



New Enhanced Symbiotic Organisms Search for Optimal Location and Sizing of Distributed Generation in Radial Distribution System

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Abstract: Large distributed generation (DG) penetration into the power system needs to be accompanied by proper planning to maximize the benefits and minimize the negative effects that may arise on the system. Determining the location and size of DGs in power systems is a complex issue because it involves hundreds or even thousands of buses and lines distribution. Various studies have been conducted to overcome these problems, including by developing existing methods or even discovering new methods. This study deals with location optimization and sizing DG in the radial distribution system to minimize power loss and voltage deviation. The location of the DG is identified using a loss reduction sensitivity factor (LRSF) while the size of the DG is determined using the improved method of symbiotic organisms search (SOS) called New Enhanced SOS (NeSOS). There are two methods developed in the NeSOS, namely random weighted inverse vector (RWIV) and dual-phase parasitism (DPP). DPP consists of classic parasitism (CP) and random weight parasitism (RWP). The NeSOS is programmed under MATLAB software and validated using 26 mathematical benchmark functions. NeSOS also tested on IEEE 33 and IEEE 69 bus test system and compared with other methods. The simulation results show that the convergence rate of NeSOS is 30% faster than SOS. NeSOS also provides an average power loss of 1.53% lower than other methods.

Keywords: Benchmark function, Classic parasitism, Dual-phase parasitism, Random weight parasitism, Random weighted inverse vector.

1. Introduction

A large DG penetration into the power system provides various technical, economic, and environmental benefits. On the other hand, non-optimal DG can lead to various new problems such as difficulty in voltage control, reactive power flow management, reduced protection sensitivity, negative effects on power quality, or even reliability and stability problems [1]. The challenge of finding the proper DG location and size has long been the center of attention of researchers and engineers.

An analytical method based on power stability and voltage sensitivity index is proposed in [2]. Optimal size and DG location based on the voltage stability index and continuation power flow are presented in [3]. Zero bus load flow and current

injection approaches are proposed in [4]. The analytical formula based iteration method is presented in [5]. Although analytical methods easily handle differentiable functions, they are not capable of solving complex problems that contain non-differentiable functions which are representing real-times problems [6, 7].

The drawbacks of analytical methods accelerate the development of heuristic methods. Various heuristics methods have been developed to address this problem, such as genetic algorithms (GA) [8], particle swarm optimization (PSO) [9], artificial bee colony (ABC) [10], etc. Those well-recognized algorithms have been successful in solving complex optimization problems.

No free lunch theory (NFL) [11] shows that there is no heuristic method that can solve all optimization problems effectively. The NFL theory

opens opportunities for researchers to improve existing algorithms to solve different problems or propose new algorithms that are more competitive than existing algorithms. In the past few years, several heuristic methods were introduced including the Flower pollination algorithm (FPA) [12]; Firefly algorithm (FA) [13]; Grey wolf optimizer (GWO) [14]; Ant lion optimizer (ALO) [15]; Crow search algorithm (CSA) [16]; In addition, improved and modified versions of these methods have also been developed.

SOS was first developed by Cheng and Prayogo for complex numerical optimization [17]. Various studies show that SOS has the robustness and good convergent speed [18, 19]. Despite its many advantages, this algorithm still has shortcomings such as lack of organisms variability [20, 21], over exploration [22-24], inefficient in computational time [22, 23, 25], and imbalance between exploration and exploitation [7, 23, 24]. To overcome this problem, various improvements have been performed to the original SOS. Selection and assignment strategies are proposed in [21] to overcome the low diversification of organisms. Panda and Pani [22] proposed orthogonal parallel SOS with an augmented Lagrange multiplier. An orthogonal array is used to increase exploration capability, while parallelism is used to reduce the computational time of the algorithm. Augmented Lagrange multiplier guarantees an optimal solution is achieved. The adaptive benefit factor and the modified parasitic vector are proposed in [23] to set the balance between exploration and exploitation. A Quasi-oppositional based learning and chaotic local search are introduced by Truong [7] to improve the balance between exploration and exploitation of original SOS. A similar method is proposed by Celik [24]. To improve exploration capability, a new parasitism strategy is also utilized in the algorithm. The parasitic vector consists of two random organisms with a probability of 0.5. Elitism, random coefficients, and modified benefit factors are introduced in [25]. Elitism and random coefficient are applied to the commensalism phase. Elitism is utilized to filter the best organisms for the next generation, while the random coefficient is used to improve the convergence speed of the algorithm. The random coefficient is limited to a range of 0.4 - 0.9. The parasitism phase is also eliminated to simplify and to reduce the computational time.

