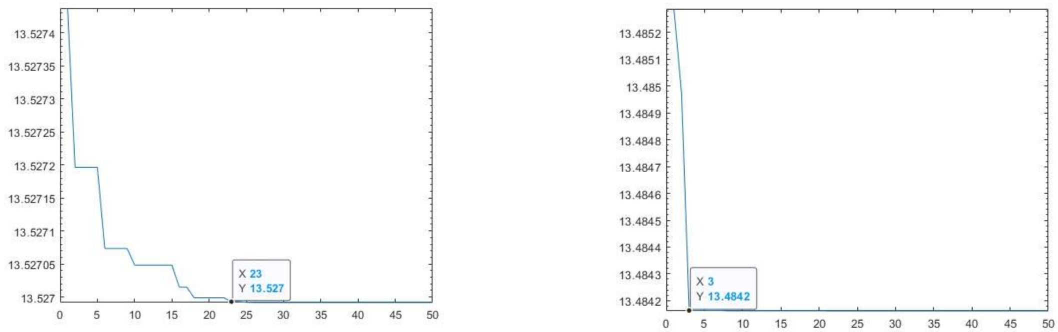
(f) Case III: DG at Bus 10



(g) Case III: DG at Bus 11



(h) Case III: DG at Bus 12



(i) Case III: DG at Bus 13

(j) Case III: DG at Bus 14

Figure 5. Convergence characteristic using PSO for case II and III.

PSO was utilized for comparison purposes to show the effectiveness of SCSO algorithm for optimal sizing and location of a single DG. Similarly, PSO was utilized and it can be noted that the power loss is 13.5869 MW as shown in Table 3. As for case II and III, it shows that DG is installed in different sizes and locations. The reduction in power loss in comparison to the base scenario is shown in the percentage of improvement column. The buses that have DG injected are represented by the bus numbers 10,11, 12, 13, and 14 respectively. For case II, DG is injected at bus 10 and the estimated active power loss is 8.7608 MW and the DG size is 93.7883 MW as indicated in the table. Case III's simulation results show that the the power loss is 13.4728 MW and the DG size is 16.4230 MVAR. In terms of losses, DG type 1 (Case II) implementation performs better than DG type 2 (Case III), which has higher losses. The PSO convergence characteristic results for case studies II and III are displayed in Figure 5.

Table 4. Comparison percentage of improvement for SCSO and PSO algorithm.

Case	Bus	% Of Improvement	
		SCSO	PSO
Case I	-	-	-
Case II	Bus 10	40.77	38.98
	Bus 11	28.96	27.35
	Bus 12	19.15	18.70
	Bus 13	33.20	31.71
	Bus 14	31.87	31.02
Case III	Bus 10	1.13	0.84
	Bus 11	0.58	0.29
	Bus 12	0.05	0.07
	Bus 13	0.73	0.44
	Bus 14	1.04	0.76

Table 4 tabulates several scenarios and the percentages of improvement for every bus. In case II, Bus 10's SCSO improved by 40.77% as compared with PSO, 38.98%. SCSO and PSO improvements for Bus 11 were 28.96% and 27.35% respectively. Bus 13's SCSO demonstrated improvement, 33.20% as compared with PSO, 31.71%. While, percentage improvement for SCSO at Bus 14 improved 31.87% as compared with PSO 31.02%.

For Case III, Bus 10 improved by 1.13% and 0.84% for SCSO and PSO, respectively and Bus 11 improved by 0.58% and 0.29% each. SCSO percentage improvement is 0.05% and PSO is 0.07% for Bus 12. For Bus 13, SCSO improved 0.73% while PSO improved 0.44%. Lastly, Bus 14 improved 0.76% in PSO and 1.04% in SCSO. Ultimately, the percentage of improvement in case II is the largest for SCSO compared to PSO, from Bus 10 until Bus 14. It can be observed that the SCSO is more superior to PSO in terms of the percentage of improvement of the power loss. As indicated in Table 4, Case II had significantly better in terms of percentage of improvement on the power loss and convergence characteristics.

4. CONCLUSION

This paper has presented the effectiveness of SCSO algorithm in solving DG sizing and location for IEEE 14-bus test system. This research formulates a three case studies which are no distributed generation (DG), DG type 1 (inject active power) and DG type 2 (inject reactive power). The study examines the implementation of DG in various locations and sizes within a system, focusing on power loss reduction. Case I shows no DG implementation, with a 13.59 MW power loss. Case

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II and III show varying DG locations and percentage of improvement. In case II, DG location at bus 10 leads to the highest percentage of improvement which is 40.77%, with a 98.4256 MW injected DG and an estimated P_{loss} of 8.0499 MW. As in comparison with PSO, DG location at bus 10 leads to 38.98% percentage of improvement with 93.7883 MW injected DG and an estimated P_{loss} of 8.7608 MW. In case III, the most optimal location using SCSO is bus 10, with a 1.13 percent improvement as compared with PSO, 0.84%. Implementing DG type 1 yields superior results, but DG size is larger in case II. As conclusion, SCSO algorithm performs better for case II and III than the PSO which is feasible to implemented in larger reliability system.

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