In this paper, a new enhanced SOS (NeSOS) is proposed for optimal placement and sizing of DG in the radial distribution system (RDS). Many studies have shown that the most crucial problems with the original SOS are poor in the exploration rates [22-

24]. Inspired by the parasitism strategy proposed in [23, 24], this study proposes dual-phase parasitism (DPP) to increase the exploration capabilities in the parasitism phase. DPP consists of classic parasitism (CP) and random weight parasitism (RWP). Another original SOS problem is inefficient in computational time [7, 23, 24]. To overcome this problem, the search space in the phase of mutualism and commensalism is limited, as indicated in [25] by using a random weighted inverse vector (RWIV). The main contributions of this research are: 1. Using RWIV and DPP to improve SOS performance; 2. Comparing NeSOS with several methods using 26 benchmark functions. 3. Using NeSOS for two real engineering problems.

The rest of this paper is organized as follows: The SOS and NeSOS algorithms are explained in section 2. Section 3 presents NeSOS validation using 26 benchmark functions and two real engineering problems. Finally, section 4 proposes the research conclusions and future work.

2. Methodology

2.1 Overview of the SOS algorithm

SOS is an algorithm that mimics the symbiotic relationship of living things in an ecosystem [17]. The most popular symbiotic relationships are mutualism, commensalism, and parasitism. The mutualism phase describes the relationship between two organisms (X_i and X_j) in the ecosystem, which are mutually beneficial. The relationship between organisms in the phase of mutualism can be formulated as follows:

$$X_{i_new} = X_i + rand(0,1) \times (X_{best} - \mu \times bf_1) \quad (1)$$

$$X_{j_new} = X_j + rand(0,1) \times (X_{best} - \mu \times bf_2) \quad (2)$$

i and j are integers $1, 2, 3, \dots$, where $i \neq j$. X_{best} is the organism with the best fitness in the ecosystem. μ is a mutual vector, which is defined as:

$$\mu = (X_i + X_j) / 2 \quad (3)$$

bf_1 and bf_2 are benefit factors that can be calculated using:

$$bf_1 = 1 + round[rand(0,1)] \quad (4)$$

$$bf_2 = 1 + round[rand(0,1)] \quad (5)$$

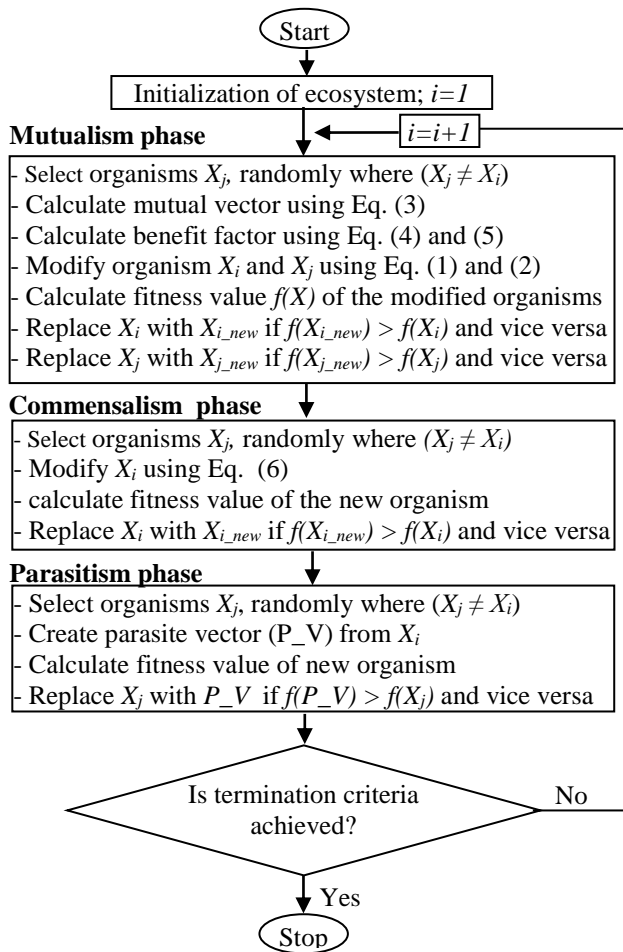


Figure.1 SOS algorithm

In the commensalism phase, the X_i organism tries to benefit from X_j . The new organism results from the interaction between X_i and X_j as shown in Eq. (6).

$$X_{i_new} = X_i + \text{rand}(-1, 1) \times (X_{best} - X_j) \quad (6)$$

The parasitism phase describes the relationship of two organisms, where one gets the advantage, while the other gets a loss. Parasitic vector (P_V) is formed from the cloning of X_i organisms that function as parasites. X_j is randomly selected to function as hosts of parasitic vectors. If parasitic vector fitness is higher than X_j , then X_j will be replaced by parasitic vector and vice versa. Fig. 1 shows the detail of the SOS algorithm.

2.2 New enhanced SOS (NeSOS)

NeSOS in this study is a development version of the original SOS. Modifications are performed in the phase of mutualism, commensalism, and parasitism. In the phase of mutualism and commensalism, modifications are performed to increase the SOS search ability by adopting random weighted differential vector (RWDV) [26] which has been

used successfully to improve the performance of the teaching-learning-based optimization algorithm (TLBO). RWDV is defined as follows:

$$RWDV = 0.5 \times [1 + \text{rand}(1, D)] \quad (7)$$

This paper proposes an RWDV modification called random weighted inverse vector (RWIV):

$$RWIV = 1 - 0.5 \times [1 - \text{rand}(1, D)] \quad (8)$$

RWIV is a random number (0.5:1). D is a dimension. Using Eq. (8), then Eq. (1) and (2) in the phase of mutualism are formulated as follows:

$$X_{i_new} = X_i + RWIV \times (X_{best} - \mu \times bf_1) \quad (9)$$

$$X_{j_new} = X_j + RWIV \times (X_{best} - \mu \times bf_2) \quad (10)$$

Adopting RWIV in Eq. (8), then Eq. (6) in the phase of commensalism is formulated as follows:

$$X_{i_new} = X_i + RWIV \times (X_{best} - X_j) \quad (11)$$

Modifications in the parasitism phase were carried out to narrow the search space by adopting random weight (RW) from the crow search algorithm (CSA) [16]. Askarzadeh uses RW to determine individual distances in m and $m+1$ iterations. The RW is formulated as follows:

$$RW = \text{rand}(0, 1) \times \text{rand}(a, b) \quad (12)$$

a and b in Eq. (12) are specified by the user. In this paper, $a = -2$ and $b = 2$. Using Eq. (12), the new position of the organism in the parasitism phase can be written as follows:

$$X_{i_new} = X_i + RW \times (X_{best} - X_i) \quad (13)$$

Pseudocode of parasitism phase	
1:	Generate a random number
2:	if $\text{rand} < 0.5\%$ classic parasitism sub-phase
3:	Generate parasitic_vector
4:	Evaluate parasitic_vector fitness
5:	Select the fittest organism
6:	else % random weight sub-phase
7:	Generate random weight_vector using (13)
8:	Evaluate the fitness of random weight_vector
9:	Select the fittest organism
10:	end if

Figure 2. Pseudocode of parasitism phase

To increase individual variability, the parasitism phase is divided into two sub-phases (dual phase parasitism), namely RWP and CP. RWP is a parasitism phase that uses Eq. (13) as a parasitic vector, while CP follows the parasitism phase of the original SOS. Modifications to the parasitism phase are explained in Fig. 2.

3. NeSOS validation

NeSOS validation is performed in two stages. In the first stage, NeSOS performance is tested using 26 complex mathematical functions. The second stage using real problems in the field of electrical engineering. In this section, NeSOS is used to optimize DG location and size by using the IEEE 33 and IEEE 69 bus testing systems.

3.1 Benchmark function

The performance of the proposed algorithm is tested using 26 benchmark functions as shown in Table 1[17]. Functions 1 through 11 are 2 dimensions, whereas functions 12 and 13 are 4 and 5-dimensional functions respectively. Functions 14 and 15 are 10-dimensional functions, and the rest are 30-dimensional functions.

3.1.1. The effect of RWIV and DPP

To determine the effect of RWIV and DPP in the algorithm, a performance test is conducted on SOS, RWIV, and DPP using the Ackley function. Ackley has a dimension of 30 and a minimum value of 0 [17]. The SOS parameters used are: Ecosystem number (n) = 50; Maximum of iteration = 3000; Error = 1×10^{-12} . The algorithm is run 20 times for each scheme. The algorithm stops if the error is smaller than 1×10^{-12} or the iteration equals the maximum iteration. The best fitness, mean, standard deviation (SD), and iterations average (Iter avg) are

Table 1. Benchmark function

No	Function	No	Function
1	Beale	14	Zakharov
2	Easom	15	Michalewicz10
3	Matyas	16	Step
4	Boha chevsky1	17	Sphere
5	Booth	18	Sum squares
6	Michalewicz2	19	Quartic
7	Schaffer	20	Schwefel 2.22
8	Six Hump Camel Back	21	Schwefel 1.2
9	Bohachevsky2	22	Rosenbrok
10	Bohachevsky3	23	Dixon-Price
11	Schubert	24	Rastrigin
12	Colville	25	Griewank
13	Michalewicz5	26	Ackley

Table 2. The effect of RWIV and DPP in the algorithms

Description	Original SOS	RWIV	DPP
Best Fitness	6.8301E-13	2.564E-14	3.7748E-13
Mean	1.13669E-12	7.16399E-13	7.68275E-13
SD	4.18995E-13	2.31214E-13	1.94675E-13
Iter avg	98.75	60.95	58.55

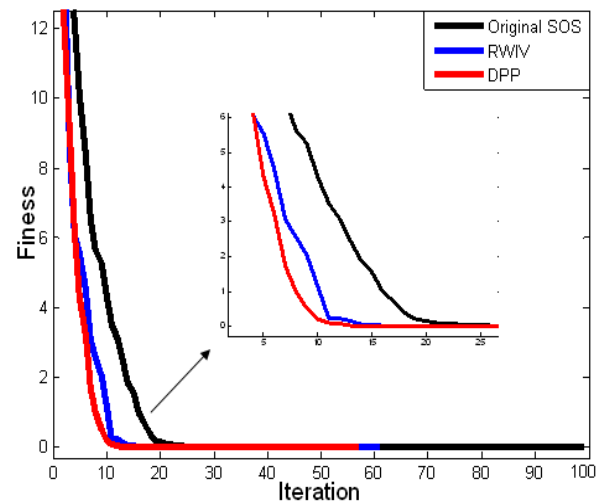


Figure.3 Convergence curve of SOS, RWIV and DPP

reported in Table 2. The convergence curve of SOS, RWIV and DPP are shown in Fig. 3.

The mutualism and commensalism phases play an important role in the process of exploitation of organisms to reach the expected convergence point. Random numbers in Eq. (1), (2) and (6) are very important in controlling the speed of algorithm convergence, but they have a wide search range so that the search space becomes large. As a result, the convergence speed becomes low. Table 2 and Fig. 3 show that narrowing the search space in the range of 0.5 to 1 using RWIV causes the convergence curve to decrease drastically, the iteration becomes smaller thereby saving computing time. In addition, the best fitness, mean and SD are better than original SOS.

The DPP Strategy in parasitism phase allows the algorithm to explore different regions of the search space while avoiding population concentration in high fitness areas, by offering around 50% of new organisms from RWP. As seen in Table 2 and Fig. 3, the DPP strategy causes the convergence curve to decrease dramatically and the number of iterations to reach the global optimum is lower. The best fitness, average and SD are better than original SOS which uses classical parasitism.

3.1.2. Validation using 26 benchmark functions

To validate the performance of the proposed algorithm, the optimization results use 26

Table 3. Comparison of NeSOS and other algorithms

No	Function	Min	Description	GA[17]	PSO[17]	BA[17]	DE[17]	SOS	NeSOS
1	Beale	0	Mean	0	0	1.88E-5	0	0	0
			SD	0	0	1.94E-5	0	0	0
			Iter avg	NA	NA	NA	NA	52.92	15.88
2	Easom	-1	Mean	-1	-1	-0.99994	-1	-1	-1
			SD	0	0	4.5E-5	0	0	0
			Iter avg	NA	NA	NA	NA	56.24	19.2
3	Matyas	0	Mean	0	0	0	0	0	0
			SD	0	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	23.64	9.8
4	Boha- chevsky1	0	Mean	0	0	0	0	0	0
			SD	0	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	24.88	12.68
5	Booth	0	Mean	0	0	0.00053	0	0	0
			SD	0	0	0.00074	0	0	0
			Iter avg	NA	NA	NA	NA	88.28	88.44
6	Micha- lewicz2	-1.8013	Mean	-1.8013	-1.57287	-1.8013	-1.8013	-1.8013	-1.8013
			SD	0	0.11986	0	0	0	0
			Iter avg	NA	NA	NA	NA	14.96	6.84
7	Schaffer	0	Mean	0.00424	0	0	0	0	0
			SD	0.00476	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	99.92	16.84
8	Six Hump Camel Back	-1.03163	Mean	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163	-1.03163
			SD	0	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	47.88	14.92
9	Boha- chevsky 2	0	Mean	0.06829	0	0	0	0	0
			SD	0.07822	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	22.8	11.8
10	Boha- chevsky 3	0	Mean	0	0	0	0	0	0
			SD	0	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	32.2	12.8
11	Schubert	-186.73	Mean	-186.73	-186.73	-186.73	-186.73	-186.73	-186.73
			SD	0	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	144.32	11.52
12	Colville	0	Mean	0.01494	0	1.11760	0.04091	0	0
			SD	0.00736	0	0.46623	0.081898	0	0
			Iter avg	NA	NA	NA	NA	1325.76	40.12
13	Micha- lewicz 5	-4.6877	Mean	-4.64483	-2.49087	-4.6877	-4.68348	-4.6877	-4.6877
			SD	0.09785	0.25695	0	0.01253	0	0
			Iter avg	NA	NA	NA	NA	127.44	213.44
14	Zakharov	0	Mean	0.01336	0	0	0	0	0
			SD	0.00453	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	75.56	21.92
15	Micha- lewicz 10	-9.6602	Mean	-9.49683	-4.00718	-9.6602	-9.59115	-9.6602	-9.6602
			SD	0.14112	0.50263	0	0.06421	0	0
			Iter avg	NA	NA	NA	NA	1394.2	1126.68
16	Step	0	Mean	1.17E+03	0	5.12370	0	0	0
			Stdv	76.56145	0	0.39209	0	0	0
			Iter avg	NA	NA	NA	NA	184.8	223.44
17	Sphere	0	Mean	1.11E+03	0	0	0	0	0
			SD	74.21447	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	60.08	23.04
18	Sum squares	0	Mean	1.48E+2	0	0	0	0	0
			SD	12.40929	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	56.8	22.28
19	Quartic	0	Mean	0.18070	0.00116	1.72E-6	0.00136	7.41498E-05	1.43324E-05
			SD	0.0271	0.00028	1.85E-6	0.00042	1.72271E-09	6.54271E-11
			Iter avg	NA	NA	NA	NA	3000	3000
20	Schwefel 2.22	0	Mean	11.0214	0	0	0	0	0
			SD	1.38686	0	0	0	0	0

			Iter avg	NA	NA	NA	NA	101.08	38.72
21	Schwefel 1.2	0	Mean	7.40E+3	0	0	0	0	0
			SD	1.14E+3	0	0	0	0	0
			Iter avg	NA	NA	NA	NA	63.96	24.52
22	Rosen- brok	0	Mean	1.96E+5	15.088617	28.834	18.20394	0.270040821	0
			SD	3.85+4	25.170196	0.10597	5.03619	0.11285849	0
			Iter avg	NA	NA	NA	NA	3000	1232.48
23	Dixon Price	0	Mean	1.22E+3	0.66667	0.66667	0.66667	0.666666667	0.666666667
			SD	2.66E+2	1E-8	1.16E-9	1.E-9	0	0
			Iter avg	NA	NA	NA	NA	3000	3000
24	Rastrigin	0	Mean	52.92259	43.97714	0	11.71673	0	0
			SD	4.56486	11.72868	0	2.53817	0	0
			Iter avg	NA	NA	NA	NA	93.48	24.4
25	Griewank	0	Mean	10.63346	0.01739	0	0.00148	0	0
			SD	1.16146	0.02081	0	0.00296	0	0
			Iter avg	NA	NA	NA	NA	62.04	23.48
26	Ackley	0	Mean	14.67178	0.16462	0	0	0	0
			SD	0.17814	0.49387	0	0	0	0
			Iter avg	NA	NA	NA	NA	99.08	38.6

Note: NA=not available

benchmark functions compared to the GA, PSO, Bees Algorithm (BA), Differential Evolution (DE) and original SOS. NeSOS was built using the Matrix Laboratory software. This program is run using a laptop with a Core 2 Duo processor and 2.0 GB RAM. The parameter settings used for GA, PSO, BA, and DE follow [17], while for original SOS, and NeSOS are as follows: Ecosystem number (n)=50; Maximum of *iteration* = 3000; *Error* = 1×10^{-12} . The algorithm is run 30 times for each benchmark function. The algorithm stops if the error is smaller than 1×10^{-12} or the iteration equals the maximum iteration. The mean, standard deviation (SD) and iteration average (iter avg) are indicated in Table 3. Bolded numbers represent the best value for each function. Mean and SD values smaller than 1×10^{-12} are considered the same as zero [17].

Table 3 shows that the proposed algorithm is more competitive compared to GA, PSO, BA, DE, and SOS. NeSOS can converge on 24 functions (except Quadratic and Dixon Price function), while SOS converge on 23 benchmark functions. GA has the worst performance, only converging on 10 of the 26 benchmark functions. PSO, DE, and BA are able to converge on 17, 18 and 19 benchmark functions respectively. GA, PSO, DE, and BA have difficulty converging on functions with larger dimensions such as Quadratic, Rosenbrok and Dixon Price functions. Although NeSOS on the Quadratic function does not reach the required error, it produces better values compared to GA, PSO, BA, DE, and SOS. For converging speed, NeSOS excels on 21 benchmarks, while SOS excels only on 3 benchmarks, namely: Step, Michalewicz 5, and Booth function. The use of RWIV and DPP

accelerates the convergence rate of NeSOS 30% faster than SOS.

3.2 Optimal location and size of DG

NeSOS performance will be tested using location optimization and DG size on the IEEE 33 and IEEE 69 bus test system. The IEEE 33 bus radial distribution system consists of 32 lines and 33 buses. The total load connected to the IEEE 33 bus system is 3.72 MW and 2.3 MVar. The IEEE 69 bus system consists of 68 lines and 69 buses. The total load connected to the system is 3.8 MW and 2.69 MVar. The optimization results using NeSOS are compared with the improved analytic method (IA), PSO, hybrid analytic-PSO (hybrid), and SOS method [28].

3.2.1 Objective functions and constraints

In the distribution systems, active power loss depends on the resistance and line current. High line resistance results in a large power loss and voltage deviations. The objective function of DG optimization is active power loss reduction:

$$F = \min\left(\sum_{i=1}^n \sum_{j=2}^n I_{ij}^2 R_{ij}\right) \quad (14)$$

Optimization is performed to determine the location and size of DG by minimizing the objective function in Eq. (14). The objective function must meet the following constraints:

- The number of DG (N_{DG}) must less or equal to the maximum number of DG ($N_{DG \max}$).

$$N_{DG} \leq N_{DG \max} \quad (15)$$

- b. The active power of DG (P_{DG}) is limited by its minimum ($P_{DG\max}$) and maximum ($P_{DG\min}$) limits.

$$P_{DG\max} \leq P_{DG} \leq P_{DG\min} \quad (16)$$

- c. The total power generated by initial sources (P_g) and DG units (P_{DG}) must cover the total load demand (P_d) and power loss (P_{loss}).

$$P_g + P_{DG} = P_d + P_{loss} \quad (17)$$

- d. The voltage on each bus i (V_i) is limited by its minimum (V_i^{\min}) and maximum (V_i^{\max}) limits.

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (18)$$

3.2.2. Identification of DG locations

The most difficult part in optimizing DG placement is determining the right locations of DG so that the objective function is optimal. For single DG, the possible combination of DG locations is the same as the number of buses in the system, so it is easy to determine. The number of DG location combinations will increase with increasing DG numbers, making it even more complicated.

Various approaches have been developed in determining DG locations. In this paper, the loss reduction sensitivity factor (LRSF) is used to identify the location of DG. LRSF value due to DG injection on the bus i is formulated as follows [27]:

$$LRSF_i = \frac{P_{Loss}^i - P_{Loss}^b}{P_{DG,i}^{inj}} \quad (19)$$

P_{Loss}^i = network loss due to DG injection on the bus i , P_{Loss}^b = system loss prior to DG injection and $P_{DG,i}^{inj}$ = power injected by DG on the bus i .

The steps to determine the optimal DG location on a distribution system using LRSF are as follows:

1. Determine the number, size, and DG capacity.
2. DG injection into the distribution system using one DG. DG capacity is gradually increased and the LRSF value for each bus is recorded until the DG capacity is met.
3. Determine the optimal DG location based on the smallest LRSF value in step 2.
4. Install DG in the optimal location according to step 3.
5. Continue steps 2-4 for the next DG unit, until all DG locations are known.

Table 4. LRSF and DG location for IEEE 33 bus System

Scheme	DG Location	Size (MW)	LRSF
1 DG	6	2.550	-0.0386
2 DG	13	0.850	-0.0265
	30	0.850	-0.0439
3 DG	13	0.850	-0.0265
	30	0.850	-0.0439
	24	0.850	-0.0499

Table 5. LRSF and DG location for IEEE 69 bus System

Scheme	DG Location	Size (MW)	LRSF
1 DG	61	1.80	-0.0215
2 DG	17	0.50	-0.087
	61	1.80	-0.0215
3 DG	11	0.50	-0.1106
	17	0.50	-0.0870
	61	1.80	-0.0215

Following the procedures above, the lowest LRSF and optimal locations of DG for IEEE 33 and IEEE 69 bus systems are presented in Table 4 and Table 5.

3.2.3. Optimal sizing of DG

After determining the optimal location of DG using LRSF, optimal sizing of DG is performed using back-forward load flow and NeSOS. The type of DG used is DG which is only capable of injecting real power. The optimization scheme consists of 3 schemes, namely 1 DG, 2 DG, and 3 DG. The optimization results are compared with hybrid PSO, PSO, IA, and SOS. The parameter settings for NeSOS and SOS are: Ecosystem number (n) = 50; maximum of iteration = 100. The algorithm is run 10 times for each scheme. Parameter settings for PSO, hybrid PSO and IA follow parameters in [28]. Tables 6 and 7 show the results of DG optimization for the IEEE 33 and the IEEE 69 bus system.

IA is an analytical method based on mathematical expressions that integrates the DG model into the load flow. It is well known that analytic methods have limitations in mathematical modelling for non differential or complex problems, which affects inaccurate results. The hybrid method combines analytic and PSO methods. PSO is used to determine the location while DG size is determined using analytic methods. PSO has precisely determined the optimal DG location, but the analytic method failed to determine the DG size accurately. PSO itself has problems with many parameters that need to be adjusted to ensure a balance between exploration and exploitation. The improper parameters settings affect the accuracy of the PSO results. Unlike PSO, NeSOS does not have special control parameters, so this algorithm is robust and

Table 6. Optimal location and size of DG on IEEE 33 bus System

Scheme	Method	Bus Location	Size (MW)	Capacity (MW)	Power Loss(kW)	Loss Reduction (%)	Iteration
No DG	-	-	-	-	211	-	-
1 DG	Hybrid [28]	6	2.49	2.49	111.7	50.356	NA
	PSO [28]	6	2.59	2.59	111.03	50.653	NA
	IA[28]	6	2.60	2.6	111.1	50.622	NA
	SOS	6	2.59	2.59	111.02	50.658	4.3
	NeSOS	6	2.59	2.59	111.02	50.658	2.5
2 DG	Hybrid [28]	13 30	0.83 1.11	1.94	87.28	61.209	NA
	PSO [28]	13 30	0.85 1.16	2.01	87.17	61.258	NA
	IA[28]	6 14	1.80 0.72	2.52	91.63	59.276	NA
	SOS	13 30	0.852 1.158	2.01	87.16	61.262	21.9
	NeSOS	13 30	0.852 1.158	2.01	87.16	61.262	9.2
3 DG	Hybrid [28]	13 24 30	0.79 1.07 1.01	2.87	72.89	67.604	NA
	PSO [28]	13 24 30	0.77 1.09 1.07	2.93	72.79	67.649	NA
	IA[28]	6 12 31	0.90 0.90 0.72	2.52	81.05	63.978	NA
	SOS	13 24 30	0.802 1.091 1.054	2.947	72.78	67.653	32.5
	NeSOS	13 24 30	0.802 1.091 1.054	2.947	72.78	67.653	13.7

Note: NA=not available

Table 7. Optimal location and size of DG on IEEE 69 bus System

Scheme	Method	Bus Location	Size (MW)	Capacity (MW)	Power Loss(kW)	Loss Reduction (%)	Iteration
No DG	-	-	-	-	225	-	-
1 DG	Hybrid [28]	61	1.81	1.81	83.37	62.947	NA
	PSO [28]	61	1.87	1.87	83.22	63.013	NA
	SOS	61	1.872	1.872	83.22	63.013	1.8
	NeSOS	61	1.872	1.872	83.22	63.013	1.6
2 DG	Hybrid [28]	17 61	0.52 1.72	2.24	71.80	68.089	NA
	PSO [28]	17 61	1.78 0.53	2.31	71.68	68.142	NA
	SOS	17 61	0.531 1.781	2.31	71.67	68.145	14.3
	NesOS	17 61	0.531 1.781	2.31	71.67	68.145	5.2
3 DG	Hybrid [28]	11 17 61	0.510 0.38 1.67	2.56	69.54	69.09	NA
	PSO [28]	11 17 61	0.460 0.44 1.70	2.60	69.54	69.09	NA
	SOS	11 17 61	0.527 0.381 1.719	2.626	69.43	69.14	24.6
	NeSOS	11 17 61	0.527 0.381 1.719	2.626	69.43	69.14	10.5

Note: NA=not available

has a good convergence speed. The integration of RWIV and DPP increases the computational time efficiency and accuracy of the NeSOS. As seen in Table 6, NeSOS has a better performance compared to Hybrid, PSO, IA, and SOS. For accuracy, NeSOS and SOS excel in all schemes of optimization.

NeSOS and SOS provide the smallest loss compared to Hybrid, PSO and IA methods. NeSOS and SOS resulted in loss 111.02 kW, 87.16 kW and 72.78 kW for schemes 1, 2 and 3 respectively. DG injection into the power system, in addition to minimizing power loss, also improves voltage deviation. The minimum bus voltage before DG injection is 0.903 pu on bus 18. DG injection increases the minimum bus voltage to 0.94 pu, 0.96 pu and 0.97 pu for the first, the second, and the third scheme respectively. The bus voltages before and after DG injection are shown in Fig. 4. In terms of convergence speed,

NeSOS is 52.6% faster than SOS. Curve convergence of NeSOS and SOS are shown in Fig. 5.

Optimization DG using IEEE 69 bus test system, NeSOS and SOS produce the smallest loss in the second and the third scheme, while in the first scheme NeSOS produce the same value as SOS and PSO. Power loss before DG placement is 225 kW. DG injection resulted in a reduction in loss of 83.22 kW, 71.67 kW and 69.43 kW for the first, the second and the third scheme respectively.

The reduction of power loss is also followed by an increase in bus voltage. The minimum bus voltage before placement of DG is 0.908 pu on bus 65. DG injection on bus 61 of 1.872 MW significantly increases the system bus voltage. The minimum bus voltage is 0.968 pu. DG injection on

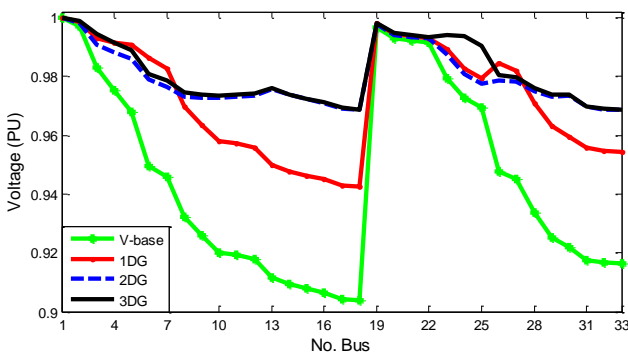


Figure. 4 Bus voltages before and after DG placement on the IEEE 33 bus system

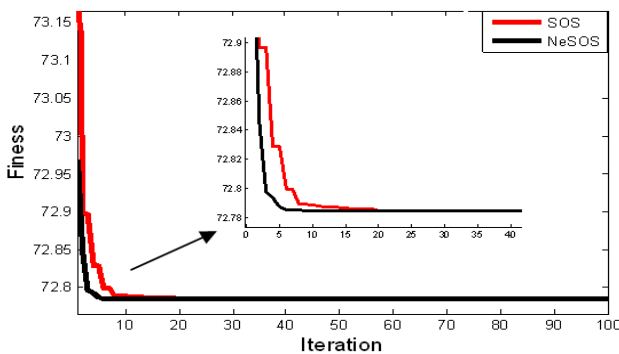


Figure. 5 Curve convergence of NeSOS and SOS

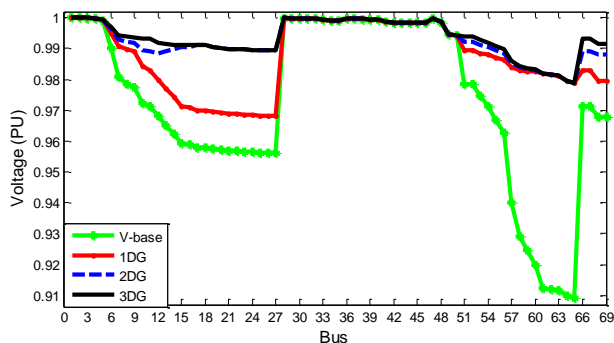


Figure. 6 Bus voltages before and after DG placement on the IEEE 69 bus system

buses 17 and 61 with a total of 2.31 MW produces a minimum bus voltage of 0.978 pu. Scheme 3 does not provide a significant increase in bus voltage. The minimum bus voltage is 0.979 pu. The bus voltage before and after DG placement on the IEEE 69 bus system is shown in Fig. 6. In terms of convergence speed, NeSOS is superior to SOS. NeSOS is 44.04% faster than SOS on average.

4. Conclusions

This research proposes improvements to the original SOS by using RWIV and DPP called NeSOS. RWIV and DPP are used to increase the variability of organisms in the ecosystem so that an optimal global is achieved. The validation results using 26 benchmark functions show that NeSOS is

superior both in terms of accuracy and convergence speed. NeSOS can converge on 24 of 26 benchmark functions with better accuracy than other methods. For converging speed, NeSOS excels on 21 benchmarks, while SOS excels only on 3 benchmarks function. NeSOS is 30% faster than SOS. NeSOS validation on DG location and size optimization shows that NeSOS has succeeded in providing the smallest loss. NeSOS provides an average power loss of 1.53% lower than other methods. Based on the results of the validation, it can be concluded that NeSOS has a higher capability in finding optimal solutions.

For further studies, it will be interesting to hybridize the SOS algorithm with other algorithms to improve its performance. In addition, comparisons with other SOS variants that exist in various kinds of literature need to be studied more deeply to check the effectiveness of the proposed algorithm. Implementation of the NeSOS algorithm in solving more complex engineering problems will be further work.

Conflicts of Interest

This article has not been published and is not under consideration for publication elsewhere. All authors have read and approved the manuscript and take full responsibility for its content. The authors have no conflict of interest in regard to this research or its funding.

Author Contributions

Conceptualization, Umar Umar; methodology, Umar Umar; software, G. Setyawan and Dimas Fajar U.P; validation, Faanzir Faanzir, Firdaus Firdaus, and Dimas Fajar UP; formal analysis, Umar Umar, and G. Setyawan; investigation, G. Setyawan; resources, Faanzir Faanzir, and Firdaus Firdaus; data curation, Faanzir Faanzir, and Firdaus Firdaus; writing—original draft preparation, Umar Umar; writing—review and editing, Umar Umar, Adi Soperijanto, and Ontoseno Penangsang; visualization, Umar Umar and Dimas Fajar U.P; supervision, Adi Soperijanto, and Ontoseno Penangsang; funding acquisition, Faanzir Faanzir, and Firdaus Firdaus.

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